ECONOMIC EFFECTS OF COVID-19 RELATED UNCERTAINTY SHOCKS

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ECONOMIC EFFECTS OF COVID-19 RELATED UNCERTAINTY SHOCKS

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EDITORIAL
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Editorial: Economic Effects of COVID-19 Related Uncertainty Shocks

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Keywords: outcomes of the COVID-19 pandemic, economic effects of the COVID-19, effects of the COVID-19 pandemic on financial market, effects of pandemics on businesses, COVID-19 related uncertainty shocks

Editorial on the Research Topic

Economic Effects of COVID-19 Related Uncertainty Shocks

In recent years, the world economy has also witnessed the rise in economic and policy uncertainty due to Brexit, the deceleration of growth in the Chinese economy, the Trump administration's trade policy. There are now more massive uncertainty shocks of the COVID-19 in every aspect of the economic system. Both developed and developing economies are experiencing risks and uncertainties due to the significant effects of the COVID-19. This Research Topic aims to understand the consequences of uncertainty shocks related to the COVID-19. The main objective of this Research Topic is to try to provide different aspects and consequences of the COVID-19 pandemic. The Research Topic contains 26 papers.

This Research Topic includes several papers on the determinants and the outcomes of the COVID-19 pandemic. Gorain et al. discuss the fighting strategies against the COVID-19 pandemic at the global level. Meng observe the different country clusters for the measures of the COVID-19 outcomes in the G20 economies. Jiang et al. find that the health levels in the United States and the United Kingdom are not significantly affected by the COVID-19-related shocks. Zhai et al. observe that conflicts are the main driver of the mortality risk of the COVID-19 in 120 countries. Wang et al. show that the COVID-19 pandemic causes geopolitical risks in 18 emerging economies. Fang et al. use the trend analysis data from the Baidu search engine to predict the pattern of the COVID-19 pandemic in China.

The Research Topic also covers several papers on the economic effects of the COVID-19 pandemic. Wu finds that pandemics-related uncertainty, measured by the Pandemic Uncertainty Index, negatively affects household consumption in 138 countries. Li and Liang observe that uncertainties related to the COVID-19, measured by the World Pandemic Uncertainty Indices, are positively related to fiscal support in 129 countries. Li Y. et al. discuss the efficiency of monetary policy implications in Brazil, China, India, Japan, and the United Kingdom during the pandemics. Chen, Lau et al. show that the pandemics-related uncertainty is positively related to the income inequality in 34 OECD economies, but the impact is negative in 107 non-OECD countries. Regarding China, where the COVID-19 pandemic first hit the economy, Shen et al. observe the significant divergence of the trend of disposable income across the Chinese cities during the COVID-19 pandemic. Li J. et al. also predict that the monthly income of migrant workers in China will be reduced due to the COVID-19 pandemic.

This Research Topic also includes several papers on the effects of the COVID-19 pandemic on financial markets. Liu and Guo show the positive impact of inclusive finance on public health in the Chinese regions during the pandemics. Pan et al. examine the possible determinants of tourism

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stock returns in China during the COVID-19 era. Ye et al. compare different models to estimate the equity performances of the health insurance companies in China during the COVID-19 pandemic. Meng et al. observe that the confirmed cases cause public searches for the COVID-19 tests, which also causes fluctuations in the infectious disease equity market volatility tracker in the United States. Wang et al. also find that the United States Dollar (USD) and the volatility indices (VIX) decrease the S&P 500 equity returns during the COVID-19 crisis. However, the newspaper-based infectious disease equity market volatility tracker is positively associated with stock market returns in the United States. Chen, Gozgor et al. also show that the economic policy uncertainty in China has a positive impact on the returns of Bitcoin during the COVID-19 era, i.e., from December 31, 2019 to May 20, 2020. Algamdi et al. find that the COVID-19 related deaths have negatively affect crude oil prices, and this evidence has provided economic implications on Saudi Arabia and the United States.

Finally, the Research Topic covers the effects of the COVID-19 pandemic and other pandemics on businesses. Su and Zhou use the case of Chongqing (China) to discuss the ecological livability of tourist towns with the outbreak of the COVID-19 pandemic. Limei and Wei take online travel booked by consumers as an example and consider Guangzhou Baiyun International Airport (China) data to analyze the influence of reviewers' creditworthiness on consumer purchase intention. Determinants of purchase intention provide several implications to be used during the COVID-19 pandemic. Song et al. evaluate the impact of the COVID-19 pandemic on China's manufacturing sector in the global value chain. Cao discusses the determinants of mobile payment adoption, which is expected to rise during the COVID-19 era for small and medium enterprises in China. Ai and Peng observe that dynamic capabilities, intra-industry networks, and social capital are the main determinants of the innovation dynamics of Chinese firms, and this evidence provides several implications for the COVID-19 crisis. In terms of global datasets, Zhu et al. show that pandemics-related uncertainty, measured by the World Pandemic Uncertainty Index, is positively related to socially responsible investments. Finally, Shang et al. provide a business history review on the effects of pandemics on economic performance.

Overall, this Research Topic covers 26 papers on the determinants and the outcomes of the COVID-19 pandemic, economic aspects of the COVID-19 pandemic and other pandemics, effects of the COVID-19 pandemic on financial markets, and the effects of COVID-19 pandemic and other pandemics on businesses.

AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct and intellectual contribution to the work, and approved it for publication.

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BRIEF RESEARCH REPORT
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Effects of Pandemics-Related Uncertainty on Household Consumption: Evidence From the Cross-Country Data

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The COVID-19 pandemic has affected various macroeconomic indicators. Given this backdrop, this research investigates the effects of the pandemics-related uncertainty on household consumption. For this purpose, we construct a simple theoretical model to study the effects of the pandemics-related uncertainty on household consumption. To estimate the theoretical model, we consider the panel dataset of 138 countries for the period from 1996 to 2017. We also use the Pandemic Uncertainty Index to measure the pandemics-related uncertainty. The theoretical model and the empirical findings from the Feasible Generalized Least Squares (FGLS) estimations indicate that the gross fixed capital formation, government consumption, balance of trade, and the Pandemic Uncertainty Index negatively affect household consumption. The results are also valid in the panel dataset of 42 high-income economies and the remaining 96 emerging economies.

Keywords: household consumption, pandemics-related uncertainty, world pandemic uncertainty index, COVID-19 related uncertainty, panel data estimations

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INTRODUCTION

COVID-19 Pandemic has negatively affected every aspect of the world economy. Since new coronavirus is more deadly than virus related to regular flu, governments have implemented various policy implications to slow down the spread of the virus. Specifically, policymakers have closed downed the public areas, including schools, restaurants, shopping malls (1) or people have voluntarily stayed at home during the COVID-19 Pandemic (2).

Although the COVID-19 Pandemic has one of the most unprecedented pandemics in the modern history, there are several pandemics in the twenty-first century, such as the Severe Acute Respiratory Syndrome (SARS) (2002–2003), Avian Flu (2003–2009), Swine Flu (2009–2010), Bird Flu (2013–2017), Ebola (2014–2016), and Middle East Respiratory Syndrome (MERS) (2014–Ongoing). It is observed that most of these pandemics have spread out at the regional level, or they have limited effects on economic indicators (3). However, these pandemics show us how the COVID-19 Pandemic can affect the macroeconomic indicators. In this paper, we aim to examine the effects of the pandemics-related uncertainty on the household consumption.

According to Altig et al. (4), economic uncertainty in the global economy during the COVID-19 Pandemic is higher than the level before the COVID-19 Pandemic. Baker et al. (5) show that the COVID-19 Pandemic related economic uncertainty has significantly macroeconomic indicators (consumption, employment, and investments) as well as it is negatively related to the stock market returns. Leduc and Liu (6) also indicate that the COVID-19 related uncertainty is the significant driver of the macroeconomic indicators. Following these papers, we focus on the Pandemic Uncertainty Index of Ahir et al. (3) to measure the pandemics-related uncertainty.

There are previous papers to investigate the effects of economic uncertainty related to the COVID-19 Pandemic on household consumption. For instance, Baker et al. (7) observe that people in the United States increased total spending by over 40% during the early March 2020, but household consumption has been reduced by around 30% during the late March 2020. The authors also show that food delivery and grocery spending are major exceptions to this reduction. Using the bank card and mobile Quick Response (QR) code transactions data, Chen et al. (8) also show that the household spending in China has significantly declined during the late January 2020. Consumption of goods and services has significantly decreased by 33 and 34%, respectively. The authors estimate that the decline of the household consumption in 2020Q1 is around 1.2% of China's GDP in 2019. Finally, Martin et al. (9) use the San Francisco Bay Area as a case study of the lockdown implications. The authors consider the household-level data to examine the effects of the COVID-19 Pandemic on the consumer spending and the poverty rate. The authors observe that there is a significant indirect macroeconomic effects of the COVID-19 Pandemic on the related variables and uncertainty related to the COVID-19 is can be defined as a typical exogenous shock, such as natural disasters. These findings motivate us to examine the effects of pandemic-related uncertainty on household consumption, but further, we aim to enhance the findings with the cross-country data.

In this paper, we construct a theoretical model to study the effects of the pandemics-related uncertainty on household consumption. To estimate our theoretical model, we consider the panel dataset of 138 countries (42 high-income economies and 96 emerging economies) for the period from 1996 to 2017. To the best of our knowledge, this is the first paper in the literature that examine the effects of the pandemics-related uncertainty on household consumption by using the cross-country data. According to the theoretical model and the empirical estimations from the FGLS method, the gross fixed capital formation, the government consumption, the balance of trade, and the Pandemic Uncertainty Index negatively affect household consumption. These results are also valid in the panel dataset of 42 high-income economies and 96 emerging economies.

The rest of the study is organized as follows. Section constructs a theoretical model to study the effects of pandemic-related uncertainty on household consumption. Section Data, empirical model and estimation procedure provides the data and the details of the model and the estimation procedure. Section discusses the empirical results. Section concludes.

THEORETICAL MODEL

In this paper, we examine the determinants of household consumption. For this purpose, we construct a theoretical framework, which is based on the income-expenditure model in an open economy [see, e.g., (10)], and it can be written as such:

$$Y_t = C_t + I_t + G_t + (X_t - M_t) \tag{1}$$

We can extract the household consumption (C_t), and ($X_t - M_t$) can be defined as the balance of trade (BOT_t) as follows:

$$C_t = Y_t - I_t - G_t - BOT_t \tag{2}$$

At this stage, we assume that the Pandemic Uncertainty Index (PUI) captures the business cycles (economic performance) and it should be negatively related to the gross domestic product (GDP) (Y_t) over time. Therefore, we replace Y_t with ($-PUI_t$) and Equation (2) can be rewritten as such:

$$C_t = -PUI_t - I_t - G_t - BOT_t \tag{3}$$

Note that I_t is also the gross fixed capital formation and G_t is the government consumption in this theoretical framework.

DATA, EMPIRICAL MODEL, AND ESTIMATION PROCEDURE

The theoretical model in Equation (3) can be estimated via the panel data in the current form, and the estimated model can be written as follows:

$$C_{i,t} = \alpha_0 - \alpha_1 PUI_{i,t} - \alpha_2 I_{i,t} - \alpha_3 G_{i,t} - \alpha_4 BOT_{i,t} \tag{4}$$

In Equation (4), $C_{i,t}$ is the household consumption, $PUI_{i,t}$ is the Pandemic Uncertainty Index, $I_{i,t}$ is the gross capital formation, $G_{i,t}$ is the government consumption, $BOT_{i,t}$ is the balance of trade in country i and time t.

Household consumption, gross capital formation, government consumption, and the balance of trade data are obtained from the Penn World Table (PWT) (version 9.1) dataset, which are provided by Feenstra et al. (11). All these variables are defined as the shares of the current Purchasing Power Parity (PPP) GDP.

The Pandemic Uncertainty Index (PUI) is introduced by Ahir et al. (3). This new dataset measures discussions about pandemics at the country level. The PUI is calculated by counting the number of words related to pandemics uncertainty (and its variants) in the Economist Intelligence Unit (EIU) country reports. Note that a higher level of the index indicates a greater pandemics-related uncertainty.[1]

At this stage, the empirical exercise is implemented in 138 countries for the period from 1996 to 2017. The selection of the sample is related to the data availability. Following the definition of the World Bank (12), we also split the data as 42

[1] Refer to https://worlduncertaintyindex.com/data for further details of the dataset.

TABLE 1 | Summary of descriptive statistics & correlation matrix.

Variable	Mean	Std. Dev.	Min.	Max.	Obs.
C	0.632	0.165	0.025	1.547	3,036
I	0.214	0.085	0.001	0.745	3,036
G	0.174	0.076	0.008	0.619	3,036
BOT	–0.031	0.139	–1.185	0.758	3,036
PUI	0.489	6.249	0.000	225.8	3,036
Variable	**C**	**I**	**G**	**BOT**	**PUI**
C	1	–	–	–	–
I	–0.5021	1	–	–	–
G	–0.2896	–0.0928	1	–	–
BOT	–0.6262	0.0434	–0.1382	1	–
PUI	–0.0241	–0.0133	0.0100	–0.0001	1

high-income economies[2] and 96 emerging (low-income, lower-middle-income, and upper-middle-income) economies.[3] Finally, a summary of descriptive statistics and the correlation matrix for variables in the estimations are provided in **Table 1**.

The correlation matrix indicates that there is a negative correlation between household consumption and the explanatory variables is negative. The PUI is negatively related to the gross capital formation and the balance of trade, while it is positively correlated with the government consumption.

We utilize the FGLS estimations to estimate the empirical model in Equation (4). At this point, we check the stationarity of the variables by implementing the panel unit root test of Pesaran (13).[4] Given that the Cross-sectional Augmented Im–Pesaran–Shin (CIPS) panel unit root test of Pesaran (13) considers the cross-sectional dependence, we check the cross-sectional dependence of the variables. Therefore, we utilize the Cross-Sectional Dependence (CD) test of Pesaran (14, 15), and then we proceed with the CIPS panel unit root test of Pesaran (13). All of these results indicate that the FGLS estimations are suitable.

[2] Australia, Austria, Belgium, Canada, Chile, Croatia, the Czech Republic, Denmark, Finland, France, Germany, Greece, Hong Kong SAR, Hungary, Ireland, Israel, Italy, Japan, Korea Republic, Kuwait, Latvia, Lithuania, the Netherlands, New Zealand, Norway, Panama, Poland, Portugal, Qatar, Romania, Saudi Arabia, Singapore, Slovakia, Slovenia, Spain, Sweden, Switzerland, Taiwan, the United Arab Emirates, the United Kingdom, the United States, and Uruguay.

[3] Albania, Algeria, Angola, Argentina, Armenia, Azerbaijan, Bangladesh, Belarus, Benin, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, Burkina Faso, Burundi, Cambodia, Cameroon, Central African Republic, Chad, China, Colombia, Congo Republic, Congo DR, Costa Rica, Côte d'Ivoire, Dominican Republic, Ecuador, Egypt, El Salvador, Ethiopia, Gabon, Gambia, Georgia, Ghana, Guatemala, Guinea, Guinea-Bissau, Haiti, Honduras, India, Indonesia, Iran, Iraq, Jamaica, Jordan, Kazakhstan, Kenya, Kyrgyzstan, Laos, Lebanon, Lesotho, Liberia, Madagascar, Malawi, Malaysia, Mali, Mauritania, Mexico, Moldova, Morocco, Mozambique, Myanmar, Namibia, Nepal, Nicaragua, Niger, Nigeria, North Macedonia, Oman, Pakistan, Paraguay, Peru, the Philippines, Russian Federation, Rwanda, Senegal, Sierra Leone, South Africa, Sri Lanka, Sudan, Tajikistan, Tanzania, Thailand, Togo, Tunisia, Turkey, Turkmenistan, Uganda, Ukraine, Uzbekistan, Venezuela, Vietnam, Yemen, Zambia, and Zimbabwe.

[4] As a robustness check, we also run the Panel-Corrected Standard Errors (PCSE) estimations, and the results are in line with the FGLS estimations. We did not report them to save space due to the page constraints.

TABLE 2 | Cross-sectional dependence (CD) Test of Pesaran (2004 and 2015).

Test statistics	C	I	G	BOT	PUI
CD-test	14.50***	39.31***	31.58***	29.21***	282.7***
P	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Absolute correlation	0.201	0.222	0.226	0.227	0.638

*The null hypothesis of cross-section independence. The probability values in [ ] ***p < 0.01.*

TABLE 3 | Cross-sectional augmented Im–Pesaran–Shin (CIPS) test of Pesaran (13).

Variable	Specification without Trend
C	–2.879*** (0)
I	–6.087*** (0)
G	–4.995*** (0)
BOT	–5.324*** (0)
PUI	–8.479*** (0)

*The null hypothesis is that the series follows a unit root process. The lags are in ( ). ***p < 0.01.*

EMPIRICAL RESULTS

Cross-Sectional Dependence (CD) Test

The results of the CD test of Pesaran (14, 15) are reported in **Table 2**.

The results in **Table 2** indicate that all variables have cross-section dependence. Therefore, we proceed with a second-generation panel unit root test rather than a first-generation panel unit root test.

CIPS Panel Unit Root Test

We also utilize the CIPS panel unit root test of Pesaran (13), and the results are provided in **Table 3**.

The findings in **Table 3** show that the null hypothesis, series follow a unit root process, are significantly rejected for all variables. Therefore, all variables in the empirical analysis are stationary, and we proceed with the FGLS estimations.

FGLS Estimations

The results of the FGLS estimations for Equation (4) are reported in **Table 4**.

The findings in Column (I) of **Table 4** provides the findings for all (138) countries, while Columns (II) and (III) report the results for 42 high-income economies and 96 emerging economies, respectively.

The results of the FGLS estimations indicate that the PUI negatively affects the household consumption. The coefficient is −0.072 for all countries, −0.028 for the high-income economies, and it is found as −0.131 for the emerging economies, respectively. The coefficients are statistically significant at the 5% level at least. Besides, the gross capital formation, government consumption, and the balance of trade are negatively associated with the household consumption. These coefficients are also statistically significant at the 1% level. The results are valid in

TABLE 4 | FGLS Estimations: pandemics and household consumption (1996–2017).

Regressors	(I) All countries	(II) High-income economies	(III) Emerging economies
Pandemic uncertainty index$_t$	−0.072*** (0.020)	−0.028** (0.014)	−0.131*** (0.022)
Gross fixed capital formation$_t$	−0.973*** (0.013)	−0.972*** (0.043)	−0.885*** (0.010)
Government consumption$_t$	−0.913*** (0.016)	−0.664*** (0.033)	−0.967*** (0.016)
Balance of trade$_t$	−0.771*** (0.012)	−0.781*** (0.016)	−0.722*** (0.011)
Constant term	Yes	Yes	Yes
Observation	3,016	924	2,112
Number of Countries	138	42	96
Wald Chi-square	15782.1***	27536.2***	13027.5***

*The dependent variable is the household consumption. Robust standard errors are in ( ). ***$p < 0.01$ and **$p < 0.05$.*

all countries, the high-income economies, and the emerging economies. Finally, the evidence from the FGLS estimations is in line with the expectation of the theoretical model provided in section Theoretical model.

CONCLUSION

In this paper, we examined the effects of pandemics-related uncertainty on household consumption in the panel dataset of 138 countries for the period from 1996 to 2017. For this purpose, we constructed a theoretical model to study the effects of pandemics-related uncertainty on household consumption. We also use the PUI measure, which is provided by Ahir et al. (3) at https://worlduncertaintyindex.com/data/. The theoretical model and the empirical results from the FGLS estimations indicate that the gross fixed capital formation, the government consumption, the balance of trade, and the Pandemic Uncertainty Index negatively affect the household consumption. The results are also valid in the panel datasets of 42 high-income economies and 96 emerging economies.

Our findings are in line with the findings of Baker et al. (7) and Chen et al. (8). However, these papers observe that household consumption has been significantly reduced during the COVID-19 Pandemic in the United States and China, respectively. In this paper, we enhanced their findings to the panel dataset of 138 countries using the pandemic-related uncertainty before the COVID-19 period. Given that our results show that consumption is negatively related to the pandemic-related uncertainty, increasing government expenditures during the pandemics can help to sustain economic performance. Future studies can use pandemic-related uncertainty indices to examine the effects of the COVID-19 related uncertainty on other financial and macroeconomic indicators. At this juncture, time-series analyses can be implemented.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: https://worlduncertaintyindex.com/ https://www.rug.nl/ggdc/productivity/pwt.

AUTHOR CONTRIBUTIONS

The author confirms being the sole contributor of this work and has approved it for publication.

REFERENCES

1. Hale T, Petherick A, Phillips T, Webster S. *Variation in Government Responses to COVID-19*. Oxford: Oxford University (2020).
2. Fetzer T, Witte M, Hensel L, Jachimowicz JM, Haushofer J, Ivchenko A, et al. *Global Behaviors and Perceptions in the COVID-19 Pandemic. Harvard Business School Working Paper, No. 20-111*. Cambridge, MA: Harvard Business School (2020).
3. Ahir H, Bloom N, Furceri D. *The World Uncertainty Index. Stanford Institute for Economic Policy Research (SIEPR) Working Paper*, No. 19-027. Stanford, CA: SIEPR (2019).
4. Altig D, Baker S, Barrero JM, Bloom N, Bunn P, Chen S, et al. Economic Uncertainty before and during the COVID-19 Pandemic. *J Public Econom*. (2020) 191:104274. doi: 10.1016/j.jpubeco.2020.104274
5. Baker SR, Bloom N, Davis SJ, Terry SJ. *COVID-induced Economic Uncertainty*. National Bureau of Economic Research (NBER) Working Paper, No. 26983. Cambridge, MA: NBER (2020).
6. Leduc S, Liu Z. *The Uncertainty Channel of the Coronavirus. Federal Reserve Bank of San Francisco (FRBSF) Economic Letters, 2020-07, 1-4*. San Francisco, CA: FRBSF (2020).
7. Baker SR, Farrokhnia RA, Meyer S, Pagel M, Yannelis C. *How Does Household Spending Respond to an Epidemic? Consumption during the 2020 COVID-19 Pandemic*. The Review of Asset Pricing Studies, forthcoming (2020).
8. Chen H, Qian W, Wen Q. *The Impact of the COVID-19 Pandemic on Consumption: Learning from High Frequency Transaction Data*. Luohan Academy Working Paper Series, No. LHA20201003, Hangzhou: Luohan Academy (2020).
9. Martin A, Markhvida M, Hallegatte S, Walsh B. Socio-economic impacts of COVID-19 on household consumption and poverty. *Econom Disast Climate Change*. (2020) 4:453–79. doi: 10.1007/s41885-020-00070-3
10. Coddington A. Keynesian Economics: The search for first principles. *J Econom Literature*. (1976) 14:1258–73.
11. Feenstra RC, Inklaar R, Timmer MP. The next generation of the penn world table. *Am Econom Rev*. (2015) 105:3150–82. doi: 10.1257/aer.20130954
12. World Bank. *World Bank Country and Lending Groups: Country Classification*. Washington, DC: World Bank (2020).
13. Pesaran MH. A simple panel unit root test in the presence of cross-section dependence. *J Appl Econometr*. (2007) 22:265–312. doi: 10.1002/jae.951
14. Pesaran MH. General Diagnostic Tests for Cross-sectional Dependence in Panels. *University of Cambridge Working Papers in Economics, No. 435*. Cambridge: University of Cambridge (2004).

15. Pesaran MH. Testing weak cross-sectional dependence in large panels. *Econometr Rev.* (2015) 34:1089–117. doi: 10.1080/07474938.2014.956623

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Fighting Strategies Against the Novel Coronavirus Pandemic: Impact on Global Economy

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Sudden outbreak of a new pathogen in numbers of pneumonic patients in Wuhan province during December 2019 has threatened the world population within a short period of its occurrence. This respiratory tract–isolated pathogen was initially named as novel coronavirus 2019 (nCoV-2019), but later termed as SARS-CoV-2. The rapid spreading of this infectious disease received the label of pandemic by the World Health Organization within 4 months of its occurrence, which still seeks continuous attention of the researchers to prevent the spread and for cure of the infected patients. The propagation of the disease has been recorded in 215 countries, with more than 25.5 million cases and a death toll of more than 0.85 million. Several measures are taken to control the disease transmission, and researchers are actively engaged in finding suitable therapeutics to effectively control the disease to minimize the mortality and morbidity rates. Several existing potential candidates were explored in the prevention and treatment of worsening condition of COVID-19 patients; however, none of the formulation has been approved for the treatment but used under medical supervision. In this article, a focus has been made to highlight on current epidemiology on the COVID-19 infection, clinical features, diagnosis, and transmission, with special emphasis on treatment measures of the disease at different stages of clinical research and the global economic influence due to this pandemic situation. Progress in the development on vaccine against COVID-19 has also been explored as important measures to immunize people. Moreover, this article is expected to provide information to the researchers, who are constantly combating in the management against this outbreak.

Keywords: SARS-CoV-2, COVID-19, combination therapy, treatment possibilities, economic impact

INTRODUCTION: CORONAVIRUS

The term "corona" has become a global threat nowadays, which has changed the world and our lives completely. The microscopic pathogen creates a circumstance, against which scientists are continuously trying to find an effective remedy. This coronavirus (CoV) was first identified in 1965 by Tyrrell and Bynoe; however, initially, this virus was named B814 for identification (1). Within the same time frame, Hamre and Procknow reported the growth of viruses with unfamiliar properties from the respiratory samples of cold-infected students (2). Simultaneous research by Almeida and Tyrrell revealed that the viruses identified by the previous groups were of similar morphology as evidenced by the electron microscopic representations. It was also revealed that these pleomorphic membrane-coated particles are of 80–150 nm in size containing the covering of widely spaced club-shaped surface projections (3). Later, in the late 1960s, this new group of the virus was named as "coronavirus" by Tyrrell and colleagues, because of the presence of crown-like surface appendages or spiked projections under the electron microscope, when they were investigating on different strains of human and animal viruses (**Figure 1A**) (4, 5). Further investigations discovered that these enveloped non-segmented viruses consist of a single-strand, positive-sense RNA genome (size 26–32 kilobases), which belong to the Coronaviridae family (order: Nidovirales) (6, 7). These CoVs are broadly distributed in humans, mammals, and birds to cause several health problems, largely respiratory, neurologic, hepatic, and enteric diseases (8, 9). Earlier to 2019, there were six species of CoV known to cause global challenges for public health, where the prevalent four species are human-CoV (HCoV) 229E, HCoV-OC43, HCoV-NL63, and HCoV-HKU1, which are responsible for causing mild human symptoms related to the common cold in immunocompetent individuals (7, 10). The other two beta-CoV species, severe acute respiratory syndrome CoV (SARS-CoV), and Middle East respiratory syndrome CoV (MERS-CoV) are of zoonotic in origin and resulted in epidemics with more than 10,000 cumulative cases (11). Among these two, the fatal rate of MERS-CoV (in 2012 in the Middle East) was higher (37%) compared to SARS-CoV (in 2002 and 2003 in China) (10%) (12, 13), where both the species were the causative agent for the severe respiratory disease (8).

In December 2019, a novel CoV (initially termed 2019-nCoV) infecting pneumonia broke out in more than 100 countries over the five continents, which was first reported in Wuhan, Hubei Province, China (8, 14). Later, this 2019-nCoV has been renamed SARS-CoV-2 by the International Committee of Taxonomy of Viruses (15). At the time of writing, on September 1, 2020, a total of 25,662,091 cases of SARS-CoV-2 infections in 215 countries were reported worldwide with a sharp trend to raise the numbers (**Figure 1B**). Of the infected cases reported, 18,817,777 cases were closed, with 17,962,425 cases of recovery (95%) and 855,352 cases of deaths (5%) (**Figures 1C,D**) (16). SARS-CoV-2 is also enveloped, single-stranded RNA beta-CoV, similar to MERS-CoV and SARS-CoV, where the genome encodes structural spike glycoprotein and non-structural papain-like protease, 3-chymotrypsin–like protease, helicase, and RNA-dependent RNA polymerase and auxiliary proteins (17).

Considering the existence of various species of animal CoVs, it is not surprising to accept a novel species to cause a severe problem in the respiratory system, SARS-CoV-2, emerged in a part of China and extends its severity throughout the world. This virus was grown in culture medium easily to enable the genome sequencing in order to correlate with existing CoV (18). In a recent report of SARS-CoV-2, it has been revealed that the sequencing of SARS-CoV-2 differed sufficiently from the known human CoVs reported earlier; there is 79.6% identity to the whole genome sequence between SARS-CoV-2 and SARS-CoV (19). Alternatively, Zhu and colleagues revealed that SARS-CoV-2 is a distinct particle from the SARS-CoV and MERS-CoV comparing the full-length sequencing and phylogenic analysis (8). Finally, relating the genome sequence analysis for the nonstructural protein domains, it has been recommended that this novel species of CoV belongs to SARS-CoV (19). The genome sequence of SARS-CoV-2 is found to be quite similar to the animal CoVs, where there is a 96% similarity to the bat CoV (19). In continuation, Zhu et al. mentioned that SARS-CoV-2 has a close similarity to bat CoV (8) as reported by the earlier group. Based on this fact, it has been postulated that the primary source of this infection is bats; however, investigations are still ongoing to report the actual source of transmission of SARS-CoV-2 to result in a pandemic.

CLINICAL CHARACTERISTICS OF COVID-19 PATIENTS

CoV disease 2019 (COVID-19) has brought a cluster of pneumonia cases in hospitals worldwide. Different researchers have presented the clinical features of the COVID-19–infected patients, which is summarized in this section of the article. Chen and colleagues have reported pneumonia infected 99 cases of COVID-19 patients, where the average age of the patients was 55.5 ±13.1 years. Of the 99 patients, acute respiratory distress syndrome (ARDS) was reported in 17 patients (17%) within a short period, where 11 (11%) of them died because of multiple organ failure. At the time of reporting, 57 (58%) of the infected patients were hospitalized for recovery of their symptoms. The clinical manifestations of these patients are presented in **Table 1** (20). Similarly, Huang and colleagues reported the clinical features of this disease in 41 hospitalized patients with COVID-19, with a median age of 49 years. The clinical manifestations are quite similar to the previous report by Chen and colleagues. A total of 29% (12 patients) acquired ARDS, whereas 12% (five patients) acquired cardiac injury, 7% (three patients) acquired shock, and 7% (three patients) had acute kidney injury. Compared to the previous reports, the percentage of deaths in COVID-19 patients was more in this report [6 (15%)] (11).

Further reports on 138 COVID-19 diseased patients provided more insights on the clinical symptoms of the pneumonia-infected patients. The median age of the patients was 56 years; the clinical manifestations of the patients are displayed in **Table 1**. The report also included a decrease in lymphocyte counts in 70.3%, prolongation of prothrombin time in 58%, and increased lactate dehydrogenase in 39.9% of patients (21). Of the 138 COVID-19 patients, 36 patients (26.1%) were transferred to the intensive care unit because of ARDS [22 (61.1%)], arrhythmia [16 (44.4%)], and shock [11 (30.6%)]. While reported, 47 patients were discharged alive (34.1%), with a mortality rate of 4.3% (6). However, the rest of the patients were still hospitalized for their recovery (21). Continuing clinical features of 51 COVID-19 patients with an average age of 49 ± 16

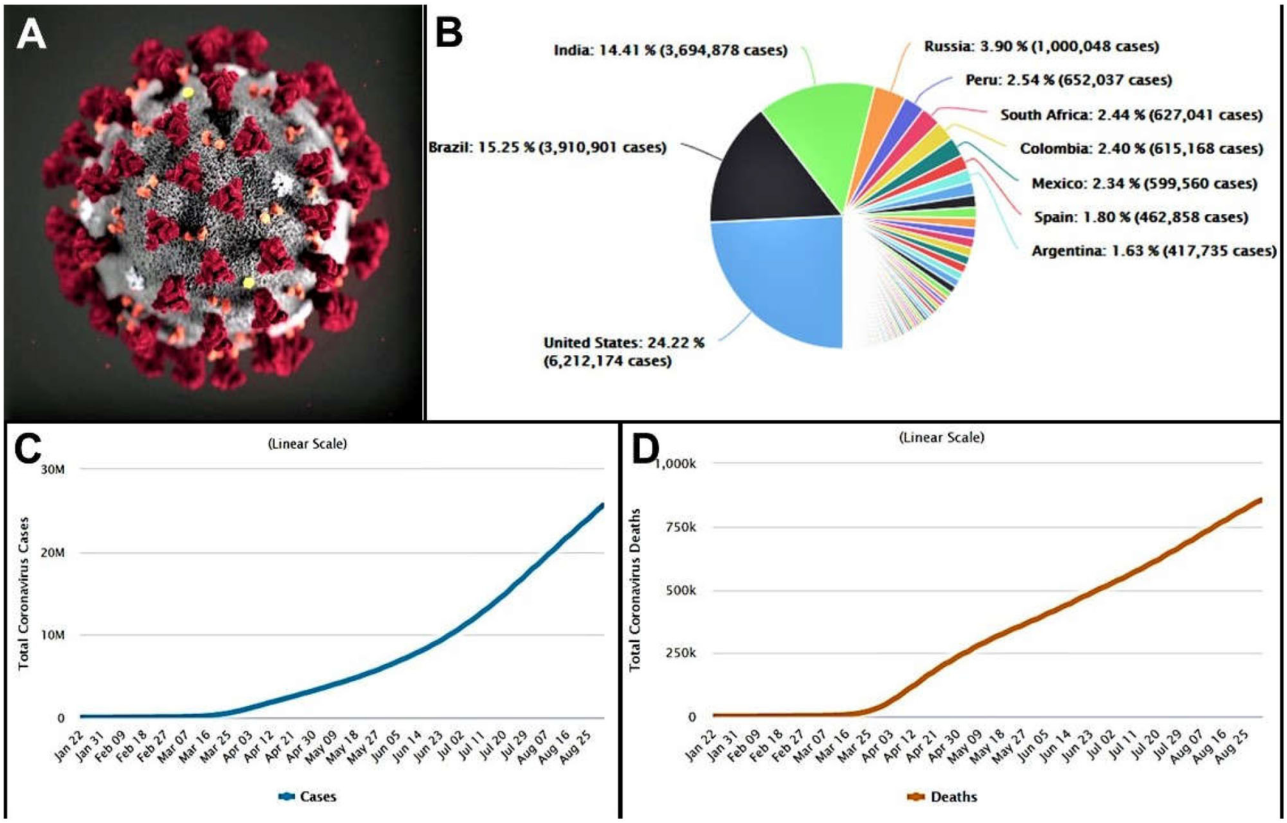

FIGURE 1 | **(A)** Morphology of the coronavirus (CDC). **(B)** Country-wise distribution of COVID-19 cases. **(C)** Total active cases of coronavirus infected people. **(D)** Total deaths of coronavirus infected patient. (data obtained on, September 1, 2020 from https://www.worldometers.info/coronavirus/).

years are depicted in **Table 1**. The symptoms of the patients are quite similar to earlier reports (22). Guan and colleagues presented a larger extracted data from 1,099 patients affected with COVID-19 recently with a median age of 47 years. The reports described the median incubation period for this virus as 4 days (interquartile range, 2–7) with a mean hospitalization period of 12.8 days. The mortality rate of this study (1.4%) was much less than the previous reports, which might be due to the number of cases and inclusion criteria of the present study (23). From the available reports in COVID-19, it is clear that SARS-CoV-2 is a combination of clinical manifestations where older patients and the patients with comorbidities are prone to reach to the fatal respiratory condition due to ARDS.

Different systemic and respiratory disorders related to COVID-19 have been picturized in **Figure 2**. Following the incubation period, these virus-infected persons started showing symptoms similar to beta-CoV; however, SARS-CoV-2 is grossly creating life-threatening conditions when invading the lower respiratory tract (25). Therefore, protecting individuals from exposing themselves in the contaminated environment, taking preventive measures from the transmission modes, and, finally, proper diagnosis of the suspected patients and immediate treatment strategies could protect patients from worsening toward fatal condition.

DIAGNOSTIC PATHWAYS FOR THE INVADING SARS-COV-2

Diagnosis of SARS-CoV-2 infection is critical to respond effectively for the proper treatment of the patients. The increasing number of patients worldwide warrants a proper guideline for diagnosing the patients at their early stages for the treatment.

Physical and Clinical Examinations

Apart from the clinical symptoms, a physical examination may help in the diagnosis of the disease at an advanced stage because the mild signs are not presenting positive signs at the early stage of the disease. At an advanced stage, the SARS-CoV-2–infected patients may show shortness of breath, weakened breath sounds, moist rales in lungs, decreased or increased tactile speech tremor, and dullness in percussion (26).

The clinical manifestations of the SARS-CoV-2–infected patients have already been discussed in the earlier section, where fever, dry cough, and fatigue are the typical symptoms to diagnose; however, biases may interfere into the proper diagnosis, which might require subsequent radiological imaging and laboratory tests or incorporation of artificial intelligence.

TABLE 1 | Representation of clinical manifestations of COVID-19 patients.

Fever	Cough	Phlegm	Anorexia	Shortness of breath	Sputum production	Muscle ache/fatigue	Confusion	Headache/ dizziness	Sore throat	Chills	Hemoptysis	Rhinorrhea/ nasal congestion	Chest pain	Diarrhea	Abdominal pain	Nausea and vomiting	References
83%	82%			32%	—	11%	9%	8%	5		—	4	2%	2%		1%	(20)
98%	76%			55%	28%	18%	—	8%	—		5%	—	—	3%		—	(11)
98.6%	59.4%		39.9%	31.2%	—	34.8%/69.6%	—	9%/9.4%	—		—	—	—	10.1%	2.2%	10.1%	(21)
96%	47%	20%	18%	14%		31%		16%				6%		10%		6%	(22)
88.7%	67.8%			18.7%	33.7%	14.9%/38.1%		13.6%	13.9%	11.5%	0.9%	4.8%		3.8%		5%	(23)

Laboratory Tests

Laboratory testing interim guidance for SARS-CoV-2 has been brought to us by the World Health Organization (WHO) to diagnose the suspected cases (10). The recommended respiratory sample from the suspected patients should be collected, and the collection could be performed from the upper or lower respiratory tract. The oropharyngeal or nasopharyngeal swab could be collected for upper-respiratory samples from the ambulatory patients, whereas for patients with severe respiratory disease, sputum (if produced) and/or endotracheal aspirate or bronchoalveolar lavage need to collect for nucleic acid amplification tests. Blood samples should also be collected from the patients to define retrospectively. The paired samples from the same patient at the first and 2–4 weeks of exposure should be collected for confirmation. Collected samples should be stored at 2–8°C if the storage period is <5 days, and for longer storage, the samples should be kept at −70°C (dry ice).

Nucleic acid sequencing of RNA of the virus is a routine confirmation of the infection by nucleic acid amplification tests, which incorporate real-time reverse transcription–polymerase chain reaction (rt-PCR). The extracted samples of RNA are amplified by rt-PCR and assayed with specific primers and probes of SARS-CoV-2 using the WHO-designed protocols in different laboratories across the globe (27). All the tests are carried out in the recommended laboratories with all the facilities and safety measures in different countries. In the case of test-positive targets for RNA-dependent RNA polymerase (open reading frame 1ab) confirming the infection of SARS-CoV-2, a second confirmation could be achieved by the positive test in nucleocapsid protein (28, 29). Details of diagnostic protocols are available in the guidelines for the detection of the presence of pneumonic infection (10, 29). Repeated sampling and analysis are confirmatory of recovery from the infection. Alternatively, the analysis of paired serum from the collected blood samples of the infected patients also provides confirmation of infection (10).

Imaging Investigations

Findings of computed tomography (CT) images vary in persons with different stages of infection at the time of infection, different ages, immunity status, presence of comorbidities, and drug interventions; however, CT imaging of the infected persons is strongly recommended for the diagnosis of the disease (26). Alternatively to CT images, ultrasound or radiograph of the lungs with bilateral opacities, presence of nodules, lobar or collapse, and volume overload may help in the diagnosis of the COVID-19, with its stages (30). The chest images would provide the characteristics of the lesions, which could be differentiated by the quantity, distribution, shape, density, and concomitant signs of the lesions. These images help to diagnose the patients at different stages of their infections, such as ultra-early stage (with no clinical manifestation of the patients with positive throat swab and negative laboratory test, when exposed to the virus-contaminated location within 1–2 weeks), early-stage (with clinical manifestations within 1–3 days), rapid progression stage (with the clinical manifestations for 3–7 days), consolidation stage (after 7–14 days of appearing clinical manifestations), and dissipation stage (2–3 weeks after the appearance of clinical

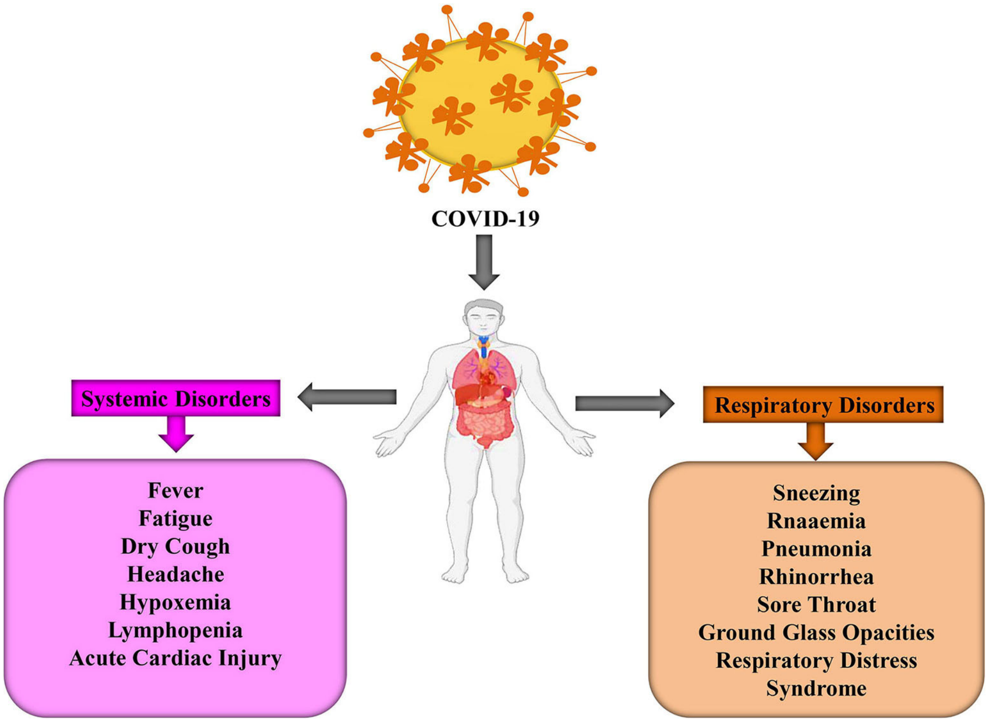

FIGURE 2 | The systemic and respiratory disorders caused by COVID-19 infection (24).

FIGURE 3 | Do's and don'ts to protect yourself from COVID-19 infection.

manifestations). For a detailed understanding of the imaging characteristics, please refer to the cited article (26).

TRANSMISSION POSSIBILITIES AND PREVENTIVE MEASURES OF COVID-19

During this critical stage of the pandemic outbreak of COVID-19, it is very much essential to control the spreading of infection by knowing and controlling all the possibilities of transmission patterns. Many reports throughout the world presented transmission dynamics in order to understand the transmission pathway of COVID-19. Even though the initial few cases of COVID-19 were of zoonotic (animal-to-human) origin, linked to the Wuhan seafood market, however, a thousand-folds increased cases point toward another source of transmission, including person-to-person (31). Recently, person-to-person transmission is one of the main concerns to control this pandemic situation, which is most commonly associated with close contact with COVID-19–infected person, where virus transmission can happen via respiratory droplets produced by the infected person upon coughing or sneezing to the mouth, eyes, or nose or directly to the lungs of the healthy person (32, 33). Sporadic imported cases, who visited China, not Wuhan wet market, have been reported in the last 4 months in different countries. In Vietnam, in one couple after visiting Wuhan, not Wuhan wet market, the 65-year-old husband with comorbid disease was reported to be CoV positive. Further, his healthy son within 3 days after spending time with him developed dry cough and fever and further after hospitalization tested positive, although his son had not visited Wuhan. Although it was not confirmed, however, his father was assumed to be the cause of infection (34). Person-to-person transmission is evident in a family cluster of six COVID-19–positive patients as well (35). The first reported case of COVID-19 in the United States, who visited Wuhan, however, had no time spent in Wuhan market as well as this person did not come in close contact with any ill patient; however, after 5 days of his return from Wuhan, nasopharyngeal and oropharyngeal swabs tested positive. Remarkably, COVID-19 virus RNA was detected in the stool sample, collected on day 7 of the patient's illness, whereas the serum sample tested negative (36). Even in China Focus News, it has been reported that top scientists isolated CoV from feces samples collected from infected patients. However, researchers urge further evidence to confirm fecal–oral transmission (37). Li et al., investigated and presented an estimate of R_0 (number of cases directly produced from one susceptible case of COVID-19) until January 4, 2020, of 2.2, which represents that on average 2.2 persons have been infected from one COVID-19 patient. The group also alerted on the epidemic increase as an estimated R_0 value was >1 and further suggested for control measure to reduce transmissibility (38). A similar representation of R_0 value of 2.2 (90% high-density interval, 1.4–3.8) was reported by another group, and similarly, the team was suspected for a continuous person-to-person transmission with sustained transmission chains (39). Besides, a recent tweet by art director Gary Warshaw presented a graphic by Robert A. J. Signer (assistant professor, University of California San Diego), stating a single infected person can transmit to 2.5 people within 5 days; the number will increase to 406 infected people within the period of 30 days. Further power of social distancing in preventing COVID-19 transmission was explained; if there is 50% less exposure, infection possibilities can be reduced to 15 people within 30 days; further, it can be reduced to 2.5 people on further reduction of exposure to 75% (**Figure 3**).

Although most reported transmission through symptomatic carriers, however, asymptomatic carriers also become the potential source of COVID-19 (40–42). Possibilities of asymptomatic infection were presented in another report (35). Therefore, the effort to stop spreading COVID-19 will be challenging, if asymptomatic carrier transmission replicated (40).

Safety of healthcare providers from COVID-19 is one of the major challenges, because of irresistible COVID-19 cases throughout the world, which strains healthcare facilities and further extended adverse events to the healthcare providers. In China, around 3,000 healthcare providers have been infected, and among them, around 22 had died (43). Another report revealed hospital-acquired infection of 57 (41%) of 138 patients, where 40 (29%) were frontline healthcare providers (21). It has been reported that mortality from COVID-19 is more frequent in older people; however, Dr. Peter Hotez, National School of Tropical Medicine at Baylor College of Medicine, revealed that younger healthcare providers are even at greater risk of serious illness (44).

Uncontrollable spreading of COVID-19 could be prevented by generating public awareness, and thus, the Centers for Disease Control and Prevention (CDC) recommended safety measures for healthcare providers for the public. As mentioned earlier, SARS-CoV-2 is not an airborne virus; it is mainly transmitted by droplet to close contact; therefore, personal protective equipment as recommended by CDC, such as N95 facemask, gloves, gown, goggles/face shield, or powered, air-purifying respirator, can prevent transmission to the healthcare provider during proximity with the infected patient (32, 43).

Similar to other flu viruses, a SARS-CoV-2–infected patient can produce approximately 3,000 aerosol droplets following a single cough, which further can land on cloth or body surface of a healthy person, or surfaces. It has been reported that the virus in an aerosol droplet can survive within the experimental period of 3 h. Further, the same group reported that the virus can survive longer on plastic and stainless-steel surfaces (>72 h), copper (<4 h) and cupboard (<24 h) (45, 46). Thus, special precautions should be taken care to inactivate the virus on the surface by using household bleach containing 0.1% sodium hypochlorite, 62–71% alcohol, or 0.5% hydrogen peroxide. The concerned persons are using different useful techniques to avoid exposure such as frequent cleaning and sanitizing their hand, using masks when in public, opening doors using their elbows, avoiding grabbing handle vehicles, avoiding greeting by a handshake or hugging, and maintaining social distancing (46). We should continue these healthy practices and share with others using social media and/or journal article platform to fight together this pandemic outbreak.

TREATMENT PROGRESS AGAINST COVID-19

The clinical signs and symptoms of the COVID-19 patients worsen during the incubation in an infected person. Initially, the condition would not be critical to hospitalize the patients immediately, according to WHO. However, during the progression of the infection to the lower respiratory tract, the condition may worsen during the second week of illness (47). All the suspected patients should be advised by the medical practitioners to be isolated in a single room or self-quarantined at home, whereas confirmed cases of COVID-19 must be admitted to the hospital wards. In case of the critical condition of the patient, it should be shifted to the intensive care unit immediately for proper care (48). Whatever the stage would be, all the patients should be monitored closely, where the severity of the progression may be influenced by older age and/or comorbid diseased conditions, such as immunocompromised conditions, lung disorder, heart failure, cancer, renal disease, cerebrovascular disease, liver disease, and pregnancy (47).

So far, there is no specific treatment available for the treatment of COVID-19; however, management of the disease demands prompt execution on prevention of the infection with control measures and supportive management of complications (47). As general treatment measures, the patients would be provided the facilities of complete bed rest with sufficient intake of calorie, water, and possible supportive treatments.

Recent reports on oral treatment with antimalarial agents, chloroquine, and an antirheumatoid arthritis agent hydroxychloroquine have shown an early promise in the treatment of COVID-19. The *in vitro* efficacy of chloroquine was reported to stop the infection caused by SARS-CoV-2 at low concentration. The half-maximal effective concentration of this agent against the pathogenic agent is 1.13 μM; however, the 50% cytotoxic concentration of the drug is $>$100 μM (49). Antiviral efficacy of chloroquine has been explained by the increase in endosomal pH to prevent fusion between the virus and cell. Simultaneously, chloroquine impedes glycosylation of cellular receptors of the virus (50, 51). A recent report revealed another possible mechanism of chloroquine in the prevention of endocytosis of the SARS-CoV-2 viral particles where the authors mentioned that clathrin-mediated endocytosis of the viral particles is prevented by the decreased expression of phosphatidylinositol-binding clathrin assembly protein (**Figure 4**) within the cells (52).

The outcome of 21 clinical trials so far (to date) for the treatment of COVID-19–induced pneumonia had shown the safety and efficacy of chloroquine or hydroxychloroquine in more than 10 hospitals in different places of China (http://www.chictr.org.cn/searchprojen.aspx?title=hydroxychloroquine&officialname=&subjectid=&secondaryid=&applier=&studyleader=&ethicalcommitteesanction=&sponsor=&studyailment=&studyailmentcode=&studytype=0&studystage=0&studydesign=0&minstudyexecutetime=&maxstudyexecutetime=&recruitmentstatus=0&gender=0&agreetosign=&secsponsor=&regno=&regstatus=0&country=&province=&city=&institution=&institutionlevel=&measure=&intercode=&sourceofspends=&createyear=0&isuploadrf=&whetherpublic=&btngo=btn&verifycode=&page=1). Treatment with chloroquine phosphate had shown superiority in the treatment in the prevention of pneumonia in the COVID-19–infected patients (50). The clinical studies with these drugs are confined not only in China; around five of the studies already registered in the National Institutes of Health, US National Library of Medicine (https://clinicaltrials.gov/ct2/show/NCT04286503?term=Chloroquine&cond=COVID&draw=2&rank=4). Treatment of COVID-19 infection with chloroquine phosphate did not exert a serious adverse effect on the users, and there are no shreds of evidence of cardiotoxicity, but reported to promote negative conversion and reduction in disease progression, as evidenced by the radiographic images of the lungs (50, 53). Although not approved, the progress of research had suggested the use of these drugs for the control of this pandemic outbreak (53).

A recent short clinical report on the combination of hydroxychloroquine and azithromycin on 36 COVID-19 patients revealed a sharp reduction of viral load in the upper-respiratory samples from infected patients within 6 days. The clinical benefits of this combination are yet to be reported; however, patients with chronic disease such as renal failure or hepatic disease or those receiving medications for arrhythmia need to take precaution with prescribing this combination, as there might be possibilities of QT prolongation. The authors suggested that the efficacy of hydroxychloroquine in the reduction of viral load could be significantly improved when combined with azithromycin (53, 54).

A combination of antiviral agents had shown potential in the management of the COVID-19 outbreak. Several nucleoside analogs (investigational: galidesivir and remdesivir and approved: ribavirin and favipiravir) are in the different stages in the clinical research. These nucleoside analogs prevent the RNA-dependent RNA polymerase and thereby inhibit viral RNA synthesis in the virus particles (17). Among the investigational drugs, remdesivir gained attention in the management of the critical pneumonic condition of COVID-19 patients. This broad-spectrum antiviral agent is intended to be administered intravenously, which terminate RNA transcription prematurely of the SARS-CoV-2, thereby inhibiting the replication of the viral genome. It has well-established activities against beta-CoVs and *in vitro* control against novel COVID pathogen (EC_{50} = 0.77 μM in Vero E6 cells) (49, 55, 56). There are several clinical researches recruiting COVID-19 patients in different stages of the clinical trial for the establishment of this investigational agent for the treatment of SARS-CoV-2 (https://clinicaltrials.gov/ct2/results?term=Remdesivir&cond=COVID).

Efficacy of the guanine-analog influenza agent, favipiravir (T-705), had shown its potential against several viruses, including SARS-CoV-2 (EC_{50} = 61.88 μM in Vero E6 cells) (49). Considering the efficacy of this nucleoside analog against COVID-19, a combination of interferon-α and favipiravir is used to evaluate the efficacy and safety in a randomized trial. The recruitment of the trial is ongoing, where the other groups

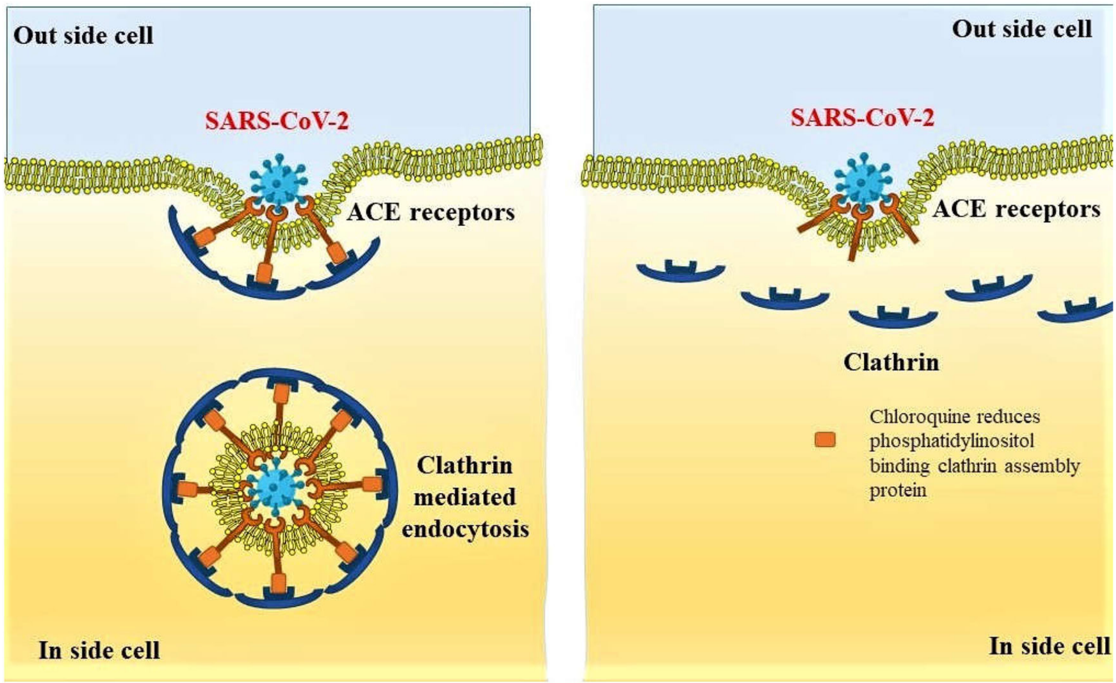

FIGURE 4 | Preventive mechanism of SARS-CoV-2 endocytosis by decreased expression of phosphatidylinositol binding clathrin assembly protein, leading to reduced internalization of the viral particles.

are receiving interferon-α and combinations of interferon-α, lopinavir and ritonavir (human immunodeficiency virus protease inhibitor antiretroviral agents) (ChiCTR2000029548) (57). Clinical trial on the combination of an approved influenza inhibitor, baloxavir marboxil, and favipiravir is also ongoing against COVID-19 (ChiCTR2000029544). Further, this favipiravir is combined with chloroquine phosphate (ChiCTR2000030987) and toclizumab, an immunosuppressant (ChiCTR2000030894) is also registered to be evaluated for the treatment of this pandemic pneumonia. Alternatively, the clinical trials on the combination of lopinavir and ritonavir are also continuing against mild cases of COVID-19 infection (ChiCTR2000029539). Additionally, the effectiveness of ribavirin is also under investigation in combination with lopinavir/ritonavir plus interferon-α (ChiCTR2000029387) (58).

Alternatively, SARS-CoV-2 enters into the lung cells by the ACE2 receptor–mediated entry, particularly through the AT2 cells of the lungs (59). This endocytosis process is influenced by the AP2-associated protein kinase 1 (AAK1). Among the 47 ligands approved for the control of different diseased conditions, 6six of them are known to have a higher affinity toward AAK1. Considering the safety of the compounds, baricitinib is suggested to be an important agent for the control of SARS-CoV-2 endocytosis within the host cells (60); however, clinical evidences are still necessary to support this treatment (61).

There is no vaccine available for SARS-CoV-2 infection yet; however, continual research has brought an investigational vaccine (mRNA-1273) for protection against COVID-19 in a phase I clinical trial. This research is initiated at Kaiser Permanente Washington Health Research Institute at Seattle, which is developed by the National Institute of Allergy and Infectious Diseases and its collaborator Moderna, Inc. The enrolment of subjects is ongoing for 45 healthy volunteers, where the first volunteer received the vaccine on March 16, 2020 (NCT04283461) (62). Another vaccine has been developed by Shenzhen Geno-Immune Medical Institute and under investigation under phase I clinical trial, where the vaccine is an engineered minigene with an efficient lentiviral vector system. The vaccine will express viral proteins and immune-modulatory genes to transform artificial antigen-presenting cells and to activate T cells (NCT04299724). A similar trial by Shenzhen Geno-Immune Medical Institute is ongoing with a synthetic vaccine to target and modify immune-modulatory dendritic cells with activation of T cells (NCT04276896). Another clinical research has been registered by CanSino Biologics Inc., for recruitment of healthy volunteers to assess safety, reactogenicity, and immunogenicity of the recombinant novel CoV vaccine (adenovirus type-5 vector) (NCT04313127). It could be said that the persistent research on small molecules and vaccines may bring novel compounds for the treatment or prevention of the disease in an effective manner to eradicate this pandemic threat.

PROGRESS OF VACCINE DEVELOPMENT AGAINST COVID-19

We are at the ninth month of disease outbreak and already covered 6 months from its announcement of pandemic. The researchers explored widely on structural biology and genomics of the viral particle during this time in order to bring a new sunrise against this COVID-19. Development of vaccine is a tiresome, lengthy, and costly process where the rate of attrition is high (63). Development of a licensed vaccine usually takes multiple candidates and several years; still there is not much evidence on the cost on development (64). However, the developmental process during the pandemic paradigm does not follow linear sequential steps of development. There will not be multiple pauses for investigating process check and analysis of data. Instead, a faster path is accomplished through parallel execution of different steps together; for example, preclinical studies can be run in parallel with the phase I clinical study (63).

Several challenges had been reported against development of vaccine against SARS-CoV-2. It has been observed that the spike protein on viral surface is immunogenic; however, designing suitable antigen is a critical task to obtain immune response against the pathogen. Previous experience toward development of SARS and MERS vaccine has raised alarms toward aggravating respiratory problems in preclinical studies. Such conditions might be a result of antibody-dependent action or direct action on the lungs by the vaccine candidates. Thus, it is necessary to perform rigorous monitoring of safety profile in suitable animal model. Alternatively, the duration of immunity development in people is also needed to ascertain for proper protection; otherwise, the same pathogen may affect the immunized person after certain period (65, 66).

However, continuous effort by researchers has brought more than 170 vaccine candidates into research by various pharmaceutical institutions and industries (67). Numbers of vaccines among those have crossed the barriers of laboratory and entered into different stages of clinical trials. According to the latest report (August 31, 2020), 49 vaccines are at phase I to early/limited use in human subjects for immunization. More elaborately, 23 candidates are in phase I, 14 candidates are in phase II, nine candidates are in phase III, and three of them have received approval for early/limited use in human subjects for immunization (68). One of the three is developed by CanSino Biologics, China. This product has entered into phase III on August 2020, and trial has been started in Saudi Arabia and Pakistan. Gamaleya Research Institute, Russia, developed the other vaccine, which was named Sputnik V by the Russian healthcare regulator. Sinovac Biotech, China, developed the third approved vaccine for early/limited use, CoronaVac. This vaccine had received an emergency approval by the Chinese Government for limited use in July 2020. However, none of the vaccine has received full approval so far for immunization of human against COVID-19.

Moderna Therapeutics is the first biotechnology company that has brought a vaccine against COVID-19, where the vaccine contains messenger RNA, which will produce viral proteins in the body. Their studies are progressing and currently at phase III of clinical research (67). Exceptionally speedy research to fight against COVID-19 has become possible by quick recognition of the viral particle and identification and determination of genetic sequencing (69). Overcoming the barriers of scale-up process of protein-based products, several vaccines are in production stages to be tested in large numbers of people to protect the world against this deadliest SARS-CoV-2.

GLOBAL ECONOMIC IMPACT OF THE COVID-19

After the most serious global health crisis of Spanish flu in 1918, COVID-19 is the most economically costly pandemic in the world. After the declaration of COVID-19 as a world health emergency by WHO, it has affected almost $90 trillion of global economy (70). Initially, there was no much coordination between many countries to combat COVID-19 pandemic. After the G-7 emergency meeting, countries pledged to combat the pandemic by coordinating research efforts, enhancing medical equipment availability, monetary and fiscal measures, mobilization of policy instruments, and lastly targeted actions to support sectors, companies, and support workers affected by the spread of COVID-19. Later, the G-20 has a broader membership, viewed in the response to the global financial crisis, and gained momentum on debt relief for low-income countries. The G-20 includes the G-7 countries plus Argentina, Australia, Brazil, China, India, Indonesia, Mexico, Russia, Saudi Arabia, South Africa, South Korea, Turkey, and the European Union (71).

COVID-19 caused sudden economic disruption in almost every area of human endeavor. The most affected are travel industry, hospitality industry, sports industry, event industry, entertainment industry, education sector, oil-dependent countries, import dependent countries, financial sectors (banks and Fintech), financial markets, etc. (72). Some important aspects in different industries are discussed in the connecting section of the article.

Travel Industry Sector

Since the inception of CoV pandemic, tourism is the first industry that has fallen immediately. The small viral particle has halted millions of trips around the globe. The imposition of travel restrictions by many countries affected indefinite suspension of tourism travel, visas on tourism, work, business, etc. Many countries imposed travel bans (both inward and outward travel) and shut down their international airports. Mass passenger cancelation led to business loss because of empty flights. Most countries' famous airline industries are already shut, and many employees lost their jobs. So far, it has been estimated that there may be more than $820 billion revenue loss in the business travel sector alone because of the COVID-19 pandemic (73, 74). However, the presented data are changing every moment as the virus is spreading. It has been estimated during the announcement of COVID-19 as a pandemic that there might be 75 million loss of employment with $2.1 trillion loss in revenue from the tourism sector (75).

Hospitality Industry Sector

To combat the pandemic, many governments announced important messages such as "social distancing, stay home" policies and movement restrictions. These restrictions led to shutdown of many businesses of street hawkers, restaurants and small and star hotels, pubs, and other related entertainment outlets. Many hotels witnessed no customers and also faced booking cancelations. Staffs who are working in these premises lost their jobs, and many owners of these outlets announced suspension of normal operations and became bankrupts (76). Governments are also providing supportive measures to the hospitality industry, such as "Eat Out to Help Out" program in the United Kingdom for 1 month, where 100 million meals were dispensed by the 84,700 restaurants (77). A very few hotels are converted to quarantine COVID patients, but the proportion is negligible (76). Additionally, there are offers to pay 50% of the diner's bill for the food and soft drinks, which helps to retain their staffs employed and helps to survive the hospitality farms (77).

Sports Industry Sector

Sports industry is one of the severely affected industries. Almost all the sports are either suspended or postponed in many parts of the world. Because of COVID outbreak, many important football leagues such as England, Scotland, European, and Turkish leagues were canceled or suspended. Olympic and Paralympic games scheduled in Tokyo got postponed. Formula One and Grand Prix were canceled, along with England's FIH Pro League games. There are plenty of other matches related to rugby, baseball, motorsports, snooker, swimming, golf, and other indoor and outdoor games either suspended or canceled. The organizers and sponsors lost their revenue in billions of dollars. In addition, many players also lost their income (72).

Impact on the Event Sector

The event sector is an important contributor to the economy. Business events generated more than $1.07 trillion of direct spending. These business events involved more than 1.5 billion participants across more than 180 countries. In addition, these events supported more than 10.3 million direct jobs globally (78). Many important events such as business exhibitions, conferences, weddings, live music shows, corporate events, parties, product launches, trade shows, etc., are largely hit. Some of the events are canceled or rescheduled or conducted online. Few famous ticketing agents or companies such as Eventbrite canceled many events and severely affected their business.

Entertainment Industry Sector

The International Alliance of theatrical stage employees reported that the global film industry incurred a huge loss in this outbreak. Millions of people lost their jobs. COVID outbreak severely affected various sectors such as the film screening sector, theater segment, live music segment, dance and stage performance segment, drama segment, etc. According to Broadcasting, Entertainment, Communications and Theater Union, unemployment levels rose to unprecedented high. Many Hollywood and regional movie productions were postponed or canceled indefinitely, and even the theaters and cinema owners are also affected because of poor audiences (79).

Pharmaceutical Industry Sector

There is a huge impact on the manufacturing of pharmaceutical and related industries too. The outbreak affected the pharmaceutical supply chain. Because of this, pharmaceutical companies around the world relied heavily on China for both active pharmaceutical ingredients (APIs) and excipients. Around 60% of pharmaceutical excipients and APIs were manufactured and supplied by China. Because of the CoV outbreak, all the manufacturing industries of excipients and APIs were closed down, and both manufacturing and supply chain were severely affected. Many manufacturing companies did not store enough of excipients and APIs before the CoV outbreak, and it severely impacted those companies and ultimately impacted the whole healthcare sector (80).

Education Sector

The majority of the governments around the world instructed schools, colleges, and universities to shut down because of this pandemic. Educators, teachers, students, parents, and all other related stakeholders were severely affected morally, financially, and psychologically and all other sorts. The pandemic effect had severe consequences on schools, colleges, and universities where there are no online learning platforms. Teachers, students, and administrators have a difficult time adapting to and adopting the technical, financial, and academic changes required to cope with the new teaching and learning strategies. More than 300 million students were affected, and in many poor countries, online education for those students was a nightmare. The radical shift from traditional classroom education to online platforms was a huge challenge for both teachers and students. Low-income countries were suffering from the affordability, technology, change management, and adaptability to online teaching (81).

Thus, COVID-19 trims global economic growth by 3.0–6% in 2020 with a partial recovery in 2021. This COVID-19 global recession is distinctive and differs from previous episodes in that global synchronized lockdowns and disturbance of financial markets strengthen one another into record economic sudden stop (71).

Table 2 highlights how the various industries are affected and approximate loss due to COVID-19. COVID-19 has created a revolution on both domestic and multinational companies to strategically approach their business models. This challenging situation has forced companies to adapt to present challenges, day-to-day operations, managing workforce, adhering to government mandates, and finally reacting to customer and employee needs. Many firms grab the opportunity of digitization. Firms are now agile and developing their capabilities to survive like education institutes. Yes, there is no doubt some companies are closed down, some are still running under loss, and some are striving hard in transition. Once the crisis subsides, "true economic value once again becomes the final arbiter of business success" (88).

INTERNATIONAL COOPERATION TOWARD COMBATING COVID-19 LEAD ECONOMIC IMPACT

The most significant threats the world is facing currently are climate change, terrorism, cybercrime, and infectious diseases. This COVID pandemic is a powerful reminder of

TABLE 2 | Global economic impact on different sectors due to the outbreak of COVID-19.

Industry	What is affected?	Approximate loss
Travel industry	• Essential travel ban • Tourism travel ban • Ban of work and immigrant visas • Shutdown of airports • Flew of empty flights • Suspensions of airlines	Aviation industry loss—$113 billon (73) GTBA business travel sector—$820 billion (82)
Hospitality industry	• Restaurant business • Shutdown of cities and states • Cancelation of hotel bookings • Staff laid off and shutdown of business	Booking cancelations $150 billion (83)
Sports industry	• Suspension of football leagues, Formula one • Olympic and Paralympic games • Hockey, cricket, rugby, baseball, motors sports, snooker, swimming, golf, etc. • Loss of revenue to the sponsors and organizers	Huge amount of loss which is difficult to estimate and recover (84)
Event industry	• Cancelation of events (live shows, exhibitions, conferences, parties, corporate events, trade shows, etc. • Business event-related travel, event ticketing segment • Direct spending by exhibitors • Millions of direct job loss	More than 1.07 trillion dollars (78)
Entertainment industry	• Postponement of Hollywood movies • Goodbye to cinema and theaters • Job loss of millions • Cancelation of movie shoots, shows	More than $5 billion (85)
Education sector/industry	• Closure of schools, universities • Disruption of 290.5 million students (86) • Unemployment in the sector • Cancelation of overseas travel and abroad programs of foreign students	More than $600 billion (87)
Financial market	• Effect on global stock market • Fall in stock market indices • Effect on share price	Global stock market lost $6 trillion from February 23 to 28 alone (72)

interconnectedness and vulnerabilities, and it has made one thing clear—that we are one human family, and the only way to mitigate is to work collaboratively. There are various platforms such as G7, G20, WHO, IMF World Bank, and many other international organizations to address the acute health, economic, and social consequences of the pandemic crisis. Recently, the European Union hosted an online summit where around 40 countries took part and pledged to help develop a CoV vaccine. A large-scale and science-based global response that is transparent and robust is required in the spirit of solidarity. Cooperation among countries is not only ethical and imperative but also an existential one.

The pandemic outbreak is causing havoc in rich countries, and the damage caused in poor countries is often overlooked. The most worrying part is that the economic crisis is not confined to one region or country; it is happening across the world. The global economy shrunk faster than at any time since World War II. This is a very crucial time, and all the developed and developing nations should come forward and support each other in whatever way possible. There are plenty of issues to address, such as raising infection rates, weak healthcare systems, massive economic damage, unemployment, disruption in supply chain, poverty, famine, etc. Hence, there is a need for an urgent global plan to address the important issues such as the following:

a. There is a need for external funding to address massive economic stimulus packages to revive the economy and reduce unemployment, prevent starvation, and address poverty.
b. The global plan should assist in stabilizing their currencies.
c. An immediate moratorium should be in place for poor countries whose debts are mainly to western governments. It is of absolute importance to assist the most vulnerable countries such as Africa. In addition, foreign-held private debt collection needs to be halted temporarily for at least 3–5 years.
d. To limit the spread of pandemic, immediate assistance is needed to strengthen the healthcare systems by increasing needs of medical supplies; exchange epidemiological and clinical data; sharing necessary materials for research and development; implementation of WHO health regulations; discovery and making use of vaccine at an affordable price on an equitable basis to the world population; and preventing the spread of other infectious diseases for a period at least 3–5 years (89).

To address the above, it may cost around $2.5 trillion. At the global level, institutions must be given the authority and resources to deal with this pandemic. Global institutions that could organize the response but need more resources such as World Bank, IMF, and WHO are being hobbled by western governments (90). Populism and xenophobia have gained ground nowadays; these can be addressed only by boosting the legitimacy and effectiveness of global institutions.

CONCLUSION AND FUTURE REMARK

This pandemic outbreak of COVID-19 has brought a tough time for the healthcare providers where the confirmed SARS-CoV-2 cases are diagnosed with mild to severe respiratory conditions to death. Thus, the rapid identification of the invasive fatal particles is the major challenge for this fast-spreading outbreak. Transmission could be prevented by the preventive measures specified by WHO, where several existing and investigational compounds are at different stages of clinical research. Several healthcare professionals are working effortlessly throughout the world to find promising ways toward effective control against this pandemic situation. Few of the tested therapeutics, such as hydroxychloroquine, remdesivir, and some other antiviral agents, has shown positive response against the treatment of the disease; however, treatments are prescribed under medical supervision for safety concern.

Various measures had been taken to prevent the transmission of the virus to the healthy person, such as complete/partial lockdown of the countries, maintaining social distancing and using protectives, isolation of the identified patients, quarantine of the suspect, extensive screening and identification of COVID-19–positive cases, contact tracing to find the cross-infected personnels; etc. Despite the several measures being taken by different countries, the scale of rising daily new cases is still sharp; hence, people are required to be more concerned toward control of this condition. Separate trained teams need to be formed to handle the infected cases effectively, whereas government aids toward novel research against combating this situation are highly needed. With the unremitting effort by researchers and healthcare providers, we pray for a SARS-CoV–free world to breathe freely with a new sunrise.

AUTHOR CONTRIBUTIONS

BG: writing—original draft. PK: writing—review & editing. RA: resources. NM: visualization. HC: supervision. All authors contributed to the article and approved the submitted version.

REFERENCES

1. Tyrrell DA, Bynoe ML. Cultivation of viruses from a high proportion of patients with colds. *Lancet.* (1966) 1:76–7. doi: 10.1016/s0140-6736(66)92364-6
2. Hamre D, Procknow JJ. A new virus isolated from the human respiratory tract. *Proc Soc Exp Biol Med.* (1966) 121:190–3. doi: 10.3181/00379727-121-30734
3. Almeida JD, Tyrrell DA. The morphology of three previously uncharacterized human respiratory viruses that grow in organ culture. *J Gen Virol.* (1967) 1:175–8. doi: 10.1099/0022-1317-1-2-175
4. Witte KH, Tajima M, Easterday BC. Morphologic characteristics and nucleic acid type of transmissible gastroenteritis virus of pigs. *Arch Gesamte Virusforsch.* (1968) 23:53–70. doi: 10.1007/bf01242114
5. Tyrrell DAJ, Almeida JD, Cunningham CH, Dowdle WR, Hofstad MS, McIntosh K, et al. Coronaviridae. *Intervirology.* (1975) 5:76–82. doi: 10.1159/000149883
6. Richman D, Whitley R, Hayden F. *Clinical Virology*. 4th edition. Washington: ASM Press (2016). Available online at: https://books.google.com/books?hl=en&lr=&id=G9zIDwAAQBAJ&oi=fnd&pg=PT8&ots=FcfFy-h5EP&sig=xNkQlwZfqZQTHvl9_-nhzX03MYg (accessed March 18, 2020).
7. Su S, Wong G, Shi W, Liu J, Lai ACK, Zhou J, et al. Epidemiology, genetic recombination, and pathogenesis of coronaviruses. *Trends Microbiol.* (2016) 24:490–502. doi: 10.1016/j.tim.2016.03.003
8. Zhu N, Zhang D, Wang W, Li X, Yang B, Song J, et al. A novel coronavirus from patients with pneumonia in China, 2019. *N Engl J Med.* (2020) 382:727–33. doi: 10.1056/NEJMoa2001017
9. Weiss SR, Leibowitz JL. Coronavirus pathogenesis. *Adv Virus Res.* (2011) 81:85–164. doi: 10.1016/B978-0-12-385885-6.00009-2
10. Laboratory testing for 2019 novel coronavirus (2019-nCoV) in suspected human cases. Available online at: https://www.who.int/publications-detail/laboratory-testing-for-2019-novel-coronavirus-in-suspected-human-cases-20200117 (accessed March 19, 2020).
11. Huang C, Wang Y, Li X, Ren L, Zhao J, Hu Y, et al. Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. *Lancet.* (2020) 395:497–506. doi: 10.1016/S0140-6736(20)30183-5
12. WHO | Summary of probable SARS cases with onset of illness from 1 November 2002 to 31 July 2003. Available online at: https://www.who.int/csr/sars/country/table2004_04_21/en/ (accessed March 18, 2020).
13. WHO. *Middle East Respiratory Syndrome Coronavirus (MERS-CoV)*. Available online at: https://www.who.int/emergencies/mers-cov/en/ (accessed March 18, 2020).
14. Coronavirus disease 2019 (COVID-19) Situation Report – 52. (2020). Available online at: https://www.who.int/docs/default-source/coronaviruse/20200312-sitrep-52-covid-19.pdf?sfvrsn=e2bfc9c0_2 (accessed March 18, 2020).
15. Gorbalenya AE, Baker SC, Baric RS, de Groot RJ, Drosten C, Gulyaeva AA, et al. The species Severe acute respiratory syndrome-related coronavirus: classifying 2019-nCoV and naming it SARS-CoV-2. *Nat Microbiol.* (2020) 5:536–44. doi: 10.1038/s41564-020-0695-z
16. Worldometer. Coronavirus Cases. (2020). Available online at: https://www.worldometers.info/coronavirus/ (accessed September 1, 2020).
17. Li G, De Clercq E. Therapeutic options for the 2019 novel coronavirus (2019-nCoV). *Nat Rev Drug Discov.* (2020) 19:149–50. doi: 10.1038/d41573-020-00016-0
18. CDC. *Grows SARS-CoV-2, the virus that causes COVID-19, in Cell Culture | CDC.* Available online at: https://www.cdc.gov/coronavirus/2019-ncov/about/grows-virus-cell-culture.html (accessed March 23, 2020).
19. Zhou P, Yang X-L, Wang X-G, Hu B, Zhang L, Zhang W, et al. A pneumonia outbreak associated with a new coronavirus of probable bat origin. *Nature.* (2020) 579:270–3. doi: 10.1038/s41586-020-2012-7
20. Chen N, Zhou M, Dong X, Qu J, Gong F, Han Y, et al. Epidemiological and clinical characteristics of 99 cases of 2019 novel coronavirus pneumonia in Wuhan, China: a descriptive study. *Lancet.* (2020) 395:507–13. doi: 10.1016/S0140-6736(20)30211-7
21. Wang D, Hu B, Hu C, Zhu F, Liu X, Zhang J, et al. Clinical Characteristics of 138 Hospitalized Patients with 2019 Novel Coronavirus-Infected Pneumonia in Wuhan, China. *JAMA - J Am Med Assoc.* (2020) 323:1061–9. doi: 10.1001/jama.2020.1585
22. Song F, Shi N, Shan F, Zhang Z, Shen J, Lu H, et al. Emerging 2019 Novel Coronavirus (2019-nCoV) Pneumonia. *Radiology.* (2020) 295:210–7. doi: 10.1148/radiol.2020200274
23. Guan W, Ni Z, Hu Y, Liang W, Ou C, He J, et al. Clinical Characteristics of Coronavirus Disease 2019 in China. *N Engl J Med.* (2020) 382:1708–720. doi: 10.1056/NEJMoa2002032
24. Hossain MF, Hasana S, Mamun AA, Uddin MS, Wahed MI, Sarker S, et al. COVID-19 outbreak: pathogenesis, current therapies, and potentials for future management. *Front Pharmacol.* (2020) 11:563478. doi: 10.3389/fphar.2020.563478

25. Rothan HA, Byrareddy SN. The epidemiology and pathogenesis of coronavirus disease (COVID-19) outbreak. *J Autoimmun.* (2020) 109:102433. doi: 10.1016/j.jaut.2020.102433
26. Jin YH, Cai L, Cheng ZS, Cheng H, Deng T, Fan YP, et al. A rapid advice guideline for the diagnosis and treatment of 2019 novel coronavirus (2019-nCoV) infected pneumonia (standard version). *Mil Med Res.* (2020) 7:1–23. doi: 10.1186/s40779-020-0233-6
27. Sharfstein JM, Becker SJ, Mello MM. Diagnostic testing for the novel coronavirus. *JAMA - J Am Med Assoc.* (2020) 323:1437–8. doi: 10.1001/jama.2020.3864
28. Drosten C, Günther S, Preiser W, Van der Werf S, Brodt HR, Becker S, et al. Identification of a novel coronavirus in patients with severe acute respiratory syndrome. *N Engl J Med.* (2003) 348:1967–76. doi: 10.1056/NEJMoa030747
29. Corman VM, Landt O, Kaiser M, Molenkamp R, Meijer A, Chu DKW, et al. Detection of 2019 novel coronavirus (2019-nCoV) by real-time RT-PCR. *Eurosurveillance.* (2020) 25:2000045. doi: 10.2807/1560-7917.ES.2020.25.3.2000045
30. Clinical management of severe acute respiratory infection when novel coronavirus (nCoV) infection is suspected. Available online at: https://www.who.int/publications-detail/clinical-management-of-severe-acute-respiratory-infection-when-novel-coronavirus-(ncov)-infection-is-suspected (accessed March 19, 2020).
31. Nishiura H, Jung S, Linton NM, Kinoshita R, Yang Y, Hayashi K, et al. The extent of transmission of novel coronavirus in Wuhan, China, 2020. *J Clin Med.* (2020) 9:330. doi: 10.3390/jcm9020330
32. Interim Infection Prevention and Control Recommendations for Patients with Suspected or Confirmed Coronavirus Disease 2019 (COVID-19) in Healthcare Settings. USA (2020). Available online at: https://www.tlchomecare.com/cdc-interim-infection-prevention-and-control-recommendations-for-patients-with-suspected-or-confirmed-coronavirus-disease-2019-covid-19-in-healthcare-settings
33. Lu C-W, Liu X-F, Jia Z-F. 2019-nCoV transmission through the ocular surface must not be ignored. *Lancet (London, England).* (2020) 395:e39. doi: 10.1016/S0140-6736(20)30313-5
34. Phan LT, Nguyen T V., Luong QC, Nguyen T V., Nguyen HT, Le HQ, et al. Importation and Human-to-Human Transmission of a Novel Coronavirus in Vietnam. *N Engl J Med.* (2020) 382:872–874. doi: 10.1056/NEJMc2001272
35. Chan JF-W, Yuan S, Kok K-H, To KK-W, Chu H, Yang J, et al. A familial cluster of pneumonia associated with the 2019 novel coronavirus indicating person-to-person transmission: a study of a family cluster. *Lancet.* (2020) 395:514–523. doi: 10.1016/S0140-6736(20)30154-9
36. Holshue ML, DeBolt C, Lindquist S, Lofy KH, Wiesman J, Bruce H, et al. First Case of 2019 Novel Coronavirus in the United States. *N Engl J Med.* (2020) 382:929–36. doi: 10.1056/NEJMoa2001191
37. Xinhua. China Focus: Chinese researchers isolate novel coronavirus strains from feces - Xinhua | English.news.cn. *XINHUANET*. (2020) Available online at: http://www.xinhuanet.com/english/2020-02/13/c_138781178.htm
38. Li Q, Guan X, Wu P, Wang X, Zhou L, Tong Y, et al. Early Transmission Dynamics in Wuhan, China, of Novel Coronavirus–Infected Pneumonia. *N Engl J Med.* (2020) 382:1199–207. doi: 10.1056/nejmoa2001316
39. Riou J, Althaus CL. Pattern of early human-to-human transmission of Wuhan 2019 novel coronavirus (2019-nCoV), December 2019 to January 2020. *Eurosurveill.* (2020) 25:2000058. doi: 10.2807/1560-7917.ES.2020.25.4.2000058
40. Bai Y, Yao L, Wei T, Tian F, Jin DY, Chen L, et al. Presumed asymptomatic carrier transmission of COVID-19. *JAMA - J Am Med Assoc.* (2020) 323:1406–7. doi: 10.1001/jama.2020.2565
41. Rothe C, Schunk M, Sothmann P, Bretzel G, Froeschl G, Wallrauch C, et al. Transmission of 2019-nCoV infection from an asymptomatic contact in Germany. *N Engl J Med.* (2020) 382:970–1. doi: 10.1056/NEJMc2001468
42. Jiang F, Deng L, Zhang L, Cai Y, Cheung CW, Xia Z. Review of the Clinical Characteristics of Coronavirus Disease 2019 (COVID-19). *J Gen Intern Med.* (2020) 35:1545–549. doi: 10.1007/s11606-020-05762-w
43. Adams JG, Walls RM. Supporting the health care workforce during the COVID-19 Global Epidemic. *JAMA - J Am Med Assoc.* (2020) 323:1439–40. doi: 10.1001/jama.2020.3972
44. Health care workers getting sicker from coronavirus than other patients, expert says - CNN. (2020). Available online at: https://edition.cnn.com/2020/03/16/health/doctors-coronavirus-health-care-hit-harder/index.html (accessed September 1, 2020).
45. Van Doremalen N, Bushmaker T, Morris DH, Holbrook MG, Gamble A, Williamson BN, et al. Aerosol and surface stability of SARS-CoV-2 as compared with SARS-CoV-1. *N Engl J Med.* (2020) 382:1564–7. doi: 10.1056/NEJMc2004973
46. Gray R. Covid-19: how long does the coronavirus last on surfaces? *BBC.* (2020) Available online at: https://www.bbc.com/future/article/20200317-covid-19-how-long-does-the-coronavirus-last-on-surfaces
47. Management of Patients with Confirmed 2019-nCoV | CDC. Available online at: https://www.cdc.gov/coronavirus/2019-ncov/hcp/clinical-guidance-management-patients.html (accessed March 19, 2020).
48. Shen K, Yang Y, Wang T, Zhao D, Jiang Y, Jin R, et al. Diagnosis, treatment, and prevention of 2019 novel coronavirus infection in children: experts' consensus statement. *World J Pediatr.* (2020) 16:223–31. doi: 10.1007/s12519-020-00343-7
49. Wang M, Cao R, Zhang L, Yang X, Liu J, Xu M, et al. Remdesivir and chloroquine effectively inhibit the recently emerged novel coronavirus (2019-nCoV) in vitro. *Cell Res.* (2020) 30:269–71. doi: 10.1038/s41422-020-0282-0
50. Gao J, Tian Z, Yang X. Breakthrough: Chloroquine phosphate has shown apparent efficacy in treatment of COVID-19 associated pneumonia in clinical studies. *Biosci Trends.* (2020) 14:72–3. doi: 10.5582/BST.2020.01047
51. Savarino A, Boelaert JR, Cassone A, Majori G, Cauda R. Effects of chloroquine on viral infections: an old drug against today's diseases? *Lancet Infect Dis.* (2003) 3:722–7. doi: 10.1016/S1473-3099(03)00806-5
52. Hu TY, Frieman M, Wolfram J. Insights from nanomedicine into chloroquine efficacy against COVID-19. *Nat Nanotechnol.* (2020) 15:247–9. doi: 10.1038/s41565-020-0674-9
53. Information for Clinicians on Therapeutic Options for COVID-19 Patients | CDC. (2020) Available online at: https://www.cdc.gov/coronavirus/2019-ncov/hcp/therapeutic-options.html (accessed March 22, 2020).
54. Gautret P, Lagier J-C, Parola P, Hoang VT, Meddeb L, Mailhe M, et al. Hydroxychloroquine and azithromycin as a treatment of COVID-19: results of an open-label non-randomized clinical trial. *Int J Antimicrob Agents.* (2020) 56: 105949. doi: 10.1016/j.ijantimicag.2020.105949
55. Sheahan TP, Sims AC, Leist SR, Schäfer A, Won J, Brown AJ, et al. Comparative therapeutic efficacy of remdesivir and combination lopinavir, ritonavir, and interferon beta against MERS-CoV. *Nat Commun.* (2020) 11:1–14. doi: 10.1038/s41467-019-13940-6
56. Sheahan TP, Sims AC, Graham RL, Menachery VD, Gralinski LE, Case JB, et al. Broad-spectrum antiviral GS-5734 inhibits both epidemic and zoonotic coronaviruses. *Sci Transl Med.* (2017) 9:eaal3653. doi: 10.1126/scitranslmed.aal3653
57. Cai Q, Yang M, Liu D, Chen J, Shu D, Xia J, et al. Experimental treatment with favipiravir for COVID-19: an open-label control study. *Engineering*. (2020) doi: 10.1016/j.eng.2020.03.007. [Epub ahead of print].
58. Zeng YM, Xu XL, He XQ, Tang SQ, Li Y, Huang YQ, et al. Comparative effectiveness and safety of ribavirin plus interferon-alpha, lopinavir/ritonavir plus interferon-alpha, and ribavirin plus lopinavir/ritonavir plus interferon-alpha in patients with mild to moderate novel coronavirus disease 2019: Study protocol. *Chin Med J (Engl).* (2020) 133:1132–4. doi: 10.1097/CM9.0000000000000790
59. Hoffmann M, Kleine-Weber H, Krüger N, Müller M, Drosten C, Pöhlmann S. The novel coronavirus 2019 (2019-nCoV) uses the SARS-coronavirus receptor ACE2 and the cellular protease TMPRSS2 for entry into target cells. *bioRxiv [Preprint].* (2020). doi: 10.1101/2020.01.31.929042
60. Sarma P, Prajapat M, Avti P, Kaur H, Kumar S, Medhi B. Therapeutic options for the treatment of 2019-novel coronavirus: an evidence-based approach. *Indian J Pharmacol.* (2020) 52:1. doi: 10.4103/ijp.IJP_119_20
61. Richardson SCW, Kolbe HVJ, Duncan R. Potential of low molecular mass chitosan as a DNA delivery system: Biocompatibility, body distribution and ability to complex and protect DNA. *Int J Pharm.* (1999) 178:231–43. doi: 10.1016/S0378-5173(98)00378-0

62. NIH clinical trial of investigational vaccine for COVID-19 begins | National Institutes of Health (NIH). Available online at: https://www.nih.gov/news-events/news-releases/nih-clinical-trial-investigational-vaccine-covid-19-begins (accessed March 22, 2020).
63. Lurie N, Saville M, Hatchett R, Halton J. Developing Covid-19 vaccines at pandemic speed. *N Engl J Med.* (2020) 382:1969–73. doi: 10.1056/NEJMp2005630
64. Gouglas D, Thanh Le T, Henderson K, Kaloudis A, Danielsen T, Hammersland NC, et al. Estimating the cost of vaccine development against epidemic infectious diseases: a cost minimisation study. *Lancet Glob Heal.* (2018) 6:e1386–96. doi: 10.1016/S2214-109X(18)30346-2
65. Diamond MS, Pierson TC. The challenges of vaccine development against a new virus during a pandemic. *Cell Host Microbe.* (2020) 27:699–703. doi: 10.1016/j.chom.2020.04.021
66. Schindewolf C, Menachery VD. Middle east respiratory syndrome vaccine candidates: Cautious optimism. *Viruses.* (2019) 11:74. doi: 10.3390/v11010074
67. Kommenda N, Hulley-Jones F. Covid vaccine tracker: when will a coronavirus vaccine be ready? | World news. *Guard*. (2020) Available online at: https://www.theguardian.com/world/ng-interactive/2020/aug/31/covid-vaccine-tracker-when-will-a-coronavirus-vaccine-be-ready (accessed September 1, 2020).
68. Coronavirus vaccine tracker. *New York Times*. (2020) Available online at: https://www.nytimes.com/interactive/2020/science/coronavirus-vaccine-tracker.html (accessed September 1, 2020).
69. Seo G, Lee G, Kim MJ, Baek SH, Choi M, Ku KB, et al. Rapid detection of COVID-19 causative virus (SARS-CoV-2) in human nasopharyngeal swab specimens using field-effect transistor-based biosensor. *ACS Nano.* (2020) 14:5135–42. doi: 10.1021/acsnano.0c02823
70. Boissay F, Rungcharoenkitkul P. Macroeconomic effects of Covid-19: an early review No 7 BIS Bulletin. (2020). Available online at: www.bis.org (accessed September 1, 2020).
71. Global Economic Effects of COVID-19. Available online at: https://crsreports.congress.gov (accessed September 1, 2020).
72. Ozili PK, Arun T. Spillover of COVID-19: impact on the global economy. *SSRN Electron J*. (2020). doi: 10.2139/ssrn.3562570
73. IATA Updates COVID-19 financial impacts -Relief measures needed. *IATA*. (2020) Available online at: https://www.iata.org/en/pressroom/pr/2020-03-05-01/ (accessed September 1, 2020).
74. Airlines Seek $50 Billion Coronavirus Aid Package - WSJ. (2020) Available online at: https://www.wsj.com/articles/airlines-seek-up-to-50-billion-in-government-aid-amid-coronavirus-crisis-11584378242 (accessed October 22, 2020).
75. How hard will the coronavirus hit the travel industry? (2020) Available online at: https://www.nationalgeographic.com/travel/2020/04/how-coronavirus-is-impacting-the-travel-industry/ (accessed October 22, 2020).
76. The government threw us under the bus: How Bristol food businesses are working to survive coronavirus - The Bristol Cable. Available online at: https://thebristolcable.org/2020/03/bristol-coronavirus-businesses-impact-food-restaurants-pubs-government-threw-us-under-bus/#article-top (accessed October 22, 2020).
77. How COVID-19 Hits Hard the Hospitality Industry and What Can Be Done. *2020* Available online at: https://impakter.com/covid-hits-hospitality-industry/ (accessed October 22, 2020).
78. COVID-19 resources. (2020) Available online at: https://eventscouncil.org/coronavirus (accessed September 1, 2020).
79. Impact of coronavirus (COVID-19) on the entertainment industry in Italy 2020. Available online at: https://www.statista.com/statistics/1103010/impact-of-coronavirus-covid-19-on-the-entertainment-industry-in-italy/ (accessed October 22, 2020).
80. Coronavirus: Singapore has sufficient healthcare facilities, Singapore News & Top Stories - The Straits Times. (2020) Available online at: https://www.straitstimes.com/singapore/spore-has-sufficient-healthcare-facilities (accessed October 22, 2020).
81. Eduventures Research and Advisory Services. (2020) Available online at: https://encoura.org/products-services/eduventures-research-and-advisory-services/ (accessed October 22, 2020).
82. U.S. Airlines say they can absorb impact of coronavirus on Travel. *New York Times*. (2020) Available online at: https://www.nytimes.com/2020/03/10/business/airlines-coronavirus.html (accessed September 1, 2020).
83. Hotel industry seeks $150 billion coronavirus relief. *Axios*. (2020) Available online at: https://www.axios.com/hotel-industry-150-billion-coronavirus-relief-34910e41-2402-4260-b4b9-8f5b738db664.html (accessed September 1, 2020).
84. COVID-19'S impact on the hotel industry. *AHLA Am Hotel Lodg Assoc*. (2020) Available online at: https://www.ahla.com/covid-19s-impact-hotel-industry (accessed September 1, 2020).
85. Pulver A. At least 170,000 lose jobs as film industry grinds to a halt due to coronavirus | Film industry. *Guard*. (2020) Available online at: https://www.theguardian.com/film/2020/mar/19/loss-of-jobs-income-film-industry-hollywood-coronavirus-pandemic-covid-19 (accessed September 1, 2020).
86. School closures caused by Coronavirus (Covid-19). (2020) Available online at: https://en.unesco.org/covid19/educationresponse (accessed September 1, 2020).
87. Coronavirus forces $600 billion higher education industry online. *Bloomberg*. (2020) Available online at: https://www.bloomberg.com/news/articles/2020-03-19/colleges-are-going-online-because-of-the-coronavirus (accessed September 1, 2020).
88. Porter ME. Strategy and the internet. *Harv Bus Rev.* (2020). Available online at: https://hbr.org/2001/03/strategy-and-the-internet (accessed September 1, 2020)
89. Schifferes S. Developing countries are facing economic disaster: four ways western nations can support them to shore up the global economy. *Conversat.* (2020). Available online at: https://theconversation.com/developing-countries-are-facing-economic-disaster-four-ways-western-nations-can-support-them-to-shore-up-the-global-economy-139083 (accessed October 23, 2020).
90. Schifferes S. How can we protect developing countries from the pandemic?. *World Econ Forum*. (2020) Available online at: https://www.weforum.org/agenda/2020/06/developing-countries-economics-covid19-poverty-coronavirus (accessed October 23, 2020).

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BRIEF RESEARCH REPORT
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Have COVID-19-Related Economic Shocks Affected the Health Levels of Individuals in the United States and the United Kingdom?

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This paper introduces a health index for measuring the health level of societies during the lockdown era, i. e., for the period from March 21, 2020 to April 7, 2020. For this purpose, individual-level survey data from the Global Behaviors and Perceptions in the COVID-19 Pandemic dataset are considered. We focus on cases in the United States and the United Kingdom, and the data come from 11,270 and 11,459 respondents, respectively. We then use unit root tests with structural breaks to examine whether COVID-19-related economic shocks significantly affect the health levels of the United States and the United Kingdom. The empirical results indicate that the health levels in the United States and the United Kingdom are not significantly affected by the COVID-19-related economic shocks. The evidence shows that government directives (such as lockdowns) did not significantly change the health levels of these societies.

Keywords: COVID-19-related shocks, measuring health level, lockdown era, individual-level survey, unit root test with structural breaks

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INTRODUCTION

The COVID-19 pandemic invoked a coordinated response from communities, governments, institutions, and organizations to mitigate the tragedy that inexorably ensued. The onset of this global crisis was a significant shock to societies. People's attitudes toward one another may have been transformed, as exemplified by the growth in voluntary groups to support vulnerable members of the community and the Thursday-night applause for frontline healthcare workers in many countries.

The onset of the COVID-19 pandemic in early 2020 has had various policy implications related to protecting public health. Governments have imposed curfews or partial lockdowns, including closures of public spaces, schools, and workplaces, and have enacted restrictions on domestic and international travel (1, 2). However, these policy decisions have increased unemployment (3–5) and created other problems in labor markets since most workers are unable to work from home (6–8). In short, COVID-19-related economic shocks have affected societies in many different ways. Therefore, it is important to analyze whether these kinds of policy implications have significantly affected the health level of society.

In this paper, we introduce a health index for society using individual-level survey data from the Global Behaviors and Perceptions in the COVID-19 Pandemic dataset. We focus on cases in the United States and the United Kingdom, covering 11,270 and 11,459 respondents, respectively. As discussed, government policies can affect the health level of society. We also examine whether COVID-19-related shocks significantly affect the health level of the United States and the United Kingdom. At this stage, our paper focuses on the period of lockdown in the United Kingdom and some regions in the United States (March 21, 2020 to April 7, 2020). This issue allows us to determine whether government decisions (such as the lockdown) have affected the health level of these societies.

We suggest that the United Kingdom and the United States are interesting cases. Indeed, Boris Johnson and Donald Trump are seeking to restore public confidence, and they have announced various policies to mitigate the effects of the COVID-19-related economic downturn. They have announced projects, such as constructing new highways, hospitals, and schools. However, these leaders have adopted a seemingly market-oriented approach to the disease, as though discounting its existence will somehow magic it away. We also suggest that altruism may exert pressure for change to a more humanitarian approach by governments and corporate enterprises, especially in the liberal free-market economies of the United States and the United Kingdom, where economic considerations are now beginning to dominate the debate, with community health seemingly discounted. Therefore, it is noteworthy to monitor the health conditions of people living in these countries.

The remainder of this paper is organized as follows. Section Data and Methodology explains the data and the procedures of the unit root tests with structural breaks; Section 3 discusses the empirical findings; and Section 4 concludes.

DATA AND METHODOLOGY

Data

In this study, we focus on individual-level survey data covering 11,270 respondents in the United States and 11,459 respondents in the United Kingdom. The original dataset was provided by Fetzer et al. (9). The individual-level survey data of Fetzer et al. (9) are created by the snowball sampling method, which includes the survey instruments. The surveys were conducted in 68 languages, and the responses have been recorded using online tools between March 21, 2020 and April 7, 2020[1].

At this stage, we consider the Health measure of the individual-level survey in Fetzer et al. (9). This measure asks respondents the following question, "How healthy are you?" The Health measure is defined as an index from 1 to 4, where 1 = poor, 2 = fair, 3 = good, and 4 = excellent. The scores of the responses are collapsed for each day throughout concern, and we create the health index scores in the United States and the United Kingdom, respectively. Next, we introduce the health index from 1 to 10. Naturally, a higher level on the health index means a greater health level in society.

Figure 1 illustrates the health levels in the United States and the United Kingdom throughout concern.

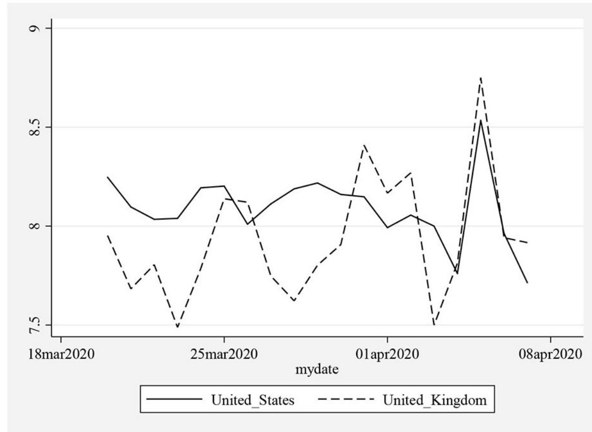

FIGURE 1 | Health Levels (Index from 1 to 10) in the United Kingdom and the United States. A higher level of the index means that there is a greater health level in the society.

In **Table 1**, a summary of the descriptive statistics is provided. The averages and the median values of the health index in the United States and the United Kingdom are found as 8.08 and 7.93, respectively. These results indicate that respondents in these countries live with "good health conditions."

The standard deviations of the health index in the United States and the United Kingdom are observed as 0.18 and 0.31, respectively. According to the results of the ANOVA *F*-test, Satterthwaite-Welch *t*-test, *t*-test, and Welch *F*-test for equality of means between the related series, there is no statistically significant difference (at the 5% level) between the mean of health levels in the United Kingdom and the United States[2]. It is also observed that both series follow a normal distribution, and there are no issues with the non-linearity of the series.

Unit Root Test Methodology

Following the preliminary evidence, we move on to the linear unit root tests to examine whether the external shocks have changed the pattern of the health indices in the United Kingdom and the United States. However, we should consider a unit root test with structural breaks, given the enacting of the Coronavirus Aid, Relief, and Economic Security (CARES) Act on March 27, 2020 in the United States. Therefore, we consider unit root tests that model the structural breaks in the series, which are proposed by Zivot and Andrews (10) and Perron (11).

EMPIRICAL FINDINGS

The results of the unit root test of Zivot and Andrews (10) are provided in **Table 2**.

[1]Refer to http://www.covid19-survey.org and Fetzer et al. (9) for detailed information.

[2]Note that there is no statistically significant difference (at the 5% level) between the median and the variances of health levels in the United Kingdom and the United States.

TABLE 1 | Summary of descriptive statistics.

Indicator	Definition	Source	Mean	Median	Standard deviation	Skewness	Kurtosis	Jarque–Bera
Health Index_UK	Index from 0 to 10	Authors' Calculation Based on Fetzer et al. (9)	7.937	7.906	0.315	0.845	3.545	2.496 [0.2869]
Health Index_USA	Index from 0 to 10	Authors' Calculation Based on Fetzer et al. (9)	8.087	8.096	0.179	0.081	4.141	1.052 [0.5908]

The probability values in [ ].

TABLE 2 | Unit root test of Zivot and Andrews (10).

Break on the Level	Test Statistic and Lag	Break	Conclusion
Health Index_UK	−4.738*** (4)	April 2, 2020	I(0)
Health Index_USA	−5.860*** (1)	April 1, 2020	I(0)
Break on the Trend	**Test Statistic and Lag**	**Break**	**Conclusion**
Health Index_UK	−4.924*** (4)	April 2, 2020	I(0)
Health Index_USA	−5.070*** (1)	April 1, 2020	I(0)
Break on Both Level and Trend	**Test Statistic and Lag**	**Break**	**Conclusion**
Health Index_UK	−4.875*** (4)	April 2, 2020	I(0)
Health Index_USA	−5.772*** (1)	April 1, 2020	I(0)

*Lags, which are selected by BIC, are in parentheses. ***p < 0.01.*
Null hypothesis: The indicator follows a unit root process.

TABLE 3 | Unit root test of Perron (11).

Break on the Level	Test Statistic and Lag	Break	Conclusion
Health Index_UK	−5.294*** (2)	April 2, 2020	I(0)
Health Index_USA	−5.975*** (0)	April 4, 2020	I(0)
Break on the Trend	**Test Statistic and Lag**	**Break**	**Conclusion**
Health Index_UK	−4.851*** (2)	April 2, 2020	I(0)
Health Index_USA	−6.324*** (0)	April 1, 2020	I(0)
Break on Both Level and Trend	**Test Statistic and Lag**	**Break**	**Conclusion**
Health Index_UK	−6.383*** (2)	April 2, 2020	I(0)
Health Index_USA	−7.981*** (0)	April 4, 2020	I(0)

*Lags, which are selected by BIC, are in parentheses. ***p < 0.01.*
Null hypothesis: The indicator follows a unit root process.

Table 2 reports the findings of the unit root in the level term, the time-trend term, and both the level and the time-trend terms. The optimal lags in unit root test are selected by the Bayesian Information Criteria (BIC). All results indicate that the null hypothesis, i.e., that health measures follow a unit root process, is rejected for the health measures in the United States and the United Kingdom. The Zivot–Andrews test statistics are statistically significant at the 1% level ($p < 0.01$).

We check the robustness of the findings of the unit root test of Zivot and Andrews (10). For this purpose, we also report the results of the unit root test of Perron (11) in **Table 3**.

Table 3 provides the results of the unit root in the level term, the time-trend term, and both the level and the time-trend terms. Similarly, the optimal lags in unit root test are selected by the BIC. All findings indicate that the null hypothesis, i.e., that the health measures follow a unit root process, is rejected for the health measures in the United States and the United Kingdom. The Perron test statistics are statistically significant at the 1% level ($p < 0.01$).

Overall, the findings are robust to different unit root test techniques. Our main findings indicate that the health levels in the United States and the United Kingdom are not significantly affected by COVID-19-related economic shocks.

CONCLUSION

In this study, we introduced a health index to measure the health level of society during the lockdown era, i.e., from March 21, 2020 to April 7, 2020. For this purpose, we considered individual-level survey data from the Global Behaviors and Perceptions in the COVID-19 Pandemic dataset of Fetzer et al. (9). We focused on cases in the United States and the United Kingdom, and the data come from 11,270 and 11,459 respondents, respectively. We then used the unit root tests with structural breaks of Zivot and Andrews (10) and Perron (11) to examine whether the COVID-19-related shocks significantly affected the health levels of the United States and the United Kingdom.

The empirical results show that the health levels in the United States and the United Kingdom are not significantly affected by the COVID-19-related shocks. This evidence shows that government policies (such as lockdowns) did not significantly change public health levels. However, it is important to note that there are some limitations to these results. For example, the respondents who filled out the health questionnaire could not be deceased, which means that if a family member of a deceased person filled out the questionnaire on that person's behalf, the results of the study might change. In addition, people filling in the questionnaire may be affected by government propaganda; for example, the Trump administration has been downplaying the impact of the epidemic. Respondents' assessment of their health conditions could be affected by publicity, and this would affect the results of the study.

Given that our paper focuses on the data of the early stages of the COVID-19 crisis, governments should focus their attention on the most vulnerable people in society. Arguably, increased support for the most vulnerable might be gained by more sympathetic treatment of health and other vital workers, as well as increased expenditures to improve both the quality and ease of access to medical services. Future papers can focus on the re-openings era of the COVID-19 crisis when individual-level survey data becomes available.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: https://osf.io/3sn2k.

AUTHOR CONTRIBUTIONS

BJ: data curation and writing—original draft preparation. ZL: writing the original draft. RS: methodology and writing—original draft preparation. LH: investigation and software. YT: conceptualization and visualization. YX: conceptualization and supervision. All authors contributed to the article and approved the submitted version.

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REFERENCES

1. Alvarez FE, Argente D, Lippi F. A Simple Planning Problem for COVID-19 Lockdown. In: *National Bureau of Economic Research (NBER) Working Paper, No. 26981*. Cambridge, MA: NBER (2020).
2. Hale T, Petherick A, Phillips T. Webster S. *Variation in Government Responses to COVID-19*. Oxford: Oxford University (2020).
3. Cajner T, Crane LD, Decker RA, Grigsby J, Hamins-Puertolas A, Hurst E, et al. The U.S. Labor Market during the Beginning of the Pandemic Recession. In: *National Bureau of Economic Research (NBER) Working Paper, No. 27159*. Cambridge, MA: NBER (2020). doi: 10.2139/ssrn.3595452
4. Coibion O, Gorodnichenko Y, Weber M. Labor Markets during the COVID-19 Crisis: A Preliminary View. In: *National Bureau of Economic Research (NBER) Working Paper, No. 27017*. Cambridge, MA: NBER (2020). doi: 10.3386/w27017
5. Forsythe E, Kahn LB, Lange F, Wiczer DG. Labor demand in the time of COVID-19: evidence from vacancy postings and UI claims. *J Public Econ*. (2020) 189:104238. doi: 10.1016/j.jpubeco.2020.104238
6. Atkeson A. What will be the economic impact of COVID-19 in the US? Rough Estimates of Disease Scenarios. In: *National Bureau of Economic Research (NBER) Working Paper, No. 26867*. Cambridge, MA: NBER (2020).
7. Cowan BW. Short-run Effects of COVID-19 on US Worker Transitions. In: *National Bureau of Economic Research (NBER) Working Paper, No. 27315*. Cambridge, MA: NBER (2020).
8. Montenovo L, Jiang X, Rojas FL, Schmutte IM, Simon KI, Weinberg BA, et al. Determinants of Disparities in Covid-19 Job Losses. In: *National Bureau of Economic Research (NBER) Working Paper, No. 27312*. Cambridge, MA: NBER (2020).
9. Fetzer T, Witte M, Hensel L, Jachimowicz JM, Haushofer J, Ivchenko A, et al. Global behaviors and perceptions in the COVID-19 pandemic. In: *Harvard Business School Working Paper, No. 20-111*. Cambridge, MA: Harvard Business School (2020).
10. Zivot E, Andrews DWK. Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis. *J Business Econ Stat*. (1992) 10:251–70. doi: 10.1080/07350015.1992.10509904
11. Perron P. Further evidence on breaking trend functions in macroeconomic variables. *J Econometr*. (1997) 80:355–85. doi: 10.1016/S0304-4076(97)00049-3

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ORIGINAL RESEARCH
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The Impact of Reviewers' Creditworthiness on Consumers' Purchase Intention in Edge Path: Implications for the Coronavirus Disease 2019 Pandemic

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Reviewers' creditworthiness is an important edge clue in the elaboration likelihood model (ELM). This paper takes the online travel booked by consumers as an example and uses the questionnaire data of 417 outbound passengers from Guangzhou Baiyun International Airport. The paper examines the influence of reviewers' creditworthiness on consumer purchase intentions in the edge path through a mediated moderation model. Investigate the mediating role of conformity behavior can influence the reviewers' creditworthiness on purchase. Thus, it examines the moderating effect of consumer involvement. The results show that the degree of consumer involvement moderates the relationship between reviewers' creditworthiness, and the purchase intention is achieved through the mediation of conformity behavior. The higher the degree of consumer involvement, the less impact the reviewers' creditworthiness has on conformity behavior, and the weaker the positive effects of its purchase intention are found. Implications for the coronavirus disease 2019 (COVID-19) era are also discussed.

Keywords: COVID-19 pandemic, elaboration likelihood model, reviewers' creditworthiness, conformity behavior, purchase intentions

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INTRODUCTION

With the advent of the coronavirus disease 2019 (COVID-19), enterprises are facing an increasing uncertainty shock and networked environment. The World Health Organization (WHO) declares that the new coronavirus may have infected about one in 10 people worldwide, 35 million cases are reported in more than 213 countries, and about 1,080,000 deaths are declared until October 2020 (1). During the COVID-19 period, people spend more time at home, watching reviews and online purchase, rather than off-line purchase; they spend much significant amount of time writing online reviews and are involved more interactively. Motivated by this issue, in this paper, we investigate how to acquire and maintain sustainable marketing management advantages in the uncertain environment of high network interconnection, which has become the research focus of management.

Online comment is one of the important channels for consumers to obtain product or service information, especially in the COVID-19 period. It generally refers to potential or actual customer comments on a product or service published on the Internet (2). As an important social interaction medium, online commentary has become an important factor in establishing an immersive and highly engaged online customer relationship, which in turn affects purchase intention. Credential credibility, as an important dimension variable for online reviews, can significantly increase consumer willingness. In the past 3 years, Internet-based online commentary has become a hot topic for scholars (3). Consumers tend to think that online reviews published by high-creditworthiness commentators are more useful and reliable, thus affecting consumers' purchase intention. At the same time, the "black box" research on the influence mechanism of online reviewers' creditworthiness on the purchase intention will always be a hot issue in marketing management (4). Besides, consumer involvement as an important feature of customer engagement has become a key variable in marketing research that cannot be ignored. China is in the critical period of pandemic and increasing the degree of Internet. Business models and consumer behavior are constantly innovating. The level of consumer participation and interaction has become a key feature that enterprises must consider when formulating marketing strategies. This study has an important implication for online purchase because everyone stays home during the COVID-19 pandemic.

Because of this, this paper aims to explore the relationship between online reviewer's creditworthiness, conformity behavior, and purchase intention based on the theory of involvement and to use consumer involvement as an adjustment variable of the intermediary link. The main contributions of this paper are as follows: firstly, based on trust theory, the mediating role of conformity psychology in the relationship between credibility and purchase intention of reviewers is examined. This paper applies the theory to the network marketing management research, further enriches the research perspective of the "black box" exploration of marketing management, and provides important inspiration for the development and application of network marketing management in the environment of increasing consumer participation. Secondly, this paper examines the influence of reviewer's creditworthiness on the formation of conformity behavior and enriches the research results of conformity mental antecedent variables. Finally, combined with the specific situation in China, this paper examines reviewers' creditworthiness in different consumer involvement scenarios. The influence of the conformity behavior and the conformity behavior on the purchase intention will change, and it is found that different consumer involvement plays a regulatory role in these two links, thus providing practical feasibility suggestions for the marketing practice of Chinese enterprises.

The rest of the paper is organized as follows. *Literature Review and Hypotheses* reviews the literature and explain the hypotheses of the research. *Research Design and Data* explains the design of the study and data. *Empirical Results* provides the empirical results, and *Conclusion* concludes.

LITERATURE REVIEW AND HYPOTHESES

Impact of Commentator Credit on Purchase Intention

Reviewers' creditworthiness refers to the reputation of the reviewer or the degree of consumer trust in the reviewer and the acceptance of the content of the review, including the professional competence and reliability of the reviewer. The professional competence of the reviewer mainly means that the reviewer has a certain field of expertise and background to provide the correct information. The credibility of the reviewer refers to the reputation of the reviewer and the credibility of the comment or a certain status in the network (such as senior members and multiple purchases). Reviewers' creditworthiness has a great impact on the impact of online reviews. Consumers tend to think that online reviews published by high-creditworthiness reviewers are more useful and reliable, thus providing more help to consumers' purchasing decisions.

Most domestic and foreign scholars study reviewers' creditworthiness from the professional competence and reliability of reviewers and study their impact on product sales, consumer purchase intentions, and so on. Senecal and Nantel (5) show that most consumers follow a more reliable source of comments or recommendations, which have a higher reference value. Chen and Dhanasobhon (6) point out that comments made by reputable commentators have a greater impact on sales than other reviews. Forman et al. (7) indicate that the increase in sales of products was related to the prevalence of reviewers' disclosure of identity information. Cheung et al. (8) and Guoqing et al. (9) reveal that reviewers' creditworthiness will affect consumers' trust, which in turn affects consumer purchase intentions. The results of Racherla and Friske (10) also confirm that the professionalism of commentators and the reputation of reviewers are positively affecting the perceived usefulness of comments. Therefore, this paper proposes the following assumptions:

H_1: Reviewers' creditworthiness is significantly positively correlated with purchase intention.

Mediation Effect of Conformity Behavior

Conformity behavior means that the consumer changes his or her evaluation of the product or behavior based on the evaluation of the purchase of others. Due to the virtual nature of the network, consumers do not have to give up their original opinions to make purchase decisions that meet the expectations of others when making online purchases. Although there will be no group pressure, the Internet provides a lot of information about other people's purchase behavior (such as online reviews and sales), which can provide a reference for their purchasing decisions. Many domestic and foreign scholars study conformity behavior by researching the characteristics of online reviews and product sales, which have an impact on purchase intention. Huang and Chen (11) show that consumers make their own decisions by referring to other people's purchase behavior and purchase evaluation when shopping online. Xu et al. (12) use brain imaging technology of neuroscience experiments and event-related potential (ERP) to explore the psychological

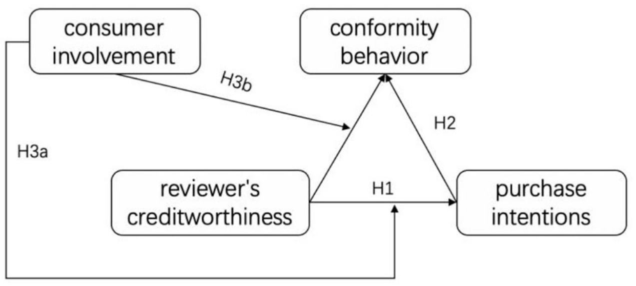

FIGURE 1 | Theoretical model.

and neural mechanisms of conflicts caused by consumer congregation and anti-conformity decisions, explaining why the phenomenon of congregation in consumer shopping is so popular. Tsao et al. (13) confirmed that conformity behavior has a positive impact on consumer hotel booking behavior. Some scholars have studied the influence of reviewers' creditworthiness on conformity behavior. Critics with higher credibility often play the role of opinion leaders, can influence the decision-making behavior of the majority, and will lead consumers to make conformity behavior. Therefore, this paper proposes the following assumptions:

H_2: Conformity behavior plays a mediating role in the relationship between reviewers' creditworthiness and purchase intention.

The Regulation of Consumer Involvement

The involved theory suggests that individuals' perceptions of objects based on their inner needs, values, and interests form an individual's motivational state of things. Among them, "object" refers to products, brands, advertisements, promotions, or certain shopping situations that consumers may be involved in (14). Sources are used as the criteria for classification and are divided into situational involvement and persistent involvement. In the process of purchasing decision making, consumers will have different levels of involvement due to factors such as personal will, external stimuli, and shopping situation. Therefore, this paper further examines that this kind of consumer involvement plays an important role in the influence of reviewers' creditworthiness and conformity behavior on purchase intention. Among them, consumer involvement refers to different levels of participation, using Zhang and Watts (15) to define the concept, specifically referring to different levels of participation.

Under low involvement, consumer attitudes are more affected by the reliability of online communities; Yaping et al. (16) found that in consumers with low involvement, positive comments are more likely to cause impulsive purchase intentions. Based on the above analysis, the lower the consumer involvement, the more inclined to process information through the edge path, reviewers' creditworthiness may be more concerned, and the high-creditworthiness reviewers often act as opinion leaders, which will make consumers produce conformity behavior and influence purchase intentions. Therefore, this paper proposes the following assumptions:

H3a: Consumer involvement plays a regulatory role in the relationship between reviewers' creditworthiness and conformity behavior; that is, high consumer involvement weakens the relationship between reviewers' creditworthiness and conformity behavior, while low consumption involvement will strengthen the relationship between the two.

H3b: The influence of consumer involvement on the relationship between reviewers' creditworthiness and the purchase intention is achieved through the intermediary of the conformity behavior. The higher the consumer involvement, the less influence the reviewers' creditworthiness has on the conformity behavior and the corresponding. The positive impact of purchase intention is weaker.
According to the research hypothesis proposed above, the theoretical model for establishing this study is shown in **Figure 1**.

RESEARCH DESIGN AND DATA

Scale Design

The questionnaire is divided into two parts: basic information and measurement scales. All variables are designed from existing literature to ensure the validity of the measurement. Investigate and measure the reliability and validity of the questionnaire firstly, remove or modify the less reliable items to improve the questionnaire, improve the measurement indicators, form a formal questionnaire, and then conduct a large-scale formal investigation according to the requirements of the sampling design. The specific measurement variables and their measurement index system are shown in **Table 1**.

Sample Selection and Data Collection

Taking the customers who intend to book outbound travel products or services online as a research object, we conducted a sample survey at the exit check-in island of Guangzhou Baiyun International Airport. From March 2018 to April 2018, it took 2 months to issue a total of 514 questionnaires. Among them, 417 were valid questionnaires, and the effective rate of the questionnaire was 81.13%.

Reliability and Validity Analyses

The reliability and validity of the scale were analyzed using the valid questionnaire data collected, and the reliability and validity information of each measurement scale was calculated, as shown in **Table 2**.

Table 2 shows that the Cronbach α of each scale is >0.58, and the total variance of the cumulative interpretation is above 50%, indicating that the questionnaire has certain credibility in the study. The results of the confirmatory factor analysis using Mplus were chi-square = 183.392, comparative fit index (CFI) = 0.929, Tucker–Lewis index (TLI) = 0.909, and root mean square error of approximation (RMSEA) = 0.062. According to the usual fitting index evaluation criteria, the model fits well, indicating that the research measurements are four independent variables.

TABLE 1 | Study variable items and sources.

Variables	Indicator system	Measurement basis
Reviewers' creditworthy-ness RR	I think the reviewers know very well about the outbound travel products or services they want to book	(8)
	I think most online reviewers have a high network reputation	
	I think most online reviewers are trustworthy	
	There are many professional reviewers (such as senior members and multiple purchases)	
Consumer involvement CI	To a large extent, I will evaluate online outbound travel products or services	(15)
	It's important for me to get information about outbound travel products or services from comments	
	I will carefully review online reviews when booking outbound travel products or services	
Conformity behavior CB	Many people who evaluate good outbound travel products or services will also buy	(17)
	Seeing that many people book this outbound travel product or service, I will not think about it	
	I will book outbound travel products or services based on the consensus of many people	
Purchase intentions PI	These comments affect whether I am booking the outbound travel product or service	(18)
	These comments have a big impact on my final scheduled outbound travel products or services	
	These comments have changed my attitude toward booking the outbound travel products or services	
	These comments are a great help for my scheduled outbound travel products or services	

TABLE 2 | Reliability and validity of the scale.

Variable	Cronbach α	KMO	Bartlett's sphericity test			Cumulative total variance
			Bangla	df	Sig.	
Reviewers' creditworthiness (RR)	0.698	0.735	272.946	6	0.000	52.682%
Consumer involvement (CI)	0.604	0.630	131.546	3	0.000	55.859%
Conformity behavior (CB)	0.588	0.633	117.357	3	0.000	54.841%
Purchase intentions (PI)	0.733	0.744	342.353	6	0.000	55.887%

KMO, Kaiser–Meyer–Olkin.

TABLE 3 | Descriptive statistics and correlation coefficients.

Variable	Mean	SD	Reviewers' creditworthiness	Consumer involvement	Conformity behavior	Purchase intentions
Reviewers' creditworthiness	5.294	0.827				
Consumer involvement	5.628	0.841	0.549***			
Conformity behavior	5.625	0.815	0.427***	0.539***		
Purchase intentions	5.454	0.842	0.628***	0.635***	0.535***	

****$p < 0.001$, **$p < 0.01$, *$p < 0.05$.*

Descriptive Statistical Analysis

The average value, standard deviation, and correlation coefficient between each measured variable are calculated, as shown in **Table 3**.

Table 3 shows that reviewers' creditworthiness, conformity behavior, and purchase intention are significantly and positively correlated, indicating that they are all factors affecting purchase intention. Reviewers' creditworthiness is significantly positively correlated with the conformity behavior and purchase intention, indicating that the conformity behavior maybe is a mediator variable between reviewers' creditworthiness and purchase intention. These results provide the necessary preconditions for analyzing the relationship between reviewers' creditworthiness, conformity behavior, and purchase intentions.

EMPIRICAL RESULTS

Intermediary Adjustment Effect Model Test

When the direction and size of the relationship between two variables depend on the third variable, there is a regulatory effect. If the modulating effect is to influence the dependent variable through the mediator variable, it becomes an intermediary regulatory effect. According to Fairchild and MacKinnon (19), the regression test procedure for the mediation mode effect model is as follows:

Regression of purchase intentions to reviewer's creditworthiness, consumer involvement, and reviewers' creditworthiness and consumer involvement is shown as follows:

$$Y = c_0 + c_1X + c_2U + c_3XU + e_1 \quad (1)$$

Among them, Y is purchase intention, X is reviewers' creditworthiness, U is the consumer involvement, XU is the interaction term between reviewers' creditworthiness and the degree of consumer involvement, and e_1 is the residual regression term. If the coefficient c_3 of XU is significant, it indicates that the adjustment effect is significant. If the coefficient c_3 of XU is not significant (the adjustment effect is not significant), it is not necessary to test whether the "mediated effect" is significant.

Regression of the interaction between the conformity behavior, reviewers' creditworthiness, the consumer involvement, and reviewers' creditworthiness and the consumer involvement is shown as follows:

$$W = a_0 + a_1X + a_2U + a_3XU + e_2 \tag{2}$$

Among them, W is a conformity behavior, X is reviewers' creditworthiness, U is the consumer involvement, XU is the interaction term between the reviewer's creditworthiness and the consumers' involvement, and e_2 is the regression residual.

Regression of the interaction between reviewers' creditworthiness, the conformity behavior, the consumer's involvement, reviewers' creditworthiness and the consumer's involvement, and the interaction between the conformity behavior and the consumer's involvement is shown as follows.

$$Y = c'_0 + c'_1X + c'_2U + c'_3XU + b_1W + b_2WU + e_3 \tag{3}$$

Among them, Y is purchase intention, X is reviewers' creditworthiness, U is the consumer involvement, XU is the interaction term between the reviewers' creditworthiness and the consumer's involvement, W is the conformity behavior, and WU is the conformity behavior. The consumer enters the interaction term of the two, and e_3 is the residual regression term. If at least one of the coefficients a_3 and b_1, a_3 and b_2, and a_1 and b2 is significant, it indicates that an intermediate adjustment model is established. If c'_3 is significant, it means that the regulatory effect is partially intervened, and if c'_3 is not significant, then the regulatory effect affects the dependent variable entirely through the mediator variable.

If the coefficients a_3 and b_1, a_3 and b_2, and a_1 and b_2 are not significant, do bootstrap or Markov chain Monte Carlo (MCMC) interval test. If at least one interval does not contain 0, then an intermediary adjustment model is established; if all three intervals contain 0, then the mediation adjustment model does not hold. This paper uses Mplus7.0 to perform hypothesis testing using the above procedure proposed by Fairchild and MacKinnon (19).

The Regulatory Role of Consumer Involvement

According to the above test procedure, the adjustment effect of the consumer involvement degree is first tested. Establish a relationship model between reviewers' creditworthiness, consumer involvement, and the interaction between the two and the purchase intention. The results are illustrated in **Figure 2**.

Since the model is a saturated model, chi-square = 0, df = 0, CFI = 1.000, TLI = 1.000, RMSEA = 0.000, and standardized root mean square residual (SRMR) = 0.000, the model fits well. As can be seen from **Figure 2**, reviewers' creditworthiness significantly predicts the purchase intention ($c_1 = 0.428$, $t = 10.948$, $p = 0.000$), assuming H_1 is verified. The interaction between reviewers' creditworthiness and the consumer involvement has a significant effect on the purchase intention ($c_3 = -0.134$, $t = -3.611$, $p = 0.000$), indicating that the consumer involvement is in reviewers' creditworthiness. Play a regulatory role in the influence of purchase intention, assuming H_3a is verified.

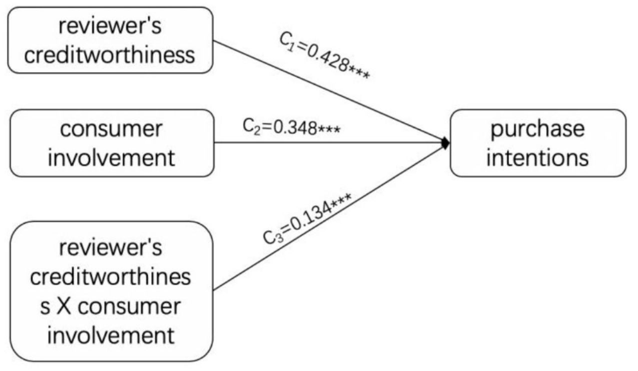

FIGURE 2 | Test of the adjustment effect of consumer involvement.

FIGURE 3 | The effect of consumer involvement on the relationship between reviewers' creditworthiness and purchase intention.

Figure 3, obtained from the simple slope analysis, reflects the impact of reviewers' creditworthiness and purchase intention for consumers with different degrees of involvement. As can be seen from **Figure 3**, compared with consumers with high involvement, the value of the reviewers' creditworthiness has a greater regression slope on purchase intention (the regression line is steeper), indicating reviewers' creditworthiness. The same degree of change can trigger a greater degree of change in purchase intention among consumers with low involvement; that is, reviewers' creditworthiness of the low-involvement consumer is more sensitive to changes in purchase intention.

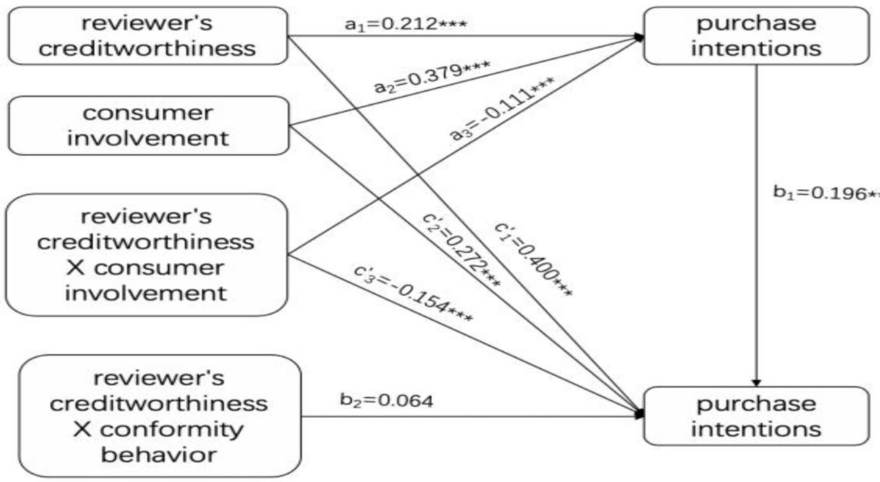

FIGURE 4 | Adjustment effect of mediation of consumer involvement.

TABLE 4 | Results of intermediary effect models.

Predictor	(1) (Dependent variable: Purchase intention)		(2) (Dependent variable: Conformity behavior)		(3) (Dependent variable: Purchase intention)	
	Standard regression coefficient	*p*-value	Standard regression coefficient	*p*-value	Standard regression coefficient	*p*-value
Reviewers' creditworthiness	$c_1 = 0.428$	0.000	$a_1 = 0.212$	0.000	$c'_1 = 0.400$	0.000
Consumer Involvement	$c_2 = 0.348$	0.000	$a_2 = 0.379$	0.000	$c'_2 = 0.272$	0.000
Reviewers' creditworthiness × Consumer involvement	$c_3 = -0.134$	0.000	$a_3 = -0.111$	0.012	$c'_3 = -0.154$	0.001
Conformity behavior					$b_1 = 0.196$	0.000
Conformity behavior × Consumer Involvement					$b_2 = 0.064$	0.158

Consumer Involvement Has an Intermediary Role in Regulation

Construct a relationship model between the purchase intention, the reviewers' creditworthiness, the conformity behavior, the consumer involvement, the commenter's credibility and the consumer's involvement, and the interaction between the conformity behavior and the consumer's involvement. The test results are shown in **Figure 4**.

The fitting indexes of the model are chi-square = 4.307, df = 1, CFI = 0.993, TLI = 0.940, RMSEA = 0.089, and SRMR = 0.012, and the model fits well. The specific model test results are shown in **Table 4**.

Table 4 shows that the reviewers' creditworthiness significantly positively predicts conformity behavior (a_1 = 0.212, $t = 4.371$, $p = 0.000$). The predictive effect of conformity behavior on purchase intention is also significant (b_1 = 0.196, $t = 4.946$, $p = 0.000$), and reviewers' creditworthiness has a significant direct effect on the purchase intention ($c'_1 = 0.400$, $t = 9.948$, $p = 0.000$), indicating that the conformity behavior plays a part in the process of reviewers' creditworthiness affecting his purchase intentions. With role, H2 is verified. At the same time, the interaction between reviewers' creditworthiness and the consumer involvement has a significant predictive effect on the conformity behavior ($a_3 = -0.111$, $t = -2.509$, $p = 0.012 < 0.05$), and the conformity behavior has a significant predictive effect on the purchase intention ($B_1 = 0.196$, $t = 4.946$, $p = 0.000$); the interaction term between the conformity behavior and the consumer involvement degree has no significant effect on the purchase intention ($b_2 = 0.064$, $t = 1.411$, $p = 0.158 > 0.05$). It shows that the adjustment effect of consumer involvement on the relationship between reviewers' creditworthiness and purchase intention is realized through the intermediary of conformity behavior; that is, consumer involvement plays an intermediary role, and H3b is verified. Because the interaction between reviewers' creditworthiness and the consumer involvement is directly predictive of the purchase intention ($c'_3 = -0.154$, $t = -3.305$, $p = 0.001$), the adjustment effect has some mediation. The adjustment effect of consumer involvement on the relationship between reviewers' creditworthiness and purchase intention is partly achieved through the intermediary of conformity behavior.

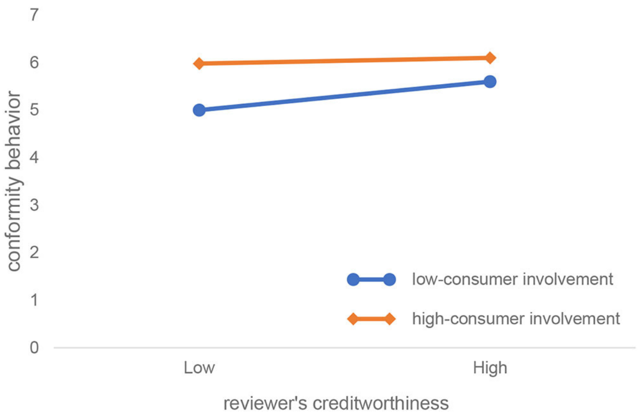

FIGURE 5 | The effect of consumer involvement on reviewer's creditworthiness and conformity behavior.

Figure 5, which is obtained by simple slope analysis, more clearly shows how reviewers' creditworthiness and consumer involvement interact to influence conformity behavior. As can be seen from **Figure 5**, compared with consumers with high involvement, the value of the reviewers' creditworthiness to the conformity behavior is larger (the regression line is steeper), indicating reviewers' creditworthiness. The same degree of change can trigger a greater change in conformity behavior in low-involvement consumers; that is, the credibility of the low-involvement consumer is more sensitive to changes in conformity behavior.

The mediation regulation model shows that the adjustment effect of consumer involvement on the relationship between credibility and purchase intention of the reviewer is realized through the intermediary of the conformity behavior. The higher the consumer involvement, the more the influence of reviewers' creditworthiness on the conformity behavior. So the corresponding positive impact on their purchase intentions is weaker.

CONCLUSION

In the process of the influence of the reviewers' creditworthiness of the edge path on the purchase intention of the consumer, the adjustment effect of the consumer involvement degree on the relationship between reviewers' creditworthiness and the purchase intention is partially realized through the intermediary of the conformity behavior, that is, the consumer involvement degree. There is an intermediary adjustment between the reviewers' creditworthiness and the purchase intention relationship. The higher the consumer involvement, the less influence the reviewers' creditworthiness has on the conformity behavior, and the weaker the positive influence on the purchase intention. This issue is because, at the high level of involvement, people are more motivated to make the necessary cognition and effort to comment on the information and will extensively search for information and carefully process and evaluate the information, which is the possibility of fine processing of the information. Sex increases, and thus the more inclined to choose the central path, the information content itself has a greater impact on the recipient's attitude. In the case of low involvement, the consumer's processing motivation and processing ability are low. Consumers will choose the edge path to process the information, which will take less time and effort to evaluate the information. The purchase behavior will often be affected by some edge clues (such as reviewer's creditworthiness), and it is more likely to occur in a conformity behavior, thus affecting their purchase intentions.

The relevant conclusions of this study can provide some meaningful revelations and implications for the enterprises in the COVID-19 period: firstly, with the advent of the pandemic, customers spend more time online and acquire more product information online, and we should pay attention to the evaluation system of reviewers' creditworthiness. In the edge path of consumers processing online comment information, reviewers' creditworthiness is an important edge clue. The enterprises can establish a consumer-level membership mechanism, or record the purchase experience of the consumer, and implement an evaluation mechanism for the published online comment. That is, others can like to praise or evaluate online reviews, thus establishing a good evaluation system for reviewers' creditworthiness. Secondly, the enterprises can distinguish customers into different groups since more and more people go shopping online in the period of the COVID-19 by dividing consumers into high-involvement or low-involvement consumers according to the consumer's past purchase experience, published comments, and other information and can adopt corresponding marketing strategies.

Given that people will spend more time at home, watching reviews and online purchase, rather than off-line purchase, they will spend much significant amount of time writing online reviews and be involved more interactively. Therefore, the implication during pandemics is that the weaker positive effects of its purchase intention will persist. Future papers can focus on how re-openings after the COVID-19 pandemic can affect online shopping.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by The survey in the study has been approved by the ethics committee of Nanjing University of Posts and Telecommunications. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

CL: data curation, writing—original draft preparation, and visualization. LW: conceptualization, investigation, software, and writing—original draft preparation. All authors contributed to the article and approved the submitted version.

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REFERENCES

1. Dong E, Du H, Gardner L. An interactive web-based dashboard to track Covid-19 in real-time. *Lancet Infect Dis.* (2020) 20:533–4. doi: 10.1016/S1473-3099(20)30120-1
2. Chen Y, Xie J. Online consumer review: word-of-mouth as a new element of marketing communication mix. *Manage Sci*. (2008) 54:477–91. doi: 10.1287/mnsc.1070.0810
3. Bi S, Liu Z, Usman K. The influence of online information on investing decisions of reward-based crowdfunding. *J Bus Res.* (2017) 71:10–8. doi: 10.1016/j.jbusres.2016.10.001
4. Septianto F, Tjiptono F, Kusumasondjaja S. Anger punishes, compassion forgives: how discrete emotions mitigate double standards in consumer ethical judgment. *J Retail Consum Serv*. (2020) 53:101979. doi: 10.1016/j.jretconser.2019.101979
5. Senecal S, Nantel J. The influence of online product recommendations on consumers' online choices. *J Retail.* (2004) 80:159–69. doi: 10.1016/j.jretai.2004.04.001
6. Chen PY, Dhanasobhon S. Analysis of the differential impact of reviews and reviewers at Amazon.com. *Twenty-Eighth International Conference on Information Systems*. Vol. 12. Montreal, QC (2007). p. 9–12.
7. Forman C, Ghose A, Wiesenfeld B. Examining the relationship between reviews and sales: the role of reviewer identity disclosure in electronic markets. *Inform Syst Res.* (2008) 19:291–313. doi: 10.1287/isre.1080.0193
8. Cheung MY, Luo C, Sia CL, Chen H. Credibility of electronic word-of-mouth: informational and normative determinants of online consumer recommendations. *Int J Electron Commerce*. (2009) 13:9–38. doi: 10.2753/JEC1086-4415130402
9. Guoqing G, Kai C, Fei H. An empirical study on the influence of perceived credibility of online consumer reviews. *Contemp Econ Manag.* (2010) 2010:17–23. doi: 10.3969/j.issn.1673-0461.2010.10.004
10. Racherla P, Friske W. Perceived 'Usefulness' of Online consumer reviews: an exploratory investigation across three services categories. *Electron Commer Res Appl*. (2012) 11:548–59. doi: 10.1016/j.elerap.2012.06.003
11. Huang JH, Chen YF. Herding in online product choice. *Psychol Market.* (2006) 23:413–28. doi: 10.1002/mar.20119
12. Xu J, Jiang L, Li Y. Service requirement for terminal delivery: an empirical study from the perspective of online shoppers. *J Indust Eng Manag.* (2013) 6:1223–7. doi: 10.3926/jiem.879
13. Tsao WC, Hsieh MT, Shih LW, Lin TMY. Compliance with eWOM: The influence of hotel reviews on booking intention from the perspective of consumer conformity. *Int J Hosp Manag.* (2015) 46:99–111. doi: 10.1016/j.ijhm.2015.01.008
14. Liyin J. The impact of internet word-of-mouth information on consumers' purchase decisions: an experimental study. *Econ Manag.* (2007) 2007:36–42.
15. Zhang W, Watts S. Knowledge adoption in online communities of practice. In: *Proceedings of the International Conference on Information Systems*, *ICIS 2003*. Seattle, WA (2003).
16. Yaping C, Wanfu X, Wu Y, Jun Y. The influence mechanism of third party commentary on impulsive purchase intention in the network environment: using product category and commentator level as the regulatory variables. *Acta Psychol Sinica*. (2012) 44:1244–64. doi: 10.3724/SP.J.1041.2012.01244
17. Lascu DN, Zinkhan G. Consumer conformity: review and applications for marketing theory and practice. *J Market Theory Pract.* (1999) 7:1–12. doi: 10.1080/10696679.1999.11501836
18. Lu S, Xiaoyan TY. *Consumer Behavioral. 8th Chinese Edition*. Beijing: Renmin University Press (2009).
19. Fairchild AJ, MacKinnon DP. A general model for testing mediation and moderation effects. *Prevent Sci.* (2009) 10:87–99. doi: 10.1007/s11121-008-0109-6

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frontiers in Public Health

BRIEF RESEARCH REPORT
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Causal Relationship Between the Spread of the COVID-19 and Geopolitical Risks in Emerging Economies

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This study investigates the causality between the spread of the COVID-19 pandemic (measured by new cases per million and new deaths per million) and geopolitical risks (measured by the index of geopolitical risks). We use the balanced panel data framework in 18 emerging economies from January 2020 to August 2020. We run the initial tests of cross-sectional dependence and the panel unit root tests with capturing cross-sectional dependence. Then, we utilize the panel Granger non-causality tests for heterogeneous stationary panel datasets. According to the findings, there is a significant causality from both measures of spreading the COVID-19 pandemic to geopolitical risks. Further tests are performed, and potential implications are also discussed.

Keywords: COVID-19 pandemic, measuring the spread of the COVID-19, geopolitical risks, emerging economies, panel granger non-causality tests

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INTRODUCTION

The new type of Coronavirus, so-called the COVID-19, emerged in the very late days of 2019 and has affected every corner of the world by providing different aspects. Governments have implemented different policy implications to address the negative consequences of the spread of the COVID-19 pandemic. Lockdowns, closing down public areas, such as public buildings, schools, and various meeting areas, have been the leading measures to slow down the spread of the novel virus (1).

The COVID-19 pandemic has negatively affected the financial markets (2). The COVID-19 pandemic also makes the economies more unstable via various channels, such as the volatility in commodity markets and financial markets. Particularly, emerging economies have experienced significant volatility in their export revenues. Therefore, there is a significant difference between the situation faced by emerging economies and developed countries when facing the COVID-19 pandemic. At this stage, the COVID-19 pandemic creates governance problems, especially in emerging economies, due to the lack of coordination capacity. On the other hand, responding to the pandemic range from very organized in China's case to chaotic Brazil and Mexico. We aim to examine whether these issues affect the geopolitical risks.

This paper aims to examine the causal relationship between the spread of the COVID-19 pandemic (measured by new cases per million and new deaths per million) and geopolitical risks (measured by geopolitical risks index). For this purpose, we use the balanced panel data framework in 18 emerging economies for the period from January 2020 to August 2020. The theoretical relationship between the COVID-19 pandemic and geopolitical risks can be positive or negative. Significant job losses from the COVID-19 have decreased people's income, and this issue may lead to an increase in violence and protests. However, the decline in global demand decreases the value of natural resources, such as oil prices. Then, there should be less conflict over control of these rentable natural resources. For instance, Bloem and Salemi (3) observe that conflicts have increased in some countries (e.g., the Philippines and Nigeria) but decreased in others (e.g., Syria) due to the COVID-19 pandemic. Similarly, Basit (4) indicates that the COVID-19 pandemic has a mixed impact on terrorism. Travel restrictions can decrease terrorism at this stage, but terrorist groups may have a higher capacity to recruit young people from the internet during the lockdown periods.

There are also several previous papers, which have similar researches objectives to our paper. For instance, Sharif et al. (5) show that the uncertainty related to the COVID-19 outbreak has a significant increasing impact on the United States' geopolitical risks. The impact is higher than the impact of uncertainty related to economic policies. However, Apergis and Apergis (6) find that the COVID-19 pandemic decreases the level of political polarization in the United States, measured by the index of partisan conflict, from January 21, 2020, to April 30, 2020. On the other hand, what might indirectly affect the geopolitical risk might be the released confirmed cases' information rather than the case itself. As a result, sentiment and news can also be important in determining the causal relationship between geopolitical risks and COVID-19 (7, 8).

To the best of our knowledge, this is the first research that investigates the causality relationship between the spread of the COVID-19 pandemic and the geopolitical risks in 18 emerging economies. At this stage, we run the initial tests of cross-sectional dependence and the panel unit root tests with capturing cross-sectional dependence. Then, we utilize the panel Granger non-causality test of Dumitrescu and Hurlin (9) for heterogeneous stationary panel datasets. This test procedure captures the heterogeneity and cross-sectional dependence among the emerging economies, which is an important aspect of examining the relationship between the COVID-19 spread and geopolitical risks. Since this test methodology also uses the bootstrapped critical values, the results are robust to the size distortion, which may be a possible issue in the relatively short period of the COVID-19 pandemic. The findings show that the significant causality from both measures of spreading the COVID-19 pandemic to geopolitical risks. Further tests are performed to check the validity of the baseline findings.

The rest of the study is structured as follows. Section Model, Data, and Estimation Procedure introduces the estimated models, the data, and the estimation methodology. Section Empirical Findings provides the empirical findings with further tests on the baseline findings. Section Conclusion concludes.

MODEL, DATA, AND ESTIMATION PROCEDURE

Estimated Models

We consider below empirical models, which are estimated by the Granger non-causality test procedures, for heterogeneous panel datasets:

$$\Delta NCPM_{i,t} = \alpha_1 + \alpha_2 GPR_{i,t-1} + \varepsilon_{i,t} \quad (1)$$

$$\Delta NDPM_{i,t} = \alpha_3 + \alpha_4 GPR_{i,t-1} + \varepsilon_{i,t} \quad (2)$$

$$GPR_{i,t} = \alpha_5 + \alpha_6 \Delta NCPM_{i,t-1} + \varepsilon_{i,t} \quad (3)$$

$$GPR_{i,t} = \alpha_7 + \alpha_8 \Delta NDPM_{i,t-1} + \varepsilon_{i,t} \quad (4)$$

In Equations (1–4), where $\Delta NCPM_{i,t}$ and $\Delta NCPM_{i,t-1}$ are the current and the lagged changes of new COVID-19 cases per million people in an emerging country i at t and t–1. Besides, $\Delta NDPM_{i,t}$ and $\Delta NDPM_{i,t-1}$ are the current and the lagged changes of new COVID-19 deaths per million people in an emerging economy i at t and t–1. Finally, $GPR_{i,t}$ and $GPR_{i,t-1}$ are the current and lagged geopolitical risks in an emerging country i at t and t–1. Note that the error term is represented by $\varepsilon_{i,t}$.

Data

In this study, we estimate the models from Equations (1–4) to examine the causality between the spread of the COVID-19 and geopolitical risks. The sample focuses on the period from January 2020 to August 2020. We include the balanced panel dataset in 18 emerging economies: Argentina, Brazil, China PR, Colombia, India, Indonesia, Israel, Korea Republic, Malaysia, Mexico, the Philippines, Russia, Saudi Arabia, South Africa, Thailand, Turkey, Ukraine, and Venezuela. The countries' selection and the starting period of the empirical analyses are based on the data's availability. The frequency of the sample is monthly.

The spread of the COVID-19 is measured by two indicators: new COVID-19 cases per million people and new COVID-19 deaths per million people. These data are obtained by the dataset of Hasell et al. (10), and they are downloaded from the *World in Data COVID-19* dataset (https://github.com/owid/covid-19-data/tree/master/public/data). We consider the cases per million people to capture countries' size in the spread of the COVID-19 pandemic (11).

Geopolitical risks are measured by the index of geopolitical risks (GPR). The data and the estimation procedure of the country-specific GPR indices are introduced by Caldara and Iacoviello (12). The related data are downloaded from the website of the authors (https://www.matteoiacoviello.com/gpr.htm#dat). A higher value of the GPR index indicates a higher level of geopolitical risks. The GPR index is based on the news related to geopolitical risk. The authors search the archives of 11 international newspapers Boston Globe, Chicago Tribune, Daily Telegraph, Financial Times, Globe and Mail, Guardian, Los Angeles Times, New York Times, Times, Wall Street Journal, and Washington Post. The authors introduce the index by calculating the news related to all news articles related to geopolitical risks. The calculation is the basis of the data at the monthly frequency.

TABLE 1 | Summary of the descriptive statistics.

Indicator	Definition	Abbreviation	Mean	Std. Dev.	Min.	Max.	Obs.
New COVID-19 cases per million	Number	NCPM	671.0	1335	0.000	6326	144
New COVID-19 deaths per million	Number	NDPM	17.00	37.28	0.000	187.0	144
Geopolitical risks	Index	GPR	98.22	43.82	34.92	243.4	144

Indicators are provided in 18 emerging economies for the period from January 2020 to August 2020.

TABLE 2 | Cross-sectional dependence test of Pesaran (13, 14).

Test statistics	NCPM	NDPM	GPR
Cross-sectional dependence test statistics	11.92*** [0.00]	12.15*** [0.00]	5.024*** [0.00]
Scaled Lagrange multiplier test statistics	17.69*** [0.00]	21.52*** [0.00]	4.874*** [0.00]

*Null hypothesis: Series are not cross-sectionally dependent. ***$p < 0.01$, and the p-values are in brackets.*

Finally, the authors normalize the values and define a benchmark value as an average of 100 for 2000 to 2009. Therefore, a value of 200 in October 2020 means that the GPR level is two-fold higher in October 2020 than the average during 2000–2009.

The GPR index news is based on six groups of searches: The first group of words includes the military-related tensions in leading countries. The second group of words includes nuclear tensions. The third group of words focuses on the articles related to war threats. The fourth group of words includes the news related to terrorist threats. The fifth and sixth words are based on the articles related to actual events, such as terrorist acts and active wars. In short, the first, the second, the third, and the fourth group of words are related to geopolitical threats, and the fifth and the sixth group of words are related to the actual geopolitical events (12).

Finally, we report a summary of descriptive statistics for three indicators in the dataset in **Table 1**.

Estimation Methodology

First, we check the cross-sectional dependence among the panel units for the new COVID-19 cases per million people (*NCMP*), the new COVID-19-related deaths per million people (*NDMP*), and the index of the geopolitical risks (*GPR*). For this purpose, we utilize the Cross-Section Dependence (CD) test of Pesaran (13, 14) to check the series' cross-sectional dependence. Since we reject the null hypothesis that series are not cross-sectionally dependent and obtain the evidence favoring cross-sectional dependence among the variables, we should apply a panel unit root test that captures the effects of cross-sectional dependence in the unit root methodology. In this paper, we run the cross-sectional dependent Im, Pesaran, and Shin (CIPS) panel unit root test of Pesaran (15).

After confirming the stationarity of indicators by following the results of the panel unit root test of Pesaran (15), we utilize the Granger non-causality test of Dumitrescu and Hurlin (9) for heterogeneous panel datasets. The test procedure of the non-causality test of Dumitrescu and Hurlin (9) is based on the simple averages of classical Granger causality test statistics for each panel unit root test (18 emerging economies in our research). The test statistics in this approach is called as the Wbar test statistic. The Wbar test statistic can also be standardized by considering standard normal distribution with the bootstrapped critical values. This test statistic is called the Zbar statistic (16).

EMPIRICAL FINDINGS

Results of the CD and CIPS Tests

Before the non-causality analysis, we firstly analyze whether there is a significant cross-sectional dependence in the panel units for *NCMP*, *NDMP*, and *GPR*. For this purpose, we run the Cross-section Dependence (CD) test proposed by Pesaran (13, 14). The related results are reported in **Table 2**.

The findings in **Table 2** provide the Cross-sectional Dependence and Scaled Lagrange Multiplier test statistics for *NCMP*, *NDMP*, and *GPR*, respectively. The findings indicate that the null hypothesis is that series are not cross-sectionally dependent are rejected at the 1% significance level ($p < 0.01$). In other words, we observe that all panel data series under concern are cross-sectionally dependent. Therefore, we should move on with the second-generation panel unit root test, which captures the panel units' cross-sectionally dependency. We proceed with the CIPS panel unit root test of Pesaran (15), and the related findings are reported in **Table 3**.

The findings in **Table 3** report the CIPS test statistics for both specifications without trend and with trend for the series of *NCMP*, *ΔNCMP*, *NDMP*, *ΔNDMP*, *GPR*, and *ΔGPR*, respectively. The results state the null hypothesis is that "series are not unit root" rejected at the 1% significance level ($p < 0.01$) for *ΔNCMP*, *ΔNDMP*, and *GPR*. Therefore, we should proceed with the stationary series (*ΔNCMP*, *ΔNDMP*, and *GPR*) by running the panel Granger non-causality test of Dumitrescu and Hurlin (9), which can successfully model the cross-sectional dependence in the stationary panel units. This evidence also shows that the related variables cannot be cointegrated (16).

Results of the Dumitrescu–Hurlin Non-causality Test

The results for panel data Granger non-causality test of Dumitrescu and Hurlin (9) are reported in **Table 4**.

The findings of the panel data Granger non-causality test of Dumitrescu and Hurlin (9) in **Table 4** indicate that there is a statistically significant causality ($p < 0.01$) from both *ΔNCPM*

TABLE 3 | Panel unit root test of Pesaran (15).

Panel unit root test (CIPS)	NCPM	ΔNCPM	NDPM	ΔNDPM	GPR	ΔGPR
Specification without trend	4.646 [0.99]	−3.217*** [0.00]	0.913 [0.82]	−4.224*** [0.00]	−2 978*** [0.00]	−19 17*** [0.00]
Specification with trend	4.155 [0.99]	−3.813*** [0.00]	2.506 [0.99]	−4.761*** [0.00]	−2 594*** [0.00]	−21 52*** [0.00]

*Null hypothesis: Series are unit root. ***p < 0.01, and the p-values are in brackets.*

TABLE 4 | Panel data granger non-causality test of Dumitrescu and Hurlin (9).

Hypothesis	W-Stat	Zbar-Stat	Prob.
ΔNCPM does not homogeneously cause GPR	4.013***	6.661***	[0.0019]
GPR does not homogeneously cause ΔNCPM	0.086	0.248	[0.7804]
ΔNDPM does not homogeneously cause GPR	3.905***	6.241***	[0.0028]
GPR does not homogeneously cause ΔNDPM	1.793	2.109	[0.1266]

****p < 0.01, and the p-values are in brackets.*

and *ΔNDPM* to *GPR*. In other words, both ΔNCPM and ΔNDPM homogeneously cause GPR in the panel dataset of 18 emerging economies from January 2020 to August 2020. The W-Stat and the Zbar-Stat test statistics are statistically significant at the 1% level ($p < 0.01$). Furthermore, there is no statistically significant causality from *GPR* to *ΔNCPM* and *ΔNCPM*, according to the W-Stat and the Zbar-Stat test statistics. These findings indicate that the spread of the COVID-19 causes geopolitical risks in emerging economies. Next, we do several further tests to enhance the implications.

Further Tests

We also implement several further tests to provide the robustness of the findings and to enhance the implications. The related results are not reported due to the page constraints, but they are available upon request.

Firstly, note that Dumitrescu–Hurlin test statistics do not show whether the coefficients of causal relationships are positive or negative in the model estimations (17). At this stage, we run the fixed-effects estimations to examine the coefficients of the effects of the spread of the COVID-19 on geopolitical risks. Theoretically speaking, the spread of the COVID-19 should increase the level of geopolitical risks and terrorism in emerging economies (18). We observe the positive effects of the spread of the COVID-19 on geopolitical risks in 18 emerging economies.

Secondly, there can be a possible omitted variable bias due to the first-differenced nature of *ΔNCPM* and *ΔNDPM*, given that our causality analysis also includes two variables. Therefore, we both include *ΔNCPM* and *ΔNDPM* together and examine their effects on geopolitical risks. We confirm that the spread of the COVID-19 increases the level of geopolitical risks in 18 emerging economies.

Thirdly, we consider different lags. We automatically define the lag structure as one lag, but the results may be changed regarding the lag length. Given that we have relatively short periods, we consider different lag selection criteria. The baseline findings do not change significantly.

Finally, there are some zero values in the sample, particularly most of emerging economies in January 2020 and February 2020. We exclude the zero values from the sample and re-estimate the causality analysis. When we exclude the zero values, we can also use both logs of *ΔNCPM* and *ΔNDPM*. At this stage, we also re-estimate the causality analysis by the natural logarithmic values of *ΔNCPM*, *ΔNDPM*, and the *GPR* index.

All results are robust to consider these issues in the causality analyses. Overall, we conclude that the spread of the COVID-19 increases the level of geopolitical risks in 18 emerging economies.

CONCLUSION

This paper examined the causal relationship between the spread of the COVID-19 pandemic and geopolitical risks. The spread of the COVID-19 is measured by new cases per million and new deaths per million. The geopolitical risks are captured by the index of the GPR. At this stage, we focused on the balanced panel data of 18 emerging countries over the period January 2020-August 2020. Firstly, we applied the tests of Cross-sectional Dependence of Pesaran (13, 14) and the panel unit root test of Pesaran (15) with capturing cross-sectional dependence. Following these tests' results, we implemented the panel Granger non-causality tests of Dumitrescu and Hurlin (9) for heterogeneous panel datasets.

The geopolitical conflicts in emerging economies may divert people's attention from the government's ineffective response to the COVID-19, or it may be the country's use of the health crisis of neighboring countries or the decline of national strength to gain benefits. In this paper, we observed a significant causality from both measures of the spread of the COVID-19 pandemic to geopolitical risks. This evidence indicates that the spread of the COVID-19 pandemic can lead to significant issues in emerging economies related to geopolitical risks. Lockdowns or other implications for slowing down the spread of the COVID-19 virus can also help emerging economies decrease geopolitical risks. Future papers on this subject can focus on specific cases of geopolitical issues, such as terrorism or civil unrest, to analyze the potential effects of the COVID-19 pandemic. Various studies can be conducted on the developments related to the COVID-19, especially in terms of geopolitical risks in each developing country.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: https://github.com/owid/covid-19-data/tree/master/public/data; https://www.matteoiacoviello.com/gpr.htm#dat.

AUTHOR CONTRIBUTIONS

LW: data curation and writing—original draft preparation. CL: writing—original draft preparation. XC: conceptualization and investigation. LZ: software and visualisation. All authors contributed to the article and approved the submitted version.

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REFERENCES

1. Hale T, Webster S, Petherick A, Phillips T, Kira B. *Oxford COVID-19 Government Response Tracker*. Oxford: Oxford University Press (2020).
2. Goodell JW. COVID-19 and finance: agendas for future research. *Finance Res. Letters*. (2020) 35:101512. doi: 10.1016/j.frl.2020.101512
3. Bloem JR, Salemi C. COVID-19 and Conflict. University of Sussex, The Institute of Development Studies, Households in Conflict Network Working Paper, No. 332. Brighton: University of Sussex. (2020). doi: 10.1016/j.worlddev.2020.105294
4. Basit A. COVID-19: a challenge or opportunity for terrorist groups? *J Polic Intell Counter Terror*. (2020) 15:263–75. doi: 10.1080/18335330.2020.1828603
5. Sharif A, Aloui C, Yarovaya L. COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US Economy: fresh evidence from the wavelet-based approach. *Int Rev Financial Anal*. (2020) 70:101496. doi: 10.1016/j.irfa.2020.101496
6. Apergis N, Apergis E. Can the Covid-19 pandemic and oil prices drive the US partisan conflict index? *Energy Research Letters*. (2020) 1:1–4. doi: 10.46557/001c.13144
7. Buckman SR, Shapiro AH, Sudhof M, Wilson DJ. News sentiment in the time of COVID-19. Federal Reserve Bank of San Francisco (FRBSF). *Economic Letter*. (2020) 8:1–5. Available online at: https://www.frbsf.org/economic-research/publications/economic-letter/2020/april/news-sentiment-time-of-covid-19/
8. Zhang R. News shocks and the effects of monetary policy. *SSRN*. (2019) 3348466. doi: 10.2139/ssrn.3348466 Available online at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3348466
9. Dumitrescu EI, Hurlin C. Testing for granger non–causality in heterogeneous panels. *Econ Model*. (2012) 29:1450–60. doi: 10.1016/j.econmod.2012.02.014
10. Hasell J, Mathieu E, Beltekian D, Macdonald B, Giattino C, Ortiz-Ospina E, et al. A cross-country database of COVID-19 testing. *Scientific Data*. (2020) 7:345. doi: 10.1038/s41597-020-00688-8
11. Tian H, Liu Y, Li Y, Wu CH, Chen B, Kraemer MUG, et al. An investigation of transmission control measures during the first 50 days of the COVID-19 epidemic in China. *Science*. (2020) 368:638–42. doi: 10.1126/science.abb6105
12. Caldara D, Iacoviello M. *Measuring Geopolitical Risk*. Washington, DC: Board of Governors of the Federal Reserve Board (2019).
13. Pesaran MH. General Diagnostic Tests for Cross-section Dependence in Panels. Institute of Labour Economics (IZA) Discussion Paper Series, No: 1240, Bonn: IZA. (2004).
14. Pesaran MH. Testing weak cross-sectional dependence in large panels. *Econometric Rev*. (2015) 34:1089–117. doi: 10.1080/07474938.2014.956623
15. Pesaran MH. A simple panel unit root test in the presence of cross-section dependence. *J Appl Econometrics*. (2007) 22:265–312. doi: 10.1002/jae.951
16. Eberhardt M, Teal F. No mangoes in the tundra: spatial heterogeneity in agricultural productivity analysis. *Oxf Bull Econ Stat*. (2013) 75:914–39. doi: 10.1111/j.1468-0084.2012.00720.x
17. Gozgor G, Can M. Causal linkages among the product diversification of exports, economic globalization and economic growth. *Rev Dev Economics*. (2017) 21:888–908. doi: 10.1111/rode.12301
18. Ackerman G, Peterson H. Terrorism and COVID-19. *Perspectives Terrorism*. (2020) 14:59–73. doi: 10.2307/26918300

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Tourism and Livable Towns Beyond the Coronavirus Disease 2019: A Case Study for Chongqing, China

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Based on the data of 812 small towns in Chongqing, China, this paper attempts to conduct an empirical analysis on whether tourist towns with excellent natural environment, policy advantage, and market preference are more ecologically livable than ordinary small towns. It is found that as a whole, tourist towns are indeed more ecologically livable than ordinary small towns. Also, from the perspective of grading, both the national and provincial tourist towns have the advantage of ecological livability, but the advantage of national ones is more prominent. Furthermore, the ecological livability of tourist towns is affected by location advantage and policy inclination. The implications of the results are discussed following the outcomes of the coronavirus disease 2019 outbreak. The suggestions beyond the coronavirus disease 2019 are also provided.

Keywords: COVID-19 outbreak, tourist towns, characteristic Chinese landscape, ecologically livable cities, Chongqing

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INTRODUCTION

The Ministry of Housing and Urban–Rural Development and the National Tourism Administration of China have jointly evaluated and elected national tourist towns since 2010. To protect tourist towns with characteristic Chinese landscape (i.e., tourist towns), further promote the rural human environment and tourism of those towns, 2010, 2011, and 2015, the first, second, and third batches of national tourist towns were selected, totaling 372 towns (1). In addition to the evaluation at the national level, provincial governments also evaluated provincial tourist towns[1]. Taking Chongqing as an example, in 2013, the Chongqing Municipal Government evaluated and selected the first batch at the provincial level, totaling 10 towns (2).

The outbreak of the coronavirus disease 2019 (COVID-19) showed that many cities are yet to meet the livability criteria and that there are urgent needs for public health systems with resilience at both national and local levels. The COVID-19 pandemic has imposed some critical challenges for cities in containing the epidemic. Achieving sustainable development goals requires cities to transform by creating spaces that foster urban mobility, resilience, and equality. Tourism may help to achieve these goals. Note that COVID-19 affects the Chinese economy. Domestic tourism has also been affected by COVID-19, given that there are tremendous precautions for visitors from China. Less mobility may negatively affect tourism demand, and domestic tourism may be a substitute for international tourism during COVID-19 (3), and this may help the natural environment of touristic towns, such as Chongqing.

[1]China's 31 administrative regions are composed of 27 provinces and 4 municipalities directly under the Central Government (Beijing, Shanghai, Tianjin, and Chongqing). The municipality directly under the Central Government is a provincial administrative region and plays an important role in politics, economy, and culture.

The population is the core of urban development, and ecological livability is one of the essential conditions to retain and attract population, no matter for tourist towns or ordinary small towns. A large number of studies have pointed out that there are significant differences between urban and rural areas in the main aspects of ecological livability—necessary public service facilities and natural environment (4–8). Under the long-term urban–rural dual system, inequality in these aspects is an important factor causing the widening gap between urban and rural areas (9, 10). Although there is a lot of literature on ecological livability, the research field is mainly concentrated in cities, and little attention has been paid to small towns (11–15). Only a few scholars, like Yang and Wang (16), have carried out relevant research. Because of the fascinating natural landscape and rich historical and cultural deposits, tourist towns have become the treasure of more than 30,000 small towns in China. In the process of Rural Revitalization and New Urbanization in China, tourist towns will play a crucial role in regional industrial integration and green development due to their advantage in promoting the tourism industry, government support, and market preference. One of the critical issues affecting the long-term development of tourist towns is whether these towns with the advantage of ecological livability are suitable for the development of the tourism industry and the residing population. This issue is not only related to the effectiveness of relevant government policies but also has a great impact on the strategy of Rural Revitalization and the construction of New Urbanization. Therefore, it has profound practical significance and theoretical connotation to investigate whether this particular group of small towns has the advantage of ecological livability.

The rest of the paper is organized as follows. Section Research Hypotheses provides the research hypotheses with different characteristics of tourism towns. Section Measuring Ecological Livability, Data, and Empirical Model explains the measurement of ecological livability, data, and empirical model. Section Empirical results discusses the empirical results, and Section Conclusion concludes.

RESEARCH HYPOTHESES

Government-Led Urbanization and the Development of Small Towns

In China's urbanization system, governments dominate the allocation of resources. Specifically, the government has direct jurisdiction over the establishment of cities and towns, the approval of land use, the change of land function, the construction of infrastructure, and many other aspects. Li et al. (17) sum up six modes of promoting urbanization in China: establishing development zones, building new districts and new towns, urban expansion, old city transformation, building central business districts, township, and village industrialization. In this sense, the government is undoubtedly the most influential designer and executor. The competition mechanism among local governments has played an essential role in the continuous and high-speed growth of China's economy (18). Economic growth is regarded as one of the most critical "competition yardsticks" among local governments (19). To achieve faster economic growth, local governments often take measures, including attracting investment and cultivating profitable industries. Unlike the eastern region in China, the western region is relatively backward in location advantage and scarce in resources endowment. Simultaneously, due to policy factors such as environmental protection, the economic development of the western region faces some policy constraints. Therefore, the tourism industry has become an essential pillar for local governments in the western region to develop its economy. Because of its geographical location, the natural environment, and ethnic customs in the western region are well-preserved. Under the government-led urbanization system, more resources will be invested in the tourism industry. Regions with high-quality tourism resources will receive preferential support, including funds, land, and other policies from the governments at a higher level and then acquire an advantage in the development of the tourism industry (20). Similar to interprovincial competition, local governments within provinces and municipalities will also tilt more resources toward industries and areas with development advantages.

Although governments play a leading role in the process of urbanization, the impact of the market on resource allocation is also enormous. In the market allocation mechanism, population, and other production factors are all seeking to maximize benefits. From the view of tourism development, with the growth of the economy and urbanization, an increasing number of urban residents are more eager to get a higher level of tourism perception (21), which is in contradiction with the types and quality of products provided in the current tourism market. At present, there are many problems in China's tourist attractions, ranging from overcommercialization to serious homogeneity. The problems of historical tourist towns are particularly prominent (20). Tourist towns are natural carriers for the development of rural tourism (22). Therefore, as the treasure of small towns in China, tourist towns will attract many production factors to upgrade the infrastructure and natural landscape. Besides, in China's current urbanization system, the government's support and guidance often mean that tourist towns will enjoy the support of land and fiscal policy. Based on the earlier analysis from the perspective of government and market, this paper puts forward the following hypotheses:

H1: Because of a better natural environment, policy support, and the favor of the market, tourist towns have a higher level of ecological livability than ordinary small towns.

H2: In regions with higher tourism dependence, the advantage in the ecological livability of tourist towns is more significant.

Government Rating: Self-Selection and Resource Guidance of Small Towns

China's tourism resources are usually graded. As for the evaluation level, it is generally divided into national and provincial ones. At the national level, due to the enormous number of selected objects and high requirements, it is more difficult for tourism resources to be rated as national ones (23). To develop the local economy, local governments often elect resources with a more competitive advantage to participate in the national evaluation and then enhance the popularity of tourism resources in their jurisdiction.

Similar to the national evaluation, in provincial evaluation, the lower level government will choose its high-quality tourism resources for evaluation out of similar motives to enhance the economic competitiveness of its region. In terms of the quality of tourism resources, the rating mechanism has formed self-selection of tourism resources within regions. From the public perspective, there are some differences in the degree of public trust between the central government and local ones (24). The public has a higher degree of trust with the central government, whereas the degree of trust with local governments is lower. In this sense, compared with tourist towns at the provincial level, the national ones can gain more public trust. In this context, whether for the needs of local governments to develop their economy or for enterprises to cater to the market and earn profits, more resources will be tilted to the national tourist towns. Based on the analysis of the selection mechanism of tourist towns and the investment motivation of local governments and enterprises, this paper puts forward the following research hypothesis:

H3: Compared with the provincial tourist towns, the advantage of national tourist towns in ecological livability is more prominent.

Three Gorges Project: State Support and Development of Small Towns in the Reservoir Area

The Three Gorges Project is the largest project ever built in the world. Two hundred seventy-seven towns have been inundated owing to the construction of the Three Gorges Project, and 1.13 million migrants have been relocated (25). For the inundated towns, governments mainly adopt the way of relocation and reconstruction. Due to the large amount of funds invested in infrastructure construction, coupled with land, tax, and other policy support, the overall development level of relocated and reconstructed towns has been dramatically improved (26). Not only in the construction process of the Three Gorges Project but also after the completion of the project, the Three Gorges Reservoir Area has enjoyed tremendous support in finance and policy. Taking the "Three Gorges Follow-up Work Plan" approved by the State Council of China in 2011 as an example, the central government planned to invest 123.8 billion yuan (∼19 billion US $) in the Three Gorges Reservoir Area from 2011 to 2020. Among them, the investment in the Chongqing Reservoir Area of the Three Gorges is approximately 80 billion yuan (∼12.6 billion US $) (27). In addition to financial support, the government has also given great support to the Three Gorges Reservoir Area in aspects including land, industry, and natural environment. Despite tremendous support gained at the national level, there are still some problems in the Three Gorges Reservoir Area, such as the hollowing of industrial structure and low level of economic development caused by the relocation of enterprises and remote location (28). Because of its unique geographical location, the natural environment of the Three Gorges Reservoir Area is fragile, which has attracted lots of attention from the government and society (29). Because the tourism industry is friendly to the environment and the Three Gorges is also a world-famous scenic spot, the tourism industry turns out to be an ideal industry for the Three Gorges Reservoir Area. Based on the earlier analysis, the following hypothesis has been put forward.

H4: Tourist towns located in the Chongqing reservoir area of the Three Gorges have a more significant advantage in ecological livability. The scarcity of industrial development resources makes the tourist towns abler to obtain a wide range of support from the government and the market.

MEASURING ECOLOGICAL LIVABILITY, DATA, AND EMPIRICAL MODEL

Measuring Ecological Livability

Located in the upper reaches of the Yangtze River, Chongqing is a national historical and cultural city with a history of more than 3,000 years and precious tourism resources. Because of its unique geographical form and distinct development conditions, Chongqing has formed a comprehensive structure of "large city, large countryside, large mountain area, and large reservoir area." It was designated as a pilot area of comprehensive urban–rural reform by the State Council of China in 2007. At the end of 2015, Chongqing had 38 districts and counties and 812 small towns. Among the two batches of national tourist towns released in 2010 and 2011, seven small towns were selected in Chongqing. In 2013, the Chongqing Municipal Government announced the first batch of provincial tourist towns, including 10 small towns (see **Figure 1**). It should be noted that none of the 10 small towns was previously rated as a national tourist town (27). To sum up, the research scope of this paper is 812 small towns in 38 districts and counties of Chongqing, including 17 tourist towns. The detailed list is shown in **Table 1**.

Referring to the research results of Mahmoudi et al. (12), Yang and Wang (16), and based on the principles of data availability, this paper constructs an evaluation index system of ecological livability of 812 small towns in Chongqing from two dimensions, namely the natural environment and human and social environment. In this paper, the ecological livability of small towns in the natural environment is estimated by six indicators, such as sewage treatment rate and waste treatment rate, which is more diverse than previous literature. Because the entropy method has the advantage of objectivity and being able to avoid overlapping information among various indicators, this paper uses the entropy method to measure the ecological livability of 812 small towns in Chongqing based on data normalization. Detailed information like indicators, entropy, redundancy, and weight are shown in **Table 2**.

It is important to note that we used three sources of data. The first is the *Basic Data of Towns and Townships in Chongqing 2016,* released by the Chongqing Urban and Rural Construction Committee. The *Basic Data of Towns and Townships in Chongqing 2016* contains 23 indicators such as gross domestic product (GDP), built-up area, and population of 812 small towns in Chongqing, which is comprehensive and authoritative statistical data on small towns in Chongqing. The

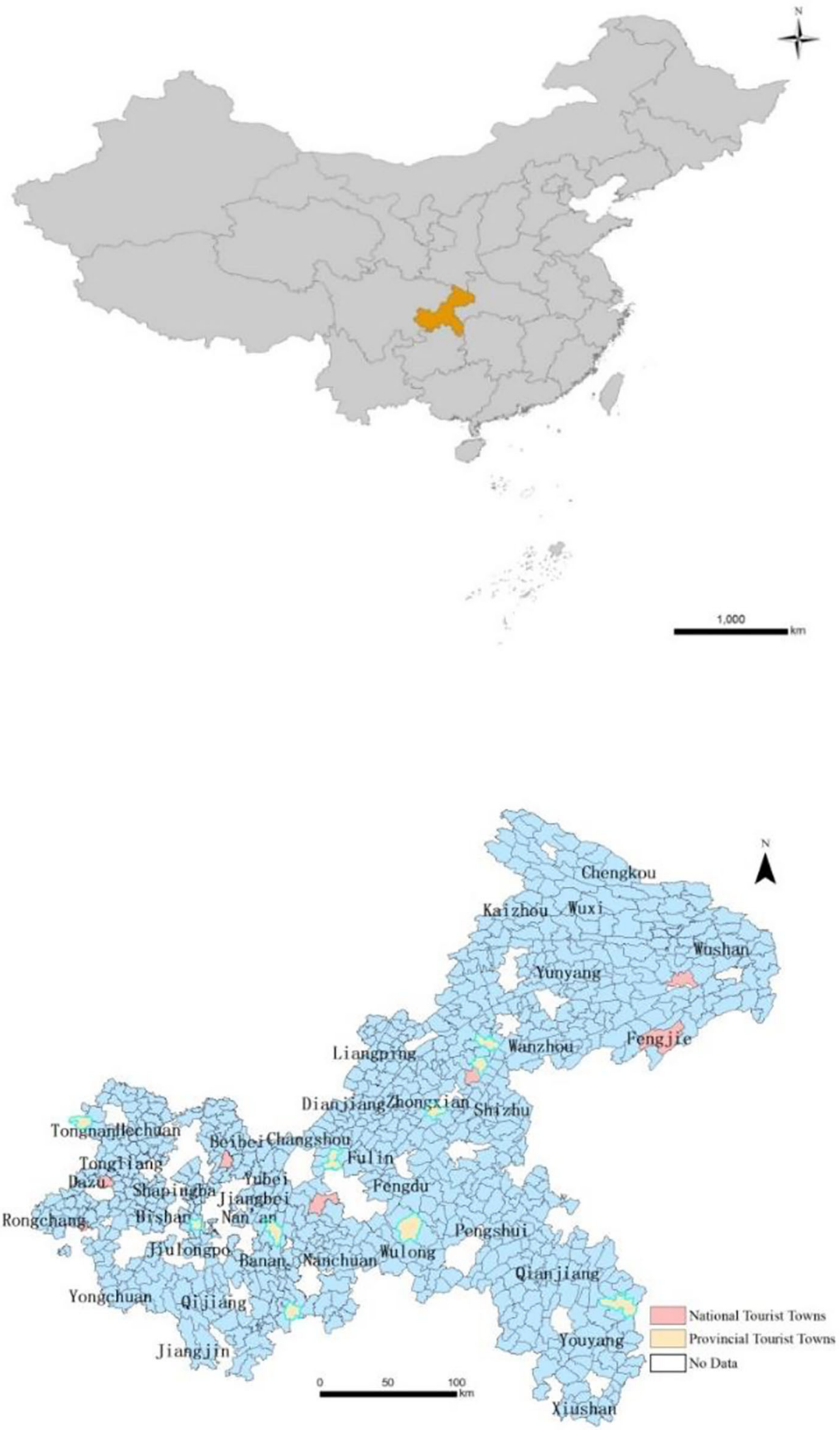

FIGURE 1 | Study area.

second one is the list of tourist towns, which include the first and second batches of national tourist towns jointly released by the Ministry of Housing and Urban–Rural Development and the National Tourism Administration of China in 2010 and 2011, respectively. The first batch of tourist towns was released by the Chongqing Municipal Government in 2013. Although the third batch was released in July 2015, this paper does not include it in the research scope due to the short period of validity. The third one is the statistical yearbooks, and the last one is Baidu Map. Statistical yearbook data come from the Chongqing Statistics Bureau, including *Chongqing Statistical Yearbook 2016* and a total number of 38 statistical yearbooks of districts and counties in Chongqing.

Data and Empirical Model

The ecological livability of small towns calculated earlier is between 0 and 1, which has non-negative truncation characteristics. For estimating such constrained explanatory variables, the general mixed effect model will distort the results. Therefore, we adopt the Tobit model to conduct the regression analysis. To reduce the influence of regression errors caused by missing variables, we take various indicators, including economic development, population urbanization, land urbanization, and population size as control variables based on the relevant research of urban economics (30, 31). It is important to note the previous literature regarding the influencing factors of human settlements in small towns. Besides, due to differences in resource endowment, government support, and other aspects, there may be some gaps in ecological livability between national and provincial tourist towns. Therefore, this paper will further explore the possible differences between the two. In this sense, this paper constructs the following econometric models:

$$Live = \alpha_0 + \alpha_1 towns + \alpha_2 \ln pgdp + \alpha_3 \ln distance + \alpha_4 \ln popur + \alpha_5 \ln landur + \alpha_6 \ln pop + \alpha_7 central + \varepsilon \quad (1)$$

$$Live = \alpha_0 + \alpha_1 towns_1 + \alpha_2 towns_2 + \alpha_3 \ln pgdp + \alpha_4 \ln distance + \alpha_5 \ln popur + \alpha_6 \ln landur + \alpha_7 \ln pop + \alpha_8 central + \varepsilon \quad (2)$$

In Equation (1), the explained variable () indicates the ecological livability of small towns, which is calculated from **Table 2**. The core explanatory variable (*towns*) is the dummy variable of the tourist towns. α_1 is the coefficient mainly concerned in the paper. In Equation (2), the core explanatory variable (*towns*) is further divided into national tourist towns and provincial ones. There are six controlled indicators in the models discussed.

Per capita GDP (*pgdp*) is mainly used to measure the economic development of small towns. Economic development and ecological livability are often closely linked. To promote economic development, local governments perhaps will increase their tolerance of environmental pollution; on the other hand, a higher level of economic development provides support for the construction and maintenance of environmental infrastructure in small towns (32). It should be noted that although there may be a certain degree of multicollinearity between per capita GDP

TABLE 1 | List of touristic towns in Chongqing.

	National tourist towns	
The first batch (2010)	Jing Guan, Wan Ling, Xing Long	3
The second batch (2011)	Bao Ding, Bai Di, Shi Bao, Lin Shi	4
	Provincial tourist towns	
The first batch (2013)	Dong Wenquan, You Shuihe, Xian Nvshan, Wu Lingshan, Hei Shan, Bai Shiyi, Cong Kan, Chang Shouhu, Xin Sheng, Gan Ning	10
Total		17

TABLE 2 | Evaluation index system of ecological livability of 812 small towns, Chongqing.

Primary indices	Secondary indices	Information entropy	Redundancy	Weight
Livability of natural environment	Sewage treatment rate (%)	0.9342	0.0658	0.0634
	Waste disposal rate (%)	0.8192	0.1808	0.1701
	Harmless treatment rate (%)	0.9762	0.0238	0.0229
	Green coverage in built-up areas (%)	0.9214	0.0786	0.0739
	Green space rate in built-up area (%)	0.9161	0.0839	0.0808
	Per capita park green space area (km^2)	0.9365	0.0635	0.0612
Livability of humanistic and social environment	Per capita road area in the built-up area (km^2)	0.9348	0.0652	0.0628
	Number of public toilets for 10,000 people	0.9525	0.0475	0.0458
	Water penetration (%)	0.9192	0.0808	0.0779
	Gas penetration (%)	0.9407	0.0593	0.0558
	Number of hospitals for 10,000 people	0.9605	0.0395	0.0381
	Number of beds for 10,000 people	0.9455	0.0545	0.0525
	Number of General primary schools for 10,000 people	0.9906	0.0094	0.0090
	Number of ordinary middle schools for 10,000 people	0.9497	0.0503	0.0484
	Urban per capita residential area (square meters)	0.9416	0.0584	0.0563
	Per capita residential area in rural areas (square meters)	0.9158	0.0842	0.0811

TABLE 3 | Descriptive statistics.

Variable	Symbol	Unit	Observation	Mean	Std. dev.	Min.	Max.
Ecological livability	*Live*	/	812	0.15	0.07	0.02	0.49
Tourist towns	*towns*	/	812	0.02	0.15	0	1
Per capita GDP	*pgdp*	10,000 yuan/person	812	2.14	4.50	0.08	82.00
Distance from district and county governments	*distance*	kilometer	812	41.24	24.30	0.50	146.30
Population urbanization	*popur*	10,000 people	812	0.80	1.19	0.01	11.46
Land urbanization	*landur*	Square kilometer	812	1.40	3.06	0.01	61.63
Population size	*pop*	10,000 people	812	2.80	2.19	0.11	22
Central town	*central*	/	812	0.13	0.34	0	1

and the central town, it will not affect the estimation results of the core explanatory variable (33).

Distance from district and county governments (*distance*) refers to the closest distance between small towns and district and county governments. It is mainly used to analyze the radiation effect of core urban areas on the ecological livability of small towns. In theory, small towns closer to the core urban areas can enjoy more spillover effects, so the economy and basic public service facilities are better. The data are obtained by using Baidu Map in June 2017.

Urban population (*popur*) is the population living in the built-up area of small towns. As an essential aspect of urbanization, population urbanization is a powerful driving force to promote the development of urban natural environments and basic public service facilities.

Land urbanization (*landur*) is the urban built-up area of small towns. The expansion of the built-up area will hurt the natural environment and will also increase the financial burden of upgrading necessary public service facilities.

Population size (*pop*) refers to the permanent population of small towns. Similar to the impact of the built-up area, the increase of population size will theoretically hinder the improvement of the ecological livability of small towns.

Central town (*central*) is a dummy variable that indicates whether a small town is a central town or not. The central town refers to the town with better location advantage, a stronger economy, better infrastructure, and greater development potential. Due to a higher level of economic development and better basic public service facilities, the central town's ecological livability may be higher. We aim to exclude the possibility that small towns are more ecologically livable because they are central towns rather than tourist towns. Therefore, we add this dummy variable.

It should be pointed out that the data of per capita GDP, population urbanization, land urbanization, population size, and central town come from the *Basic Data of Towns and Townships in Chongqing 2016*. Besides, the total tourism revenue and GDP of each district and county in the following analysis are derived from the *Statistical Yearbook of 2016* of each district and county. All control variables, except dummy variables, are logarithmically processed. is the random error term. The descriptive statistics of related variables are shown in **Table 3**.

TABLE 4 | Results of benchmark and hierarchical regression.

Dependent variable: ecological livability of small towns				
Explanatory variables	**(1)**	**(2)**	**(3)**	**(4)**
Tourist towns	0.053*** (0.016)	0.039** (0.015)		
National tourist towns			0.052** (0.024)	0.040* (0.024)
Provincial tourist towns			0.023** (0.011)	0.020** (0.009)
Per capita GDP		0.068*** (0.005)		0.072*** (0.005)
Distance from district and county governments (logarithm)		−0.028*** (0.004)		−0.028*** (0.003)
Population urbanization (logarithm)		0.006* (0.003)		0.007* (0.004)
Land urbanization (logarithm)		−0.002 (0.003)		−0.002 (0.003)
Population size (logarithm)		−0.012* (0.005)		−0.010** (0.005)
Central town		0.011*** (0.003)		0.011*** (0.003)
Constant	0.150*** (0.002)	0.252*** (0.014)	0.150*** (0.002)	0.252*** (0.014)
Observation number	812	812	812	812
Log likelihood	1,039.902	1,096.18	1,039.903	1,096.205
LR test	10.87	123.43	10.87	123.48

*Values in parentheses are standard deviation, and ***, **, and * indicate the significant levels of 1, 5, and 10%, respectively.*

EMPIRICAL RESULTS

Results of Benchmark and Hierarchical Regression

Firstly, this paper analyzes whether tourist towns have better ecologically livable environment compared with ordinary small towns and then divides them into national and provincial tourist towns. As mentioned earlier, national tourist towns usually have a better natural environment than provincial ones. Besides, the differences between national and provincial titles probably have a significant impact on the attraction to tourists, which may

TABLE 5 | Tourism dependence of 38 districts and counties in Chongqing.

Category	District and County	National tourist towns	Provincial tourist towns
Low tourism dependence	Yu Bei, Ba Nan, Fu Ling, Chang Shou, Feng Jie, Yun Yang, Wu Shan, Wu Xi, Wan Zhou, Kai Zhou, Zhong Xian, Feng Du, Wu Long, Shi Zhu	Xing Long, Shi Bao, Ling Shi, Bai Di	Dong Wenquan, Xian Nvshan, Chang Shouhu, Xin Sheng, Gan Ning
High tourism dependence	Jiang Bei, Sha Pingba, Jiu Longpo, Nan An, Bei, Da Dukou, Qi Jiang, Wan Sheng, Da Zu, Qian Jiang, He Chuan, Yong Chuan, Nan Chuan, Rong Chang, Tong Nan, Liang Ping, Cheng Kou, Dian Jiang, Xiu Shan, You Yang, Peng Shui	Jing Guan, Wan Ling, Bao Ding	You Shuihe, Hei Shan, Bai Shiyi, Cong Can

drive local governments and tourism enterprises to invest more resources in national tourist towns. Therefore, national tourist towns can get more policy support and capital investment. In contrast, the resources for provincial tourist towns will be relatively limited, which results in the difference in ecological livability between national and provincial tourist towns. Out of this consideration, this paper will divide tourist towns into national and provincial tourist towns, and then, the test of Hypothesis 3 will be conducted from the perspective of grading. According to **Table 1**, there are a total of seven small towns in Chongqing rated as national tourist towns and 10 small towns rated as provincial ones. The regression results are shown in **Table 4**.

Based on columns (1) and (2), we can notice that the coefficient of tourist towns is positive and significant at the level of 1%. This result shows that compared with ordinary small towns, tourist towns have a higher level of ecological livability due to government support, enterprise investment, or their pleasant natural environment. The results of columns (3) and (4) indicate that both national and provincial tourist towns have a higher level of ecological livability. Also, as previously analyzed, owing to the differences in natural environment and policy inclination, the advantage in the ecological livability of national tourist towns is more prominent than provincial ones. That is to say, Hypothesis 3 of this paper is valid.

In terms of the relationship between ecological livability of small towns and the distance from small towns to the district and county governments, the farther the distance is, the weaker the radiation effect produced on the ecological livability of small towns by the core urban areas will be, which is in line with the reality. Besides, the research conclusion of Combes et al. (34) on population urbanization promoting urban development has been confirmed at the level of small towns, namely population urbanization has indeed played a particular role in promoting the ecological livability of small towns. Unlike population urbanization, land urbanization hurts the ecological livability of small towns, but the impact is small and has not passed the significant test. The expansion of the population-scale does not improve the ecological livability of small towns. Instead, it plays a reverse role. This evidence is closely related to the fact that Chongqing has more mountains and fewer plains, and a large number of rural populations is sparsely scattered, thus restricting the improvement of necessary public service facilities. As for the relationship between the ecological livability and central towns, the results prove that the ecological livability of central towns is significantly better.

TABLE 6 | Results based on the division of tourism dependence.

Dependent variable: ecological livability of small towns				
Explanatory variables	(1)	(2)	(3)	(4)
	Regions with low tourism dependence		Regions with high tourism dependence	
Tourist towns	0.025 (0.018)		0.048** (0.021)	
National tourist towns		0.036 (0.026)		0.057*** (0.020)
Provincial tourist towns		0.015 (0.025)		0.020** (0.008)
Per capita GDP	0.068*** (0.006)	0.069*** (0.005)	0.078*** (0.002)	0.080*** (0.004)
Distance from district and county governments (logarithm)	−0.037*** (0.005)	−0.037*** (0.005)	−0.015** (0.006)	−0.016*** (0.006)
Population urbanization (logarithm)	0.001 (0.005)	0.001 (0.005)	0.008 (0.007)	0.008 (0.007)
Land urbanization (logarithm)	−0.002 (0.005)	−0.002 (0.005)	−0.004 (0.005)	−0.004 (0.005)
Population size (logarithm)	−0.021*** (0.006)	−0.021*** (0.006)	−0.015** (0.006)	−0.015** (0.006)
Central town	0.015*** (0.004)	0.015*** (0.004)	0.009* (0.005)	0.009* (0.005)
Constant	0.292*** (0.018)	0.292*** (0.018)	0.221*** (0.024)	0.222*** (0.024)
Observation number	356	356	234	234
Log likelihood	521.103	521.275	343.347	343.785
LR test	74.93	75.28	41.00	41.88

*Values in parentheses are standard deviation, and ***, **, and * indicate the significant levels of 1, 5, and 10%, respectively.*

Results Based on Tourism Dependence

In addition to economic development, the importance of tourism in the local economy is also a key factor affecting how much resources the local government will invest in protecting and developing tourist towns. The more significant the proportion of tourism revenue in the local economy, the stronger local governments' motivation to protect and develop tourist towns. In this sense, the higher the tourism dependence is, the more prominent the advantage of tourist towns in ecological livability will be; on the other hand, the advantage of regions with lower tourism dependence will not be significant. Based on this

TABLE 7 | Chongqing reservoir area and non-reservoir area of three gorges project.

Region	District and County	National tourist towns	Provincial tourist towns
Reservoir area	Yu Bei, Ba Nan, Fu Lin, Jiang Jin, Chang Shou, Feng Jie, Yun Yang, Wu Shan, Wu Xi, Wan Zhou, Kai Zhou, Zhong Xian, Feng Du, Wu Long, Shi Zhu	Xing Long, Shi Bao, Lin Shi, Bai Di	Dong Wenquan, Xian Nvshan, Wu Lingshan, Chang Shouhu, Xin Sheng, Gan Ning
Non-reservoir area	Jiang Bei, Sha Pingba, Jiu Longpo, Nan An, Bei, Da Dukou, Qi Jiang, Wan Sheng, Da Zu, Qian Jiang, He Chuan, Yong Chuan, Nan Chuan, Rong Chang, Tong Nan, Liang Ping, Cheng Kou, Dian Jiang, Xiu Shan, You Yang, Peng Shui	Jing Guan, Wan-Ling, Bao Ding	You Shuihe, Hei Shan, Bai Shiyi, Cong Kan

consideration, this paper takes the proportion of tourism revenue to GDP as a measure of tourism dependence so that the difference in ecological livability of tourist towns scattered in regions with various tourism dependence will be studied, which is also a test for the Hypothesis 2 proposed by this paper. Taking the median of tourism dependence of 38 districts and counties in Chongqing as the dividing line, this paper divides them equally into two groups of regions with low and high tourism dependence. The detailed results are shown in **Table 5**. Among the 19 districts and counties with low tourism dependence, there are 10 tourist towns, of which the number of national tourist towns is 4, and the number of provincial tourist towns is 6. Among the 19 districts and counties with high tourism dependence, there are seven tourist towns, where the number of national and provincial tourist towns is 3 and 4, respectively.

Based on the division of 38 districts and counties in Chongqing, this paper further investigates whether tourist towns are still more ecologically livable in regions with different tourism dependence. The regression results are shown in **Table 6**.

From the results of columns (1) and (2) in **Table 6**, it is noticeable that the advantage in the ecological livability of 10 tourist towns located in regions with low tourism dependence is not significant, which is consistent with the expected results. Furthermore, both the national and provincial tourist towns are no more ecologically livable than ordinary small towns. According to the results of columns (3) and (4), in regions with high tourism dependence, tourist towns have a remarkably higher level of ecological livability. From the perspective of grading, the advantage in the ecological livability of national tourist towns and provincial ones is significant. This result is consistent with Hypothesis 2. Also, this result proves that under the current urbanization development pattern in China, the development and construction of small towns are closely related to local governments' support.

Results Based on the Division of Reservoir Area and Non-reservoir Area of the Three Gorges Project

As discussed earlier, compared with small towns in the non-reservoir area, the primary public service facilities of small towns in the reservoir area have been rebuilt or improved during the construction of the Three Gorges Project. Besides, those towns have received plenty of support in finance and policy from the central government and local governments after completing the project. Owing to the fragility of the Three Gorges Reservoir Area and the particularity of geographical location, its natural environment has always been the focus of attention. The unique advantage of these small towns in the reservoir area is likely to have a significant and positive impact on their natural environment and necessary public service facilities, which will lead to some differences between small towns scattered in the reservoir area and non-reservoir area. In such a unique geographical unit such as the reservoir area, whether tourist towns will be attached more importance so that their advantage in ecological livability will be more outstanding is also one of the main focuses of this paper. Also then, this paper divides Chongqing into the reservoir area and non-reservoir area and inspects whether the advantage in ecological livability of tourist towns is significant or not in different regions, that is, whether Hypothesis 4 of this paper is valid or not. **Table 7** summarizes tourist towns located in the reservoir area and non-reservoir area.

Among the 15 districts and counties in the reservoir area, there are nine tourist towns, including four national tourist towns and five provincial ones. Among the 23 districts and counties in the non-reservoir area, there are eight tourist towns, including four national tourist towns and four provincial ones. Based on this division, this paper further empirically tests the vital issue of this paper, namely whether tourist towns are more ecologically livable than ordinary small towns. The detailed regression results are shown in **Table 8**.

According to the results of column (1) in **Table 8**, nine tourist towns in the reservoir area are indeed more ecologically livable than ordinary small towns. Compared with the results in column (6) of **Table 4**, the coefficient is 0.53, which is significantly higher than that (0.39) in column (6) of **Table 4**, which indicates tourist towns located in the reservoir area are with a prominent advantage in ecological livability. The results of column (2) show that national tourist towns have a significant and massive advantage in ecological livability over ordinary small towns, whereas the provincial ones are no more ecologically livable. The results of columns (3) and (4) mean that eight tourist towns in the non-reservoir area are no more ecologically livable than ordinary small towns. Only the national tourist towns remain the advantage. From the discussed results, it is self-evident that Hypothesis 4 is valid. That is to say, compared with the non-reservoir area, tourist towns located in the reservoir area of the Three Gorges, which receive more financial resources and inclined policy support, still own the advantage in ecological livability.

TABLE 8 | Results based on the division of reservoir and non-reservoir areas.

Dependent variable: ecological livability of small towns				
Explanatory variables	**(1)**	**(2)**	**(3)**	**(4)**
	Reservoir area		**Non-reservoir areas**	
Tourist towns	0.053*** (0.019)		0.026 (0.022)	
National tourist towns		0.082*** (0.024)		0.066** (0.032)
Provincial tourist towns		0.008 (0.030)		−0.012 (0.031)
Per capita GDP	0.066*** (0.005)	0.070*** (0.005)	0.078*** (0.003)	0.079*** (0.009)
Distance from district and county governments (logarithm)	−0.017*** (0.005)	−0.016*** (0.004)	−0.033*** (0.005)	−0.033*** (0.005)
Population urbanization (logarithm)	0.014*** (0.004)	0.014*** (0.005)	−0.001 (0.005)	−0.001 (0.005)
Land urbanization (logarithm)	−0.015*** (0.004)	−0.015*** (0.004)	0.007* (0.004)	0.007* (0.004)
Population size (logarithm)	−0.010 (0.007)	−0.009 (0.007)	−0.009 (0.006)	−0.008 (0.006)
Central town	0.007** (0.003)	0.007** (0.003)	0.014*** (0.004)	0.014*** (0.004)
Constant	0.210*** (0.021)	0.208*** (0.021)	0.261*** (0.018)	0.261*** (0.018)
Observation number	386	386	426	426
Log likelihood	540.392	542.266	573.053	574.613
LR test	36.56	40.30	103.32	106.44

*Values in parentheses are standard deviation, and ***, **, and * indicate the significant levels of 1, 5, and 10%, respectively.*

CONCLUSION

Cities have always been strongly linked with tourism and travel. The COVID-19 crisis may be an opportunity to rethink these relationships, help tourism recover, and in turn, shape more sustainable urban environments. In fact, for decades now, many cities have had to confront exactly the reverse effect of the COVID-19 standstill, struggling to deal with too much tourism, with residents' livability sometimes heavily impacted because of disruption, noise, or overcrowded transport. However, tourist towns are in a related industry, such as hotels or restaurants, and these are economically essential because fewer tourists and their less spending mean fewer jobs and strained city budgets.

Under the background that Rural Revitalization has become a national strategy of China, this paper takes tourist towns as the research object and analyzes the core issue that whether the financial support and tourism aura endow tourist towns with the advantage in ecological livability over ordinary small towns. Based on the *Basic Data of Towns and Townships in Chongqing 2016* and other relevant data, this paper conducts empirical tests on the core issue. The main conclusions are as follows: Firstly, according to the results of benchmark regression, compared with ordinary small towns, tourist towns are more ecologically livable. This result proves that the policy of tourist towns indeed endows those towns with the advantage of ecological livability. Secondly, both national and provincial tourist towns are more ecologically livable than ordinary small towns, but the advantage of national tourist towns is more prominent. This paper divides tourist towns into two categories: national tourist towns and provincial ones, and then, the study on the core issue is extended. The results indicate that the coefficients and significance levels of both national and provincial tourist towns are stable. Thirdly, in regions with low tourism dependence, tourist towns are not more ecologically livable than ordinary small towns, whereas in regions with high tourism dependence, the advantage of tourist towns is still very significant. Lastly, tourist towns in the reservoir area of the Three Gorges Project are more ecologically livable than ordinary small towns.

In contrast, the advantage of the 23 tourist towns in the non-reservoir area is not significant. Also, national tourist towns in the reservoir area and non-reservoir area are more ecologically livable than ordinary small towns. In contrast, the provincial-level towns do not have such an advantage. The COVID-19 pandemic shows us to integrate nature-based solutions into urban planning as a means to preserve local ecosystems while enhancing local resilience and improving residents' quality of life. The COVID-19 crisis in 2020 demonstrates that current systems and communities are not resilient enough. It is essential to use nature-based solutions that can improve social, economic, and environmental benefits for inclusive urban development and ensures that its residents have access to good quality, safe, and attractive open spaces. At this stage, the green infrastructures should be developed in the leading public spaces where residents and tourists enjoy their leisure time. Building multipurpose cities, such as Chongqing, can provide more economically resilient cities and regions beyond COVID-19.

Different from developed countries, the urbanization rate of developing ones is quite low. Also, there are still millions of people living in towns. During the process of urbanization, how to improve the efficiency of resource allocation is a core issue. In this sense, this paper's conclusion has essential policy significance, and it is only limited to China. Therefore, future studies can focus on the case of other large developing economies, such as Brazil and India.

DATA AVAILABILITY STATEMENT

The raw/processed data required to reproduce these findings cannot be shared at this time as the data are under the supervision of Chongqing Housing and Urban Rural Development Commission. The list of towns can be found at: Chongqing Municipal Government (2). People's Government Portal. Ministry of Housing and Urban-Rural Construction of the People's Republic of China (1). Central Government Portal.

AUTHOR CONTRIBUTIONS

KS: data curation, investigation, supervision, and writing—original draft preparation. CZ: conceptualization, methodology, software, and visualization.

REFERENCES

1. Ministry of Housing and Urban-Rural Construction of the People's Republic of China. *Central Government Portal*. China: Ministry of Housing and Urban-Rural Construction of the People's Republic of China (2020).
2. Chongqing Municipal Government. *People's Government Portal*. Chongqing: Chongqing Municipal Government (2020).
3. Gössling S, Scott D, Hall CM. (2020). Pandemics, tourism and global change: a rapid assessment of COVID-19. *J Sustain Tourism.* 29:1–20. doi: 10.1080/09669582.2020.1758708
4. Berman EM, Bowman JS, West JP. *Human Resource Management in Public Service: Paradoxes, Processes, Problems.* California: Sage Publications (2012).
5. Boyne G, Powell M, Ashworth R. Spatial equity and public services: an empirical analysis of local government finance in England. *Public Manag. Rev.* (2001) 3:19–34. doi: 10.1080/14719030122423
6. Knight J, Song L. *The Rural-Urban Divide: Economic Disparities and Interactions in China.* Oxford: Oxford University Press (1999).
7. Paudel U, Adhikari SR, Pant KP. Economics of environmental effects on health: a methodological review based on epidemiological information. *Environ. Sustain. Indic.* (2020) 5:100020. doi: 10.1016/j.indic.2020.100020
8. Warner M, Hefetz A. Applying market solutions to public services: an assessment of efficiency, equity, and voice. *Urban Affairs Rev.* (2016) 38:70–89. doi: 10.1177/107808702401097808
9. Hannum E. Political change and the urban-rural gap in basic education in China, 1949-1990. *Comp Educ Rev*. (1999) 43:193–211. doi: 10.1086/447554
10. Marialaura DD, Paul T, Helen H. Social economy involvement in public service delivery: community engagement and accountability. *Reg Stud.* (2009) 43:981–92. doi: 10.1080/00343400701874180
11. Chan CK, Yao X. Air pollution in megacities in China. *Atmosp Environ.* (2008) 42:1–42. doi: 10.1016/j.atmosenv.2007.09.003
12. Mahmoudi M, Ahmad F, Abbasi B. Livable streets: the effects of physical problems on the quality and livability of Kuala Lumpur streets. *Cities.* (2015) 43:104–14. doi: 10.1016/j.cities.2014.11.016
13. Omuta GED. The quality of urban life and the perception of livability: a case study of neighbourhoods in Benin City, Nigeria. *Soc Indic Res.* (1988) 20:417–40. doi: 10.1007/BF00302336
14. Sakamoto A, Fukui H. Development application of a livable environment evaluation support system using Web GIS. *J Geogr Syst.* (2004) 6:175–95. doi: 10.1007/s10109-004-0135-2
15. Zheng S, Kahn ME, Liu H. Towards a system of open cities in China: home prices, FDI flows, and air quality in 35 major cities. *Reg Sci Urban Econ.* (2010) 40:1–10. doi: 10.1016/j.regsciurbeco.2009.10.003
16. Yang XZ, Wang Q. Evaluation of rural human settlement quality difference and its driving factors in tourism area of southern Anhui Province. *Acta Geographica Sinica.* (2013) 68:851–67.
17. Li Q, Chen YL, Liu JM. On the development mode of Chinese urbanization. *Chinese Soc. Sci.* (2012) 7:82–100.
18. Qian Y. *How Reform Worked in China: The Transition from Plan to Market.* Cambridge, MA: MIT Press (2017). doi: 10.7551/mitpress/8098.001.0001
19. Zhou LA. Governing China's local officials: an analysis of promotion tournament model. *Econ Res J.* (2007) 7:36–50.
20. Yang Y, Liu ZH, Qi Q. Domestic tourism demand of urban and rural residents in China: does relative income matter? *Tourism Manag.* (2014) 40:193–202. doi: 10.1016/j.tourman.2013.05.005
21. Park DB, Yoon YS. Segmentation by motivation in rural tourism: a Korean case study. *Tourism Manag.* (2009) 40:2063–117.
22. Sun F, Wang D. The spatial distribution and development pattern of tourism towns and villages with characteristic landscape. *Tourism Tribune.* (2017) 32:80–93.
23. Wei YHD. Restructuring for growth in urban China: transitional institutions, urban development, spatial transformation. *Habitat Int.* (2012) 36:396–405. doi: 10.1016/j.habitatint.2011.12.023
24. Steinhardt HC. Discursive accommodation: popular protest and strategic elite communication in china. *Eur Polit Sci Rev*. (2016) 1:62–86.
25. Edmonds RL. Recent developments and prospects for the Sanxia. (Three Gorges) Dam. In: *China's Economic Growth.* London, UK: Palgrave Macmillan (2000). 161–183p.
26. Wilmsen B. Damming China's rivers to expand its cities: the urban livelihoods of rural people displaced by the three gorges dam. *Urban Geogr.* (2018) 39:345–66. doi: 10.1080/02723638.2017.1328578
27. Chongqing People's Congress. *Official Website of Chongqing People's Congress*. Chongqing People's Congress. (2020). Available online at: http://www.ccpc.cq.cn/
28. Fu BJ, Wu BF, Lu YH, Xu ZH, Cao JH, Niu D, et al. Three gorges project: efforts and challenges for the environment. *Prog Phys Geogr*. (2010) 34:741–54. doi: 10.1177/0309133310370286
29. Zhang Q, Lou Z. The environmental changes and mitigation actions in the three gorges reservoir region, China. *Environ Sci Policy.* (2011) 14:1132–8. doi: 10.1016/j.envsci.2011.07.008
30. Duranton G, Puga D. Micro-foundations of urban agglomeration economies. In: *Handbook of Regional and Urban Economics, Vol. 4.* (Amsterdam: Elsevier) (2004). 2063–117p.
31. Glaeser E. *Triumph of the City: How our Greatest Invention Makes us Richer, Smarter, Greener, Healthier, and Happier*. London, UK: Penguin Press (2012).
32. Li H, Gozgor G, Lau CKM, Paramati SR. Does tourism investment improve the energy efficiency in transportation and residential sectors? Evidence from the OECD economies. *Environ Sci Pollut Res.* (2019) 26:18834–45. doi: 10.1007/s11356-019-05315-7
33. Wooldridge JM. *Introductory Econometrics: A Modern Approach.* Toronto: Nelson Education (2015).
34. Combes P-P, Duranton G, Gobillon L, Puga D, Roux S. The productivity advantages of large cities: distinguishing agglomeration from firm selection. *Econometrica*. (2012) 80:2543–94. doi: 10.3982/ECTA8442

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An Evaluation of the Impact of Monetary Easing Policies in Times of a Pandemic

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This article tests five major economies of the world, United Kingdom, Japan, Brazil, Chin and lastly, India, for the changes in the monetary policy decisions that have been implemented following the Covid-19 outbreak. The assessment was undertaken in the form of an event study analysis, further substantiated with a regression analysis conducted for exploring the significance of CPI and real GDP in predicting the policy interest rates in the economy. The results of the event study analysis presented that the abnormal changes in the interest rates were statistically significant in the case of the United Kingdom, Brazil, and China, while the abnormal changes were found to be statistically insignificant in the case of India and Japan.

Keywords: COVID-19 outbreak, monetary policy, event-study analysis, CPI, real GDP

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BACKGROUND OF THE STUDY

Monetary policy can be explained as the decisions and actions undertaken by the central banks to manage money supply and availability of credit in the economy. A majority of the economies, in the present-day scenario, make use of the monetary policy initiatives to foster economic growth and propel economic momentum. Among the top monetary policy tools available for the policymakers is the management of the interest rates in the economy. Policy interest rates are used to control the supply of money in the economy, in the sense that as the interest rates increase in the economy, the supply of money is limited which limits the demand of money as the acquisition of funds becomes more expensive (1). As there are inflationary pressures in the economy, the monetary policy theory dictates that the interest rates are decreased by the policymakers to enhance the production capacity and increase in the aggregate supply (2). However, inflationary and deflationary pressures in the economy are a part of the cyclical fluctuations. However, in a series of unprecedented events, the normal business cycles are disrupted by the occurrence of unprecedented events and crises which shock the normal economic flow, which bring the economic variables to a sudden standstill. The erratic consequences of the economic shocks include changes in the consumer price index or inflation and the production, aggregate supply and consumption demand in the economy (3).

Monetary policy tools, both conventional and unconventional, endeavor to bring about price stability in the economy while enabling economic growth and development. The conventional methods for controlling the monetary base in the economy entail controlling for lending and bank interest rates in the economy (4). As the economy is faced with choppy waters, the policymakers try and ensure normalcy by giving a slight push to the industries by lowering the interest rates and easing credit availability in the economy (5). This ensures that the productive capacity is brought at par, and the output gap within the economy narrows down. On the consumption end, releasing credit availability allows an increase in the consumption demand as credit availability increases the aggregate supply, lowering the general price level in the economy. This hands-on approach toward the management of credit availability allows the policymakers to maintain financial and economic stability in the face of the cyclical economic fluctuations. However, as discussed, there are several unforeseen errants or shocks, which might affect the economic operations.

Considering to the shortage of research studies examining effects of monetary policy on main economies' development in Covid-19 as well as the scarcity of the existing literature on the relationship between monetary policy with the pandemic, this study is motivated to contribute to the expansion of the existing literature on this topic by providing an evidence from the effects of monetary policy in different countries under the Coronavirus pandemic. It aims to clarify how different economies' monetary policy are how to affect the real economy and price level within the Coronavirus pandemic. The Covid-19 pandemic is one such unprecedented event which has shaken the world economy (6). Starting off with the news associated by with viral outbreak in China began surfacing, and the world bank issued guidelines for undertaking preventive measures against the spread of the virus (7). These safeguards include the national shutdowns, import restrictions and travel restrictions which have limited the growth and productive capacity of the countries. The current article delves on the impact of the coronavirus outbreak on the monetary policy on the major world economies of the United Kingdom, Japan, Brazil, China, and India.

REVIEW OF LITERATURE

The novel coronavirus originated in China has been declared as an emergency pandemic situation having a significant impact on the economies all over the world. The virus has impacted the output yields and investments in all industries as well as consumption among households. Generally, the policymakers, in order to contain the impact of the pandemic, use monetary policies to affect the funds available in the financial system which in turn affects the interest rate and eventually the asset prices. With the change in interest rates and asset pricing, the consumption and investment pattern changes, allowing the economy to sustain and grow. The current study discusses the impact of Covid-19 pandemic on the consumption, manufacturing, and investment in the economies of Germany, UK, and France and the influence of monetary policies of the central banks in curtailing the impact of the pandemic.

Sudden Stops and Their Impact on the Economy

Sudden stops have been studied in the empirical and theoretical literature since the late 1990s. In the times of globalization and high capital mobility, sudden stops have become a major issue in economics and international finance. The focus on sudden stops has been increased after the Global Financial Crisis of 2007–2008 with a growing literature reviewing the role of macroprudential regulation in obviating financial crisis. Sudden stops are economic fluctuations characterized by a sudden contraction or loss of capital inflows and associated irregularities due to reduced access to international financial markets. The economic term' sudden stops' was coined with the abrupt drying up of capital inflows during the Mexican crisis of 1994. The phrase was then referred in many following crises like an Argentine crisis (1995), Russian crisis (1998), the Brazilian crisis (1999), and others (8). Sudden stops are often associated with currency crashes as it results in the fall of the foreign exchange rate.

The awareness about capital inflow volatility and reversals has increased in the policy community based on which International Monetary Fund (IMF) has developed new and more sympathetic capital control as well as international capital markets intervention policies. An example of a sudden stop is the "taper tantrum" of 2013 when Federal Reserve was expected to taper its purchase of securities which would have resulted in a market crash with a rise in US interest rates leading to capital outflow from emerging economies. This suggests that sudden stops are growing disruptive. These sudden stops have real and financial implications. The financial effects occur first with depreciation in the exchange rate, a decline in reserves, and a fall in equity prices. It also leads to a deceleration in GDP growth, a slowdown in investment, and strengthening of the current account. In the first four quarters of the sudden stop, the GDP falls by 4% year on year (9). GDP declines even faster in the second subperiod demonstrating a global level shock. These financial effects can only be partially offset using macroeconomic positions.

In the 1990s, the countries responded to sudden stops by reducing the exchange rate, floating currency, and following the new exchange rate, or implement a tighter monetary policy as policy responses. These countries, in the worst-case scenario, also resort to IMF for aid in the form of fiscal tightening, trade reforms, and privatization of public enterprises (10). However, in the second phase, even less tightening of monetary and fiscal policy work. In order to support economic activity and capital markets, some companies resort to reducing policy interests. With currency depreciation, little monetary stringency would work as countries had lowered mismatches in foreign currency, reducing damage in balance sheet due to depreciation. The impact of sudden stops differs for a country with a fixed foreign exchange rate policy than for a country with a flexible foreign exchange rate policy. This is because a country with fixed exchange rate regime is not able to offset the reduction in demand through expansionary monetary policy or achieve exchange rate adjustment with the help of nominal depreciation (11). Countries with stronger fiscal balance are able to deal with the sudden stops with minimum fiscal consolidation. In the 2000s, resorting to IMF for aid was reduced as countries had accumulated a reserve of international currency and moved to flexible exchange rates.

Emerging markets have been experiencing the impact of sudden stops despite flexible exchange rates, stronger fiscal budgets, stronger financial markets, and less foreign currency differentiation. The occurrence of these sudden stops have not reduced, and any benefit from stronger fiscal and monetary positions of countries does not offset the sudden stops coming from different countries. The progress on the fiscal and monetary policies have also not reduced the implications of the stops in a

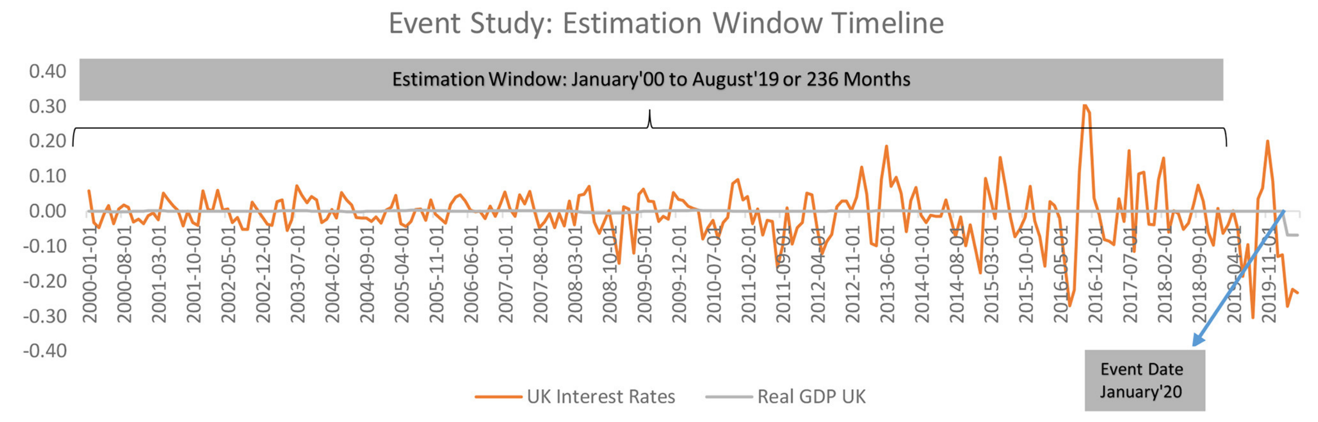


FIGURE 1 | Event timeline: Covid-19 pandemic.

significant manner (12). The output reduction in the first quarter is slightly higher than the second subperiod. With increased globalization and transaction in international financial markets, countries experience capital flow reversal more often due to sudden stops and these reversals have unruly output impacts (9). It is disturbing that neither the national officials with their monetary or fiscal policies nor the international financial institutions with their increased new financial facilities have helped in reducing the impacting of sudden stops in the emerging markets. The frequency and severity of sudden stops remain the same in all subperiods. The decline in GDP second subperiod as the capital inflows in the preceding subperiod is higher and large capital reversals are experienced when the sudden shock shift to the second subperiod. During the sudden stops, changes are observed in the global economic conditions and policies and characteristics of affected countries. Stronger policies, however, had an impact at the national level, as shown in **Figure 1**. During sudden stops, it is essential for the emerging countries having high budget deficits and high inflation rate to tighten fiscal and monetary policies. According to Efremidze et al. (13), sudden stops have a negative impact on financial deficits and require governments to take painful steps to reduce the effect on financial markets. Paradoxically, exchange rate policy, tightening of monetary, and fiscal policies as a response to the stops have been found to be effective at a national level, but at the global level, the reversal of international capital flows enhances the effect of external stops. Low trade openness and low financial globalization reduces the possibility of a spillover of a sudden stop and also minimize the impact of sudden stops on the countries.

Monetary Policy and Fiscal Stability in Pandemic Times

Covid-19 has given an economic shock to countries across the globe with its alarming speed and gigantic magnitude. This led to steep recessions in many industries across countries. Despite the global policy support, the pandemic is estimated to impact the global economy in the form of a 5.2% dip in the GDP in 2020, the highest in eight decades. The per capita incomes of emerging and developing economies have been contracted by far this year. The impact on the global economy would worsen if the pandemic took longer to get controlled and financial stress persists. The pandemic highlights the need for economic actions apart from urgent health-related policy actions to reduce the vulnerable consequences and improve the capacity of countries' system of dealing with the pandemic in future. Severe outbreaks in these countries result in international spillovers and negative impact on the global value chains and financial markets. GDP growth of regions such as Latin America, Central Asia, and Europe has been contracted due to international spillover from South Asia's GDP downgrade and the domestic outbreak of the pandemic resulting in lockdown measures. Many countries mitigated the impact of the pandemic by adopting strict fiscal and monetary policies. Per capita income is also expected to downgrade in 2020 in all emerging and developing economies. Covid-19 will leave lasting scars to the economies creating a devastating impact on the already fragile developing economies.

Monetary and fiscal policy measures can mitigate the short-term impact of the pandemic on the economy and productivity while comprehensive reforms would be required to minimize the long-term impact of the pandemic on the growth of the nation by improving governance, public health policies, and general business environment. The Covid-19 outbreak has led to a collapse in demand for oil, an upwelling oil inventories and the lowest decline in oil prices. In the initial stage of the pandemic, with all the lockdown restriction, oil prices cannot buffer the impact of Covid-19, but it can certainly help the economy to recover once the restrictions are lifted. The fiscal positions of energy-exporting emerging economies have been strained for a while now, and the pandemic has resulted in a collapse in their oil revenues. Thus, fiscal policy needs to be implemented for a sustainable economic position in a country. Recently, a sharp rise in the number of virus patients has been witnessed even in the developed economies let alone emerging and developing economies. The second wave of infection has resulted in the loss of income, trade, and investments. In these scenarios, the government fiscal policies and central bank's monetary policies are likely to renew the collapsed consumption of households. The low income restrained the borrowing capacity of households, and therefore, they could not maintain the consumption. The loose monetary policy would provide liquidity and purchasing power to the households to maintain their basic level of consumption despite a low level of savings. The ability of monetary policy and welfare systems to reduce income losses differ from country to country and is generally lower in low-income countries. The domestic investment comes to a halt during uncertainty like pandemics, and the outputs worsen. Restrictions imposed due to COVID-19 reduce the ability of fiscal and monetary policies to limit the consequences of the pandemic. Businesses are affected due to lack of demand, shortage of raw material, and costs of providing safety to employees from the virus. In some sectors, even fiscal stimulus is ineffective as the processes are completely shut (6). In such cases, the global recession is expected with high fiscal debts for low-income countries.

Role of Central Banks and Effect of Interest Rates: Delphic and Odyssean Monetary Policy Theory

The output and aggregate demand in an economy are not only influenced by the monetary policy, but interest rates also play a major role. Since interest rates have an impact on the economic policies and decisions, information revealed by the central banks about the future rates is an important medium based on which the monetary policy influence the macroeconomy.

Such impact reveals that central banks can control the aggregate demand by expressing that interest rates will remain low for a long time when the policy rate cannot be lowered due to effective lower bound (ELB). Other than the planned money supply injection and interest rates influence, sudden stops, and natural occurrences also have an influence on the yield curve. A piece of bad macroeconomic news impacts the yield curve, and as a reaction to it, the central bank needs to adjust its monetary policy. There are generally two kinds of surprises that have a macroeconomic impact on the central bank policy. As discussed by Campbell et al. (14), one of these sudden stops or natural occurrences has been termed as "Delphic" shocks as it explains the reaction of the central bank to the bad macroeconomic news by giving an oracle. The second type of shock is termed as "Odyssean" shock in which the central bank "ties its hands to the mast" by promising to twig to the announced plan for the interest rate. Central banks provide Delphic and Odyssean information even though guidance policies have been implemented. It is generally observed that Odyssean surprises are effective in improving aggregate demand and output in the economy. A central bank announcement has a Delphic nature if it raises interest rates and creates positive inflation expectations. When the inflation expectations reduce as a result of central bank announcements, Odyssean shocks occur. These announcements from a central bank not only makes the investors pessimistic or optimistic about the future of their investment, but the existence of these two shocks also helps in analyzing the response of financial and economic variables to monetary policy expectations (15). D'Amico and King (16) explained the variations and expectations of variables interest rates, output and inflation using VAR. They imposed different sign restrictions on short-term interest rate pattern as well as tracked expected inflation and GDP. This sign imposition allowed the authors to identify the domination of Delphic guidance on the Odyssean pattern

Research Gap

A wide literature discussing the impact of sudden stops such as financial crisis or pandemics on the economy and suggesting the importance of monetary easing policies in boosting money supply in the economy during the times of crisis is available. However, the specific impacts of monetary easing policies on curtailing the pandemic effects are limited specifically for the economies such as Germany, France, and the United Kingdom. Thus, the present study aims to critically assess the short-term effects of monetary easing policies on the money supply in the economy especially during the times of pandemic with consideration on the recent scenario of Covid-19. Majority of the studies have discussed the impact of monetary and fiscal policies on the economy using the VAR model. Our study would adopt a mixed methodology to answer the research questions in the context of the recent Covid-19 crisis, discussed in the following section.

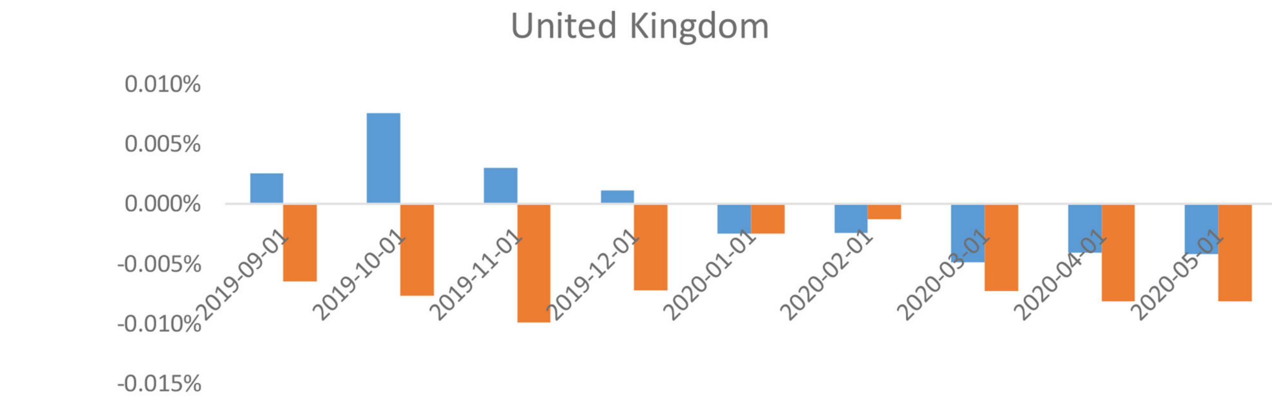
METHODOLOGY

This section describes the research methodology used to answer the research questions. It explains the data and variables used and the analysis method adopted to conduct the research. It also details out the measures and methods used for analyzing data, the findings and results of which have been discussed in the following section.

Data Description

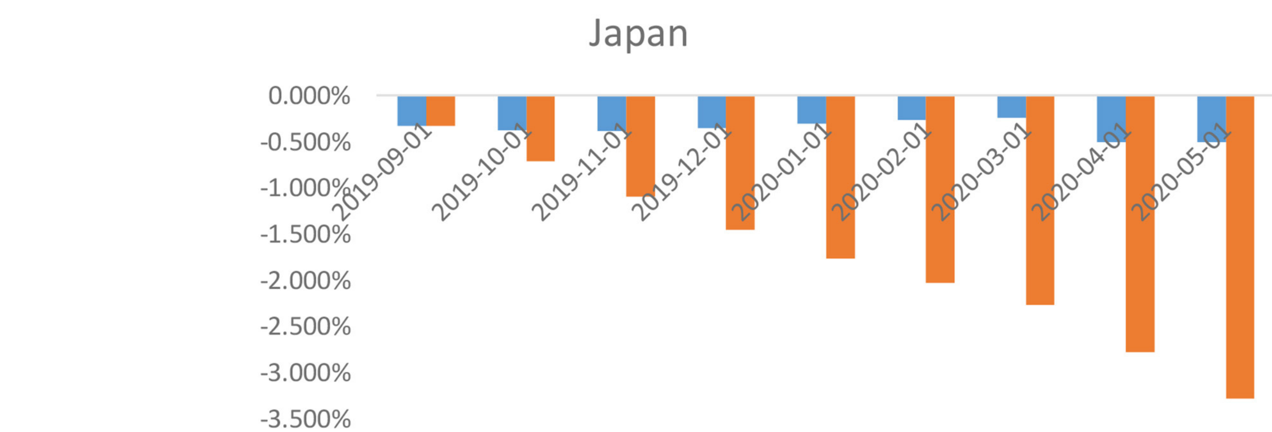
The study analyses the macroeconomic variables and financial factors of the countries UK, China, Brazil, India, and lastly Japan to evaluate the role of monetary policies in curtailing the pandemic consequences and in aiding the recovery of the economy. The monetary policies involve fixing a refinancing operations rate that is unique for every country. The study analysis considered variables with the capability of measuring economic activity such as inflation rate measured using Consumer Price Index (CPI) and real GDP. The data for real GDP was available in the form of an index with 2015 as the base year, harmonized for each of the countries being examined.

The quantitative easing in unconventional monetary policy is expected to raise inflationary pressures in the economy, which, in turn, impact the prices. The higher inflation rate is expected to increase current expenditure because of higher expected inflation, and thus, the price level also increases. As studied by scholars, the monetary policy has the capability to reduce the negative consequences of the pandemic by improving consumption and investment patterns. The current study, therefore, analyses the impact of the federal fund rate on the interest rate and real GDP of an economy during the times of pandemic Covid-19.



	2019-09-01	2019-10-01	2019-11-01	2019-12-01	2020-01-01	2020-02-01	2020-03-01	2020-04-01	2020-05-01
Expected Change	0.003%	0.008%	0.003%	0.001%	-0.002%	-0.002%	-0.005%	-0.004%	-0.004%
Abnormal Change	-0.006%	-0.008%	-0.010%	-0.007%	-0.002%	-0.001%	-0.007%	-0.008%	-0.008%

FIGURE 2 | Abnormal changes in policy interest rates over the event window: United Kingdom.



	2019-09-01	2019-10-01	2019-11-01	2019-12-01	2020-01-01	2020-02-01	2020-03-01	2020-04-01	2020-05-01
Abnormal Change	-0.331%	-0.382%	-0.387%	-0.354%	-0.310%	-0.269%	-0.239%	-0.505%	-0.505%
Cumulative Abnormal Change	-0.331%	-0.713%	-1.100%	-1.454%	-1.764%	-2.033%	-2.273%	-2.777%	-3.282%

FIGURE 3 | Abnormal changes in policy interest rates over the event window: Japan.

Variables and Measures

The study uses the monetary policy premise, as discussed by Taylor (17) in his study. It explains that the interest rates prevailing in an economy are a result of the real income estimates intruded by the monetary policy refinancing operations. Based on the analysis conducted by Taylor (17) in his paper "*Discretion vs. policy rules in practice*," the current study aims to find the relationship between federal funds rate and macroeconomic variables such as inflation rate and real GDP using a predefined equation model. The study has been conducted in the context of UK, China, Brazil, India, and lastly Japan's monetary policy determining the inflation rate to curb the negative impact of the pandemic and boost aggregate demand and consumption through inflation rate moderation. The data period under study ranges from the fourth quarter of 2019 (beginning of the pandemic Covid-19) to the third quarter of the year 2020 (current period). The variables under study are as follows:

1. Real GDP (deviation from the target)
2. Federal Funds Rate in percentage
3. The inflation rate over the past four quarters.

The Taylor's Rule applied in the Taylor (17) study can be reiterated using a model equation as presented below:

$$r = p + 0.5y + 0.5\left(p - 2\right) + 2$$

Where

P denotes inflation rate, computed using the average Consumer Price Index (CPI) for the past 4 months;

Y represents the real GDP which is the per cent deviation from the target GDP set by the policymakers or monetary authorities.

Although the size of the coefficients can vary because of lack of consensus, the current study uses a representative policy rule of the countries under consideration. The rule states that the federal fund rate increases in case the inflation rate rise above the 2% target or the real GDP increases above the trend GDP. The federal fund rate would be twice if the inflation rate and real GDP matches the target.

The analysis would present the descriptive statistics for the above-discussed variables as well as to conduct a trend analysis of how these macroeconomic variables have changed over the past four quarters due to the occurrence of the pandemic.

Methods

Regression Model

The empirical model used Taylor's model to examine the relationship between the federal funds rate and the macroeconomic variables such as real GDP and inflation rates in the context of the United Kingdom, Japan, Brazil, China, and India. The figures of the past 20 years have been considered as they would reflect the pandemic situation and impact of monetary policies of the government in controlling the pandemic situation. The study uses a quantitative model, and the data has been collected through reliable secondary sources. The secondary sources used for data collection are FRED Economic Research database which has reliable data for the past 20 years (18). It is a digital library with a compilation of data related to economic and financial factors, and public access is available for a million data points. The reliability of the data source comes from its publication by the Federal Reserve Bank of St. Lois Review.

The model equation used in this context has been presented as follows.

$$\textit{Federal Funds Rate} = \alpha + \beta 1\left(\textit{real GDP}\right) + \beta 2(\textit{inflation rate})$$

The equation represents the federal funds rate as a function of the macroeconomic variables (real GDP and the inflation rate). The analysis process would start off with the assessment of the factors affecting the monetary policy interest rates in the real-world scenario. Starting off with Taylor's monetary policy rule formula for computing the federal funds rate, we take a standpoint for examining the nature and direction of the factors that a make up the policy interest rates. This has been undertaken with the help of estimating a series of regression models for the five countries under consideration. The data has been analyzed using Microsoft Excel, and the results of the same have been presented in the following section.

Event Study Methodology

To examine the impact of WHO announcing the Covid-19 pandemic on the monetary interest rates and the real GDP using the event study methodology. This particular methodology has been used in a large number of studies to decipher the impact of the announcement of an event on the value of a firm or for a policy interpretation (15, 19). Making use of the event study methodology is that it encapsulates the short-term impact of a given economic/ financial or even business events. In the current scenario, the event study analysis has allowed us to assess the monetary policy impact caused by the coronavirus outbreak as instigated by the changes in the real GDP due to the event.

The Covid-19 pandemic struck the global landscape sometime around later November to early December 2019. However, the WHO issued a series of guidelines for the world leaders regarding the safeguards against the spread of the coronavirus pandemic on 10 January 2020, which has been taken as a guideline for the event declaration (20). The impact of the global pandemic can be seen through a slump in the economic activity worldwide through the nationwide shutdowns enforced by the governments and the policymakers (21). This, in turn, has presented a decrease in the aggregate demand and aggregate output in the economy and thereby a slump in the real GDP in various parts of the world. The impact of the pandemic outbreak, as seen on the macroeconomic indicators like the output levels in the economy has also been mitigated by the policymakers through changes made in the monetary policy response packages. This has been examined through event study analysis for the impact of the Covid-19 event on the economies of the United Kingdom, Japan, China, India and lastly, Brazil (as shown in **Figures 2–6**).

The estimation and time window can thus be illustrated as;

Here, as can be seen, the estimation window has been constructed for 236 months ranging from 01 January 2000 till 01 August 2019, comprising of 236 months in **Figure 7**. The estimates have been developed as a monthly change in the value of the policy interest rates in the current period over the preceding time period.

$$V = \frac{V1 - V0}{V0}$$

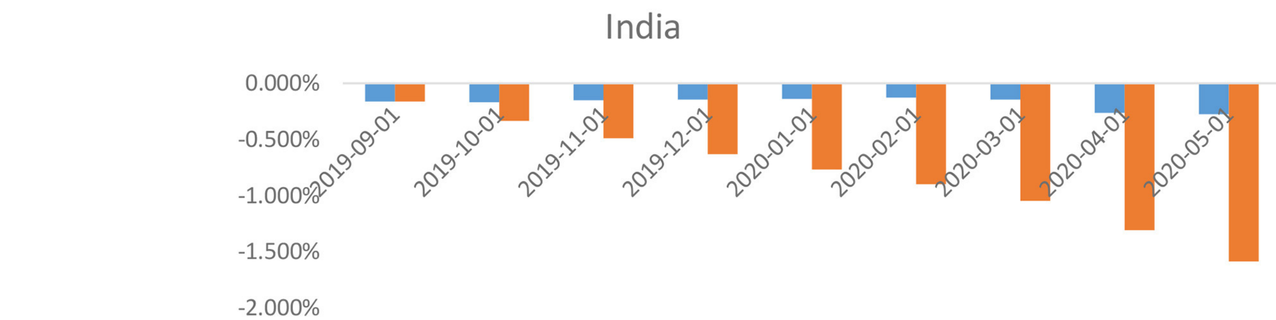
Where, V1 is the value of the estimate in the current time period, and V0 is the value in the preceding time period while V represents the value estimated as a monthly change in the values observed for the policy interest rates and real GDP.

The event study methodology empirically entails the assessment of the abnormal changes (increase or decrease) of performance variables upon the announcement of a particular event. The abnormal changes in the policy interest rates have been estimated every month of the event window ranging from September 2019 till May 2020 has been estimated as;

$$AC_{i,t} = OC_{i,t} - TC_{i,t}$$

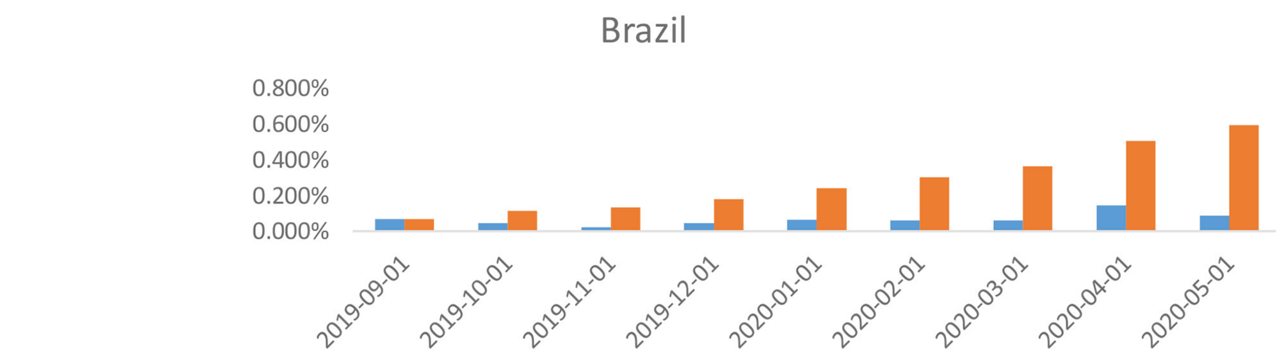
Where in,

$AC_{i,t}$ represents the abnormal changes in the policy interest rate "i" in the month "t;"



	2019-09-01	2019-10-01	2019-11-01	2019-12-01	2020-01-01	2020-02-01	2020-03-01	2020-04-01	2020-05-01
Abnormal Change	-0.166%	-0.168%	-0.153%	-0.145%	-0.137%	-0.130%	-0.147%	-0.264%	-0.278%
Cumulative Abnormal Change	-0.166%	-0.334%	-0.487%	-0.632%	-0.770%	-0.899%	-1.046%	-1.310%	-1.588%

FIGURE 4 | Abnormal changes in policy interest rates over the event window: India.



	2019-09-01	2019-10-01	2019-11-01	2019-12-01	2020-01-01	2020-02-01	2020-03-01	2020-04-01	2020-05-01
Abnormal Change	0.068%	0.045%	0.022%	0.044%	0.062%	0.061%	0.059%	0.143%	0.087%
Cumulative Abnormal Change	0.068%	0.113%	0.135%	0.179%	0.241%	0.302%	0.361%	0.504%	0.591%

FIGURE 5 | Abnormal changes in policy interest rates over the event window: Brazil.

$OC_{i,t}$ represents the observed changes in the policy interest rate "i" in the month "t," over the length of the event window;

And $TC_{i,t}$ represents the theoretical changes in the policy interest rate "i" in the month "t," over the length of the estimation window.

The theoretical variations in the policy interest rates of each of the countries have been estimated as a consequence of the regression equation comprising of the policy interest rate as the dependent variable and the real GDP as the independent variable.

$$Changes\ in\ Interest\ Rates_{i,t} = \alpha + \beta(Changes\ in\ Real\ GDP_{i,t})$$

Deriving a slope and the intercept values for the real GDP and the interest rates allows us to draw a theoretical value for the changes in the interest rates as instigated by the changes in the real GDP in the economy. Once the observed changes and theoretical changes in the policy interest rates have been categorized, we move on to the assessment of the observed abnormalities in the policy interests in the countries under consideration. This has been undertaken with the help of the application of a cross-sectional Student's t-test. The estimation formula used for the same has been presented below;

$$Student's\ T\ Test_t = \frac{Cumulative\ Abnormal\ Change_t}{Standard\ error\ of\ the\ TC}$$

Where in the cumulative abnormal changes refer to the abnormal changes in the policy interest rates for every month passed in the event window. The formula can also be presented as;

$$Cumulative\ Abnormal\ Change_t = \frac{\sum_{i=1}^{N} AC_{i,t}}{N}$$

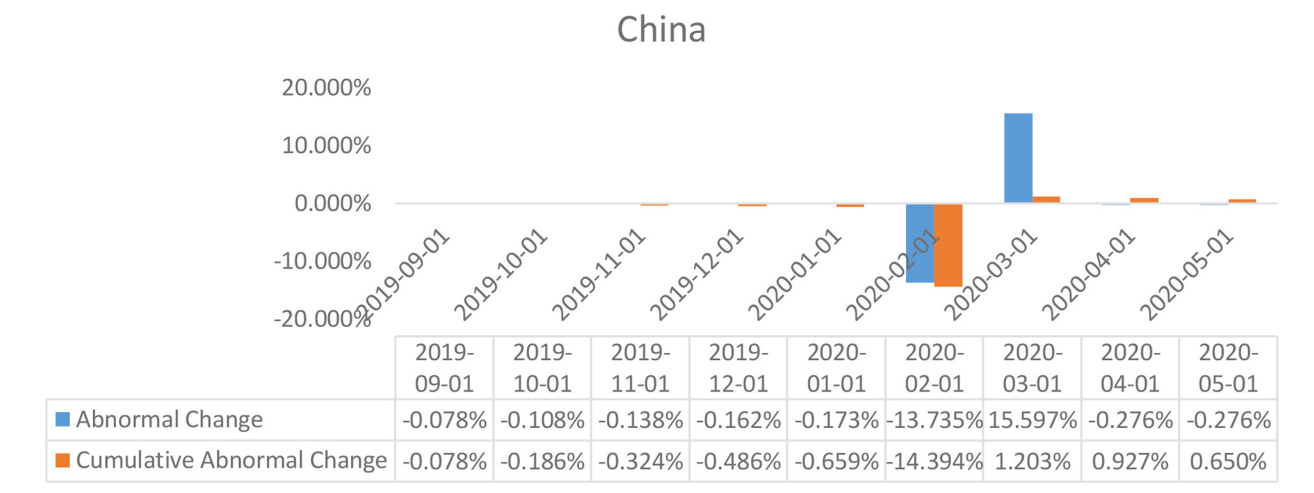


FIGURE 6 | Abnormal changes in policy interest rates over the event window: China.

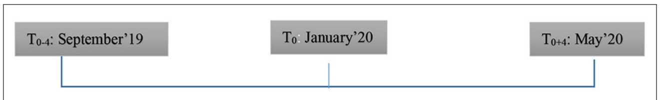


FIGURE 7 | Event window.

Where N is the length of the event window. Next, the standard error of the theoretical changes has been estimated using the STEYX function of the excel and can be theorized by the following formula;

$$Standard\ Error = \frac{\sum \left(Yi - Yi'\right)^2}{n-2}$$

Where in, Yi represents the values for Observed Changes and Yi' represents the predicted values or the theoretical changes in the policy interest rates. The estimated values for the *t*-test have then been used to examine the statistical significance of the abnormal changes observed in the policy interest rates in the case of each of the five countries being examined.

EMPIRICAL RESULTS

Regression Estimates

Starting with the assessment of the impact of the irregularity represented by the spread of the Covid-19 pandemic on the economies all across the world, and in order to deliver robust results for the assimilated data, we conduct a regression analysis in order to examine the factors affect the policy interest rates in an economy. Drawing inspiration from Taylor's Rule, we conduct a regression analysis with the policy interest rates as a dependent variable and real GDP and inflation as the independent variables.

For each of the countries, the following regression equation has been computed;

$$Policy\ Interest\ Rate_i = \alpha + \beta_1\,(CPI_i) + \beta_2\left(Real\ GDP_i\right) + \varepsilon$$

Where,

The exchange rate is the policy interest rate

CPI is the consumer price index

Real GDP, as acquired from the open access sources reflects on the index of real GDP I country i

ε is the residual noise

α is the intercept.

The results of the regression analysis conducted have been summarized in **Table 1**.

The results from **Table 1** indicate that both the regressor have a statistically significant impact over determining the policy interest rates in each of the countries under consideration, United Kingdom, Japan, Brazil, China, and India. However, the nature and direction of the relationship between the independent and dependent variable varied in each of the cases. In the case of the UK, while the real GDP index had a positive relationship with the policy interest rate, CPI had a negative relationship with the interest rates in the economy. This, however, is in line with the theoretical implications of the monetary policy theory, that inflation (represented by the consumer price index in the economy) has an inverse relationship with the interest rates and real GDP has a direct relationship with the interest rates (22). Similar results were reported in the case of the Chinese economy wherein the CPI had an inverse relationship with the interest rates and real GDP had a positive relationship with the dependent variable. In the case of the Japanese economy, both CPI and real GDP had a positive impact on interest rates. On the other hand, in the case of the Indian economy, real GDP had a negative impact over the interest rates while CPI had a positive

TABLE 1 | Regression model.

	UK	Japan	India	China	Brazil
Intercept	7.9384**	−7.2397**	20.3858**	−4.3242**	159.5891**
	[4.8021]	[−7.4804]	[3.5698]	[−2.2484]	[9.7853]
CPI	−0.1265**	0.0123**	0.0085**	−0.0030*	−0.1164**
	[−47.4029]	[2.2820]	[3.4107]	[−1.7095]	[−14.2460]
Real GDP	0.0675**	0.0633**	−0.1421**	0.0768**	−1.3163**
	[4.2273]	[7.8101]	[−2.4873]	[3.9809]	[−8.0939]
R square	0.9081	0.2144	0.0675	0.0687	0.5146

***Implies that the probability value of the t-statistic of the regression coefficient is less than 0.05, making the coefficient statistically significant at 95% level of significance.*
**Implies that the probability value of the t-statistic of the regression coefficient is less than 0.10, making the coefficient statistically significant at 90% level of significance.*

impact on the interest rates, which contrasts the inference of the model presented in the case of the UK. Lastly, in the case of the Brazilian economy, it was observed that both CPI and real GDP had an inverse relationship with the policy interest rates observed.

Overall, the findings from the regression models constructed for the five economies under consideration present sufficient support for the explanatory variables, i.e., CPI and real GDP having a significant impact over the policy interest rates, as being helpful while determining the future trends of the interest rates for the economies. This comes in especially helpful in examining the impact of the Covid-19 pandemic on the real GDP in the economy and the resultant impact on the policy interest rates (23–25).

Event Study Results

The results of the event study analysis carried out for United Kingdom, Japan, Brazil, India, and China over the length of the given estimation window have been summarized in **Table 2** (for UK, Brazil, and Japan) and **Table 3** (for India and China). The assessment of the abnormal changes in the interest rates, egged against the cumulative interest rates reflects on a significant downward movement for both the estimates for the United Kingdom, Japan, and India. This can be explained by a constant deterioration in the observed values of interest rates by the British and Indian policymakers as a response to the Covid-19 outbreak. Also affecting the estimates are the deteriorating real GDP estimates for each of the economies in the first 3 months of 2020, which was a direct consequence of the widespread government-imposed nationwide shutdowns. Peculiar observations can be seen in the case of the policy interest rates abnormalities in the case of China, wherein, despite being the worst hit epicentre of the coronavirus outbreak, the policymakers did not resort to monetary relaxations, and no particular changes were observed in the policy interest rates. However, the Chinese economy did suffer considerably, owing to the limited production activities underway due to the shutdowns.

In the case of the United Kingdom, based on the t-test for the abnormal changes, the abnormal changes in the interest rates were statistically significant after the event announcement in the post event window. And thus, it can be considered that the policy interest rates in the United Kingdom were significantly impacted by the changes in the values for Real GDP as triggered by the Covid-19 pandemic outbreak.

In the case of Japan, the abnormal changes in the policy interest rates came out to be statistically insignificant in a larger part of the estimation window, which can be explained by the lack of observed changes in the policy interest rates in the country.

In the case of the Indian economy, the t-test of the abnormal changes was found to be statistically insignificant which presented that the abnormal changes in the policy interest rates in the economy were not impacted by the changes in the real GDP as triggered by the outbreak of the Covid-19 global pandemic.

In the specific case for the Brazilian economy, it is evident from the student's T-test results that the changes in the policy interest rates were unaffected by the changes in the real GDP or by the announcement of the coronavirus outbreak by the World Health Organization.

The Chinese economy, as can be seen from the results of the t-test of abnormal changes, reflected statistically significant results. This allows us to decipher that a lack of variation in policy interest rates, as ought to be theoretically triggered by the changes in the real GDP, caused an abnormal pattern to arise in the policy interest rates in the current scenario. This abnormality can, however, be explained by the controlled economic structure in China, a notion which is evident in the constant policy rates exercised by the monetary authorities in the economy.

The results of the event study analysis can be simplified by describing a basic macroeconomic scenario which involves the announcement of a global pandemic which is likely to affect the existing labor pool and the productive capacity of the economy in the short-run. The impact of the outbreak being such that the production in the country slows down considerably, and the demand side of the economy is impacted by the limitations put in place by the policymakers. This scenario would lead to a deterioration of the real GDP of an economy in the months just after the announcement is made and the economy prepares to shut down. Subsequently, economies revoked the economic shutdowns, and the economy opens up. However, the government lowers the interest rates to propel the productive capacity and bring back the economy

TABLE 2 | Estimation window: the United Kingdom, Brazil, and Japan.

Date	United Kingdom				Japan				Brazil			
	Expected change (%)	Abnormal change (%)	Cumulative abnormal change (%)	AR *T*-test	Expected change (%)	Abnormal change (%)	Cumulative abnormal change (%)	AR *T*-test	Expected change (%)	Abnormal change (%)	Cumulative abnormal change (%)	AR *T*-test
2019-09-01	0.003	−0.006	−0.065	−0.48092	0.003	−0.331	−0.331	−1.65109	0.026	0.068	0.068	0.326262
2019-10-01	0.008	−0.008	−0.014	−0.57052	0.003	−0.382	−0.713	−1.90376	0.045	0.045	0.113	0.216793
2019-11-01	0.003	−0.010	−0.240	−0.73541	0.003	−0.387	−1.100	−1.92852	0.067	0.022	0.135	0.106298
2019-12-01	0.001	−0.007	−0.312	−0.53604	0.003	−0.354	−1.454	−1.76777	0.046	0.044	0.179	0.212715
2020-01-01	−0.002	−0.002	−0.336	−0.18419	0.003	−0.310	−1.764	−1.54647	0.030	0.062	0.241	0.301054
2020-02-01	−0.002	−0.001	−0.349	−0.09614	0.003	−0.269	−2.033	−1.34078	0.033	0.061	0.302	0.2967
2020-03-01	−0.005	−0.007	−0.122	−50.4693	0.003	−0.239	−2.273	−1.19405	0.038	0.059	0.361	0.283356
2020-04-01	−0.004	−0.008	−0.937	−50.7862	0.003	−0.505	−2.777	−2.51666	0.048	0.143	0.504	0.690663
2020-05-01	−0.004	−0.008	−0.750	−50.7747	0.003	−0.505	−3.282	−2.51666	0.104	0.087	0.591	0.420762

from its economic slump. This scenario describes the current market scenario rather closely, and the lowering of the policy interest rates by the major world economies presents itself as a piece of evidence for the monetary expansion sought by the governments worldwide. In summary, this study compares with the significance of the policy interest rate affected by real GDP among above five countries, we find that there is a significant difference between the change of policy interest rate and real GDP in the United Kingdom and China, however, the effect of real GDP of Japan, India, and Brazil on the change of policy interest rate is not significant. As the representatives of emerging market countries, such as China, Brazil, and India, the regional identification of policy interest rate is weaker than that of developed economies. The reason is that the policy interest rate system of emerging countries is immature, the degree of marketization is low, and the policy interest rate has not experienced a free and complete evolution process. In particular, since the outbreak of the Covid-19 epidemic, the economic situation of all countries in the world has been affected by the impact of the Covid-19 epidemic. Therefore, governments around the world have adopted more loose monetary policies to release monetary liquidity in order to strengthen the role of economic recovery. This abnormality can, however, be explained by the controlled economic structure in China, a notion which is evident in the constant policy rates exercised by the monetary authorities in the economy. Although the United Kingdom and Japan are both developed countries with a high degree of financial marketization, the main reasons why Japan's real GDP has no significant effect on policy interest rate are the high degree of aging, low labor productivity and the end of the credit boom. After the asset price bubble crisis, Japanese business departments and family departments were deeply in debt, leading to the rapid evolution of their optimization process from profit maximization to debt minimization, resulting in a shrinking demand for loans. Moreover, the life cycle characteristics of residents' asset liability structure tend to weaken the channels of monetary interest rate and credit, but strengthen the channels of wealth effect. Therefore, the effect of monetary policy in the aging economy ultimately depends on the relative importance of each transmission channel (26–29). Therefore, Japan's real GDP has no significant effect on the policy interest rate.

Considering that the theoretical change of a country's policy interest rate is always affected by some factors, such as fiscal policy, monetary policy, balance of payments, inflation, and so on. It is difficult to select one of these indicators to directly replace the theoretical change of policy interest rate. Therefore, this study follows the research method of Baker et al. (30) and uses the "principal component analysis" method to construct the policy interest rate index to reflect the theoretical change of policy interest rate as a whole. In this method, many indexes with certain correlation are recombined into a new group of comprehensive indexes by the way of principal component dimension reduction to replace the original indexes. As a result, this study selects industrial added value, net fiscal expenditure, balance of payments, foreign exchange reserves, M2 and unemployment rate as principal component analysis indicators, and constructs

TABLE 3 | Estimation window: China and India.

Date	China				India			
	Expected change (%)	Abnormal change (%)	Cumulative abnormal change (%)	AR *T*-test	Expected change (%)	Abnormal change (%)	Cumulative abnormal change (%)	AR *T*-test
2019-09-01	0.004	−0.078	−0.078	−0.72768	−0.011	−0.166	−0.166	−1.13455
2019-10-01	0.004	−0.108	−0.186	−1.00997	−0.004	−0.168	−0.334	−1.14898
2019-11-01	0.004	−0.138	−0.324	−1.28823	−0.011	−0.153	−0.487	−1.05058
2019-12-01	0.004	−0.162	−0.486	−1.51871	−0.011	−0.145	−0.632	−0.99481
2020-01-01	0.004	−0.173	−0.659	−1.61524	−0.011	−0.137	−0.770	−0.93844
2020-02-01	0.004	−13.735	−14.394	−128.414	−0.011	−0.130	−0.899	−0.8872
2020-03-01	0.004	15.597	1.203	145.8241	0.012	−0.147	−1.046	−1.00322
2020-04-01	0.004	−0.276	0.927	−2.58472	−0.011	−0.264	−1.310	−1.80783
2020-05-01	0.004	−0.276	0.650	−2.58472	0.003	−0.278	−1.588	−1.90524

the theoretical change of policy interest rate index. Furthermore, this study selects the policy interest rate index instead of the initial theoretical change as the dependent variable to recalculate the above linear regression model. The results are as follows. The robustness test in **Table A1** of Appendix results are basically consistent with the above conclusions, and it is proved that the estimation results are robust.

Overall, governments aim to get risk of adverse effects of Coronavirus outbreak on the economy by lowering their policy interest rates. In this period, lowering of the policy interest rates by the major economies is for stimulating the economic development and increasing the price level. This study suggests the changes in the monetary policy, as instigated by the unprecedented natural or even man-made events, are rather sporadic and cannot be expected to perform against the theoretical models constructed based on the historical observations of the macroeconomic variables like inflation and output.

CONCLUSION

The monetary policy allows the policymakers to control the supply of money and credit in the economy. Taking two opposite directions, we have the two forms of monetary policies, expansionary and contractionary. Out of these two, the expansionary monetary policy is sought as a way out for the policymakers to pull the economy from a period of the economic slump through injecting credit into the economy and promoting economic growth within the economy. As the economies run along the course of business cycles, depression, and recovery is a part of their cyclical economic fluctuations, reducing and increasing policy interest rate relative to the changes in the real GDP and inflation is rather common. However, the cyclical fluctuations in the business cycles can be led astray by the occurrence of unprecedented events and/or natural disasters which affect the productive capacity of the economy in short-run, along with having long-run repercussions. One such event which surfaced on the world economic landscape was the outbreak of the coronavirus, in January 2020, as declared by the World Health Organization. The virus outbreak soon gained momentum and evolved into a global pandemic, which sent the policymakers into a flurry of safety procedures and several stringent measures were imposed including national lockdowns as well as travel restrictions and public curfews. The series of events that followed had a detrimental impact on the production and consumption levels in the economies worldwide. This event can be seen as a trigger for changes being made in the monetary policies worldwide to ensure that the productive capacity of the economies is not majorly affected and the economy does not fall to the abyss of economic recession.

This article examined five major economies of the world, United Kingdom, Japan, Brazil, Chin and lastly, India, for the changes in the monetary policy decisions that have been implemented following the Covid-19 outbreak. The assessment was undertaken in the form of an event study analysis, further substantiated with a regression analysis conducted for testing the significance of CPI and real GDP in predicting the policy interest rates in the economy. The results of the regression analysis produced significant results in each of the five economies, which then paved the way for the event study method to be implemented. The WHO issued a series of instructions to the world leaders against a possible virus outbreak originating from China on 10 January 2020, which served as the core event being examined and thereby allowing us to draw up an event window of 9 months ranging from 19 September till 20 May. The estimation window was framed over 20 years, spanning from January 2000 till May 2020. The impact was sought in the form of changes in the policy interest rates, relative to the changes observed in the real GDP as triggered by the announcement of the event. The results of the event study analysis presented that the abnormal changes in the interest rates were statistically significant in the case of the United Kingdom, Brazil, and China, while the abnormal changes were found to be statistically insignificant in the case of India and Japan. This leads to infer the abnormalities in the patterns of changes observed in the policy interest rates in these economies was not substantiated by the changes in the real GDP. In certain cases, the changes made in the interest rates were negligible, as was the case of China and Japan and in other cases the changes made to counteract the economic impact of the Covid-19 outbreak were sporadic. This presents us with the conclusion that the changes in the monetary policy, as instigated by the unprecedented natural or even manmade events, are rather sporadic and cannot be expected to perform against the theoretical models constructed based on the historical observations of the macroeconomic variables like inflation and output.

Further examining the long-standing economic impact of the Covid-19 crisis on the world economies cannot be yet fully examined as the event is still afresh and the event window is rather small and the post-event window being absent. It would be interesting to examine the state of the monetary policy changes, as triggered by the changes in the rates of inflation and real GDP, as triggered by the global pandemic by the end of 2020.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

YL: writing, discussion, and analysis. YS: data analysis, writing, and supervision. MC: writing and data collection. All authors: contributed to the article and approved the submitted version.

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REFERENCES

1. Bernanke BS. The new tools of monetary policy. *Am Econ Rev.* (2020) 110:943–83. doi: 10.1257/aer.110.4.943
2. Cologni A, Manera M. Oil prices, inflation and interest rates in a structural cointegrated VAR model for the G-7 countries. *Energy Econ.* (2008) 30:856–88. doi: 10.1016/j.eneco.2006.11.001
3. Braggion F, Christiano LJ, Roldos J. Optimal monetary policy in a 'sudden stop'. *J Monetary Econ.* (2009) 56:582–95. doi: 10.1016/j.jmoneco.2009.03.010
4. Ellison M, Tischbirek A. Unconventional government debt purchases as a supplement to conventional monetary policy. *J Econ Dyn Control.* (2014) 43:199–217. doi: 10.1016/j.jedc.2014.03.012
5. Zhang R. *News Shocks and the Effects of Monetary Policy* (2019). doi: 10.2139/ssrn.3348466
6. Guerrieri V, Lorenzoni G, Straub L, Werning I. *Macroeconomic Implications of COVID-19: Can Negative Supply Shocks Cause Demand Shortages?* NBER Working Paper No. w26918, 1–37. (2020). doi: 10.2139/ssrn.3570096
7. Stock JH. *Reopening the Coronavirus-Closed Economy*, Vol. 60. Technical Report. Hutchins Center Working Paper (2020).
8. Cavallo EA. *International Capital Flow Reversals*. Working Papers. IDB Publications (2020).
9. Eichengreen B, Gupta P. *Managing Sudden Stops*. Central Banking, Analysis, and Economic Policies Book Series, 25 (2018).
10. Edwards S. Financial openness, sudden stops, and current account reversals, *Am Econ Rev.* (2004) 94:59–64. doi: 10.1257/0002828041302217
11. Al Munyif M. *Currency crises and sudden stops: Measures and relationships* (Doctoral dissertation) (2016). The Claremont Graduate University, Claremont, CA, United States.
12. Cavallo EA, Izquierdo A, León JJ. *Domestic Antidotes to Sudden Stops*. IDB Publications (Working Papers) (2020). doi: 10.18235/0000825
13. Efremidze L, Kim S, Sula O, Willett TD. The relationships among capital flow surges, reversals and sudden stops. *J Financial Econ Policy.* (2017) 9:393–413. doi: 10.1108/JFEP-03-2017-0021
14. Campbell JR, Evans CL, Fisher JD, Justiniano A, Calomiris CW, Woodford M. Macroeconomic effects of federal reserve forward guidance. In: *Brookings Papers on Economic Activity*. U.S. (2012). p. 1–80. doi: 10.1353/eca.2012.0004
15. Gertler M, Karadi P. Monetary policy surprises, credit costs, economic activity. *Am Econ J Macroecon.* (2015) 7:44–76. doi: 10.1257/mac.20130329
16. D'Amico S, King TB. *What Does Anticipated Monetary Policy Do?* Working Paper Series. (2015).
17. Taylor JB. *Discretion Versus Policy Rules in Practice*. North Holland, Carnegie-Rochester (1993). p. 195–214.
18. FRED. *Economic Data*. (2020). Available online at: https://fred.stlouisfed.org/ (accessed July 20, 2020).
19. Duso T, Gugler K, Yurtoglu B. Is the event study methodology useful for merger analysis? A comparison of stock market and accounting data. *Int Rev Law Econ.* (2010) 30:186–92. doi: 10.1016/j.irle.2010.02.001
20. Sun Y, Bao Q, Lu Z. Coronavirus (Covid-19) outbreak, investor sentiment, and medical portfolio: evidence from China, Hong Kong, Korea, Japan, and U.S, *Pacific Basin Finance J.* (2021) 65:101463. doi: 10.1016/j.pacfin.2020.101463
21. Bofinger P. *The Covid-19 Crisis: Inflationary or Deflationary?* Social Europe (2020). Available online at: https://www.socialeurope.eu/the-covid-19-crisis-inflationary-or-deflationary (accessed August 8, 2020).
22. Lee KS, Werner RA. Reconsidering monetary policy: an empirical examination of the relationship between interest rates and nominal GDP growth in the US, UK, Germany and Japan. *Ecol Econ.* (2018) 146:26–34. doi: 10.1016/j.ecolecon.2017.08.013
23. Wynne MA, Zhang R. Estimating the natural rate of interest in an open economy. *Empirical Econ.* (2018) 55:1291–318. doi: 10.1007/s00181-017-1315-5
24. Wynne MA, Zhang R. Measuring the world natural rate of interest. *Econ Inquiry.* (2018) 56:530–44. doi: 10.1111/ecin.12500
25. Grossman V, Martínez-García E, Wynne MA, Zhang R. *Ties that bind: estimating the natural rate of interest for small open economies*. Social Science Electronic Publishing (2019). doi: 10.2139/ssrn.3354898
26. Miles D. Should monetary policy be different in a greyer world. In: *Aging, Financial Markets and Monetary Policy*. Berlin: Springer (2002). p. 243–76.
27. Yoshino N, Miyamoto H. Declined effectiveness of fiscal and monetary policies faced with aging population in Japan[J]. *Japan World Econ.* (2017) 42:32–44. doi: 10.1016/j.japwor.2017.06.002
28. Imam PA. Shock from graying: is the demographic shift weakening monetary policy effectiveness[J]. *Int J Finance Econ*. (2015) 20:138–54.
29. Chen WY. Demographic structure and monetary policy effectiveness: Evidence from Taiwan. *Qual Quant*. (2017) 51:2521–44. doi: 10.1007/s11135-016-0407-1
30. Baker IT, Prihodko L, Denning AS, Goulden M, Miller S, da Rocha HR. Seasonal drought stress in the Amazon: Reconcilingmodels and observations. *J Geophys Res*. (2008) 113:G00B01. doi: 10.1029/2007JG000644

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

APPENDIX

TABLE A1 | Robustness check.

	UK	Japan	India	China	Brazil
Intercept	6.3656 [3.7630]	−6.8371 [−6.7638]	15.5741 [4.8731]	−3.7798 [−1.5783]	110.7238 [6.8934]
CPI	−0.1576 [−32.8739]	0.0058*** [2.3870]	0.0193** [2.9834]	−0.0369** [−1.0039]	−0.1877 [−9.8933]
Real GDP	0.0583** [5.8955]	0.0762** [6.0324]	−0.2831 [−1.9032]	0.0379** [2.4461]	−1.2291 [−7.9062]
R square	0.8723	0.3117	0.0589	0.0436	0.7099

****Implies that the probability value of the t-statistic of the regression coefficient is less than 0.01, making the coefficient statistically significant at 99% level of significance.*

***Implies that the probability value of the t-statistic of the regression coefficient is less than 0.05, making the coefficient statistically significant at 95% level of significance.*

**Implies that the probability value of the t-statistic of the regression coefficient is less than 0.10, making the coefficient statistically significant at 90% level of significance.*

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Clusters in the Spread of the COVID-19 Pandemic: Evidence From the G20 Countries

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This study tests the validity of the club convergence clustering hypothesis in the G20 countries using four measures of the spread of the COVID-19 pandemic: total number of confirmed cases per million people, new cases per million people, total deaths per million people, and new deaths per million people. The empirical analysis is based on the daily data from March 1, 2020, to October 10, 2020. The results indicate three clusters for the per capita income, two clusters for total cases per million people, and new cases per million people. Besides, there are only one and two clusters for total deaths per million people and new deaths per million people. Potential policy implications are also discussed in detail.

Keywords: the COVID-19 pandemic, the COVID-19 cases, the COVID-19 deaths, convergence clustering test procedure, the G20

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INTRODUCTION

In this paper, we examine the validity of the club convergence clustering hypothesis in the G20 countries using four indicators of the spread of the COVID-19 pandemic: total number of confirmed cases per million people, new confirmed cases per million people, total deaths per million people, and new deaths per million people. It is essential to examine the validity of the convergence clustering hypothesis in the G20 countries related to the indicators of the spread of the COVID-19 pandemic. Indeed, whether there are significant clusters in the spread of the COVID-19 pandemic can be particularly important for policy implications, such as lockdowns and limitations on business and social life. COVID-19 pandemic significantly affects every aspect of the global economy (1, 2). Therefore, forecasting the COVID-19 pattern in different countries is significant.

There are previous papers to analyze the spread of the pattern of the COVID-19 pandemic. For example, Katul et al. (3) show a significant global convergence in the generic spread mechanisms of the COVID-19. However, the authors focus on the data until early 2020. Kuniya (4) also examines the impact of an emergency state for the first wave of the COVID-19 in Japan for the period from April 7 to May 25, 2020. The author finds that the state of emergency has provided to 80% decline in the contact rate. Therefore, there is a significant convergence in the spread of the COVID-19 pandemic in Japan during concern. Chimmula and Zhang (5) forecast the infectious diseases related to the COVID-19 outbreak in Canada. The authors show that the spread of the COVID-19 pandemic in Canada follows a stationary forecasting process. Shabani and Shahnazi (6) considered the data of the COVID-19 cases from February 9, 2020, to July 27, 2020, to analyze COVID-19's spatial distribution dynamics. For this purpose, the authors applied the Markov Chain, while also used the Spatial Markov Chain. The findings indicate that the COVID-19 in 40 Asian countries have a unit root characteristics with the domestic policies. Besides, the neighboring countries have significant effects on the spread of COVID-19. Ismail et al. (7) confirm the evidence of convergence for the indicators on the spread of COVID-19 in 187 countries.

This study follows the current developments in the literature. It aims to examine the validity of the club convergence clustering hypothesis in the G20 countries using four indicators of the spread of the COVID-19 pandemic: total cases per million people, new cases per million people, total deaths per million people, and new deaths per million people. We use the daily data from March 1, 2020, to October 10, 2020.

A thorough search of the relevant literature yielded only one related article. This is the first study to use the club convergence clustering method to examine the spread of the COVID-19 pandemic in different countries. The results indicate two clusters for the per capita income, three clusters for total cases per million people, and new cases per million people. Besides, there are only one and two clusters for total deaths per million people and new deaths per million people. These findings suggest some substantial implications in the G20 countries. For example, the policymakers in these should implement measures for controlling the spread of the COVID-19 pandemic, and some countries have different dynamics in the spread of the COVID-19 pandemic. This main evidence should be some significant policy implications for these countries since the risks related to the COVID-19 significantly greater in some countries than others. Furthermore, emerging countries are seemed to be heavily affected by the COVID-19 pandemic.

The remaining parts of the study are structured as follows: Section Data and Club Convergence Methodology provides the details of the data and the club convergence methodology. The empirical results are stated in Empirical Findings. Section Conclusion concludes the study with possible implications of the findings.

DATA AND CLUB CONVERGENCE METHODOLOGY

Data

We examine possible cluster and club convergence dynamics for four indicators of the spread of the COVID-19 pandemic: total cases per million people, new cases per million people, total deaths per million people, and new deaths per million people. The empirical analysis is based on the daily data for the period from March 1, 2020, to October 10, 2020, in the G20 countries (19 countries excluding the European Union): Argentina, Australia, Brazil, Canada, China PR, France, Germany, India, Indonesia, Italy, Japan, Mexico, the Russian Federation, Saudi Arabia, South Africa, South Korea, Turkey, the United Kingdom, and the United States. The list of countries, including the country id of the countries in the empirical analyses, are provided in **Table 1**. The frequency of the panel data is daily. The data are downloaded from the dataset of Hasell et al. (8), so-called the *Data on COVID-19 (Coronavirus) by Our World in Data* project (https://github.com/owid/covid-19-data/tree/master/public/data).

Descriptive statistics of four indicators of the spread of the COVID-19 pandemic: total cases per million people, new cases per million people, total deaths per million people, and new deaths per million people are reported in **Table 2**.

TABLE 1 | Countries in the dataset.

ISO Code	Country	Country ID
ARG	Argentina	1
AUS	Australia	2
BRA	Brazil	3
CAN	Canada	4
CHN	China, PR	5
FRA	France	6
DEU	Germany	7
IND	India	8
IDN	Indonesia	9
ITA	Italy	10
JPN	Japan	11
MEX	Mexico	12
RUS	Russian Federation	13
SAU	Saudi Arabia	14
ZAF	South Africa	15
KOR	South Korea	16
TUR	Turkey	17
GBR	The United Kingdom	18
USA	The United States	19

TABLE 2 | Descriptive statistics.

Indicator	Total Cases per Million People	New Cases per Million People	Total Deaths per Million People	New Deaths per Million People
Mean	2,858	34.83	144.8	1.287
Max.	23,785	380.8	703.9	74.14
Min.	0.002	0.000	0.000	0.000
Std. Dev.	4,135	53.36	199.6	2.588
Obs.	4,256	4,256	4,256	4,256

Club Convergence Methodology

Phillips and Sul (9, 10) propose a novel approach for identifying the stochastic properties of convergence and defining different convergence clubs among the panel units over time. The methodology assumes the time-varying model with nonlinear nature, and it offers a mechanism of nonlinear transition. The best way of this approach is that it can also be applied in the panel data with unit root, or it does not assume homogeneous (common) factors in the data-generating algorithm. Besides, Phillips and Sul (9, 10) club convergence methodology captures each country's heterogeneity within the panel dataset. Hence, the club convergence procedure considers the dynamics of the COVID-19 spread among the G20 countries in a panel dataset. The COVID-19 spread rate in each county can be defined by the panel dataset, which may follow different convergence dynamics. Therefore, the club convergence procedure is a suitable test for the convergence dynamics of the COVID-19 spread among the G20 countries. This paper aims to examine the different convergence club features in the COVID-19 spread among the

G20 countries. We can define the club convergence procedure as such:

The series X_{it} captures an indicator of the COVID-19 spread for country i at time t, and $i = 1,2,\ldots, N$; $t = 1,2,\ldots,19$. At this stage, Phillips and Sul (9, 10) decompose the variable into two components: First is the common component of cross-sectional dependence in a panel dataset, g_{it}, and transitory component, a_{it}, as such:

$$X_{it} = g_{it} + a_{it} \tag{1}$$

Phillips and Sul (9, 10) define the Equation (1) as the common and the idiosyncratic components. At this stage, the variable follows nonlinear stochastic properties, as such:

$$X_{it} = \left(\frac{g_{it} + a_{it}}{\mu_t}\right)\mu_t = \delta_{it}\mu_t \text{ for all i and t,} \tag{2}$$

Where, μ_t captures the common component and δ_{it} indicates the time-varying idiosyncratic component. δ_{it} denotes the relative difference between common trend component μ_t and the value of X_{it} is an indicator of the spread of the COVID-19 in a country i at time t.

Let us take the deaths from the COVID-19 per million people as an example. μ_t denotes a common trend of the COVID-19 per million people in whole 19 countries. δ_{it} captures each country's relative share in terms of the COVID-19 per million people in the common trend in the G20 countries. The baseline approach of club convergence approach of Phillips and Sul (9, 10) is to define the time-varying load δ_{it}, and time-varying load will determine the dynamics of the club convergence in terms of the power of convergence. Furthermore, Phillips and Sul (9, 10) calculate a transition coefficient, which can be defined as h_{it}. Transition coefficient is based on the time-varying factor loadings (δ_{it}), as such:

$$h_{it} = \frac{X_{it}}{\frac{1}{N}\sum_{i=1}^{N} X_{it}} = \frac{\delta_{it}\mu_t}{\frac{1}{N}\sum_{i=1}^{N} \delta_{it}\mu_t} = \frac{\delta_{it}}{\frac{1}{N}\sum_{i=1}^{N} \delta_{it}} \tag{3}$$

In Equation (3), h_{it} indicates a transition term, which measure δ_{it} related to the average of the panel at time t. At this stage, the transition term defines a transition nature for source countries i relative to the average of the panel dataset of the G20 countries. All indicators used the filter provided by Hodrick and Prescott (11) to remove the cyclical component. Following Ravn and Uhlig (12), lambda is defined $1600 \times (365/4)^{\wedge 4}$ for daily data. The filtered coefficient for transition parameter is represented by $\hat{h}_{it}$, and an extracted time-trend is defined as $\hat{X}_{it}$.

Furthermore, the club convergence test procedure also defines the cross-sectional variance ratio, $\frac{H_1}{H_t}$, which can be defined as follows:

$$H_t = \frac{1}{N}\sum_{i=1}^{N}\left(\hat{h}_{it} - 1\right)^2 \tag{4}$$

At this stage, Phillips and Sul (9, 10) show that the transition parameter H_t is defined within a limit form, which can be written as such:

$$H_t \sim \frac{A}{L(t)^2 t^{2\alpha}} \; as\ t \to \infty \tag{5}$$

In Equation (5) A is a constant term, and $A > 0$, $L(t)$ is the function of time, and α indicates the speed of convergence. Phillips and Sul (9, 10) define *log t* regression to test the validity of the null hypothesis of convergence. The null hypothesis can be written as $H_0 : \delta_i = \delta$ and $\alpha \geq 0$ and against $H_1 : \delta_i \neq \delta$ for all i or $\alpha < 0$.

Furthermore, Phillips and Sul (9, 10) estimate the following Ordinary Least Squares (OLS) equation:

$$\mathrm{Log}\left(\frac{H_1}{H_t}\right) - 2\log L(t) = \hat{a} + \hat{b}\log t + \hat{c}(\log t)^2 + \hat{u}_t \tag{6}$$

In Equation (6), $L(t) = \log(t+1)$, the fitted coefficient of log t is $\hat{b} = 2\hat{\alpha}$, and $\hat{\alpha}$ is the estimate of α in the null hypothesis. The authors include the *squares of log t* to enhance the test procedure's power by capturing nonlinearity in the series. The test procedure considers the initial condition by removing a fraction of the sample in the estimated regression. The initial condition requires a starting point $t = [rT]$ with $r > 0$. Phillips and Sul (9, 10) set $r = 0.3$. The authors estimate the coefficient of $\hat{b}$ by providing the standard errors in the use of Heteroskedasticity and Autocorrelation Consistent (HAC) of the long-run variance in residuals to perform the one-sided *t*-test of null $\alpha \geq 0$. Hence the *t*-test statistic $t_{\hat{b}}$ is based on the normal distribution, and if $t_{\hat{b}} < -1.645$, the null hypothesis of club convergence will be rejected.

Finally, Phillips and Sul (9, 10) discuss that the rejection of the null of club convergence does not mean that there cannot be sub-group convergence in the panel dataset. It is important to note that the club convergence test procedure is defined for detecting cluster units. Using the club convergence test procedure, we examine the club convergence dynamics in the G20 countries over the period under concern. The club convergence is defined as log t regressions with the following main issues:

1) Ordering: Order the X_{it} series following the last observation in the panel dataset.
2) Group Formation: Calculate t-statistic $t_{\hat{b}}(k)$ for each country (k) and select country or countries for the core group.
3) Membership of the Club: Find the country for membership in the core group by including each remaining country separately, following the results of *log t* tests. A new county will be added to the club if the calculated t-statistic is higher than zero.
4) Recursion and Stop: Finally, log *t*-tests are applied for the group of unselected countries. If the cluster of countries converges in the first club, a second club will be formed. If there is no club convergence, sub-convergent club clusters will be investigated. If no subgroups are defined for the remaining countries, they will be defined as countries with a divergence pattern.

EMPIRICAL FINDINGS

Table 3 provides the club convergence results for four indicators of the spread of the COVID-19 pandemic: total cases per million people, new cases per million people, total deaths per million people, and new deaths per million people.

TABLE 3 | Results of the club convergence tests for indicators of the spread of the COVID-19.

Indicators of the spread of the COVID-19	Clubs										$\hat{b}$	*t*-statistic
Total cases per million people	(1)										−0.025	−0.550
	1	3	5	7	8	9	11	12	13	15		
	16	17	19									
	(2)										−0.090	−0.146
	6	14	18									
	(3)										0.417	74.4
	2	4	10									
New cases per million people	(1)										−0.098	−2.011
	1	2	3	4	5	6	7	8	9	10		
	11	12	15	16	17	18	19					
	(2)										−0.820	−0.919
	13	14										
Total deaths per million people	(1)										0.651	179.6
	1	2	3	4	5	6	7	8	9	10		
	11	12	13	14	15	16	17	18	19			
New deaths per million people	(1)										0.031	0.191
	1	2	3	5	8	9	11	12	13	14		
	15	16	17	19								
	(2)										−0.868	−3.689
	4	6	7	10	18							

In terms of the findings of the club convergence test for the total COVID-19 cases per million people, there are three clubs. The log t regression results for the first club consisting of 13 countries with the t-statistic of −0.55, and the null hypothesis of convergence can be rejected. The second club consists of three countries (France, Saudi Arabia, and the United Kingdom) with the t-statistic −0.146, and the null hypothesis of convergence can be rejected. Finally, the third club shows three countries (Australia, Canada, and Italy) with the t-statistic 74.4, and the null hypothesis of convergence cannot be rejected.

There are two clubs in terms of the club convergence test results for the new COVID-19 cases per million people. The log t regression findings for the first club consisting of 17 countries with the t-statistic of −2.011 and the null hypothesis of convergence cannot be rejected. The second club includes two countries (the Russian Federation and Saudi Arabia) with a t-statistic −0.82, and the null hypothesis of convergence can be rejected.

When we look at the club convergence test findings for the total COVID-19 deaths per million people, only one club consists of all countries in the dataset. The log t regression results for the only club consisting of all countries with the t-statistic of 179.6 and the null hypothesis of convergence cannot be rejected.

There are two clubs in terms of the club convergence test results for new deaths per million people. The log t regression findings for the first club consisting of 14 countries with the t-statistic of 0.191 and the null hypothesis of convergence can be rejected. Furthermore, the second club consists of five countries (Canada, France, Germany, Italy, and the United Kingdom) with a t-statistic −3.689, and the null hypothesis of convergence cannot be rejected.

CONCLUSION

In this paper, we examined the validity of the club convergence clustering hypothesis in the G20 countries using four indicators of the spread of the COVID-19 pandemic: total cases per million people, new cases per million people, total deaths per million people, and new deaths per million people. We used the daily data from March 1, 2020, to October 10, 2020. We followed the club convergence clustering methodology of Phillips and Sul (9, 10) to model the time-varying nature of the spread of the COVID-19 pandemic and capture different fighting policy pandemic strategies. We observed that the cases and deaths related to the COVID-19 pandemic have a nonlinear nature and converge among the G20 countries.

We observed three clusters for the per capita income and two clusters for total cases per million people and new cases per million people. Besides, there are only one and two clusters for total deaths per million people and new deaths per million people. These results indicate that although policymakers in different countries have different solutions to the total pandemic deaths per million, they have similar stochastic properties in the G20 countries. This evidence can be related to the fact that the treatment of the COVID-19 virus has not been fully provided in the globe and the deaths due to the COVID-19 virus has somehow a random nature. Our results also indicate that if there will be no prevention, the countries with the low-level of COVID-19 spread will converge toward a pandemic's long-run level, which is the United States' case. Different characteristics of the countries have negligible effects on the spread of the COVID-19, particularly when we focus on the club convergence dynamics of the death ratios related to the COVID-19.

In terms of new deaths, Canada, France, Germany, Italy, and the United Kingdom are different countries. The death ratios per million people have decreased in these countries over time, creating a new club for these countries. In terms of other developed and developing G20 countries, there is another club convergence procedure. When we look at the new cases for the COVID-19, only the Russian Federation and Saudi Arabia have a different nature for convergence. Other countries have a similar pattern for the new cases for the COVID-19. The differences between the Russian Federation and Saudi Arabia are related to these countries' leading oil-exporters in the World economy. Note that the oil prices have significantly declined during the COVID-19.

Given that there are autocratic regimes in these countries, they may be underestimating the number of new cases to show the situation better. In terms of total cases for the COVID-19, there are three different clubs, and they are hard to explain. This issue is the limitation of our study. Future papers can focus on more countries to analyze the club convergence clustering hypothesis's validity in larger panel datasets, which should have more countries and higher time dimensions.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: https://github.com/owid/covid-19-data/tree/master/public/data.

AUTHOR CONTRIBUTIONS

The author confirms being the sole contributor of this work and has approved it for publication.

REFERENCES

1. McKibbin WJ, Fernando R. *The Global Macroeconomic Impacts of COVID-19: Seven Scenarios. Centre for Applied Macroeconomic Analysis (CAMA) Working Paper, No. 19/2020*. Canberra: CAMA (2020). doi: 10.2139/ssrn.3547729
2. Ozili P, Arun T. *Spillover of COVID-19: Impact on the Global Economy. Munich Personal RePEc Archive (MPRA) Paper, No. 99317*. Munich: University Library of Munich (2020). doi: 10.2139/ssrn.3562570
3. Katul GG, Mrad A, Bonetti S, Manoli G, Parolari AJ. Global convergence of COVID-19 basic reproduction number and estimation from early-time SIR dynamics. *PLoS ONE.* (2020) 15:e0239800. doi: 10.1371/journal.pone.0239800
4. Kuniya T. Evaluation of the effect of the state of emergency for the first wave of COVID-19 in Japan. *Infect Dis Model.* (2020) 5:580–7. doi: 10.1016/j.idm.2020.08.004
5. Chimmula VKR, Zhang L. Time series forecasting of COVID-19 transmission in Canada Using LSTM Networks. *Chaos Solit Frac.* (2020) 135:109864. doi: 10.1016/j.chaos.2020.109864
6. Shabani ZD, Shahnazi R. Spatial distribution dynamics and prediction of COVID-19 in Asian Countries: Spatial Markov Chain approach. *Regional Science Policy and Practice* (2020) forthcoming. doi: 10.1111/rsp3.12372
7. Ismail L, Materwala H, Znati T, Turaev S, Khan MA. Tailoring time series models for forecasting coronavirus spread: case studies of 187 countries. *Comp Struct Biotechnol J.* (2020) 18:2972–3206. doi: 10.1016/j.csbj.2020.09.015
8. Hasell J, Mathieu E, Beltekian D, Macdonald B, Giattino C, Ortiz-Ospina E, et al. A cross-country database of COVID-19 testing. *Sci Data.* (2020) 7:345. doi: 10.1038/s41597-020-00688-8
9. Phillips PCB, Sul D. Transition modeling and econometric convergence tests. *Econometrica.* (2007) 75:1771–855. doi: 10.1111/j.1468-0262.2007.00811.x
10. Phillips PCB, Sul D. Economic transition and growth. *J Appl Econ.* (2009) 24:1153–1185. doi: 10.1002/jae.1080
11. Hodrick RJ, Prescott EC. Postwar U.S. business cycles: an empirical investigation. *J Money Credit Bank.* (1997) 29:1–16. doi: 10.2307/2953682
12. Ravn MO, Uhlig H. On adjusting the Hodrick-prescott filter for the frequency of observations. *Rev Econ Stat.* (2002) 84:371–6. doi: 10.1162/003465302317411604

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COVID-19 Deaths Cases Impact on Oil Prices: Probable Scenarios on Saudi Arabia Economy

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The purpose of this paper is to discuss death cases on the World, exacerbated investor fears, uncertainties, and increased volatility of crude oil prices in financial markets. The reaction absorbed the epidemic gradually until January 22. Still, the market situation changed soon with a sharp drop in prices, and prices slowly recovered after that until June 14. The data of this research using an econometric model, the ARDL (Autoregressive Distributed Lag), according to the Gets methodology, using daily data, January 22 –June 14, 2020. Our ARDL shows, the death ratio has a significant negative effect on oil price dynamics. However, the death ratio has an indirect impact on volatility in Crude Oil prices. The findings show that the death toll of COVID-19 has a significant impact on oil prices in Saudi Arabia (KSA). However, the preliminary results mainly influence by the situation reported in the USA. When we assess the case outside the USA, and we see the positive effect of the COVID-19 death figures on oil prices, therefore, stress the amplification of death-related risks to the financial market and the real economy, caused by increased, policy-induced economic uncertainty in the United States.

Keywords: COVID-19, oil prices, epidemic, ARDL, Saudi Arabia (KSA)

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INTRODUCTION

In Saudi Arabia, the oil industry is essential and has significant spills over into certain services industries like travel, Business, IT, and religious tourism. The slump in oil prices will not have a substantial impact on export earnings, as a favorable regulatory framework drives oil production stability. Since oil prices are an exact driver of inflation, the fall in oil prices will have a positive effect on the consumer price index, and the most significant impact of the shock in oil prices will be the decline in investment. Covid-19 economic disorder led to substantial decreases in energy demand and prices, particularly of oil and industrial metals (1). Declines in commodity prices might interfere with financial uncertainty and investments and growth in producing and exporting oil and metals countries. Still, they could be beneficial for importers, business users, and consumers (2).

Believed to be the downturn in general economic activity and transport in particular, which accounts for two-thirds of world oil demand, has seriously affected oil markets. Between January and April, oil prices declined by two thirds with a record sharp 1 month decline compounded by the OPEC-Partnership Deal breakdown leading to a supply slump. Oil exporters are affected by falling prices, and their economies are expecting to sink by 4.4% in 2020 (3).

It is well-known that the historical and predictive routes of global oil demand and economic growth have been outlined in **Figure 1**. There is a quick "V" shaped economic recovery in the second half of 2020 under the single-wave scenario, but oil demand does not fully recover from the prepandemic trend. The pessimistic scenario is that oil demand hits 2019 peaks only and remains far below the pre-pandemic rate until 2023. The latest pandemic progress indicates that some countries that an outcome similar to this catastrophic scenario is more probable.

Generally accepted in the long run, new models of service, replacement of video conferencing for transportation, continuing travel constraints, and individual travel resistance may lead to an ongoing reduction in demand for travel and fuel (5). Pressures on global supply chains, re-shore production, and domestic import substitution may also reduce the demand (6).

Until now, the Kingdom of Saudi Arabia, one of the countries affected by the Coronavirus outbreak, has taken steps to slow the spread of the pandemic with a growing number of cases, and governments are likely to face economic repercussions as the company slows down. People and wealth movement and investment, but the epidemic has made the collapse of stock markets a reality in all parts of the World (7, 8), and will cause damage (9, 10). The economic outlook was expected, at least in the short term, which cannot be avoided. Many countries around the World are in a recession (11, 12). The negative consequences expected to worsen, and lower oil prices may lead to additional financial pressures on the economy.

LITERATURE REVIEW

The OPEC+ member strategy to reduce supply to support price recovery now focusses aggressively not only on stocks but also on the shape of the oil curve and the nature of an approach to supporting the short-term market (8, 13, 14). spot prices are higher than futures contracts, allowing refiners and traders to sell off oil inventories (15).

(16) has provided some preliminary estimates about the behavior of oil-stock nexus during COVID-19 pandemic. The results were suggesting that the probability of having negative oil and stock returns during the pandemic may be due to uncertainty associated with the relevant markets. Also, (17) results in study, that daily changes in overall reported cases and total cases of daily deaths induced by COVID-19 have a substantial negative impact on stock returns. With the negative impact of COVID-19 on stock returns becoming more prominent as the study uses total cases of deaths to proxy the effect of this infectious disease.

A recent review of the literature on this topic, the Brent price curve remains in contagion phases attack, where long-term oil was more expensive than short (18). So, the price difference between contracts for delivery now and in 6 months remains in contagion (19). However, it has narrowed significantly over the last 2 months. For the OPEC +, the ideal scenario is to move the curve shape from the current contagion, when comparing prices are lower than future prices (14, 20), into a mild backwardation,

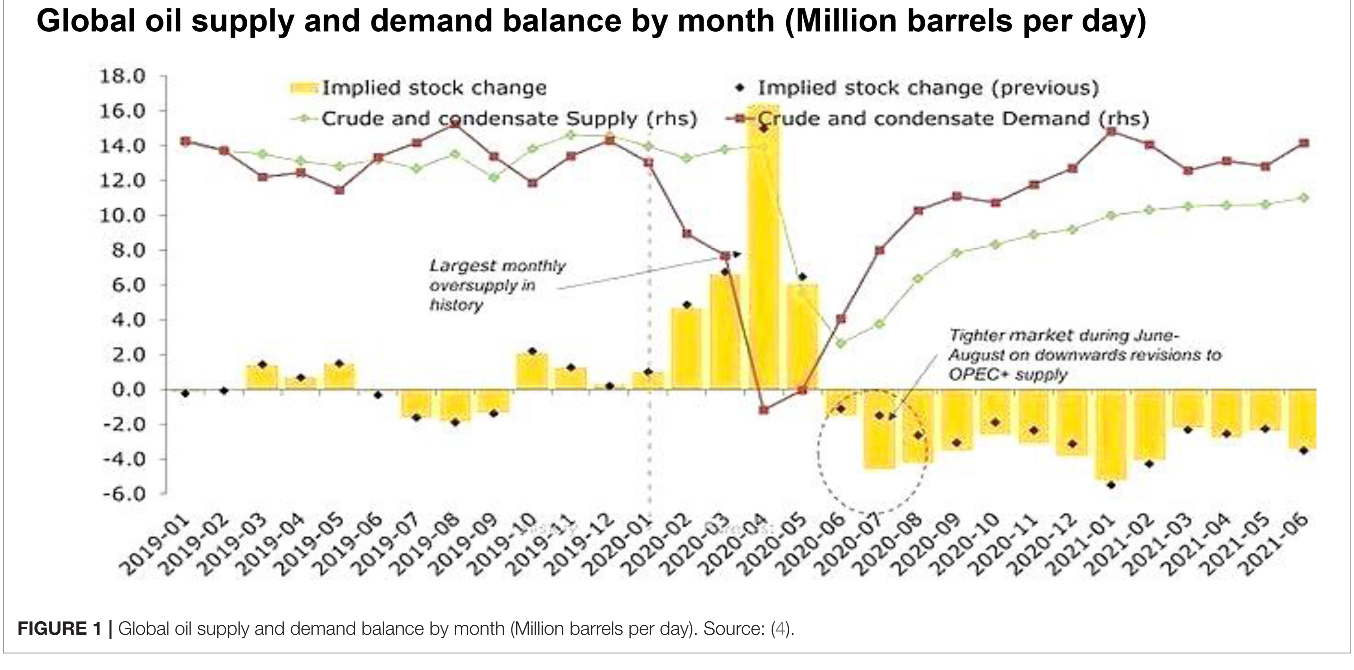

FIGURE 1 | Global oil supply and demand balance by month (Million barrels per day). Source: (4).

with spot prices higher than forward ones. OPEC is still focusing on increasing revenues sustainably through a combination of higher prices and a more significant market share (21).

Research has tended to focus on COVID-19 Cases rather than COVID-19 deaths. An additional problem is now opinion presents a new approach to gives an insight into the relationship between oil prices and the number of deaths caused by Coronavirus. Also, the rapid spread of COVID-19 deaths triggers shockwaves on both the stock market and the oil crude, as well, in the real economy. Then, the depth of the new economic downturn will impact on the policy response to the coronavirus crisis through economic, traffic, trade, financial, and public behavior prevention (22, 23).

Arouri and Fouquau (24) and Arouri et al. 2012 (25) which reviewed the long-term relation between GCC stock markets and oil prices, also came to the opposite conclusion. Surprisingly, the two studies showed that positive data shows that there is a robust long-term correlation in all countries except Saudi Arabia (is negative).

Nevertheless, Albulescu (26) believes Coronavirus (COVID-19) creates fear and uncertainty, hitting the global economy and amplifying the volatility of the financial market. The study investigates the impact of COVID-19 numbers on crude oil prices while controlling for the impact of financial volatility and the United States (US) economic policy uncertainty. The finding shows that the new cases and new deaths have a marginally negative impact on the crude oil prices in the long run.

Concerns have arisen, the increase in the death rate for COVID-19 causes more stagnation and less production, travel, and commercial ties, which explains the decrease in oil prices (27, 28). That describes the countries implementation of large-scale prevention policy, and an attempt to revitalize the economy, through the budget and job support, allowing for a slight recovery in the market supported by preventive measures (28, 29).

According to Matuka (30) study, the COVID-19 outbreak is causing shock waves in financial markets and the real economy around the World, and a policy reaction is depending on the depth of the future recession. The study discusses the effect on the uncertainty of the US economic strategy of COVID-19 (measured by the number of new cases and deaths) and oil prices. The study results suggest that new cases in the USA have a substantial impact on the market. However, there are no significant impacts on economic policy uncertainty in death cases. Also, there is a reverse relationship between branch oil prices and political uncertainty which can boost economic policy uncertainty as branch oil prices decline. A similar relationship observed between the number of cases and the VIX index (31).

The empirical evidence concerning the correlation between oil prices and the disease of Coronavirus, and the explanations that affected they are positive (32) investigated the impact of the COVID-19 pandemic on the Chinese stock market. The prevalence of COVID-19 has measured by the daily growth in total confirmed cases and the daily growth in total deaths from COVID-19. The results of their estimate show that the reduction in both daily growth in total confirmed cases and total deaths from COVID-19 involves Increase equity returns across all companies. They also demonstrate that the control variables are negative and meaningful.

Also, Al-Marri et al. (33) used the Swamy-Arora method to analyze panel data to examine the Tunisian stock market's reaction to the current COVID-19 pandemic. COVID-19 measured by the daily growth of confirmed cases, the daily growth of the death toll and the daily growth of recovered cases. They concluded that the daily growth of confirmed cases has a positive relationship with inventory returns, while the daily growth of mortality cases adversely affects stock returns performance. On the contrary, the daily growth of recovered cases has a positive but not significant effect. At the same time, they support that the Tunisian authorities have an essential role to play in combating the spread of the epidemic by taking early preventive measures to protect the population and save the economy.

Also, using the daily change in the main stock index and the daily growth in confirmed COVID-19 cases and death data from 64 countries, (34) confirms that stock markets are responding negatively to the increase in confirmed COVID-19 cases. It also documents a weak stock market response to the growth in the number of deaths due to COVID-19.

Overall, the effect on China's stock market returns and the uncertainty of the COVID-19 pandemic. (34) results of the study indicate that changes daily in overall reported cases of COVID-19 in China, as total deaths and as daily cases, have significant negative impacts in inventory returns with a more pronounced negative effect on inventory returns through COVID-19. Deaths decrease the impact of this contagious epidemic. The findings further show that COVID-19 has a favorable effect on the volatility of these stock returns and has convergent validity. We have recently seen that infectious diseases, such as COVID-19, may have a significant effect on the stock yield and uncertainty. The findings are essential to consider the effect on the Chinese stock market of COVID-19.

Saudi Arabia supported the stability of high oil price levels and is seeking to take steps to help open rapidly to the outside World (35, 36), and its implications for prices. The effects of a delayed investment in China and Europe will eventually help economic recovery by only managing the epidemic and reducing mortality rates. Provided that the impact of more favorable monetary policies and targeted government fiscal responses generates a recovery, so oil prices are likely to hit new reasonable levels and medium-term rehab (29, 37, 38).

Widely considered to be the most important, COVID-19 spreads human suffering around the World. At the same time, the pandemic in KSA is less advanced, and the economic effect is significant due to its large amounts of arrivals and strong precautionary measures in comparison with other countries.

The next decade is likely to see OPEC and Saudi Arabia are confronted with daunting tasks to challenge group unity. If OPEC is to manage effectively this decade, the quality of research, strategy, and decision-making must be significantly improved in light of coronavirus deaths cases increasing.

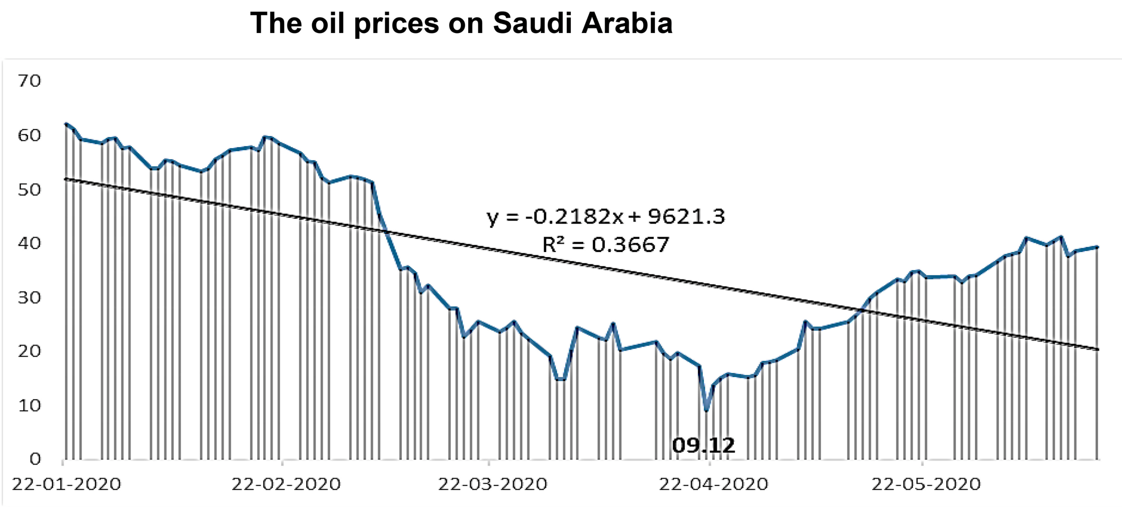

FIGURE 2 | The oil prices on Saudi Arabia. Source: Authors' calculations based on data from oil-price-charts.

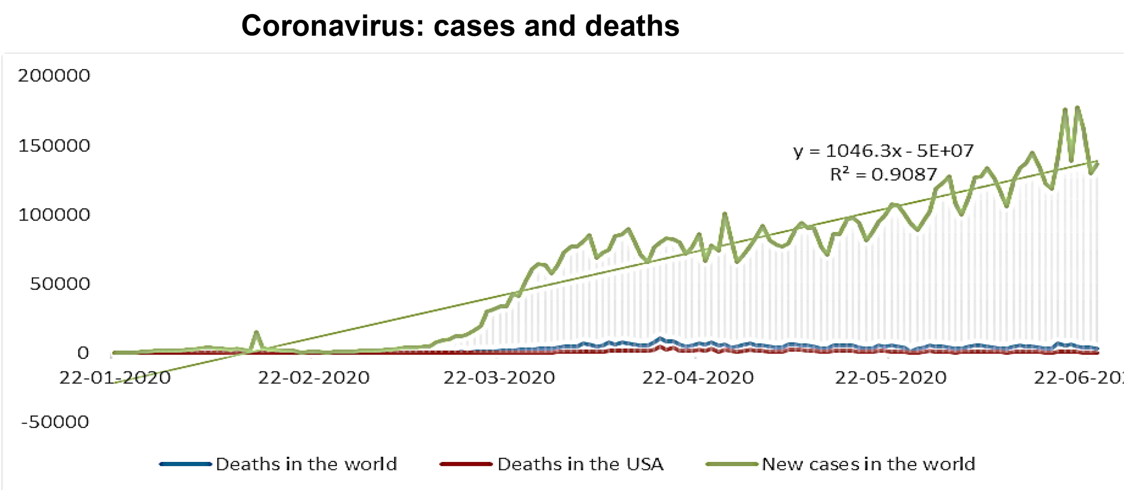

FIGURE 3 | Coronavirus: cases and deaths. Source: Authors' calculations, based on who.int data.

Also, many experts now contend hypotheses regarding COVID-19 deaths appear to be ill-defined debatable. There is a significant negative relationship between the confirmed cases and death cases from COVID-19 and the volume trading on the stock exchange in KSA. In the short term, it will be challenging to adapt supply to the possibly faltering demand for recovery because of the recovery of output from non-OPEC (oil prices stability). Despite this interest, no one, to the best of our knowledge, examined the nature of the impact that correlates coronavirus deaths cases with crude oil prices in the Kingdom of Saudi Arabia and its economy, and COVID-19 spillover using ARDL specification.

MATERIALS AND METHODS

Data and Variables

This study explores the current economic situation and the potential effects of COVID-19 death cases on the economy of the Kingdom of Saudi Arabia, based on trends critical financial market indicators of crude oil prices. The involves an assessment of the possible economic impacts and necessary activities (recommendations and findings).

The study data consisted of a daily time series of oil prices in Saudi Arabia (See: https://oilprice.com/oil-price-charts), and the development of COVID 19 cases in the World and the United States of America (See: https://ourworldindata.org/coronavirus-source-data), from the beginning of the Corona pandemic (January 22, 2020) to (June 14, 2020).

Hence, the study variables were dependent variable daily oil prices in Saudi Arabia, independent variables: death (the number of deaths in the World), and deaths_USA (the number of deaths in the United States of America).

ARDL Models

The data of the study, using an econometric model, what has called the Autoregressive-Distributed Lag (ARDL) models, which introduced by Pesaran and Shin (39) and developed by Pesaran et al. (40) to examine the relationship between death cases and oil prices in Saudi Arabia, according to the following equation: See (41).

$$PP_{t} = \beta_0 + \sum_{i=1}^{k} \beta_i * PP_{t-i} + \sum_{i=1}^{k} \gamma_i * Death_{t-i} + \sum_{i=1}^{k} \alpha_i Death_{t-i}$$

After assessing the model, several tests performed, the most important of which was the test of the significant of the parameters. Then every time we deleted the non-significant parameters. Finally, we came up with the optimal model that achieves the significance of all parameters and assumptions regarding residuals (42), according to the automatic selection method (Gets) General to specifics methodology (43). All this done automatically using OxMetrics.

OIL PRICES AND CORONAVIRUS CASES

Oil Prices in Saudi Arabia

The **Figure 2**. indicates exactly that oil prices are constantly decreasing according to the equation ($y = -0.2182x + 9621.3$), until they reached their minimum level (9.12 dollars per barrel) on April 21 2020 and then increased again until they reached (39.44 dollars per barrel. There is evidence to suggest the negative impact of the Corona pandemic on oil prices in Saudi Arabia and other countries (44). It is very probable OPEC decision to cut supply until the market regains balance, as prior inquiries centered on OPEC behavior.

Kaufmann (45) and Frondel and Horvath (46) they studied OPEC's effect on oil prices and found that OPEC supply quotas and OPEC's capacity to offset export capacities to maintain medium to long market stability.

Coronavirus: Cases and Deaths

Figure 3 illustrates that the cases of Coronavirus are continually increasing according to the equation ($y = 1046.3x - 5E+07$). In contrast, the deaths in the World after April 16, 2020, where they arrived (10,520 cases in the World) have begun to decline. Thus, confirms the beginning and knowledge of different countries of the World how to deal with patients with HIV (47). See more detail: WHO, Situation Report −164, July 2, 2020 (48).

TABLE 1 | Descriptive statistics.

Normality test for oil prices	
Observations	145
Mean	35.991
Std. Devn.	15.021
Skewness	0.28134
Excess Kurtosis	−1.3263
Minimum	9.1200
Maximum	62.110
Median	33.875
Madn	19.518
Asymptotic test: Chi^2 (2) = 12.540 (0.0019)**	
Normality test: Chi^2 (2) = 30.773 (0.0000)**	
Normality test for death in KSA	
Observations	145
Mean	3021.1
Std. Devn.	2616.0
Skewness	0.15682
Excess Kurtosis	−1.3995
Minimum	0.00000
Maximum	8468.0
Median	3413.0
Madn	4047.5
Asymptotic test: Chi^2 (2) = 12.428 (0.0020)**	
Normality test: Chi^2 (2) = 27.721 (0.0000)**	
Normality test for death in USA	
Observations	145
Mean	26.050
Std. Devn.	22.296
Skewness	0.56192
Excess Kurtosis	−0.54419
Minimum	0.00000
Maximum	84.210
Median	21.660
Madn	30.527
Asymptotic test: Chi^2 (2) = 12.610 (0.0018)**	
Normality test: Chi^2 (2) = 28.234 (0.0000)**	

***Significant at 0.01.*

Table 1 demonstrates the mean oil prices in the study period reached (35.99), and this indicates a decline in oil prices due to the Corona pandemic, despite their variation in the minimum value (9.12 $ per barrel) and the maximum value (62.11 $ per barrel) and explained by High standard deviation (15.02). However, during the study time, Coronavirus deaths mean 3,021 deaths in the World and only 26 deaths in the USA. With the standard deviation that reflects the apparent dispersion of coronavirus deaths, a period of record-high rates (8,468 deaths in the World and 84 deaths in the USA), and times decrease (0 deaths in the World and the USA) with the onset of the pandemic.

This apparent dispersion in both oil prices and corona deaths requires a robust econometric model (the ARDL model).

EMPIRICAL RESULTS

Using the automatic selection method according to the Gets (General to specifics) methodology, we entered the ARDL model (7.7.7). After a comparison of dozens of models, we've obtained the ARDL (1.4.4) model that achieves parameter significance and strong characterization according to the tests used, as shown in **Table 2**.

ARDL Model Test

It is apparent from **Table 2** the significance of all parameters (according to t-prob, which are <0.05) as the effect coefficient was 0.84 concerning oil prices for the previous period, −0.00037 about death KSA, and −0.073 with death USA. The coefficient of determination was 0.9886, which means the high explanatory power of the model. All other descriptive studies have shown good model results.

It can see in It is also in the World and the United States of America that oil prices in Saudi Arabia are adversely affected by deaths (prices began to rise as mortality rates fell) (37). It explains why Saudi Arabia's economy linked to the financial market trends and oil policy and vice versa. The ARDL model (1.4.4) can write in the following formula:

$$PP_t = 8.23 + 0.84{*}PP_{t-1} - 0.0037{*}Death\ KSA_{t-4} - 0.073{*}Death\ USA_{t-4}$$

TABLE 2 | The ARDL model tests.

	Coefficient	Str. error	*t*-value	*t*-prob	Part.R^2
OP	0.849330	0.02918	29.1	0.0000	0.8696
Canstant	8.23057	1.636	5.03	0.0000	0.1661
Death KSA	−0.000370447	0.0001150	−3.22	0.0016	0.0756
Death USA	−0.0738713	0.01261	−5.86	0.0000	0.2128
Sigma	1.59361	RSS		322.52902	
R^2	0.988629		$F_{(3,127)}$ = 3,681 (0.000) **		
Adj. R^2	0.988361	Log−likelihood	−244. 896		
No. of observations	131	No. of parameters		4	
Mean (OP)	34.5298	Se (OP)		14.7713	

1- step (ex post) forecast analysis 2020-06-08 - 2020-06-14

Parameter constancy forecast tests:

Forecast Chi^2 (7) = 6.2776 (0.5077)

Chow *F* $_{(7,127)}$ = 0.88364 (0.5215)

AR 1 - 2 test: $F_{(2,125)}$ = 0.42427 (0.6552)

ARCH 1-1 test: $F_{(1,129)}$ = 1.5791 (0.2112)

Normality test: Chi^2(2) = 38.228 (0.0000)**

Hetero test: $F_{(6,124)}$ = 2.4359 (0.0292)*

Hetero-X test: $F_{(9,121)}$ = 1.7695 (0.0808)

RESET23 test: $F_{(2,125)}$ = 0.12899 (0.8791)

***Significant at 0.01.*

Estimated and real values

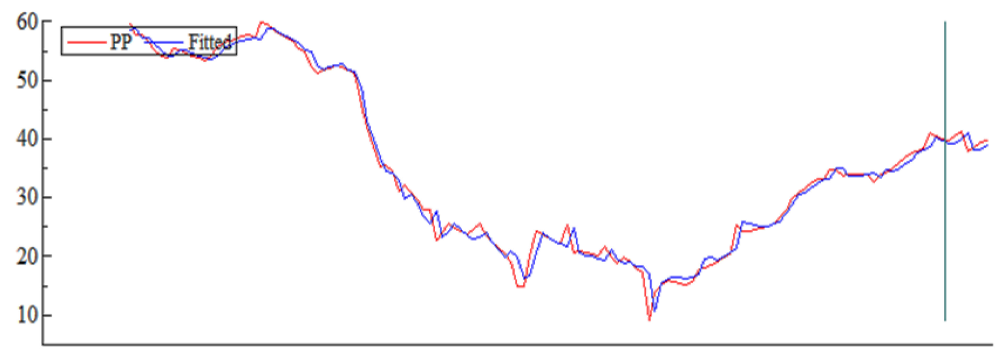

FIGURE 4 | Estimated and real values.

For the estimated period, it was from January 22 to June 7; we kept seven observations to compare the predictive value with the real value, as shown in **Figure 4**.

Histogram, we can see a broad match between the estimated values and the real values, as evidenced by the chow test in **Table 2**; this confirms the validity of the ARDL model that links deaths in the World as independent variables and oil prices in Saudi Arabia as dependent variables.

Modeling and Dynamic Analysis

The table below represents the long-term effects.

Table 3. highlights that the impact factor of death rates in the United States −0.49 was much more significant than the impact factor of the number of deaths in the World −0.0024, which reflects the impact of the United States and its economy on changes in oil prices in Saudi Arabia (49, 50).

TABLE 3 | The long-term effects.

	Coefficient	Std. Error	*t*-value	*t*-prob
Solved static long-run equation for OP				
Canstant	54.6265	1.658	33.0	0.0000
Death KSA	−0.00245866	0.0004081	−6.02	0.0000
Death USA	−0.490285	0.04763	−10.3	0.0000
Long-run sigma = 10.5768				

Shock Analysis

The following figure shows the long and negative impact of a shock on the independent variables, and how this effect begins to decrease until it fades after about 30 days.

Figure 5 shows a clear trend of high uncertainty of death between March 12 and April 9; the period has been characterizing by a very rapid global spread of the virus, followed by a significant rise in deaths in Italy, especially France, Spain, and the USA. The volatility curve of the Crude Oil Index indicates high volatility between July 24 and August 14.

DISCUSSION OF RESULTS

With the spread of the COVID-19 epidemic, growth, travel, and trade stagnated, and the price of oil decreases. So, it explains the interest conflict of debt producers with different budget requirements, fiscal deficits, and market expectations, this substantiates previous findings in the literature.

There has been some disagreement concerning Saudi Arabia hopes to keep oil prices high, and Russia seeks to achieve a share of world oil markets and their impact on prices. Moreover, later spending in China and Europe, once the epidemic is under control, will ultimately promote economic recovery, since the effect of better monetary policy and targeted fiscal responses from governments will lead to recovery. As such, oil prices are likely to reach new lower levels, but a medium-term recovery is in sight.

We have found that investors changed their investment strategy as oil spot prices reported a first decline that contributed to high volatility in the future commodity market during the first cycle of coronavirus spread. Our results are consistent with

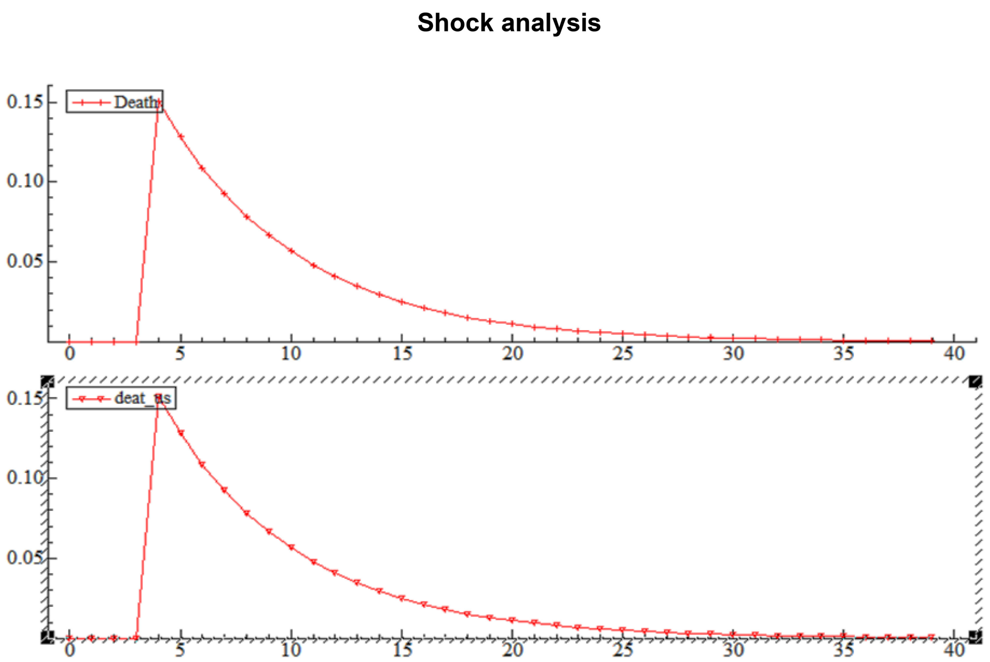

FIGURE 5 | Shock analysis.

a theory of future expectations on the market, which shows that speculators can predict future price patterns as economic agents (51).

We believe that the quick spread of COVID-19 deaths causes a shock wave of the economy, oil, and real estate of the financial market and the depth of the economic downturn depends on the political response to the crises of the Coronavirus by opening up the markets, investment, trade, industrial growth, and public prevention. The excess oil stocks would weigh the oil price in the short term; strict OPEC discipline will need to clear these stocks over the next few years, faced with a slow rebound in demand (52) has provided some preliminary estimates about the behavior of oil-stock nexus during COVID-19 pandemic. The results were suggesting that the probability of having negative oil and stock returns during the pandemic, maybe due to uncertainty associated with the relevant markets. Unexpected situations such as a pandemic can have a significant effect on market fundamentals in the short term, and there have been correlations with indexes and oil.

Our study provides additional support, OPEC must also handle the recovery of crude oil output as demand and oil prices increase. The analysis calls for the two possibilities to involve OPEC Crude Oil. In the middle of 2020, in the negative case, the demand for OPEC crude oil increased to 32 MMbpd in 2024 and then fell to 31 MMbpd. The market for OPEC oil growth in the 2030s, following secular declines of several major non-OPEC producers, especially Russia. The plant remarkably counts from the main basins for the two Covid-19 scenario models in the spring of 2020, the delays due to both falling and rising oil prices.

This result not anticipated, the reason for this is probably, after the Covid-19 pandemic, the widening gap between oil demand and supply in the US, triggered by the high death rate in the mid-2020s. The fundamental explanation expected for this is the decline in US production from 2020 to 2024. In the early 2020s, net oil imports projected to hit 3–4 MMbpd. Coronavirus has a significant effect on the global economy, and thus oil demand, in particular in the most likely cause of a deep and sustained recession linked to a prolonged pandemic. Until mid-2023, the average crude oil price will remain below $50/bbl without active OPEC action.

The results indicate that COVID-19 deaths toll has a significant impact on oil prices. However, it mainly influences the situation reported in the United States. If we evaluate the case outside the United States, we can see the positive impact on oil prices of the estimates of the COVID-19 death. Hence the amplification of mortality risks in the stock market and the real economy caused by the increasing economic instability in the United States.

The evidence from this study suggests the impact of the pandemic will surely reach oil prices, which will continue to decline, at least in the short term, as a result of lower demand for crude oil. Here comes the role of OPEC, a central element in reducing oil price losses through the consent of OPEC members. The reduction in market production thus promotes crude oil prices and improves cash resources.

Our work has led us to conclude OPEC and Saudi Arabia are confronted with daunting tasks to challenge group unity. If OPEC is to manage effectively this decade, the quality of research, strategy, and decision-making must be significantly improved. In the short term, it will be challenging to adapt supply to the possibly faltering demand for recovery because of the recovery of output from non-OPEC.

CONCLUSION

The study focuses on modeling the effects of the COVID-19 deaths on oil prices in KSA during the period from January 22, 2020, to June 14, 2020, using an ARDL estimation approach. The oil prices of the USA is the endogenous variable while COVID-19 daily deaths case is the Corona prevalence's measure. Previous researches about the effects of the COVID-19 deaths epidemic on oil prices limited, while this study is a contribution to this recently emerging literature.

The results indicate the substantial effect of COVID-19 death numbers on the oil price. However, the situation in the United States has significantly affected these findings. When we analyzed the case outside the US, it founded that COVID-19 death numbers have a positive impact on the price of oil. We are therefore stressing a rise in the risk of deaths on the financial market and on the real economy attributable to a growing economic instability caused by a policy in the United States.

Our research suggests that the policymakers should encourage there is an urgent need to develop prudent policies describing the magnitude of the COVID-19 epidemic and potential social and economic devastation, Because of the severe human, societal, and economic consequences. We think that our findings could provide an overview of the possible effects of a pandemic on the oil market. COVID-19 will lead to increasingly shattered losses (10). Intense multispectral efforts needed for determining the potential economic impacts of an outbreak, to explain how the economy affects different outbreak scenarios, rather than providing the best predictions for the epidemic scale (7). So that the World of GDP growth expected to slow, as, despite the negative impact on COVID−19, the Organization for Economic Co-operation and Development predicts a global recession as growth remains positive in all areas of the economy (9, 53, 54). Gherghina examined the linkages in financial markets during coronavirus disease 2019 (COVID-19) pandemic outbreak for the following economies: USA, Spain, Italy, France, Germany, UK, China, and Romania. The quantitative approach reveals a negative effect of the new deaths' cases from Italy on the 10-year Romanian bond yield both in the short-run and long-run (55).

Further work needs to done many economies have already adopted absolute policies, and many nations, in particular the United States of America, have reduced interest rates, continued the 2019 facilitation round, and have taken financial support steps (56).

The aim is to direct policies to calculate the risk of a pandemic so that prevention and rapid response costs can adequately assess. The worst-case scenario is expected in the event of a rise in viral infection in the countries of the region, the effect of lower oil demand, the rise in OPEC supply and severe coronavirus consequences.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found at: https://ourworldindata.org/coronavirus-source-data~https://oilprice.com/oil-price-charts.

AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct and intellectual contribution to the work, and approved it for publication.

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REFERENCES

1. Baek S, Mohanty SK, Glambosky M. COVID-19 and stock market volatility: an industry level analysis. *Finan Res Lett*. (2020) 37:101748. doi: 10.1016/j.frl.2020.101748
2. Hu M, Zhang D, Ji Q, Wei L. Macro factors and the realized volatility of commodities: a dynamic network analysis. *Res Policy*. (2020) 68:101813. doi: 10.1016/j.resourpol.2020.101813
3. Andam KS, Edeh H, Oboh V, Pauw K, Thurlow J. *Estimating the Economic Costs of COVID-19 in Nigeria*. Vol. 63. Washington, DC: International Food Policy Research Institute (2020). doi: 10.2499/p15738coll2.133846
4. Rystad Energy. *Rystad Energy Research Analysis, OilMarketcube*. (2020). Available online at: https://www.rystadenergy.com/energy-themes/commodity-markets/oil/oil-market-cube/ (accessed April 30, 2020).
5. Wheeler CM, Baffes J, Kabundi A, Kindberg-Hanlon G, Nagle PS, Ohnsorge F. Adding fuel to the fire: cheap oil during the COVID-19 pandemic. In: *Prospects Group Analysis*. Washington, DC: The World Bank Group (2020). doi: 10.1596/1813-9450-9320
6. Lucas B. *Impacts of Covid-19 on Inclusive Economic Growth in Middle-Income Countries*. (2020). Available online at: https://opendocs.ids.ac.uk/opendocs/handle/20.500.12413/15310 (accessed September 20, 2020).
7. McKibbin WJ, Fernando R. *The Global Macroeconomic Impacts of COVID-19: Seven Scenarios*. (2020). Available online at: https://papers.ssrn.com/ (accessed September 20, 2020).
8. Weko S, Eicke L, Quitzow R, Bersalli G, Lira F, Marian A, et al. (2020) *Covid-19 and Carbon Lock-In: Impacts on the Energy Transition*. Available online: https://www.iass-potsdam.de/en/
9. Fernandes N. *Economic Effects of Coronavirus Outbreak (COVID-19) on the World Economy*. (2020). Available online at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3557504 (accessed September 20, 2020).
10. Ozili PK, Arun T. *Spillover of COVID-19: Impact on the Global Economy*. (2020). Available online at: https://SSRN3562570-papers.ssrn.com (accessed September 20, 2020).
11. Baldwin R, Weder di Mauro B. *Economics in the Time of COVID-19*. London: CEPR Press (2020).
12. Wei WE, Li Z, Chiew CJ, Yong SE, Toh MP, Lee VJ. Presymptomatic transmission of SARS-CoV-2—Singapore, January 23–March 16, 2020. *Morbidity Mortality Weekly Rep*. (2020) 69:411–5. doi: 10.15585/mmwr.mm6914e1
13. Goldthau A, Hughes L. Saudi on the Rhine? Explaining the emergence of private governance in the global oil market. *Rev Int Political Econ*. (2020) 27:1–23. doi: 10.1080/09692290.2020.1748683
14. Noreng Ø. OPEC–from peak to peak: the history of 'peak oil' and its relevance for OPEC. In: *Handbook of OPEC and the Global Energy Order*. Boca Raton, FL: Routledge (2020). p. 325–37. doi: 10.4324/9780429203190-311
15. Alweqyan D. The role of OPEC in reducing oil prices under international law: the 2014. downfall and today's relevance. *J East Asia Int Law*. (2020) 13:97–119. doi: 10.14330/jeail.2020.13.1.05
16. Salisu AA, Ebuh GU, Usman N. Revisiting oil-stock nexus during COVID-19 pandemic: some preliminary results. *Int Rev Econ Finance*. (2020) 69:280–94. doi: 10.1016/j.iref.2020.06.023
17. Apergis N, Apergis E. The role of Covid-19 for Chinese stock returns: evidence from a GARCHX model. *Asia-Pacific J Acc Econ*. (2020) 27:1–9. doi: 10.1080/16081625.2020.1816185
18. Considine J, Galkin P, AlDayel A. *Market Structure, Inventories and Oil Prices: An Empirical Analysis* (No. ks—2020-dp02) (2020). doi: 10.30573/KS-2020-DP02
19. Baldwin R, Tomiura E. *Thinking Ahead About the Trade Impact of COVID-19. Economics in the Time of COVID-19* (2020).
20. Miao H, Ramchander S, Wang T, Yang D. Influential factors in crude oil price forecasting. *Energy Econ*. (2017) 68:77–88. doi: 10.1016/j.eneco.2017.09.010
21. Álvarez IA, Di Nino V, Venditti F. *Strategic Interactions and Price Dynamics in the Global Oil Market* (2020).
22. Albulescu C. Do COVID-19 and crude oil prices drive the US economic policy uncertainty? *arXiv preprint*. (2020) 2–7. doi: 10.2139/ssrn.3555192
23. Khan N, Fahad S, Faisal S, Naushad M, Akbar A. *Situation of COVID-2019 Before 15th July, 2020 in the World*. (2020). Available online at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3655613 (accessed September 20, 2020).
24. Arouri MEH, Fouquau J. On the short-term in?uence of oil price changes on stock markets in GCC countries: linear and nonlinear analyses. *Econ Bull*. (2009) 29:806–15.
25. Arouri MEH, Rault C. Oil prices and stock markets in GCC countries: empirical evidence from panel analysis. *Int J Finance Econ*. (2012) 17:242–53. doi: 10.1002/ijfe.443
26. Albulescu C. *Coronavirus and Oil Price Crash: A Note*. Working Papers hal-02507184. HAL. (2020).
27. Barua S. Understanding coronanomics: the economic implications of the coronavirus (COVID-19) pandemic. *SSRN Electron J*. (2020) 1–44. doi: 10.2139/ssrn.3566477
28. Taskinsoy J. *Diminishing Dollar Hegemony: What Wars and Sanctions Failed to Accomplish, COVID-19 has*. *COVID-19 Has*. (2020). doi: 10.2139/ssrn.3570910
29. Beine M, Bertoli S, Chen S, D'Ambrosio C, Docquier F, Dupuy A, et al. *Economic Effects of Covid-19 in Luxembourg: Synthesis of the RECOVid Working Note*. (2020) Availble online at: URL: https://www.liser.lu/documents/RECOVID/RECOVid_working-note_full-1.pdf (accessed July 18, 2020).
30. Matuka A. *COVID-19 Outbreak and US Economic Policy Uncertainty: An ARDL Approach*. (2020). doi: 10.2139/ssrn.3685346
31. Sari SS, Kartal T. The relationship of COVID-19 pandemic with gold prices, oil prices and VIX index. *Erzincan Univ J Soc Sci Instit*. (2020) 13:93–109. doi: 10.46790/erzisosbil.748181
32. Al-Awadi SJ, Ghareeb AM, AL-Tayie SR, Zedan TH, Abd A. In?uence of the genetic polymorphism of Angiotensin-converting Enzyme 2 receptor on the susceptibility of Middle East populations to SARS-CoV-2 infection. *Eurasian J Biosci*. (2020) 14:5033–9.

33. Al-Marri AN, Nechi S, Ben-Ayed O, Charfeddine L. Analysis of the performance of TAM in oil and gas industry: factors and solutions for improvement. *Energy Rep*. (2020) 6:2276–87. doi: 10.1016/j.egyr.2020.08.012
34. Ashraf BN. Stock markets' reaction to COVID-19: cases or fatalities? *Res Int Business Finance*. (2020) 54:101249. doi: 10.1016/j.ribaf.2020.101249
35. Guliyev M. ACCELERATING Economic diversification in azerbaijan: challenges, shaping prospect. In : *Economics, and Social Development: Book of Proceedings*. Lisbon (2020). p. 352–60.
36. Moshashai D, Leber AM, Savage JD. Saudi Arabia plans for its economic future: Vision 2030. the national transformation plan and Saudi fiscal reform. *Br J Middle Eastern Stud*. (2020) 47:381–401. doi: 10.1080/13530194.2018.1500269
37. Jefferson M. A crude future? COVID-19s challenges for oil demand, supply and prices. *Energy Res Soc Sci*. (2020) 68:101669. doi: 10.1016/j.erss.2020.101669
38. Miyajima K. *What Influences Bank Lending in Saudi Arabia? Islamic Economic Studies* (2020).
39. Pesaran MH, Shin Y. An autoregressive distributed-lag modelling approach to cointegration analysis. *Econ Soc Monographs*. (1998) 31:371–413. doi: 10.1017/CCOL0521633230.011
40. Pesaran MH, Shin Y, Smith RJ. Bounds testing approaches to the analysis of level relationships. *J Appl Econ*. (2001) 16:289–326. doi: 10.1002/jae.616
41. Hassler U, Wolters J. Autoregressive distributed lag models and cointegration. In: *Modern Econometric Analysis*. Berlin; Heidelberg: SpringerLink (2006). p. 57–72. doi: 10.1007/3-540-32693-6_5
42. Ghysels E, Marcellino M. *Applied Economic Forecasting Using Time Series Methods*. Oxford: Oxford University Press (2018).
43. Ericsson N, Campos J, Hendry D. (2005) *General-to-Specific Modeling: An Overview and Selected Bibliography* (No. 838). Board of Governors of the Federal Reserve System (US). doi: 10.17016/IFDP.2005.838
44. Mzoughi H, Urom C, Uddin GS, Guesmi K. *The Effects of COVID-19 Pandemic on Oil Prices, CO2 Emissions and the Stock Market: Evidence From a VAR Model. CO2 Emissions and the Stock Market: Evidence From a VAR Model*. (2020). doi: 10.2139/ssrn.3587906
45. Kaufmann P. Introduction to psychoanalysis: contemporary theory and practice by Anthony Bateman and Jeremy Holmes London/New York: Routledge. *Psychoanalytic Books*. (1998) 9:189–93.
46. Frondel M, Horvath M. The us fracking boom: Impact on oil prices. *Energy J*. (2019) 1–27. doi: 10.5547/01956574.40.4.mfro
47. WHO. *Coronavirus Disease (COVID-19): Situation Report 164*. (2020). Available online at: https://www.who.int/docs/default-source/coronaviruse/situation-reports/; https://www.who.int/data/
48. WHO. *Coronavirus Disease (COVID-19): Situation Report 164*. (2020). Availble online at: https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200702-covid-19-sitrep-164.pdf?sfvrsn=ac074f58_2 and https://www.who.int/data/ (accessed August 02, 2020).
49. Long DE. *The United States and Saudi Arabia: Ambivalent Allies*. Boca Raton, FL: Routledge (2019). doi: 10.4324/97804293 15725
50. Riedel B. *Kings and Presidents: Saudi Arabia and the United States Since FDR*. Washington, MA: Brookings Institution Press (2019).
51. Kaldor N. (1987) *Economic problems of* Chile.
52. Štifanić D, Musulin J, Miočević A, Baressi Šegota S, Šubić R, Car Z. Impact of COVID-19 on forecasting stock prices: an integration of stationary wavelet transform and bidirectional long short-term memory. *Complexity*. (2020) 1–26. doi: 10.1155/2020/1846926
53. Guerrieri V, Lorenzoni G, Straub L, Werning I. *Macroeconomic Implications of COVID-19: Can Negative Supply Shocks Cause Demand Shortages?* (No. w26918). Cambridge, MA: National Bureau of Economic Research (2020). doi: 10.2139/ssrn.3570096
54. Jindal BD. *Climate Change Action or Economic Recovery? It's the Economy, Stupid*. (2020). Available online at: http://aidiaasia.org/images/contents/pdf/KYy1c-covid-&-climate.pdf (accessed September 10, 2020).
55. Gherghina C, Armeanu D, Jolde CC. Stock market reactions to Covid-19 pandemic outbreak: quantitative evidence from ARDL bounds tests and Granger causality analysis. *Int J Environ Res Public Health*. (2020) 17:6729. doi: 10.3390/ijerph17186729
56. Courtemanche C, Garuccio J, Le A, Pinkston J, Yelowitz A. Strong social distancing measures in the United States reduced the COVID-19 growth rate: study evaluates the impact of social distancing measures on the growth rate of confirmed COVID-19 cases across the United States. *Health Affairs*. (2020) 10:1377. doi: 10.4324/9781003141402-20

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BRIEF RESEARCH REPORT
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Determinants of the Fiscal Support of Governments in Response to the COVID-19 Pandemic

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Fiscal support measures have different implications for public finances in the near term and beyond the COVID-19 pandemic. For this purpose, this paper examines the determinants of governments' fiscal support in response to the COVID-19 pandemic. The empirical analysis is based on the cross-sectional data estimations from 129 developed and developing countries. The estimation results indicate that a higher level of uncertainty related to COVID-19 (measured by the World Pandemic Uncertainty Indices) is positively related to fiscal support. Besides, countries with a higher total population and population over 65 years and older provide higher fiscal support. These results are valid when considering the developed countries separately. Policy implications for public finances during the COVID-19 pandemic are also discussed.

Keywords: COVID-19 pandemic, COVID-19 uncertainty, world pandemic uncertainty indices, response to the COVID-19 pandemic, fiscal support

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INTRODUCTION

Decreasing the spread ratio of the COVID-19 virus is the priority of policymakers since COVID-19 has a higher death ratio than the common flu. It also creates massive pressure on the health system. Therefore, most countries have implemented various mitigation measures, such as the closure of public areas, restaurants, shopping centers, and schools. Some countries have introduced lockdown policies to decrease the spread ratio of COVID-19 (1, 2). However, these policy implications created tremendous uncertainty in economic policies (3). According to Baker et al. (4, 5), the COVID-induced economic uncertainty is one of the leading uncertainties that the modern economy has faced. This issue is related to the evidence that the COVID-19 crisis has caused both supply and demand-side shocks (6). The mitigation measures declined household consumption and production (7); thus, they created external shocks in demand and supply (8). These measures included business cash-flow and income-raising household measures (9, 10) and have distorted tax revenues (11).

At this stage, policymakers aim to enhance consumption and investment by providing stimulus packages. These stimulus packages include fiscal support measures, which have different public financial implications during the COVID-19 pandemic. Most countries have adopted a mixed approach of fiscal support tools, such as reducing taxes, direct benefits, loan guarantees, asset purchase or debt assumptions, equity injections, and quasi-fiscal operations (12).

There are previous papers that examine the determinants of fiscal policies during the COVID-19 pandemic. For instance, Benmelech and Tzur-Ilan (12) examine fiscal policy determinants during the COVID-19 pandemic. According to their findings, credit rating is the most important driver of fiscal support during the COVID-19 pandemic. High-income economies, which have a lower level of interest rates, provide non-conventional monetary policy implications. As a result, the lack of a solid credit rating and higher interest rates have been tagged as lower fiscal support during the COVID-19 pandemic. Finally, the authors observe that high-income economies provide a greater fiscal support level than middle-income and low-income economies. Following this evidence, we separately examine the case of developed countries, and the selection is based on the definition of high-income economies. Faria-e-Castro (13) theoretically examines the different types of fiscal policies on economic activity in the United States. The author finds that unemployment insurance benefits and liquidity assistance programs effectively stabilize households' income. Bredemeier et al. (14) also theoretically show that fiscal policies, particularly the decline in labor taxes, could increase total employment in different sectors during the COVID-19 crisis.

Furthermore, Kaplan et al. (15) show that economic uncertainty in pandemic-related developments is significantly correlated with financial vulnerability. Besides, fiscal policy responses to the COVID-19 pandemic create an uneven distribution of economic welfare costs. Siddik (16) investigates the determinants of stimulus packages in 168 countries and finds that the median age and health indicators (number of hospitals, beds per capita, and health care expenditures) are the main drivers of stimulus packages.

Given this backdrop, in this paper, we examine the determinants of governments' fiscal support in response to the COVID-19 pandemic. We utilize empirical analysis based on the cross-sectional data estimations from 129 developed and developing countries. We find that a higher level of uncertainty related to COVID-19 (measured by the World Pandemic Uncertainty Indices) is positively related to fiscal support. Besides, we observe that countries with a higher total population and population over 65 years and older provide higher fiscal support. These findings are robust when considering the developed countries separately.

The rest of the paper is organized as follows. The *Model, Data, and Estimation Procedures* section explains the details of the model, the data, and the estimation procedures. The *Empirical Results* section discusses the empirical results. The *Concluding Remarks* section provides the concluding remarks.

MODEL, DATA, AND ESTIMATION PROCEDURES

In this paper, we estimate the following model via a cross-sectional data method in 129 developing and developed countries:

$$FISCAL_i = \beta_0 + \beta_1 X_i + \varepsilon_i \tag{1}$$

where $FISCAL_i$ is the fiscal support, X_i is the set of explanatory variables (per capita GDP, population, human development index, life expectancy, age 65 and older, and the World Pandemic Uncertainty Indices) in country i, and ε_i is the error term in the estimation.

Fiscal support is the total fiscal support, and it is the sum of the following supports: spending or foregone revenues (health sector and non-health sector) and liquidity support (asset purchase or debt assumptions, equity injections, guarantees, loans, and quasi-fiscal operations). Total fiscal support is defined as the share of gross domestic product (GDP). These data were obtained from the International Monetary Fund (IMF) (17) website (https://www.imf.org/en/Topics/imf-and-covid19/Fiscal-Policies-Database-inResponse-toCOVID-19).

We use several explanatory variables. For instance, we use the per capita GDP [measured by the Purchasing Power Parity (PPP) $ prices], population (in millions), the human development index (index from 0 to 1), life expectancy (in years), and age 65 and older (% of total population). These data were obtained from Hasell et al. (18) at the website (https://github.com/owid/covid-19-data/tree/master/scripts/scripts/testing).

Furthermore, we use the World Pandemic Uncertainty Indices (WPUI), which were provided by Ahir et al. (19) at the website (https://worlduncertaintyindex.com/data/). These indices provide the number of articles about the COVID-19 pandemic across the countries. The WPUI is provided by searching for words related to uncertainty in the COVID-19 pandemic country reports in the Economist Intelligence Unit (EIU) dataset. At this stage, a greater value of the WPUI provides a higher uncertainty related to the COVID-19 pandemic. The WPUI is used in the logarithmic form.

The fiscal support data are based on the total fiscal support from January 2020 to October 2020. Besides, the WPUI is the average of the values in 2020Q1, 2020Q2, and 2020Q3. Other variables are provided by Hasell et al. (18) at the cross-country level. The estimation procedures are utilized in 129 countries via cross-sectional data estimation. The selection of the countries is related to the availability of the data. Besides, we follow World Bank (20) and consider 39 developed countries[1] whose per capita income is higher than $12,536 and above. Therefore, there are other 90 low-income and middle-income economies[2]

[1]Australia, Austria, Belgium, Canada, Chile, Croatia, the Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Israel, Italy, Japan, Korea Republic, Kuwait, Latvia, Lithuania, the Netherlands, New Zealand, Norway, Poland, Portugal, Qatar, Romania, Saudi Arabia, Singapore, Slovakia, Slovenia, Spain, Sweden, Switzerland, the United Arab Emirates, the United Kingdom, the United States, and Uruguay.

[2]Afghanistan, Albania, Algeria, Angola, Argentina, Armenia, Azerbaijan, Bangladesh, Benin, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, Burkina Faso, Burundi, Cambodia, Cameroon, Central African Republic, Chad, China PR, Colombia, Congo Republic, Costa Rica, Côte d'Ivoire, Democratic Republic of the Congo, Dominican Republic, Egypt, El Salvador, Ethiopia, Gabon, Georgia, Ghana, Guatemala, Guinea, Guinea-Bissau, Haiti, Honduras, India, Indonesia, Iraq, Iran, Jamaica, Jordan, Kazakhstan, Kenya, Kyrgyz Republic, Lesotho, Liberia, Libya, Madagascar, Malawi, Malaysia, Mali, Mauritania, Mexico, Moldova, Mongolia, Morocco, Mozambique, Myanmar, Namibia, Nepal, Nicaragua, Niger, Nigeria, Pakistan, Panama, North Macedonia, Paraguay, Peru, Philippines, Russia, Rwanda, Senegal, Sierra Leone, South Africa, Sri Lanka,

TABLE 1 | Descriptive statistics: all countries.

Variable	Definition	Tag	Mean	Standard deviation	Minimum	Maximum	Observation
Fiscal support (total)	% of total GDP	FISCAL	6.676	7.268	0.100	39.20	129
Per capita GDP (PPP $)	Log form	Log GDPC	9.203	1.247	6.494	11.66	129
Population (millions)	Log form	Log POP	16.68	1.368	14.45	21.08	129
Human development index	Index from 0 to 1	HDI	0.709	0.161	0.354	0.953	129
Life expectancy	years	LIFE_EXP	72.56	7.941	53.28	84.63	129
Age 65 and older (ratio)	% of total population	AGED_65 OLDER	9.059	6.570	1.144	27.05	129
World Pandemic Uncertainty Indices	Index	Log WPUI	5.714	0.168	5.236	6.242	129

TABLE 2 | Correlation matrix: all countries.

Indicator	FISCAL	Log GDPC	Log POP	HDI	LIFE_EXP	AGED_65 OLDER	Log WPUI
FISCAL	1.000	–	–	–	–	–	–
Log GDPC	0.516	1.000	–	–	–	–	–
Log POP	0.140	−0.052	1.000	–	–	–	–
HDI	0.563	0.857	−0.067	1.000	–	–	–
LIFE_EXP	0.523	0.856	−0.018	0.824	1.000	–	–
AGED_65 OLDER	0.676	0.685	−0.082	0.784	0.749	1.000	–
Log WPUI	0.109	−0.475	−0.247	−0.488	−0.413	−0.393	1.000

in the dataset, whose per capita income is lower than the related threshold. The descriptive statistics are reported in **Table 1** for all countries in the dataset.

Finally, we provide a correlation matrix in **Table 2** for all countries in the dataset.

The findings in **Table 2** show the positive correlation between fiscal support and all right-side variables. Furthermore, the WPUI is negatively correlated with the remaining explanatory variables. There is a negative correlation between per capita GDP and population. In contrast, per capita GDP correlates with the human development index, life expectancy, and population of 65 years and older. However, the population is negatively correlated with the human development index, life expectancy, and 65 years and older population. Finally, there are positive correlations among the human development index, life expectancy, and 65 years and older population.

EMPIRICAL RESULTS

In **Table 3**, the results of the cross-sectional data estimations for 129 countries are reported.

The first column includes only a log of the per capita GDP. In the second column, a log of total population is also added. The third column considers the log of per capita GDP, the log of the total population, and the human development index. The fourth column also includes the variables in the third column as well as life expectancy. The fifth column considers the variables in the fourth column and the share of the 65 years and older population in the total population. Finally, the sixth column considers all variables in the fifth column and the log of the World Pandemic Uncertainty Indices.

The results indicate that the coefficients of the log of the total population, the share of the population of 65 years and older in the total population, and the World Pandemic Uncertainty Indices are statistically significant (at a 5% level at least) in each case. All of these variables are also positively related to fiscal support.

Next, we provide the results in 39 developed countries. According to the IMF (17) data, fiscal support in developed countries is significantly higher than the other remaining 90 countries. In **Table 4**, the findings of the cross-sectional data estimations in 39 developed countries are provided.

Like the structure in **Table 3**, the first column considers only the per capita GDP log. In the second column, the log of the total population is also included. The third column uses a log of per capita GDP, a log of the total population, and the human development index. Besides, the fourth column considers all variables in the third column as well as life expectancy. The fifth column includes the fourth column variables and the share of the 65 years and older population in the total population. Finally, the sixth column considers all variables in the fifth column and the log of the World Pandemic Uncertainty Indices.

The results show that the coefficients of the log of the total population, the share of the population of 65 years and older in the total population, and the World Pandemic Uncertainty Indices are statistically significant (at a 5% level at least) in each case. These indicators are also positively associated with the fiscal support in developed countries. Overall, the fiscal support's baseline determinants are robust when considering the countries at different income levels.

Sudan, Tajikistan, Thailand, Togo, Tunisia, Turkey, Uganda, Ukraine, Uzbekistan, Vietnam, Zambia, and Zimbabwe.

TABLE 3 | Cross-sectional data estimations for all countries: fiscal support in response to the COVID-19 pandemic.

Indicators	(1)	(2)	(3)	(4)	(5)	(6)
Log GDPC	3.009*** (0.442)	3.060*** (0.436)	1.879 (1.469)	2.123 (1.536)	1.001 (1.454)	1.077 (1.421)
Log POP	–	0.889** (0.397)	0.971** (0.381)	1.001** (0.386)	1.067*** (0.341)	0.857** (0.343)
HDI	–	–	39.87*** (11.37)	46.33*** (16.15)	0.118 (16.23)	4.933 (15.97)
LIFE_EXP	–	–	–	−0.101 (0.180)	−0.107 (0.159)	−0.141 (0.156)
AGED_65 OLDER	–	–	–	–	0.731*** (0.122)	0.738*** (0.119)
Log WPUI	–	–	–	–	–	8.278*** (3.178)
Constant Term	−21.01*** (4.110)	−36.33*** (7.955)	−20.55** (8.852)	−15.97 (12.02)	−19.24* (10.63)	−64.82*** (20.35)
Countries	129	129	129	129	129	129
R-squared (Adjusted)	0.261	0.283	0.342	0.339	0.484	0.507

The dependent variable is total fiscal support in response to the COVID-19 pandemic, % of GDP (FISCAL).
*Standard errors are reported in parentheses. ***p < 0.01, **p < 0.05, and *p < 0.10.*

TABLE 4 | Cross-sectional data estimations for developed countries: fiscal support in response to the COVID-19 pandemic.

Indicators	(1)	(2)	(3)	(4)	(5)	(6)
Log GDPC	0.323 (3.906)	0.362 (3.293)	6.010* (3.371)	5.260 (3.374)	4.458 (4.657)	2.974 (4.645)
Log POP	–	4.213*** (1.051)	3.197*** (0.978)	3.056*** (0.971)	3.018*** (0.887)	2.633*** (0.901)
HDI	–	–	108.1*** (32.49)	64.65 (45.10)	0.972 (47.12)	26.03 (48.66)
LIFE_EXP	–	–	–	0.856 (0.625)	0.539 (0.582)	0.204 (0.606)
AGED_65 OLDER	–	–	–	–	0.816*** (0.293)	0.781*** (0.287)
Log WPUI	–	–	–	–	–	10.38** (4.510)
Constant Term	16.70 (41.37)	−51.98 (38.85)	−71.57** (34.85)	−107.6** (43.35)	−141.1*** (41.38)	−172.2*** (44.90)
Countries	39	39	39	39	39	39
R-squared (Adjusted)	0.002	0.270	0.429	0.443	0.535	0.556

The dependent variable is total fiscal support in response to the COVID-19 pandemic, % of GDP (FISCAL).
*Standard errors are reported in parentheses. ***p < 0.01, **p < 0.05, and *p < 0.10.*

CONCLUDING REMARKS

Fiscal support measures have different implications for public finances in the near term and beyond the COVID-19 pandemic. This paper investigated potential determinants of governments' fiscal support in response to the COVID-19 pandemic. We used cross-sectional data in 129 developed and developing countries. We found that a greater level of uncertainty related to COVID-19 measured by the World Pandemic Uncertainty Indices is positively associated with fiscal support. Moreover, the countries with a higher total population and the population over 65 years and older provide higher fiscal support to the COVID-19 pandemic. These findings remain unchanged when we focused on the developed countries.

Our results indicate that fiscal support is higher in countries that have higher uncertainty related to COVID-19. This evidence indicates that World Pandemic Uncertainty Indices are a suitable measure to capture the economic effects of COVID-19. The total population is positively related to fiscal support. Given that the spread ratio of the new type of coronavirus is higher in crowded countries than in small countries, this evidence contradicts theoretical expectations. Similarly, countries with an elderly population (measured by the population over 65 years and older) provide more fiscal support related to COVID-19.

Interestingly, our results indicate that the fiscal support is not significantly related to the per capita income or development indicators. This evidence shows us that governments have looked at the COVID-19-related uncertainty outcomes and want to protect the whole population in general, older people in particular. Other specific groups (e.g., job losers) can be included in the fiscal stimulus packages.

Note that our findings are limited to total stimulus packages. Future papers can focus on the fiscal support determinants in different sectors (e.g., education and health) in developed and developing economies. Another research plan can examine fiscal support determinants in commodity exporter and commodity importer countries since some countries' fiscal situation has been worsened by commodity price shocks.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

AUTHOR CONTRIBUTIONS

S-KL conceputalization and econometric analysis. XL conceputalization and writing. XL review and writing. All authors contributed to the article and approved the submitted version.

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REFERENCES

1. Gozgor G. Global evidence on the determinants of public trust in governments during the COVID-19. In:*Center for Economic Studies and Ifo Institute (CESifo) Working Paper*, *No. 8313*. Munich: CESifo (2020).
2. Hale T, Petherick A, Phillips T, Webster S. *Variation in Government Responses to COVID-19*. Oxford: Oxford University (2020).
3. Altig D, Baker S, Barrero JM, Bloom N, Bunn P, Chen S, et al. Economic Uncertainty before and during the COVID-19 Pandemic. *J Public Econom.* (2020) 191:104274. doi: 10.1016/j.jpubeco.2020.104274
4. Baker SR, Bloom N, Davis SJ, Terry SJ. COVID-induced economic uncertainty. In: *National Bureau of Economic Research (NBER) Working Paper, No. 26983.* Cambridge, MA: NBER (2020). doi: 10.3386/w 26983
5. Baker SR, Bloom N, Davis SJ, Kost K, Sammon M, Viratyosin T. The unprecedented stock market reaction to COVID-19. *Rev Asset Pricing Stud.* (2020) 10:742–58. doi: 10.1093/rapstu/raaa008
6. Guerrieri V, Lorenzoni G, Straub L, Werning I. Macroeconomic implications of COVID-19: can negative supply shocks cause demand shortages? In: *National Bureau of Economic Research (NBER) Working Paper, No. 26918.* Cambridge: NBER (2020). doi: 10.2139/ssrn.3570096
7. Dong D, Gozgor G, Lu Z, Yan C. Personal consumption in the United States during the COVID-19 crisis. *Appl Econom.* (forthcoming). doi: 10.1080/00036846.2020.1828808
8. Eichenbaum MS, Rebelo S, Trabandt M. *The Macroeconomics of Epidemics National Bureau of Economic Research (NBER) Working Paper*, *No. 26882.* Cambridge, MA: NBER (2020).
9. Bayer C, Born B, Luetticke R, Müller G. *The Coronavirus Stimulus Package: How Large is the Transfer Multiplier? Center for Economic Policy Research* (*CEPR) Discussion Paper*, *No. 14600*. London: CEPR (2020).
10. Landais C, Saez E, Zucman G. A Progressive European Wealth Tax to Fund the European COVID Response. In: Bénassy-Quéré A, Di Mauro BW, editors. *Vox eBook Chapters. Europe in the Time of Covid-19*, *1st ed, Vol. 1, Chapter 1*. London: Centre for Economic Policy Research (2020). p. 113–8.
11. Clemens JP, Veuger S. Implications of the COVID-19 pandemic for state government tax revenues. In: *National Bureau of Economic Research (NBER) Working Paper, No. 27426.* Cambridge, MA: NBER (2020). doi: 10.3386/w27426
12. Benmelech E, Tzur-Ilan N. The determinants of fiscal monetary policies during the COVID-19 crisis. In: *National Bureau of Economic Research (NBER) Working Paper, No. 27461.* Cambridge, MA: NBER (2020). doi: 10.3386/w27461
13. Faria-e-Castro M. Fiscal policy during a pandemic. In: *Federal Reserve Bank of St. Louis Working (FRB) Working Paper*, No. 2020-006, St. Louis: FRB (2020). doi: 10.20955/wp.2020.006
14. Bredemeier C, Juessen F, Winkler R. Bringing back the jobs lost to Covid-19: the role of fiscal policy. *Covid Econom Vetted Real Time Papers.* (2020) 29:99–140. Available online at: https://cepr.org/content/covid-economics-vetted-and-real-time-papers-0
15. Kaplan G, Moll B, Violante G. The great lockdown the big stimulus: tracing the pandemic possibility frontier for the US. In: *National Bureau of Economic Research (NBER) Working Paper, No. 27794.* Cambridge, MA: NBER (2020). doi: 10.3386/w27794
16. Siddik MNA. Economic stimulus for COVID-19 pandemic and its determinants: evidence from cross-country analysis. *Heliyon*. (2020) 6:e05634. doi: 10.1016/j.heliyon.2020.e05634
17. International Monetary Fund (IMF). *Fiscal Monitor Database of Country Fiscal Measures in Response to the COVID-19 Pandemic*. Washington, DC: IMF (2020).
18. Hasell J, Mathieu E, Beltekian D, Macdonald B, Giattino C, Ortiz-Ospina E, et al. A cross-country database of COVID-19 testing. *Sci Data.* (2020) 7:345. doi: 10.1038/s41597-020-00688-8
19. Ahir H, Bloom N, Furceri D. The world uncertainty index. In: *Stanford Institute for Economic Policy Research (SIEPR) Working Paper*, No. 19–027, Stanford, CA: SIEPR (2019). doi: 10.2139/ssrn.3275033
20. World Bank. *World Bank Country and Lending Groups: Country Classification*. Washington, DC: World Bank (2020).

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Economic Policy Uncertainty in China and Bitcoin Returns: Evidence From the COVID-19 Period

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This paper analyses the effects of the Chinese Economic Policy Uncertainty (CEPU) index on the daily returns of Bitcoin for the period from December 31, 2019 to May 20, 2020. Utilizing the Ordinary Least Squares (OLS) and the Generalized Quantile Regression (GQR) estimation techniques, the paper illustrates that the current CEPU has a positive impact on the returns of Bitcoin. However, the positive impact is statistically significant only at the higher quantiles of the current CEPU. It is concluded that Bitcoin can be used in hedging against policy uncertainties in China since significant rises in uncertainty leads to a higher return in Bitcoin.

JEL Codes: G32; G15; C22

Keywords: COVID-19 pandemic, bitcoin, cryptocurrency markets, Chinese economy, EPU

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INTRODUCTION

The Global Financial Crisis (henceforth GFC) of 2008-09 destabilized the economic and financial stability of economies around the world and created high uncertainty about future economic security across the globe. During the GFC of 2008-09, Nakamoto (1) launched Bitcoin as an alternative to traditional currencies, which emerged as the most popular secure digital currency. However, as per its protocol design, the supply of Bitcoin is limited to 21 million. The occurrence of later financial crisis such as; the European Sovereign Debt Crisis of 2010-2013 and the Cypriot Banking Crisis of 2012-2013 further increased Bitcoin's popularity and established it as a "safe-haven" asset for investors (2–6).

As opposed to fiat currencies, cryptocurrencies are decentralized and act independently from government-regulated banking and other financial institutions. For instance, Corbet et al. (7) and Ji et al. (8) show that Bitcoin is independent of conventional assets and global financial system. Whereas, Demir et al. (9) state that cryptocurrencies provide solutions to the financial system's fragility and economic framework. Therefore, during times of economic and financial instability, investors withdraw their investment from traditional financial assets (like bonds, stocks etc.) to re-invest in Bitcoin to secure positive returns (9–12). Although initially introduced as an alternative to traditional currency, Bitcoin quickly emerged as a lucrative investment asset against conventional assets, so-termed Bitcoin as a "digital gold" (13).

Since Bitcoin behave independently from economic and financial developments (14); therefore, during times of extreme uncertainty or risk, Bitcoin offers significant diversification benefits for the investors. Bitcoin has the largest market capitalization and is considered as an alternative currency and medium of exchange. Bitcoin appears to be commodity money without gold, fiat money without state, and credit money without debt (15). The authors argued that Bitcoin provides a different opportunity for investments (16) as it embodies innovative technology and high security (17). Bitcoin has also created huge media attention in recent years, mainly due to its price fluctuations and potential for profit opportunities and transparency (18). Scholars have a different opinion about Bitcoin; some argue that Bitcoin is an efficient market (19, 20), others argue that Bitcoin is moving consistently toward efficiency (21). The researchers also argue that there are significant instability and bubbles in the Bitcoin. As a result, there is a speculative investment tendency related to Bitcoin (22). The year 2017 witnessed a drastic increase and decrease in Bitcoin demand, which brought scholars' attention to increasingly investigate Bitcoin's economic and financial determinants. It is the most widely used cryptocurrency, followed by Ethereum and Ripple (23).

In this paper, we re-examine the determinants of Bitcoin returns. For this purpose, we examine the effects of the index of economic policy uncertainty (EPU) in China on Bitcoin returns during the COVID-19 era since China has the largest mining pools for Bitcoin (24). Here, it is essential to know that the existing literature examining the impact of EPU on Bitcoin returns still inconclusive to present an undisputed argument with regards to Bitcoin hedging effectiveness against economic policy uncertainty capturing the COVID-19 period (25–28). Bitcoin returns can also affect households' consumption-savings trade-off in the COVID-19 period (29). Various studies assessing the role of economic policy uncertainty on different investment assets conclude that economic policy uncertainty has a positive influence not only on Bitcoin (9) but also on bonds (30) and commodities (31, 32). The empirical research has proved that Bitcoin remained resilient during times of uncertainty and stress, signifying its hedging capacity [see e.g., (6, 10–12)]. Whereas, Fang et al. (33), mainly reporting on the hedging effectiveness of Bitcoin, concludes that EPU has a relatively weak impact on Bitcoin's hedging performance, this finding contradicts that of (9). Since the literature on the impact of EPU on the hedging effectiveness of Bitcoin is still inconclusive; therefore, it is imperative to investigate this phenomenon further because such an inference is beneficial for the predictability of Bitcoin returns and improves investor's diversification and hedging decisions depending upon the level of economic policy uncertainty.

Therefore, the purpose of this study is to analyze the effects of the index of the Chinese Economic Policy Uncertainty (CEPU) on the daily returns of Bitcoin, considering the COVID-19-time period when uncertainty related to economic policy is higher. Furthermore, since the empirical literature examining the relationship between global economic policy uncertainty and Bitcoin returns is an under-researched area of study, therefore this study aims at investigating the role of Bitcoin to act as a hedging tool against economic policy uncertainty by considering the uncertainty caused by COVID-19 era in source country (China). Finally, we apply the OLS and the GQR estimation techniques to investigate (how Bitcoin returns are affected by the China EPU index) on the methodology side. This method allows us to see how extreme uncertainty affects Bitcoin returns and whether the CEPU can explain extreme Bitcoin returns. Considering the above factors, we relate our study to the existing empirical literature investigating the relationship and hedging effectiveness of Bitcoin against various variants of the EPU indices [see e.g., (9, 33–37)].

In the backdrop of the above information, the study continues as follows. Section Literature review provides the literature review. Section Data, model, and estimation procedure describes the data and the estimation procedure. Section Empirical Findings presents the empirical analysis and discussion of results. Section Conclusion provides concluding remarks.

LITERATURE REVIEW

Bitcoin has become the most popular digital currency since its launch in 2008. The independent framework in which it operates without the regulations of central governments and traditional financial institutions has given Bitcoin much popularity. The cryptocurrency market technology depends on mass collaboration, and its decentralized system validates Bitcoin transactions to prevent fraud. The distributed ledger named Blockchain digitally stores all the transactions, thus ensuring security and integrity.

Recently, scholars have started to investigate the economic and financial traits of Bitcoin due to; Bitcoin's price volatility (38), bubble formation (7, 39, 40), mounting regulatory scrutiny and market manipulation (41), and speculative nature (40, 42). Scholars also investigated Bitcoin's use for money laundering purposes (43) or Ponzi schemes (44). Amongst financial scholars modeling Bitcoin volatility is a widely researched topic. Several studies used different models to analyze Bitcoin volatility persistence and spillovers [see e.g., (45–49)]. However, most of these studies have used GARCH-based models because of their ability to illustrate Bitcoin's conditional variance.

Similarly, another strand of literature relating to Bitcoin's international diversification and hedging ability is also increasingly explored by scholars. Several studies [see e.g., (2, 10, 42, 45, 50, 51)] investigated the role of Bitcoin as an effective hedging instrument, diversifier etc. For instance, using the multivariate quantile model, Wang et al. (5) examined the risk spillover effect from the U.S. EPU index to Bitcoin. It concluded that the effects are negligible/insignificant, affirming that Bitcoin can act as a safe-haven asset and a diversifier against EPU shock. Similarly, Wu et al. (37) compared Bitcoin and gold by investigating their hedge or safe-haven roles against EPU. The authors use the GARCH model and quantile regression with dummy variables, and the results indicate that the following results. First, both assets are unsuccessful at average to act as a reliable hedge or safe-haven against the EPU. Second, considering extreme market conditions, Bitcoin and Gold both act weakly against uncertainty shocks. Third, Bitcoin is more resilient against EPU shocks as compared to gold. These findings correspond to other studies [see e.g., (5, 9, 34)].

The extant empirical literature shows that the factors determining Bitcoin price are markedly different than those of conventional assets, for e.g., internet or google searches (52), the total number of unique Bitcoin transactions per day (53), information on media and google trends (54). Certain unique factors also determine Bitcoin price, e.g., energy prices (55), social sentiment (14, 56), technology (57), the ratio of exchange-traded volume and the hash rate (56). On investigating the potential drivers of Bitcoin (58) examined the determinants of Bitcoin returns by considering twenty-one potential variables that could drive Bitcoin returns. Using the least absolute shrinkage and selection operator (LASSO) regression, the authors conclude that search intensity, gold returns and policy uncertainty are the most significant drivers for Bitcoin returns.

Recently, a research topic that has become popular amongst scholars is the effect of uncertainty (i.e., uncertainty caused by geopolitical risk, trade policy uncertainty or economic policy uncertainty) on Bitcoin returns. Various empirical studies have examined the impact of uncertainty on Bitcoin returns to observe it's hedging effectiveness. For instance, Aysan et al. (59) examined the impact of geopolitical risks on Bitcoin returns and volatility. The authors used the GPR index developed by Caldara and Iacoviello (60) to measure global terrorism, wars, and tensions among states. Using the Bayesian graphical structural vector autoregressive model, Aysan et al. (59) find that GPR has a predictive power on price volatility and Bitcoin returns, therefore, signifying Bitcoin's ability to act as a useful hedging tool at times of higher global geopolitical risks.

Similarly, Gozgor et al. (36) explored the relationship between the trade policy uncertainty index and the Bitcoin returns of the United States. Using Wavelet Power Spectrum, Wavelet Coherency and Cross-Wavelet Techniques, the study results indicate that Bitcoin is positively related to the trade policy uncertainty index. However, at extreme periods of uncertainty, Bitcoin fails to serve as a hedge. In another study, Bouri et al. (34) investigate the relationship between global financial stress and Bitcoin returns. The authors used the global financial stress index as a proxy for global stress rather than using volatility indices (since the former better captures global stress). By employing a Copula-based approach to dependence and causality in the quantiles, the authors conclude that Bitcoin remained resilient during times of financial stress. Their findings correspond with other studies investigating Bitcoin returns' valuable role [see e.g., (2, 8, 51, 61)]. In their previous study, Bouri et al. (11) used volatility indices of 14 advanced and developing stock markets as a proxy for global uncertainty to examine whether Bitcoin acts as a hedging tool against global uncertainty. Using the standard OLS and quantile regression, the findings show that bitcoin is a useful hedging tool against uncertainty at higher quantiles and shorter frequency movements of Bitcoin returns.

It is a fact that the macroeconomic situation is a crucial factor that determines cryptocurrency returns (35). However, limited studies (9, 35, 37) have empirically examined if cryptocurrencies' returns are also affected by economic policy uncertainty. And this is the area where we intend to contribute to the literature. For example, Demir et al. (9) analyzed the U.S. EPU index's effect to predict Bitcoin returns. By applying the OLS and GQR estimations, the study results indicate that the EPU index has a predictive power for Bitcoin returns. The impact of EPU on Bitcoin returns is seen significantly positive at both lower and higher quantiles, which indicates that Bitcoin can be used as a hedging instrument against economic policy uncertainty. The authors conclude that EPU is very useful in predicting Bitcoin returns by arguing that investors lack confidence in traditional fiat currencies with an increase in economic policy uncertainty. Therefore, demand for cryptocurrencies increases.

In another study, Cheng and Yen (35) applied the predictive regression model, examining China's EPU index's impact on predicting major cryptocurrencies' returns (such as Bitcoin, Ethereum, Litecoin, and Ripple). The findings show that the China EPU index has significant predictive power for Bitcoin returns, whereas the EPU index of the U.S, Korea, and Japan has weak predictive power. The results also indicate that other than Bitcoin, the China EPU index does not possess predictive ability for other cryptocurrencies returns. Cheng and Yen (35) particularly highlight the U.S. EPU index results, which show no significant ability to predict Bitcoin returns and reported that their findings contradict Demir's et al. (9) findings. Cheng and Yen (35) argue that focusing on the long-run effect using monthly data and the U.S. EPU index possesses no predictive power for Bitcoin monthly returns. Similarly, Fang et al. (33) explored whether the volatility and hedging effectiveness of Bitcoin and other global assets is affected by economic policy uncertainty. The results indicate that Bitcoin's long-term volatility is significantly affected by EPU, whereas Bitcoin has weak hedging effectiveness against EPU.

The empirical studies (9, 11, 34, 59) proved that the association between Bitcoin and uncertainty change in upper quantiles implies that Bitcoin acts as a hedge only at times of higher uncertainty and risk. From the review of the above studies, we report that this study's results are similar and correspond to

TABLE 1 | Results of the OLS and the GQR estimations.

Quantiles	CEPU	CEPU(−1)	CEPU(−2)	CEPU(−3)
0.05	−0.166 (0.130)	0.662 (1.127)	−1.244 (1.121)	1.516 (1.374)
0.10	−0.363 (0.969)	0.673 (0.730)	−1.741 (0.930)	1.514 (0.974)
0.15	−1.103 (0.797)	0.597 (0.584)	−0.979 (0.910)	1.287 (0.899)
0.20	−0.923 (0.593)	0.390 (0.496)	−0.607 (0.667)	1.026 (0.956)
0.25	−0.816 (0.498)	0.663 (0.526)	−0.487 (0.630)	0.222 (0.548)
0.30	−0.134 (0.477)	0.240 (0.422)	−0.064 (0.586)	0.103 (0.524)
0.35	−0.074 (0.491)	0.052 (0.449)	−0.021 (0.613)	0.039 (0.538)
0.40	−0.003 (0.051)	0.013 (0.466)	−0.092 (0.616)	0.014 (0.538)
0.45	0.003 (0.053)	0.188 (0.477)	−0.435 (0.563)	0.045 (0.550)
0.50	0.113 (0.545)	0.303 (0.481)	−0.461 (0.561)	0.205 (0.568)
0.55	0.005 (0.051)	0.239 (0.494)	−0.767 (0.516)	0.291 (0.567)
0.60	0.026 (0.052)	−0.017 (0.545)	−0.796 (0.507)	0.264 (0.558)
0.65	0.168 (0.545)	−0.019 (0.567)	−0.776 (0.493)	0.601 (0.541)
0.70	0.287 (0.555)	−0.240 (0.596)	−1.330 (0.519)	1.189 (0.743)
0.75	0.776** (0.358)	−0.304 (0.857)	−0.962 (0.637)	1.053 (0.708)
0.80	1.030** (0.511)	−0.255 (0.896)	−0.660 (0.576)	0.879 (0.611)
0.85	1.029** (0.463)	−0.007 (0.821)	−0.198 (0.543)	0.131 (0.512)
0.90	0.474** (0.205)	−0.936 (1.158)	0.214 (0.565)	0.103 (0.484)
0.95	0.175*** (0.072)	−0.175 (0.102)	2.187 (1.642)	1.792 (1.508)
OLS	0.071 (0.076)	0.206 (0.776)	0.587 (0.807)	0.721 (0.820)

***$p < 0.05$ and ***$p < 0.01$. The Newey–West standard errors are in parentheses.*

ones [e.g., (35)]. We conclude that higher uncertainty levels lead to positive returns on Bitcoin, which shows Bitcoin resilience and hedging capacity against the Chinese EPU index.

DATA, MODEL, AND ESTIMATION PROCEDURE

Data and Model

This empirical study uses daily frequency data and covers the period from December 31, 2019, to May 20, 2020. There are 142 observations; the sample period is purely dependent upon the data availability. The data for Bitcoin's logarithmic returns, which is treated as the dependent variable, is sourced from www.coindesk.com/price/. The daily China EPU index data, which is treated as an independent variable, is sourced from https://economicpolicyuncertaintyinchina.weebly.com/ constructed by Huang and Luk (62) following the methodology of Baker et al. (63). The pairwise correlation between the dependent and independent variable is 0.076. To investigate the return predictability of the China EPU index for Bitcoin returns, we estimate the following predictive model:

$$\Delta \ln (BCP)_t = \alpha_0 + \alpha_1 \Delta \ln (CEPU)_t + \varepsilon_t \quad (1)$$

Where $\ln (BCP)_t$ represents the change rate of daily logarithmic returns of Bitcoin prices at time t; and $\ln (CEPU)_t$ represents the change rate of the EPU index in China at time t. ε_t represents the error term.

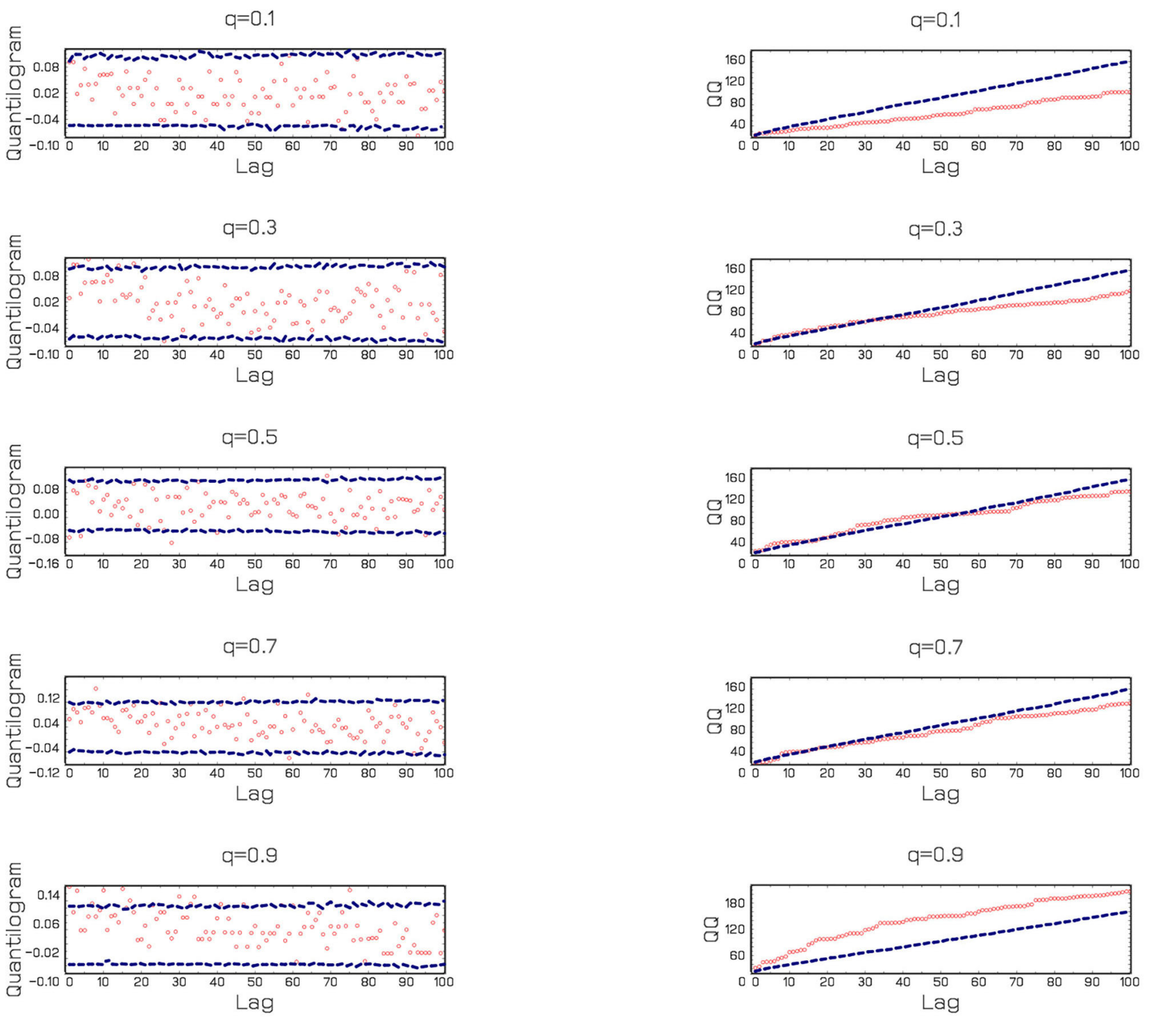

FIGURE 1 | Results of the Q–Q Estimations of Sim and Zhou (64).

Estimation Procedure

In this empirical investigation, we try to resolve different issues such as; misidentification of equations and implausible restrictions assumption (9, 34, 59). For example, Bouri et al. (34) predict the BRICS stock market returns using the VIX index to predict financial and macroeconomic variables. Therefore, following Bouri et al. (34), we assume the CEPU index as a potential predictor of the Bitcoin returns.

Moreover, in this empirical research, we use the Ordinary Least Squares (OLS) and the Generalized Quantile Regression (GQR) to model the quantile of Bitcoin returns (including various frequencies) as a function of the quantile of the CEPU index, which represents each point of their distributions. Additionally, the lagged effects of CEPU (up to 4 lags) on Bitcoin returns have also been examined in the empirical analysis.

EMPIRICAL FINDINGS

Table 1 presents the results of OLS and GQR estimations to understand the nature of this relationship. From the empirical results of OLS estimations, it is evident that the effects of CEPU and the lagged CEPU (up to 4 lags) are positive and statistically insignificant, which implies an increase in the EPU will not result in a jump in the Bitcoin returns or vice versa. However, at higher quantiles (see the quantiles from 0.75 to 0.95), the effects of the current CEPU on Bitcoin returns are still positive and statistically significant at the 5% level at least. The effects of the lagged CEPU on Bitcoin return is not statistically significant. Therefore, during higher quantiles, Bitcoin can serve as an effective hedging instrument against the Chinese policy uncertainty. Hence, investors are urged to consider China's daily economic policy uncertainty before investing in cryptocurrencies, enabling investors to predict Bitcoin returns better.

Figure 1 also provides additional results by running the Q-Q estimations procedure of Sim and Zhou (64). The findings indicate that the effects of CEPU on Bitcoin returns are positive in general. However, only quantile 0.9 exceeds the interval meaning that Bitcoin can hedge against the EPU in China at higher quantiles. This evidence shows that an event with extreme uncertainty is positively correlated to extreme Bitcoin returns.

As a robustness check, following the previous papers' models [e.g., (58, 65)], we have included control variables. However, we do not have a search intensity measure since the data are available at the Google Trends and Google Trends data do not capture China. We include gold returns at this stage, and our results are robust to include this measure (see **Table 2**).

The empirical analysis findings indicate that Bitcoin can serve as an effective alternative hedging instrument against uncertainty. This evidence also provides potential implications for portfolio diversification and hedging (i.e., risk management). This study's results correspond to the findings of Bouri et al. (11) and Demir et al. (9), which conclude a positive relationship between economic policy uncertainty and Bitcoin returns. However, during extreme market conditions, Bitcoin can serve as a hedging tool against uncertainty. However, in times of normal market conditions, Bitcoin can be used for portfolio diversification.

TABLE 2 | Results of the OLS and the GQR estimations (extended model with gold returns).

Quantiles	CEPU	GOLD
0.05	−0.056 (0.055)	−0.349 (0.302)
0.10	−0.050 (0.054)	−0.348 (0.251)
0.15	−0.035 (0.042)	−0.268 (0.214)
0.20	−0.024 (0.037)	−0.237 (0.184)
0.25	−0.018 (0.036)	−0.192 (0.159)
0.30	−0.014 (0.044)	−0.157 (0.160)
0.35	−0.003 (0.003)	−0.169 (0.167)
0.40	−0.001 (0.003)	−0.147 (0.173)
0.45	0.010 (0.029)	−0.090 (0.185)
0.50	0.024 (0.039)	−0.061 (0.208)
0.55	0.046 (0.042)	−0.042 (0.247)
0.60	0.144 (0.093)	−0.066 (0.264)
0.65	0.121 (0.144)	−0.054 (0.282)
0.70	0.154 (0.147)	−0.108 (0.281)
0.75	0.181*** (0.053)	−0.082 (0.301)
0.80	0.205*** (0.082)	−0.068 (0.414)
0.85	0.162** (0.076)	−0.120 (0.401)
0.90	0.123** (0.063)	−0.284 (0.421)
0.95	0.166** (0.084)	−1.288 (0.803)
OLS	0.037 (0.051)	−0.150 (0.264)

***$p < 0.05$ and ***$p < 0.01$. The Newey–West standard errors are in parentheses.*

Since the Bitcoin market is still at its early stage, the policymakers in China should consider that any uncertainty related to their economic policy could significantly affect the Bitcoin returns. This evidence is also established from this study's findings that the CEPU can effectively predict Bitcoin returns at higher quantiles. From this empirical analysis, it can be assumed that the Cryptocurrency market is quite vulnerable at the hands of uncertainty. Similarly, investors should weigh uncertainty related to economic policy and the existing natural uncertainty of cryptocurrencies before making investment decisions.

CONCLUSION

This empirical investigation analyzed the relationship between China EPU (CEPU) index and Bitcoin returns from December 31, 2019 to May 20, 2020. We employ the OLS and the GQR estimations to investigate whether EPU in China has a predictive power on Bitcoin returns. It is observed that primarily, the Bitcoin returns are positively related to the CEPU at the higher quantiles. The results also indicate that the impact is significant and positive at the higher quantiles, which implies that Bitcoin can undoubtedly be used as a hedging instrument when uncertainty related to economic policy is higher. We suggest that the mechanism of the cryptocurrency market and its potential determinants should to understand better. Our findings are limited to the COVID-19 era and Bitcoin market. Given that we focus on the Chinese economic policy uncertainty, future research should explore the impacts of uncertainty on cryptocurrency markets (including altcoins) to disentangle economic uncertainty and COVID-19 related uncertainty measures in the post-COVID-19 era.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found at: www.coindesk.com/price/; https://economicpolicyuncertaintyinchina.weebly.com.

AUTHOR CONTRIBUTIONS

CL, SC, and TC: formal analysis. TC and CK: funding acquisition and resources. CL: methodology. CL and TC: project administration. All authors contributed to the article and approved the submitted version.

REFERENCES

1. Nakamoto S. *Bitcoin: A Peer-to-Peer Electronic Cash System*. (2008). Available online at: https://bitcoin.org/bitcoin.pdf
2. Dyhrberg AH. Hedging capabilities of bitcoin. Is it the virtual gold? *Finance Res Lett.* (2016) 16:139–44. doi: 10.1016/j.frl.2015.10.025
3. Shahzad SJH, Bouri E, Roubaud D, Kristoufek L, Lucey B. Is bitcoin a better safe-haven investment than gold and commodities? *Int Rev Financ Anal.* (2019) 63:3222330. doi: 10.1016/j.irfa.2019.01.002
4. Shahzad SJH, Bouri E, Roubaud D, Kristoufek L. Safe haven, hedge and diversification for G7 stock markets: gold versus bitcoin. *Econ Model.* (2020) 87:2122224. doi: 10.1016/j.econmod.2019.07.023
5. Wang GJ, Xie C, Wen D, Zhao L. When bitcoin meets economic policy uncertainty (EPU): measuring risk spillover effect from EPU to bitcoin. *Finance Res Let.* (2019) 31:489–97. doi: 10.1016/j.frl.2018.12.028
6. Weber B. Bitcoin and the legitimacy crisis of money. *Cam J Econom.* (2014) 40:17–41. doi: 10.1093/cje/beu067
7. Corbet S, Meegan A, Larkin C, Lucey B, Yarovaya L. Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Econ Lett.* (2018) 165:28–34. doi: 10.1016/j.econlet.2018.01.004
8. Ji Q, Bouri E, Gupta R, Roubaud D. Network causality structures among bitcoin and other financial assets: a directed acyclic graph approach. Department of Economics Working Paper, No. 201729; University of Pretoria. (2017). doi: 10.1016/j.qref.2018.05.016
9. Demir E, Gozgor G, Lau CKM, Vigne S. Does economic policy uncertainty predict the bitcoin returns? An empirical investigation. *Finance Res Lett.* (2018) 26:145–9. doi: 10.1016/j.frl.2018.01.005
10. Bouri E, Molnár P, Azzi G, Roubaud D, Hagfors LI. On the hedge and safe haven properties of bitcoin: is it really more than a diversifier? *Finance Res Lett.* (2017) 20:192–8. doi: 10.1016/j.frl.2016.09.025
11. Bouri E, Gupta R, Tiwari AK, Roubaud D. Does bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. *Finance Res Lett*. (2017) 23:87–95. doi: 10.1016/j.frl.2017.02.009
12. Luther WJ, Salter AW. Bitcoin and the bailout. *Q Rev Econ Finance.* (2017) 66:50–6. doi: 10.1016/j.qref.2017.01.009
13. Popper N. *Digital Gold: The Untold Story of Bitcoin*. London: Penguin Books Limited (2015).
14. Kristoufek L. What are the main drivers of the Bitcoin price? Evidence from wavelet coherence analysis. *PLoS ONE.* (2015) 10:e0123923. doi: 10.1371/journal.pone.0123923
15. Klein T, Thu HP, Walther T. Bitcoin is not the new gold – a comparison of volatility, correlation, and portfolio performance. *Int Rev Finan Anal.* (2018) 59:105–16. doi: 10.1016/j.irfa.2018.07.010
16. Nadarajah S, Chu J. On the efficiency of bitcoin. *Econ Lett.* (2017) 150:6–9. doi: 10.1016/j.econlet.2016.10.033
17. Shi Y, Tiwari AK, Gozgor G, Lu Z. Correlations among cryptocurrencies: evidence from multivariate factor stochastic volatility model. *Res Int Bus Finance.* (2020) 53:101231. doi: 10.1016/j.ribaf.2020.101231
18. Urquhart A. What causes the attention of bitcoin? *Econ Lett.* (2018) 166:40–4. doi: 10.1016/j.econlet.2018.02.017
19. Jiang Y, Nie H, Ruan W. Time-varying long-term memory in the bitcoin market. *Finance Res Lett.* (2018) 25:280–4. doi: 10.1016/j.frl.2017.12.009
20. Urquhart A. The inefficiency of bitcoin. *Econ Lett.* (2016) 148:80–2. doi: 10.1016/j.econlet.2016.09.019
21. Bariviera AF. The inefficiency of bitcoin revisited: a dynamic approach. *Econ Lett.* (2017) 161:1–4. doi: 10.1016/j.econlet.2017.09.013
22. Blau BM. Price dynamics and speculative trading in bitcoin. *Res in Int Bus Finance.* (2017) 41:493–9. doi: 10.1016/j.ribaf.2017.05.010
23. Liu W, Semeyutin A, Lau CKM, Gozgor G. Forecasting value-at-risk of cryptocurrencies with RiskMetrics type models. *Res Int Bus Finance.* (2020) 54:101259. doi: 10.1016/j.ribaf.2020.101259
24. Ma J, Gans JS, Tourky R. *Market Structure in Bitcoin Mining*. National Bureau Economic Research. Working Paper No. 24242 (2018). doi: 10.3386/w24242
25. Bouri E, Gupta R. Predicting bitcoin returns: comparing the roles of newspaper-and internet search-based measures of uncertainty. *Finance Res Lett.* (2019) 38:101398. doi: 10.1016/j.frl.2019.101398
26. Conlon T, McGee R. Safe haven or risky hazard? Bitcoin during the COVID-19 bear market. *Finance Res Lett*. (2020) 35:101607. doi: 10.1016/j.frl.2020.101607
27. Corbet S, Larkin C, Lucey B. The contagion effects of the covid-19 pandemic: evidence from gold and cryptocurrencies. *Finance Res Lett.* (2020) 35:101554. doi: 10.1016/j.frl.2020.101554
28. Goodell JW, Goutte S. Co-movement of COVID-19 and bitcoin: evidence from wavelet coherence analysis. *Finance Res Lett.* (2020) 38:101625. doi: 10.2139/ssrn.3597144
29. Dong D, Gozgor G, Lu Z, Yan C. Personal consumption in the United States during the COVID-19 Crisis. *Appl Econ.* (2020) 53:1–6. doi: 10.1080/00036846.2020.1828808
30. Ioannidis C, Ka K. *Economic Policy Uncertainty and Bond Risk Premia.* Mimeo (2018)
31. Shahzad SJH, Raza N, Balcilar M, Ali S, Shahbaz M. Can economic policy uncertainty and investors sentiment predict commodities returns and volatility? *Resourc Policy.* (2017) 53:208–18. doi: 10.1016/j.resourpol.2017.06.010
32. Yin L, Han L. Macroeconomic uncertainty: does it matter for commodity prices? *Appl Econ Lett.* (2014) 21:711–6. doi: 10.1080/13504851.2014.887181
33. Fang L, Bouri E, Gupta R, Roubaud D. Does global economic uncertainty matter for the volatility and hedging effectiveness of bitcoin? *Int Rev Financ Anal.* (2019) 61:29–36. doi: 10.1016/j.irfa.2018.12.010
34. Bouri E, Gupta R, Lau CKM, Roubaud D, Wang S. Bitcoin and global financial stress: a copula-based approach to dependence and causality-in-quantiles. *Q Rev Econ Finan.* (2018) 69:297–307. doi: 10.1016/j.qref.2018.04.003
35. Cheng HP, Yen KC. The relationship between the economic policy uncertainty and the cryptocurrency market. *Finance Res Lett.* (2020) 35:101308. doi: 10.1016/j.frl.2019.101308
36. Gozgor G, Tiwari AK, Demir E, Akron S. The relationship between bitcoin returns and trade policy uncertainty. *Finance Res Lett*. (2019). *29*:75–82. doi: 10.1016/j.frl.2019.03.016
37. Wu S, Tong M, Yang Z, Derbali A. Does gold or bitcoin hedge economic policy uncertainty? *Finance Res Lett.* (2019) 31:171–8. doi: 10.1016/j.frl.2019.04.001

38. Bouri E, Gil-Alana LA, Gupta R, Roubaud D. Modelling long memory volatility in the bitcoin market: evidence of persistence and structural breaks. *Int J Finance Econ*. (2019) 24:412–26. doi: 10.1002/ijfe.1670
39. Bouri E, Shahzad SJH, Roubaud D. Co-explosivity in the cryptocurrency market. *Finance Res Lett*. (2019) 29:178–83. doi: 10.1016/j.frl.2018.07.005
40. Cheah ET, Fry J. Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. *Econ Lett.* (2015) 130:32–6. doi: 10.1016/j.econlet.2015.02.029
41. Gandal N, Hamrick JT, Moore T, Oberman T. Price manipulation in the bitcoin ecosystem. *J Monet Econ.* (2018) 95:86–96. doi: 10.1016/j.jmoneco.2017.12.004
42. Baur DG, Dimpfl T, Kuck K. Bitcoin, gold the US. dollar – A replication and extension. *Finance Res Lett*. (2018) 25:103–10. doi: 10.1016/j.frl.2017.10.012
43. Moser M, Bohme R, Breuker D. An inquiry into money laundering tools in the Bitcoin ecosystem. *eCrime Researchers Summit (eCRS)*. (2013). doi: 10.1109/eCRS.2013.6805780
44. Vasek M, Moore T. There's no free lunch, even using Bitcoin: tracking the popularity and profits of virtual currency scams. In: *International Conference on Financial Cryptography and Data Security* Berlin: Springer (2015). p. 44–61.
45. Baur DG, Hong K, Lee AD. Bitcoin: medium of exchange or speculative assets? *J Int Financ Mark Insti Money*. (2018) 54:177–89. doi: 10.1016/j.intfin.2017.12.004
46. Chu J, Chan S, Nadarajah S, Osterrieder J. GARCH modelling of cryptocurrencies. *J Risk Financ Manage*. (2017) 10:17. doi: 10.3390/jrfm10040017
47. El Sayed A, Gozgor G, Lau CKM. Causality and dynamic spillovers among cryptocurrencies and currency markets. *Int J Finance Econ Forthcom.* (2021). doi: 10.1002/ijfe.2257
48. Engle RF, Ghysels E, Sohn B. Stock market volatility and macroeconomic fundamentals. *Rev Econ Stat*. (2013) 95:776–97. doi: 10.1162/REST_a_00300
49. Katsiampa P. Volatility estimation for bitcoin: a comparison of GARCH models. *Econ Lett.* (2017) 158:3–6. doi: 10.1016/j.econlet.2017.06.023
50. Bouri E, Azzi G, Dyhrberg AH. *On the Return-Volatility Relationship in the Bitcoin Market Around the Price Crash of 2013*. Economics Discussion Papers No. 41 (2016). doi: 10.2139/ssrn.2869855
51. Dyhrberg AH. Bitcoin, gold and the dollar –a GARCH volatility analysis. *Finance Res Lett*. (2016) 16:85–92. doi: 10.1016/j.frl.2015.10.008
52. Glaser F, Zimmermann K, Haferkorn M, Weber MC, Siering M. Bitcoin-asset or currency? Revealing users' hidden intentions. revealing users' hidden intentions. In *ECIS Conference 2014*. Paper No. 2425247 (2014).
53. Ciaian P, Rajcaniova M, Kancs DA. The economics of bitcoin price formation. *Appl Econ.* (2016) 48:1799–815. doi: 10.1080/00036846.2015.1109038
54. Garcia D, Tessone C, Mavrodiev P, Perony N. The digital traces of bubbles: feedback cycles between socio-economic signals in the bitcoin economy. *J R Soc Interface*. (2014) 11:1–8. doi: 10.1098/rsif.2014.0623
55. Hayes AS. Cryptocurrency value formation: an empirical study leading to a cost of production model for valuing bitcoin. *Telemat Informat*. (2017) 34:1308–21. doi: 10.1016/j.tele.2016.05.005
56. Bouoiyour J, Selmi R. What does bitcoin look like? *Ann Econ Finance*. (2015) 16:449–492.
57. Li X, Wang CA. The technology and economic determinants of cryptocurrency exchange rates: the case of bitcoin. *Deci Support Syst.* (2017) 95:49–60. doi: 10.1016/j.dss.2016.12.001
58. Panagiotidis T, Stengos T, Vravosinos O. On the determinants of bitcoin returns: a LASSO approach. *Finance Res Lett.* (2018) 27:235–40. doi: 10.1016/j.frl.2018.03.016
59. Aysan AF, Demir E, Gozgor G, Lau CKM. Effects of geopolitical risks on the bitcoin returns and volatility. *Res Int Bus Finance.* (2019) 47:511–8. doi: 10.1016/j.ribaf.2018.09.011
60. Caldara D, Iacoviello M. *Measuring Geopolitical Risk*. Board of Governors of the Federal Reserve Board Working Paper (2018). doi: 10.17016/IFDP.2018.1222
61. Brière M, Oosterlinck K, Szafarz A. Virtual currency, tangible return: portfolio diversification with bitcoin. *J Asset Manage.* (2015) 16:365–73. doi: 10.1057/jam.2015.5
62. Huang Y, Luk P. Measuring economic policy uncertainty in China. *China Econ Rev*. (2020) 59:101367. doi: 10.1016/j.chieco.2019.101367
63. Baker SR, Bloom N, Davis SJ. Measuring economic policy uncertainty. *Q J Econ.* (2016) 131:1593–636. doi: 10.1093/qje/qjw024
64. Sim N, Zhou A. Oil prices, US stock return, and the dependence between their quantiles. *J Bank Finance.* (2015) 55:1–8. doi: 10.1016/j.jbankfin.2015.01.013
65. Gozgor G, Lau CKM, Sheng X, Yarovaya L. The role of uncertainty measures on the returns of gold. *Econ Lett*. (2019) 185:108680. doi: 10.1016/j.econlet.2019.108680

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Effects of Pandemic Outbreak on Economies: Evidence From Business History Context

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The coronavirus pandemic has highlighted the capitalist dysfunction showing that considering profit over people can be deadly. The study reveals the LME economies were more responsive toward the impact of the disease outbreaks as compared to the CME economies wherein the impact of the disease was moderated by the government involvement. This allows us to draw that the impact of the disease outbreaks can be moderated by increasing the involvement of the government authorities.

Keywords: coronavirus, pandemic outbreak, business history, LME economies, CME economies

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INTRODUCTION

Infectious diseases are one of the major causes of death responsible for the quarter to one-third of the mortality worldwide. Despite major developments in the pharmaceutical industry, the spread of infectious diseases is rising due to globalization, increased travel and trade, urbanization, populated cities, changes in human behavior, reviving pathogens and improper use of antibiotics (1). The recent virus outbreak Covid-19 shows that infectious diseases spread easily due to open economies and easily threaten nations' economic stability. Previous infections such as Black Death, SARS, Influenza H1N1, and Swine Flu had caused similar economic impacts worldwide. Covid-19 is more contagious, and its ability to sustain on surfaces makes it more challenging to curb. It is considered more contagious than influenza and swine flu as it transmits between people easily. The second feature is the delay in developing treatment drugs and their approval because the initial infection causes significant mortality and damage to the economy. Another feature of Covid-19 is the constant evolution and resistance of microbes toward antibacterial agents, making them a continuous and recurring threat. The majority of the outbreaks are recurring, and the current Covid-19 outbreak may evolve and recur as it is considered to be the second strain of severe acute respiratory syndrome (SARS-CoV-2), the first strain of which occurred in 2002–03 (SARS-CoV-1) (2).

The coronavirus pandemic has highlighted the capitalist dysfunction, which is considered to be partly based on the priority given to profit rather than people's need. Pharmaceutical companies would have started developing the vaccine for coronavirus a long time ago if the society had not been capitalist. The novel coronavirus spreading fast around the world belongs to the family of coronavirus (SARS and MERS) that are already familiar to us for a long time. It could have been possible to begin search for coronavirus vaccine and treatments long time ago so that the most recent outbreak of coronavirus could be prevented to some extent. But pharmaceutical companies did not initiate this research because the treatment did not seem to be profitable enough (3). It takes 12–18 months for researchers to develop vaccine to fight against Covid-19. As per the epidemiologists, coronavirus could kill up to 50 million people worldwide (4). Many of these deaths could have been avoided if the vaccine was introduced. And the vaccine has not been developed as it was not profitable for pharmaceutical companies.

The rest of the paper is organized as follows. Section A General Equilibrium Approach discusses a general equilibrium approach to the impacts of pandemic outbreak and provides brief literature review. Section Methodology and Empirical Model explains the methodology and empirical model. Section Empirical Findings discusses the empirical findings. Section Conclusion concludes.

A GENERAL EQUILIBRIUM APPROACH

The characteristics of coronavirus pandemic can be analyzed through consistent characteristics of historical pandemic outbreaks. The economic effects of pandemics have been analyzed in the existing studies. A partial equilibrium approach is only focused on the health sector and the forgone earnings due to the mortality from the disease. It ignores its impact on other sectors and the other parts of the country. It is, therefore, perceived as an incomplete approach. We applied a general equilibrium approach to the economic impact of pandemic outbreaks and health diseases as the equilibrium approach is an appropriate method of comprehensively study the consequences. Under a general equilibrium approach, the health, economic and social impacts of the pandemic can be analyzed.

Health Impacts

The health impacts of pandemics are disastrous. During the Black Death pandemic, ∼30–50% of the population of Europe wiped out. In the 1980s, 35 million people died due to HIV, AIDS, and Ebola in 2014, which caused 10,600 deaths in Guinea, Sierra Leone, and Liberia in West Africa (5). Pandemic affects the young and economically active population disproportionately. The morbidity and mortality rates are higher for younger people as they tend to have lower immunity than the older generation. Thus, the pandemic's major impact is that it causes a significant increase in the years of life lost.

Moreover, many infectious diseases have lifelong consequences, and it can become more severe in pandemics. For example, the medication of Zika virus has life-long chronic effects on the health of the patient. Pandemics' indirect effects on health include the depletion of resources for routine healthcare and decreased childhood immunization rates, and reduced healthcare access due to the inability to travel. During the influenza pandemic in 2009, a surge in hospital admissions due to influenza and pneumonia caused an increase in deaths due to stroke and heart attack. Therefore, it is difficult to distinguish between the deaths attributable to the pandemic and other unassociated diseases that are merely coincidental. Healthcare workers' ability to provide care is also reduced as they fall ill themselves, are required to take care of family members or children, or even the fear of catching the disease also makes them receptive.

Economic Impacts

Pandemics cause a short-term fiscal impact and a long-term economic impact on the nations around the world. Efforts to curb the pandemic include imposing quarantine, preparing health facilities, isolating infectious cases, and tracing contacts involving public health resources, human resources and implementation costs. It also involves health system expenditures to provide health facilities to infectious cases and the arrangement of consumables such as antibiotics, medical supplies, and personal protective equipment.

Pandemics can also result in declined tax revenues and increased expenditure, which causes fiscal stress, especially in lower-middle-income countries (LMICs) where fiscal constraints are higher, and tax systems still need improvement. This economic impact severity was observed during the Ebola virus in Liberia due to the rise in public health expenditure, economic downfall, and revenue decline due to the government's inability to raise revenue because of quarantine and curfews. Economic shocks are common during pandemics due to shortage of labor because of illness, rise in mortality, and a fear-induced behavior. Other than labor shortages, disruption of transportation, closed down of workplaces, restricted trade and travel, and closed land border are reasons for the pandemic's economic slowdown.

Social and Political Impacts

Pandemics have significant social and political impacts such as clashes between nations, population displacement, and increased social tension and discrimination. Many pre-modern pandemics have caused serious demographic shifts, morality shocks, and social and political disturbance. Empirical evidence suggests that pandemics can create political tensions and unrest, especially in nations with weak institutions. The 2014 Ebola virus resulted in political and social unrest in the state as government-imposed quarantine and curfews to mitigate the disease's spread with security forces that the general public perceived as a conspiracy and opposing the government. This issue caused riots and violence in the country, involving threats to health care personnel and damaging healthcare facilities and supplies. Modern pandemics have subtle social disruptions such as anxiety, social isolation, fear-inducing behavior, and economic hardships.

Varieties of Capitalism and Business History

The "Varieties of Capitalism" framework designed by Peter Hall and David Soskice has become a benchmark in the political literature on advanced industrial economies. The framework (6) discusses two capitalist arrangements: coordinated market economies (CME) and liberal market economies (LME). This framework also suggests that market pressures, such as globalization and industrial pressures, will ultimately lead to the convergence of the most efficient capitalism form. The idea of the "Varieties of Capitalism" framework is that although both the models represent different capitalism arrangements, yet both are durable and logical even in the challenging industrial environment. Many people who are supportive of egalitarian capitalism believe that the coordinated market economies (CME) are on the verge of a breakdown. This theory of

"Varieties of Capitalism" is influential and provides reassurance to the people who are concerned about the breakdown of institutions characteristics.

The varieties model of capitalism has also been criticized by scholars for its overemphasizing on the flexibility of capitalism models for the reason that many countries define their institutional arrangement, especially when the coordinated market economies are under pressure and facing reforms. The critics of the framework believe that the economies are shifting toward liberalization and this pervasive shift negates the basic explanation of this model. By undermining the differentiation, it portrays between coordinated market economies and liberal market economies (7). The supporters of varieties framework typically respond by defending the differentiation of liberal and coordinated market economies. The varieties framework is, thus, an inconclusive debate among supporters and critics. For companies to succeed in this globalized economy, state support is essential either directly or implicitly. Market economies such as Japan and South Korea have experienced capitalist maturity, that is, businesses have experience of investment, technological and managerial decisions and the support of government have helped them make space in the foreign markets and succeed (8). Thus, coordination plays an important role, but the participation of association is highly essential.

For this study, we consider UK, Australia, Canada, and New Zealand representing liberal market economies (LME) and Japan, Germany, and Sweden representing coordinated market economies (CME).

Covid-19 and Global Development

Covid-19 highlights the need to understand contemporary global challenges rather than focus on a narrower international development approach. The international development paradigm focuses on bilateral relations based on aids provided to each other, while a global development approach discovers the processes and issues related to the countries. Global international development focused on joint problems and shared issues such as global warming, terrorism, pandemics, etc. Global development is concerned with recognizing that an equitable world is formed through cooperation and shared values rather than just transforming a developing economy to a developed one. The global development paradigm is based on three important aspects. First, the interrelationship between contemporary capitalist countries goes beyond the national boundaries (9). Second, there are several challenges that nations all around the world are facing together. Third, global development is about helping each other deal with the common challenges and reduce global inequality. These goals have been recognized and part of the global Sustainable Development Goals (SDGs) and other agreements and treaties. Covid-19 makes it an urgency to use a global development approach for dealing with the common problems and challenges. The interconnected world has led to the spread of COVID-19 in a very short time. Indeed, it is a good example of the countries' common challenges and the global public good's failure. The pandemic has caused distressing economic, health and social impacts worldwide (10). The impact of COVID-19 cannot be only assessed in economic terms. It had devastating mortality and fatal rates across the United States and European countries in the North. China, Brazil, Mexico, Africa, and other Southern countries also had high infectious rates.

Apart from the health impacts, the pandemic has created the worst social and economic impact on humans' lives (11). There has been a loss of employment and livelihood, and people suffer from anxiety due to social contacts' loss. The global development paradigm's importance can be examined by assessing the impact of the Covid-19 pandemic across global value chains, debt, and digitalization.

Global Value Chains

Covid-19 has severely impacted the global value chains across the globe, especially the agricultural and industrial forms over the past 30 years (12). The pandemic caused a serious shortage in supplies of goods manufactured in China, especially the shortage of medical supplies affected many countries' health scenario. Due to growing nationalism and protectionism for industrial sovereignty, many countries have imposed export ban, which resulted in the shortage of medical supplies such as pharmaceutical drugs, personal protective equipment (PPE kits), and other medical products. As a result, the pressure on domestic value chains has increased, and de-globalization has emerged again. The value chains will have to be restructured after the pandemic to improve the quality and quantity of jobs and ensure sustainable transitions.

Debt

Public finances have been negatively affected by the Covid-19 pandemic. The closing of economies and reduced lending opportunities has decreased the value of local currencies making repayment of dollar-denominated debt harder (13). Governments are also facing a fiscal deficit due to increased social protection expenditure for the unemployed and poor and reduced tax revenues. The debt from Covid-19 is different from that of the financial crisis of the 1980s or 2007–08 and will not be explainable through the international development paradigm (14).

Digitalization

A positive impact of COVID-19 on third world economies has been the increase in digitalization. With the increasing threat of infection transmission through physical contact, the virtual space of transactions has gained popularity (15). The chance of its spread through social contact has accelerated online working platforms and digitally organized logistics. With online transactions and digital platforms for work, there is an opportunity to develop a centralized database that can serve as an economic asset. It has become essential to be a part of the global digital drive for improved socio-economic fortunes and mitigate the impact of the Covid-19 pandemic through digitalization.

Thus, Covid-19 requires a global development perspective rather than an international development paradigm as a global development paradigm can effectively confront the challenges. It prioritizes the collaboration on a global level rather than focusing on national and state issues as the countries' problems require a foresighted approach.

METHODOLOGY AND EMPIRICAL MODEL

The study examines the trend in capitalist economies during times of pandemic with a business history perspective. Both qualitative and quantitative analysis would be conducted to assess the economic consequences on Coordinated Market economies (CME) and Liberal Market Economies (LME).

Quantitative Analysis

The study uses Computable General Equilibrium (CGE) to model the pandemic outbreak's economic implications on capitalist economies. CGE model involves using actual economic data to assess the changes in an economy as a reaction to change in external factors such as technological change, policy change, etc. It works on the assumption that countries have no barriers and are constantly engaged in trade with perfectly competitive markets and homogenous technologies. The model discusses economic activity in all countries as a function of world economic output. The economic output involves using five major inputs—capital, skilled and unskilled labor, natural resources and land.

Our research considers labor and capital as major functions of output based on their mobility across nations. Land and natural resources are fixed in nature. Moreover, wages and capital usage prices are uniform across nations while rent on land and natural resources vary across different industries. Thus, capital accumulation, investment and the labor market would be studied to understand the capitalist economies' economic change. So the entire study is based on the idea that as the economic disruption is propelled by the events like epidemics and, in the current case, a pandemic, the dynamics of the investment and capital market, the labor market and the general wage levels, as well as the rate of inflation, are affected, which cause a cumulative change in the rate of economic growth in the economy. This issue can be understood better with a functional representation of the impact of economic and environmental shocks on the economy.

1) Capital Accumulation and Investment

Under the perfectly competitive markets, the capital stock of a nation at a particular period can be denoted as:

$$K_r^{t+1} = K_r^t + I_r^t - D_r^t \tag{1}$$

Where K_r^{t+1} represents the stock of capital accumulated in an economy r in a given year. K_r^t is the available capital in region r in year t, I_r^t is the investment in new capital in region r and year t and D_r^t is the depreciation on the capital of region r in year t. This functional relationship allows us to decipher how capital accumulation is achieved in the economy. Next, we move on to the labor markets.

2) The Labor Supply

We start by examining the supply of labor in the labor market of the economy, which is denoted by the following equation:

$$\frac{LS_r^t}{Pop_r^t} = \left(RW_r^t\right)^{\beta} A_r^t \tag{2}$$

Where, LS_r^t can be described as the supply of labor in an economy in the period t and region r. Pop_r^t Denotes the population share in year t and region r. On the right-hand side is the variable $\left(RW_r^t\right)^{\beta} A_r^t$ which denotes the real post-tax wage of labor type l in year t and region r with A_r^t and β being the positive constants determining the labor supply in the economy (1).

As the pandemics and epidemics hit the global economy, the death rates escalate, and the population and the pool of available labor resources dwindle in the economy. In turn, it causes a deterioration of the post-tax wage of labor in the economy, which is a further decline in the demand for labor as the economies come to a slow down. We consider the nature and the extent of the impact of the pandemics and epidemics on the economic capital usage and labor supply. The economic implications would be assessed using growth variables such as GDP, investment, consumption pattern, and the wage rates would be examined in the economies while studying the changes emerging along the length of the disease spread of SARS, which stretched from the first quarter of 2002 till the last quarter of 2004, the H1N1 swine flu which stretched from the first quarter of 2009 till the last quarter of 2010 and lastly the current pandemic. The past 2 years' quarterly economic data will be assessed for CME and LME economies to examine the difference in economic growth pre- and post-pandemic times and CME (Japan, Sweden, Germany) and LME (United Kingdom, Australia, Canada, and New Zealand) nations. The study variables' data collection sources include the IMF, World Bank, and OECD database, and the ILOStats. The analysis period has been split across the periods that marked the heart of the disease outbreak, undertaken as a panel data spanning across disrupted timelines and two groups of nations. As part of the research objectives, the qualitative analysis conducted includes studying secondary data to understand capitalist economies' business history during pandemic times. Impact of various pandemic conditions such as SARS (Cov-1 and Cov-2), Influenza H1N1, or the swine flu and the current case of Covid-19 on the economic growth of capitalist nations (comparative analysis of CME and LME nations) has been examined, and recommendations for financial recovery have been made.

EMPIRICAL FINDINGS

We start the analysis process by explaining the exact impact that the recent most disease outbreak, associated with that of the SARS virus and the H1N1 virus, had on the economies under consideration. The analysis then veers off to assess the COVID 19 virus outbreak's impact on the global economy so far. The key variables taken as a proxy for the impact of the disease outbreaks include the hours worked in a week, the rate of unemployment, the inflation rate, the government's investments, and the variable of economic growth.

Impact of the SARS Outbreak

The next section seeks to distinguish the impact of changes in the economy's various sectors and facets, as triggered by the disease outbreak on the economic growth of the coordinated market

FIGURE 1 | SARS hit China's retail sales [Source (23)].

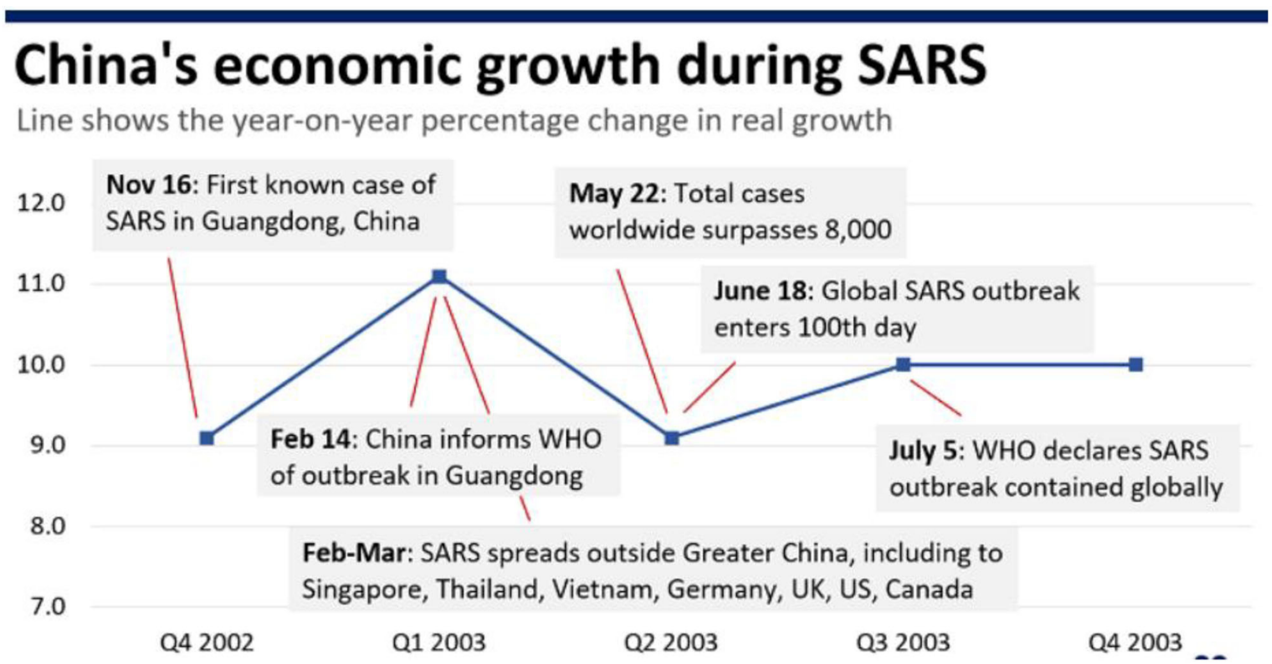

FIGURE 2 | China's economic growth during SARS [Source (23)].

economies and liberal market economies. **Figure 1** indicates that Severe Acute Respiratory Syndrome (SARS) is a viral respiratory disease that is contagious among humans. The disease emerged from the Guangdong province of China in 2002 and was infectious as a cold virus, as shown in **Figure 2**. It was transmitted to countries like South Africa, Hong Kong, Canada,

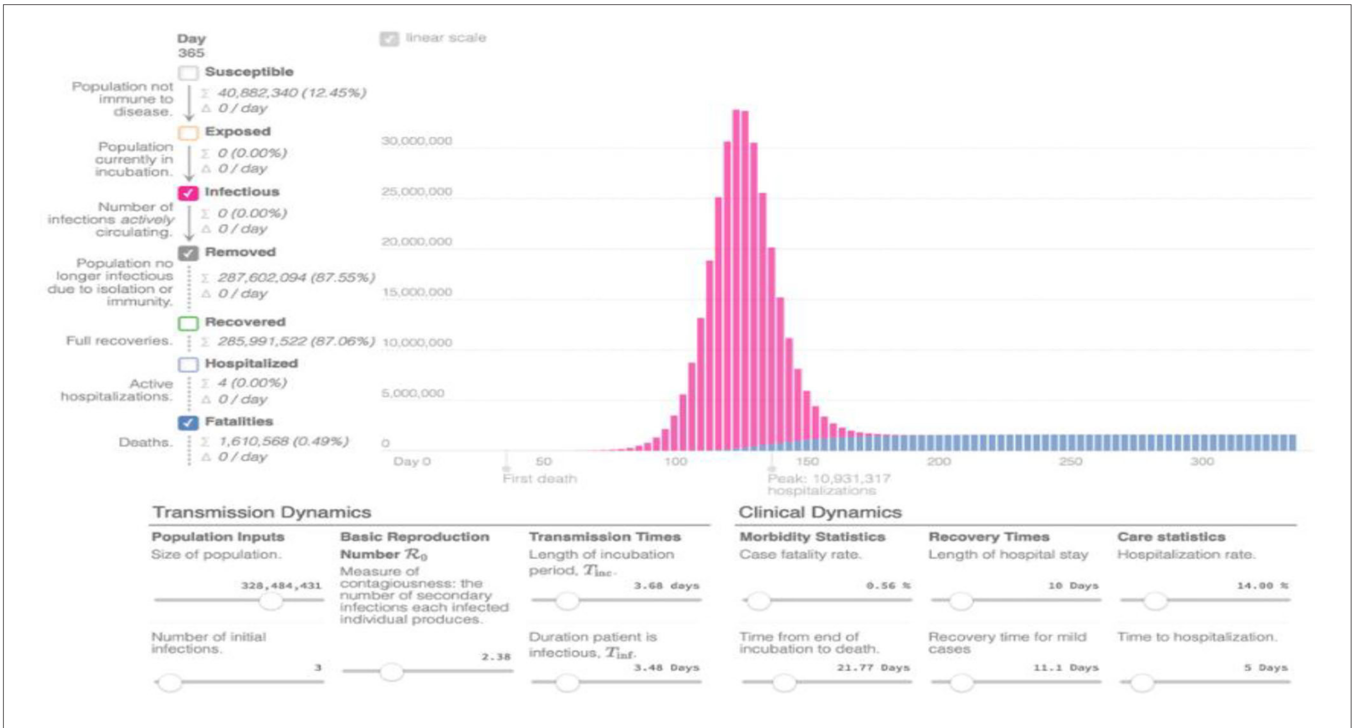

FIGURE 3 | Graph of cases projected in response to the influence model [Source (24)].

TABLE 1 | SARS (2002 Q1–2004 Q4): LME vs. CME Nations.

	LME		CME	
	Fixed effect	**Random effects**	**Fixed effect**	**Random effects**
Hours worked in a week	0.0224749	**−0.148513**	0.2416416	0.1001597
	[0.1259515]	[0.0495946]	[0.2235569]	[0.2049271]
Unemployment rate	−0.0556879	−0.0595368	−0.0046404	0.0715892
	[0.091426]	[0.0773679]	[0.085952]	[0.068064]
Inflation rate (CPI)	−0.1355335	−0.1040501	−0.0962139	−0.0392919
	[0.108938]	[0.083778]	[0.2129351]	[0.2152652]
Investment GFCF	0.030037	0.1673616	0.1673616	0.175525
	[0.024467]	[0.0239144]	[0.1108818]	[0.1140778]
Constant	0.7112889	**6.755407**	−8.294725	−4.333864
	[4.470376]	[2.569059]	[8.511295]	[8.260209]
R squared	0.6364	0.8224	0.2718	0.2034
Hausman test statistic	**17.04**		1.94	

Tables in BOLD reflect statistical significance at 95% level of significance.

Australia, Brazil, Spain, and the USA and was contained by July 2003. Approximately 10,000 people were infected, out of which 10% died, and the impact of SARS was devastating on the infected people's health (16). SARS also had an economic impact that became a global concern as major industries involving the gathering of people in public places such as restaurants, travel and tourism, entertainment, and retail establishments.

Various estimations and models anticipated the impact of SARS and the analysis reflected that the influence of SARS on the economies was catastrophic, especially in east Asian and Canadian economies. SARS had a major impact on the investment, retail and tourism industries of China and Hong Kong, making them the most affected areas. China and Hong Kong experienced a significant death toll as well as large short-term economic losses.

These losses corresponded to a short time after which the consumer confidence was restored and many stocks were replenished. The economic consequences of SARS in terms of health expenditure and demographic impacts are small compared to epidemics' economic consequences like HIV/AIDS or malaria.

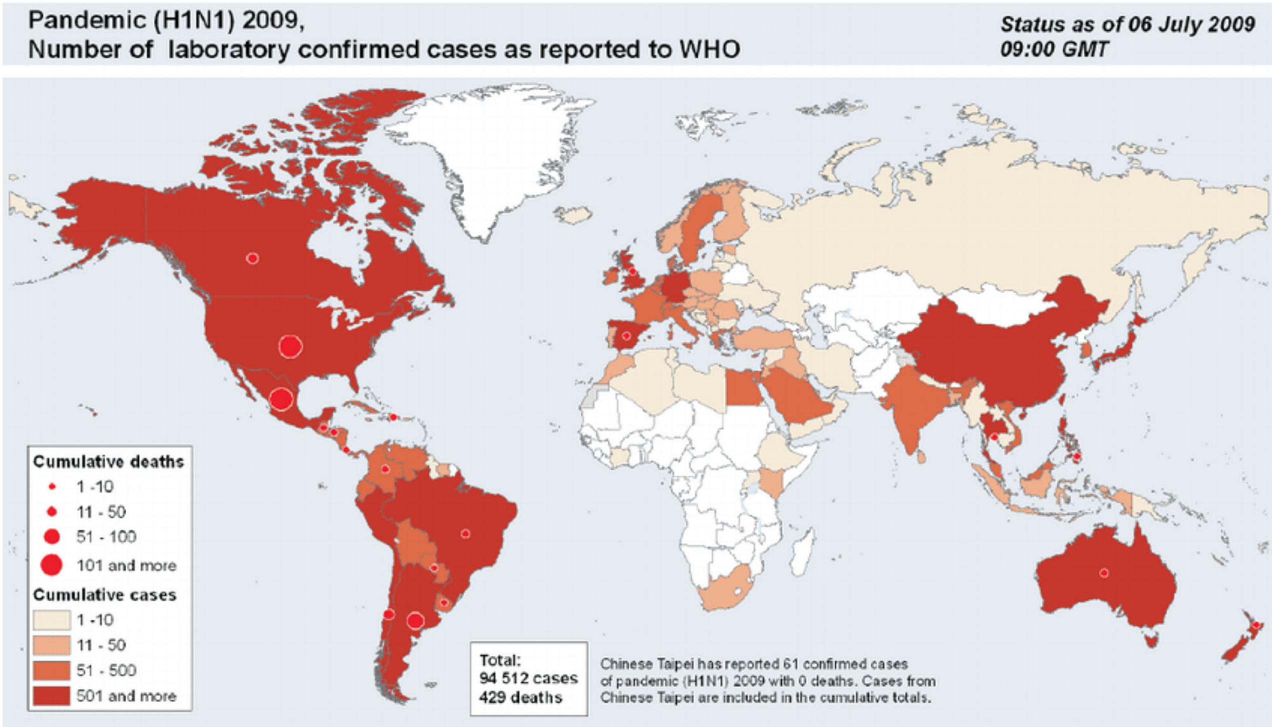

FIGURE 4 | Graph showing the impact of H1N1 pandemic all over the world.

The SARS epidemic was declared over within a year (17). The disease SARS' economic consequences have more indirect damages than direct damages in the affected areas and sectors, as shown in **Figure 3**. This evidence is because the disease spread quickly across the countries, impacting the residents' health, and the economy was also devastated due to trade and financial linkages among the countries. The economic costs include the private and government medical expenses associated with the disease to diagnose and treat the disease, the cost to sterile environments, take preventive measures and invest in basic research. Due to non-working days lost due to illness or mortality/morbidity, the income foregone is also counted as the epidemic's cost. The foregone income is the capitalized value of future earnings, which is lost because of the deaths and illnesses caused by the disease. Apart from the decline in consumer demand, investments in many sectors have also been impacted. The cost of disease prevention is another economic cost. The global economic impact is enormous because of the transmission of the disease.

We first examine the impact of the SARS outbreak on the UK, Australia, Canada, and New Zealand economies, which can be seen in the first panel of **Table 1**. Here as is evident, the regression model had an r-squared coefficient of 0.6364, which implies that ∼63.64% of the changes in the dependent variable, economic growth, are explained by the changes in the other macroeconomic variables under consideration. Further, it can be noted that in the case of the LMEs that the rate of unemployment and rate of inflation negatively impacted the economic growth. In contrast, the labor force's average hours and the government's investments positively impacted the level of economic growth. However, changes if we move from a fixed-effects model to a random-effects model of economic growth wherein the average hours worked in a week can be seen to have a negative relationship with the level of economic growth. Based on the Hausman test results, which is performed for the null hypothesis that the random-effects model results are more suitable, it can be deciphered that since the test result is statistically significant, we chose the fixed effects model 95% confidence.

Likewise, the second panel reflects the same model constructed in the CMEs, Japan, Germany, and Sweden to gauge the SARS outbreak's impact. It starts with the r-squared coefficient of 0.2718, reflecting that 27.18% of the dependent variable changes, economic growth, are explained by the changes in the other macroeconomic variables under consideration. Further, it can be noted that in the case of the CMEs, the rate of unemployment and rate of inflation negatively impacted the economic growth. In contrast, the labor force's average hours and the government's investments positively impacted the level of economic growth. However, changed in the random-effects model for the CMEs wherein only the inflation rate negatively impacted economic growth. Based on the Hausman test results, the test estimate is statistically insignificant, making the random effects model more suitable for the CMEs.

TABLE 2 | H1N1 Swine Flu (2009 Q1–2010 Q4): LME vs. CME Nations.

	LME		CME	
	Fixed effect	**Random effects**	**Fixed effect**	**Random effects**
Hours worked in a week	**0.6525314**	**0.0553695**	**0.6543426**	**0.4723728**
	[0.254869]	[0.0761379]	[0.2675615]	[0.1857754]
Unemployment rate	**−0.2074054**	**−0.2199893**	0.0485426	**0.1136841**
	[0.05994]	[0.0574449]	[0.1252462]	[0.0419675]
Inflation rate (CPI)	**0.4279377**	**0.4722499**	0.1117892	0.3471743
	[0.214858]	[0.209494]	[0.384277]	[0.3097005]
Investment GFCF	**0.3413916**	**0.3655099**	**0.4214208**	**0.431975**
	[0.037242]	[0.0371364]	[0.1087446]	[0.1052326]
Constant	**−21.16356**	−0.1264334	**−24.46609**	**−18.8801**
	[9.12589]	[2.907771]	[9.030853]	[7.163458]
R squared	0.6485	0.4107	0.325	0.7187
Hausman test statistic	**13.26**		1.34	

Tables in BOLD reflect statistical significance at 95% level of significance.

TABLE 3 | COVID 19 (2019 Q1–2020 Q2): LME vs. CME Nations.

	LME		CME	
	Fixed effect	**Random effects**	**Fixed effect**	**Random effects**
Hours worked in a week	**1.27869**	**−0.0104511**	**1.401871**	**1.103879**
	[0.369166]	[0.0701911]	[0.434022]	[0.3162875]
Unemployment rate	**−0.6886533**	**−0.8512298**	−0.0284523	0.0332361
	[0.0594945]	[0.0685536]	[0.3330152]	[0.0425666]
Inflation rate (CPI)	**0.4554238**	0.3974084	1.846953	**2.58637**
	[0.2853351]	[0.3771379]	[1.253874]	[0.7055796]
Investment GFCF	**0.3532495**	**0.3952025**	**1.088862**	**1.024693**
	[0.0212801]	[0.0279858]	[0.1760394]	[0.1625048]
Constant	**−37.37288**	**9.344054**	**−52.10929**	**−42.97107**
	[13.10738]	[2.968868]	[16.9909]	[11.94268]
R squared	0.3243	0.9154	0.0419	0.9357
Hausman test statistic	**10.59**		1.3	

Tables in BOLD reflect statistical significance at 95% level of significance.

Impact of the H1N1 Swine Flu Outbreak

In his book "Against Empire," Michael Parenti says that "The essence of capitalism is to turn nature into commodities and commodities into capital. The live green earth is transformed into dead gold bricks, with luxury items for the few and toxic slag heaps for the many." As we know now, the world has evolved with each pandemic or invention it had to face, good or bad, as shown in **Figure 4**. From time immemorial, disasters like the Great Fire of London in 1666, the Galveston hurricane, the sinking of the Titanic in 1912 and diseases like the Bubonic plague and very recently the Coronavirus pandemic, all have had their fair share of impact on the capitalistic economy (18).

It is no jargon when one says that a pandemic can leave a nation extremely handicapped and stripped raw, especially when observed in industry evaluation and equity analysis. Speaking specifically in terms of the H1N1 Swine Flu, which was caused by a strain of the influenza virus commonly found in pigs and having symptoms mirroring influenza, the disease saw a huge economic recession post it's spread, which entailed a severe crash in the stock market values of industries, crashing established policies, to name a few. The idea behind smart investments, like that in Gold, was then tested. Despite thinking tanks at work constantly designing mathematical models that predict and theories that considered almost all the permutations and combinations of the possible worst-case scenarios, some economic shocks surfaced. The following are the effect of H1N1 on a capitalistic economy.

- There was a surge in demand for hospital and other medical services.
- There was a temporary upsurge in sick leave and school closures requiring the withdrawal of working-class parents.
- There were unprecedented deaths with a corresponding permanent reduction in the labor force.

- There was a cap on international tourism and business travel.
- Poverty in developing counties and the quality of health care systems in these economies make it harder for them to recover from big losses (19).

From this, will it be safe to conclude that outbreaks such as these break the system irrevocably, and nothing can be done about it? Not. A quick observation will not leave us privy to the fact that these pandemics have strengthened the global health system by urging the authorities in many countries to develop pandemic response plans, each more responsive and flexible than the last, an idea which has successfully been backed by WHO. Although these pandemics come as a massive shock initially and are extremely significant, all economies must understand that it is over relatively quickly if all the forces above come into play.

The current section presents the differences between the impact of changes in the various sectors and facets of the economy, as triggered by the disease outbreak on the economic growth of the coordinated market economies and liberal market economies. We first examine the impact of the H1N1 outbreak on the UK, Australia, Canada, and New Zealand economies, which can be seen in the first panel of **Table 2**. Here the goodness of fit of the regression model can be interpreted through its r-squared coefficient of 0.6485, which implies that ∼64.85% of the changes in the dependent variable, economic growth, are explained by the changes the other macroeconomic variables as caused by the spread of H1N1 virus. Further, it can be noted that in the case of the LMEs that the rate of unemployment negatively impacted the economic growth. In contrast, the labor force's average hours and the government's investments positively impacted the economic growth level—the nature of the random-effects model's relationship. Based on the Hausman test results, it can be deciphered that since the test result is statistically significant, we chose the fixed effects model with 95% confidence.

Likewise, the second panel reflects the same model constructed in the context of the CMEs, Japan, Germany, and Sweden to gauge the impact of the H1N1 outbreak. In the case of the CMEs, the independent variables, including unemployment rate, weekly hours worked, inflation rate and investments made by the government, positively impacted the economic growth during the H1N1 virus outbreak. This evidence did not change in the random-effects model for the CMEs, which held similar relationships. Based on the Hausman test results, the test estimate is statistically insignificant, making the random effects model more suitable for the CMEs.

We now move forth to examining the nature of issues being faced due to the COVID 19 crisis.

Impact of the COVID 19 Outbreak

Covid-19 has impacted the societies in far more ways than impacting the health of the affected. It is affecting the societies as well as the economies at the core. The impact of the pandemic is severe and vary from country to country. It is likely to increase the economic costs among nations and increase the inequalities at a global level (20). The pandemic has disrupted the lives of people and affected world trade and movements, as seen in **Table 3**. At this stage, the pandemics negatively affect the manufacturing sector. Various industries and sectors have slowed down because of the disease, such as tourism, pharmaceutical industry, solar power sector, information, and electronics industry. There have been short-term challenges like a halt in tourism and entertainment and long-term consequences such as disruptions in trade and investments (21). The disease has extensive consequences on the healthcare, economic, and social sector.

Healthcare Impact

The healthcare sector faces challenges in the pandemic regarding diagnosis, treatment, and disease prevention. The medical system's functioning has become a burden, and patients with other medical problems are getting neglected. The lives of doctors and other health professionals are at very high risk. Pharmaceutical shops are overloaded, and the medical supply chain is disrupted.

Economic Impact

Due to the lockdown and the risk of spreading the disease, the manufacturing of essential goods has slowed down. The supply chain of products has been disrupted, and national and international businesses face losses (22). The cash flow in the market is poor, slowing down the revenue growth in the economy. Millions of workers have lost their jobs as industries have shut down. The GDP of many economies have also been impacted due to production in industries being disrupted.

Social Impact

The society has been impacted in a lot of ways. The service sector has not been able to serve people due to the unavailability of products. Large-scale events and sports tournaments have been postponed or canceled to avoid public gatherings. National and international traveling has been banned, and cultural and religious events have also been disrupted. There has been witnessed undue stress among people as they have to maintain social distancing from peers, family, and friends. The closure of hotels, restaurants, and cinemas has also disrupted the lives of people. The education industry has also been impacted in many ways, such as postponement of examinations and class cancellation.

As can be seen from **Figure 5**, the incidence of deaths caused by COVID-19 increased monumentally since the onset of the second quarter of 2020, which forced the governments to venture forth with the idea of nationwide lockdowns.

We examine the nature of the relationship between macroeconomic variables and the economic growth triggered by the Coronavirus outbreak. Here, it can be noted that in the case of the LMEs that the rate of unemployment negatively impacted the economic growth. In contrast, the labor force's average hours, rate of inflation and the government's investments positively impacted economic growth. However, if we move from a fixed-effects model to a random-effects economic growth model wherein the average hours worked in a week can negatively affect economic growth and the unemployment

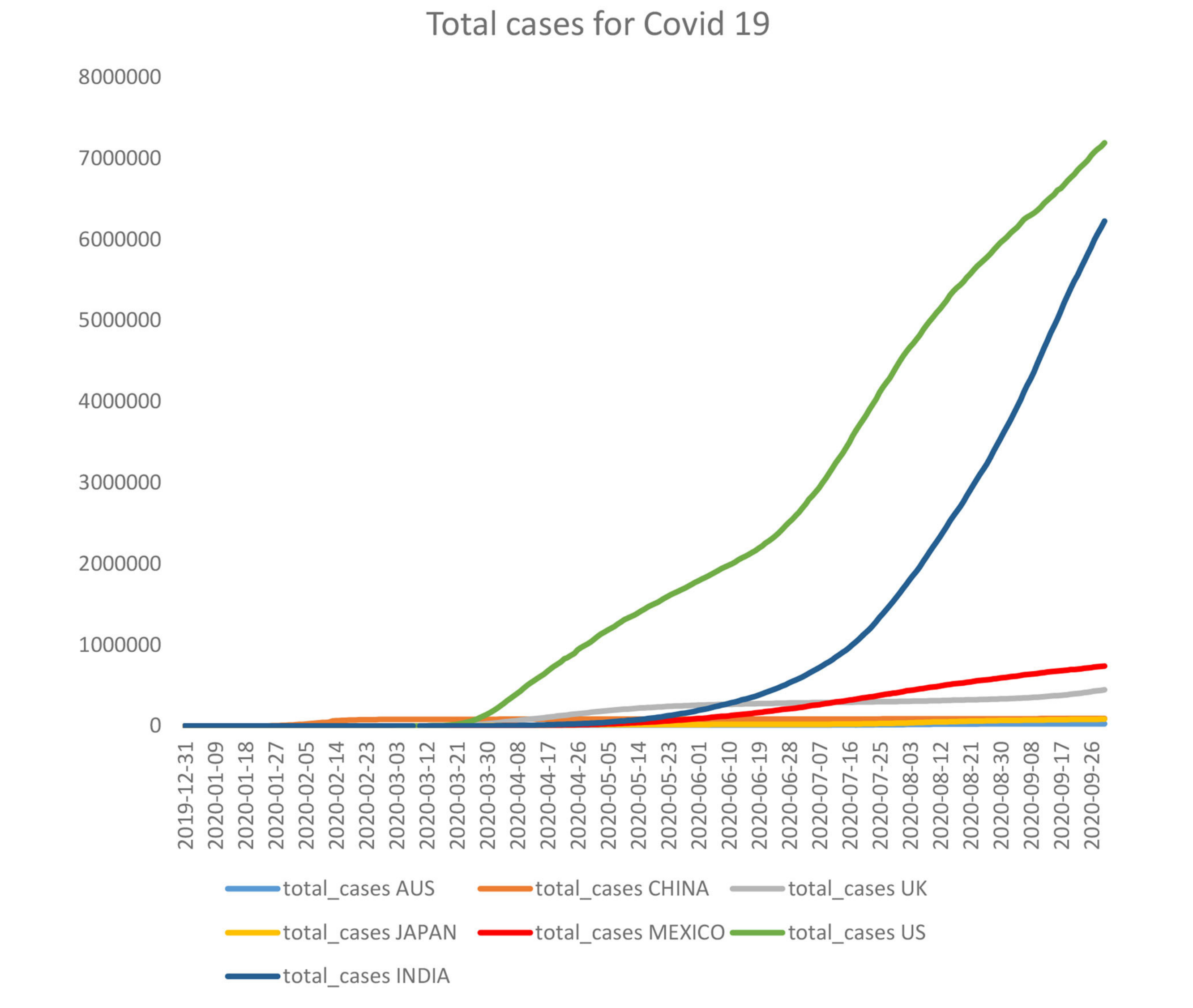

FIGURE 5 | Number of deaths caused by COVID-19 (Source: self-generated).

rate. Based on the Hausman test results, it can be deciphered that since the test result is statistically significant, we chose the fixed effects model with 95% confidence. In the case of the impact of coronavirus spread in the CME economies, every macroeconomic variable, including unemployment, average hours worked, inflation rate, and government investments, positively impacted economic growth. This evidence is changed in the random-effects model for the CMEs wherein only the inflation rate negatively impacted economic growth. Based on the Hausman test results, the test estimate is statistically insignificant, making the random effects model more suitable for the CMEs.

Thus, it can be deciphered that considerable differences exist in how the economies are affected by the disease outbreaks. The LME economies, including the UK, Canada, and Australia sample, reflected that the unemployment rate and inflation rate negatively impacted economic growth. In contrast, government investment positively impacted the economic growth, as was expected. On the other hand, in the CME economies, the variables all positively related to the economy's economic growth. This evidence can be explained by the intrinsic nature of the coordinated market economies wherein the issues faced by the businesses are resolved by the government institutions (25). Thus, as the governments control the macro variables, the shocks presented by the events like disease outbreaks do not impact the nation's economic growth. This finding explains the positive relationship between the macroeconomic variables and economic growth. This issue is different in the case of the Liberal market economies, wherein the market forces act together to determine the macro variables' flow.

CONCLUSION

As the disease outbreaks occur, they stand to impact various facets of the economy, including the capital markets, labor markets, foreign trades, and the consumption and production sectors. The current study sought to examine the impact of the disease outbreaks like the current coronavirus pandemic on the economy, differentiated by the varieties of capitalist structures. The data analysis included the assessment of the impact of the SARS virus, H1N1 virus and the COVID19 virus, computed in the context of the coordinated market economies of Germany, Sweden, and Japan and liberal market economies of Australia, New Zealand, the United Kingdom, and Australia. The analysis revealed that the LME economies were more responsive to the impact of the disease outbreaks than the CME economies, wherein the government involvement moderated the disease's impact. This evidence allows us to conclude that increasing government authorities' involvement can moderate the disease outbreaks' impact.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

YS: conceptualization, methodology, formal analysis, writing—original draft preparation, project management, and funding acquisition. HL: conceptualization, methodology, writing—original draft preparation, and funding acquisition. RZ: methodology, writing—review, and editing. All authors have read and agreed to the published version of the manuscript.

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REFERENCES

1. Verikios G. The dynamic effects of infectious disease outbreaks: the case of pandemic influenza and human coronavirus. *Socio Econ Plann Sci.* (2020) 71:100898. doi: 10.1016/j.seps.2020.100898
2. World Health Organization. The world health report 2004: changing history. *J Interprof Care.* (2004) 21:1–2.
3. Henderson, R. Reimagining capitalism in the shadow of the pandemic. *Harvard Business Review*. (2020). Available online at: https://hbr.org/2020/07/reimagining-capitalism-in-the-shadow-of-the-pandemic (accessed September 26, 2020).
4. French N. How capitalism kills during a pandemic. *Jacobin*. (2020). Available online at: https://www.jacobinmag.com/2020/03/capitalism-pandemic-coronavirus-covid-19-single-payer (accessed September 26, 2020).
5. Perry J, Sayndee TD. *Social Mobilization and the Ebola Virus Disease in Liberia.* Rowman & Littlefield (2016).
6. Thelen K. Varieties of capitalism and business history. *Business Hist Rev.* (2010) 84:646–8. doi: 10.2307/27917300
7. Huber E, Petrova B, Stephens JD. *Financialization and Inequality in Coordinated and Liberal Market Economies.* LIS Working papers (2018).
8. McLaughlin C, Wright CF. The role of ideas in understanding industrial relations policy change in liberal market economies. *Indus Relat J Econ Soc.* (2018) 57:568–610. doi: 10.1111/irel.12218
9. Horner R. Towards a new paradigm of global development? Beyond the limits of international development. *Progress Hum Geogr.* (2020) 44:415–36. doi: 10.1177/0309132519836158
10. Abrams EM, Szefler SJ. COVID-19 and the impact of social determinants of health. *Lancet Respir Med.* (2020) 8:659–61. doi: 10.1016/S2213-2600(20)30234-4
11. Anner M. *Abandoned? The Impact of Covid-19 on Workers and Businesses at the Bottom of Global Garment Supply Chains.* (2020).
12. Barrientos S. *Gender and Work in Global Value Chains: Capturing the Gains?* Cambridge: Cambridge University Press (2019).
13. Brooks R, Ribakova E, Lanau S, Fortun J, Hilgenstock B. *Capital Flows Report: Sudden Stop in Emerging Markets.* Washington, DC: Institute of International Finance (2020). Available online at: https://www.iif.com/Portals/0/Files/content/2_IIF2020_April_CFR.pdf (accessed September 18, 2020).
14. Kentikelenis A, Gabor D, Ortiz I, Stubbs T, McKee M, Stuckler D. Softening the blow of the pandemic: will the International Monetary Fund and World Bank make things worse? *Lancet Global Health.* (2020) 8:e758–9. doi: 10.1016/S2214-109X(20)30135-2
15. Huang Y, Sun M, Sui Y. How digital contact tracing slowed Covid-19 in East Asia. *Harvard Business Review*. (2020). Available online at: https://hbr.org/2020/04/how-digital-contact-tracing-slowed-covid-19-in-east-asia (accessed September 18, 2020).
16. Keogh-Brown MR, Smith RD. The economic impact of SARS: how does the reality match the predictions? *Health Policy.* (2008) 88:110–20. doi: 10.1016/j.healthpol.2008.03.003
17. Lee JW, McKibbin WJ. Estimating the global economic costs of SARS. In: *Learning From SARS: Preparing for the Next Disease Outbreak: Workshop Summary*. Washington, DC: National Academies Press (2004). p. 92–109.
18. Verikios G, Sullivan M, Stojanovski P, Giesecke J, Woo G. *The Global Economic Effects of Pandemic Influenza.* (2011).
19. Mckibbin W. *The Swine Flu Outbreak and Its Global Economic Impact*. (2009). Available online at: https://www.brookings.edu/on-the-record/the-swine-flu-outbreak-and-its-global-economic-impact/ (accessed 9 May 2020).
20. Sumner A, Hoy C, Ortiz-Juarez E. *Estimates of the Impact of COVID-19 on Global Poverty.* WIDER Working Paper Series (2020).
21. Walker P, Whittaker C, Watson O, Baguelin M, Winskill P, Hamlet A, et al. The impact of COVID-19 and strategies for mitigation and suppression in low- And middle-income countries. *Science.* (2020) 369:eabc0035. doi: 10.1126/science.abc0035
22. Bartik AW, Bertrand M, Cullen Z, Glaeser EL, Luca M, Stanton C. The impact of COVID-19 on small business outcomes and expectations. *Proc Natl Acad Sci USA*. (2020) 117:17656–66. doi: 10.1073/pnas.2006991117

23. Lee Y. 4 charts show how SARS hit China's economy nearly 20 years ago. *China Economy*. (2020). Available online at: https://www.cnbc.com/2020/02/11/coronavirus-4-charts-show-how-sars-hit-chinas-economy-in-2003.html (accessed September 4, 2020).
24. Rossman J. *Coronavirus: What the 2009 Swine Flu Pandemic Can Tell Us About the Weeks to Come*. (2020). Available online at: https://theconversation.com/coronavirus-what-the-2009-swine-flu-pandemic-can-tell-us-about-the-weeks-to-come-134076 (accessed October 24, 2020).
25. Ebner A. Varieties of capitalism and the limits of entrepreneurship policy: institutional reform in Germany's coordinated market economy. *J Indus Competition Trade*. (2010) 10:319–41. doi: 10.1007/s10842-010-0086-x

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Pandemic Uncertainty and Socially Responsible Investments

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This paper examines the effects of pandemic uncertainty on socially responsible investments. We use the overall corporate sustainability performance index in the *Global-100 Most* Sustainable Corporations in the World dataset to measure socially responsible investments. The global pandemic uncertainty is also measured by the World Pandemic Uncertainty Index. We focus on the panel dataset from 2012 to 2020, and the results show that the World Pandemic Uncertainty Index is positively related to socially responsible investments. The main findings remain significant when we utilize various panel estimation techniques.

Keywords: pandemics uncertainty, COVID-19 pandemic, COVID-19 uncertainty, socially responsible investments, panel data estimators

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INTRODUCTION

Socially responsible investment (henceforth SRI) on the stock market means investment strategies that combine social and environmental benefits with financial return. It links many investors' issues, such as social issues, ethical issues, ecological issues, economic issues, etc. Several papers have investigated the difference in financial performance between conventional funds and SRI funds. Some of these studies found no significant difference in the SRI funds' performance among conventional market indices in developed markets, such as those in Australia and Canada (1, 2). However, other results point toward findings that demonstrate significant differences in the SRI portfolios' performance compared to the benchmark market indices. For instance, Brzeszczynski and McIntosh (3) found that the annual average returns of the SRI portfolios (with dividends) were 5.26 and 5.69% higher relative to the benchmarks the Financial Times Stock Exchange (FTSE) 100 and the FTSE4GOOD indices (in their total return versions), respectively. However, the Fama–French–Carhart multifactor models' estimations showed that the SRI portfolio's return needs to consider more factors and cannot always be explained by traditional factors other than market factors. These findings provide new ideas for future research on the SRI stock returns and the SRI portfolios' explanatory factors.

There is another related stream of research that has mainly paid attention to investigating the types of intra-regional transmission and inter-regional transmission of information across stock markets. In the study, researchers have to use stock market indices data to understand the global channels of information transmission across markets worldwide [see, e.g., (4)]. Nevertheless, a small study has been conducted concerning different behavioral finance indicators in the SRI investments. Several research gaps are still needed for promotion. Over time, corporate social responsibility (CSR) investments have become a very important issue, which is of great significance to stock market investors and policymakers because it enhances their understanding of financial markets' interconnectedness (5). In portfolio investment, investors are more inclined to choose social responsibility companies and pay more attention to ethical investment.

We motivate these issues and aim to examine the effects of pandemic-related uncertainties on socially responsible investments. Unlike previous papers, we control pandemic-related uncertainty effects to capture the role of uncertainty on the socially responsible investments nexus.

On the one hand, for factors considered by socially responsible investors for enterprises, Rosen et al. (6) indicated that more individuals and institutions are inclined to invest in companies to support society, which has become a growing trend regarding corporate social responsibility. However, these investors are not willing to sacrifice too much financial return to achieve this even if they value the socially responsible behavior of the companies they invest in Campbell (7). For instance, Kadiyala (8) stated that a typical SRI portfolio shows that the SRI funds can serve as a relatively safe haven during high-risk aversion periods. Still, the evidence supporting this claim is weak in this literature. All in all, the authors show that the continued demand for the SRI funds cannot be attributed solely to purely altruistic motives. Vickman et al. (9) pointed out that uncertainty is considered one-factor affecting investment, and investors need to consider this before making an informed decision. At the same time, contingent and perceived uncertainties need to be taken into account in dealing with finance and other aspects of investment. The combination of macro variables and micro variables creates a more three-dimensional environment in which the valuation methodology provides a framework for the SRI accounting. Berry and Junkus (10) collected many individual investors' independent data and exploited them to infer individual investors' attitudes toward the SRI. It is found that whether investors are inclined to the CSR investments or not, environmental issues are listed as the most important issue.

On the other hand, regarding the CSR investments in the uncertain market environment, Godfrey (11) presented that moral capital can provide shareholders with intangible assets protection similar to insurance, which is based on relationships and helps increase shareholders' wealth. Yanjun and Yong (12) focused on enterprises with negative events as research objects to discuss how to maintain a corporate reputation and how to protect shareholders' wealth in a crisis and expands the research on the role of corporate social responsibility reputation insurance. Take advertising expenditure as an example; Servaes and Tamayo (13) found that enterprises' social responsibility with high customer awareness is positively correlated with enterprise value. Simultaneously, it is pointed out that in the enterprises with poor corporate citizenship reputation, the impact of discovery consciousness on the relationship between the CSR investments and value is the opposite. This view is consistent because corporate social responsibility activities can increase enterprises' value under certain circumstances. Jihui et al. (14) showed that the transfer of funds during market uncertainty has positive economic consequences on corporate social responsibility information and security investment. The fund's safe investment transfer improves the fund's performance and stability and is of great significance for protecting investors' interests. Many studies have shown that the CSR reputation can protect investors' interests and has a certain impact on corporate value.

Additionally, concerning corporate governance during a pandemic, at the beginning of 2020, the new global epidemic had a significant impact on people's way of production and life and a comprehensive impact on people's moral values. It will also have a great impact on the concept and practice of corporate social responsibility. Gefei (15) put forward seven changes brought about by the epidemic to the CSR investments, including the responsibility of employees in basic positions becoming an important focus for enterprises to fulfill their social responsibility in the future, companies paying more attention to reducing negative impacts on the economy, society, and the environment, or avoiding secondary social responsibility problems in solving urgent problems and so on. At this stage, several papers have pointed out changes in the role of business in society during the epidemic. For instance, Zhen et al. (16) said that enterprise is not only important to market entities, promoting the development of high quality in the new period, because of their economic properties and microstructure but can effectively participate in public social management and promote the progressive development of the national systems of governance. Therefore, the enterprise should take social responsibility, and this issue has become part of the COVID-19 era.

There are previous papers that examine the determinants of SRI during the COVID-19 era. For instance, Huo et al. (17) indicated that the spreading threat of COVID-19 could be reduced by researching corporate social responsibility activities and the corresponding measures. Much of the literature has pointed out that social responsibility should be integrated into the corporate governance structure and become the bottom line of enterprise operation during pandemics, including COVID-19. Brammer et al. (18) discussed socially disruptive extreme events, such as the COVID-19, and argued they significantly affect the role of business in the United States. Crane and Matten (19) also indicated that the COVID-19 pandemic has significantly changed the CSR concepts and practices, including its political economy, societal risk, stakeholders, and supply chain responsibility. Garcia-Sanchez and Garcia-Sanchez (20) used the data of the large Spanish companies to determine the objectives of the companies during the COVID-19 pandemic. The authors found that several firms protected the interests of shareholders and investors. Na et al. (21) also discussed the performance of the dilution of corporate social responsibility. It is suggested that enterprises should strengthen the correct values and so on, and guide enterprises to balance profit orientation and social responsibility. He and Harris (22) also discussed several ways in which COVID-19 will change the CSR. Particularly, marketing behavior is significantly affected by the COVID-19 pandemic.

Given this background, we examined the effects of pandemic-related uncertainty on CSR investments. Our main hypothesis is that uncertainty related to the pandemics are positively associated with CSR investments. To the best of our knowledge, ours is the first paper to examine the effects of pandemic-related uncertainty on CSR investments. For this purpose, we used the World Pandemic Uncertainty Index (WPUI) of Ahir et al. (23). We found that the WPUI is positively related to CSR investments.

TABLE 1 | Description of summary statistics.

Variables	Observation	Mean	Std. Dev.	Min.	Max.
World Pandemic Uncertainty Index (WPUI)	693	0.0638	0.0993	0.0000	0.3894
Corporate Social Responsibility (CSR) Index (Overall Score)	693	0.5922	0.0931	0.1042	0.8519

The remainder of the study is organized as follows. **Data, Model, and Methodology** section defines the data, sets the empirical model, and explains the methodology. **Empirical Results** section discusses the empirical results. **Conclusion** section concludes.

DATA, MODEL, AND METHODOLOGY

Data

This study used the 'Global-100 Most Sustainable Corporations in the World' dataset, which is available at (*www.global100.org*). We selected the world's top 100 SRI companies from the list to analyze the relationship between the "overall score" and the pandemic uncertainty from 2012 to 2020. The selection of the period is related to the data availability. The overall score is based on the annual ranking of corporate sustainability performance (CSP). The ranking is based on publicly disclosed data (e.g., financial filings and sustainability reports). The "overall score" commutation is based on 17 key performance indicators (KPIs), such as clean revenue, covering resource, employee, financial management, and supplier performance. The detailed methodology can be accessed from *https://www.corporateknights.com/reports/2021-global-100/2021-global-100-ranking-16115328/*.

The list of the 'Global-100 Most Sustainable Corporations in the World' is a new and unique data set that has never been used in previous research. It was published every January before the World Economic Forum (WEF) at Davos. This list was initiated by Corporate Knights Inc. We used this list because it classifies international CSR companies. These companies make a list because they have demonstrated better ability and better corporate ethics than their peers to identify and effectively manage factors such as physical environment and social governance. Overall, we use the overall index of the CSP as the dependent variable in the panel data estimations. We focused on the country of the corporations.

Moreover, the "World Pandemic Uncertainty Index" is obtained from Ahir et al. (23). The dataset is downloaded from the website https://worlduncertaintyindex.com/data/. We use the aggregate World Pandemic Uncertainty Index (WPUI). The original data are provided for 143 countries from 1996 to 2020. The original dataset is defined at quarterly frequencies. We use the annual frequency data, which is the sum of the quarterly WPUI values. The WPUI index is created by counting the number of times uncertainty is mentioned within proximity to a word related to pandemics in the Economist's Economist Intelligence Unit (EIU) country reports. At this point, the WPUI is the percentage of the word that is "uncertain," and the variant words related to uncertainty are related to the pandemic terms in the EIU country reports. The ratio has been multiplied by 1,000. It is important to note that a greater value of the WPUI indicates a higher level of uncertainty related to pandemics and vice versa (23).

Model and Estimation Methodology

The relationship between the Corporate Sustainability Performance (CSP) index and the World Pandemic Uncertainty Index (WPUI) is based on the fixed-effect estimations. The baseline model can be specified as follows:

$$CSP_{i,t} = \alpha_i + \beta WPUI_{i,t} + \theta_t + \varepsilon_{j,t}\ (1) \tag{1}$$

where α_j is the country-fixed effects, and θ_t is the time fixed-effects. $\varepsilon_{j,t}$ is a random error term. We estimate models with robust standard errors, which are clustered at the country level as errors may be correlated within countries. Along with the fixed-effects estimations, we also consider the Ordinary Least Squares (OLS) and the random-effects estimations. **Table 1** shows the summary statistics.

The cross-sectional dependence may be a problem, so the null hypothesis in the Lagrange Multiplier (LM) test of independence is that residuals across entities are not correlated and tested. The p-value is <0.05, so we need a model with cross-sectional dependence.

However, if we found evidence of the cross-sectional dependence in the panel dataset, we need to apply heterogeneous panel estimators as follows.

At this stage, we estimate the following simple model: for $i = 1, \ldots, N$ and $t = 1, \ldots, T$ let

$$CSP_{it} = \beta_i WPUI_{it} + u_{it} \tag{2}$$

$$where\ u_{it} = \alpha_{1i} + \lambda_i f_t + \varepsilon_{it} \tag{3}$$

$$WPUI_{it} = \alpha_{2i} + \lambda_i f_t + y_i g_t + e_{it} \tag{4}$$

where WPI and TS_{it} are observable variables, β_i is a country-specific slope of an observable regressor, and u_{it} captures the unobservable variables. The error term is denoted by ε_{it}. Note that ε_{it} and e_{it} are assumed to be a white noise process. The unobservable variables in Eq. 3 are defined by the country fixed-effects and α_{1i}, captures the time-invariant heterogeneity across the countries and an unobserved common factor f_t with the heterogeneous factor loadings. At this stage, λ_i captures the time-variant heterogeneity across the countries, and it models possible cross-section dependence.

It is important to note that the factors f_t and g_t are not only based on the linear approach over the period under concern. These factors can also be non-linear and non-stationary, with certain implications for possible cointegration analysis. At this stage, we implement various unit root tests with structural breaks. We observe the variables' stationarity. However, some biases can occur because the regressors are driven by several common factors in the observable variables. That is, the presence of f_t in Eqs 3, 4 provides potential endogeneity in the estimations as was indicated by Coakley et al. (24) and Eberhardt and Teal (25). We also use the Common Correlated Effect Mean Group (CCEMG) estimator of Pesaran to solve this potential endogeneity problem (26).

EMPIRICAL RESULTS

Table 2 reports results for the OLS (Column 1), the fixed-effects (Column 2), and the random-effects (Column 3). The OLS result shows that there is a positive relationship between CSR and the WPUI. At this stage, these results are the same with either the fixed-effects and the random effects. The p-value for the Hausman test is 0.0523; therefore, the fixed-effects method was used as the benchmark model in the analysis. To see if the time fixed-effects are needed, we performed a joint test to see if the dummies for all years are equal to 0. If they are, then no time fixed-effects are needed. We rejected the null that the coefficients for all years are jointly equal to zero (as p-value is 0); therefore, the time fixed-effects are needed in this case (see **Table 2**, Column 4). The coefficient for the WPUI is 1.078, indicating that the WPUI increase by 1 unit leads to a 1.078 unit increase in the CSR (see **Table 2**, Column 4).

Because the cross-sectional dependence was found therefore we perform a panel test with cross-sectional dependence, and the results are presented in **Table 3**. We also performed the slope homogeneity test in panels following Pesaran and Yamagata (27). The null hypothesis of the test is homogenous slopes, implying that all slope coefficients are identical across cross-sectional firms. However, the test statistics showed a value of −5.79, implying that all slope coefficients are not identical across the cross-sectional firms.

However, the OLS, the fixed-effects, and the random-effects estimations can be biased due to the heterogeneous slope coefficients. As the robustness is checked, we implement several panel time-series estimators that allow for heterogeneous slope coefficients across group members and correlate with panel members. Column 1 in **Table 3** reports the Pesaran and Smith's (28) Mean Group Estimator (MGE) with each group-specific regression to be augmented with a linear trend term. Column 2 in **Table 3** constructs the coefficient weighted averages across panel members following the weighting method in Verardi and Croux (29). Finally, Column 3 in **Table 3** implements the Pesaran (26) CCEMG estimator (26). The result indicates that the WUPI increase by 1 unit leads to a 0.119-unit increase in TS (see **Table 3**, Column 3).

TABLE 2 | Results of the fixed-effects and the random-effects estimations.

Variables	(1) OLS	(2) Fixed-Effects	(3) Random-Effects	(4) Fixed-Effects
WPUI	0.126***	0.137***	0.133***	1.078***
	(0.0251)	(0.0238)	(0.0237)	(0.179)
2012				−0.0763***
				(0.0159)
2013				−0.000701
				(0.0158)
2014				−0.173***
				(0.0155)
2015				−0.0246**
				(0.0115)
2016				−0.157***
				(0.0198)
2017				−0.378***
				(0.0611)
2018				−0.0595***
				(0.0140)
2019				−0.0791***
				(0.0115)
2020				−0.0843***
				(0.2314)
Constant Term	0.578***	0.577***	0.578***	0.572***
	(0.00546)	(0.00387)	(0.00699)	(0.00995)
Observations	693	693	693	693
R-squared	0.027	0.053		0.483
Number of Panel Member		100	100	100

The dependent variable is the CSP index to measure the CSR. The robust standard errors in parentheses.
****$p < 0.01$ and **$p < 0.05$.*

TABLE 3 | Results of the heterogeneous panel estimations.

Variables	(1) MGE with Time Trend	(2) MGE with Weighted Average	(3) CCEMG Estimator
WPUI	0.220***	0.123***	0.119**
	(0.0555)	(0.00528)	(0.0526)
Time Trend	0.0127***	0.0137***	
	(0.00109)	(0.000464)	
Constant Term	0.440***	0.445***	0.0299
	(0.0121)	(0.0102)	(0.0475)
Observations	680	680	689
Number of Panel Member	95	95	98

The dependent variable is the CSP index to measure the CSR. The robust standard errors in parentheses.
****$p < 0.01$ and **$p < 0.05$.*

CONCLUSION

This paper examines the effects of the pandemic uncertainty on socially responsible investments. We focused on the world's top

100 SRI companies from the list to model the "overall score" from 2012 to 2020. The overall score is based on the annual ranking of corporate sustainability performance (CSP). The pandemic uncertainty is also measured by the WPUI of Ahir et al. (23). We observe that the WPUI is positively associated with the overall index of the CSP investments. We utilize different econometric techniques, such as the OLS, the fixed-effects, the random-effects, the MGE with the time trend and the weighted average, and the CCEMG estimations. The main finding is robust and used different estimation techniques. This finding is in line with the results of Garcia-Sanchez and Garcia-Sanchez (20). Our findings show that CSP investments are positively associated with extreme events, such as pandemics.

Our findings show that top-100 firms have provided a significant commitment to society and have implemented social responsibilities to reduce pandemics' outcome. However, it is important to note that our findings are limited from 2012 to 2020, and our data capture the effects of the COVID-19 on social responsibility investments. Future studies can include the post-COVID era data and re-examine the global pandemics' effects on corporate responsibility indicators.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: https://www.corporateknights.com/reports/2021-global-100/2021-global-100-ranking-16115328/; https://worlduncertaintyindex.com/data/.

AUTHOR CONTRIBUTIONS

WZ: writing original manuscript and project administration. JY: writing original manuscript and estimations. HL: data collection and rephrasing the manuscript. MZ: conceptualization and writing original manuscript. All authors contributed to the article and approved the submitted version.

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REFERENCES

1. Bauer R, Derwall J, Otten R. The ethical mutual fund performance debate: new evidence from Canada. *J Bus Ethics.* (2007) 70:111–24. doi: 10.1007/s10551-006-9099-0
2. Cummings LS. The financial performance of ethical investment trusts: an Australian perspective. *J Bus Ethics.* (2000) 25:79–92. doi: 10.1023/A:1006102802904
3. Brzeszczyński J, McIntosh G. Performance of portfolios composed of British SRI stocks. *J Bus Ethics.* (2014) 120:335–62. doi: 10.1007/s10551-012-1541-x
4. Yarovaya L, Brzeszczyński J, Lau CKM. Intra-and inter-regional return and volatility spillovers across emerging and developed markets: evidence from stock indices and stock index futures. *Int Rev Financ Anal.* (2016) 43:96–114. doi: 10.1016/j.irfa.2015.09.004
5. Aguilera RV, Rupp DE, Williams CA, Ganapathi J. Putting the S back in corporate social responsibility: a multilevel theory of social change in organizations. *Acad Manage Rev.* (2007) 32:836–63. doi: 10.5465/amr.2007.25275678
6. Rosen BN, Sandler DM, Shani D. Social issues and socially responsible investment behavior: a preliminary empirical investigation. *J Consum Aff.* (1991) 25:221–34. doi: 10.1111/j.1745-6606.1991.tb00003.x
7. Campbell JL. Why Would corporations behave in socially responsible ways? An institutional theory of corporate social responsibility. *Acad Manage Rev.* (2007) 32:946–67. doi: 10.5465/amr.2007.25275684
8. Kadiyala P. Socially responsible investing: moral and optimal? *Invest Manage Financ Innovations.* (2009) 6:165–78. doi: 10.2139/ssrn.687202
9. Vickman S, Larsson A, Olsson L. Prerequisites for decision aid in socially responsible investment appraisals. *Int J Eng Manage Econ.* (2013) 3:359–77. doi: 10.1504/IJEME.2012.052405
10. Berry TC, Junkus JC. Socially responsible investing: an investor perspective. *J Bus Ethics.* (2013) 112:707–20. doi: 10.1007/s10551-012-1567-0
11. Godfrey P. The relationship between corporate philanthropy and shareholder wealth: a risk management perspective. *Acad Manage Rev.* (2005) 30:777–98. doi: 10.5465/amr.2005.18378878
12. Yanjun J, Yong X. The impact of corporate social responsibility on shareholder wealth in the event of negative events. *Manage Res.* (2012) 7:102–20. Available online at: https://kns.cnki.net/kcms/detail/detail.aspx?dbcode=CCJD&dbname=CCJDLAST2&filename=PZDG201201009&v=a87AthG4guLUZPg6Ypz5sUirVHh4LU0phi%25mmd2FBsHebs7lqvK9I07A0J102Ecijll8j
13. Servaes H, Tamayo A. The impact of corporate social responsibility on firm value: the role of customer awareness. *Manage Sci.* (2013) 59:1045–61. doi: 10.1287/mnsc.1120.1630
14. Jihui X, Yuting C, Wenping P. Market environment, corporate social responsibility and fund security investment transfer. *Audit Econ Res.* (2020) 35:63–77. Available online at: https://kns.cnki.net/kcms/detail/detail.aspx?dbcode=CJFD&dbname=CJFDLAST2021&filename=SJYJ202006007&v=Y8JMAQeudUjXtMwJ1z6y0XKiiBTh0TO9MwhU6Rf%25mmd2Bk777k84dx3549JmivwCIOqwo
15. Gefei Y. The epidemic will bring seven changes to CSR. *Econ Guide Sustain Develop.* (2020) 2020:57–8. Available online at: https://kns.cnki.net/kcms/detail/detail.aspx?dbcode=CJFD&dbname=CJFDLAST2021&filename=WTOK202012022&v=juBSZXaWNBS5bUvPpKQhbPMdUCHApEaUiqdTVkG2ShPpA9HaYHApGz7Q7JggOx3V
16. Zhen Y, Ximing Y, Jin C. Innovation of platform corporate social responsibility governance under the background of epidemic situation. *Chin J Manage.* (2020) 17:1423–32. Available online at: https://kns.cnki.net/kcms/detail/detail.aspx?dbcode=CJFD&dbname=CJFDLAST2020&filename=GLXB202010001&v=UE0fSNGm5eEaEKZMEQiRk2t2KIE7b6s%25mmd2B9yXn5NvU28M1G7WRtMxGYrs%25mmd2F44Y9PPbv
17. Huo C, Dar AA, Nawaz A, Hameed J, Pan B, Wang C. Groundwater contamination with the threat of COVID-19: insights into CSR theory of Carroll's pyramid. *J King Saud Univ Sci.* (2021) 33:101295. doi: 10.1016/j.jksus.2020.101295
18. Brammer S, Branicki L, Linnenluecke MK. COVID-19, societalization, and the future of business in society. *Acad Manage Rev.* (2020) 34:493–507. doi: 10.5465/amp.2019.0053
19. Crane A, Matten D. COVID-19 and the future of CSR research. *J Manage Stud.* (2021) 58:278–82. doi: 10.1111/joms.12642
20. Garcia-Sanchez IM, Garcia-Sanchez A. Corporate social responsibility during COVID-19 pandemic. *J Open Innovation.* (2020) 6:126. doi: 10.3390/joitmc6040126
21. Na S, Rui-chan H, Bao-ping W. On corporate governance and corporate social responsibility under the background of epidemic situation. *Financ Manage Res.* (2020) 12:103–6. Available online at: https://kns.cnki.net/kcms/detail/detail.aspx?dbcode=CJFD&dbname=CJFDLAST2021&filename=CWGL202012019&v=1nRBay4uEF%25mmd2BX52dSWs09dBuu6WkauUYn%25mmd2FkJndGboaDe1VjKNlAjhcczNoqZSad%25mmd2FT

22. He H, Harris L. The impact of Covid-19 pandemic on corporate social responsibility and marketing philosophy. *J Bus Res.* (2020) 116:176–82. doi: 10.1016/j.jbusres.2020.05.030
23. Hites A, Bloom N, Furceri D. *The World Uncertainty Index* (October 29, 2018). doi: 10.2139/ssrn.3275033. Available online at: https://ssrn.com/abstract=3275033
24. Coakley J, Fuertes AM, Smith R. Unobserved heterogeneity in panel time series models. *Comput Stat Data Anal.* (2006) 50:2361–80. doi: 10.1016/j.csda.2004.12.015
25. Eberhardt M, Teal F. Econometrics for grumblers: a new look at the literature on cross-country growth empirics. *J Econ Surv.* (2011) 25:109–55. doi: 10.1111/j.1467-6419.2010.00624.x
26. Pesaran MH, Smith R. Macroeconometric modelling with a global perspective. *Manchester Sch.* (2006) 74:24–49. doi: 10.1111/j.1467-9957.2006.00516.x
27. Pesaran MH, Yamagata T. Testing slope homogeneity in large panels. *J Econom.* (2008) 142:50–93. doi: 10.1016/j.jeconom.2007.05.010
28. Pesaran MH, Smith R. Estimating long-run relationships from dynamic heterogeneous panels. *J Econom.* (1995) 68:79–113. doi: 10.1016/0304-4076(94)01644-F
29. Verardi V, Croux C. Robust regression in Stata. *Stata J.* (2009) 9:439–53. doi: 10.1177/1536867X0900900306

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The Study of Factors on the Small and Medium Enterprises' Adoption of Mobile Payment: Implications for the COVID-19 Era

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The coronavirus disease 2019 (COVID-19) pandemic pushes people looking for shopping alternatives, seeking to avoid handling cash in favor of a safe and quick mobile payment. At this juncture, this paper examines the determinants of the adoption of mobile payment services among small and medium enterprises (SMEs) in China. The study proposes four-dimensional factors (business factors, technological competence, environment, and consumers' intentions) based on the literature review findings to understand the challenges of adopting mobile payment. A questionnaire is designed to solicit information from the participants. The findings reveal that business factors, technological competencies of SMEs in China, and the environment positively influence mobile payment adoption. Consumer intention has almost no influence on the adoption of mobile payment. Potential implications for the COVID-19 era are also discussed.

Keywords: COVID-19, mobile payment, small and medium enterprises, SMEs, adoption factors

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INTRODUCTION

The use of mobile devices to provide financial services is widely accepted in advanced countries. It affects communication culture and greatly impacts most commercial and non-commercial systems, including financial activities (1). Many researchers have developed an interest in exploring mobile payment services since their remarkable effects and acceptance by consumers and giant telecommunication companies, financial institutions, and small and medium enterprises (SMEs) (2, 3). Most SMEs have embraced Apple Pay, Samsung Pay, PayPal, WeChat Pay, Alipay, and China MTN mobile transfer. At this stage, mobile banking and Facebook Libra cryptocurrency are also increasing competition (4). Overall, mobile payment is a growing business.

China has the leading mobile payment infrastructure. The mobile payment usage rate globally takes the first position for 3 years by 2020, about 805 million users, occupying 85.7% of the internet users (5). The rise in mobile payment in the domestic economy also has a spillover effect on developed countries. For instance, over 50% of the merchants surveyed in the United States and the United Kingdom state that Chinese customers' flow increased after they provided Alipay access (5). Particularly, during the COVID-19 pandemic, there is a growing share of mobile payments adoption since there is a significant reduction in the physical usage of cash, credit cards, and debit cards (6).

China's customers' usage rate is not much seen in SMEs (7). To enhance mobile payment understanding of SMEs, Shao et al. (8) indicate that a mobile payment requires a higher technological innovation than classical payment methods. Most developing countries lack technology. Therefore, despite the positive effects of mobile payment, many SMEs face challenges in applying the mobile payment system.

This study aims to examine key factors that hinder the adoption of mobile payment services among SMEs and compare and contrast the mobile payment initiative in China to a technologically advanced country, China. We also offer both practical and theoretical implications for SMEs for the coronavirus disease 2019 (COVID-19) pandemic. This study also offers several suggestions to SMEs in China, government institutions, and agencies. At this stage, policymakers and management of companies or institutions using mobile payment should make strategic decisions to combat the COVID-19 pandemic's future challenges. Given that China has the largest e-commerce and mobile payment, China's startup initiative can also consider the mobile payment demand's potential determinants.

The rest of the paper is organized as follows. *Literature Review and Theoretical Framework* provides a brief literature review and sets the theoretical framework. *Basic Features of Data and Findings* explains the survey data details, provides basic features of the collected data, and discusses the empirical findings. *Conclusion with Implications* concludes the paper by discussing potential implications.

LITERATURE REVIEW AND THEORETICAL FRAMEWORK

Previous Studies

A new paradigm has emerged under the mobile name payment (M-payment). Mallat (9) defines mobile payments as using a mobile device to conduct a payment transaction. According to Abrahão et al. (10), mobile payment systems provide flexibility, mobility, and efficiency to solve everyday problems or satisfy their users' wishes. Contribution to the M-payment definitions is transferring money to services or goods over mobile devices via Short Message Service (SMS), Browser, payment applications, and Quick Response (QR) code.

Mobile payment is also important for SMEs, but they can be defined according to different criteria in the various sectors: manufacturing, construction, and quarrying and mining sectors. For the retailing, miscellaneous, motor trades, and wholesale trades sectors, the sales turnover criterion is used. Whereas, the road transport sector uses several vehicles, the catering sector is based on ownership. In China, the definition of an SME is complex. It depends on a series of variables such as the industry it belongs to, its operating cost, its total assets, and its number of employees. SMEs constitute an overwhelming majority of the enterprises in China. They are the main part of economic development, as they represent 99.6% of China's companies, offer more than 80% of the job positions, and hold more than 70% of the patents (5).

Mobile payment system is becoming a leading payment method in developed economies (3) and developing markets such as China and Malaysia (11). Mobile payments further intensified the ease of online transactions (12). The introduction of innovative forms of Information and Communications Technology (ICT) services by SMEs to deliver financial services to all population segments is crucial for improving previous business processes. The ability to optimize ICT use has become a major criterion for promoting and enhancing future economic mobility in developing countries. However, the mobile payment system's tremendous benefits for SMEs have not been fully utilized in various emerging economies (13). Mun et al. (14) also found out that the perceived credibility (PC) is significantly associated with consumers' intention to use mobile payment services. The authors defined the PC as the consumers' judgment on mobile payment services' privacy and security issues. However, some authors also highlight that the usability problems are responsible for the low adoption of various payment systems (15, 16). Karsen et al. (17) opinioned that mobile devices should be used for payment by an authentication system to ensure every transaction's safety and comfort. Mobile payment service in China is a technological innovation product, which is the force of industrial evolution (18). Most of the developing countries are far from mobile payment development since they lack the required human capital, technological, environmental, and organizational requirements to adopt mobile payment for their SMEs (19). Dahbi and Benmoussa (20) reviewed the mobile payments adopting factors and categorized them into several headings such as organizational, technological, environmental, financial, and sociocultural basis. The authors conclude that security, trust, usability, government regulations, and institutional factors are the leading determinants of mobile payment adoption.

This paper aims to fill in the empirical literature gap by examining mobile payment determinants in China. Our novelty of the research is that we provided a survey in 2020, which captures the COVID-19 era. Therefore, our results may be interesting due to the changing pattern of the country's payment habits.

Theoretical Framework and Hypothesis

The study proposes four-dimensional factors based on the literature review findings to understand the challenges of adopting mobile payment. The main factors are institutions, technology, consumers' intentions, and business unit or SMEs. These four variables define the critical path for analysis, and organizations need to consider them when adopting a mobile payment system.

The institution that could interplay in the adoption of mobile payment includes banks or financial corporations, internet service providers, telecommunication networks, trading partners, software applications, and government support. The extended unified theory of acceptance and use of technology (UTAUT2) as a basic model to accomplish the objectives (21). Besides, perceived usefulness, easy access, and mobile payment usage are considered under technology acceptance. SMEs proactively measure the outcome of adoption, cost and managerial implications, and the technical experts needed to accomplish mobile payment services.

Measures with proven reliability and validity are applied to operationalize the variables of the research model. The items are rated on a 5-point Likert scale, ranging from "strongly disagree" to "strongly agree" (see **Table 1**). **Table 2** also explains the measurement variables, sources of the variables, and theoretical foundations.

Based on the above analysis, four hypotheses are given as the following:

H1: Business factors have a positive influence on the adoption intention.
H2: Technological competence has a positive influence on the adoption intention.
H3: Environment has a positive influence on the adoption intention.
H4: Consumer intention has a positive influence on the adoption intention.

BASIC FEATURES OF DATA AND FINDINGS

Population Data and Sample Size

Many review studies have considered the inclusion and exclusion criteria so far irrespective of research fields (18). The researcher purposively targeted five small and medium businesses in China for the first set of the questionnaire. Three main criteria were used: (1) must be in operations for more than 5 years, (2) must have licensed and legally recognized with no bad history, and (3) must be either B2B or B2C business type. This issue helps the researcher satisfy the research model and obtain all necessary information for further analysis. One hundred and eight respondents participated in the first section.

Users of mobile payments and businesses were invited to participate in the study. The businesses include delivery agencies, malls, KFC, McDonald's, etc. Generally, the study obtains information from 90 respondents in China and 90 respondents in other Chinese regions (Hong Kong, Macau, and Taiwan) for the second set.

Data are collected by conducting a field survey questionnaire from participants. The questionnaire has five sections: background information of respondents, institutional or external factors, technological factors, consumer behaviors, and business unit analysis. Two sets of questionnaires are prepared in English and Chinese. Before the questionnaire is administered, it is screened. A pilot test is conducted by sending the questionnaire to five friends to assess flexibility, grammatical errors, and appropriateness. Afterward, the questionnaire is reviewed and arranged to devoid of unethical issues.

The data are taken using the WeChat survey application. The questionnaires are filled in the app with due diligence. The following settings are done to ensure high reliability and validity of the data: (1) the app is set to anonymous, (2) respondents answers are strictly private, (3) response cannot be resubmitted once submitted, and (4) all questions are mandatory therefore a full set of data are obtained in every submission.

TABLE 1 | Measuring scale.

Strongly Disagree (SD)	Disagree (D)	Neutral (N)	Agree (A)	Strongly Agree (SA)
1	2	3	4	5

After designing the online questionnaire and cross-checking everything, it was posted in WeChat groups of business-oriented background. Clear instruction and confidentiality information accompanied the post. The first set of questions are administered to Chinese people only. This survey lasts for 2 weeks, and a total of 180 responses are received. After 3 days, the second part or set of questions is administered. The paper analyzes 180 responses for the second questionnaire analysis. Online data is obtained from the WeChat survey App.

Background Information of the Respondents

According to the research questionnaire, the reliability and validity of the primary structure data of the respondents' background information are analyzed. The respondents' background information is gender, age range, educational qualifications, type of business engagement, and working years.

Table 3 illustrates the gender of the respondents; 69.4% are male, and 30.6% are female. Gender disparity does not influence the results of the study.

Table 4 shows the age range of the respondents. The majority of the participants are 21–30 years old, and they represent 69.4%. Those within 31–40 years were 30 representing 27.9%. Only five respondents were below 20 years, and none had more than 50 years of age.

Educational level of staff and owners of small business contributes to M-payment adoption. **Table 5** shows that 75 of the respondents, constituting 69.4%, were in their postgraduate level, while 29.6% had college or university education. High school was 0.9%, and none had no formal education.

Table 5 shows the educational background of respondents; postgraduate accounts for 69.3%, which shows that the respondents are highly educated,

The respondents' sector of business engagement is shown in **Table 6**. Most of the respondents are students, accounting for 69.4%, doing business is the smallest part, only accounting for 2.8%.

Table 7 indicates the years of work. One hundred and sixteen of the respondents had between 11 and 15 years, representing 41.4%. This evidence is followed by 6–10 years, 65 respondents, and it represents 23.2%.

Reliability and Validity Analysis

The main construct variables affecting mobile payment adoption by SMEs are business factors, technological competence, environment, and consumer intention. The reliability and validity of the scale are analyzed using the valid questionnaire data collected. The reliability and validity of the information of each measurement scale are calculated as shown in **Table 8**.

TABLE 2 | Measurement variables, sources, and theoretical foundations.

Factors	Items	Sources	Theoretical basis
Business Factors	Customer Preferences Security, effort needed, management and employees level of knowledge, size of business, cost implications	Chhonkera et al. (18) and Kujala et al. (22)	Expectancy Theory
Technological Competence	Protection of privacy, instant transaction confirmation, familiarity of payment, system, software applications, internet connectivity and speed, security of transactions	Chhonkera et al. (18)	Unified Theory of Acceptance and Use of Technology (UTAUT)
Environment	Regulatory policies and support, incorporated payment facilities available, access to internet facilities and its price, language options available and literacy, institutional factors, government regulations, pressure from trading partners, pressure from competitors	Shao et al. (8)	Institutional Theory
Consumers Intention	Aware of mobile payments, the usefulness of mobile payments, use of electronic payments, transparency of transaction, authentication of payment, transaction confidentiality, optimistic, trust, usability etc.	Chhonkera et al. (18) and Kujala et al. (22)	Consumer Behavior Theory

TABLE 3 | Gender.

Item	Frequency	Percent (%)
Male	195	69.6
Female	85	30.4
Total	280	100.0

TABLE 4 | Age Range.

Item	Frequency	Percent (%)
Below 20	5	1.8
21–30	194	69.3
31–40	78	27.8
41–50	3	1.1
Total	280	100.0

TABLE 5 | Educational background of respondents.

Items	Frequency	Percent (%)
High school	3	1.1
College/university	83	29.6
Postgraduate	194	69.3
Total	280	100.0

TABLE 6 | Sector of businesses.

Item	Frequency	Percent (%)
Private/company	21	7.4
Public	18	6.5
Self-employed	39	13.9
Student	194	69.4
Yet to do business	8	2.8
Total	280	100.0

TABLE 7 | Years of working.

Item	Frequency	Percent (%)
Below 5	60	21.4
6–10	65	23.2
11–15	116	41.4
16–20	34	12.2
21 above	5	1.8
Total	280	100.0

It can be seen from **Table 8** that the Cronbach α of each scale is >0.63, and the total variance of the cumulative interpretation is above 52%, indicating that the questionnaire has certain credibility in the study. The results of the confirmatory factor analysis using Mplus were chi-square = 192.895, comparative fit index (CFI) = 0.938, Tucker–Lewis index (TLI) = 0.929, and root mean square error of approximation (RMSEA) = 0.082. This model fits well according to the current criteria, showing that the research measurements are four independent variables.

Descriptive Statistical Analysis

The average value, standard deviation, and correlation coefficient between each measured variable are calculated as shown in **Table 9**.

Business factors, technological competence, environment, and consumer intentions are significantly and positively correlated, indicating that they are all factors affecting adoption. Business factors is significantly positively correlated with the technological competence, environment and customer intention. The above provides the necessary preconditions for analyzing the relationship between the variable.

Then, the data validity test of Kaiser–Meyer–Olkin (KMO) and Bartlett is performed based on SPSS. KMO test is a measure of how suited the data are for analysis. The test measures the sampling adequacy for the variables in the model. KMO sampling adequacy is 0.824, which is meritorious. Bartlett's test of sphericity is a <0.05 (Sig. 000). The chi-square results

TABLE 8 | Reliability and validity.

Variable	Cronbach α	KMO	Bartlett's sphericity test			Cumulative total variance
			Bangla	df	Sig.	
Business Factors (BF)	0.768	0.726	227.846	6	0.000	52.682%
Technological Competence (TC)	0.634	0.688	121.545	3	0.000	55.859%
Environment (EN)	0.698	0.646	116.343	3	0.000	54.841%
Consumer Intention (CI)	0.683	0.722	258.476	3	0.000	56.443%
Adoption Intention (AI)	0.742	0.716	352.358	6	0.000	55.887%

TABLE 9 | Descriptive statistics and correlation coefficients.

Variable	M	SD	Business factors	Technological competence	Environment	Consumer intentions
Business factors	3.294	0.829				
Technological competence	3.628	0.848	0.596***			
Environment	3.625	0.821	0.474***	0.586***		
Consumer intentions	3.454	0.835	0.675***	0.683***	0.583***	
Adoption intention	3.545	0.832	0.688***	0.636***	0.576***	0.642***

*Significance level ***means 0.1%.*

are significant $\chi^2 = 880.889$. This test and the Cronbach alpha reliability test validate the data for all further analysis (see **Table 10**).

Factors That Hinder Mobile Payment Adoption Among SMEs in China

This article divides the factors that influence mobile payment adoption challenges among Chinese SMEs into four main categories to investigate how each field and some variables affect SMEs carefully. This analysis covers factors that influence SMEs in adopting a mobile payment service system. It includes cost of adoption, employees' education level, business types, mobile payment readiness, and technology competency (21, 23).

Business Factors

The business or SMEs' characteristics that effectively hinder the business idea of accepting mobile payment service in China are revealed and illustrated in **Table 11**.

Table 11 shows the mean, standard deviation, and average variance of business or SMEs factors that hinder mobile payment adoption in China. Regarding the cost of adoption, the respondents agree or strongly agree that it significantly militates against mobile payment services. The average cost of adoption is 3.90. Implicitly, all the business factor category figures were wholly accepted and reaffirmed that it indeed hinders SMEs' proposal to practice mobile payment system. The highest item is business readiness of SMEs (4.15); education level of employees is 3.83, and the lowest average level is business 3.40.

Technological Competence

SMEs that have implemented mobile payment system and others that have the idea to practice cannot swerve from technological issues. A survey is conducted to analyze which technological issues affect the Chinese SMEs' attempt to adopt mobile payment (see **Table 12**).

Table 12 emphasizes that the technological factors are the key in impeding SMEs in mobile payment adoption. The most strongly agreed item is network connection among payment partners (4.33, strongly agreed). Network connection is a great challenge among SMEs since its good network connection is limited to a few urban areas, making it difficult for more business units to embrace mobile payment. The connection to bridge quality payment service among all the mobile payment partners suffer handicap. This item is followed by the availability of internet connectivity (4.09), where there is poor network; slow and unavailability of internet also exist. Moreover, the remaining factors are the reliable software applications (3.98), technological level of payment facilities (3.91), and compatibility of payment facilities available (3.86).

Environment

The external factors are challenges of other technology and own business limitations that hinder mobile payment adoption. These factors are sometimes beyond the SMEs' control and need government or industrial interventions to facilitate implementations.

Table 13 shows that the ICT infrastructure of China affects SMEs to adopt mobile payment services. This evidence was strongly agreed with a total value of (4.06). Another external factor is cooperation from telecom providers and banks (3.96). Most banks cannot provide security and trust effective transaction coupled with network connectivity challenges for mobile payment to be perfect.

TABLE 10 | KMO and Bartlett's test.

Test		Result
Kaiser–Meyer–Olkin Measure of Sampling Adequacy		0.824
Bartlett's Test of Sphericity	Approx. chi-square	880.889
	df	210
	Sig.	0.000

TABLE 11 | Descriptive statistics of business factors.

Variable Description	*N*	Mean	Std. Deviation	Variance
Cost of adoption	280	3.90	1.046	1.145
Education level of employees	280	3.83	0.786	0.621
Type of business	280	3.40	1.251	1.586
Business readiness	280	4.15	0.634	0.424

TABLE 12 | Descriptive statistics of technological factors.

Variables	*N*	Mean	Std. Deviation	Variance
Availability of internet connectivity and speed	280	4.09	1.054	1.083
Network connection among payment partners	280	4.33	0.861	0.756
Reliable software applications	280	3.98	1.066	1.118
Technological level of payment facilities	280	3.91	0.930	0.826
Compatibility of payment facilities available	280	4.32	0.902	0.818

TABLE 13 | Descriptive statistics of environment.

Description	Mean	Std. Deviation	Variance
Regulatory policies and support by government	3.75	0.926	0.842
Cooperation from telecom providers and banks	3.96	0.918	0.825
Pressure from competitors and stakeholders	3.66	1.026	1.044
ICT infrastructure level in China	4.06	0.916	0.832
Perceived public awareness and compatibility	3.39	1.185	1.380
Language options available and literacy	3.88	1.036	1.053

Consumer Intention

The author investigated many consumer intentions factors, and the respondents reacted in different views. The result is tabulated in **Table 14**.

Table 14 depicts the consumer aspects that limit SMEs for adopting mobile payment system. The most strongly agreed factor from the respondents is "perceived trust and security" (4.25). With mobile, internet, and bank fraud in China community, consumers find it difficult to believe in the mobile payment system. However, the m-payment system could be successful depending on the relative advantage over cash payment (4.06). "Perceived ease and usefulness" (3.96) and "familiarity and complexity to users" (3.91).

TABLE 14 | Descriptive statistics of consumer factors.

Description	*N*	Mean	Std. Deviation	Variance
Familiarity and complexity to users	280	3.91	0.918	0.845
Perceived trust and security	280	4.25	0.856	0.724
Consumers readiness	280	3.85	0.848	0.716
Perceived ease and usefulness	280	3.96	0.796	0.628
Relative advantage	280	4.06	0.877	0.758

Hypothesis Verification

This paper uses Mplus7.0 to perform path analysis and hypothesis testing. According to the above test procedure, a relationship model is established between business factors, technological competence, environment, consumer intention and adoption intention (see **Figure 1**). The test results are shown in **Figure 2**.

Since chi-square = 0, df = 0, CFI = 1.000, TLI = 1.000, RMSEA = 0.000, standardized root mean square residual (SRMR) = 0.000, the model fits well. As can be seen from **Figure 2**, business factors significantly predict the adoption intention (c1 = 0.458, t = 10.932, p = 0.000), assuming H1 is verified. Technological competence significantly influences adoption intention (c2 = −0.563, t = −8.611, p = 0.000), indicating that the technological competence predicts adoption intention, assuming H2 is verified. Environment also influences adoption intention (c2 = −0.334, t = 12.082, p = 0.000), indicating that environment is also a key factor influencing the adoption intention, then H3 is verified. Besides, customer intention may have no influence on adoption intention (c4 = −0.148, t = −1.018, p = 0.067), then H4 is not verified. Business factors, technological competence, and environment positively influence mobile payment's adoption intention, but the SMEs' customer intention does not influence the adoption intention (22).

CONCLUSION WITH IMPLICATIONS

The COVID-19 pandemic is expected to have a significant effect on the payment card market. Contactless payment is tagged as a more hygienic and safer way of making payments (24). This issue promotes mobile payment. The COVID-19 pushes people to look for alternative payments in shopping and seeking to avoid handling cash and other materials to safely and quickly check out. However, as the COVID-19 enhances mobile payments, it is important to secure online and digital transactions (4). At this stage, the SMEs problems have posed many challenges for mobile payment service adoption in China. This study reveals that "business factors, technology competence of SMEs in China, mobile payment environment form major factors that influence mobile payment acceptance."

The questionnaire results reveal important observations and emphasize that technological factors impede SMEs in mobile payment adoption. The most strongly agreed item is "network connection among payment partners."

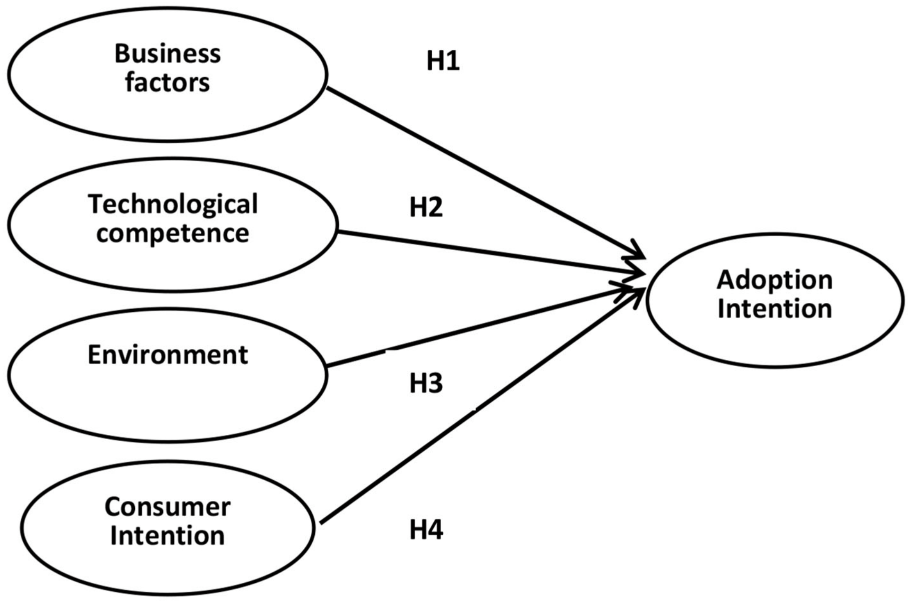

FIGURE 1 | Proposed four-dimensional model.

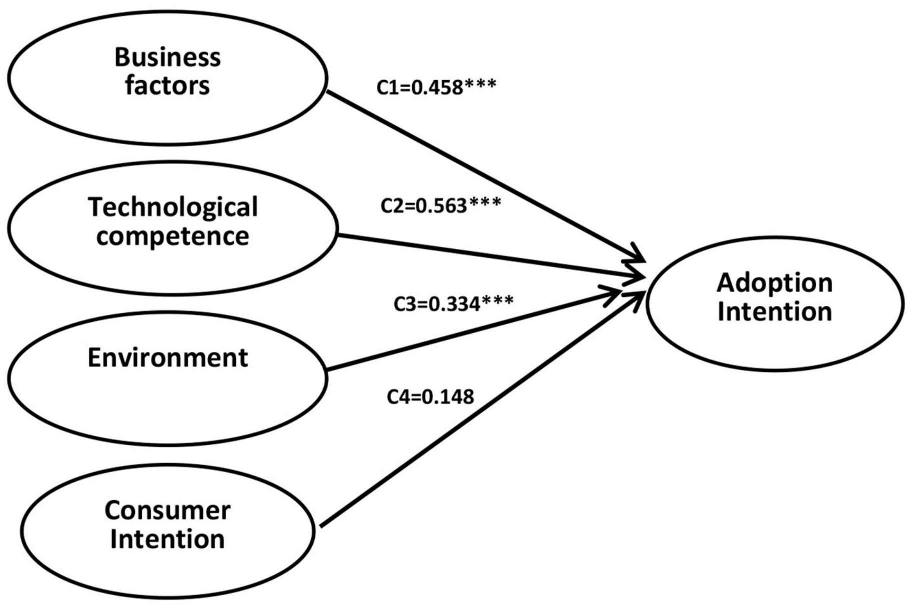

FIGURE 2 | Test of hypothesis. Significance level ***means 0.1%.

Another challenge is the poor and slow internet connectivity; moreover, reliable software applications, technological level of payment facilities, and compatibility of payment facilities are available.

Some of the main external factors that affect the adoption of mobile payment systems by China small- and medium-sized enterprises revealed by this study are ICT infrastructure in China and cooperation from telecom providers and banks. Most banks cannot secure and trust effective transactions and network connectivity challenges for mobile payment to be perfect. The external environment factors do not facilitate mobile payment and are not ready due to the large technological and network gap. The basic infrastructure to incorporate all the mobile payment partners seems too expensive, thereby discouraging China's payment system.

We investigated many consumer intentions factors, and the respondents reacted in different views. The most strongly agreed factor from the respondents is "perceived trust and security." With mobile, internet, and bank fraud in Chinese community, consumers find it difficult to believe in the mobile payment system. However, the m-payment system could be successful depending on the relative advantage over cash payment. According to the technology acceptance model (TAM) model, it suggests that perceived usefulness and ease of use are the determinants of users' willingness to accept and use systems. This evidence implies that consumers' perceived usefulness of mobile payment over cash shows a positive emotional enjoyment and will be accepted if SMEs implement mobile payment adoption.

Based on the study's findings, we recommend the following for SMEs management, owners, government, and other mobile payment partners. In technology, internet, and network connections, the national communication authority should quickly find reliable measures to offer quality internet access and good network coverage connection in collaboration with the private network providers. China should also embark on ICT infrastructure to facilitate a mobile payment system. Management of SMEs or business units should train their staff to acquire more relevant mobile payment system knowledge. In addition, we suggest that SMEs seek credit to facilitate the cost of mobile payment adoption and upgrade their technological equipment on business factors. Future studies can focus on the post-COVID-19 era for analyzing the determinants of mobile payment adoption in other developing countries.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by The survey in the study has been approved by the ethics committee of the Nanjing Institute of Technology. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

The author confirms being the sole contributor of this work and has approved it for publication.

REFERENCES

1. Merhi M, Kate H, Tarhini A. A cross-cultural study of the intention to use mobile banking between Lebanese and British consumers: extending UTAUT2 with security, privacy and trust. *Technol Soc*. (2019) 59:101–15. doi: 10.1016/j.techsoc.2019.101151
2. Gong X, Zhang KZ, Chen C, Cheung CM, Lee MK. What drives trust transfer from web to mobile payment services? The dual effects of perceived entitativity. *Inform Manag*. (2020) 57:103250. doi: 10.1016/j.im.2019.103250
3. Liébana-Cabanillas F, Molinillo S, Japutra A. Exploring the determinants of intention to use P2P mobile payment in Spain. *Inform Syst Manag*. (2021) 10:1–16. doi: 10.1080/10580530.2020.1818897
4. Pandey N, Pal A. Impact of digital surge during Covid-19 pandemic: a viewpoint on research and practice. *Int J Inform Manag*. (2020) 55:102171. doi: 10.1016/j.ijinfomgt.2020.102171
5. Liu T, Pan B, Yin Z. Pandemic, mobile payment, and household consumption: micro-evidence from China. *Emerg Mark Finance Trade*. (2020) 56:2378–89. doi: 10.1080/1540496X.2020.1788539
6. Ren T, Tang Y. Accelerate the promotion of mobile payments during the COVID-19 epidemic. *Innovation*. (2020) 1:100039. doi: 10.1016/j.xinn.2020.100039
7. Pal D, Vajirasak V, Papasratorn B. An empirical analysis towards the adoption of NFC mobile payment system by the end user, procedia computer *Science*. (2015) 69:13–25. doi: 10.1016/j.procs.2015.10.002
8. Shao Z, Zhang L, Li XT, Guo Y. Antecedents of trust and continuance intention in mobile payment platforms: the moderating effect of gender. *Electr Commerce Res Appl*. (2019) 33:1–10. doi: 10.1016/j.elerap.2018.100823
9. Mallat N. Exploring consumer adoption of mobile payments – a qualitative study. *J Strateg Inform Syst*. (2016) 16:413–32. doi: 10.1016/j.jsis.2007.08.001
10. Abrahãoa RS, Moriguchib SN, Andradeba DF. Intention of Adoption of mobile payment: an analysis in the light of the Unified Theory of Acceptance and Use of Technology (UTAUT). *RAI Rev Administr Inovação*. (2016) 13:221–30. doi: 10.1016/j.rai.2016.06.003
11. Ting H, Yusman Y, Lona L, Ming LW. Intention to use mobile payment system: a case of developing market by ethnicity. *Proc Soc Behav Sci*. (2016) 224:368–75. doi: 10.1016/j.sbspro.2016.05.390
12. Zhou ZY, Jin XL, Fang YL. The moderating role of gender in the relationships between perceived benefits and satisfaction in social virtual world continuance. *Decis Support Syst*. (2014) 65:69–79. doi: 10.1016/j.dss.2014.05.004
13. Dennehy D, Sammon D. Trends in mobile payments research: a literature review. *J Innov Manag*. (2015) 3:49–61. doi: 10.24840/2183-0606_003.001_0006
14. Mun YP, Khalid H, Nadarajah D. Millennials' perception on mobile payment services in Malaysia. *Proc Comput Sci*. (2017) 124:397–404. doi: 10.1016/j.procs.2017.12.170
15. Gao L, Waechter KA. Examining the role of initial trust in user adoption of mobile payment services: an empirical investigation. *Inform Syst Front*. (2017) 19:525–48. doi: 10.1007/s10796-015-9611-0
16. Fontes T, Costa V, Ferreira MC, Li SX, Zhao PJ, Dias TG. Mobile payments adoption in public transport. *Transport Res Procedia*. (2017) 24:410–17. doi: 10.1016/j.trpro.2017.05.093
17. Karsen M, Chandra YU, Hanny H. Technological factors of mobile payment: a systematic literature review. *Proc Comput Sci*. (2019) 157:489–98. doi: 10.1016/j.procs.2019.09.004
18. Chhonkera M. S., Deepak V, and Kumar K. A. (2017). Review of Technology Adoption frameworks in Mobile Commerce, Procedia Computer *Science*. 122, 888–895. doi: 10.1016/j.procs.2017.11.451
19. Beck T, Haki P, Ravindra R, Burak RU. Payment instruments, finance and development. *J Dev Econ*. (2018) 133:162–86. doi: 10.1016/j.jdeveco.2018.01.005
20. Dahbi S, Benmoussa C. What hinder SMEs from adopting E-commerce? A multiple case analysis. *Proc Comput Sci*. (2019) 158:811–8. doi: 10.1016/j.procs.2019.09.118

21. Alalwan AA, Yogesh KD, Nripendra PR. Factors influencing adoption of mobile banking by Jordanian bank customers: extending UTAUT2 with trust. *Int J Inf Manage*. (2017) 37:99–110. doi: 10.1016/j.ijinfomgt.2017.01.002
22. Kujala S, Mugge R, Talya M. The role of expectations in service evaluation: a longitudinal study of a proximity mobile payment service. *Int J Hum Comput Stud*. (2017) 98:51–61. doi: 10.1016/j.ijhcs.2016.09.011
23. Jamal A, Johari BF. Enhancing active participation of SMEs and Islamic banks towards economic diversification in Oman. *Proc Econ Finance*. (2015) 31:677–88. doi: 10.1016/S2212-5671(15)01156-9
24. Kar AK. What affects usage satisfaction in Mobile Payments? Modelling User Generated Content to Develop the "Digital Service Usage Satisfaction Model." *Inf Syst Front*. (2020) 1–21. doi: 10.1007/s10796-020-10045-0

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Determinants of Tourism Stocks During the COVID-19: Evidence From the Deep Learning Models

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This paper examines the determinants of tourism stock returns in China from October 25, 2018, to October 21, 2020, including the COVID-19 era. We propose four deep learning prediction models based on the Back Propagation Neural Network (BPNN): Quantum Swarm Intelligence Algorithms (QSIA), Quantum Step Fruit-Fly Optimization Algorithm (QSFOA), Quantum Particle Swarm Optimization Algorithm (QPSO) and Quantum Genetic Algorithm (QGA). Firstly, the rough dataset is used to reduce the dimension of the indices. Secondly, the number of neurons in the multilayer of BPNN is optimized by QSIA, QSFOA, QPSO, and QGA, respectively. Finally, the deep learning models are then used to establish prediction models with the best number of neurons under these three algorithms for the non-linear real stock returns. The results indicate that the QSFOA-BPNN model has the highest prediction accuracy among all models, and it is defined as the most effective feasible method. This evidence is robust to different sub-periods.

Keywords: COVID-19 era, deep learning, backpropagation neural network, quantum step fruit fly optimization algorithm, quantum particle swarm optimization algorithm, quantum genetic algorithm

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INTRODUCTION

With the outbreak of the COVID-19, tourism suffered huge losses, and the stock prices of tourism were influenced dramatically. Simultaneously, the tourism industry's economic sustainability in the digital economy has been impacted by the epidemic as its growth has shifted from a steady increase to an unstable state. To better explore the tourism industry's economic sustainability and learn about the trend of tourism stock price, one must establish an excellent stock forecasting model. Stock price prediction has been regarded as an intractable task due to the stock market's intrinsic non-linearity and instability.

Since the end of 2019, the epidemic has impacted the economy and society, both in China and globally. China's National Bureau of Statistics announced a 6.8% year-on-year decline in real GDP for the first quarter of 2020. In terms of the micro-sector situation, China's tourism industry lost more than RMB 550 billion in revenue, equivalent to 2% of GDP in the first quarter, due to measures such as the travel ban imposed during the epidemic. With the epidemic under effective control in China, China's domestic tourism revenue during the May Day holiday in 2020 was RMB 47.56 billion, a recovery of 31.2% compared to the first quarter. In the digital economy, the tourism industry has always had good development opportunities. Still, the outbreak of the epidemic caused a short-term downturn in the tourism industry during this period. It can be seen from the above data that the economic sustainability of the tourism industry has been greatly impacted. As the tourism industry has been affected by the epidemic, stock prices in China's tourism industry are in a state of volatility. Also, they cannot be predicted accurately due to their stochastic features. The volatile stock price trends require better stock forecasting models to predict them.

In previous studies of stock prediction models, numerous scholars have pursued greater prediction accuracy. Kleijnen et al. (1) and Wang et al. (2) applied statistical analysis methods to predict stock price, including exponential smoothing method, linear regression method, moving average (MA) and autoregressive integrated moving average (ARIMA). Devi et al. (3) and Ariyo et al. (4) indicated that the ARIMA model is a suitable model to analyze time-series data. It is widely applied to analyze linear time series data. Nevertheless, Abu-Mostafa and Atiya (5) proposed that the stock price is non-linear and complex.

Some scholars combined a swarm intelligence algorithm with a stock prediction model to obtain higher prediction accuracy. For example, Zhang and Yan (6) constructed a single-step forward deep learning compound prediction model, the CEEMD-LSTM model, for the stock market based on the concept of "Decomposition-Reconstruction-Synthesis" and the deep learning prediction methodology. Many scholars invoked swarm intelligence algorithms to optimize stock prediction models' parameters to obtain higher prediction accuracy. For example, Wang and Zhuo (7) applied the FOA algorithm to optimize SVR parameters and combine them with support vector machines to develop a PCA-FOA-SVR stock price prediction model with high accuracy non-linear planning. However, compared with the QFOA algorithm, the FOA algorithm has a limited application range and a slightly lower parameter optimization accuracy. Bao et al. (8) adopted the GA algorithm to adjust the traditional LSTM model parameters, which outperformed the traditional LSTM model in predicting the data for CSI 500.

With artificial intelligence and science and technology development, more and more people pay attention to applying a deep learning model in the financial field. Nowadays, deep learning, especially backpropagation neural networks, has been widely used in data mining and prediction, which can effectively model non-linear statistical data. Wang et al. (2) proposed a hybrid approach combining ESM, ARIMA, and BPNN to utilize the most advantageous of all three models, and the weight of the proposed hybrid model (PHM) is determined by a genetic algorithm (GA). Shi et al. (9) proposed a hybrid method combining autoregressive and moving average (ARMA), backpropagation neural network (BPNN) and Markov model to forecast the stock price. Wu and Yong (10) used BPNN to predict the Shanghai Stock Exchange trend and pointed out that BPNN has its advantages in forecasting non-linear systems. Feng (11) adopted Levenberg-Marquardt (LM) algorithm for BPNN training to build a stock price prediction model. Sun et al. (12) proposed the Bayesian regularization method to optimize the training process of the BPNN to improve the generalization ability of the model and did empirical research about the closing price of Shanghai Stock. Huo et al. (13) established a three-layer BPNN. They utilized the LM-BP algorithm to forecast stock price, which has a faster convergence rate and overcomes the samples' redundancy and noise. Cao and Wang (14) constructed a stock price prediction study based on PCA and BP neural network algorithm. Yu et al. (15) used a local linear embedding dimensional reduction algorithm (LLE) to reduce the dimension of variables at first and then put the variables into BPNN to forecast stock price.

Although BPNN has achieved great success in stock price forecasting, there is still a question needed to solve how many nodes should be used in each layer. Despite abundant researches on the application of multilayer-BPNN, it's still a hard task to define the optimal architecture. If there are too few nodes in each layer, the architecture cannot learn from the data properly, whereas if there are too many nodes, it causes waste inefficiency of training the Neural Network. Thomas and Suhner (16). In general, there is no clear theoretical guidance for setting the number of nodes in each hidden layer. Some researches focused on this topic. For instance, Beigy and Meybodi (17) pointed out that the determination of the optimal topology of neural networks belongs to the class of non-deterministic polynomial-time (NP)-hard problems and proposed a survival algorithm to determine the number of hidden units of three layers neural networks. Thomas and Suhner (16) proposed a pruning approach to determine the optimal structure of neural networks. Khan et al. (18) conducted empirical research that indicated that BPNN for predicting stock prices with two hidden layers is more accurate than the sing layer and three and four hidden layers. However, Zhang and Shen (19) compared single hidden layer prediction models and the multiple hidden layers prediction model. The result showed that the three hidden layers' model has a better predictive ability than the former. Therefore, we consider that the number of hidden layers depends on the different data set and there is no absolutely optimal number of hidden layers.

Several papers in the literature examine the determinants of stocks during the COVID-19 era [see, e.g., (20–24)]. Still, several scholars seldom studied how to use the swarm intelligence algorithms to optimize the structure of BPNN for the pre-COVID era. However, these papers have not considered the NP-hard problems for the COVID-19 era. At this stage, the swarm intelligence algorithm is a good way to solve NP-hard problems. Therefore, a new Quantum Step Fruit Fly Optimization Algorithm (QSFOA) is proposed in this paper. This issue is the main contribution of our paper. Besides, quantum swarm intelligent algorithms (QSIAs), including QSFOA, QPSO and QGA, are respectively used to optimize the number of neurons in the multilayer-BPNN. The tourism industry's stock data is then applied to test the three models' predictive power as proof of the feasibility and superiority of the method proposed in the paper.

The structure of this paper is as follows. Section Research Method is to narrate the application of the relevant research methodologies in this paper. In section Empirical Analyses, the stock prediction model developed in this paper is measured by applying the stock data of two leading tourism companies in China. Besides, section Empirical Analyses introduces the comparison with the predictive ability of the QSFOA-BPNN model, QPSO-BPNN model and QGA-BPNN model. The findings of this paper and recommendations will be presented in section Conclusion.

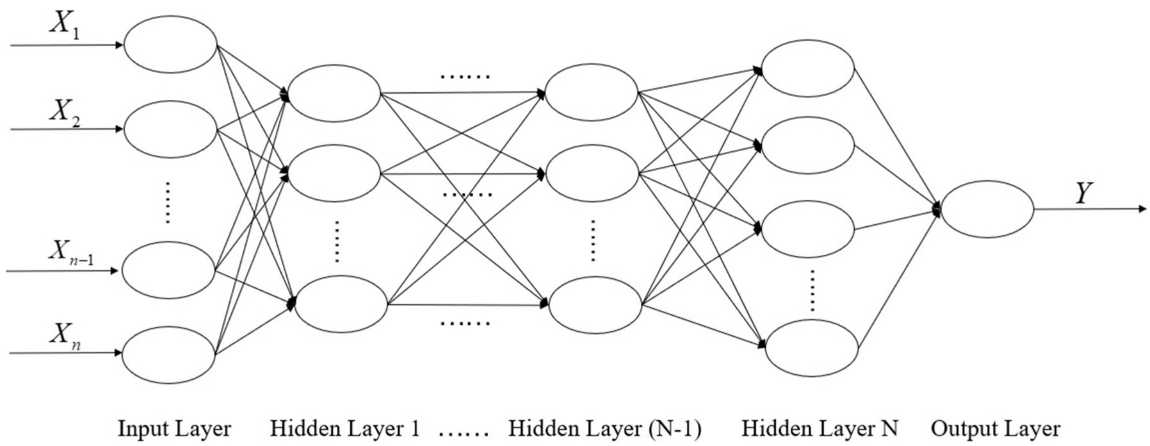

FIGURE 1 | The structure of multilayer-BPNN.

RESEARCH METHOD

Deep learning is a neural network with multiple hidden layers, whose concept is derived from artificial neural network research. It combines various neural network structures and is an extension of a Neural Network. And the neural network is a kind of machine learning technique that simulates the human brain to achieve artificial intelligence. This paper optimizes the deep learning models, multilayer-BPNN, using quantum swarm intelligence algorithms (QSIA) to design its network structure, including the number of neurons and the number of hidden layers. Therefore, some theories about BP Neural Networks and QSIA are introduced as follows.

BP Neural Network

BP neural network is one of the most commonly used artificial neural networks, which is also known as an error backpropagation neural network. BPNN is a kind of multilayer perceptron (MLP), and it is a feedforward network. It trains the network by error backpropagation algorithm. The training purpose of BPNN is to establish a non-linear mapping between input values X and output value Y. The weights and thresholds are adjusted continuously through error backpropagation, and finally, the error signal reaches the minimum. The training process of BPNN is mainly divided into two stages. The first stage is the forward propagation of the signal from the input layer to the hidden layer and finally to the output layer. The second stage is the backpropagation of errors, from the output layer to the hidden layer, and finally to the input layer, adjusting the hidden layer's weight and bias to the output layer to the hidden layers in turn. BPNN consists of three parts including input Layer, hidden layer and output layer. The structure of multilayer-BPNN is shown in **Figure 1**.

QSIA

Normal swarm intelligence algorithms cannot deal with the shortcomings of premature convergence. Consequently, many scholars have applied quantum computing and other quantum principles to swarm intelligence algorithms to optimize better performance and faster convergence speed and algorithms such as Quantum Particle Swarm Optimization (QPSO), Quantum Genetic Algorithm (QGA).

This paper proposes a new Quantum Step Fruit Fly Optimization Algorithm (QSFOA) and compares its performance with QPSO and QGA. Thus, we will introduce basic knowledge about quantum computing at first. Secondly, we explain a few necessary steps and procedures about QSFOA in detail and then briefly introduce QPSO and QGA.

Quantum Computing

Quantum bit boding

A quantum bit is a two-state quantum system in which a quantum bit is the smallest unit of information. A quantum bit is an inter-state between |1> and |0>. Namely, the different superposition states of |1> and |0>, so the state of a quantum bit can be indicated.

$$|\psi>=\alpha|0>+\beta|1>$$

In the above formula, |0> and |1> stand for the states of 0 and 1. α and β are satisfied by the following normalization conditions.

$$|\alpha|^2+|\beta|^2=1$$

$|\alpha|^2$ and $|\beta|^2$ are the probability values between 0 and 1.

It can have seen that: if there is a system with m quantum bits, 2 m states enable to be represented simultaneously. It can be described as

$$\begin{bmatrix}\alpha_1 & \alpha_2 & \cdots & \alpha_m \\ \beta_1 & \beta_2 & \cdots & \beta_m\end{bmatrix}$$

The above formula satisfies $|\alpha|^2+|\beta|^2=1, \mathrm{i}=1,2,\cdots,\mathrm{m}_\circ$

Quantum Gate Update

In This article, the quantum rotating gate is chosen to update the probability amplitude before and after. The specific adjustment operation is as follows.

$$U(\theta_i) = \begin{bmatrix} cos(\theta_i) & -\sin(\theta_i) \\ \sin(\theta_i) & \cos(\theta_i) \end{bmatrix}$$

Update the process as follows:

$$\begin{bmatrix} \alpha_i' \\ \beta_i' \end{bmatrix} = U(\theta_i) \begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix} = \begin{bmatrix} cos(\theta_i) & -\sin(\theta_i) \\ \sin(\theta_i) & \cos(\theta_i) \end{bmatrix} \begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix}$$

$(a_i, \beta_i)^T$ and $\left(\alpha_i', \beta_i'\right)^T$. The probability amplitude before and after the rotational gate update of the i-th quantum bit of the chromosome for the rotation angle is represented.

QSFOA

The original FOA is a swarm intelligence optimization algorithm based on fruit fly foraging behavior proposed by Pan (25). Inspired by quantum computing, we propose a new Quantum Step Fruit Fly Optimization Algorithm (QSFOA) to address the shortcomings of FOA. The detailed procedure of QSFOA is as follows.

(1) Randomly determine the initial population location.
X_axis = 10*rand();
Y_axis = 10*rand();

(2) Randomly determine the initial quantum bits chromosome.

$$Q_q(t) = \begin{vmatrix} \alpha_1^q \\ \beta_1^q \end{vmatrix} \begin{matrix} \alpha_2^q \\ \beta_2^q \end{matrix} \begin{vmatrix} \alpha_3^q \\ \beta_3^q \end{vmatrix} \begin{matrix} \alpha_4^q \\ \beta_4^q \end{matrix} \begin{vmatrix} \alpha_5^q \\ \beta_5^q \end{vmatrix} \begin{matrix} \cdots \\ \cdots \end{matrix} \begin{vmatrix} \alpha_p^q \\ \beta_p^q \end{vmatrix}$$

(3) Measure the qubit chromosome$Q_q(t)$ and obtain the binary coded chromosome.

a) Firstly, the measurement process will generate a matrix $QP_q(t)$.

$$QP_q(t) = \left|r_1^q\right| r_2^q \left|r_3^q\right| r_4^q \left|r_5^q\right| \cdots \left|r_p^q\right|$$

b) Secondly, "r" in the (2.1.2) is a random number between 0 and 1. When $\left|a_p^q\right|^2 > r_p^q$, p_p^q equals 0; otherwise, p_p^q equals 1.

c) Thirdly, the state $P_q(t)$ is obtained after measurement comparison.

$$P_q(t) = \left|p_1^q\right| p_2^q \left|p_3^q\right| p_4^q \left|p_5^q\right| \cdots \left|p_p^q\right|$$

d) Fourthly, by converting a binary code to a decimal number δ, the following result is decoded the following result.

$$\delta = \sum_{i=1}^{10} b_i \cdot 2^{i-1}, X = U1 + \frac{U_2 - U_1}{2^{10} - 1} x$$

(4) Random direction and distance to the fruit fly individual using smell to search for food.

X(i) = X_axis+2*rand()-δ;
Y(i) = Y_axis+2*rand()-δ;

(5) Estimate the distance from the origin (Dist) because of the unknown food location, and then calculate the taste density determination value (S), which is the reciprocal of the distance.

$$\text{Dist (i)} = \sqrt{X(i)^2 + Y(i)^2}$$
$$S(i) = 1/\text{Dist (i)}$$

(6) The smell concentration judgment value (S) is substituted into the smell concentration judgment function (or called Fitness function) and then figure out the smell concentration (Smell) of individual fruit flies in different locations.
Smell(i) = objective function (S(i)) = RMSE

(7) Identify the best concentration of flavor in this population of fruit flies.
[bestSmell bestindex] = min(Smell);

(8) Keep the best taste concentration value and the x, y coordinates. At this time, the fruit fly swarm will fly to this position by vision.
X_axis = X(bestindex);
Y_axis = Y(bestindex);
Smellbest = bestSmell;
If failure to find the minimum of root mean square error (RMSE), a quantum rotating gate is used to change $Q_q(t)$.

(9) Iteratively find the optimal value until minimum RMSE is found. Steps 3–6 need to be repeated and determined whether the flavor concentration is superior to the previous iteration of flavor concentration, and if so, step 7.

QPSO

Sun et al. (26) proposed a particle swarm optimization with quantum behavior with few parameters and a simple equation.

The QPSO, to increase the randomness of particle position, cancel the particle's movement direction property, using quantum mechanics, makes each particle have quantum behavior. The specific steps are as follows.

(1) Initialize the locations of particles in space. The position vector of the particle is

$$x_i(t) = (x_{i1}(t), x_{i2}(t), \cdots, x_{iD}(t)), i = 1, 2, \cdots, M;$$
$$pbest_i = x_i$$

In the above formula, $pbest_i$ is the optimal position of individual particles.

(2) Calculate the value of fitness function on each particle and select the particle with the best value to be globally optimal particle *gbest*;

(3) Determine each particle's local factor as p_i;

$$p_i = \varphi \times pbest_i + (1 - \varphi) \times gbest$$
$$\varphi = \frac{\phi_1}{\phi}$$

(4) Update $Mbest$(mean particle best position);

$$\text{Mbest} = \frac{1}{M}\sum_{i=1}^{m} pbest_i$$

In the above formula, M represents the size of the particle group, and the average value of is represented by$Mbest$.

(5) Modify the search range of particles, which is $L_i\ (t\ )$;

$$L_i\ (t) = 2\beta \cdot \left|Mbest - x_i(t)\right|$$

β is Contraction-Expansion coefficient, controlling convergence speed.

(6) Particles undergo a new evolution;

$$x_{ij}\ (t) = p_{ij}\ (t) \pm \beta \left|Mbest - x_{ij}\ (t)\right| \cdot \ln(\frac{1}{u_{ij}\ (t)})$$

(7) Calculate a current fitness value of the particles, comparing it with the individually optimal fitness value that it has gone through, then designate the particle with the highest adaptation as the new $pbest_i$;
(8) All of particles' current adaptation value is compared to the globally optimal fitness value in the population, and the particle with the highest adaptation is designated as $gbest$;
(9) Repeat steps 2–8 until the minimum RMSE is reached, then it is terminated.

QGA

Han and Kim (27) proposed a new quantum genetic algorithm based on quantum chromosome coding. The key to the new genetic algorithm is the introduction of quantum revolving gates to the parent generation. The specific process of quantum genetics used in this paper is as follows.

(1) An initial population is first performed to randomly generate n chromosomes encoded in quantum bits.
(2) Take one measurement for each individual in the initial population to obtain the corresponding deterministic solution.
(3) Perform an adaptation assessment for each deterministic solution and record the optimal individual and their fitness value.
(4) They are determining whether the conditions for termination have been met.
(5) Measurement of all individuals in the population and their fitness value to defined values.
(6) Apply adjustments to individuals using quantum revolving gates to obtain new populations.
(7) Recording the optimal individual and the corresponding fitness value.
(8) Increase the number of iterations, and continue with step (4) until the smallest RMSE is found.

EMPIRICAL ANALYSES

Sample Data and Variables

After finding the price and total value of numerous tourism stocks and other relevant information through Eastmoney, this paper compares the data and preliminarily identifies ten enterprises such as China Tourism Group Duty-Free Corporation Limited, and further randomly selects two leading enterprises, Utour Group Co., Ltd. and China Tourism Group Duty-Free Corporation Limited. Therefore, this paper collects these two enterprises' daily stock information from the Wind database from October 25, 2018, to October 21, 2020, with 483 observations. We first import all the data from 16 indexes of the two tourism enterprises' stocks into the R language, then discretize the data using the "discretization" function in the rough set calculation method. Finally, the function "FS.all.reducts.computation" is used to reduce the indexes. After eliminating the useless indexes through a rough set, the 16 technical indexes such as opening price are reduced to 12 technical indexes such as opening price, highest price, lowest price, turnover (million RMB) and RSI as the independent variables in this paper.

In this paper, MATLAB R2019a software is used for the analysis. Eighty percent of entire data sets (if it's not an integer, round it off) are used as training data to construct the model. The rest of the 20% data are then used as test data to perform the prediction accuracy analysis of the QSFOA-BPNN, QPSO-BPNN and QGA-BPNN. The basic information on the two enterprises' technical indexes can be seen in **Tables 1**, **2**. Furthermore, the price movement chart of the two companies can be seen in **Figure 2**.

It can be observed from **Figure 2** that a trend of constant fluctuation existed in the closing price levels of the two enterprises from October 2018 to April 2019. At the beginning of the epidemic, Utour Group Co., Ltd.'s closing price showed a small upward trend, but the overall trend was still downward. China Tourism Group Duty-Free Corporation Limited's closing price also showed a downward trend. However, after April 2020, the two enterprises' closing prices have risen rapidly and have maintained a relatively high level.

Since the architecture of BPNN will influence the predictive ability of BPNN, while existing methods cannot enable BPNN to get a great predictive ability, it shall be studied. In this paper, quantum swarm intelligence algorithms (QSIA) are used to determine the number of neurons in each hidden layer independent. In the meantime, the dependent variable is the root mean square error (RMSE). The RMSE is the objective function in these three QSIA, and the QSIA is aimed to find the minimum of RMSE corresponding to each structure of BPNN.

The way to use QSFOA to optimize BPNN is to calculate the distance between the fruit flies' location and the origin coordinate (0, 0). Then, we calculate the reciprocal that is smell concentration judgment value (S). If it's not an integer, we need to round it off, which refers to the number of neurons in each hidden layer. The number is substituted into the BPNN and train BPNN through the data set and then record the RMSE. The specific algorithm flow chart of QSFOA-BPNN is shown in **Figure 3**.

In our research, the difference between the prediction result of the QSFOA-BPNN, QPSO-BPNN, and QGA-BPNN is calculated firstly to be used as an error term. In the BP neural network, we adopt MATLAB to a self-edit program to perform the error

TABLE 1 | The descriptive statistical value of technical indexes for Utour Group Co., Ltd.

	N	Minimum	Maximum	Mean	SD	Variance
Opening price (¥)	483	4.46	12.05	6.50	1.45	2.11
Highest price (¥)	483	4.60	12.92	6.67	1.53	2.35
Lowest price (¥)	483	4.46	10.92	6.36	1.37	1.89
Turnover (million)	483	6.91	1358.47	128.06	148.85	22157.21
Volume	483	1396500	118807800	17762687	15730330	247443289300921
MA (10)	483	25.06	44.35	37.67	5.69	32.39
MA (20)	483	25.02	43.79	37.49	5.67	32.13
MA (60)	483	24.75	42.15	36.79	5.71	32.56
MA (120)	483	24.47	41.81	35.74	6.06	36.76
MACD	483	−2.41	3.08	0.25	0.96	0.92
TECH_DIFF	483	−2.41	3.08	0.25	0.96	0.92
RSI	483	7.12	99.22	55.98	22.86	522.80
Closing price (¥)	483	4.52	11.92	6.52	1.46	2.13

TABLE 2 | The descriptive statistical value of technical indexes for China tourism group duty-free corporation limited.

	N	Minimum	Maximum	Mean	SD	Variance
Opening price (¥)	483	47.96	246.99	99.30	48.72	2373.19
Highest price (¥)	483	50.85	249.00	101.59	50.66	2566.88
Lowest price (¥)	483	47.90	226.00	97.40	47.05	2213.89
Turnover (million)	483	236.84	9194.45	1302.75	1332.35	1775148.81
Volume	483	3163100	46052300	11861732	6551572	42923104422383
KDJ(D)	483	16.05	94.01	56.02	18.68	348.78
KDJ(J)	483	−19.12	117.18	55.82	34.66	1200.98
MA(10)	483	53.66	223.33	98.22	47.70	2275.11
MA(20)	483	54.67	215.73	96.65	46.05	2120.69
MA(60)	483	56.82	212.13	90.46	37.52	1407.51
MA(120)	483	58.92	168.14	83.33	23.74	563.65
RSI	483	10.95	95.81	55.31	17.05	290.84
Closing price (¥)	483	48.12	243.00	99.58	48.82	2383.79

term's prediction. The parameter setting values of BPNN include iterative number of 100, train goal of 10^{-5}, learning rate of 0.1. The input layer has 12 nodes (that is, 12 input variables which refer to 12 technical indexes), and the output layer has one node (that is, one output variable which refers to the closing price).

Concerning BPNN with multiple hidden layers, there is no clear theoretical guidance for setting the number of each hidden layer. To figure out the best architecture of multilayer-BPNN, we set up the number of layers in BPNN as $L \in \{3, 4, 5\}$. According to Zurada (28), in this paper, we adopted the following formula to determine the number of neurons in each hidden layer.

$$h_i = \sqrt{m+1} + \alpha$$

Where $i \in \{1, 2, \ldots, L\}$, m denotes the neurons count of the input layer, and [0, 10]

Since there are 12 variables taken as an input vector, the input layer consists of twelve neurons. This definition is $m = 12$. Meanwhile, the following day's closing price is taken as the output, so we have $n = 1$.

Based on the equation, it can be found that $4 \leq h \leq 14$. Therefore, we fetch h in the set of {4, 5, ..., 14}. It can be seen from the above equations that with increasing the value of m, the suitable range of neurons in hidden layers should be enlarged. Therefore, the upper of neurons in each hidden layer is 14, and the lower limit is four.

Then, concerning the initial parameter set up of QSFOA, the random initialization fruit fly swarm location range is [−10, 10], the quantum fly step of iterative fruit fly food searching is [−5, 5], the iteration number is 100, fruit fly population is 5, the length of step-binary coding is 10. Concerning the setting of QPSO, the iteration number is 100, and the particle population is 5. About the setting of QGA, the iteration number is 100, the population is five, and the length of binary coding is 10.

In the different number of hidden layers, we calculate RMSE separately, record the number of neurons corresponding to the minimum of RMSE, and finally compare the RMSE under each hidden layer to find out the number of hidden layers and neurons corresponding to the minimum RMSE, to determine the best neural network structure.

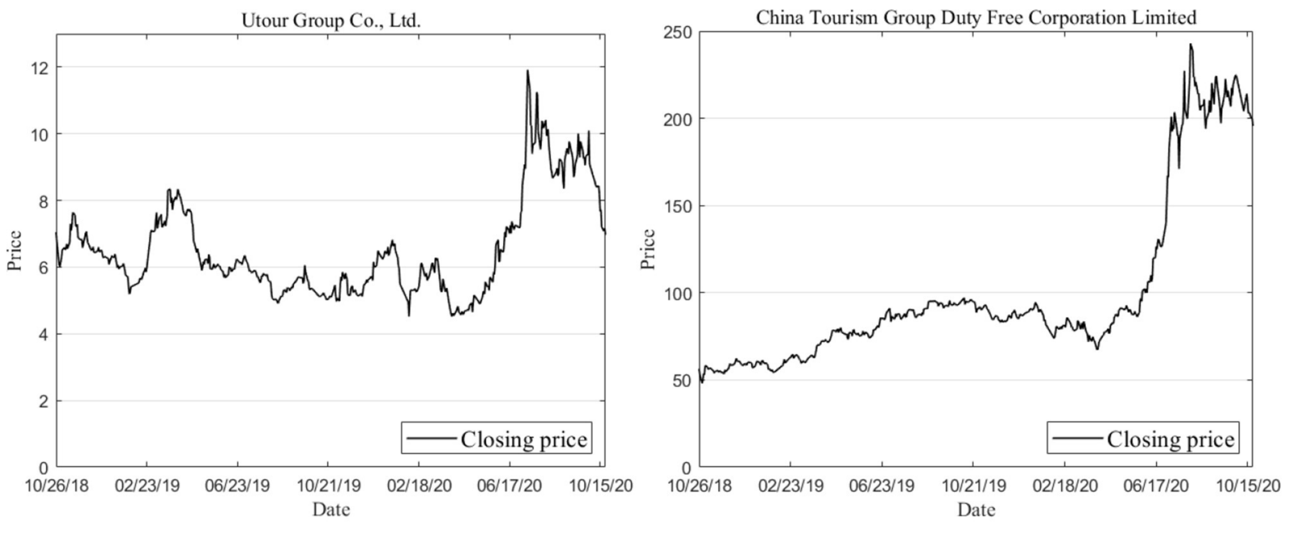

FIGURE 2 | Movement of closing prices of two enterprises.

General Comparison of the Prediction Capabilities of Three Models

All of the algorithms are run five times independently, and the best results obtained from runs are saved. The final results of the test data are shown in **Table 3**, and the best structure is shown as a vector that $(m, h_1, h_2, \ldots, h_L, n)$ where m denotes the neurons count of the input layer and L denotes the number of hidden layers and h_i $(i = 1, 2, \ldots, L)$ denotes the ith hidden layer. **Figure 4** shows the trend chart of RMSE's iterative decline under the best results in times running, and it also shows the fruit fly flying route of QSFOA while optimizing the BPNN.

Four evaluation indexes are used to compare the forecasting ability of three models, and the formula of four indexes separately is:

Coefficient of efficiency (CE), whose formula is:

$$CE = 1 - \frac{\sum (X_t - \hat{X}_t)^2}{\sum (X_t - \bar{X}_t)^2}$$

Root Mean Squared Error (RMSE), whose formula is:

$$RMSE = \sqrt{\frac{\sum (y_i - \hat{y}_i)^2}{n}}$$

Mean Absolute Percentage Error (MAPE), whose formula is:

$$MAPE = \frac{1}{n}\sum_{n}^{1} \frac{\left|y' - y\right|}{y}$$

Median Absolute Deviation (MAD), whose formula is:

$$MAD = \frac{1}{n}\sum_{i=1}^{n} \left|X_i - m(x)\right|$$

Among the four evaluation indexes, the closer the first index(CE) to one, the accurate the model. On the contrary, the closer the second to fourth index to zero, the accurate the model. Besides, the best structure optimized by these three QSIA about two companies is shown in the fifth index, and the last one is the running time of different algorithms.

We can find from **Table 3** that QSFOA-BPNN model evaluation indexes in the first group of data are as follows, MAPE is 1.2416, which is not much different from the other two models. While CE is 0.9850, RMSE is 0.1025, and MAD is 0.0772, all of which are better than the other two models. Therefore, the prediction performance of stock 002707.SZ gives a ranking result about the three models of QSFOA-BPNN > QGA-BPNN > QPSO-BPNN. The QSFOA-BPNN model has a MAPE of 1.2416 and a MAD of 1.0127, which is in the middle of the three models from the secondary data set. While the CE is 0.9814 and the RMSE is 1.8054, the QSFOA-BPNN model has the best goodness of fit and the lowest error compared to the remaining two models. The prediction performance of stock 601888.SH shows that QSFOA-BPNN > QPSO-BPNN > QGA-BPNN.

The upper half part of **Figure 5** shows the trend chart, where the three algorithms in sample data from 002707.SZ presents a continuous decrease in RMSE between calculated predictive value and target value during the optimization process. The research results show that RMSE between the predictive value and target value is 0.1025 after iterative optimization of the number of BPNN neurons by QSFOA; that is 0.1639 after iterative optimization of the number of BPNN neurons by QPSO; that is 0.1637 after iterative optimization of the number of BPNN neurons by QGA, so it demonstrates that QSFOA has the best ability in terms of BPNN optimization.

The lower half of **Figure 5** shows the trend chart, where the three algorithms in sample data from 601888.SH presents a continuous decrease in RMSE between calculated predictive

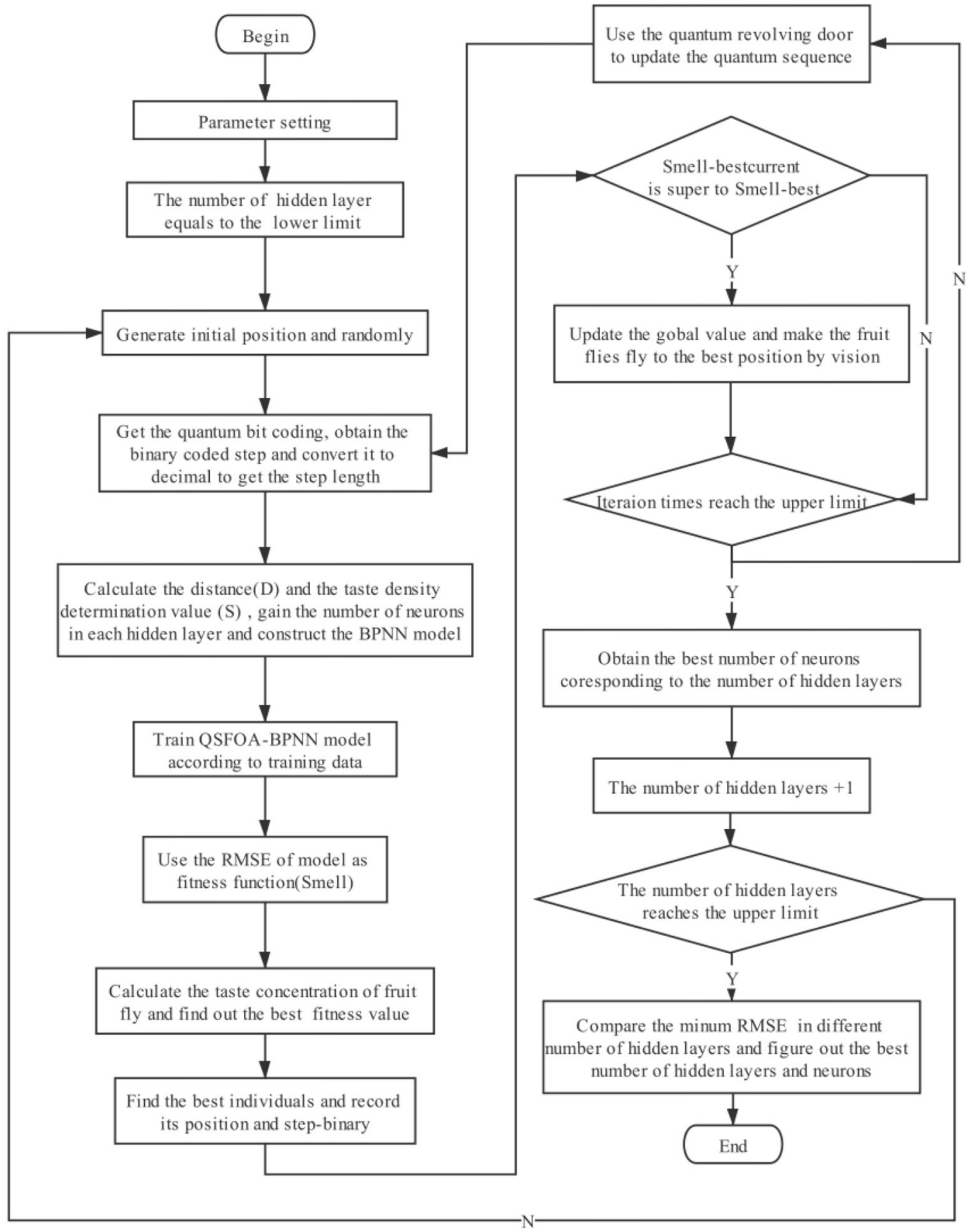

FIGURE 3 | Specific algorithm flow chart of QSFOA-BPNN.

TABLE 3 | Final prediction results of three models.

Stock	Model	CE	RMSE	MAPE	MAD	Best structure
002707.SZ	QSFOA-BPNN	0.9850	0.1025	1.2416	0.0772	12,11,9,14,1
	QPSO-BPNN	0.9773	0.1639	1.4314	0.0978	12,14,9,10,1
	QGA-BPNN	0.9782	0.1637	1.0749	0.0879	12,11,6,8,11,1
601888.SH	QSFOA-BPNN	0.9814	1.8054	1.0137	1.0127	12,10,7,12,1
	QPSO-BPNN	0.9791	2.2620	0.7659	0.8578	12,8,9,10,6,1
	QGA-BPNN	0.9664	3.7008	1.1512	1.5050	12,9,6,4,1

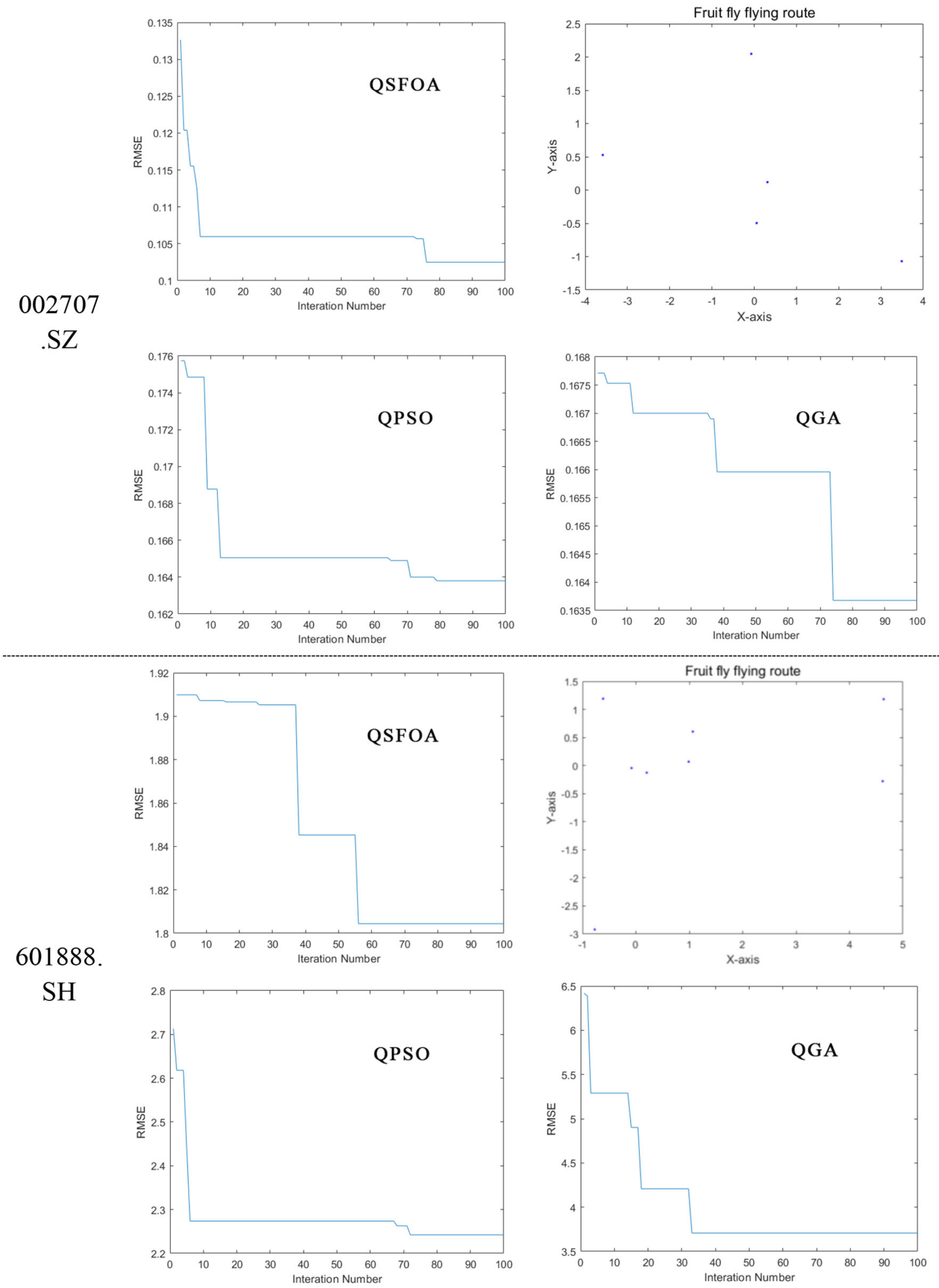

FIGURE 4 | Trend chart of RMSE's iterative decline and fruit fly flying route.

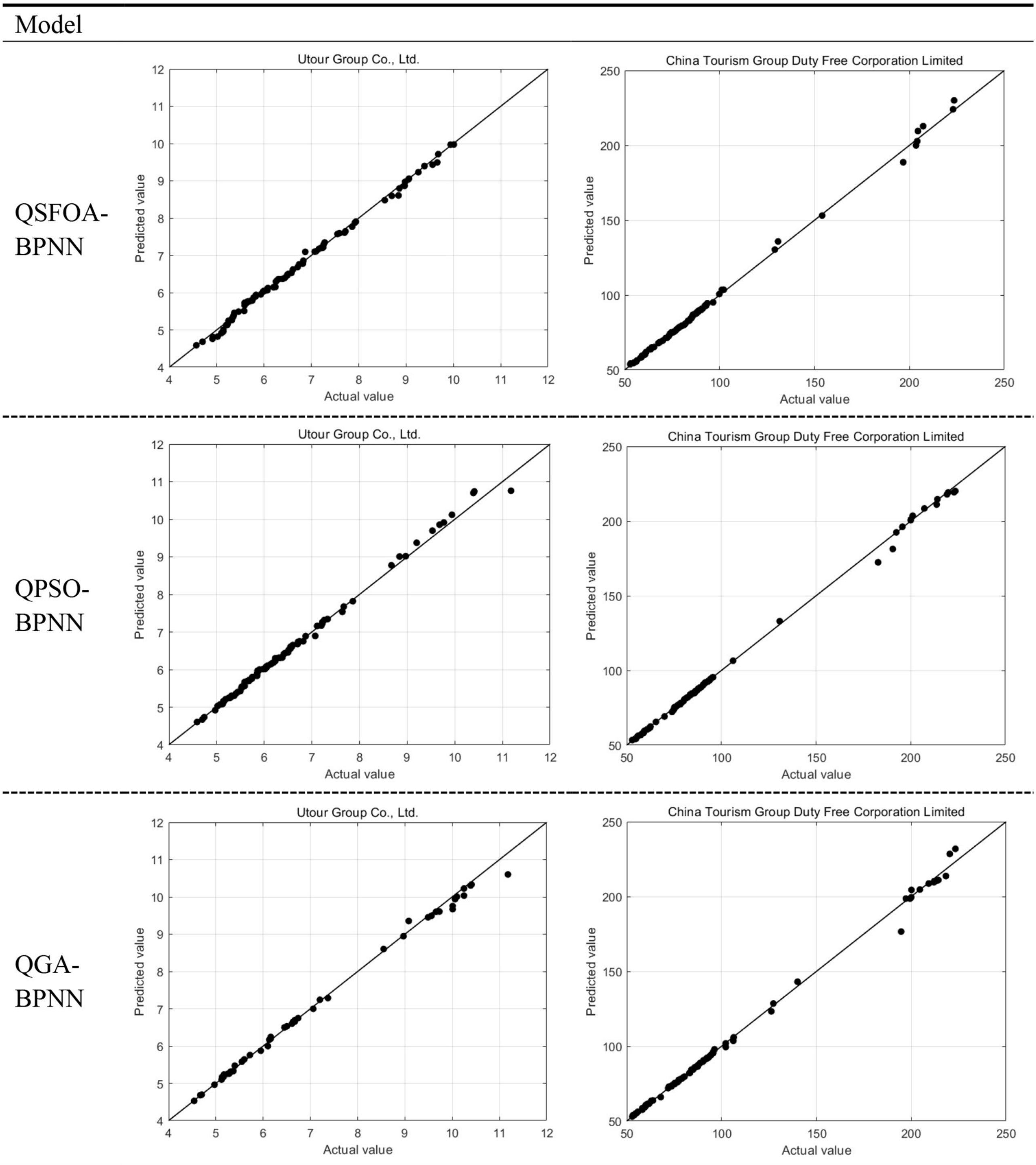

FIGURE 5 | The sample points clustering trend chart of the prediction results.

value and target value during the optimization process. The research results show that RMSE between the predictive value and target value is 1.8054 after iterative optimization of the number of BPNN neurons by QSFOA; that is 2.2720 after iterative optimization of the number of BPNN neurons by QPSO; that is 3.7008 after iterative optimization of the number of BPNN neurons by QGA, so it demonstrates that QSFOA has the best ability in terms of BPNN optimization.

TABLE 4 | Average running time(s) of three models that have been tested for five times.

Algorithm		QSFOA-BPNN	QPSO-BPNN	QGA-BPNN
002707.SZ	Running time (s)	1428.1995	1929.3138	2028.0438
601888.SH	Running time (s)	965.2677	1384.6192	1069.0291

The fruit fly flying routes in the two stock models reveal that all the fruit flies in the QSFOA-BPNN model have very random flight paths, making fruit flies easily jump out of the solution of local extreme value and find the solution of the global optimum. Therefore, QSFOA has a high optimization capability.

In our research, we analyze that some of the algorithms may be stuck at local minima, and they cannot find the best nodes number of the current structure of hidden layers. Simultaneously, it has reached the iteration time, which may be why the best structure under different QSIA has a different number of hidden numbers.

All of the algorithms are implemented in an Intel Core (TM) i5-8300H CPU 2.30 GHz processor, 8.00 GB DDRIII of RAM. Furthermore, this article uses the sample data to test three prediction models for two stock closing prices five times. The test results are shown in **Table 4**. We can learn from **Table 4** that QSFOA performs best in the running time because it reduces calculating complexity with high calculating speed in general.

Figure 5 shows the prediction results of the test data in QSFOA-BPNN, QPSO-BPNN and QGA-BPNN. The horizontal axis corresponds to the stock's closing price of actual value, while the vertical axis is the closing price of the predicted value. The closer the sampling point is to the diagonal, the more accurate the prediction results will be. According to the samples' clustering trend, we can see that the three models have a good predictive ability. However, the model optimized by QSFOA can predict the closing price of the two tourism companies more accurately than the model optimized by QGA and QPSO.

CONCLUSION

Based on the information trend of tourism in the digital age, this paper takes the closing prices of tourism stocks and observes their trends to develop a prediction model for tourism stocks with better prediction accuracy. We explore the future economic sustainability of tourism driven by the digital age covering the COVID-19 era. We establish the deep learning models for forecasting, considering that a better structure of BPNN enables us to get better prediction results. For this purpose, this paper adopts the quantum swarm intelligence algorithms (QSIA), including the QSFOA, the QPSO and the QGA, associated with the BPNN adjusted with the number of neurons hidden layer independent variable accuracy analysis for the prediction of the closing price of the stocks. The QSFOA-BPNN model results show that the Utour Group Co., Ltd and China Tourism Group Duty-Free Corporation Limited performs more accurately with the QPSO-BPNN and the QGA-BPNN approaches. It is important to note that our models do not apply to the large volume of data to validate the prediction capability. Therefore, the QSFOA-BPNN model optimized by the QSFOA algorithm can be used as a research direction for future papers.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

W-TP, Z-YY, and Y-NP: wrote the paper. Q-YH: data collection and wrote the paper. F-YZ: methodology and software. M-EZ: funding access and reviewed the paper. All authors contributed to the article and approved the submitted version.

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REFERENCES

1. Kleijnen JPC, Mithram GA. Statistical techniques in simulation. *IEEE Trans Syst Man Cybern.* (1977) 7:680. doi: 10.1109/TSMC.1977.4309813
2. Wang JJ, Wang JZ, Zhang ZG, Guo SP. Stock index forecasting based on a hybrid model. *Omega.* (2012) 40:758–66. doi: 10.1016/j.omega.2011.07.008
3. Devi BU, Sundar D, Alli P. An Effective Time Series Analysis for Stock Trend Prediction Using ARIMA Model for Nifty Midcap-50. *Int. J. Data Mining Knowl Manage Process*. (2013) 3:65–78. doi: 10.5121/ijdkp.2013.3106
4. Ariyo AA, Adewumi AO, Ayo CK. Stock price prediction using the ARIMA model. In: *Proceedings of the 2014 UKSim-AMSS 16th International Conference on Computer Modelling and Simulation.* Cambridge: IEEE Computer Society (2014). doi: 10.1109/UKSim.2014.67
5. Abu-Mostafa YS, Atiya AF. Introduction to financial forecasting. *Appl Intell.* (1996) 6:205–13. doi: 10.1007/BF00126626
6. Zhang YA, Yan BB. Deep learning hybrid forecasting model for stock market. *Comput Sci.* (2020) 47:255–67.
7. Wang WH, Zhuo PY. Research on stock price prediction based on PCA-FOA-SVR. *J Zhejiang Univ Technol.* (2016) 44:399–404.
8. Bao ZS, Guo JN, Xie Y, Zhang WB. Model for stock price trend prediction based on LSTM and GA. *Comput Sci.* (2020) 47:467–73. doi: 10.11896/JsJkx.190900128
9. Shi SZ, Liu WL, Jin ML. Stock price forecasting using a hybrid ARMA and BP neural network and Markov model. In: *IEEE International Conference on Communication Technology*. Guilin (2013).
10. Wu MT, Yong Y. The research on stock price forecast model based on data mining of BP neural networks. In: *Third International Conference on Intelligent System, Design and Engineering, Applications.* Hong Kong (2013).
11. Feng L. Research on prediction model of stock price based on LM-BP neural network. In: *LEMCS-14*. Shenyang (2014). doi: 10.2991/lemcs-14.2014.177

12. Sun Q, Che WG, Wang HL. Bayesian regularization BP neural network model for the stock price prediction. *Adv Intell Syst Comput*. (2014) 213:521–31. doi: 10.1007/978-3-642-37829-4_45
13. Huo L, Jiang B, Ning T, Yin B. *A BP Neural Network Predictor Model for Stock Price. Lecture Notes in Computer Science*. Cham: Springer International Publishing (2014) p. 362–8. doi: 10.1007/978-3-319-09339-0_37
14. Cao JS, Wang JH. Exploration of stock index change prediction model based on the combination of principal component analysis and artificial neural network. *Soft Comput*. (2019) 24:7851–60. doi: 10.1007/s00500-019-03918-3
15. Yu ZX, Qin L, Chen YJ, Parmar MD. Stock price forecasting based on LLE-BP neural network model. *Phys A Statal Mechan Appl*. (2020) 553:124197. doi: 10.1016/j.physa.2020.124197
16. Thomas P, Suhner MC. A new multilayer perceptron pruning algorithm for classification and regression applications. *Neural Process. Lett*. (2015) 42:437–58. doi: 10.1007/s11063-014-9366-5
17. Beigy H, Meybodi MR. A learning automata-based algorithm for determination of the number of hidden units for three-layer neural networks. *Int J Syst*. (2009) 40:101–118. doi: 10.1080/0020772080 2145924
18. Khan AU, Motwani M, Sharma S, Khan AS, Pandey M. Stock rate prediction using backpropagation algorithm: results with different number of hidden layers. *J Softw Eng*. (2007) 1:13–21. doi: 10.3923/jse.2007. 13.21
19. Zhang PP, Shen CH. Choice of the number of hidden layers for back propagation neural network driven by stock price data and application to price prediction. *J Phys*. (2019) 1302:022017. doi: 10.1088/1742-6596/1302/2/022017
20. Alfaro L, Chari A, Greenland AN, Schott PK. Aggregate and firm-level stock returns during pandemics, in real time. In: *National Bureau of Economic Research (NBER) Working Paper, No. 26950*. Cambridge, MA: NBER (2020). doi: 10.3386/w26950
21. Ashraf BN. Stock markets' reaction to COVID-19: cases or fatalities? *Res Int Bus Finan*. (2020) 54:101249. doi: 10.1016/j.ribaf.2020. 101249
22. Baker SR, Bloom N, Davis SJ, Kost KJ, Sammon MC, Viratyosin T. The unprecedented stock market reaction to COVID-19. *Rev Asset Pricing Stud*. (2020) 10:705–41. doi: 10.1093/rapstu/raaa008
23. Mazur M, Dang M, Vega M. COVID-19 and the March 2020 stock market crash. *Evid S&P1500 Finan Res Lett*. (2021) 38:101690. doi: 10.1016/j.frl.2020.101690
24. Wang J, Lu X, He F, Ma F. Which popular predictor is more useful to forecast international stock markets during the coronavirus pandemic: VIX vs EPU? *Int Rev Finan Anal*. (2020) 72:101596. doi: 10.1016/j.irfa.2020.101596
25. Pan WT. A new fruit fly optimization algorithm: taking the financial distress model as an example. *Knowl Based Syst*. (2012) 26:69–74. doi: 10.1016/j.knosys.2011.07.001
26. Sun J, Feng B, Xu W. Particle swarm optimization with particles having quantum behavior. In: *Proceedings of the 2004 Congress on Evolutionary Computation (IEEE Cat. No.04TH8753)*. Portland, OR (2004). doi: 10.1109/CEC.2004.1330875
27. Han KH, Kim JH. Genetic quantum algorithm and its application to combinatorial optimization problem. In: *Proceedings of the 2000 Congress on Evolutionary Computation. CEC00 (Cat. No.00TH8512)*. La Jolla, CA: IEEE (2002).
28. Zurada JM. *Introduction to Artificial Neural Systems*. Eagan, MN: West Publishing Company.

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Inclusive Finance, Environmental Regulation, and Public Health in China: Lessons for the COVID-19 Pandemic

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The slow-down of the Chinese economy and the depression in the global economy during the COVID-19 show that governments should provide stimulus packages. These policies should be inclusive in terms of financial gains. Using the panel data of 30 regions in China from 2006 to 2016, this paper uses the Poisson Pseudo-Maximum Likelihood (PPML) estimator to analyze the impact of inclusive finance on public health. The results show that inclusive finance has a significant positive effect on public health. The performance of the eastern region is significantly better than that of the central and western regions. When we consider the combined effect of environmental regulation, the improvement effect of inclusive finance on public health is still significant, and the coefficient increases in the eastern region. Similarly, there is also a significant improvement effect in the central and western regions. Our findings reveal that environmental regulation promotes the beneficial effect of inclusive finance. Therefore, it is important to improve the inclusive financial development mechanism and enhance environmental regulation intensity for solving public health issues. Lessons related to the COVID-19 pandemic are also discussed.

Keywords: public health, COVID-19, inclusive finance, environmental regulation, PPML estimator

INTRODUCTION

The wheel of history has left two deepest marks on China in the great journey of more than 40 years of reform and opening up: the sustained and rapid economic take-off and the sharp deterioration of human health and the ecological environment. Pollution makes human beings face huge health costs and survival threats. It causes rapid depreciation of human health capital, which constitutes an important source of economic and social development inequality in the world (1). Health risks caused by environmental pollution require environmental regulations, which will have positive effects on public health. This paper examines the effects of the inclusive finance on public health in China. During the COVID-19, it is observed that the low degree of inclusiveness cannot effectively meet the real economy's needs and market entities for financial development and financial innovation. The slow-down of the Chinese economy and the depression in the global economy during the COVID-19 show that governments should provide stimulus packages. These policies should be inclusive in terms of financial gains.

To deal with this thorny problem, environmental regulation, as the preferred tool and weapon of all countries, came into being (2). In 2007, China formulated the first programmatic document in the environment and health, *the National Environment and Health Action Plan (2007-2015)*. In 2014, the eighth meeting of the Standing Committee of the 12th National People's Congress voted and passed the amendment to the environmental protection law, completing the first amendment to the environmental protection law. However, the challenge brought by pollution far exceeded the imagination and expectation of all sectors of society. According to the *Environmental Green Paper: China's Environmental Development Report (2016-2017)*, the Beijing Municipal Government twice issued the early red warning of heavy air pollution in just over a month from 2015 to the beginning of 2016. This is the first time Beijing launched the early red warning after introducing the four-level response policy of air pollution in 2013. Do these facts mean that China's environmental regulation is invalid? This is why we are exploring the internal relationship and mechanism between environmental pollution, environmental regulation, and residents' health is of great help to recognize and measure the high cost of environmental pollution and highlight the necessity and importance of formulation and implementation of government environmental regulation policy. Therefore, it is urgent to speed up the formulation and promulgation of relevant environmental regulation policies and efficient environmental pollution control. More importantly, it is necessary to strengthen the overall awareness among regions, enhance the exchange and cooperation between governments in the formulation and implementation of pollution control and environmental regulation to achieve the good effect of "$1 + 1 > 2$."

Since China's reform and opening up to finance and trade, financial repression has resulted in the abnormal wealth distribution mechanism of the residents' sticking back to the enterprises, meaning that the financial resources have not been effectively allocated. As inclusive finance can effectively optimize the allocation of financial resources and adjust the return on capital to a reasonable range, inclusive finance has become an important means to improve countries' financial systems in the world. Inclusive finance refers to improving financial infrastructure, reducing transaction costs, and effectively expanding the scope and population of financial services. In this sense, this paper uses panel data of 30 provinces from 2006 to 2016 as research samples. It adopts Poisson's pseudo maximum likelihood estimation method (PPML) to analyze the impact of inclusive finance on Global Trade Finance Program GTFP based on environmental regulation. It is of great practical significance to reveal the combined effect of inclusive finance and environmental regulation on public health, which is conducive to improving the quality and efficiency of medium and long-term social public welfare. This research is the first study to analyze the effects of financial inclusion on public health in China using the region-level dataset to the best of our knowledge.

The rest of the paper is organized as follows. Section Literature Review reviews the related literature. Section Empirical Model and Variable Selection explains the empirical model and variable selection criteria. Section Empirical Results and Analysis provides the empirical findings. Section Conclusions concludes.

LITERATURE REVIEW

In terms of the definition of inclusive finance and the construction of indicators, Beck et al. (3) first defined inclusive finance. The authors constructed the indicators from two dimensions: availability and usability. Sarma (4) further improved and developed the content of inclusive finance. He constructed a comprehensive index of inclusive finance from three dimensions of financial penetration, availability and usability. In terms of the advantages of inclusive finance, Bruhn and Love (5) suggested that compared with traditional finance, inclusive finance has a wider coverage, which can also optimize the allocation of capital and create preconditions for the upgrading of industrial structure and the development of science and technology. At present, scholars have provided little research on the application of inclusive finance. These papers mainly focused on the impact of inclusive finance on labor income and industrial structure. Huang and Zhang (6) analyzed the regional data from China and found that inclusive finance had a significant positive impact on labor income. With the improvement of inclusive finance, China's share of labor income would also rise.

Theoretically speaking, environmental regulation will increase the expenditure on pollution control and investment of new technology. Although internal financing can alleviate some financing constraints, it is necessary to use the financial system's external financing due to large capital demand, tight governance time, and insignificant short-term return. A higher level of financial development is conducive to environmental regulation and the realization of a "win-win" between environmental governance and technological innovation (7) since financial development can restrain the economic fluctuation caused by environmental regulation (8). At the same time, environmental regulation can significantly improve the quantity and quality of environmental information disclosure, provide information screening for financial institutions, promote green credit, boost green technology innovation, and have a significant positive impact on public health (9). Besides, environmental regulation also forces financial reform and guides financial institutions to develop the blue ocean market of environmental protection. It can be seen that financial development, environmental regulation and their synergistic interaction play an important role in public health.

There are two main research threads on environmental regulation and public health: one is to assess the health risks caused by environmental pollution and demonstrate the adverse health effects of pollution. According to the research purpose, Cropper (10) introduced environmental pollution into the model as an important variable that significantly affected human health and made gradual and continuous improvement based on Grossman's health production function. Albertini et al. (11) explored the reasons behind the phenomenon that residents in heavily polluted areas were generally faced with accelerated depreciation of health stock and found that despite age, environmental pollution is a major cause of the further increase of health depreciation rate accelerated decrease of health stock. Ebenstein (12) explained the incidence rate of digestive tract cancer in China based on the new perspective of river water pollution. The study found that every 1% decrease in water quality will cause nearly 10% of digestive tract cancer incidence. The pollution of river water has become a hidden tumor that endangers our residents' health and threatens their survival. Saygin et al. (13), based on the Grossman model, empirically analyzed the substantial harm of PM10 and SO_2 to residents' health from a micro perspective. The research showed that it was particularly urgent to use all effective measures to effectively control air pollution and curb the continuous decline of air quality. Secondly, to deal with the worsening situation of environmental conditions and residents' health, this paper discussed how to formulate environmental policies scientifically and reasonably and further analyzed the environmental performance and economic impact of this government behavior. Based on the data of Dublin, Ireland, Boogaard et al. (14) verified that the formulation and implementation of environmental regulation policies were indeed conducive to the improvement of environmental quality, greatly reducing the emissions of pollutants, thus highlighting the importance and necessity of government environmental regulation. Cao et al. (15) combined the Arrow-Romer production function with the Grossman utility function and used China's cross-regional data to explore environmental regulation policy's economic impact. The study found that: because health investment might crowd out physical capital, excessive health investment might negatively affect economic growth.

By summarizing the existing literature, we can find that scholars have done comprehensive research on the health effect of environmental pollution and the economic effect of environmental regulation. Still, there is almost no literature on the internal relationship and mechanism among inclusive finance, environmental regulation and public health. Firstly, few scholars theoretically analyzed the mechanism of financial development, environmental regulation and their synergy on public health and verified the collective impact based on empirical methods. Secondly, financial development and environmental regulation are often measured by a single indicator, which cannot effectively measure and reflect them (16, 17).

EMPIRICAL MODEL AND VARIABLE SELECTION

Model Setting

The error term violating the assumption of the same variance may raise the problem of endogeneity bias. However, the dynamic panel data estimators measure the short-term impact of related variables on the total factor productivity rather than the long-term relationship. Thus, this paper uses the Poisson Pseudo-maximum Likelihood (PPML) estimators proposed by Silva and Teneyro (18, 19) as regression estimation. Silva and Teneyro (18, 19) proposed the PPML estimation method to solve the above two problems and exemplified the gravity model used in international trade research. Note that the PPML estimator is scale-invariant since we have used the log-transformed dependent variable (20). Besides, the PPML method can solve a possible endogeneity bias. Simultaneously, Arvis and Shepherd (21) confirmed the effectiveness of the method. Based on the PPML estimation method, our paper examines the impact of inclusive finance and environmental regulation on public health in 30 provinces except Tibet in 2006–2016 in China. The benchmark model is constructed as following the control variables in previous papers [see, e.g., (22)]:

$$\begin{aligned} Hd_{i,t} &= \alpha_0 + \alpha_1 \ln ifi_{i,t} + \alpha_2 \ln envi_{i,t} + \alpha_3 \ln pgdp_{i,t} \\ &\quad + \alpha_4 \ln urban_{i,t} + \alpha_5 \ln medi_{i,t} + \alpha_6 \ln fiscal_{i,t} + \varepsilon_{i,t} \quad (1) \end{aligned}$$

Where i and t represent provinces and years, respectively. *Hd* stands for public health; *ifi* represents the inclusive finance. In terms of control variables, *envi*stands for environmental regulation [see, e.g., (23)]; *pgdp* is GDP per capita [see, e.g., (24)]; *urban* stands for urbanization rate (25); *medi* stands for medical service [see, e.g., (26)]; *fiscal* stands for proportion of medical and health expenditure [see, e.g., (24)]; ε is the random error term.

Following the spirit of Van Zoest and Hopman (27), Model (1) focuses on the impact of inclusive finance on public health. To further consider the regulatory role of environmental regulation on the impact of inclusive finance on public health, this paper constructs the following regression model based on the benchmark model:

$$\begin{aligned} Hd_{i,t} &= \alpha_0 + \alpha_1 \ln ifi_{i,t} + \alpha_2 \ln ifi_{i,t} * \ln envi_{i,t} + \alpha_3 \ln envi_{i,t} \\ &\quad + \alpha_4 \ln pgdp_{i,t} + \alpha_5 \ln urban_{i,t} + \alpha_6 \ln medi_{i,t} \\ &\quad + \alpha_7 \ln fiscal_{i,t} + \varepsilon_{i,t} \quad (2) \end{aligned}$$

Where $\ln ifi_{i,t} * \ln envi_{i,t}$ represents the combined effect of inclusive finance and environmental regulation. When the coefficient is significantly >0, the improvement of environmental regulation will assist inclusive finance in promoting public health; on the contrary, public health will be hindered.

Variable Selection and Data Source

This paper will use the data of 30 provinces except Tibet from 2006 to 2016 in China as the research sample. The main data sources include provincial statistical yearbooks, China regional financial operation reports and China health and family planning statistical yearbooks. Due to the significant differences in economic development and financial development between regions in China, this paper will divide the 30 provinces into three regions: the eastern region, the central region and the western region based on the comprehensive study. The eastern region includes 11 provinces, including Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan; the central region includes eight provinces, including Heilongjiang, Jilin, Shanxi, Anhui, Jiangxi, Henan, Hubei and Hunan; the western region includes 11 provinces, including inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shanxi, Gansu, Qinghai, Ningxia and Xinjiang 11 Provinces and municipalities.

Inclusive Finance

This paper uses the inclusive financial index (IFI) proposed by Sarma (4) to represent. Inclusive finance includes three dimensions: financial penetration, availability and usability. The larger the index value is, the higher the level of inclusive financial development becomes. This paper cannot get financial penetration data due to data availability limitation, so we analyze it from financial availability and usability. In this paper, the number of banking outlets per 100,000 people and the number of banking services per 100,000 people are used to measure financial usability, and the weight of both is 1/2. At the same time, this paper uses the ratio of total deposits and total loans to GDP to measure financial availability, and the weight of both is 1/2. The specific measurement formula of inclusive financial index (IFI) is as follows:

$$IFI = 1 - \frac{\sqrt{(w_1 - d_1)^2 + (w_2 - d_2)^2 + ... + (w_n - d_n)^2}}{\sqrt{{w_1}^2 + {w_2}^2 + ... + {w_n}^2}}$$
$$d_i = w_i \frac{A_i - m_i}{M_i - m_i}, 0 \leq w_i \leq 1, i = 1, 2, ..., n \quad (3)$$

The above formula A_i represents the real value of dimension i; m_i and M_i represent the minimum value and maximum value of dimension i, respectively; w_i represents the weight of dimension i.

Environmental Regulation

At present, there is no unified environmental regulation index in the academic circle, and the commonly used alternative indicators are the emission intensity of a certain pollutant, the operation cost of pollution control facilities, the income of sewage charges, etc. Besides, some scholars constructed a relevant composite index to characterize the intensity of environmental regulation. The formulation of environmental regulation is measured by the number of proposals (pieces) of the National People's Congress on environmental protection; regulation implementation is measured by the proportion of environmental pollution control investment in GDP (%) and the proportion of industrial pollution control investment in industrial added value (%); regulatory supervision is measured by the proportion (%) of sewage fee income in industrial added value.

In terms of other control variables, GDP per capita (*pgdp*) is the ratio of GDP to the number of permanent residents; urbanization rate (*urban*) is the proportion of urban population in the total population; medical service (*medi*) is health professionals per 1,000 population; the proportion of medical and health expenditure (*fiscal*) is the proportion of medical and health expenditure in financial expenditure.

EMPIRICAL RESULTS AND ANALYSIS

Benchmark Regression Results

Table 1 shows the regression results. In column (1), this paper uses the static panel estimation method and then compares it with the PPML estimation results. After the Hausman test, it is found that the p-value rejects the original hypothesis, and then this paper chooses the fixed-effects estimation method. In columns (2)–(8), the PPML method is used to estimate and control variables are added gradually to test the robustness of the estimation results.

It can be seen from the estimation results in column (1) that inclusive finance does not significantly promote public health. Although the coefficient is 0.149, it has not passed the significance test. From the results of column (2), inclusive finance shows a significant improvement in public health after regression estimation with the PPML. With the increase of control variables, the significant positive effect of inclusive finance on GTFP is relatively stable. Although the significance level decreases, it still passes the significance test at the level of 10%. Through the comparison of the estimation results of columns (1) and (2)–(8), it is noticeable if we use the regression results of the fixed-effect estimations method based on the static panel, we will come to the wrong conclusion that inclusive finance cannot promote public health.

From the results of control variables, the coefficient of environmental regulation is positive. This evidence is in line with Wagner (23). It has passed the significance level test, which shows that environmental regulation has an obvious improvement effect on public health. The coefficient of per capita GDP is positive in columns (4)–(8). It is significant at the level of 1%, which indicates that public health will be greatly improved with further economic development improvement. This result is in line with the findings of Edeme et al. (24), which show that more local pillar industries have changed from the second industry to the third industry with less pollution. The urbanization rate coefficient is significantly negative, which shows that urbanization development in China is at the environment's expense. This finding is different from previous papers. The coefficients of medical service and the proportion of medical and health expenditure are positive. Both coefficients pass the 1% significance level, which shows that the two's improvement has a significant positive role in promoting public health. This evidence is in line with Shah (26).

Regional Regression Results

Based on the regression analysis above, this paper will divide the 30 provinces into the eastern region, the central region and the western region, and then analyze and discuss the impact of inclusive finance on public health. **Table 2** is the detailed regression results.

Table 2 shows significant differences in the impact of inclusive finance on public health among regions. Compared with the central and western regions, inclusive finance plays the most important role in improving public health in the eastern region. The coefficient reaches 0.192 and passes the significance level of 5%. This result shows that inclusive finance keeps a positive role in promoting public health and is higher than the national average level in **Table 1** and the central and western regions in **Table 2**, which fully reflects the leading advantages of inclusive finance in the eastern region. Taking the number of banking outlets as an example, the average number in the eastern region is 9,043, while the average number in the central and western

TABLE 1 | Regression estimation results of inclusive finance on public health.

	FE	PPML	PPML	PPML	PPML	PPML	PPML	PPML
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln *ifi*	0.149 (1.05)	0.084** (2.45)	0.123** (2.37)	0.128** (2.42)	0.135** (2.21)	0.140* (1.89)	0.152* (1.85)	0.156* (1.75)
ln *envi*	0.256** (2.34)		0.272*** (2.58)	0.070*** (1.56)	0.273** (2.45)	0.275** (2.48)	0.275** (2.47)	0.272** (2.31)
ln *pgdp*	0.053*** (3.02)			0.049*** (3.56)	0.056*** (3.58)	0.050*** (3.42)	0.059*** (3.21)	0.063*** (3.22)
ln *urban*	0.072 (1.34)				−0.126** (−2.34)	−0.083** (−2.08)	−0.081* (−1.83)	−0.085** (−1.97)
ln *medi*	0.106*** (2.61)					0.109** (2.27)	0.108** (2.40)	0.108** (2.42)
ln *fiscal*	0.134** (−2.21)						0.113* (1.69)	0.115* (1.77)
Constant	0.529*** (5.59)	−0.634*** (−5.66)	−0.633*** (−5.21)	−0.658*** (−8.51)	−0.690*** (−5.61)	−0.753*** (−6.56)	−0.724*** (−7.93)	−0.723*** (−7.55)
R^2	0.856	0.513	0.505	0.513	0.520	0.526	0.525	0.531
Time-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Reg.-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	330	330	330	330	330	330	330	330

****, **, * represent the 1, 5, and 10% levels of significance, respectively. The values reported in brackets are t-statistics.*

TABLE 2 | Regional regression results.

Explanatory variable	Eastern regions		Central regions		Western regions	
	(1)	(2)	(3)	(4)	(5)	(6)
ln *ifi*	0.206** (2.45)	0.192** (2.27)	0.105** (2.03)	0.097* (1.92)	0.146* (1.89)	0.133* (1.70)
ln *envi*		0.245*** (2.65)		0.232** (2.42)		0.236** (2.37)
ln *pgdp*		0.124*** (4.86)		0.160*** (4.21)		0.035** (2.01)
ln *urban*		−0.097** (−2.31)		−0.062** (−2.22)		−0.058** (−1.98)
ln *medi*		0.119*** (2.71)		0.107** (2.32)		0.108** (1.97)
ln *fiscal*		0.192** (2.30)		0.133* (1.82)		0.130* (1.89)
Constant	−0.652*** (−5.99)	−0.641*** (−5.70)	−0.735*** (−6.31)	−0.756*** (−6.45)	−0.620*** (−5.79)	−0.608*** (−5.66)
R^2	0.521	0.535	0.515	0.520	0.502	0.513
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Region effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	121	121	88	88	121	121

****, **, * represent the 1, 5, and 10% levels of significance, respectively. The values reported in brackets are t-statistics.*

regions is 8,336 and 7,578, respectively. From this data, we can see that the eastern region is more prominent in financial advantages. In the central region, the coefficient of inclusive finance is 0.097; in the western region, the coefficient of inclusive finance is 0.133, and both pass the significance level test. From the comparison between the central region and the western region, inclusive finance has a greater influence on public health in the western region and a relatively smaller influence on public health in the central region, which is closely related to the long-term adherence to the "western development" policy and the stronger marginal role of inclusive finance in the western region.

Regression Results Under the Effect of Environmental Regulation

The impact of inclusive finance on public health depends on its development and is affected by environmental regulation. We also test whether the environmental regulation can promote the significant positive effect of inclusive finance on public health. Therefore, we use model (2), which adds the multiplier of inclusive finance and environmental regulation. Because of the strong correlation between the cross multiplication term and the independent variables, the model is with the multicollinearity problem. Since the decentralization of the cross-multiplication terms can effectively alleviate the multicollinearity problem (28), this paper adopts the method of Wooldridge (28) to decentralize all the cross multiplication terms in the model (2). The regression results are shown in **Table 3**.

From the regression results in column (2) of **Table 3**, it can be seen that under the combined effect of environmental regulation, inclusive finance has an improvement effect on public health of the whole country, and its coefficient is greater, indicating that the environmental regulation promotes the role of inclusive finance in public health. From the perspective of regions, the combined effect of inclusive finance and environmental regulation can significantly improve public health in the eastern region and significantly improve the vast central and western regions. For the central and western regions,

TABLE 3 | Regression results under the effect of environmental regulation.

Explanatory Variable	Whole Country		Eastern Regions		Central Regions		Western Regions	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln *ifi*	0.126**	0.148*	0.213**	0.181**	0.105*	0.083*	0.125*	0.139*
	(2.45)	(1.72)	(2.45)	(2.07)	(1.89)	(1.92)	(1.72)	(1.70)
ln *envi*	0.011	0.012	0.048	0.054	0.027	0.032	0.023	0.042
	(1.30)	(1.29)	(1.52)	(1.60)	(1.26)	(1.42)	(1.44)	(1.37)
ln *ifi* × ln *envi*	0.281***	0.323***	0.356**	0.315**	0.292**	0.278*	0.211**	0.216**
	(2.74)	(2.69)	(2.21)	(2.30)	(2.06)	(1.93)	(1.98)	(1.97)
ln *pgdp*		0.072***		0.162***		0.145***		0.036**
		(3.45)		(4.34)		(4.08)		(2.30)
ln *urban*		−0.090*		−0.109**		−0.065**		−0.062**
		(−1.86)		(−2.34)		(−2.34)		(−2.07)
ln *medi*		0.108**		0.121**		0.110**		0.108*
		(2.35)		(2.14)		(2.23)		(1.79)
ln *fiscal*		0.123**		0.130**		0.132**		0.148*
		(2.39)		(2.31)		(1.99)		(1.89)
Constant	−0.509***	−0.662***	−0.652***	−0.734***	−0.703***	−0.714***	−0.620***	−0.573***
	(−7.72)	(−8.74)	(−5.99)	(−6.35)	(−5.36)	(−6.17)	(−5.79)	(−5.32)
R^2	0.498	0.517	0.502	0.514	0.495	0.508	0.461	0.475
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	330	330	121	121	88	88	121	121

****, **, * represent the 1, 5, and 10% levels of significance, respectively. The values reported in brackets are t-statistics.*

the combined effect of inclusive finance and environmental regulation can significantly improve public health, which shows that environmental regulation greatly promotes inclusive finance in the two regions. This result is related to catching up with and surpassing the heavy industry economy implemented for a long time in China. Due to the regional conditions and relative disadvantages of resources in the central and western regions' economic development, local governments rely more on industry to develop regional economies. Simultaneously, most of the bank's increased loans also flow to the state-owned enterprises with heavy capital, so the intermediary financial efficiency in the central and western regions is significantly lower than that in the eastern regions.

CONCLUSIONS

Finance is an important mechanism and path to promote the development of public health in China. At present, many scholars mainly pay attention to financial deepening indicators such as financial scale and total amount, but researches on inclusive finance aiming at solving financial repression are limited. Because of its important role in green development and industrial structure upgrading, the construction of an inclusive financial system and its effect has become one of China's main financial development contents. Based on the regional data from 2006 to 2016, this paper uses the PPML estimation method to analyze the impact of inclusive finance on public health. Further, it investigates the collective impact of environmental regulation.

The results show that, on the whole, inclusive finance has a significant effect on improving public health. Besides, from the perspective of regions, inclusive finance has a stronger effect on improving public health in the eastern region than in the central and western regions. In comparison, the western region has a stronger effect on improving public health than the central region. In general, the crossover term between environmental regulation and inclusive finance is significantly positive. Its coefficient is significantly greater, meaning that environmental regulation has played an accelerating role in promoting the effect of inclusive finance. Finally, under the effect of environmental regulation, inclusive finance has a most significant improvement effect on public health in the eastern region, and the improvement effect on the central and western regions is relatively small, which is closely related to the regional economic development endowment, industrial development policy and long-term credit policy.

There are various main implications and lessons for the COVID-19 pandemic following our results. Firstly, policymakers should actively build and improve inclusive finance's development mechanism. The low degree of inclusiveness cannot effectively meet the real economy's needs and market entities for financial development and financial innovation. Simple financial deepening cannot effectively solve the structural contradictions in China's financial resource allocation. When reforming and improving the current financial system, we should pay more attention to the real economy's inclusive financial needs. Therefore, policymakers should focus on constructing an inclusive financial system and mechanism and improving financial innovation's ability to break the reform. At this stage, people's trust in policymakers will be vital during the COVID-19 (29).

Secondly, policymakers should establish differentiated inclusive financial green development mechanisms according to local conditions. There are significant differences in economic, financial conditions and resource endowment between the eastern region, the central region and the western region. More importantly, the low degree of marketization has become one of the main obstacles to inclusive finance's green effect in the middle and western regions. Therefore, they should actively build an inclusive financial green development mechanism to expand market participation and further promote the central region's green development and the western region.

Finally, government should improve financial efficiency and strengthen inclusive finance in promoting the environment. For a long time, China's credit mechanism is relatively abnormal. A large number of financial resources flow to state-owned enterprises, resulting in the overall low efficiency of financial intermediary in China, which also affects the play of inclusive finance on the improvement effect of GTFP. Therefore, to make full use of inclusive finance on green development, policymakers should take credit policy as a breakthrough to effectively improve financial intermediaries' efficiency in China. Future studies can use the indicators in our paper by updating the data until the post-COVID-19 period.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: https://data.stats.gov.cn/.

AUTHOR CONTRIBUTIONS

XL: writing the original draft and econometric analyses. SG: writing the original draft and data access. Both authors contributed to the article and approved the submitted version.

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REFERENCES

1. Boyce MR, Attal-Juncqua A, Lin J, McKay S, Katz R. Global Fund contributions to health security in ten countries, 2014–20: mapping synergies between vertical disease programmes and capacities for preventing, detecting, and responding to public health emergencies. *Lancet Global Health*. (2021) 9:e181–8. doi: 10.1016/S2214-109X(20)30420-4
2. Zhao J, Jiang Q, Dong X, Dong K. Would environmental regulation improve the greenhouse gas benefits of natural gas use? A Chinese case study. *Energy Econ.* (2020) 87:104712. doi: 10.1016/j.eneco.2020.104712
3. Beck T, Demirguc-Kunt A, Martinez Peria MS. Reaching out: access to and use of banking services across countries. *J Financial Econ.* (2007) 85:234–66. doi: 10.1016/j.jfineco.2006.07.002
4. Sarma M. Measuring financial inclusion. *Econ Bull.* (2015) 35:604–11. doi: 10.1057/978-1-137-58337-6_1
5. Bruhn M, Love I. The real impact of improved access to finance: evidence from Mexico. *J Finance*. (2014) 69:1347–76. doi: 10.1111/jofi.12091
6. Huang Y, Zhang Y. Financial inclusion and urban-rural income inequality: long-run and short-run relationships. *Emerg Mark Finance Trade*. (2020) 56:457–71. doi: 10.1080/1540496X.2018.1562896
7. Yuan B, Xiang Q. Environmental regulation, industrial innovation and green development of Chinese manufacturing: based on an extended CDM model. *J Clean Prod.* (2018) 176:895–908. doi: 10.1016/j.jclepro.2017.12.034
8. Brooks C, Oikonomou I. The effects of environmental, social and governance disclosures and performance on firm value: a review of the literature in accounting and finance. *Br Account Rev.* (2018) 50:1–15. doi: 10.1016/j.bar.2017.11.005
9. Guo LL, Qu Y, Tseng ML. The interaction effects of environmental regulation and technological innovation on regional green growth performance. *J Clean Prod.* (2017) 162:894–902. doi: 10.1016/j.jclepro.2017.05.210
10. Cropper ML. Measuring the benefits from reduced morbidity. *Am Econ Rev.* (1981) 71:235–40.
11. Alberini A, Cropper M, Fu TT, Krupnick A, Liu JT, Shaw D, et al. Valuing health effects of air pollution in developing countries: the case of Taiwan. *J Environ Econ Manag.* (1997) 34:107–26. doi: 10.1006/jeem.1997.1007
12. Ebenstein A. The consequences of industrialization: evidence from water pollution and digestive cancers in China. *Rev Econ Stat.* (2012) 94:186–201. doi: 10.1162/REST_a_00150
13. Saygin M, Gonca T, Öztürk Ö, Has M, Çalişkan S, Has ZG, et al. To investigate the effects of air pollution (PM10 and SO2) on the respiratory diseases asthma and chronic obstructive pulmonary disease. *Turk Thorac J.* (2017) 18:33. doi: 10.5152/TurkThoracJ.2017.16016
14. Boogaard H, van Erp AM, Walker KD, Shaikh R. Accountability studies on air pollution and health: the HEI experience. *Curr Environ Health Rep.* (2017) 4:514–22. doi: 10.1007/s40572-017-0161-0
15. Cao Y, Wan N, Zhang H, Zhang X, Zhou Q. Linking environmental regulation and economic growth through technological innovation and resource consumption: analysis of spatial interaction patterns of urban agglomerations. *Ecol Indicat.* (2020) 112:106062. doi: 10.1016/j.ecolind.2019.106062
16. Limei C, Wei L. The impact of reviewers' creditworthiness on consumers' purchase intention in edge path: implications for the coronavirus disease 2019 pandemic. *Front Public Health*. (2020) 8:619263. doi: 10.3389/fpubh.2020.619263
17. Zhou Y, Xu Y, Liu C, Fang Z, Fu X, He M. The threshold effect of China's financial development on green total factor productivity. *Sustainability*. (2019) 11:3776. doi: 10.3390/su11143776
18. Silva JS, Tenreyro S. The log of gravity. *Rev Econ Stat.* (2006) 88:641–58. doi: 10.1162/rest.88.4.641
19. Silva JS, Tenreyro S. Further simulation evidence on the performance of the Poisson pseudo-maximum likelihood estimator. *Econ Lett.* (2011) 112:220–2. doi: 10.1016/j.econlet.2011.05.008
20. Motta V. Estimating Poisson pseudo-maximum-likelihood rather than log-linear model of a log-transformed dependent variable. *RAUSP Manag J.* (2019) 54:508–18. doi: 10.1108/RAUSP-05-2019-0110
21. Arvis JF, Shepherd B. The Poisson quasi-maximum likelihood estimator: a solution to the 'adding up' problem in gravity models. *Appl Econ Lett.* (2013) 20:515–9. doi: 10.1080/13504851.2012.718052
22. Zhang S, Chen C. Does outward foreign direct investment facilitate China's export upgrading? *China World Econ.* (2020) 28:64–89. doi: 10.1111/cwe.12328

23. Wagner WE. The "bad science" fiction: reclaiming the debate over the role of science in public health and environmental regulation. *Law Contemp Problems*. (2003) 66:63–133. doi: 10.1016/j.erss.2018.09.001
24. Edeme RK, Emecheta C, Omeje MO. Public health expenditure and health outcomes in Nigeria. *Am J Biomed Life Sci.* (2017) 5:96–102. doi: 10.11648/j.ajbls.20170505.13
25. Moore M, Gould P, Keary BS. Global urbanization and impact on health. *Int J Hyg Environ Health*. (2003) 206:269–78. doi: 10.1078/1438-4639-00223
26. Shah MN. The formation of the emergency medical services system. *Am J Public Health*. (2006) 96:414–23. doi: 10.2105/AJPH.2004.048793
27. Van Zoest J, Hopman M. Taking the economic benefits of green space into account: the story of the Dutch TEEB for Cities project. *Urban Clim.* (2014) 7:107–14. doi: 10.1016/j.uclim.2014.01.005
28. Wooldridge JM. *Econometric Analysis of Cross section and Panel Data.* Cambridge, MA: MIT Press (2010).
29. Gozgor G. Global evidence on the determinants of public trust in governments during the Covid-19. *Appl Res Qual Life.* (2021) 5:1–20. doi: 10.1007/s11482-020-09902-6

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BRIEF RESEARCH REPORT
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Baidu Index and COVID-19 Epidemic Forecast: Evidence From China

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With the global spread of the Coronavirus epidemic, search engine data can be a practical tool for decision-makers to understand the epidemic's trends. This article uses trend analysis data from the Baidu search engine, the most widely used in China, to analyze the public's attention to the epidemic and the demand for N95 masks and other anti-epidemic materials and information. This kind of analysis has become an important part of information epidemiology. We have analyzed the use of the keywords "Coronavirus epidemic," "N95 mask," and "Wuhan epidemic" to judge whether the introduction of real-time search data has improved the efficiency of the Coronavirus epidemic prediction model. In general, the introduction of the Baidu index, whether in-sample or out-of-sample, significantly improves the prediction efficiency of the model.

Keywords: Baidu index, coronavirus epidemic, N95 masks, Wuhan epidemic, forecast

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INTRODUCTION

In recent years, with the rapid development of mobile networks, web search data has been widely used in epidemiological research. Internet search data not only helps governments and medical institutions to make market forecasts quickly and effectively, but the Internet has also become an important platform for the government to issue epidemic and stay-at-home orders. The general public has gradually formed the habit of searching for epidemic information, treatment methods, and drug purchases using the Internet. As a result, Internet search data has gradually become a new and time-sensitive data source for studying epidemic trends and public opinion. Starting with the SARS epidemic in China in 2003, the continued existence of MERS-CoV in the Middle East since 2012, and the Coronavirus epidemic from 2019 to the present, the public's attention to epidemics has increased. Determining how to make use of the public's attention as a reference point for government and medical system decision-making is becoming the focus of information epidemiology.

During the COVID-19 pandemic, most countries adopted stay-at-home policies in order to prevent the virus' spread. This led to a decrease in the number of patients in some outpatient clinics. However, their diseases were hidden or postponed after the COVID-19 pandemic. Home isolation policies further promoted the widespread use of search engines and have had a profound impact on the lifestyle of the general public. People are increasingly seeking solutions through the Internet, including searching for information about health problems, symptoms, and treatment options. Especially in the midst of the epidemic, information on COVID-19 treatment options and drugs is crucial to safeguarding public health. It can be expected that during the current COVID-19 pandemic, the number of people using the Internet to retrieve health information will greatly increase. Therefore, a survey of public trends using search engine data may provide clues about the frequency of certain diseases during the COVID-19 epidemic. However, epidemic research using Chinese Internet search data has just started.

Due to the fact that China cannot use Google search services, most people use Baidu as an information search tool. Baidu had a market share of 78.4% in China in February 2021. Thus, disease keywords frequently searched on the Baidu search engine can provide information about the disease spectrum of the population. Data from Baidu can provide timely and effective information transmission channels for epidemic monitoring, emergency response, and public opinion guidance. Many studies have used Google Trends to measure interest in infectious diseases and public awareness of diseases. However, it is uncommon to apply the Baidu index to research in emerging information epidemiology. Therefore, we use the Baidu index as a data analysis tool to establish a theoretical analysis model to compare the model containing the Baidu index and the benchmark model. This analysis provides a reference for the formulation of epidemic policies by relevant decision-making agencies.

Research on COVID-19 has been extensive. And most of the existing literature has been concentrated on those disease-related Google Trends keywords that were searched during the epidemic, namely skin diseases, smoking cessation, hand washing, and smell (1). Some studies consider epidemic trend forecasts (2–4). Sousa-Pinto et al. (5) investigates the change in the purpose that Google Trends has been used for. In recent years, the purpose of Google Trends has shifted from public opinion monitoring to trend predicting (6, 7). There are also some studies that argue that monetary policy and stock market may respond to the news contained in the Baidu index and using the Baidu index to monitor and predict the trend in the number of confirmed cases in China (8–17).

DATA SOURCE AND KEYWORD SELECTION

Most Chinese Internet users use Baidu, a search engine similar to Google. Data such as the number and regional distribution of certain keywords searched by Chinese users will be reflected through the Baidu index. The Baidu index allows the collection of data about user searches. In this case, we can use Baidu trend data to judge or predict the epidemiological characteristics of China. The search language is Chinese.

The Baidu index roughly follows the principle proposed by (18). The data collected from the Baidu index is standardized, and researchers can select data from different geographic regions, across genders and other characteristics, from a custom sample time range.

To examine Chinese people's attention to the epidemic, we chose "Coronavirus epidemic," "N95 mask," and "Wuhan epidemic" as search keywords from December 31, 2019 to March 11, 2021. The peak for the keyword "Coronavirus epidemic" was January 23, 2020. The peaks of the keywords "N95 mask" and "Wuhan epidemic" both appeared on January 25, 2020. However, it is worth noting that searches using the keyword "N95 mask" on December 31, 2019, the day the Wuhan epidemic was declared, increased by six times the search volume for masks the day before. There was no second peak following the peaks for these keywords. This is different from other countries or regions where we see several peaks. This is because the Chinese government announced on January 23, 2020 that Wuhan would be closed down, which had an immediate effect on the control of the epidemic. The public's attention to the epidemic never returned to the level of the first peak.

An interesting fact is that the first new case appeared on January 21, 2021, which is 21 days after the significant increase in the use of the "N95 masks" search term according to the Baidu index. In other words, by analyzing the Baidu index search terms, signs of the epidemic can be detected 21 days in advance. Similarly, when new cases reached a short-term peak on August 13, 2020, Baidu index-related search terms such as "Coronavirus epidemic," "N95 mask," and "Wuhan epidemic" reached their peaks 16, 15, and 7 days earlier, respectively. Thus, search engine trend data can be used as leading indicators for epidemic monitoring, early warning, and preparation of medical supplies.

Because data on the keyword "Coronavirus epidemic" was not available until February 26, 2020, the data sample period for the empirical part of this study is from February 26, 2020 to March 11, 2021.

From the Baidu index, we can also see a significant trend: Chinese people pay more attention to the epidemic in their own country. The global epidemic has no significant impact on the number of searches. For example, on February 11, 2020, the World Health Organization announced the official name of the epidemic, COVID-19. However, the search index did not rebound significantly after this official announcement. At that time, the epidemic in China had been significantly controlled. This is significantly different from epidemic trends in other countries and regions. Data on new cases in China comes from the National Health Commission, and the data interval covers February 26, 2020 to March 11, 2021.

STATISTICAL DESCRIPTION AND EMPIRICAL RESEARCH

Given that Baidu is the most popular Internet search engine in China. This article uses Baidu index data to reflect the public's focus on the epidemic, and applies it to the forecast of epidemic trends. A higher number means more users search for the keywords within the set location and time period. The Baidu index is a real-time example of Baidu search data, which has been available since January 1, 2011. Downloading data from the Baidu index is a paid service, whereas Google Trends data is available for free. We use the Baidu index to measure the degree to which Chinese people are paying attention to COVID-19 and to improve capacity to predict new COVID-19 cases.

During the period of our study, the highet number of new cases of COVID-19 was 3,622 (**Table 1**), occurring on February 27, 2020, and there has generally been on a downward trend since then. The minimum value is 0, obtained on June 21, 2020. The maximum value of search keywords for "Coronavirus epidemic" is 2,803, obtained on July 24, 2020. The minimum value is 448, obtained on March 5, 2021. This is mainly due to the fact that most of the recent epidemics in China have been imported from

TABLE 1 | Statistical description of the main variables.

	COVID	Corona epidemic	N95 Mask	Wuhan epidemic
Mean	148.5053	1197.234	1727.184	3274.85
Median	19	975	696	2,296
Maximum	3,622	2,803	25,176	20,712
Minimum	0	448	219	854
Std. Dev.	470.1087	464.9004	3378.473	2897.205
Skewness	4.641613	0.88965	4.938219	2.491931
Kurtosis	25.72972	2.959039	29.67639	10.29989
Jarque-Bera	9544.629	50.15347	12811.92	1237.015
Probability	0	0	0	0
Sum	56,432	454,949	656,330	1,244,443
Sum Sq. Dev.	83759843	81,914,168	4.33E+09	3.18E+09
Observations	380	380	380	380

TABLE 2 | Forecast results of different models.

	Model (0)	Model (1)	Model (2)	Model (3)	Model (4)
$COVID_{t-1}$	0.944***	0.943***	0.795***	0.914***	0.752***
Coronavirus epidemic		0.003			−0.043***
N95 Mask			0.023***		0.027***
Wuhan epidemic				0.006***	0.008***
Obs.	379	379	379	379	379
S.E.	79.322	79.416	75.649	78.663	74.411
Adj. R^2	0.969	0.969	0.972	0.970	0.973
F	11856.65	5914.385	6537.191	6031.729	3381.952

****Significance level of 1%.*

abroad, and the public's attention to the epidemic has dropped significantly. The maximum search term of "N95 mask" was 25,176, which was also obtained on February 27, 2020, shortly after the outbreak began. The minimum value was obtained on February 15, 2021. The maximum value of the keyword "Wuhan Epidemic" was obtained on February 26, 2020, which was the first day of the sample period. The data has been repeated since then; while all increased slightly, none exceeded their previous peak.

We use an autoregressive model to check the relationship between new COVID-19 cases and the Baidu index. The model is as follows:

$$Y_t = \sigma + \sum_{i=1}^{n} \beta_i Y_{t-i} + \varepsilon_t \tag{1}$$

To examine the impact of the Baidu index of different keywords on the new cases of COVID-19, we added the Baidu index to the model. The extended model is as follows:

$$Y_t = \sigma + \sum_{i=1}^{n} \beta_i Y_{t-i} + \theta X_t + \varepsilon_t \tag{2}$$

Among them, Y_t represents the number of new COVID-19 cases in China every day, Y_{t-i} is a lagging item, and C represents the Baidu index level of keywords such as "Coronavirus epidemic," "N95 mask," and "Wuhan epidemic." σ, β_i, and θ are parameters. ε_i is the error term.

The calculation results in **Table 2** show that, except for the coefficient of the "Coronavirus epidemic" keyword in Model 1, which failed the significance test, the other models passed the 1% significance test. The calculation results of Model 4 show that the greater the number of people who used the search term "N95 masks," the more serious the epidemic and the stronger the enthusiasm of people to buy N95 masks to enhance their self-protection. Similarly, the greater the number of people using the search term "Wuhan epidemic," the more severe the epidemic. People want to know more about the progress of the epidemic. The number of searches for "N95 mask" and "Wuhan epidemic" is directly proportional to the new cases of COVID-19. However, the coefficient of the search term "Coronavirus epidemic" is negative. This is because searching for "Coronavirus epidemic" indicates that people feel more concerned about the severity of the epidemic and their internet searches enhance their awareness of protection measures, helping to control the spread of the epidemic. The coefficients of Model 2 and Model 3 are also positive, and the value of the coefficients does not change much, which shows that the model has a certain robustness.

Although most of the above three keywords passed the significance test, we still need to examine the stability of the coefficients of equation (2) during the rolling regression period of the sub-sample. To examine this result, we compressed the data sample from February 26, 2020 to August 25, 2020. Model 2 is used as the regression base of half a year for rolling estimation until the end of the sample period. In other words, the second regression is estimated to be from February 27, 2014 to August 26, 2020, and so on. The calculation results are shown in **Figure 1**.

In the process, parameter θ of the independent variable is extracted. The value of the θ parameter is mainly used to investigate the stability of the relationship between the independent variable and the dependent variable. The ideal situation is that the parameters do not change significantly during the sample period. **Figure 1** shows the evolution trend of the coefficients of the three Baidu indexes.

First, the coefficient of the "Wuhan Epidemic" keyword is relatively stable. Except for the large change in the coefficient at the beginning of the sample period, the coefficients thereafter fluctuate at around 0.1, and the fluctuation range gradually narrows.

Previously, the coefficient of "N95 masks" fluctuated greatly, and most were positive before November 2020. The coefficient was negative in November and December 2020 and gradually changed to positive after January 2021. This shows that people's retrieval of N95 mask keywords changes with the fluctuation of the epidemic, so the overall performance of the parameters is unstable.

The "Coronavirus epidemic" coefficient fluctuations are also relatively large. From September 21, 2020 to January 31, 2021, the coefficient is positive. However, in the rest of the period, the coefficient is negative and fluctuates greatly. This is related to

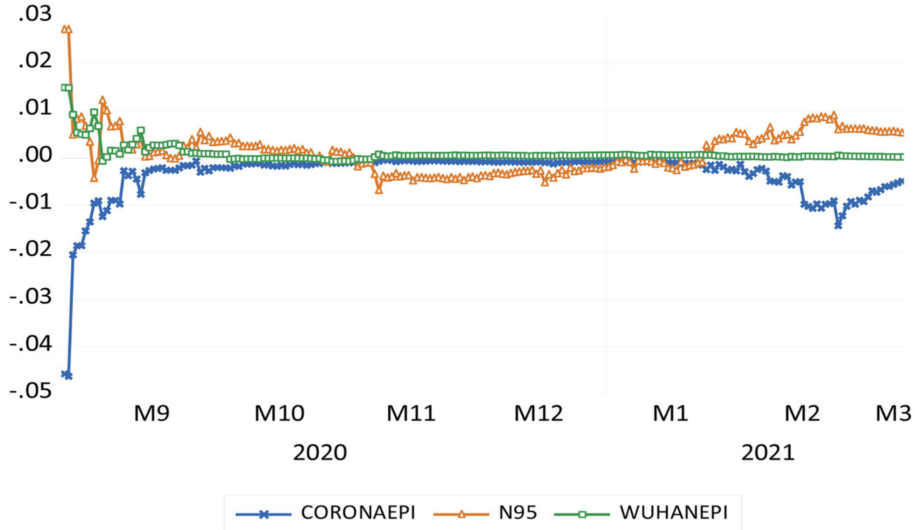

FIGURE 1 | Time-varying parameter trends of independent variables.

the serious epidemic situation at the beginning of the sample and the repeated epidemic situation in some periods.

The Baidu index helps us to make early judgments about changes in the epidemic. If the forecast is accurate, it will be possible to gain insight into the epidemic's trend and the public's demand for information before official data is released. We use the one-step forward method to compare the prediction performance of the Baidu index expansion model and the benchmark model. This benchmark model is defined as a constant forecast, that is, the epidemic trend changes at the same rate as the previous observations. The new model is expanded on this basis: the one-step forward prediction on September 3, 2020 is based on the regression equation of Model 2, and the sample range is from February 26, 2020 to September 2, 2020. We use the root mean square prediction error (RMSFE) to evaluate the accuracy of the model's prediction. That is, we compare the improvement degree of the extended model relative to the root mean square prediction error of the benchmark model to evaluate the overall performance of the model.

Table 3 provides one-step forward prediction performance of various extended models relative to the benchmark model. On the whole, the extended model performs somewhat better than the prediction of the benchmark model. Among them, Model 4 performed best in one-step forward prediction, with an improvement of 24.7%. The improvement of Model 3 is small.

TABLE 3 | Out-of-sample forecast performance.

	Model (0)	Model (1)	Model (2)	Model (3)	Model (4)
RMSFE	143.3993	109.9745	116.9652	138.9774	108.0304
RMSFE/BENCH	1.00	0.767	0.816	0.969	0.753
Percentage improvement	n/a	23.3%	18.4%	3.1%	24.7%
Theil inequality coefficient	0.148833	0.124738	0.126399	0.153554	0.116358

RESEARCH CONCLUSIONS AND POLICY RECOMMENDATIONS

As the COVID-19 epidemic continues to spread around the world, the public's awareness of self-protection continues to increase. People are actively looking for official information about epidemics, drugs, and other concerns on the Internet. Therefore, in the context of a global pandemic, we use the Baidu index to monitor the trend of the epidemic in China in real time, and to detect symptoms that have not been identified so far. The Baidu index can even be used to identify those with mild or asymptomatic symptoms. These people may not receive the attention of traditional medical channels. Therefore, this trend judgment tool has extremely attractive prospects. This article uses the monitoring tool of the Baidu index to judge the peak of public attention to the epidemic's trends. This can not only help identify disease-related symptoms, but also further identify the affected population and improve the accuracy of epidemic forecasts.

Our findings show that since the public searches for health-related information on the Internet, web search queries are a valuable source of information about collective health trends. The Baidu index provides an effective experimental tool. We can monitor and analyze the behavior of seeking information on epidemics and medical care through the query forms of search engines to detect outbreaks in near real time. We use the Baidu index to test this in the context of the epidemic in China. Preliminary tests have shown that analyzing data from the Baidu index to judge epidemic trends can allow us to detect outbreaks of COVID-19 7–21 days earlier than official data. Relying on traditional laboratory and clinical data to publish weekly statistics for countries and regions usually results in a lag of 1–2 weeks. This is also consistent with our calculation results.

Judging from the calculation results of the time-varying parameter model of the three search terms—"Coronavirus epidemic," "N95 mask," and "Wuhan epidemic"—the coefficients of the keyword "Wuhan epidemic" is relatively stable, and the coefficients of "Coronavirus epidemic" and "N95" fluctuate greatly, closely related to the repeated epidemics in some periods. The extended model shows that the prediction improvement of Model 4 relative to the benchmark model reaches 24.7%.

Based on the above research, we believe that real-time monitoring and early warnings of outbreaks will help the public and health care professionals to formulate epidemic prevention and control measures in time, detect cases on time, and ensure that patients receive adequate treatment, thereby reducing incidence and death rates. Whether it is SARS, Middle East Respiratory Syndrome, or COVID-19, this research reminds the international community of the need for the real-time monitoring of new infectious diseases, bioterrorism, and pandemics. The big data generated by the epidemic is not only useful for public health practice, but also helps to improve the efficiency of clinical decision-making and research. Our research shows that experts in the medical field, through cross-field cooperation, can use the data processing methods of the Baidu Index to improve the efficiency of disease surveillance and build tools for infectious disease surveillance. In addition, with the increasing dependence of the general public on the Internet, big data monitoring of the collective wisdom of the population can track the trends of infectious diseases and epidemics faster than traditional monitoring systems. The use of these innovative technologies brings us closer to true real-time outbreak monitoring.

Finally, we need to develop novel ways to communicate with the public about infectious diseases like COVID-19. The use of digital tools not only helps policy makers understand the public interest, but also allows for tailored, targeted messages for the public, making it possible to improve the effectiveness of epidemic propaganda. The analysis of Baidu index and other data can complement the advantages of traditional public health monitoring systems, improve the emergency response capabilities of the medical care system, and improve the benefits for stakeholders and the level of medical care services. The Baidu index data might be used by government to monitor the trend of the epidemic. This has remarkable significance for promoting international cooperation in epidemic surveillance and the cross-border distribution of vaccines.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found at: http://index.baidu.com.

AUTHOR CONTRIBUTIONS

JF: writing-original draft. XZ: policy suggestions. YT: literature. YX: investigation and software. HL: proofreading. KW: conceptualization and supervision. All authors contributed to the article and approved the submitted version.

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REFERENCES

1. Zitting KM, Lammers-van der Holst HM, Yuan RK, Wang W, Quan SF, Duffy JF. Google trends reveals increases in internet searches for insomnia during the 2019 coronavirus disease (COVID-19) global pandemic. *J. Clin. Sleep Med*. (2021) 17, 177–84. doi: 10.5664/jcsm.8810
2. Hu D, Lou X, Xu Z, Meng N, Xie Q, Zhang M, et al. More effective strategies are required to strengthen public awareness of COVID-19: evidence from google trends. *Public Health*. (2020) 10:011003. doi: 10.7189/jogh.10.0101003
3. Fantazzini D. Short-term forecasting of the COVID-19 pandemic using google trends data: evidence from 158 countries. *Appl. Econ.* (2020) 59:1–26. doi: 10.2139/ssrn.3671005
4. Larson WD, Sinclair TM. Nowcasting unemployment insurance claims in the time of COVID-19. *Int. J. Forecast.* (2021). doi: 10.1016/j.ijforecast.2021.01.001. [Epub ahead of print].
5. Sousa-Pinto B, Anto A, Czarlewski W, Anto JM, Fonseca JA, Bousquet J. Assessment of the impact of media coverage on COVID-19-related google trends data: infodemiology study. *J. Med. Internet Res.* (2020) 22:e19611. doi: 10.2196/19611
6. Ashraf BN. Stock markets' reaction to COVID-19: cases or fatalities? *Res. Int. Bus. Finan*. (2020) 54:101249. doi: 10.1016/j.ribaf.2020.101249
7. Baker SR, Bloom N, Davis SJ, Kost KJ, Sammon MC, Viratyosin T. The unprecedented stock market reaction to COVID-19. *Rev. Asset Pricing Stud.* (2020) 10:742–758. doi: 10.1093/rapstu/raaa008
8. Gozgor G. Inflation targeting and monetary policy rules: further evidence from the case of Turkey. *J. Appl. Finan. Bank.* (2012) 2:127.
9. Balke NS, Fulmer M, Zhang R. Incorporating the beige book into a quantitative index of economic activity. *J. Forecast.* (2017) 36:497–514. doi: 10.1002/for.2450
10. Gozgor G, Lau CKM, Sheng X, Yarovaya L. The role of uncertainty measures on the returns of gold. *Econ. Lett*. (2019) 185:108680. doi: 10.1016/j.econlet.2019.108680
11. Fang J, Gozgor G, Yan C. Does globalisation alleviate polarisation? *World Econ*. (2021) 44:1031–52. doi: 10.1111/twec.13048
12. Sharif A, Aloui C, Yarovaya L. COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: fresh evidence from the wavelet-based approach. *Int. Rev. Finan. Anal.* (2020) 70:101496. doi: 10.1016/j.irfa.2020.101496
13. Wang J, Lu X, He F, Ma F. Which popular predictor is more useful to forecast international stock markets during the coronavirus pandemic: VIX

vs EPU? *Int. Rev. Finan. Anal.* (2020) 72:101596. doi: 10.1016/j.irfa.2020.101596
14. Mazur M, Dang M, Vega M. COVID-19 and the march 2020 stock market crash. Evidence from SandP1500. *Finan. Res. Lett*. (2021) 38:101690. doi: 10.1016/j.frl.2020.101690
15. Zhang R, Martínez-García E, Wynne MA, Grossman V. Ties that bind: estimating the natural rate of interest for small open economies. *J. Int. Money Finan.* (2021) 113:102315. doi: 10.1016/j.jimonfin.2020.102315
16. Zhang R. News shocks and the effects of monetary policy. Available at SSRN 3348466 (2019). doi: 10.2139/ssrn.3348466
17. Jiang B, Liu Z, Shen R, Huang L, Tong Y, Xia Y. Have COVID-19-related economic shocks affected the health levels of individuals in the United States and the United Kingdom? *Front. Public Health.* (2020) 8:799. doi: 10.3389/fpubh.2020.611325
18. Mavragani A, Ochoa G. Google Trends in infodemiology and infoveillance: methodology framework. *JMIR Public Health Surveil*. (2019) 5:e13439. doi: 10.2196/13439

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An Empirical Study on the Equity Performance of China's Health Insurance Companies During the COVID-19 Pandemic—Based on Cases of Dominant Listed Companies

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The health insurance industry in China is undergoing great shocks and profound impacts induced by the worldwide COVID-19 pandemic. Taking for instance the three dominant listed companies, namely, China Life Insurance, Ping An Insurance, and Pacific Insurance, this paper investigates the equity performances of China's health insurance companies during the pandemic. We firstly construct a stock price forecasting methodology using the autoregressive integrated moving average, back propagation neural network, and long short-term memory (LSTM) neural network models. We then empirically study the stock price performances of the three listed companies and find out that the LSTM model does better than the other two based on the criteria of mean absolute error and mean square error. Finally, the above-mentioned models are used to predict the stock price performances of the three companies.

Keywords: COVID-19 pandemic, uncertain impact, stock price of the health insurance company, ARIMA model, BP neural network model, LSTM neural network model

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INTRODUCTION

The COVID-19 pandemic is first and foremost inducing instability and uncertainty in the high-quality development of China's economy, not only impacting industries of transportation and tourism but also causing significant fluctuations in the financial market (1–4). As a barometer of the economy, stock prices reflect the current conditions and future trends in the development of industries. During the pandemic, China's stock market is on the whole decline, while the stock prices of the health insurance sector continue to rise as market demand expands. It is of practical significance to study the stock price performances of China's health insurance companies during the pandemic and to provide insights into the impacts of the pandemic and trends in the development of this industry.

The impacts of the COVID-19 pandemic on the stock market have become a focus in recent research. Duan (5) explored the impacts of the pandemic on the stock returns of listed companies in China's pharmaceutical industry using the event analysis method. The empirical results show that the pandemic is having a significantly positive short-term impact on the stock returns in this industry. Based on data of 3,550 listed companies in China in the early stage of the pandemic, Wang et al. (6) studied the impacts of new confirmed cases in the place of company registration on the fluctuations of stock prices. Using the panel vector autoregression model, individual fixed effects model, and dynamic econometric model, they found a U-shaped relationship between daily stock prices and numbers of new confirmed cases. Similarly, Xia and Hu (7) used the Fama-French three-factor model and panel regression to analyze the performances of 223 pharmaceutical stocks during the pandemic in Shanghai and Shenzhen 300 index. Sun et al. (8) found out, in their case studies, about a stronger positive correlation between investor sentiment and stock returns during the pandemic than in previous periods. Mazur et al. (9) explored the stock market performances in the United States during the pandemic and found that the stock prices in natural gas, food, healthcare, and software industries showed an upward trend, while the stock prices in oil, real estate, entertainment, and hotel industries showed the opposite. Heyden and Heyden (10) studied the short-term reaction in stock markets of the United States and Europe at the early stage of the pandemic. Their results showed that fiscal measures had a negative impact on stock returns, while monetary policy had a stabilizing effect on the market.

Stock price fluctuations during the pandemic directly affect the stability of the financial market and healthy development of national economy. Thus, the prediction of stock price performances becomes a hot topic in recent research. The most often used methods include the autoregressive integrated moving average (ARIMA), back propagation (BP) neural network, and long short-term memory (LSTM) neural network models. Bai (11) and Shi et al. (12) used the ARIMA method to model the stock prices of the Shanghai composite index, established an improved model in their short-term prediction, and then proved the effectiveness of both models. Chen (13) constructed the ARIMA and BP neural network models to predict the stock prices of two famous companies in the IT industry of China, namely, Baidu and Alibaba. Both models are found to have ideal prediction accuracy and short-term prediction effect. Some research specifically aim to tackle the redundant problem of the experimental samples. For example, Cai and Chen (14) and Huo et al. (15), respectively, proposed the stock price prediction models of the principal component analysis–BP neural network and LM–BP algorithm and verified their high accuracy in short-term prediction. With a view to improve prediction accuracy, Peng et al. (16) constructed the LSTM neural network model of different layers for stock price prediction and found out about the appropriate numbers of LSTM layers and hidden neurons. Furthermore, Song et al. (17) proposed a LSTM neural network model based on particle swarm optimization, which matched the characteristics of stock prices with network topology so as to improve prediction accuracy. However, research and studies have mostly focused on the stock price performances in industries of real estate, Internet, medicine, and some others. With the COVID-19 pandemic ongoing and health insurance becoming a most important foundation of people's livelihood, the prediction of stock prices in this industry is of great significance for analyzing its prospects. Seeing this, this paper constructs a stock price prediction method using the ARIMA, BP neural network, and LSTM neural network models to study the impacts of the pandemic on China's health insurance industry from the perspective of stock price fluctuations.

This paper is organized as follows: section Trend Analysis of Stock Closing Prices makes a descriptive statistical analysis of the stock prices of the three dominant health insurance listed companies during trading days from 2015 to 2020. In section Methodology, we introduce three prediction models, namely, the ARIMA, BP neural network, and LSTM neural network models. Those models are applied to the stock price predictions of the three companies in section Stock Price Prediction, and a comparative analysis of the empirical results using various models is also given. Section Conclusion and Prospect gives the conclusion of this paper.

TREND ANALYSIS OF STOCK CLOSING PRICES

Variables

This paper observes data of stock closing prices of the three dominant health insurance listed companies, namely, China Life Insurance, Ping An Insurance, and Pacific Insurance, in 1,461 consecutive trading days from January 1, 2015 to December 31, 2020. Lagrange's interpolation is used to solve the problem of missing data of Pacific Insurance for 16 trading days (from January 15 to 22, 2016 and February 3 to 16, 2017).

Descriptive Analysis

Figure 1 gives the time series charts of the stock closing prices of the three companies, namely, China Life Insurance, Ping An Insurance, and Pacific Insurance from 2015 to 2020, respectively.

Figure 1 shows that the stock price fluctuations of China Life Insurance and Ping An Insurance were roughly the same during this period. As a matter of fact, the stock prices of these two companies seemed to have been fluctuating with the market. Soon after the outbreak of the pandemic, the stock prices of both companies fell sharply with the entire market in quarter 1 of 2020. Then, from quarter 2 with the advancement of China's pandemic prevention and control, economic growth turned positive, and the stock market gradually recovered. The stock prices of both companies even rose to levels higher than before the outbreak. For example, the stock closing price of China Life Insurance reached to a peak of 51.96 RMB on October 21, 2020, higher by 49.01% than that on December 31, 2019. Even after a gradual fall and hitting a bottom of 37.25 RMB on December 24, 2020, the stock price was still higher than before the pandemic. Similar stories could be observed in the case of Ping An Insurance. Furthermore, **Figure 1** indicates something different for Pacific Insurance. Before the outbreak of the pandemic, its stock prices had been undergoing an overall decline over years since reaching a peak in June 2015. However, the stock price still showed a slight increase in April 2020.

Table 1 further depicts the changes in stock prices of the above-mentioned three companies before and after the pandemic, where MAX and MIN, respectively, denote the

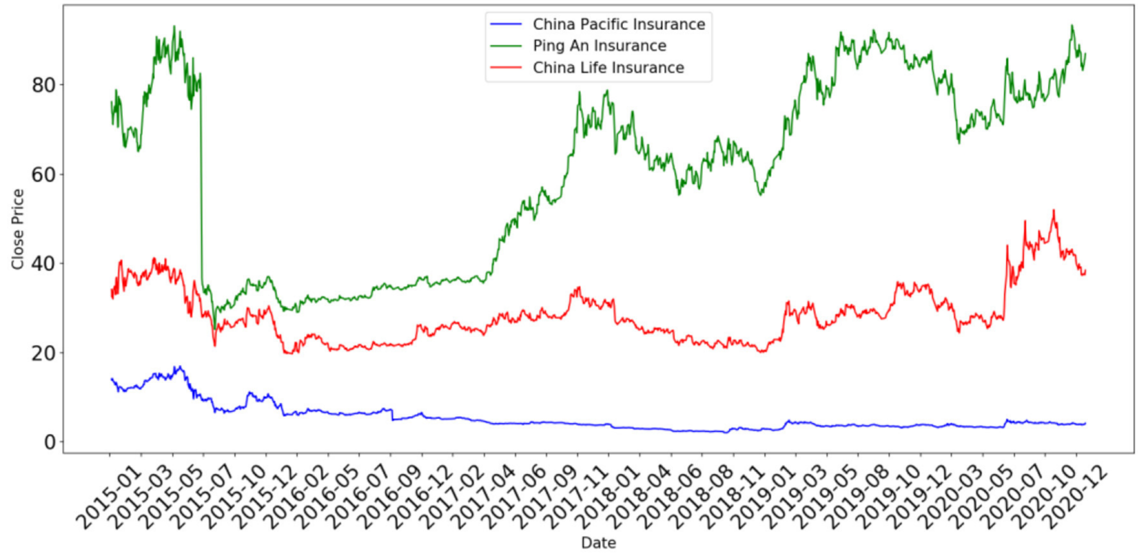

FIGURE 1 | Time series charts of the stock closing prices of the three health insurance companies. The data are from NetEase Finance (http://quotes.money.163.com/ stock).

TABLE 1 | Descriptive statistics of the stock closing prices of three health insurance companies.

Company	Period	MAX	MIN	Mean	CV
China Life Insurance	Before the outbreak	41.19	19.66	27.08	0.18
	After the outbreak	51.96	24.33	35.65	0.21
Ping An Insurance	Before the outbreak	93.17	25.11	57.51	0.36
	After the outbreak	93.38	66.76	78.67	0.07
Pacific Insurance	Before the outbreak	16.92	1.97	5.62	0.60
	After the outbreak	4.92	3.10	3.76	0.11

Since December 31, 2019, the Health Commission of Wuhan Municipality started to release the pandemic information. Take this day as a symbolic date of pandemic outbreak with an outburst of new confirmed cases nationwide.

maximum and minimum of the stock closing prices, and CV denotes the coefficient of variation.

From **Table 1**, the MAX, MIN, and mean values of stock prices of China Life Insurance and Ping An Insurance after the outbreak of the pandemic were all higher than before, indicating that both companies were impacted at least not negatively. As for Pacific Insurance, since its stock prices had been continuing to decline for years, it would not be appropriate to use the MAX and mean values to illustrate the changes in stock prices before and after the pandemic, and thus the MIN values were observed instead. The results show that the MIN value after the outbreak was significantly higher than before. It appears that the stock prices of all three companies were boosted, only to different extents. In addition, the CV indexes show a slight increase in the deviation of stock prices for China Life Insurance, with significant decreases for the other two companies, indicating that their stock prices were fluctuating less intensely than before. In summary, although shocked by the outbreak of the pandemic in the short term, the stock prices of the three dominant health insurance companies recovered quickly with the gradual advancement of China's pandemic prevention and control and the resumption of work and production. The stock prices showed an obvious upward trend and, in some cases, even rose above previous levels and fluctuate less fiercely.

METHODOLOGY

To study the impacts of the pandemic on the stock price performances, we use the three models of ARIMA, BP neural network, and LSTM neural network to construct a stock price prediction methodology. The ARIMA model uses the weighted modeling of the historical value, current value, and lagged stochastic disturbance term to explain and predict the trend of time series. The BP and LSTM neural network models use activation function and network layer extension to enhance the processing ability of nonlinear data and therefore are widely used in stock price prediction.

ARIMA Model

ARIMA (p, d, q) is a differential autoregressive (AR) moving average (MA) model, where p, q, and d denote the orders of the AR process, MA process, and difference required to change the original time series into stationary time series, respectively. Since the ARIMA model is a combination of differential operation and ARMA model, the model can be expressed as follows (18):

$$\begin{cases} \Phi(B)\nabla^d x_t = \theta(B)\varepsilon_t \\ E(\varepsilon_t) = 0, Var(\varepsilon_t) = \sigma_\varepsilon^2, E(\varepsilon_t\varepsilon_s) = 0, s \neq t \\ E(\varepsilon_t\varepsilon_s) = 0, \forall s < t, \end{cases}$$

where B is the delay operator, $\nabla^d = (1-B)^d$, $\Phi(B) = 1 - \varphi_1 B - \cdots - \varphi_p B^p$ is the AR polynomial of the ARMA model, and

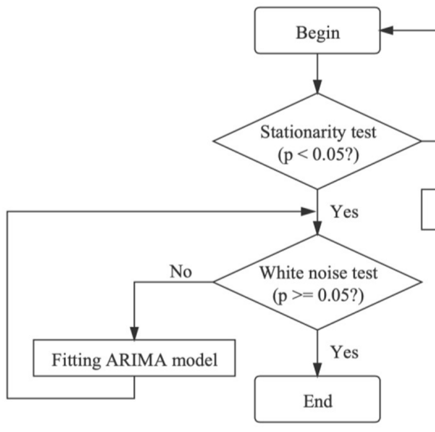

FIGURE 2 | Flow chart of the autoregressive integrated moving average model [from Li et al. (18)].

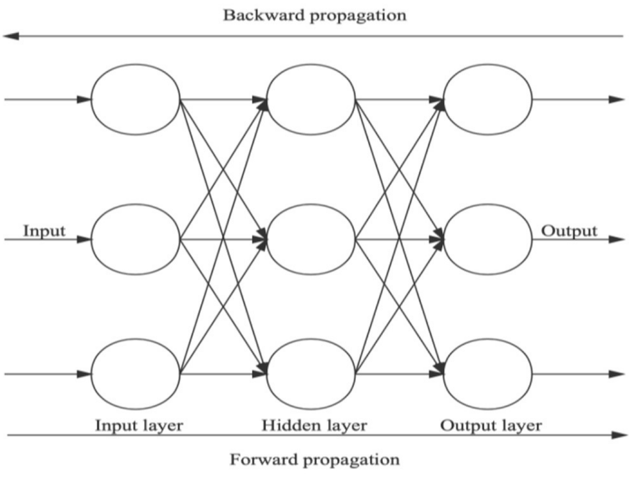

FIGURE 3 | Three-layer back propagation neural network topology [from Chen et al. (19)].

$\theta(B) = 1 - \theta_1 B - \cdots - \theta_q B^q$ is the MA polynomial of the ARMA model. ε_t denotes the random error, and φ_i and θ_j are the AR coefficient and MA coefficient of the ARMA model, respectively. The flow chart is described as follows.

As shown in **Figure 2**, we firstly perform the stationarity test for the original time series and then make a difference for non-stationary data. Secondly, the parameters of stabilized data are estimated by the auto.arima function and BIC heat map in R software, and the white noise test is used to judge whether the residual is a white noise sequence. Finally, the data are analyzed and predicted by the significant model.

BP Neural Network Model

The BP neural network model is the activation function model of linear weight (19). The learning process is divided into two parts, including forward propagation process and backward propagation process, as shown in **Figure 3**.

Forward propagation refers to the process in which neurons in the input layer receive external information and then pass it to the hidden layer. Through the control and conversion of the hidden layer, the output layer finally outputs the calculation results. The backward propagation process is aimed at the error, using the gradient descent method to adjust the continuous parameters for each layer, and the propagation direction is transferred from the output layer to the input layer. Through forward propagation and backward propagation processes, the connection parameters among layers are gradually optimized. For the BP neural network stock price prediction model, the network structure is set as follows:

1. The number of network layers: Since the three-layer BP neural network model can fit any non-linear function with any accuracy and the increase in the number of hidden layers does not significantly improve the generalization ability and prediction accuracy of the network, a three-layer BP neural network structure including only one hidden layer is used for learning.
2. Number of neurons in each layer: Select the opening price, highest price, lowest price, trading volume, and closing price of N consecutive trading days as the network input. The predicted result is the closing price of the next trading day, so the numbers of neurons in the input layer and output layer are $5N$ and 1, respectively. The number of neurons in the hidden layer of the BP neural network is 3 by the method of trial and error.
3. Activation function: Since the sigmoid function can compress the input value with a large range of changes to the interval (0, 1), the processing capacity of the network is greatly improved. Therefore, this paper uses the sigmoid function in the BP neural network model.
4. Training method and optimizer selection: The goal of this paper is to predict the future closing price of stocks; thus, MSE is selected as the loss function. Due to the characteristics of fast convergence speed and good learning effect, the Adam optimizer is used for optimization training.

LSTM Neural Network Model

Based on the BP neural network model, the LSTM neural network model is obtained by solving the long sequence dependency problem of time series data. The network structure of the model adopts a control gate mechanism, which is composed of memory cells, input gates, output gates, and forget gates (16). The calculation steps for each control gate are as follows:

Let W_i, W_c, W_f, and W_0 denote the weights and b_i, b_c, b_f, and b_o denote the biases; X_t denotes input at time t, and h_{t-1} denotes memory state information at time $t-1$. Firstly, calculate the value of the input gate i_t at time t and the candidate state value $\tilde{C}_t$ of the input cell:

$$i_t = \delta(W_i * (X_t, h_{t-1}) + b_i), \tilde{C}_t = \tanh(W_c * (X_t, h_{t-1}) + b_c),$$

where δ represents the activation function. Secondly, calculate the activation value f_t of the forget gate at time t:

$$f_t = \delta(W_f * (X_t, h_{t-1}) + b_f).$$

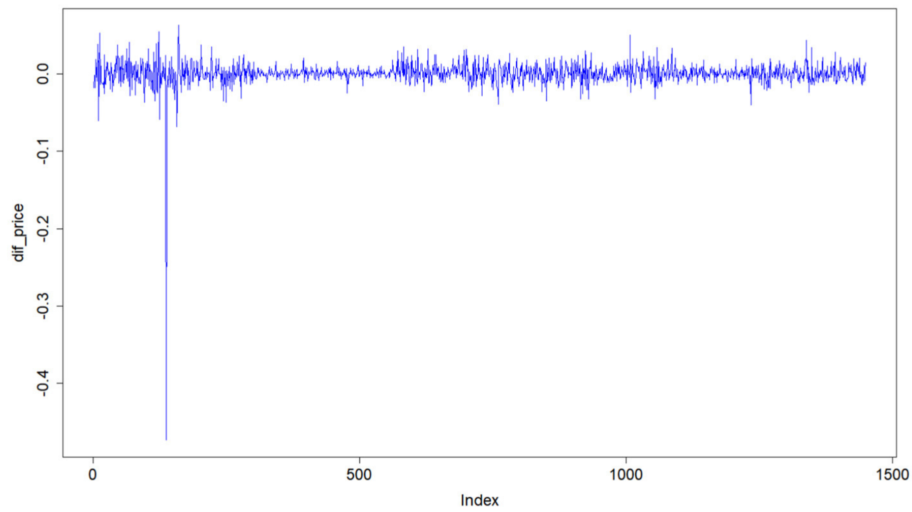

FIGURE 4 | Time series diagram after the first order difference of Ping An Insurance.

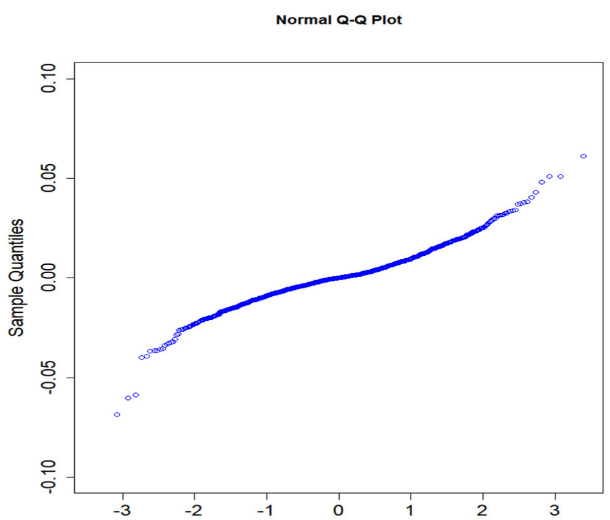

FIGURE 5 | Q-Q plot of Ping An Insurance.

Furthermore, the cell state update value C_t at time t can be obtained:

$$C_t = i_t * \tilde{C}_t + f_t * C_{t-1}.$$

Finally, calculate the value of the output gate O_t:

$$O_t = \delta(W_o * (X_t, h_{t-1}) + b_o).$$

Through the steps given above, the LSTM neural network structure can effectively use the input to make itself have a long-term memory function. Furthermore, the LSTM neural network structure is set as follows:

1. The number of network layers: The LSTM neural network model uses a two-layer hidden layer network. Then, the problem of overfitting is solved by the dropout function.
2. The number of neurons in each layer: Set the number of neurons in the input layer and output layer to five and one, respectively. Furthermore, the number of neurons in the first hidden layer is 60, and the number of neurons in the second hidden layer is 120 by the method of trial and error.
3. Time step: For selecting the network input sequence, we take the stock data of N consecutive trading days as a set of input, and the purpose of learning is to obtain the closing price of the stock on the $N + 1$ trading day. In this paper, the step size N is set to 5 and 10, respectively, and comparative analysis is performed.
4. Activation function: Replace the sigmoid function with the ReLU function to solve the vanishing gradient problem. When the input of the activation function is negative, the output is 0, and the neuron will not be activated. Only some neurons are activated at the same time, which makes the network sparse and improves computational efficiency.

STOCK PRICE PREDICTION

Prediction With ARIMA Model

Stationarity Test

To improve the accuracy of stock price prediction, we carry out a Box–Cox transformation for the original data of Ping An Insurance. Since the stock prices of Ping An Insurance are non-stationary, as shown in **Figure 1**, the data is stabilized by the first-order difference (see **Figure 4**). The time series of the stock prices after the first-order difference fluctuates around the constant 0, and the p-value of the unit root test is <0.05, that is, the data are stabilized after the first-order difference. Similarly, the data of China Life Insurance and Pacific Insurance are stabilized after the first- and second-order differences, respectively.

Model Fitting

The parameters p and q are determined by the auto.arima function in R software, and the fitting model of the stock price of Ping An Insurance is ARIMA (1, 1, 1). Then, Q–Q plot is used to conduct the normality test for the residual (see **Figure 5**). The x-coordinate and y-coordinate denote the quantiles of normal distribution and sample, respectively. From **Figure 5**, the stock price residual of Ping An Insurance approximately follows a normal distribution. Furthermore, the p-value of the white noise test is higher than 0.05, that is, the residual is a white noise sequence, so the fitting model is significantly effective. Similarly, it can be proved that the fitting model of the stock prices for China Life Insurance is ARIMA (1, 1, 1) and that for Pacific Insurance is ARIMA (1, 2, 1).

Prediction Effect of the ARIMA Model

In this section, the ARIMA model is constructed to predict the stock prices of the three health insurance companies. Sample data are taken from the stock closing prices of the above-mentioned companies in trading days from December 18 to 31, 2020. **Table 2** gives the specific prediction results and their errors. The error range between the predicted values and actual values of the three companies is 0–6.96%, showing a high prediction accuracy of the model and an accurate reflection of fluctuations in stock prices. Furthermore, the MAE and MSE of the stock prices of the three companies are calculated (see **Table 3**). The MAE of the ARIMA model ranges from 0.0880 to 3.5670, and the MSE ranges from 0.0120 to 14.7188. Based on these criteria, the ARIMA model is considered to have presented a good fitting effect.

TABLE 2 | Prediction results and errors of stock prices of three health insurance companies.

Date	Company	Actual value	Predicted value	Prediction error
2020/12/18	China Life Insurance	38.91	39.84	2.39%
	Ping An Insurance	87.79	88.99	1.37%
	Pacific Insurance	3.83	3.87	1.04%
2020/12/21	China Life Insurance	39.09	39.83	1.89%
	Ping An Insurance	87.05	88.98	2.22%
	Pacific Insurance	3.87	3.87	0.00%
2020/12/22	China Life Insurance	37.38	39.83	6.55%
	Ping An Insurance	84.15	88.99	5.75%
	Pacific Insurance	3.73	3.87	3.75%
2020/12/23	China Life Insurance	37.40	39.83	6.50%
	Ping An Insurance	84.85	88.99	4.88%
	Pacific Insurance	3.76	3.87	2.93%
2020/12/24	China Life Insurance	37.25	39.83	6.93%
	Ping An Insurance	84.20	88.99	5.69%
	Pacific Insurance	3.72	3.86	3.76%
2020/12/25	China Life Insurance	37.52	39.83	6.16%
	Ping An Insurance	83.20	88.99	6.96%
	Pacific Insurance	3.80	3.86	1.58%
2020/12/28	China Life Insurance	37.40	39.83	6.50%
	Ping An Insurance	84.62	88.99	5.16%
	Pacific Insurance	3.80	3.86	1.58%
2020/12/29	China Life Insurance	37.71	39.83	5.62%
	Ping An Insurance	85.50	88.99	4.08%
	Pacific Insurance	3.84	3.86	0.52%
2020/12/30	China Life Insurance	37.38	39.83	6.55%
	Ping An Insurance	85.88	88.99	3.62%
	Pacific Insurance	3.94	3.86	2.03%
2020/12/31	China Life Insurance	38.39	39.83	3.75%
	Ping An Insurance	86.98	88.99	2.31%
	Pacific Insurance	4.08	3.85	5.64%

TABLE 3 | Prediction effect of the autoregressive integrated moving average (ARIMA) model.

Model	Mean absolute error	Mean square error
ARIMA (1,1,1) (China Life Insurance)	3.5670	14.7188
ARIMA (1,1,1) (Ping An Insurance)	1.9880	4.3788
ARIMA (1,2,1) (Pacific Insurance)	0.0880	0.0120

Prediction With BP and LSTM Neural Network Models

Data Normalization

The degrees of gradient descent for each parameter are proportional to the magnitude in training the neural network model. However, the parameters in this paper are different in magnitude, so it is necessary to normalize the original data and map the data to the interval [0, 1] by the following formula:

$$x_n = \frac{x - x_{\min}}{x_{\max} - x_{\min}},$$

where x_n and x represent the normalized data and original data, respectively, and $x_{\min}$ and $x_{\max}$ represent the minimum and maximum of the original data, respectively. In particular, to facilitate the subsequent comparative analysis, we make the reverse normalization of the results and restore the data to the original magnitude.

Prediction Effects of BP and LSTM Neural Network Models

In this section, Keras in Python is used to construct the BP and LSTM neural network models. The 5- and 10-day stock data are used as the input samples to build the prediction models. Let RS, PA, and TPY represent the three companies of China Life Insurance, Ping An Insurance, and Pacific Insurance, respectively. Besides this, Y6, D5, and D10 represent the span of the data set of 6 years and the samples of five consecutive trading days and 10 consecutive trading days, respectively. The prediction effects of the BP and LSTM neural network models are measured by the MAE, MSE, and discriminant coefficient R^2. The results are given in **Table 4**.

Under the structures of Y6 and D5, we further analyze the prediction effects for the three companies with two neural network models. Under the RSY6D5 structure, compared with the BP neural network model, the MAE and MSE of the

TABLE 4 | Prediction effects of back propagation (BP) and long short-term memory (LSTM) neural network models.

Model structure	Mean absolute error		Mean square error		R^2	
	BP	LSTM	BP	LSTM	BP	LSTM
RSY6D5	1.4255	1.2417	5.6332	4.7662	0.8770	0.8960
PAY6D5	1.8684	1.6298	5.4513	4.1271	0.9150	0.9357
TPYY6D5	0.1544	0.1086	0.0325	0.0294	0.8261	0.8429
RSY6D10	2.1694	0.9474	10.2784	1.9913	0.7756	0.9565
PAY6D10	3.4425	1.5166	18.1472	3.7957	0.7171	0.9408
TPYY6D10	0.1742	0.0986	0.0754	0.0220	0.5963	0.8822

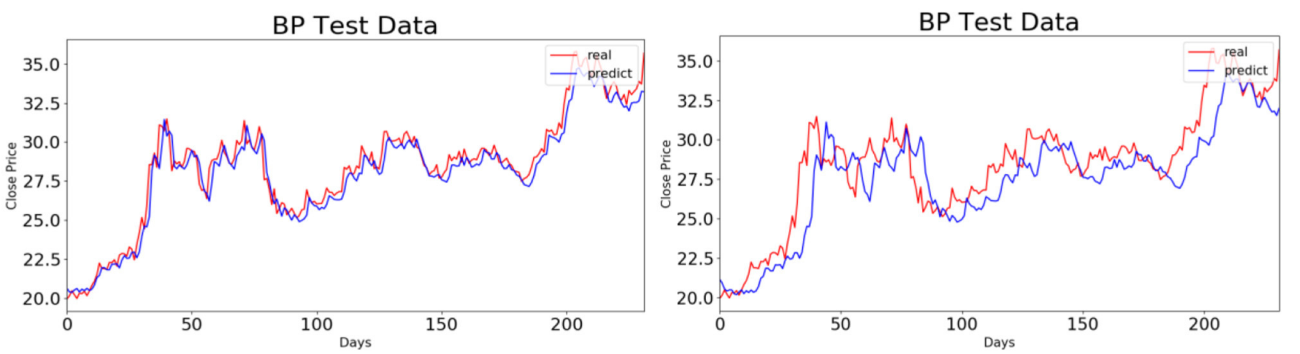

FIGURE 6 | Fitting effect diagrams of back propagation neural network model in two test sets.

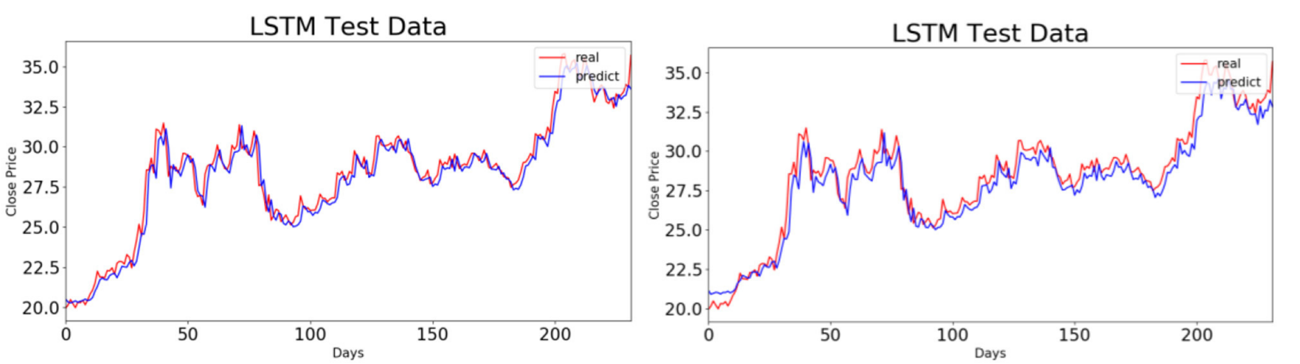

FIGURE 7 | Fitting effect diagrams of long short-term memory neural network model in two test sets. The diagrams on the left and right represent RSY6D5 and RSY6D10, respectively.

LSTM neural network model decreased by 12.89 and 15.39% respectively, while R^2 increased by 2.17%. The MAE and MSE of the LSTM neural network model under the PAY6D5 structure decreased by 12.77 and 24.29%, respectively, and R^2 increased by 2.26%. The MAE and MSE of the LSTM neural network model under the TPYY6D5 structure are reduced by 29.66 and 9.54%, respectively, and R^2 increased by 2.03%, that is, for all the three observed companies, the prediction effect of the LSTM neural network model is better than that of the BP neural network model, and it still holds under the structures of Y6 and D10.

To compare the BP and LSTM neural network models graphically, we take China Life Insurance, for instance, to give the fitting effect diagram of the above-mentioned two models in the test set. The results are shown in **Figures 6**, **7**. When the BP neural network model is used for prediction, the prediction model with a time step of five trading days has a higher accuracy than the one with a time step of 10 trading days. When the LSTM neural network model is used, however, there is no significant difference in the prediction effects under the above-mentioned two kinds of time steps. Combined with **Table 4**, it is obvious that the prediction effect of the LSTM neural network model improves with the increase in time steps.

In summary, for the three health insurance companies that we observed, the stock price prediction effect of the LSTM neural

TABLE 5 | Predicted stock closing prices on January 4, 2021.

Company	Model		
	Autoregressive integrated moving average (ARIMA)	Back propagation (BP)	Long short-term memory
China Life Insurance	39.83	36.62	38.10
Ping An Insurance	89.23	83.98	85.84
Pacific Insurance	3.85	3.90	3.92

ARIMA and BP models with a time step of 5, LSTM model with a time step of 10.

network model is better than those of the ARIMA and BP neural network models under the MAE and MSE criteria. Moreover, the prediction effect of the LSTM neural network model improves with the increase in time steps, while the prediction effect of the BP neural network model shows the opposite. It is also found that the LSTM neural network model could deal with the problem of longer sequences and excavate the information of long-term dependence. Therefore, we consider it more appropriate to use the LSTM neural network model in stock price prediction.

Based on the above-mentioned analysis, we use the ARIMA model, BP neural network model with a time step of 5, and LSTM neural network model with a time step of 10 to predict the stock closing prices of China Life Insurance, Ping An Insurance, and Pacific Insurance on January 4, 2021. The predicted results are shown in **Table 5**.

CONCLUSION AND PROSPECT

This paper mainly studies the equity performance of China's health insurance companies during the COVID-19 pandemic, aiming to analyze the impacts of the pandemic on the stock prices of dominant companies and establish more accurate stock price prediction models. Clearly, the stock prices of China Life Insurance, Ping An Insurance, and Pacific Insurance fell overall in the first quarter of 2020. With the advancement of China's pandemic prevention and control as well as the resumption of work and production, the stock prices quickly recovered and showed an overall rising trend. In spite of slight fluctuations, the stock prices generally rose above levels before the pandemic.

Then, three models of the ARIMA, BP, and LSTM neural network are used to predict the stock prices of the three health insurance companies in China. Firstly, for the ARIMA model, the parameters of the stabilized data are estimated by the auto.arima function and BIC heat map in R software, and a significant model is obtained by the white noise test. By calculation, the value ranges of MAE and MSE are 0.0880–3.5670 and 0.0120–14.7188, respectively, that is, the ARIMA model performs well in the fitting. Secondly, based on the normalized stock price data of the three companies, BP and LSTM neural network models are trained by Python and applied to the test set data. The LSTM neural network model is more accurate in stock price prediction than the BP neural network model under the criteria of MAE, MSE, and R^2. In conclusion, the prediction effect of the LSTM neural network model is better than those of the ARIMA and BP neural network models under the criteria of MAE and MSE. Furthermore, since the LSTM neural network model can deal with longer time series problems, this paper recommends this model for predicting the stock prices of China's health insurance listed companies.

In this paper, we use three models to analyze the stock price trends of the three health insurance companies during the pandemic. The above-mentioned research results can be applied to the whole health insurance industry by expanding the sample scope and also provide references for stock price prediction in other industries such as the Internet and real estate. We will further our research in several aspects, including discussing the influence of time steps on the LSTM neural network model, in the future. This research will help to improve the fitting effect and prediction accuracy of the LSTM neural network model.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct and intellectual contribution to the work, and approved it for publication.

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REFERENCES

1. Liu YZ, Wang CH. Analysis of epidemics from the behavioral perspective: a review of causes, effects, and countermeasures. *J Financ Res.* (2020) 6:1–19. Available online at: http://bmw82.cn/vjL32
2. Zhang XH. The impact of novel coronavirus outbreak on small and micro enterprises in China and countermeasures. *China Bus Mark.* (2020) 34:26–34. doi: 10.19313/j.cnki.cn10-1223/f.2020.03.004
3. Zhen JH, Fu YF, Tao J. Impact of the Covid-19 epidemic on consumption economy and countermeasures analysis. *Consum Econom.* (2020) 36:3–9. Available online at: http://aakn.cn/ejlCA
4. Feng QB, Han B. The effects of COVID-19 epidemic on China's finance and economy and relevant countermeasures. *Public Finance Res.* (2020) 4:15–21. doi: 10.19477/j.cnki.11-1077/f.2020.04.003
5. Duan YY. The impact of COVID-19 epidemic on my China's stock market: an empirical analysis based on the pharmaceutical industry.

China J Commerce. (2020) 817:34–6. doi: 10.19699/j.cnki.issn2096-0298.2020.18.028

6. Wang Q, Wang ZL, Li SX, Xue FZ. The immediate impact of COVID-19 on China's stock price fluctuation. *Rev Economy Manage.* (2020) 36:16–27. doi: 10.13962/j.cnki.37-1486/f.2020.06.002
7. Xia Y, Hu W. Impact of COVID-19 attention on pharmaceutical stock prices based on internet search data. In: *International Conference on Big Data Analytics for Cyber-physical-systems*. Singapore: Springer. (2020) 1213–20. doi: 10.1007/978-981-33-4572-0_174
8. Sun YC, Wu MY, Zeng XP, Peng Z. The impact of COVID-19 on the Chinese stock market: sentimental or substantial? *Finance Res Lett.* (2020) 38:101838. doi: 10.1016/j.frl.2020.101838
9. Mazur M, Dang M, Vega M. COVID-19 and March 2020 stock market crash. Evidence from S&P1500. *Finance Res Lett.* (2020) 35:101690. doi: 10.2139/ssrn.3586603
10. Heyden KJ, Heyden T. Market reactions to the arrival and containment of COVID-19: an edvent study. *Finance Res Lett.* (2020) 38:101745. doi: 10.1016/j.frl.2020.101745
11. Bai YS. Forecast and analysis of Shanghai stock index based upon ARIMA model. *Sci Technol Eng.* (2009) 9:4885–8. doi: 10.3969/j.issn.1671-1815.2009.16.075
12. Shi HY, You ZJ, Chen ZJ. Analysis and prediction of Shanghai composite index by ARIMA model based on wavelet analysis. *Math Pract Theory.* (2014) 44:66–72. Available online at: http://45dwz.com/pBz8y
13. Chen XL. Prediction of stock-price based on ARIMA model and neural network model. *J Quantitative Econ.* (2017) 34:30–4. doi: 10.16339/j.cnki.hdjjsx.2018.04.006
14. Cai H, Chen RY. Stock price prediction based on PCA and BP neural network. *Comput Simulat.* (2011) 28:365–8. doi: 10.3969/j.issn.1006-9348.2011.03.088
15. Huo L, Jiang B, Ning T, Yin B. A BP neural network predictor model for stock price. In: *International Conference on Intelligent Computing*. (2014). p. 362–8. doi: 10.1007/978-3-319-09339-0_37
16. Peng Y, Liu YH, Zhang RF. Modeling and analysis of stock price forecast based on LSTM. *Comput Eng Appl.* (2019) 55:209–12. doi: 10.3778/j.issn.1002-8331.1811-0239
17. Song G, Zhang YF, Bao FX, Qin C. Stock prediction model based on particle swarm optimization LSTM. *J Beijing Univ Aeronaut Astronaut.* (2019) 45:2533–42. doi: 10.13700/j.bh.1001-5965.2019.0388
18. Li WY, Li JZ, Wang T. Improved ARIMA model traffic flow prediction method based on Box-Cox exponential transformation. *J Wuhan Univ Technol.* (2020) 44:974–7. doi: 10.3963/j.issn.2095-3844.2020.06.006
19. Chen YY, Zhang ZX, Li WB. Neural network based stock price predictionmodel. *Comput Appl Software.* (2014) 31:89–92. doi: 10.5120/15499-4141

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COVID-19 and Regional Income Inequality in China

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This study investigates the impact of COVID-19 and social distancing policies on regional income inequality. We base our study on a sample of 295 prefecture (and above) cities in 31 provinces in China. A distribution dynamics approach is employed to reveal the trend and movement of disposable income per capita in each city before the COVID-19 pandemic, during the COVID-19 pandemic, and in the period when the COVID-19 was under the control. The findings reveal significant negative economic consequences of the COVID-19 in the first quarter of 2020 and show that most cities will converge to a level of disposable income which is much less than the Pre-COVID level if the COVID pandemic persists. Regional income inequality has intensified in the cities that have a longer duration of stringent social distancing policies during the COVID-19 pandemic and disappeared in the cities with policies of short duration. Disposable income per capita for urban residents recovered quickly when the transmission of coronavirus was effectively contained; and yet the impact of the pandemic on rural residents remains unresolved, if not intensified. This study demonstrates a significant divergence of the trend of disposable income across cities with different durations of social distancing policies and between urban and rural residents. It also highlights the importance of stringent social distancing policies in containing the spread of virus in a short time and calls for special policy attention for rural regions in the recovery from the COVID-19.

Keywords: regional income inequality, distribution dynamics, China, COVID, rural-urban disparity

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INTRODUCTION

Up to March 2021, the COVID-19 pandemic has infected millions and caused millions of deaths across the globe[1]. Many countries have adopted strict social distancing policies, including travel restriction, school closure and even the lockdown policies (1). The pandemic also lead to substantial economic loss: according to the data from International Monetary Fund (IMF), the GDP growth in 2020 is a negative 4.4% in the world, a negative 5.8% in the advanced economies, and a negative 3.3% in emerging market and developing economies[2]. Some studies show that the COVID-19 crisis may intensify the income inequality across the groups of employees by gender, education, earnings level and ethnicity and working style (2, 3), and cross countries (4). However, how COVID-19 crisis affects income inequality within countries has not been explored, although different regions in a country may expose to different levels of coronavirus transmission risks, adopt different policies to contain the spread of the virus, have different capacity to cope with the outbreak of the virus

[1] According to the statistics at Johns Hopkins University, the numbers of global infected cases and death cases are 121,845,601 and 2,692,235 up to March 19, 2021. See: https://coronavirus.jhu.edu/map.html.
[2] See: https://www.imf.org/en/Data.

and suffer the different mortality and economic loss. This study fills this gap by investigating the impacts of COVID-19 and the associated social distancing policies on regional income inequality in China.

Whether COVID-19 intensifies or mitigates regional income inequality in China is an interesting question for several reasons. First, despite that overall income inequality could decline after four decades of rapid economic growth, urban and rural income equalities across regions, e.g., eastern region vs. western region, are widened due to the gaps in economic development, industrial structure, urban-rural divide, fiscal capacity, and others [e.g., Xie and Zhou (5)]. COVID-19 may cause more loss to low-income regions as they have weak fiscal capacity and lower government efficiency to deal with the crisis. On the other hand, high-income regions have closer connections with Wuhan, the epicenter of COVID-19, and are more likely to have more infections and deaths as well as aggressive social distancing policies than low-income regions (4). Thus, the impact of COVID-19 on income inequality between high-income and low-income regions remain an empirical question that we explore in this study.

We explore the effect of COVID-19 on city-level income inequality using a sample of 295 prefecture (and above) cities in 31 provinces[3]. Our sample contains disposable income per capita, disposable income per capita of urban households, and disposable income per capita of rural residents in these cities in 2019 and 2020. We focus on the disposable incomes before the outbreak of COVID-19 (2019Q4), the quarter of outbreak (2020Q1), and the quarters after the coronavirus was under control in most of regions (2020Q2 and 2020Q3)[4]. All 31 provinces had launched a Level I Emergency Response Situation (ERS) in the late January, 2020; from then stringent social distancing policies, including the policies of "closed management of communities" and "family outdoor restrictions," had been implemented in more than 250 prefecture cities outside Hubei (6, 7). In late February 2020, some cities downgraded the ERS to Level II or even Level III after the pandemic had relieved, and while the top ERS remained in some cities. According to the duration of the Level I ERS, we divide the cities in our sample into three groups and explore the potential impacts of COVID-19 on income inequality in cities with different response policies.

We apply a distribution dynamics approach to investigate the trend and movement of disposable incomes across cities with different levels of social distancing policies and between rural and urban regions. The dynamics of quarterly disposable income per capita (all residents, urban households and rural residents) in relative to the average value of disposable income in all the cities are presented in the pre-COVID period, during the COVID period and in the post-COVID period. The findings show that disposable incomes per capita in all cities significantly reduce during the COVID period and the income inequality across cities was intensified in the cities with longer duration of Level I ERS. Most cities would converge to a level of disposable income which is much less than the pre-COVID level if the pandemic persists. We find that the disposable incomes of urban residents recover quickly from the second quarter of 2020; and yet the negative shock of the pandemic on the disposable income of rural residents remains unresolved in the post-COVID period. Rural residents are more severely affected by the COVID-19 pandemic and the social distancing policies (2, 8).

This study contributes to two streams of literature: regional income inequality in China and the economic consequences of the COVID-19. Previous studies show that the income inequality between coastal and inland regions, and between rural and urban regions worsens since mid-1980s [e.g., (5, 9)], although it is plateauing in recent years (10). Our results indicate that the pandemic and the duration of stringent social distancing policies affect the regional income inequality. We are also the first study that explores the effect of the COVID-19 pandemic and the social distancing policies on the income inequality within a country. Deaton (4) shows that global income inequality across countries decreased in 2020 because rich countries suffered more deaths and larger declines in income per capita. Our study shows that the regional income inequality could be intensified due to the economic consequence of the COVID-19, especially for rural residents.

BACKGROUND AND LITERATURE REVIEW

COVID-19 Pandemic in China

The outbreak of COVID-19 started in the late January 2020 in China, spreading from Wuhan, the capital of Hubei Province and the most populous city in central region of China to all 31 provinces. The numbers of confirmed cases arose fast during the period of the last week of January 2020 and the first 2 weeks of February 2020. The numbers of new daily cases in Hubei Province reached a peak of 14,840 on February 12 when the Chinese Center for Disease Control and Prevention (CDC) began to include clinically diagnosis. The peak of daily confirmed cases in the 30 non-Hubei provinces occurred on February 3, 2020 with a number 890. The epidemic curve had been significantly flattened after the third week of February, 2020; and most provinces outside Hubei had effective contained the transmission of coronavirus. The number of new daily cases outside Hubei fall to a one digit 9 on February 24, 2020, although there were several waves of infections in many cities after the first quarter of 2020[5]. Around 3 weeks later, the numbers of new daily cases in Hubei also fall to one digit or even zero in the mid-March 2020; and the situation of low or zero infections maintained subsequently. **Appendix 1** presents the numbers of new daily cases in overall 31 provinces, in Hubei and in non-Hubei provinces from January 20, 2020 to December 30, 2020.

Flattening the epidemic curve in < 6 weeks in most regions in China could be attributed to a systematic and quick government response to the outbreak. Provinces that are geographically close

[3] We exclude Hong Kong, Macau, and Taiwan in our analysis.

[4] After a massive break of COVID-19 in China from the last week of January 2020, the government adopted aggressive social distancing policies to restrict the spreading of the virus. The cumulative confirmed cases reached a peak on February 5, 2020, and the epidemic curve had been flattened significantly after February 26, 2020. Many cities reported zero new confirmed cases since then.

[5] For instance, a second wave of infections occurred in Beijing with 256 new local cases between June 11, 2020 and June 23, 2020.

TABLE 1 | The numbers of confirmed cases, ESR announcement dates, and durations of Level I ERS in 31 provinces.

Province	No. of cases on Jan 23	No. of cases in 2020Q1	Level I ERS Date	Downgrade to Level II	Downgrade to Lever III	Days of Level I	Level I Duration
Hubei	549	66,907	24/1/2020	2/5/2020	13/6/2020	99	Long
Beijing	26	413	24/1/2020	30/4/2020	6/6/2020	97	Long
Hebei	2	318	24/1/2020	30/4/2020	6/6/2020	97	Long
Tianjin	7	136	24/1/2020	30/4/2020	6/6/2020	97	Long
Shanghai	20	337	24/1/2020	24/3/2020	9/5/2020	60	Long
Henan	9	1,272	25/1/2020	19/3/2020	5/5/2020	54	Long
Jiangxi	7	935	24/1/2020	12/3/2020	20/3/2020	48	Long
Shandong	9	756	24/1/2020	12/3/2020	20/3/2020	48	Long
Hunan	24	1,018	23/1/2020	10/3/2020	31/3/2020	47	Long
Chongqing	27	576	24/1/2020	10/3/2020	24/3/2020	46	Long
Heilongjiang	2	480	25/1/2020	4/3/2020	25/3/2020	39	Medium
Tibet	0	1	27/1/2020	6/3/2020		39	Medium
Zhejiang	43	1,205	23/1/2020	2/3/2020	23/3/2020	39	Medium
Ningxia	2	73	25/1/2020	28/2/2020	6/5/2020	34	Medium
Qinghai	0	18	26/1/2020	–	26/2/2020	34	Medium
Shaanxi	3	245	25/1/2020	–	28/2/2020	34	Medium
Fujian	5	296	24/1/2020	26/2/2020	26/2/2020	33	Medium
Sichuan	15	538	24/1/2020	26/2/2020	25/3/2020	33	Medium
Anhui	15	990	24/1/2020	25/2/2020	15/3/2020	32	Short
Guangdong	53	1,349	23/1/2020	24/2/2020	9/5/2020	32	Short
Hainan	8	168	25/1/2020	–	26/2/2020	32	Short
Jilin	3	93	25/1/2020	26/2/2020	20/3/2020	32	Short
Guangxi	13	252	24/1/2020	–	24/2/2020	31	Short
Inner Mongolia	1	75	25/1/2020	–	25/2/2020	31	Short
Xinjiang	2	76	25/1/2020	25/2/2020	7/3/2020	31	Short
Yunnan	2	174	24/1/2020	–	24/2/2020	31	Short
Guizhou	3	146	24/1/2020	–	23/2/2020	30	Short
Jiangsu	9	631	25/1/2020	24/2/2020	27/3/2020	30	Short
Shanxi	0	133	25/1/2020	24/2/2020	10/3/2020	30	Short
Liaoning	4	122	25/1/2020	–	22/2/2020	28	Short
Gansu	2	91	25/1/2020	–	21/2/2020	27	Short

ESR announcement dates are collected from official websites. The numbers of confirmed cases are from China CDC.

to Wuhan launched Level I Emergency Response Situation on or before January 24, 2020, followed by announcements in next day from cities located in the western and northern regions of the country[6]. Systematic intervention measures from central government, including social distancing policies, quarantine strategies, tracing and managing close contracts of COVID-19 confirmed cases, etc., were executed by local governments. While Wuhan and other cities in Hubei were completely shut down after January 23, 2020, some cities outside Hubei were also partially shut down (6) and more than 250 prefecture level cities had implemented very stringent social distancing policies such as closed management of communities and family outdoor restrictions (7). Public transportation was suspended in cities; residents were restricted to enter and exit communities; and only one family member was allowed to go outside once every 1 or 2 days. The lockdown policies lasted for several days to several weeks in different cities. The human mobility gradually returned to normally when the travel restrictions were removed. Three provinces, i.e., Guangdong, Jiangsu and Shanxi, downgraded the ERS to Level II on February 24, 2020; and some remote provinces, such as Gansu, Guizhou, and Yunan issued a downgrade to Level II ERS from February 21, 2020. **Table 1** reports the numbers of confirmed cases on January 23, 2020 and in the first quarter of 2020 in 31 provinces and the dates to announce Level I ERS and downgrade to Level II/II.

Hubei was the last province that issued a downgrade of ERS to Level II on May 2, 2020. The duration of Level I ERS is as long as 99 days, followed by 97 days in Beijing-Tianjin-Hebei integration area. According to the numbers of days with Level I ERS, we divide the cities in our sample into three groups: long duration group, medium duration group and short duration group. Studies in COVID-19 show that strong social distancing

[6]Based on the size and severity of causality, China established a four tiers of emergency response situation. The Level I is the top ERS. Tibet was the last province that announced Level I ERS on January 27, 2020.

TABLE 2 | The number of cities, average GDP growth in 2019, average GDP per capita in 2019, and located regions in three groups by duration of Level I ERS.

Group	No. of cities	2019 GDP growth	2019 GDP per capita	Eastern (%)	Central (%)	Western (%)	Northeastern (%)
Short duration	141	6.80%	61,804	26.24%	19.15%	39.01%	15.60%
Medium duration	71	7.41%	64,845	28.17%	0.00%	54.93%	16.90%
Long duration	84	8.07%	65,066	35.71%	63.10%	1.19%	0.00%

Eastern region includes Beijing, Tianjin, Shanghai, Fujian, Guangdong, Hainan, Hebei, Jiangsu, Shandong, Zhejiang; central region includes Anhui, Jiangxi, Henan, Hubei, Hunan, and Shanxi; western region includes Chongqing, Gansu, Guangxi, Guizhou, Inner Mongolia, Ningxia, Qinghai, Shaanxi, Sichuan, Tibet, Xinjiang, and Yunnan; and northeast western includes Liaoning, Jilin, and Heilongjiang. GDP data are from CEIC.

TABLE 3 | Disposable income per capita by quarter in 2019 and 2020.

Unit: RMB	2019Q1	2019Q2	2019Q3	2019Q4	2020Q1	2020Q2	2020Q3	2020Q4
Disposable income	9023.23	7297.92	8035.04	7853.57	8761.19	7412.35	8310.62	8157.07
Disposable income: urban	10566.15	9068.06	10023.37	9809.43	10334.16	9227.04	10204.75	10308.53
Disposable income: rural	5429.44	3915.97	4702.84	4626.76	5039.11	3921.92	4810.21	5083.89

Data source: CEIC.

policies such as lockdowns increase unemployment (11), reduce consumer spending (12, 13) and temporarily improve air quality due to the restriction of human mobility (14, 15). Cities with longer duration of Level I ERS maintained stringent social distancing policies for a longer time, and hence could suffer more negative economic impacts from COVID-19. On the other hand, cities in the cities with short duration of Level I ERS could recover from recession faster. The changes of economic outputs and disposable incomes in Chinese cities may be affected by the duration of Level I ERS.

Table 2 shows the statistics of cities in the three groups by the durations of Level I ERS. The numbers of cities in the groups of short duration, medium duration and long duration are 141, 71, and 84, respectively. Cities in the short duration group have lower GDP growth rate and GDP per capita in 2019 than cities in medium and long durations, indicating that these cities are located in relatively low-income regions; and while cities with longest duration have largest GDP growth rate and GDP per capita. The long duration group contains more cities from eastern and central parts of China, as these cities had closer connections with Wuhan and on average suffered to more infections. Cities located in western region are more likely to have short duration or medium duration of Level I ERS.

Literature Review

Regional income inequality, including the disparities between coastal and inland regions, and urban and rural regions, in China has been widely studied in the literature. Several studies document that after the reform from 1978, regional income inequality first declined and then widened as coastal cities in the eastern regions grew much faster than cities in the central and western regions (16, 17). The regional income disparity can be attributed to geographical advantages/disadvantages (18), fiscal decentralization (9), labor mobility and urbanization (18, 19), decreasing labor share and rising profit share (20), migration and city population size (21), etc. Xie and Zhou (5) show that income inequality in China since 2005 can be largely explained by regional disparities across cities and rural-urban divide. The inequality between urban and rural areas is caused by urban-biased economic policies in China (22, 23). A recent study by Kanbur et al. (10) shows that inequalities between rural and urban areas or coastal and inland regions started to plateau or even decline after 2008. They argue that the decreasing inequality could be explained by the lower rural-urban wage differentials, infrastructure investment in rural regions, inequality-mitigating transfer and other government policies that benefit rural residents.

The COVID-19 pandemic has caused a large amounts of deaths and brought substantial economic loss to all countries. The economic consequences of COVID-19 and associated social distancing policies may vary across groups and intensify income inequality. Bonaccorsi et al. (24) find that low-income individuals in Italy are exposed more to the economic consequences of lockdown policies. The evidence from UK indicates low-income individuals are more likely to experience economic hardship than others during lockdown period (8). Young workers, self-employed workers and workers on low incomes are more likely to lose jobs or reduce earnings more than high-income workers during the lockdown (2); and working from home could intensify the existing inequalities in the labor market as it favors high-education and high-income individuals (2, 3). Overall, COVID-19 and the lockdown exacerbate income inequality between the poor and the rich.

Whether income inequality across regions in a country worsens has not been thoroughly examined. Deaton (4) shows that rich countries suffered more deaths in the COVID-19 pandemic and hence income per capita fell more than poor countries, despite that they had better health systems, higher incomes and better preparedness for the pandemic. The international income inequality decreased in 2020. It is not clear whether the regional income inequality, across cities and between urban and rural areas in China, widened due to the COVID-19.

On the one hand, there were more confirmed cases and deaths in the regions with better economic development, which could cause longer duration of stringent social distancing policy (e.g., Level I ERS) and more potential economic loss. In this sense, income per capita could fall more in the rich regions (i.e., coastal regions and urban regions) than in the poor regions (i.e., inland regions and rural regions); and the regional income disparity may decline (4). On the other hand, poor regions may have lower fiscal capacity (24), poorer government efficiency (25), and less preparedness (4) to cope with the COVID-19 pandemic. Lower-income individuals in the poor regions may lose jobs or have more reductions of earnings because they were restricted to migrate to the rich regions. Apart from the question whether regional income inequality is affected by COVID-19, it is also important to know whether this potential effect is temporary which will disappear when the coronavirus is under the control, or it is a long-lasting effect. We examine these questions by analyzing the disposable income per capita of prefecture cities in China.

DATA AND METHODOLOGY

Data and Sample

Our sample contains 295 prefecture (and above) cities in China[7]. We collect quarterly city-level income data from CEIC database, including overall disposable income per capita, disposable income per capita for urban households, and disposable income per capita for rural residents[8]. **Table 3** reports average disposable income per capita in each quarter of 2019 and 2020.

Table 3 shows that per capita disposable incomes for all residents, urban residents and rural residents all decreased in 2020Q1, in comparison with incomes in 2019Q1[9]. The quarter-to-quarter changes are −2.90, −2.20, and −7.19%, respectively. The results indicate that the COVID-19 pandemic negatively affect disposable incomes to all the residents, and the effect is much more pronounced for rural residents. The findings are consistent with previous studies (8, 24) that low-income individuals were more severely hit by the COVID-19 and the social distancing policies. As the spreading of coronavirus was effectively contained in China after the first quarter of 2020, disposable incomes for all residents, urban and rural residents slightly increase in the second quarter in comparison to 2019Q2. The disposable incomes continue to rise in the second half year of 2020 as the economy in China recovered from the recession. Despite the negative shock caused by the COVID-19 outbreak, the average per capita disposable incomes in 295 cities still increase in 2020[10].

We are interested in examining the effect of the COVID-19 pandemic on regional income inequality. The analysis of the mobility of disposable income is separated into three-time episodes: the Pre-COVID period (from 2019Q3 to 2019Q4), the COVID period (from 2019Q4 to 2020Q1), and the Post-COVID period (from 2020Q1 to 2020Q2)[11]. To remove the seasonal pattern and the CPI effect on disposable incomes, we calculate a relative disposable income per capita (RDIPC) for all residents, urban residents and rural residents in a city. The relative disposable income per capita is calculated as the disposable income per capita in a city in quarter divided by the mean of 295 cities in that quarter. To investigate the varying impacts of social distancing policies, the cities in the sample are divided into three groups based on the duration of Level 1 ERS: long duration group, medium duration group, and short duration group.

Methodology

In this study, the distribution dynamics approach is used to evaluate the impacts on the income distribution. Many scholars have studied the impacts of the pandemic by using econometrics techniques, however, it is notable that regression just cannot provide information on the evolution of the distribution across time. Therefore, a non-parametric method of stochastic kernels is employed in this study as we would like to understand the changes in the distribution in detail.

It is worth noting that distribution dynamics analysis is a very powerful tool as it can reveal the changes in distribution. Although the econometrics model can only provide a forecast of the dependent variable based on the changes in the independent variables, however, it is just impossible to predict the changes of distribution by using econometrics as the distribution is a two-dimensional entity while the econometrics model can only provide a point estimation of the data. As the major aim of this study is to examine the impacts on income distribution in China, so distribution dynamics analysis is a much better tool for this purpose. Moreover, this approach can also provide an estimation of the probability of the movement of the entities within the distribution, thereby unveiling the underlying trend of the changes of the distribution in detail.

The distribution dynamics analysis was first proposed by Quah (26) and it has been employed in many studies focusing on distribution, for example, Li and Cheong (27) and Zhang et al. (28). The stochastic kernel approach is used in this research because it can avoid the problem of distortion due to the discretization of data and it can also overcome the limitations of selection of the boundary values [please refer to Cheong and Wu (29) for details].

[7]There are 337 prefecture (and above) cities in 31 provinces in China (excluding Hong Kong, Macau, and Taiwan). Some cities are not included in the sample as the data are not available.

[8]CEIC complies the data of disposable income per capita from Municipal Bureau of Statistics in each city.

[9]Per capita disposable incomes are normally highest in the first quarter of each year as residents could receive extra salary and bonus before Chinese New Year. The statistics also show a significant gap of disposable incomes between urban residents and rural residents.

[10]The figures are consistent with official statistics that the average disposable income in China fell by 3.9% in the first quarter of 2020 but rose by 2.1% in the whole year of 2020. See: http://news.cctv.com/2020/04/17/ARTIpIS9jocjvL5g0dR1haG5200417.shtml; http://news.voc.com.cn/article/202101/202101181012395850.html.

[11]Our analysis focuses on the quarters before the COVID-19 pandemic, during the pandemic, and after the pandemic in China, as the virus was effectively contained in the first quarter of 2020. **Table 3** shows that disposable incomes after the pandemic quickly bounce back to a higher level than the same quarters in the previous year since 2020Q2.

The kernel estimator can be represented by the following equation:

$$f_{t,t+\tau}\left(y,x\right)=\frac{1}{nh_xh_y}\sum\nolimits_{i=1}^{n}K\left(\frac{x-x_i}{h_x},\frac{y-y_i}{h_y}\right) \tag{1}$$

where x_i is the RDIPC value of a city at time t and y_i is the RDIPC value of that city at time $t+\tau$. h_x and h_y are the bandwidth of variable of x and y, respectively. $K(\cdot)$ is the normal kernel function, n is the total number of transitions in the data. The optimal values of the bandwidth were determined by the procedures proposed by Silverman (30).

The conditional density function $g_\tau\left(y|x\right)$ can be computed by using $f_t\left(x\right)$ and $f_{t,\,t+1}\left(y,\,x\right)$:

$$g_\tau\left(y|x\right)=\frac{f_{t,t+1}\left(y,x\right)}{f_t\left(x\right)} \tag{2}$$

By using Equation (2) and repeating the process continuously, the ergodic distribution can be found. It is the steady state distribution in the long run. And it can be represented by the following:

$$f_\infty\left(y\right)=\int_0^\infty g_\tau\left(y|x\right)f_\infty\left(x\right)dx \tag{3}$$

The ergodic distribution can provide vital information on the final distribution if the distribution dynamics remain unchanged. Given that the issue of COVID-19 was resolved very soon in China, so it is of interest to learn about the consequences and the impacts on China for a what-if scenario, namely, what will happen if the spread of the coronavirus went out of control. The ergodic distribution is very useful as it can be used to evaluate this scenario and reveal the impacts on income distribution in the long run when China cannot handle coronavirus. This finding is very important as it can disclose the details and the consequences for many developing countries with a large population.

Cheong and Wu (29) developed the mobility probability plot (MPP) and proposed a new framework in distribution dynamics analysis. Future movement of the cities within the distribution can be estimated by the MPP which is the probability of net upward movement of the cities. It is in the form:

$$p\left(x\right)=\int_x^\infty g_\tau\left(z|x\right)dz-\int_0^x g_\tau\left(z|x\right)dz \tag{4}$$

The MPP is the probability of moving upward minus the probability of moving downward for the cities. A positive value of $p(x)$ implies intuitively that the city will have a higher tendency to move up in the next period, and a negative value suggests that the city will have a higher tendency of moving downward in the next period. By observing the MPP, one can know the future movement of the cities at different levels of RDIPC. After the development of this model, it has been applied in different areas, including energy (31) and industrial output (29).

DISCUSSION

This section will present the distribution dynamics analysis of the economic impacts of the COVID-19 on regional income inequality in China. The findings can reveal the overall pattern of income distributions of all 295 cities before, during, and after the pandemic. The cities are divided into three groups based on the duration of Level 1 ERS: long, medium, and short duration. Urban and rural residents in a city of each duration groups are separately analyzed to see if the pandemic has different economic impacts on urban and rural residents.

RDIPC of All Residents

RDIPC of All Residents in Cites With Long Duration of Level I ERS

The three-dimensional kernel-based transition probabilities for the RDIPC of all residents in cities with the longest duration of Level I ERS during the Pre-COVID, COVID, and Post-COVID periods are demonstrated in **Figure 1A**. The relative frequency—the height of a three-dimensional graph—shows the probability of transition at the province level from one specific RDIPC value in quarter t to another RDIPC value in quarter $t+1$. Note that the RDIPC is measured relative to the global average; hence, the average of the RDIPC is one. It follows the measurement that a value less than one indicates a below-average RDIPC, whereas a value larger than one implies that the value is above average.

Along with the transition dynamics, contour maps for the RDIPC of all residents in cities with the longest duration of Level I ERS alert for three different periods are presented in **Figure 1B**. The contour maps provide the top views of the three-dimensional graphs. Thus, each vertical intersection of a contour map at period t denotes a probability density function, showing the transition probabilities from a particular RDIPC value at period t to another value at period $t+1$. For cities situated on the diagonal line, the RDIPC levels will remain the same before and after the transitions.

Figure 1B(1) shows that the peaks of the probability mass lie along the diagonal line during the Pre-COVID period. It implies that the RDIPCs of all residents in cities with the longest duration of Level I ERS tend to remain in their present positions without moving upwards or downwards in the transition dynamics. Two different probability mass concentrations of the transition probability can be observed; the tallest peak appears at around the RDIPC values of (0.8, 0.8), whereas the secondary peak appears at around the values of (1.5, 1.5). This pattern of concentrations indicates that while most cities have a slightly below-average RDIPC, a small group of cities has a high relative income per capita before the pandemic. Based on the relative income of all residents in each city, it is concluded that there is a noticeable imbalance in the economic development of cities with the longest duration of Level I ERS during the Pre-COVID period. Hence, it is clear from **Figures 1A**(1), **1B**(1) that the economic development is uneven and a slow process in cities with the longest duration of Level I ERS.

As shown in the contour map for cities with the longest duration of Level I ERS in **Figure 1B**(2), it is obvious that the peaks of the probability mass no longer lie along the diagonal

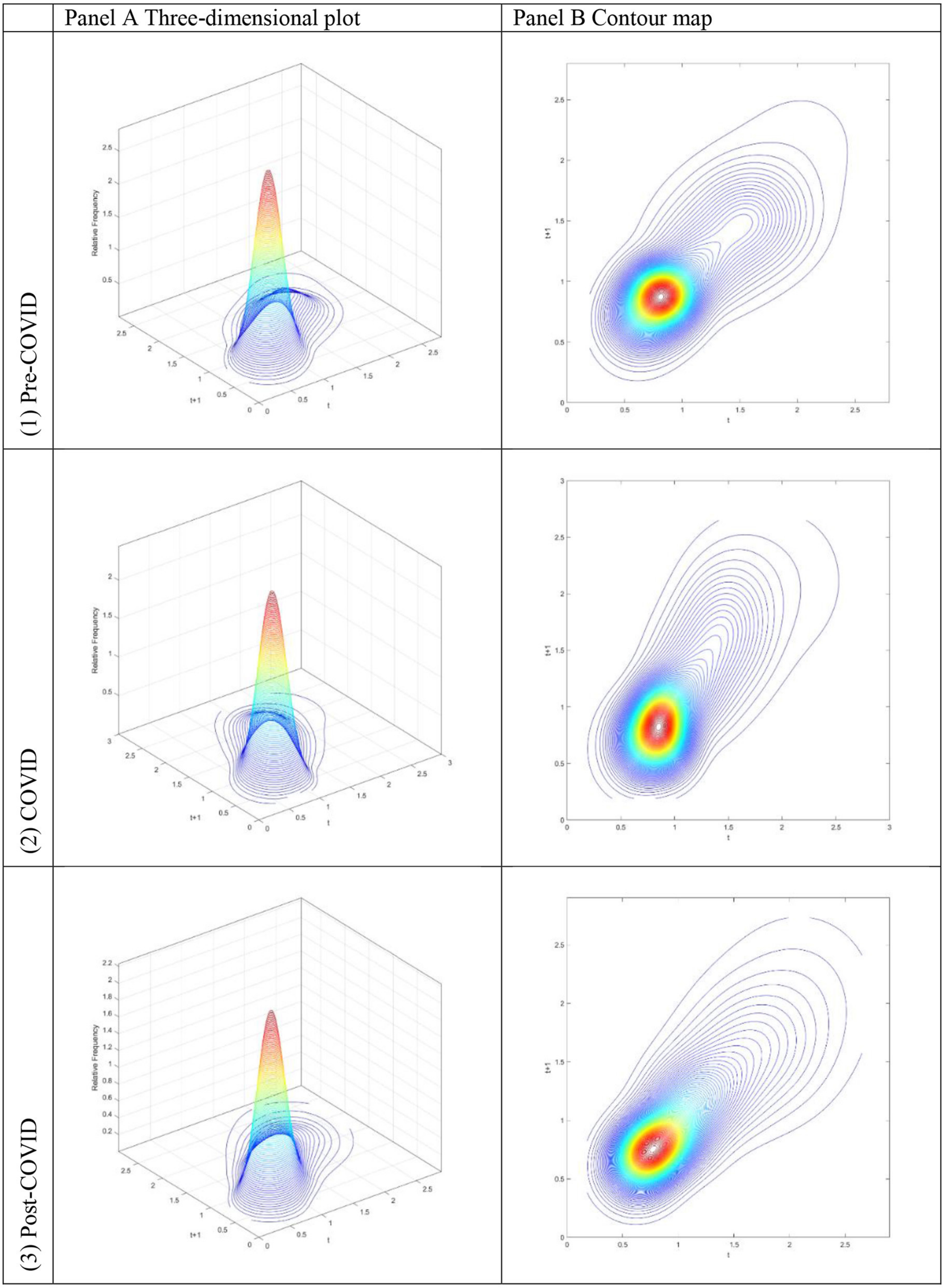

FIGURE 1 | Three-dimensional plot **(A)** and Contour map **(B)** of transition probability kernel for the RDIPC of all residents in cities with the longest duration of Level I ERS with quarterly transitions during the (1) Pre-COVID, (2) COVID, and (3) Post-COVID periods. Source: authors' calculation.

line during the COVID period; it tilted upward. It indicates that cities with a relatively high RDIPC value will have a greater tendency to move upwards from their present positions during the COVID period. **Figure 1A**(2) shows two different probability mass concentrations of the transition probability; the tallest peak appears at around the RDIPC values of (0.75, 0.75) and the secondary peak appears at around the values of (1.75, 2.25). It can be observed that the tallest peak appears at lower RDIPC values while the secondary peak appears at higher RDPIC values, in comparison to the peaks in the Pre-COVID period. Furthermore, cities with high RDIPC values show a greater tendency to move upward compared with those with low RDIPC values. These observations indicate that the pandemic has a negative economic impact on the cities with the longest duration of Level I ERS and the disparity that appeared during the Pre-COVID period has been intensified in the COVID period.

During the Post-COVID period, the contour lines of the probability mass are more condensed at around the RDIPC value of 1.5, as shown in the contour map for cities with the longest duration of Level I ERS in **Figure 1B**(3). Moreover, a single peak is located at around the RDIPC values of (0.7, 0.7) with no other peaks. It seems the disparity that appeared during the Pre-COVID and the COVID periods disappeared during the Post-COVID period.

The transition dynamics shown in **Figure 1** contain a great deal of information. However, it is extremely hard to determine the location of the greatest portion of the probability mass in the three-dimensional plot or the contour map. Consequently, it is difficult to access a city's mobility in the disposable income (i.e., the probability of moving upwards or downward in the distribution). The mobility probability plot (MPP) can offer a direct interpretation of the probability mass in this regard.

The MPP marks the probability of net upward mobility as a percentage against the values of RDIPC. The net upward mobility ranges from −100 to 100; a positive value denotes that a city has a positive net probability of moving upward, while a negative value indicates that a city has a negative probability of moving up. Note that the MPP will intersect the horizontal axis whenever it moves from above the horizontal axis to the region below the horizontal axis. Thus, cities on the left-hand side of the intersection point have a positive chance to move upwards while cities on the right-hand side have a net probability of moving downwards. Consequently, these cities will congregate around the intersection points where the MPP moves from above the horizontal axis to the region below the horizontal axis. The intersection points will be referred to as the INTERSECTs hereafter. The transition dynamics underlying the MPP will eventually translate into a city-level long-run steady-state RDIPC distribution. In general, each INTERSECT in the MPP will translate into a peak appearing in the ergodic distribution, as cities will congregate around these INTERSECTs if the transition dynamics remain unchanged.

Figure 2 shows the MPPs of the RDIPCs of all residents in cities with the longest duration of Level I ERS during the Pre-COVID, COVID, and Post-COVID periods. The shape of the MPPs for three different periods in **Figure 2** confirmed what can be observed from the transition dynamics in **Figure 1**. First, cities congregate roughly around the INTERSECTs. Second, the distance of the INTERSECTs is longer during the COVID period compared with the Pre-COVID period, indicating that the disparity has been intensified during the COVID period. Third, the disparity disappears during the Post-COVID period as the Post-COVID MPP has only one INTERSECT. As shown in **Figures 1**, **2**, the transition dynamics underlying the MPP will eventually translate into a city-level long-run steady-state RDIPC distribution.

The long-run steady-state ergodic distributions for the cities with the longest duration of Level I ERS are shown in **Figure 3**. It can be observed that during the Pre-COVID period, many cities will converge toward an RDPIC value of 0.93—the highest peak that can be observed from the distribution when the transition dynamics in **Figure 1** during the Pre-COVID period remain unchanged. Convergence club at a higher level can be found as a minor peak is located at the RDIPC value of 1.54. This implies that the disposable incomes of most cities will be remarkably close to the country mean, while the incomes for a few of them will be 1.5 times higher than the average. These values indicate that a certain degree of income disparity appears in these cities. These results are consistent with previous studies which showed that regional income inequality is severe in China [e.g., Xie and Zhou (5)]; and the disparity is large even in the cities located in provinces with relatively high GDP per capita, i.e., cities are with Level I ERS.

Figure 3 shows that as compared with the Pre-COVID ergodic distribution, the tallest peak of the COVID ergodic distribution shifted down from the RDPIC of 0.93–0.78, thus indicating that the COVID-19 and the social distancing policy have a significantly depressing effect on the disposable incomes in most cities. The secondary peak, on the other hand, shifted up from the RDPIC of 1.51–1.79. The downward movement of the tallest peak (from 0.93 to 0.78) indicates that the cities where RDIPC converges toward the country mean under the Pre-COVID dynamics will have the RDIPC converge below the country mean under the COVID dynamics. Furthermore, the upward movement of the secondary peak (from 1.51 to 1.79) along with the downward movement of the primary peak indicates that the pandemic intensifies income disparity among the cities with the longest duration of Level I ERS.

Figure 3 also shows the comparison of the Post-COVID ergodic distribution with the Pre-COVID and the post-COVID ergodic distributions. It can be observed that the tallest peak of the Post-COVID ergodic distribution is higher than that of the COVID ergodic distributions but less than that of the Pre-COVID ergodic distributions. Thus, it can be concluded that the adverse economic impacts brought by the pandemic diminished during the Post-COVID period, indicating a quick recovery from the COVID-19 recession in China. Secondly, a minor peak located near the RDIPC value of 1.32 can be vaguely observed. Since the distance between the convergence clubs during the COVID period (i.e., 0.78, 1.79) is larger than that of the Post-COVID period (i.e., 0.833, 1.32), the disparity in economic development triggered by the pandemic faded away.

In sum, we observe different mobility patterns of disposable incomes in cities with the longest duration of Level I ERS during the three periods. If the COVID dynamics persist, most cities

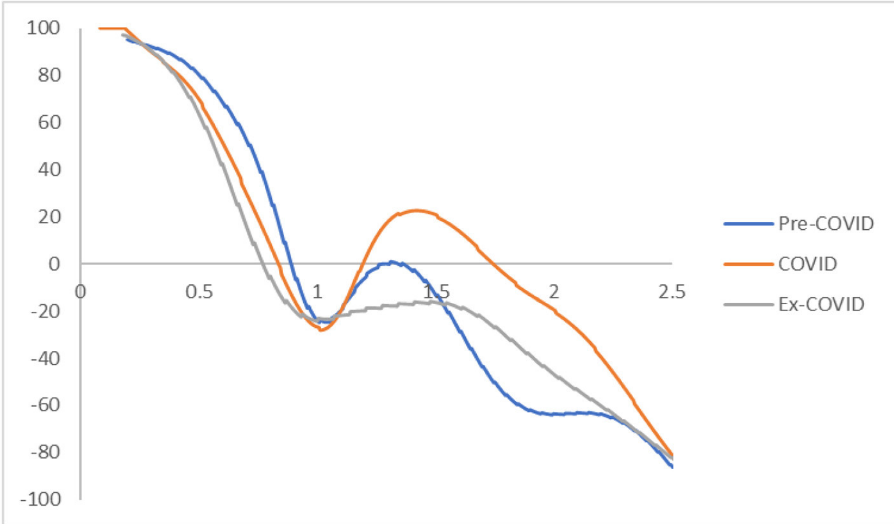

FIGURE 2 | Mobility probability plot (MPP) for the RDIPC of all residents in cities with the longest duration of Level I ERS with quarterly transitions. Source: authors' calculation. N.B. The vertical axis indicates net upward mobility (%) and the horizontal axis indicates RDIPC values.

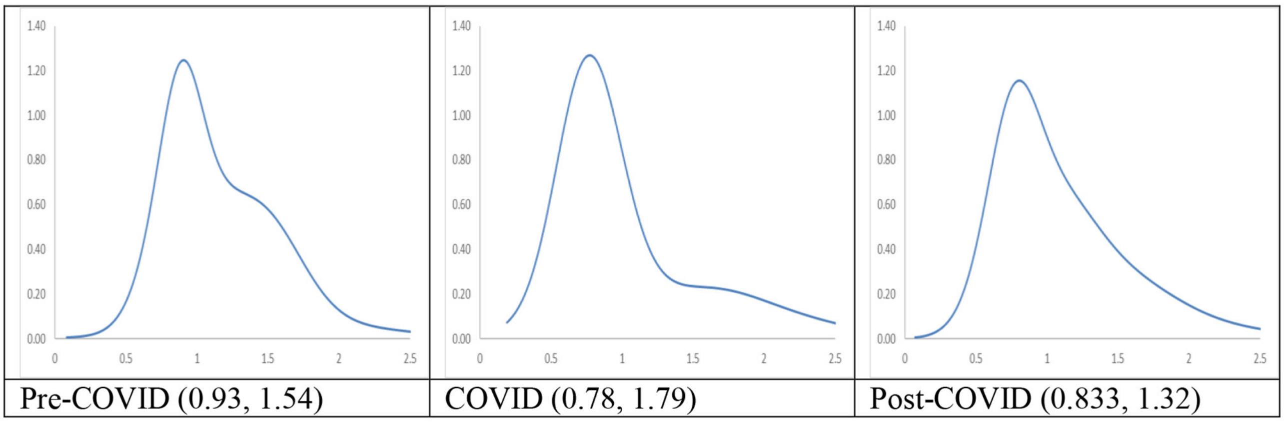

FIGURE 3 | Ergodic distributions for the RDIPC of all cities with the longest Level I ERS duration. Source: authors' calculation. N.B. The vertical axis indicates the density of probability, the horizontal axis indicates RDIPC values, and the value of the peaks are in parentheses.

will converge to RDIPC value which is less than the Pre-COVID level and disparity will be intensified due to the pandemic. However, the evidence shows that the cities with the longest duration of Level I ERS have recovered from the pandemic during the Post-COVID period, i.e., the convergence clubs have gradually restored to the Pre-COVID levels during the Post-COVID periods. It indicates that the prevention measures in these cities are effective.

RDIPC of All Residents in Cities With Medium Duration of Level I ERS

The three-dimensional plots and the contour maps of RDIPC of all residents in cities with a medium duration of Level I ERS during the Pre-COVID, COVID, and Post-COVID periods are shown in **Figure 4**. As in the cities with the longest duration of Level I ERS, the peaks of the probability mass lie along the diagonal line during the Pre-COVID period. It indicates that the RDIPCs of all residents in cities with a medium duration of Level I ERS tend to remain in their present positions without moving upwards or downwards in the transition dynamics. During the COVID period, it is obvious that the peaks of the probability mass no longer lie along the diagonal line; it tilted upward. It indicates that during the COVID period, cities with a relatively high RDIPC value will have a greater tendency to move upwards from their present positions. The transition dynamics of the Post-COVID period share a similar shape with that of the Pre-COVID period.

The MPP of RDIPC of all residents in cities with a medium duration of Level I ERS during the Pre-COVID, COVID, and Post-COVID periods are shown in **Figure 5**. The shape of the

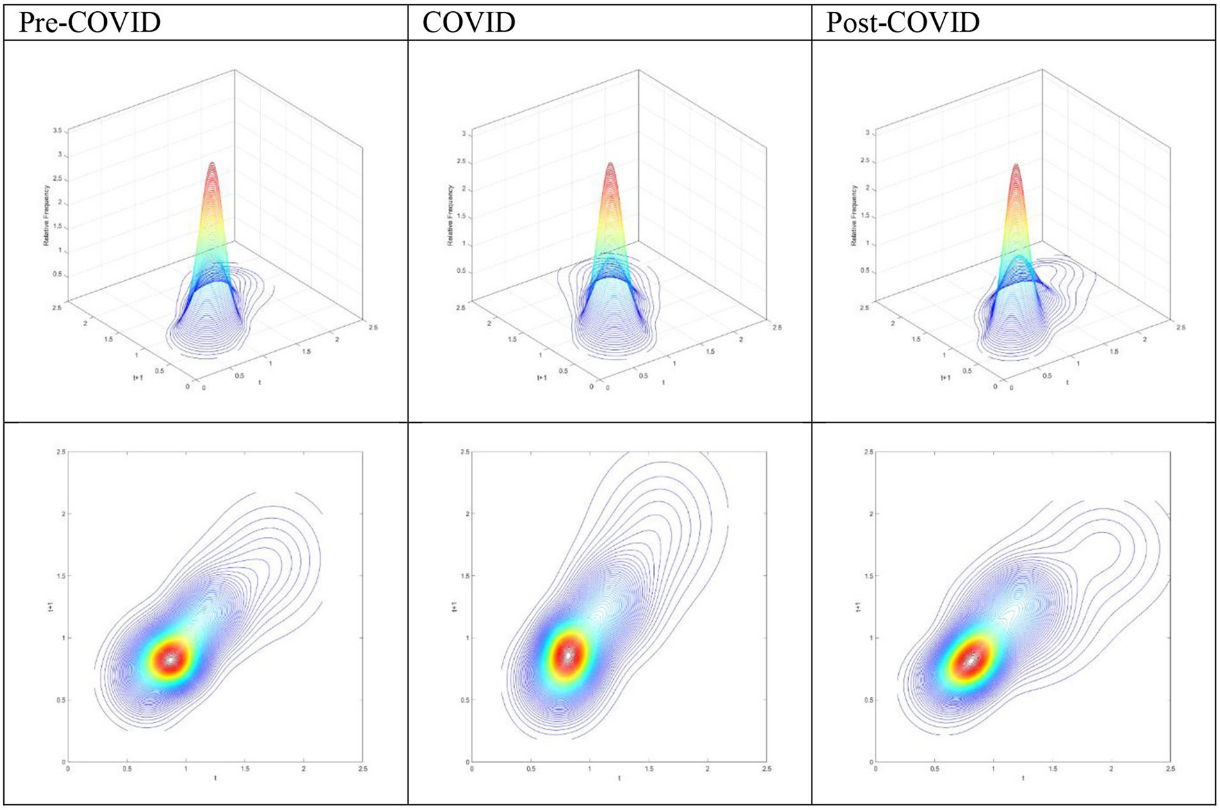

FIGURE 4 | Three-dimensional plot and Contour map of transition probability kernel for the RDIPC of all residents in cities with medium duration of Level I ERS with quarterly transitions during the Pre-COVID, COVID, and Post-COVID periods. Source: authors' calculation.

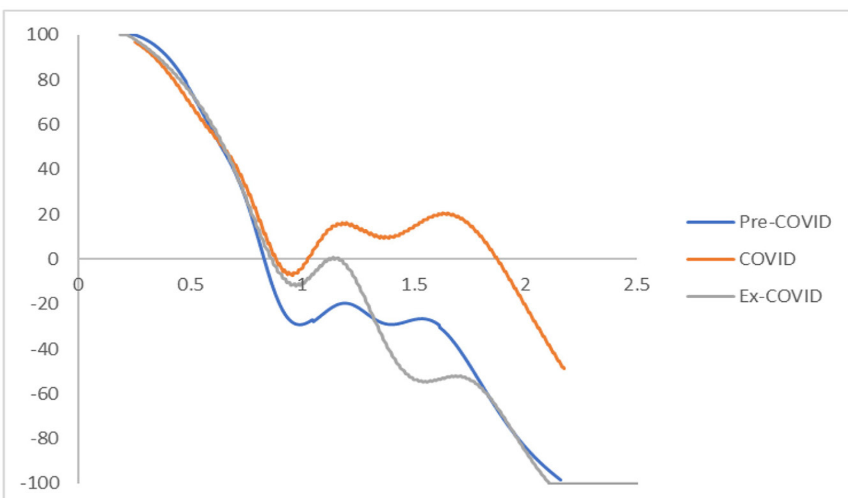

FIGURE 5 | Mobility probability plot (MPP) for the RDIPC of all residents in cities with medium duration of Level I ERS with quarterly transitions. Source: authors' calculation. N.B. The vertical axis indicates net upward mobility (%) and the horizontal axis indicates RDIPC values.

MPPs confirmed what can be seen in the transition dynamics. During the COVID period, the MPP is above the horizontal line when the RDIPC value is above 1 and < 1.89, indicating that the cities with higher-than-average RDIPC values will have a positive chance to move upwards. The Pre-COVID and Ex COVID MPPs share a similar shape. It indicates that the transition dynamics

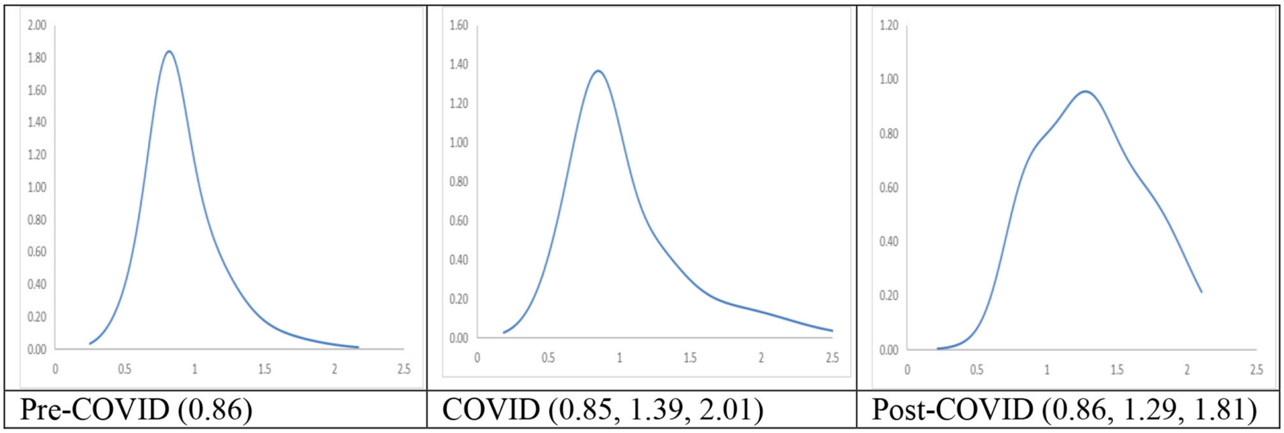

FIGURE 6 | Ergodic distributions for the RDIPC of all cities with medium duration of Level I ERS. Source: authors' calculation. N.B. The vertical axis indicates the density of probability, the horizontal axis indicates RDIPC values, and the value of the peaks are in parentheses.

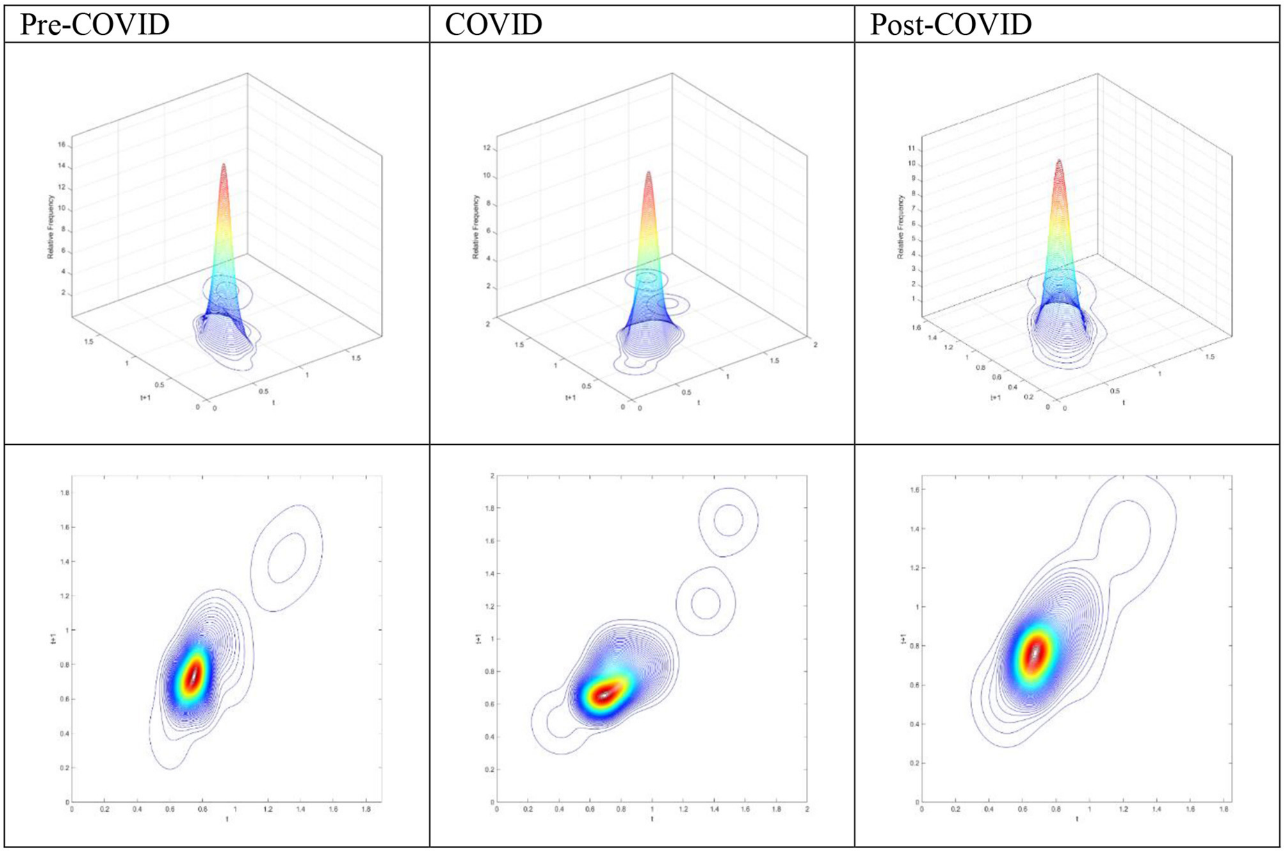

FIGURE 7 | Three-dimensional plot and Contour map of transition probability kernel for the RDIPC of all residents in cities with the shortest duration of Level I ERS with quarterly transitions during the Pre-COVID, COVID, and Post-COVID periods. Source: authors' calculation.

of the Post-COVID period have been recovered to the Pre-COVID scenario.

The long-run steady-state ergodic distributions and the MPP of RDIPC of all residents in cities with a medium duration of Level I ERS during the Pre-COVID, COVID, and Post-COVID periods are shown in **Figure 6**. If the Pre-COVID condition remains unchanged, it can be observed that most cities will converge to the RDIPC value of 0.86 with no other peaks.

If the COVID condition persists, most cities will converge to the RDIPC value of 0.85, a remarkably similar figure to the Pre-COVID condition. However, compared with the Pre-COVID distribution, the COVID distribution is more dispersed, indicating that a larger proportion of cities will converge to a lower RDIPC value. As in the cities with the longest duration of Level I ERS, the disparity will be intensified if the COVID condition persists, as two minor peaks appear at the RDIPC values of 1.39 and 2.1, which, however, is not obvious. During the Post-COVID period, convergence clubs are located at the RDIPC values of 0.86, 1.29, and 1.81. Similar to the cities with the longest duration of Level I ERS, the distance of the convergence clubs is shorter during the Post-COVID than the COVID period. Thus, it can be concluded that pandemic-driven disparity fades away in the cities with a medium duration of Level I ERS. Additionally, the cities with a medium duration of Level I ERS recovered from the pandemic during the Post-COVID period.

RDIPC of All Residents in Cities With Short Duration of Level I ERS

We have shown that the mobility patterns of disposable incomes in the cities with long and medium duration of Level I ERS are similar. However, the economic impact of the pandemic on cities with the shortest duration of Level I ERS is not the same as in the cities with a long and medium duration of Level I ERS.

The three-dimensional plots and the contour maps of RDIPC of all residents in cities with a short duration of Level I ERS during the Pre-COVID, COVID, and Post-COVID periods are shown in **Figure 7**. The three-dimensional plots and the contour maps for the Pre-COVID and Post-COVID periods share a similar shape. The peaks of the probability mass during the COVID period tilted downwards from the diagonal line as compared with the Pre-COVID condition when the RDIPC values are < 1.2. It indicates that the probability of a city with an RDIPC smaller than 1.2 to move upwards from its current position is less during the COVID period than the Pre-COVID and Post-COVID periods. However, when the RDIPC values are > 1.2, a small group of cities manages to move upwards from their present positions.

The MPP of RDIPC of all residents in cities with a short duration of Level I ERS during the Pre-COVID, COVID, and Post-COVID periods are shown in **Figure 8**. The MPPs in **Figure 8** confirm what can be observed from the transition dynamics. The MPP during the COVID period has negative values when the RDIPC values range from 0.6 to 1.2 and positive values when the RDIPC value is above 1.2 and below 1.7.

The long-run steady-state ergodic distributions and the MPP of RDIPC of all residents in cities with a short duration of Level I ERS during the Pre-COVID, COVID, and Post-COVID periods are shown in **Figure 9**. Two peaks at 0.83 and 1.42 can be observed from the Pre-COVID ergodic distribution. The convergence clubs indicate that income disparity exists before the pandemic since a group of cities converges to an RDIPC value less than the country mean, while another group of cities converges to an RDIPC value 1.4 times more than the country mean.

The entire ergodic distribution of the COVID period shifts to the left with a single peak located around the RDIPC value of 0.65. It indicates that most of the cities converge to an RDIPC value which is less than the below-the-average peak in the Pre-COVID ergodic distribution[12]. It can be seen that if the COVID dynamics persist, most cities will converge to RDIPC value which is less than the Pre-COVID level. However, the disparity will disappear during the COVID period due to the upward transition limit, i.e., a city has a positive chance to move upwards. The two peaks of the Post-COVID ergodic distribution are located at RDIPC values of 0.83 and 1.48, respectively. They are almost the same level as in the Pre-COVID case. Thus, it can be concluded from the transition dynamic analysis that the pandemic was under control during the Post-COVID period and the cities with the shortest duration of Level I ERS successfully recovered from the pandemic.

Taken together, our findings show that COVID-19 pandemic yields negative impacts on the average disposable incomes in the 295 Chinese cities. The negative impacts are more substantial in the cities with the longest duration of Level I ERS (the value of the convergence club decreases from 0.93 in the pre-COVID period to 0.78 during the COVID period), probably due to a longer time of economic freeze, and in the cities with shortest duration of Level I ERS (from 0.83 to 0.65). This is because these cities are poorer and more vulnerable to the economic shock. Another consequence of the COVID-19 is that the regional income inequalities would be intensified in some cities if the pandemic persists. The mobility patterns of disposable incomes in the post-COVID period show that most cities in China have recovered from the COVID-19 recession, although the level of disposable income in the cities with longest duration of Level I ERS did not restored to the level in the pre-COVID period (0.83 in the post-COVID period vs. 0.93 in the pre-COVID period). The stringent social distancing policies adopted in China effectively contained the spread of virus in < 1 month in most cities and the economy was restored quickly in the second quarter of 2020. However, a long duration of stringent social distancing policies, e.g., more than 1 month, could generate negative economic impact on cities after the pandemic was under the control (25).

RDIPC of Urban Residents

As shown in the previous section, the transition dynamics can be fully interpreted from the MPP. Thus, we only discuss the MPPs and the ergodic distributions for the rest of this section.

In the MPPs for the RDIPC of urban residents in **Figure 10**, it can be observed that the Pre-COVID and Post-COVID MPPs

[12]Note that the MPP during the COVID period has positive values when the RDIPC value is above 1.2 and below 1.7 and has an INTERSECT at an RDIPC of 1.7. However, the positive upward mobility fails to translate into a convergence club in the long run, since cities with RDIPC > 1 can hardly be observed from the COVID ergodic distribution. This failure can be explained in the following way: since the MPP shows only the probability of transition without showing the transition value, it is possible that some cities with positive upward mobility at RDIPC of 1.7 transit to a slightly higher position. Other cities with RDIPC of 1.7, on the other hand, transit to an exceptionally low position in the distribution. If this is the case, cities will not be able to congregate at the INTERSECT with RDIPC of 1.7. Thus, it can be concluded that during the COVID period, cities with RDIPC higher than the country mean experienced an upward transition limit, i.e., the city has a positive chance to move upwards. However, the upward movement has an upward limit; it cannot transit to a high level of RDIPC.

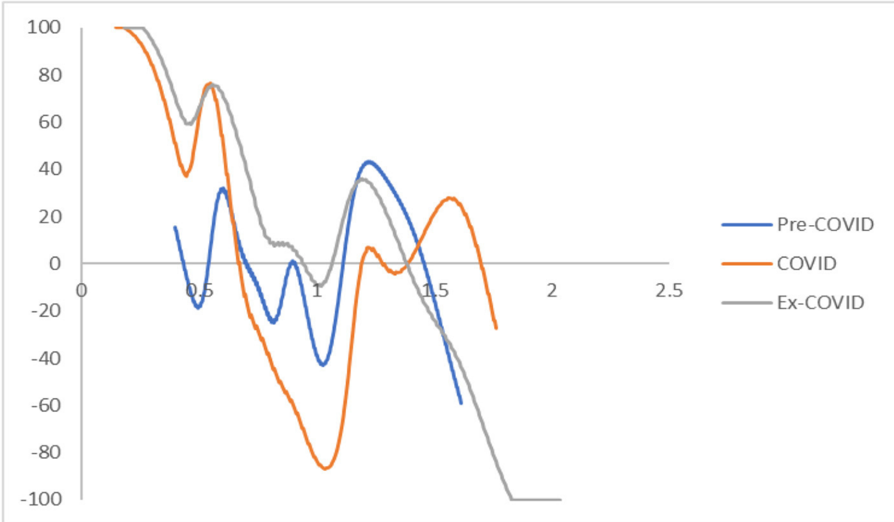

FIGURE 8 | Mobility probability plot (MPP) for the RDIPC of all residents in cities with the shortest duration of Level I ERS with quarterly transitions. Source: authors' calculation. N.B. The vertical axis indicates net upward mobility (%) and the horizontal axis indicates RDIPC values.

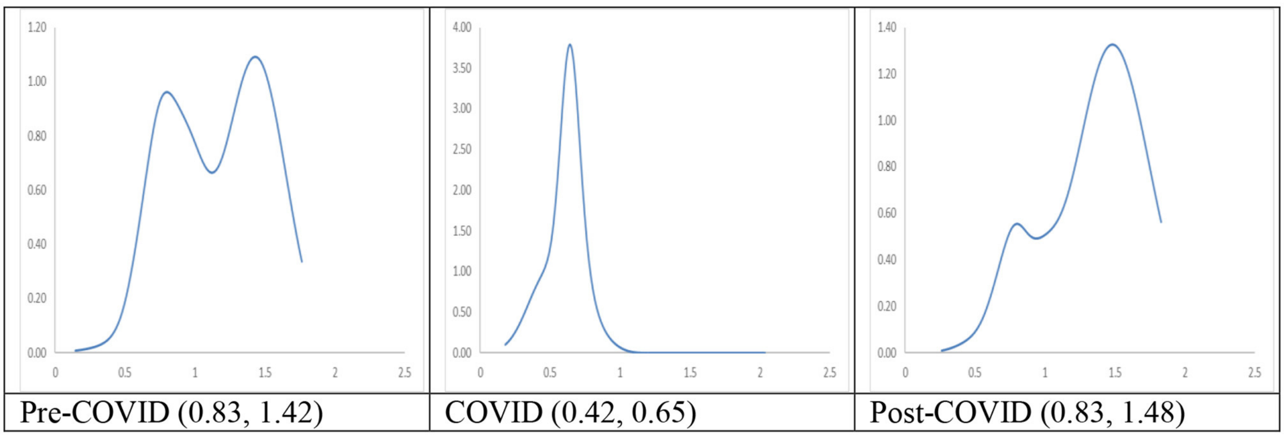

FIGURE 9 | Ergodic distributions for the RDIPC of all cities with short duration of Level I ERS. Source: authors' calculation. N.B. The vertical axis indicates the density of probability, the horizontal axis indicates RDIPC values, and the value of the peaks are in parentheses.

share similar shapes. The transition dynamics underlying the MPPs during the COVID periods are distinguishably different from the other two periods. The distinctive features include: First, the COVID MPP for urban residents in cities with the longest duration of Level I ERS is the MPP with the most negative net upward mobility. It indicates that the cities experienced a difficult period to move upward in the distribution during the COVID period. Second, the COVID MPP for urban residents in cities with medium and short duration of Level I ERS share a similar feature, i.e., the tail of the MPP tilted upwards. It indicates that during the COVID period, cities with relatively high RDIPC have a higher chance of moving upward in the distribution. The above features are distinctive for the COVID period and the shape of the MPP reverts to the Pre-COVID case for all durations of Level I ERS. Therefore, it can be concluded that the effects of the pandemics, if any, disappeared or faded away during the Post-COVID period.

The transition dynamics underlying the MPPs will eventually translate to the ergodic distributions, as shown in **Figure 11**. Notably, the Pre-COVID and Post-COVID ergodic distributions have similar shapes whereas the COVID ergodic distribution looks completely different from the other two periods. The peaks in the cities with the longest and shortest duration of Level I ERS are reduced from a higher level in the pre-COVID period (0.92/0.92) to a lower level (0.85/0.86), thus indicating that the COVID-19 and the social distancing policies have negative impacts on the cities in these two groups. Surprisingly, the peak in the cities with medium duration increases slightly. The COVID distributions exhibit unimodal distribution in the three groups while the Pre-COVID and Ex-COVID

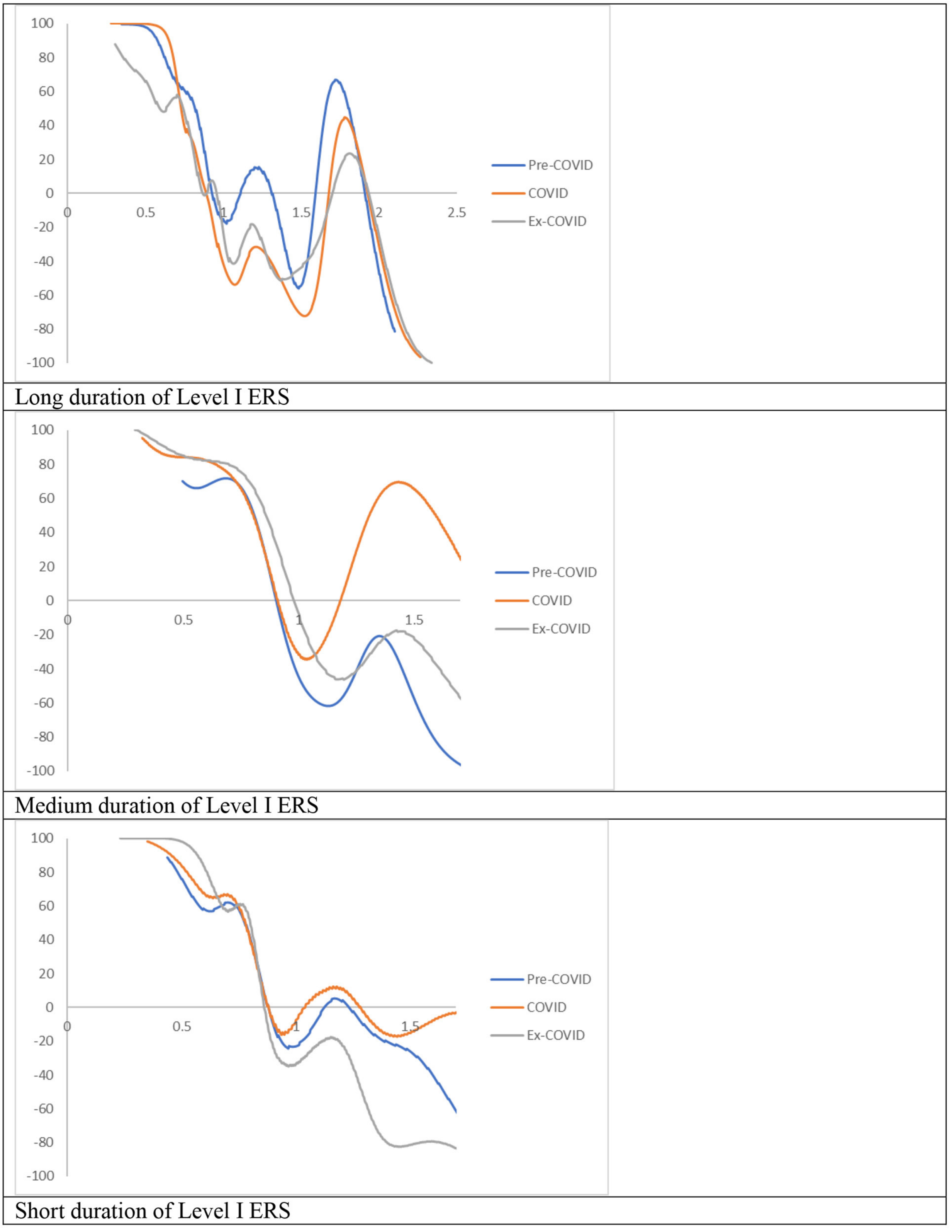

FIGURE 10 | Mobility probability plot (MPP) for the RDIPC of urban residents in cities with long, medium, and short duration of Level I ERS with quarterly transitions. Source: authors' calculation. N.B. The vertical axis indicates net upward mobility (%) and the horizontal axis indicates RDIPC values.

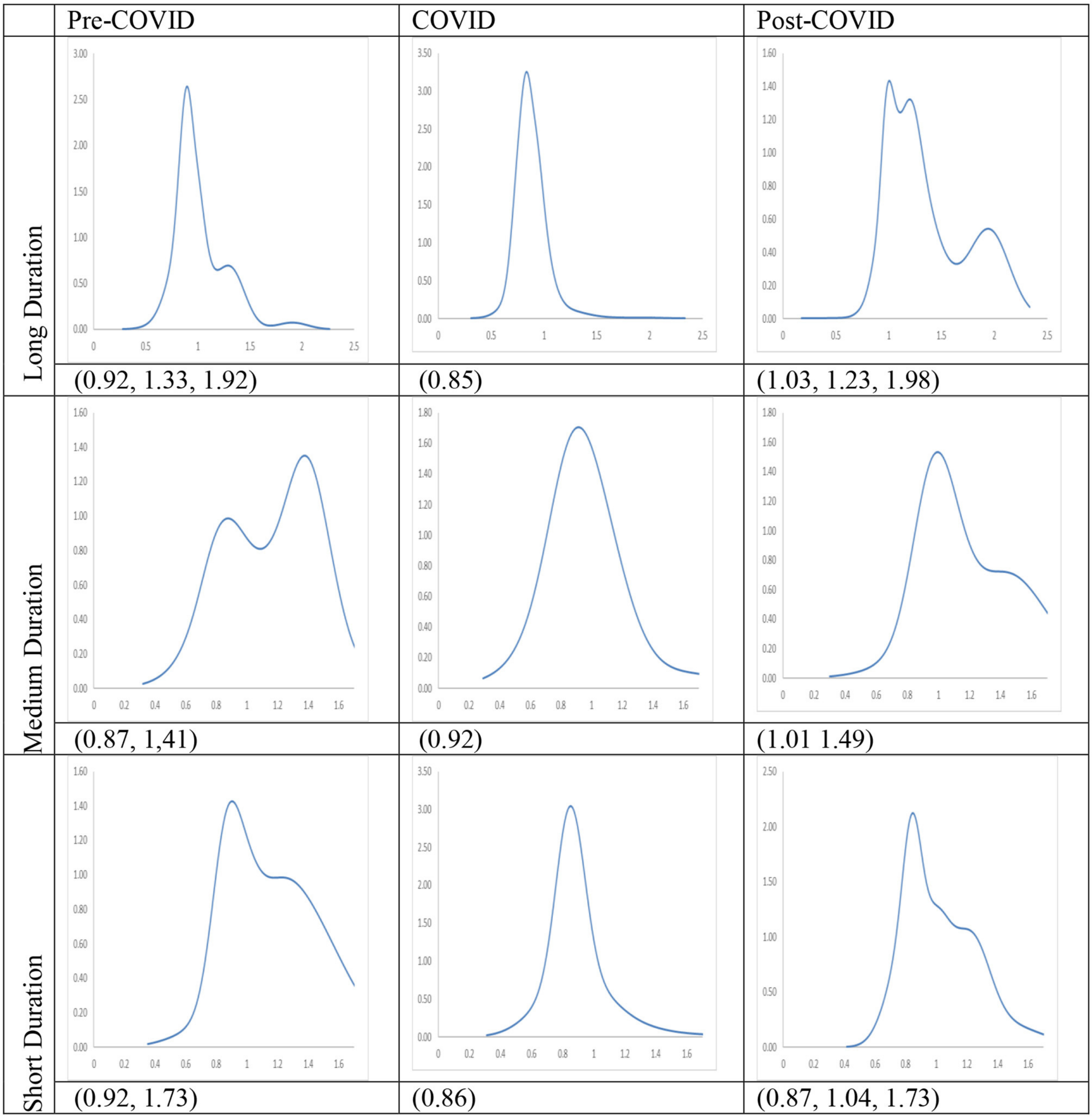

FIGURE 11 | Ergodic distributions for the RDIPC of urban residents in cities with long, medium, and short duration of Level I ERS. Source: authors' calculation. N.B. The vertical axis indicates the density of probability, the horizontal axis indicates RDIPC values, and the value of the peaks are in parentheses.

distributions have multiple peaks. Similar to the aforementioned mentioned observations, all urban residents in cities with long, medium, and short duration of Level I ERS faced an upward transition limit during the COVID period; the regional disparity disappears during the COVID period due to the upward transition limit.

All these ergodic distributions with different durations of Level I ERS shift back to the right and exhibit multiple peaks when the pandemic was over, as shown by the Post-COVID ergodic distributions. The first peaks in the cities with long and medium duration of Level I ERS are 1.03 and 1.01, respectively, which are even higher than the first peaks in the pre-COVID period (0.92 and 0.87). The results indicate that disposable incomes of urban residents in these cities even increase in the second quarter of 2020 due to the economic recovery. In contrast, urban disposable incomes in the cities with short duration of

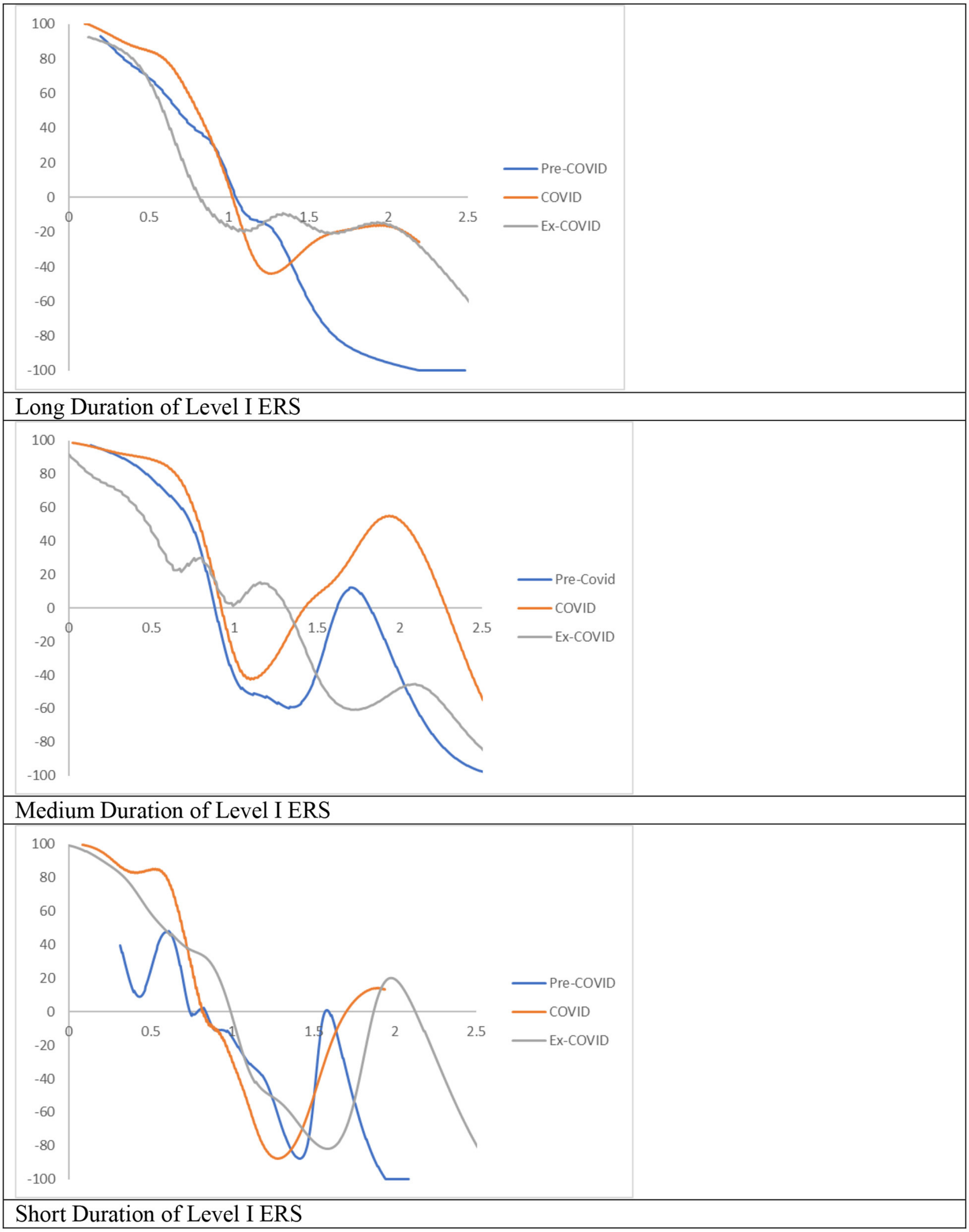

FIGURE 12 | Mobility probability plot (MPP) for the RDIPC of rural residents in cities with long, medium, and short duration of Level I ERS with quarterly transitions. Source: authors' calculation. N.B. The vertical axis indicates net upward mobility (%) and the horizontal axis indicates RDIPC values.

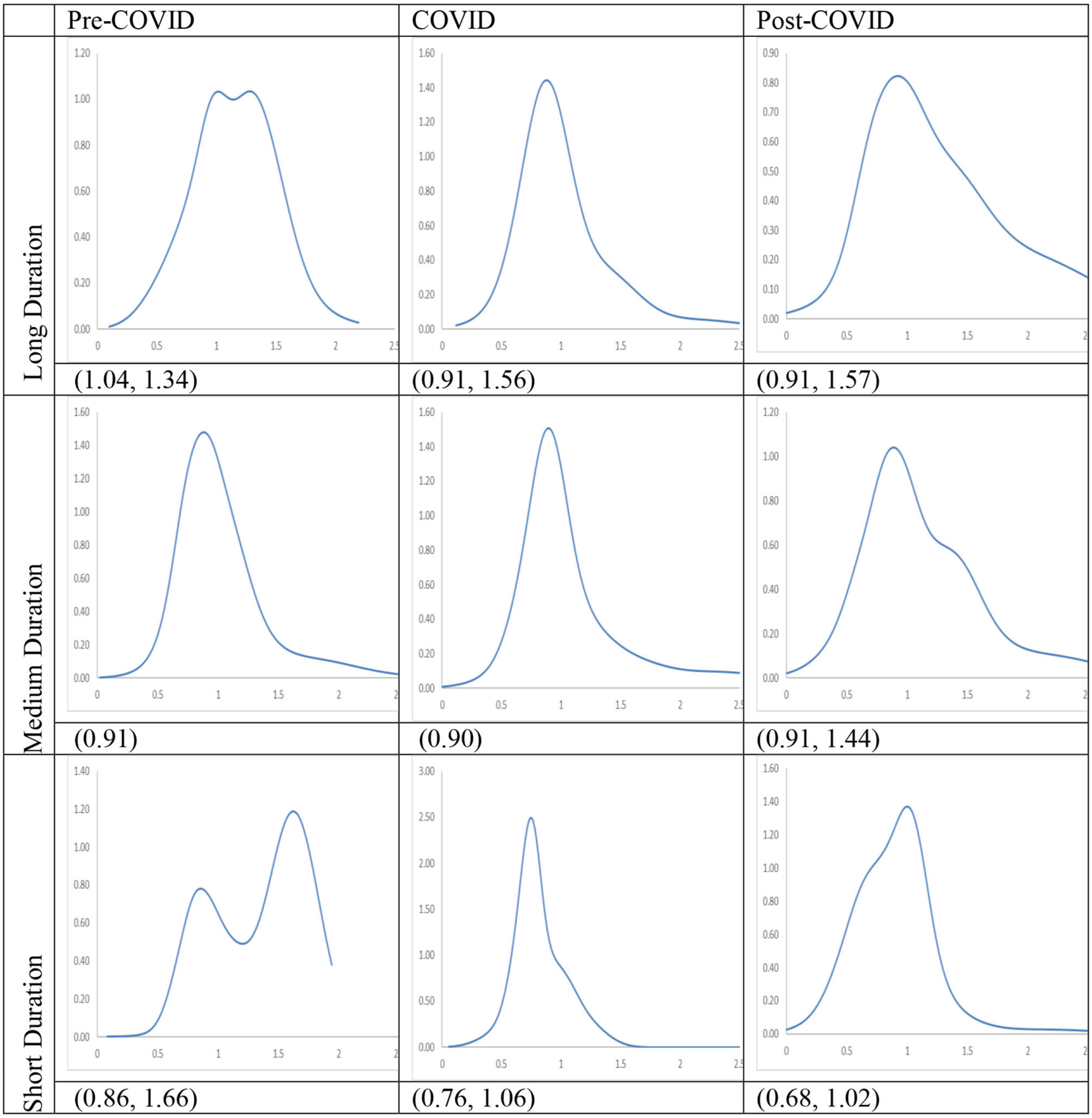

FIGURE 13 | Ergodic distributions for the RDIPC of urban residents in cities with long, medium, and short duration of Level I ERS. Source: authors' calculation. N.B. The vertical axis indicates the density of probability, the horizontal axis indicates RDIPC values, and the value of the peaks are in parentheses.

Level I ERS are not restored to the level in the pre-COVID period. Even though these cities did not have as many confirmed cases as cities in the other two groups and implemented stringent social distancing policies in a shorter time, the economy was hit harder than other cities and the recovery was slow. The results also show that regional income inequality appear again in all cities during the post-COVID period, as reflected in the multiple peaks in the ergodic distributions.

RDIPC of Rural Residents

Recovery from the pandemic is less promising for rural residents, shown in the **Figures 12**, **13**. For cities with a long and medium duration of Level I ERS, two distinctive features can be observed. First, the ergodic distribution shifts to the left due to the pandemic. Second, the tail of the COVID MPP tilted upward. Thus, cities with a relatively high level of RDICPs have a more positive net upward mobility during the pandemic that intensified income disparity during the COVID period. These features remain the same, if not intensified, during the Post-COVID period. The first peaks in the ergodic distributions in the Post-COVID periods are 0.91, which are almost identical to the peaks in the COVID period. Thus, it can be concluded that there is yet to be a full recovery from the pandemic during the Post-COVID period. The regional income inequality, however, is exacerbated as the distances between two peaks become larger (e.g., 0.91, 1.57 in the cities with long duration in the Post-COVID period vs. 1.04, 1.34 in the Pre-COVID period).

For cities with the shortest duration of Level I ERS, it can be observed that the peaks of the COVID ergodic distribution (i.e., 0.76, 1.06) are below the peaks of the Pre-COVID ergodic distribution (i.e., 0.86, 1.66). Additionally, the peaks of the Post-COVID ergodic distribution (i.e., 0.68, 1.02) are also below the peaks of the Pre-COVID ergodic distribution. It indicates that the adverse impacts have been intensified during the Post-COVID period. The COVID-19 pandemic has a lasting adverse impact on the disposable incomes of rural residents in the relatively poor cities, even after the removal of the social distancing policies. One possible reason is that small and medium firms may be shut down during the pandemic and run at partial capacity after the pandemic (32), which cause lower demand for the labor. The rural residents in the western regions are affected more than rural residents in the rich regions as they are more likely to be migrant workers and hence, may be restricted to return due to the social distancing policies in the destination cities in the eastern regions' destination cities.

In sum, if the COVID dynamics persist, the relative disposable income for rural residents in cities with all durations will converge to RDIPC value which is less than or equal to the Pre-COVID level, and the disparity will be intensified due to the pandemic. Unlike urban residents, the impact of the pandemic on rural residents remains unresolved, if not intensified, during the Post-COVID period. Among the three groups of cities, the residents in the cities with the shortest duration of Level I ERS suffered the largest loss from the COVID-19 pandemic, in both urban and rural areas.

CONCLUSION

In this study, we examine the impacts of the COVID-19 and the duration of Level 1 ERS on income inequality across 295 cities in China. The distribution dynamics approach is used to analyse the trend and movement of disposable income per capita in a city before the COVID-19, during the COVID-19 pandemic and in the Post-COVID period when the virus was largely contained. The results show that the COVID-19 has significant negative economic consequences: if the COVID pandemic persists, most cities will converge to a level of disposable income which is less than the Pre-COVID level. The regional income disparity will be intensified due to the pandemic in the cities with long and medium durations of Level I ERS. On the other hand, the disparity that appeared in the Pre-COVID period will disappear during the COVID period due to the upward transition limit, i.e., a city has a positive chance to move upwards but has an upward limit. These findings confirm that social distancing policies have significant economic consequences and could exacerbate the regional income inequality (24).

This study also reveals that cities in all the three groups of Level I ERS durations have recovered from the pandemic during the Post-COVID periods. However, recovery from the pandemic is less promising for rural residents than for urban residents, and for cities in the western regions. The economic impact triggered by the pandemic faded away in the urban residents in eastern and central regions; despite this, the impact of the pandemic on rural residents remains unresolved, if not intensified, during the Post-COVID period. In addition, regional income disparity in the rural residents also worsens, especially in the regions with longer Level I ERS duration. The results are consistent with the previous findings that low-income individuals are more severely affected by the economic consequences of the social distancing policies (2, 8).

This study yields several important policy implications. Our findings suggest that stringent nation-wide social distancing policies adopted in China are effective as the economy recovered quickly when the transmission of coronavirus was contained. If a country can flatten the curve in a short time, e.g., several weeks, the economic loss can be limited. The long duration of strict social distancing policy however may intensify the regional income equality. Special policy attention is required for rural regions as the effect of the pandemic could be long-lasting. China has adopted poverty alleviation programme since 2013 to eliminate the extreme rural poverty in 2020, and lifted 100 million rural residents out of poverty. As rural regions, especially those in the western areas, were hit more severely by the COVID-19 pandemic, more efforts should be spent to prevent rural residents slipping back into poverty.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found at: https://www.ceicdata.com/en.

AUTHOR CONTRIBUTIONS

All authors contributed to the conception and design of the study. JS compiled the data and conducted the literature review. WS wrote the discussions. TC prepared the data and conducted the analysis. LW wrote the data preparation process and methodology section. All authors contributed to manuscript revision, read, and approved the submitted version.

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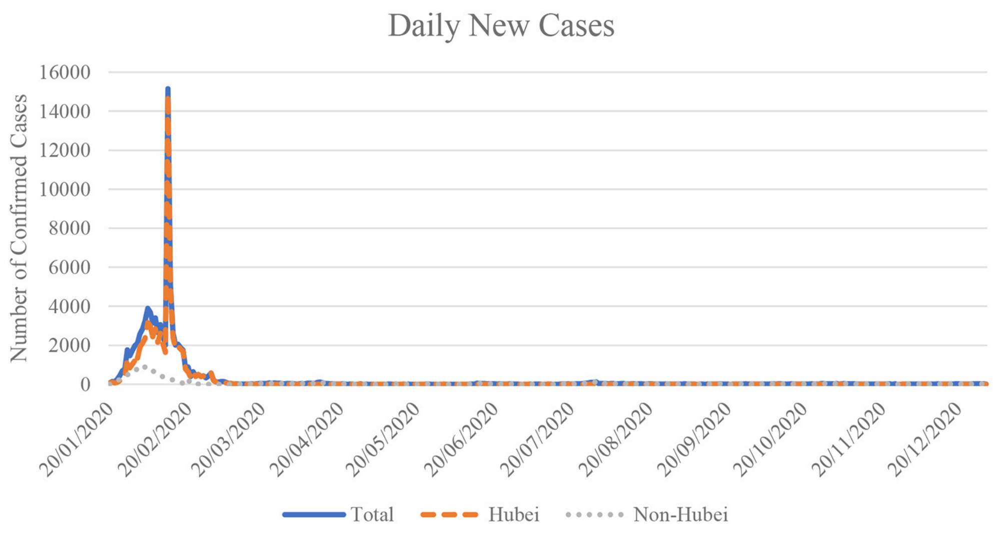
REFERENCES

1. Hale T, Angrist N, Goldszmidt R, Kira B, Petherick A, Phillips T, et al. A global panel database of pandemic policies (oxford COVID-19 government response tracker). *Nat Hum Behav.* (2021) 5:529–38. doi: 10.1038/s41562-021-01079-8
2. Blundell R, Costa Dias M, Joyce R, Xu X. COVID-19 and inequalities. *Fiscal Stud.* (2020) 41:291–319. doi: 10.1111/1475-5890.12232
3. Bonacini L, Gallo G, Scicchitano S. Working from home and income inequality: risks of a 'new normal'with COVID-19. *J Popul Econ.* (2021) 34:303–60. doi: 10.1007/s00148-020-00800-7
4. Deaton A. *COVID-19 and Global Income Inequality, National Bureau of Economic Research, No. w28392.* (2021). doi: 10.3386/w28392
5. Xie Y, Zhou X. Income inequality in today's China. *Proc Natl Acad Sci USA.* (2014) 111:6928–33. doi: 10.1073/pnas.1403158111
6. Fang H, Wang L, Yang Y. Human mobility restrictions and the spread of the novel coronavirus (2019-ncov) in China. *J Public Econ.* (2020) 191:104272. doi: 10.1016/j.jpubeco.2020.104272
7. Qiu Y, Chen X, Shi W. Impacts of social and economic factors on the transmission of coronavirus disease 2019 (COVID-19) in China. *J Popul Econ.* (2020) 33:1127–72. doi: 10.1007/s00148-020-00778-2
8. Witteveen D. Sociodemographic inequality in exposure to COVID-19-induced economic hardship in the United Kingdom. *Res Soc Stratif Mobil.* (2020) 69:100551. doi: 10.1016/j.rssm.2020.100551
9. Song Y. Rising Chinese regional income inequality: the role of fiscal decentralization. *China Econ Rev.* (2013) 27:294–309. doi: 10.1016/j.chieco.2013.02.001
10. Kanbur R, Wang Y, Zhang X. The great Chinese inequality turnaround. *J Comp Econ*. (2020). doi: 10.1016/j.jce.2020.10.001
11. Kong E, Prinz D. Disentangling policy effects using proxy data: Which shutdown policies affected unemployment during the COVID-19 pandemic? *J Public Econ.* (2020) 189:104257. doi: 10.1016/j.jpubeco.2020.104257
12. Chen H, Qian W, Wen Q. *The Impact of the COVID-19 Pandemic on Consumption: Learning From High Frequency Transaction Data.* (2020). Available online at: https://ssrn.com/abstract=3568574 (accessed March 28, 2021).
13. Sheridan A, Andersen AL, Hansen ET, Johannesen N. Social distancing laws cause only small losses of economic activity during the COVID-19 pandemic in Scandinavia. *Proc Natl Acad Sci USA.* (2020) 117:20468–73. doi: 10.1073/pnas.2010068117
14. He G, Pan Y, Tanaka T. The short-term impacts of COVID-19 lockdown on urban air pollution in China. *Nat Sustain.* (2020) 3:1005–11. doi: 10.1038/s41893-020-0581-y
15. Dang HH, Trinh T. Does the COVID-19 lockdown improve global air quality? New cross-national evidence on its unintended consequences. *J Environ Econ Manag.* (2021) 105:102401. doi: 10.1016/j.jeem.2020.102401
16. Chen J, Fleisher BM. Regional income inequality and economic growth in China. *J Comp Econ.* (1996) 22:141–64. doi: 10.1006/jcec.1996.0015
17. Jian T, Sachs JD, Warner AM. Trends in regional inequality in China. *China Econ Rev.* (1996) 7:1–21. doi: 10.3386/w5412
18. Hu D. Trade, rural–urban migration, and regional income disparity in developing countries: a spatial general equilibrium model inspired by the case of China. *Reg Sci Urban Econ.* (2002) 32:311–38. doi: 10.1016/S0166-0462(01)00075-8
19. Wang X, Shao S, Li L. Agricultural inputs, urbanization, and urban-rural income disparity: evidence from China. *China Econ Rev.* (2019) 55:67–84. doi: 10.1016/j.chieco.2019.03.009
20. Molero-Simarro R. Inequality in China revisited. the effect of functional distribution of income on urban top incomes, the urban-rural gap and the Gini index, 1978–2015. *China Econ Rev.* (2017) 42:101–17. doi: 10.1016/j.chieco.2016.11.006
21. Chen B, Liu D, Lu M. City size, migration and urban inequality in China. *China Econ Rev.* (2018) 51:42–58. doi: 10.1016/j.chieco.2018.05.001
22. Yang DT. Urban-biased policies and rising income inequality in China. *Am Econ Rev.* (1999) 89:306–10. doi: 10.1257/aer.89.2.306
23. Lu M, Chen Z. Urbanization, urban-biased policies, and urban-rural inequality in China, 1987-2001. *Chinese Econ.* (2006) 39:42–63. doi: 10.2753/CES1097-1475390304
24. Bonaccorsi G, Pierri F, Cinelli M, Flori A, Galeazzi A, Porcelli F, et al. Economic and social consequences of human mobility restrictions under COVID-19. *Proc Natl Acad Sci USA.* (2020) 117:15530–5. doi: 10.1073/pnas.2007658117
25. Li X, Hui ECM, Shen J. *Institutional Development and the Government Response to COVID-19 in China.* (2020). Available online at: http://ssrn.com/abstract=3813691 (accessed March 28, 2021).
26. Quah D. Empirical cross-section dynamics in economic growth. *Eur Econ Rev.* (1993) 37:426–34. doi: 10.1016/0014-2921(93)90031-5
27. Li S, Cheong TS. Convergence and mobility of rural household income in China: new evidence from a transitional dynamics approach. *China Agric Econ Rev.* (2016) 8:383–98. doi: 10.1108/CAER-09-2015-0126
28. Zhang H, Shi X, Cheong TS, Wang K. Convergence of carbon emissions at the household level in China: a distribution dynamics approach. *Energy Econ.* (2020) 92:104956 doi: 10.1016/j.eneco.2020.104956
29. Cheong TS, Wu Y. Convergence and transitional dynamics of China's industrial output: a county-level study using a new framework of distribution dynamics analysis. *China Econ Rev.* (2018) 48:125–38. doi: 10.1016/j.chieco.2015.11.012
30. Silverman BW. *Density Estimation for Statistics and Data Analysis.* (1986) New York, NY: Chapman and Hall.
31. Cheong TS, Wu Y, Wu J. Evolution of carbon dioxide emissions in Chinese cities: trends and transitional dynamics. *J Asia Pac Econ.* (2016) 21:357–77. doi: 10.1080/13547860.2016.1176642
32. Dai R, Feng H, Hu J, Jin Q, Li H, Wang R, et al. The impact of COVID-19 on small and medium-sized enterprises (SMEs): Evidence from two-wave phone surveys in China. *China Econ Rev.* (2021) 67:101607. doi: 10.1016/j.chieco.2021.101607

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

APPENDIX



Appendix 1 | Daily new cases in China. Data source: China CDC.

frontiers in Public Health

BRIEF RESEARCH REPORT
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Epidemics, Public Sentiment, and Infectious Disease Equity Market Volatility

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Background : This article studies the relationship between the COVID-19 epidemic, public sentiment, and the volatility of infectious disease equities from the perspective of the United States. We use weekly data from January 3, 2020 to March 7, 2021. This provides a sufficient dataset for empirical analysis. Granger causality test results prove the two-way relationship between the fluctuation of infectious disease equities and confirmed cases. In addition, confirmed cases will cause the public to search for COVID-19 tests, and COVID-19 tests will also cause fluctuations in infectious disease equities, but there is no reverse correlation. The results of this research are useful to investors and policy makers. Investors can use the number of confirmed cases to predict the volatility of infectious disease equities. Similarly, policy makers can use the intervention of retrieved information to stabilize public sentiment and equity market fluctuations, and integrate a variety of information to make more scientific judgments on the trends of the epidemic.

Keywords: COVID-19, public sentiment, infectious disease equities, epidemic, confirmed cases

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INTRODUCTION

Since the initial outbreak of COVID-19, this global epidemic has spread rapidly. According to data from Johns Hopkins Coronavirus Resource Center on March 23, 2021, the global number of Coronavirus cases has reached 123.6 million, of which the United States accounts for 29.9 million. Because the virus is highly contagious, countries have adopted strict quarantines, resulting in the forced closure of a large number of commercial activities. According to the U.S. Bureau of Labor Statistics, the unemployment rate in the United States in April 2020 was as high as 14.7%. Previous outbreaks of infectious diseases such as SARS and MERS-CoV did not have such a strong impact on the equity market as the COVID-19 pandemic. This shows that in response to the current coronavirus epidemic, government restrictions on business activities and stay-at-home policies have had a direct negative impact on the service-oriented economy. This is the main reason why the U.S. equity market's response to COVID-19 is stronger than its response to previous pandemics.

Many empirical studies have shown that various direct and indirect factors, such as the epidemic situation and investor attention, play an important role in equity market volatility. Compared with other sectors in the economy and financial system, the equity market will respond more directly to epidemics such as COVID-19. Li et al. (1) and Mazur et al. (2) have examined the impact of COVID-19 on U.S. and European equity markets. However, most of these authors examined the impact of the number of COVID-19 cases and deaths on the equity market and seldom examined the relationship between public sentiment, the epidemic, and equity market volatility.

Information epidemiology has become a research hotspot in the context of the spread of the COVID-19 epidemic (3). This area of research involves scanning the Internet, traditional media, and other public channels to obtain health-related data and content. In recent years, scholars have used the data collected by Google Trends and Google Flu Trends to conduct much of their research. Google Trends shows the keywords that the public searches using Google. The data is normalized according to search frequency and displayed in relative search volume. Data can be selected in different regions and time periods according to needs. Researchers can use Google Trends data to investigate people's search needs for coronavirus information around the world, and can choose five keywords for comparative analysis each time. This data is especially useful for studying seasonal infectious diseases, mental health conditions, and other diseases. This article uses Google Trends to analyze the public's judgment and information needs on epidemic trends.

It is generally believed that industries related to people's livelihoods, such as healthcare, food, software and technology, and natural gas, are performing better during the epidemic. The negative impact of the epidemic on the real estate, aviation, hotel, tourism, and entertainment industries is even more pronounced. So, what is the impact of COVID-19 on the volatility of infectious disease equities? To examine equity market volatility, Baker et al. (4) constructed a newspaper-based infectious disease equity market volatility tracker, which is different from traditional equity market volatility indicators. The data spans January 1985 to the present, and the data frequency is updated once a day. In contrast, our article is not only based on Google Trends, but also uses the volatility of infectious disease equities constructed based on traditional newspaper media to examine the relationship between the epidemic, public sentiment, and the volatility of infectious disease equities. This is of great significance to investors and decision makers.

LITERATURE REVIEW

Research on COVID-19 has been extensive, and most studies consider disease-related keywords that the public searched for on Google during the epidemic, such as skin diseases, quitting smoking, and washing hands. Kutlu (5) uses Google Trends to judge the trends of skin diseases in Turkey and Italy during the COVID-19 pandemic. The study found that from March 11 to June 1, 2020, there was a statistically significant positive correlation between the number of COVID-19 cases and the search terms of general dermatology in Turkey. The search terms for "hair loss" and "acne" in these two countries increased during the COVID-19 epidemic. This may be related to emotional stress, anxiety, and depression. The increasing number of "acne" search terms in Google Trends may be related to the curfew and other blockade measures imposed on young people in Turkey and Italy. In addition, the widespread use of masks may also cause acne. Interestingly, during the COVID-19 pandemic, the significant reduction in sexually transmitted disease search terms may be related to the fact that social distancing, gatherings, and stay-at-home campaigns have led to a decrease in extramarital sexual activity. In addition, in the summer, the closure of many tourist centers led to a decrease in the search term "sunscreen." The article points out that understanding the trends of skin diseases and the impact on public perception during the COVID-19 pandemic will help dermatologists better prepare.

Springer et al. (6) believes that people's searches on the Internet are mainly based on rational information needs and demographic needs in order to prepare for the pandemic and to protect themselves. This includes terms such as "hand washing" and "social distancing." This reflects an increase in people's fear of infection. These search terms all reflect global attention. According to Strzelecki (7), the peak time for new cases occurs within 10–14 days after the keyword peaks of search terms such as "COVID-19 symptoms," "social distance," and "isolation." Heerfordt and Heerfordt (8) points out that smokers are not only more susceptible to flu and Middle East respiratory syndrome and other coronavirus infectious diseases, but the consequences are also more serious. Studies have found that among hospitalized patients with COVID-19, smokers are two to nine times more likely to have serious complications than non-smokers. Quitting smoking can not only reduce respiratory symptoms and bronchial responsiveness, but also effectively prevent lung function decline. Walker et al. (9) show that there is a significant correlation between the use of search terms related to "odor" and the number of coronavirus cases and deaths. This correlation exists widely in the sample countries examined. Generally, the detection of the first coronavirus death is significantly consistent with the time of the outbreak in the country. This shows that during the spread of the coronavirus epidemic, the sudden increase in the frequency of searches for keywords related to sense of smell deserves the attention of epidemic surveillance agencies.

Other studies look at the forecast of epidemic trends. Ortiz-Martínez et al. (10) present the evaluation results of the relationship between Colombian COVID-19 cases and Google searches. They find that after the first case in the country, search volume begins to increase significantly. After this, there is a high correlation between the incidence of COVID-19 in Colombia and Google searches. Although Internet searches and social media data are related to traditional surveillance data, Internet search data can predict the outbreak of a disease several days or weeks in advance. Analysis shows that Google Trends can potentially determine the appropriate time and place to implement risk communication strategies for the affected population. Gozgor et al. (11), Ashraf (12), Ortiz-Martínez et al. (10), Fang et al. (13), Sharif et al. (14), Wang et al. (15), and Wu et al. (16) believe that in countries that lack diagnostic and surveillance capabilities, Google Trends or Baidu index can be used to monitor search changes related to COVID-19 and stock markets.

Sulyok et al. (17) point out that the use of Internet search data can improve the accuracy of COVID-19 pandemic disease modeling. It is believed that integrating Google Trends data into the distributed lag model can significantly improve the prediction quality of the disease model. But Springer et al. (6) also point out the limitations of the use of Google Trends, arguing that Google Trends can only represent the interest of the crowd and cannot clearly distinguish fear, worry, or pure interest. Therefore,

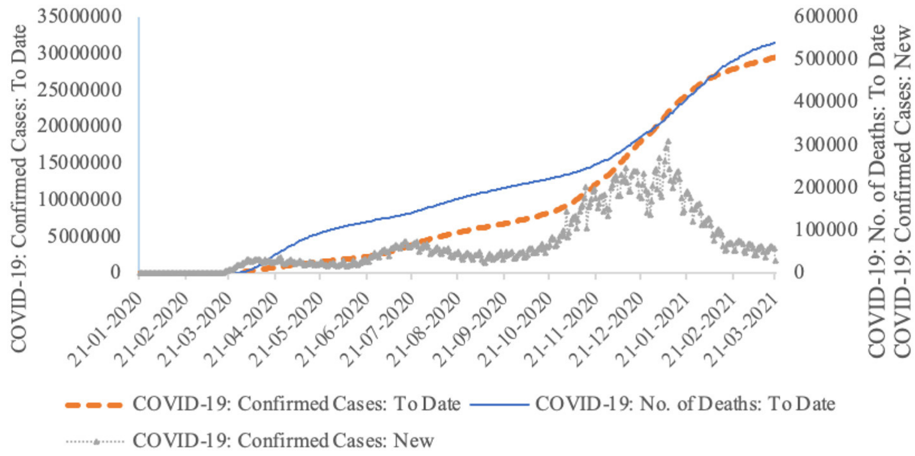

FIGURE 1 | U.S. epidemic data released by Centers for Disease Control and Prevention.

researchers are cautioned to pay attention to this issue when using Google Trends.

Sousa-Pinto et al. (18) argue that the use of Google Trends has changed. In recent years, Google Trends has shifted from monitoring to predicting changes. Therefore, linking Google Trends with other data sources can help overcome the limitations of using only search information. The study by Springer et al. (6) also shows that the current population's main interest is in medical treatment. Apart from individual reports, people's interest in possible virus carriers or animal origins and repositories is also decreasing. For example, the authors find that the search term "COVID-19" and the search term "vaccine" have a high correlation, but the correlation with "pangolin" and "bat" is weak.

VARIABLE DESCRIPTION AND STATISTICAL DESCRIPTION

As of March 23, 2021, the United States has become the country with the largest number of confirmed COVID-19 cases and deaths in the world, reaching 29.5 million and 543,000, respectively (**Figure 1**). Although the number of new cases in a single day has fallen sharply, it is still close to 30,000. Based on the availability and continuity of data, this article uses newly confirmed cases of COVID-19 as an alternative indicator of the U.S. epidemic, denoted by CONFIRMEDCASE. Data come from CEIC database.

Due to public concern about the possibility of becoming infected with COVID-19 during the epidemic, people try their best to engage in coronavirus surveillance or to search for relevant information. Therefore, we use the keyword search in Google Trends to express public sentiment. This article uses the keyword "COVID-19 test" to represent public sentiment concerning the epidemic. We use Baker et al. (4) to construct a newspaper-based infectious disease equity market volatility tracker to represent the volatility of infectious disease equities.

TABLE 1 | Statistical description of the main variables.

	CONFIRMEDCASE	COVID-19 TEST	INFECTIOUSEQUITY
Mean	77498.46	51.24074	24.95998
Median	52847	47	21.283
Maximum	243448	100	65.931
Minimum	44	9	13.159
Std. Dev.	67254.04	20.57562	10.56136
Skewness	1.094862	0.661805	2.095552
Kurtosis	2.878847	2.930416	7.511875
Jarque-Bera	10.82152	3.952763	85.32532
Probability	0.004468	0.13857	0
Sum	4184917	2767	1347.839
Sum Sq. Dev.	2.40E+11	22437.87	5911.747
Observations	54	54	54

We use INFECTIOUSEQUITY to express this. The statistical description of the main variables is shown in **Table 1**.

Google Trends data is on a weekly basis; therefore, our daily-based new confirmed cases and infectious disease equity market volatility tracker data must be averaged on a weekly basis. As such, part of the data contains a decimal point. **Table 1** shows that the maximum number of newly confirmed cases is 243,448, which was obtained on January 3, 2021. The minimum value is 44, which was obtained on March 1, 2020, at the beginning of the epidemic. The maximum value of COVID-19 TEST data is 100, which was obtained on June 21, 2020. Although the epidemic in the United States was not very serious at the time, the southern states of the United States allowed companies to reopen, resulting in a surge in confirmed cases. Public concern and media propaganda caused searches to soar rapidly. The minimum value is 9, which is also obtained on March 1, 2020 at the beginning of the sample period. The maximum value of the infectious disease equity market volatility was obtained on March 15, 2020, and the minimum value was obtained on February 7, 2021.

TABLE 2 | ADF and PP test results.

Variables	ADF		PP	
	Level	1st difference	Level	1st difference
	Intercept	Without trend and intercept	Intercept	Without trend and intercept
CONFIRMEDCASE	−2.451	−3.976***	−1.574	−3.825***
Covid-19 Test	−2.793*	−6.095***	−3.200**	−6.076***
INFECTIOUSEQUITY	−2.351	−8.243***	−2.268	−9.985***

****, **, and * indicate the significance levels at 1%, 5%, and 10% levels, respectively.*

TABLE 3 | Granger causality test results.

Null hypothesis	Obs	F-statistic	Prob.
INFECTIOUSEQUITY does not Granger Cause CONFIRMEDCASE	52	10.1390	0.0002
CONFIRMEDCASE does not Granger Cause INFECTIOUSEQUITY		16.4139	4.00E-06
COVID-19 TEST does not Granger Cause CONFIRMEDCASE	52	1.08637	0.3458
CONFIRMEDCASE does not Granger Cause COVID-19 TEST		2.52758	0.0907
COVID-19 TEST does not Granger Cause INFECTIOUSEQUITY	52	2.78003	0.0723
INFECTIOUSEQUITY does not Granger Cause COVID-19 TEST		0.30440	0.739

EMPIRICAL RESEARCH

The correlation between the main variables shows that confirmed cases are positively correlated with COVID-19 TEST. This shows that the more confirmed cases, the greater the public's attention to the epidemic and the more they are willing to retrieve COVID-19 TEST related information. There is a negative correlation between confirmed cases and the INFECTIOUSEQUITY variable, but the correlation between them is not strong.

Table 2 uses ADF and PP to investigate the unit root test results. The ADF and PP tests are based on the following assumptions: testing the null hypothesis of unit roots (non-stationary) and the alternative hypothesis of no unit roots (stationary). The model estimates the presence and absence of trends, levels, and first-order differences. When the level value contains a trend, the ADF and PP test results of the three variables reject the null hypothesis that the unit root is at the 1% significance level. This means that these series are not stationary at their level values. When the first-order difference does not include trend and intercept, all three variables pass the 1% significance test. This shows that the first difference of the three variables is a stationary time series.

Table 3 shows the test results of Granger causality. We have selected an appropriate lag period according to the Akaike Information Criteria (AIC). The test results show that INFECTIOUSEQUITY does not Granger Cause CONFIRMEDCASE, rejecting the null hypothesis at the 1% level. Similarly, CONFIRMEDCASE does not Granger Cause INFECTIOUSEQUITY, rejecting the null hypothesis at the 1% significance level. This means that there is a two-way Granger causality between INFECTIOUSEQUITY and CONFIRMEDCASE. In other words, the increase in confirmed cases will cause fluctuations in epidemic equities. Similarly, the fluctuation of equity information about the epidemic also reflects the progress of confirmed cases. In sharp contrast, CONFIRMEDCASE does not Granger Cause COVID-19 TEST, rejecting the null hypothesis at a significance level of 10%, but the opposite is not true. COVID-19 TEST does not Granger Cause INFECTIOUSEQUITY, also rejecting the null hypothesis at a significance level of 10%, and vice versa.

The results of the cointegration test show that there is a cointegration relationship between the three variables. Therefore, we can conduct a VAR inspection and impulse response function analysis.

The impulse response function in **Figure 2** mainly examines the impact of one variable in different lag periods on other variables. The calculation results show that the response of CONFIRMEDCASE to the INFECTIOUSEQUITY shock and the response of CONFIRMEDCASE to the COVID-19 TEST shock are relatively stable. However, the impact of CONFIRMEDCASE on itself first increases and then decreases, and there is a long lag period. INFECTIOUSEQUITY is always negative for the response from CONFIRMEDCASE. INFECTIOUSEQUITY's response to the shock from the COVID-19 TEST changed from positive to negative. The impact of INFECTIOUSEQUITY on itself continues to decline. The response of COVID-19 TEST to shocks from the other two variables is similar, rising first and then falling in both cases. However, the response of COVID-19 TEST from its own shock continues to decline.

CONCLUSIONS AND POLICY RECOMMENDATIONS

This study empirically examines the relationship between the volatility of infectious disease equities, public sentiment, and the

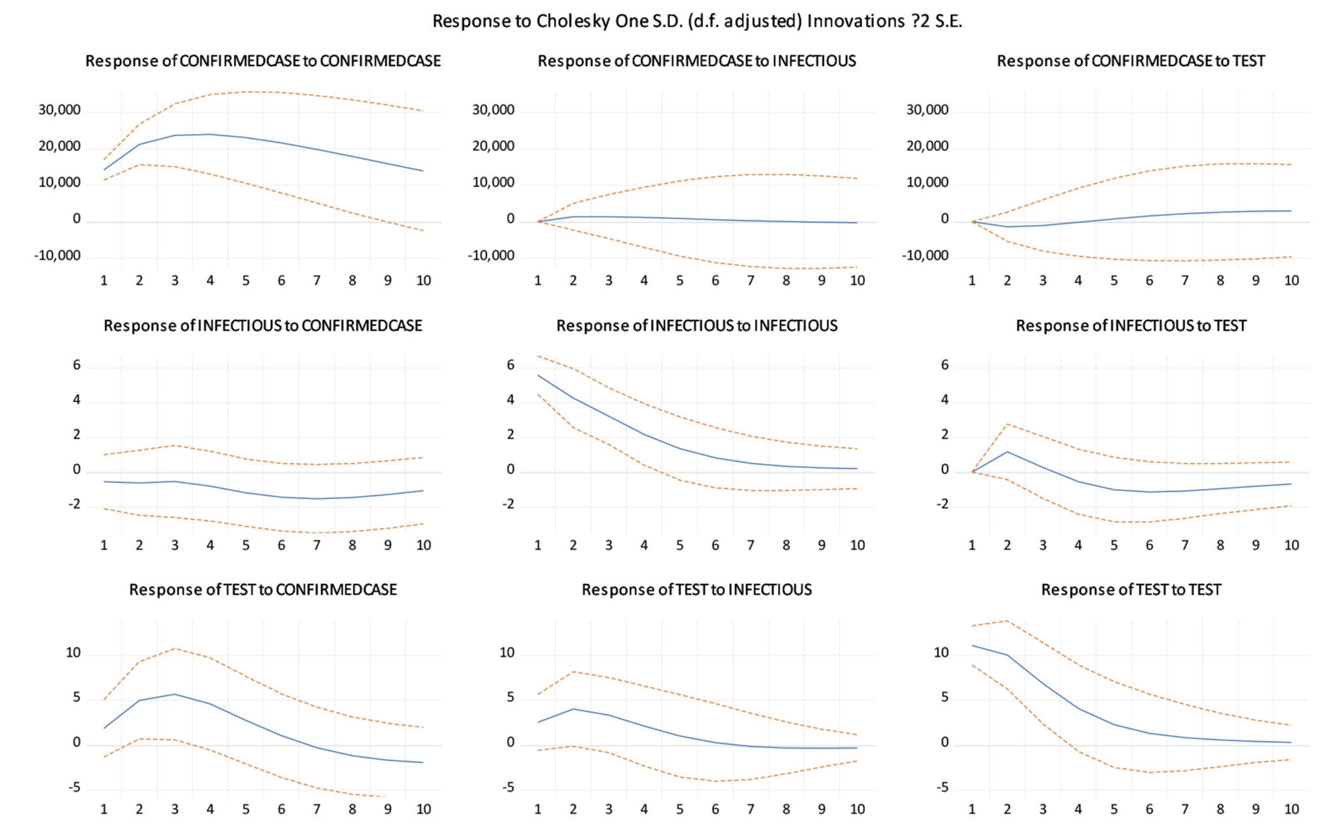

FIGURE 2 | Impulse response function.

COVID-19 epidemic from the perspective of the United States. This study uses weekly data from January 3, 2020 to March 7, 2021. The research results show that the confirmed cases in the United States are positively correlated with COVID-19 TEST. This shows that the more confirmed cases, the greater the public's attention to the epidemic and the more willing they are to retrieve COVID-19 TEST related information. There is a negative correlation between confirmed cases in the United States and the INFECTIOUSEQUITY variable. In other words, as more cases are confirmed, the equities related to the epidemic will gain, thereby reducing the volatility of related equities; there is a negative correlation between the two. The results of the Granger causality test show that there is a two-way Granger causality relationship between INFECTIOUSEQUITY and CONFIRMEDCASE. In other words, the increase in confirmed cases will cause fluctuations in epidemic equities. Similarly, the fluctuation of equity information about the epidemic reflects the progress of confirmed cases. In sharp contrast, CONFIRMEDCASE can cause COVID-19 TEST. COVID-19 TEST will cause INFECTIOUSEQUITY, but the reverse is not true. That is, there is a one-way causal relationship between them. The impulse response function calculation results based on the VAR model show that the impulse response of the three variables from their own shock is stronger, but there is a longer lag period. The impact of the other two variables is relatively stable.

Based on the above research conclusions, we believe that real-time monitoring of epidemic trends will not only help determine the volatility of epidemic-related equities, but it will also help policy makers to intervene before major equity market volatility occurs, thereby preventing excessive equity market volatility. Secondly, monitoring the equity information of the epidemic can also help reveal undetected epidemics or the needs for medicines and anti-epidemic materials in specific areas or among groups of people, so as to provide targeted epidemic prevention and medical services for specific groups. In addition, providing effective COVID-19 test services in accordance with the epidemic's trends will also help control the epidemic in the United States and prevent the global spread of the epidemic (19). The number of testing services will also help determine the epidemic and the prosperity index of medical equities and industries in advance and improve the medical industry's ability to respond to the epidemic.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found at: trends.google.com.

AUTHOR CONTRIBUTIONS

JM: writing-original draft. QS: writing—review and editing. JZ: resources. LW: investigation and software. RX: proofreading. CY: draft writing, design, and literature part. All authors contributed to the article and approved the submitted version.

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REFERENCES

1. Li Y, Liang C, Ma F, Wang J. The role of the IDEMV in predicting European stock market volatility during the COVID-19 pandemic. *Financ Res Lett.* (2020) 36:101749. doi: 10.1016/j.frl.2020.101749
2. Mazur M, Dang M, Vega M. COVID-19 and the march 2020 stock market crash. Evidence from SandP1500. *Finan Res Lett.* (2021) 38:101690. doi: 10.1016/j.frl.2020.101690
3. Jiang B, Liu Z, Shen R, Huang L, Tong Y, Xia Y. Have COVID-19-related economic shocks affected the health levels of individuals in the United States and the United Kingdom? *Front Public Health.* (2020) 8:611325. doi: 10.3389/fpubh.2020.611325
4. Baker SR, Bloom N, Davis SJ, Kost KJ, Sammon MC, Viratyosin T, et al. The unprecedented stock market reaction to COVID-19. *Rev Asset Pricing Stud.* (2020) 10:742–758. doi: 10.3386/w26945
5. Kutlu Ö. Analysis of dermatologic conditions in Turkey and Italy by using Google Trends analysis in the era of the COVID-19 pandemic. *Dermatol Ther.* (2020) 33:e13949. doi: 10.1111/dth.13949
6. Springer S, Menzel LM, Zieger M. Google trends reveals: focus of interest in the population is on treatment options rather than theories about COVID-19 animal origin. *Brain Behav Immun.* (2020) 87:134–5. doi: 10.1016/j.bbi.2020.05.005
7. Strzelecki A. The second worldwide wave of interest in coronavirus since the COVID-19 outbreaks in South Korea, Italy and Iran: a Google Trends study. *Brain Behav Immun.* (2020) 88:950–1. doi: 10.1016/j.bbi.2020.04.042
8. Heerfordt C, Heerfordt IM. Has there been an increased interest in smoking cessation during the first months of the COVID-19 pandemic? A Google Trends study. *Public Health.* (2020) 183:6–7. doi: 10.1016/j.puhe.2020.04.012
9. Walker A, Hopkins C, Surda P. Use of Google Trends to investigate loss-of-smell-related searches during the COVID-19 outbreak. *Int Forum Allergy Rhinol.* (2020) 10:839–847. doi: 10.1002/alr.22580
10. Ortiz-Martínez Y, Garcia-Robledo JE, Vásquez-Castañeda DL, Bonilla-Aldana DK, Rodriguez-Morales AJ. Can Google trends predict COVID-19 incidence and help preparedness? The situation in Colombia. *Travel Med Infect Dis.* (2020) 37:101703. doi: 10.1016/j.tmaid.2020.101703
11. Gozgor G, Lau CKM, Sheng X, Yarovaya L. The role of uncertainty measures on the returns of gold. *Econ Lett.* (2019) 185:108680. doi: 10.1016/j.econlet.2019.108680
12. Ashraf BN. Stock markets' reaction to COVID-19: Cases or fatalities? *Res Int Bus Financ.* (2020) 54:101249. doi: 10.1016/j.ribaf.2020.101249
13. Fang J, Gozgor G, Lau CKM, Lu Z. The impact of Baidu index sentiment on the volatility of China's stock markets. *Financ Res Lett.* (2020) 32:101099. doi: 10.1016/j.frl.2019.01.011
14. Sharif A, Aloui C, Yarovaya L. COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: fresh evidence from the wavelet-based approach. *Int Rev Financ Anal.* (2020) 70:101496. doi: 10.1016/j.irfa.2020.101496
15. Wang J, Lu X, He F, Ma F. Which popular predictor is more useful to forecast international stock markets during the coronavirus pandemic: VIX vs EPU? *Int Rev Financ Anal.* (2020) 72:101596. doi: 10.1016/j.irfa.2020.101596
16. Wu W, Su Q, Li C, Yan C, Gozgor G. Urbanization, disasters, and tourism development: evidence from RCEP countries. *Sustainability.* (2020) 12:1221. doi: 10.3390/su12031221
17. Sulyok M, Ferenci T, Walker M. Google trends data and COVID-19 in Europe: correlations and model enhancement are European wide. *Transbound Emerg Dis.* (2020). doi: 10.1111/tbed.13887. [Epub ahead of print].
18. Sousa-Pinto B, Anto A, Czarlewski W, Anto JM, Fonseca JA, Bousquet J. Assessment of the Impact of media coverage on COVID-19-related google trends data: infodemiology study. *J Med Internet Res.* (2020) 22:e19611. doi: 10.2196/19611
19. Gozgor G. Global evidence on the determinants of public trust in governments during the COVID-19. *Appl Res Q Life.* (2021). 1–20. doi: 10.1007/s11482-020-09902-6. [Epub ahead of print].

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The Impact of the COVID-19 Pandemic on China's Manufacturing Sector: A Global Value Chain Perspective

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This paper, based on the notion of Trade in Value Added (TiVA), combines the global trade analysis project (GTAP) model with the value-added model in seeking to simulate and assess the impact of the COVID-19 pandemic on China's manufacturing sector in global value chain (GVC) reconfiguration. The empirical study provides three major results. First, at the macroeconomic level, the pandemic wreaks a negative impact on all the economies, including the U.S., in regard to import & export trade, GDP and social welfare policy. Second, nation-level simulation shows that there's a remarkable disparity across different pandemic scenarios in the level of division of labor and of GVC participation for China and its trade partners. Third, sector-level analysis shows that the impacts of the pandemic include promoting the level of GVC participation and of labor division in China's manufacturing sector (electromechanical equipment and computer goods). This paper also provides policy advice for Chinese government: participation in higher-end GVCs, introduction of further structural reforms and retention of foreign investors, and active responses to GVC reconfiguration and cross-border capital flow.

Keywords: COVID-19 pandemic, GVC reconfiguraiton, GTAP model, manufacturing sector, China

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INTRODUCTION

Economic globalization has made the world smaller. With the increasing flow of trade, capital and labor, the COVID-19 pandemic has quickly proliferated across the world, the most remarkable difference when compared with any previous public health crisis at the world level. As the pandemic spreads, more and more countries have implemented border closures in order to effectively contain virus transmission. However, the pandemic hit a vast number of economies hard with significantly delayed business recovery and damaged production network. A multitude of sectors are facing a shortage of supply which dislocates the upstream and downstream supply chains, thereby bringing an impact on the global value chains (GVC), supply chains, trade & investment which accelerates the trend of anti-globalization (1). In consideration of medical supply security and less reliance for foreign assistance, many countries have implemented manufacturing revitalization strategy while retracting overseas investment to the domestic market. These measures might bring significant change to the existing system of global economy and further dim the prospects of globalization (2). Using real trade openness instead of nominal trade openness Gozgor (3) recalculated the KOF economic globalization index from 1970 to 2013, and concluded that economic globalization has a positive effect on economic growth. GVC reconfiguration in the context of anti-globalization will certainly exerts heavy impact on the Chinese economy.

The COVID-19 crisis makes countries to rethink their role in the GVCs and the associated risks. Furthermore, it is expected to accelerate GVC reconfiguration because post-pandemic GVC configuration takes into account not only cost factors; in addition, some countries and multinational corporations are considering a transition to economic detachment and the self-developed value chains, leading to GVC instability and the resulting risk of GVC relocation. GVC localization and regionalization are looming as two prominent factors. As the largest manufacturing economy in the world, the value added of China's manufacturing sector reached 26.9 trillion in 2019, accounting for 28.1% of the global total. As China moves steadily to the upper end of the GVCs, the proliferating pandemic will unavoidably exerts a serious impact on the intra-industry GVC division of labor. Then will the pandemic exert some impact on GVC reconfiguration? If the answer is in the affirmative, how the impact on China's value chain reconfiguration can be measured? How the impacts on China's level of GVC participation and on the country's role in labor of division can be measured across different industries? What policy responses should China take to these impacts? The answers to the questions help China play its due role in GVC reconfiguration. Therefore, it's of great significance to precisely define the pandemic's impact on China's role in GVCs.

The existing investigations deal primarily with the impact of the severe public health crises on regional economic growth and the impact of the COVID-19 pandemic on the global and Chinese economies.

Most of recent studies believe that the impact of the outbreak of major public health emergencies on the global economy or regional economic growth tends to be temporary, although negative. Based on the historical epidemiological economic data of the British flu, Keogh-Brown and Smith (4) built a compact model, finding that if the 1957 or 1968 flu recurred, they would have only a temporary economic impact, causing the British GDP to suffer 3.35% loss in the quarter from the outbreak and a 0.58% loss for the whole year. Verikiosa et al. (5) built a Modified Monash Model (MMM) to assess the impact of swine flu on the Australian economy and found that in spite of the massive investment intention curtailments and the consumer market slumps, the long-term effect on the regional economy remains yet to be established. Bloom and Mahal (6) collected the data about 51 developing economies and industrialized economies for a study of the correlation between AIDS prevalence and per capita GDP growth; the empirical study affirms that an AIDS epidemic will retard economic growth. In contrary, Brainerd and Siegler (7) conducted empirical research on the impact of the Spanish flu on the U.S. economy and, based on the empirical data, established that the disease contributed positively to the economy of the states. Prager et al. (8) studied the impact of a potential flu pandemic on the overall U.S. economy, finding that GDP loss can be effectively lessened by virtue of the government's preventative control measures, e.g., vaccination.

The global COVID-19 pandemic has attracted broad attention from researchers in regard to its impact on the world economy, the preventative control policies made by different countries and the differential effects. McKibbin and Fernando (9), Alvarez et al. (10), Jones et al. (11), and Baker et al. (12) studied the pandemic's impact on the global economy, the balance between pandemic containment and economic performance, and the serious impact of transmission uncertainties on the economic activity. Fornaro and Wolf (13) and Shahbaz et al. (14) proposed the economic depression as a result of the pandemic which will not only lead to a global supply & demand crisis, but also impact heavily on regional employment, productivity growth and foreign direct investment. As states and GVC restrict each other during the COVID-19 pandemic, attention should be paid to GVC structure, states and their interactions (15). From the perspective of a sharp shortage of medical supplies, Gereffi (16) pointed out that during the COVID-19 pandemic the U.S. shortage of N95 respirators is a policy failure more than a market failure. From the perspective of Gourinchas (17), the pandemic's negative impact will loom large in many ways, including corporate supply chain disruption, labor shortage, shutdowns, close-downs, intensely shrinking consumer demand, and credit crunches. Baldwin and Mauro (18), Brightman and Treussare (19), and Ayittey et al. (20) argue that the pandemic's negative impact on the global economy is looming increasingly in the form of global supply chain disruption and trade restriction and the transmission rate exerts a tremendous impact on GVC stability.

Some scholars conducted research on the pandemic's impact on the Chinese economy. Liu (21) carried out a profound analysis of the dynamics of economic globalization in the wake of the pandemic from the perspective of GVC reconfiguration. Zhi and Luo (22) investigated in detail the pandemic's impact on the Chinese economy in both the long term and the short term. Liu (23) sorted out and dissected the characteristics of the pandemic's impact on the Chinese economy and the associated risks while advising on policy-making by pointing out the pandemic does more harm to the producer services sector than to the consumer services sector. Tong et al. (24) analyzed the impact of the proliferating global plague on the Chinese economy and the global economy as well as the countermeasures in response. Wen et al. (25) ascertained that the strict city closures implemented in China after the outbreak wreaks a direct impact on business and extensive close-downs while driving down capacity utilization, level of investment and consumer demand. The strict city closures have worsened China's trade environment and are not conducive to foreign direct investment (26, 27). Some scholars pointed out that in the post-epidemic era, to improve China's position in the global value chain, we must attach importance to technological innovation and improve the quality of export products (28, 29). Zhou et al. (30) employed the econometric ridge regression model to conduct a predictive analysis of the impact sustained by the 2020 growth rate of the Chinese economy. The findings show the vast part of the impact mostly occurred in the first and second quarters before diminishing.

To sum up, literature relevant to the pandemic's impact on the economy agrees that preventative control measures intended to effectively control the extent of the pandemic and lessen its negative impact may pose tremendous potential challenges to a multitude of sectors, e.g., supply & demand, production and financing. Compared with the existing studies, this paper conducts a quantitative analysis based on the GTAP 10 database which is extended to 2020 using Walmsley's dynamic recurrence method. In addition, this paper combines the global trade analysis project (GTAP) model with the value-added model in seeking to simulate and assess the impact of the COVID-19 pandemic on China's manufacturing sector in global value chain (GVC) reconfiguration. The contribution of this paper mainly includes the following three components. First, the author conducts an in-depth, systematic study of the economic impact of the outbreak of public health emergencies, especially epidemics. Particularly, the author builds an accurate computable general equilibrium (CGE) model to assess to what extent the pandemic affects China's GVC participation. Second, based on the aforesaid theoretical findings the author introduces model calibration and model linking to the pandemic to complete data processing for China's GVC participation. Third, the aforesaid linkage model is used for policy simulation and simulation results presentation to interpret the pandemic's effects on China's GVC participation, on both the state level and the industry level.

As for the outline of the subsequent content of the paper, Part 2 analyzes primarily the pandemic's impact on Chinese manufacturing in regard to GVC reconfiguration. Part 3 introduces the linkage model and constructs indices by elaborating on how to link the global trade analysis project (GTAP) model with the decomposition of trade in value added (31) and construct such core indices as forward GVC participation, backward GVC participation, GVC participation and division of labor. Part 4 presents the database and scenarios. Part 5 includes an in-depth simulation-based interpretation of the pandemic's effects on Chinese manufacturing in regard to GVC reconfiguration in such dimensions as the Chinese economy and China's location in division of labor in GVC participation. Part 6 deals with the research and policies.

COVID-19 PANDEMIC AND GVC RECONFIGURATION

Currently, GVCs are faced with two major challenges, the pandemic and global trade dispute. Particularly, the U.S.–China trade war in combination with the pandemic has contributed to the world's major economic uncertainty, which might threaten the GVCs. What causes China's role in GVC participation so vulnerable to these challenges?

First, integration into the GVCs makes China more vulnerable to external impacts. The country's exports account for about 20% of its GDP, indicating its deep integration into the GVCs (UN Comtrade Database, 2020). The goods exported from the country reached the value of $4.576126 trillion, accounting for 13.2% of the world's total, an increase of 0.4% over 2018. There was a steadily-growing share in export on the international market (**Figure 1**); goods import accounted for 10.8% of the world's total, soaring to a historic high (UN Comtrade Database, 2020). Besides, there was a rise in China's share of the international market (Ministry of Commerce, 2020). In 2019, China's trade with the U.S. totaled $4.1435.8 trillion in value, a 1.5% annual drop as the following statistics show. As shown in **Figure 2**, the U.S., EU and Japan, major trade partners of China, suffer heavily from the pandemic. Hence the global demand for Chinese capital goods and intermediate goods suffers a significant negative shock. The initial outbreak of the pandemic has resulted in a sharp and intense fall of export of Chinese goods as well as a break of the value chains. The paralysis of the global

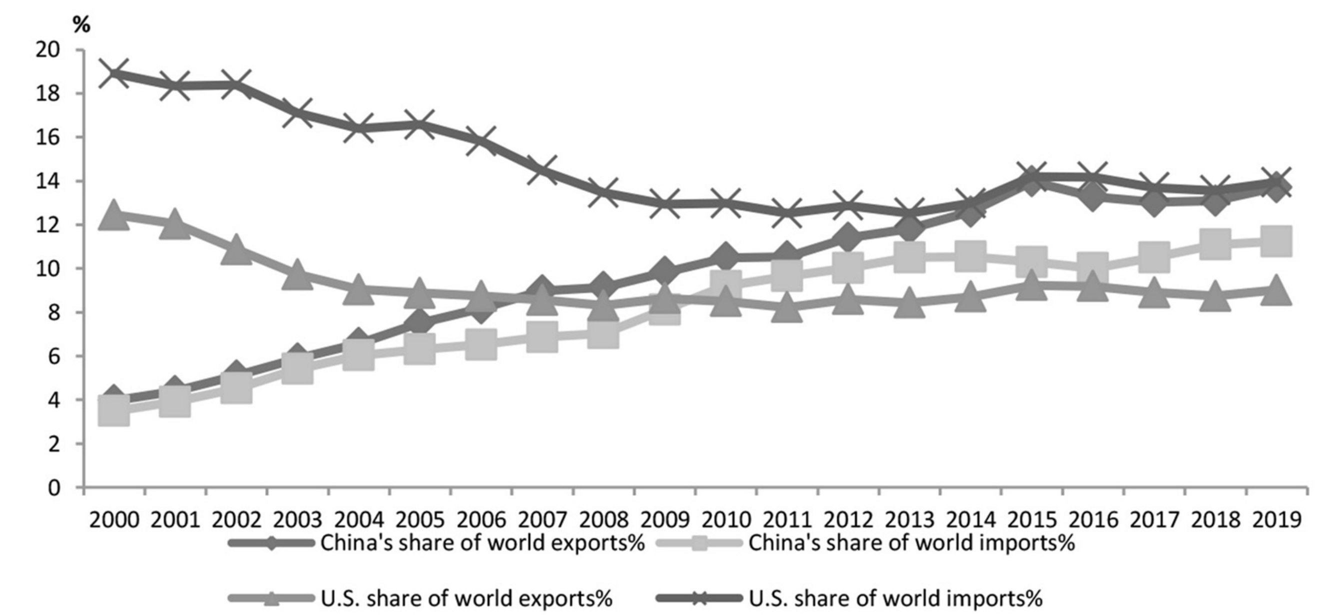

FIGURE 1 | Changes in China and the United States' share of global imports and exports. Data source: UN Comtrade Database.

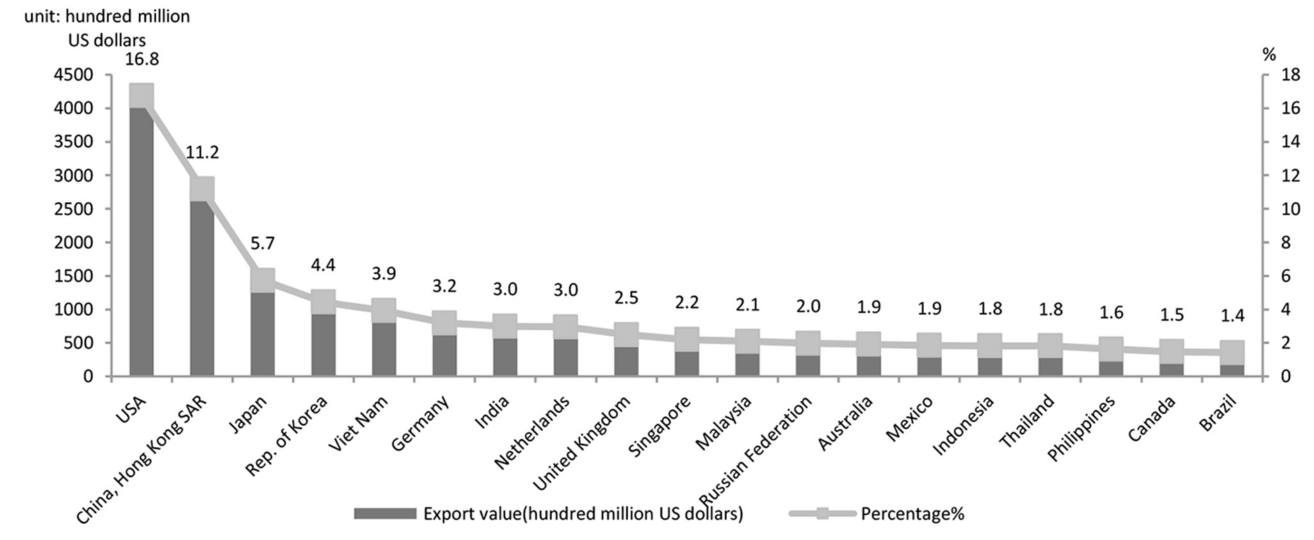

FIGURE 2 | China's export partners in 2019. Data source: WITS.

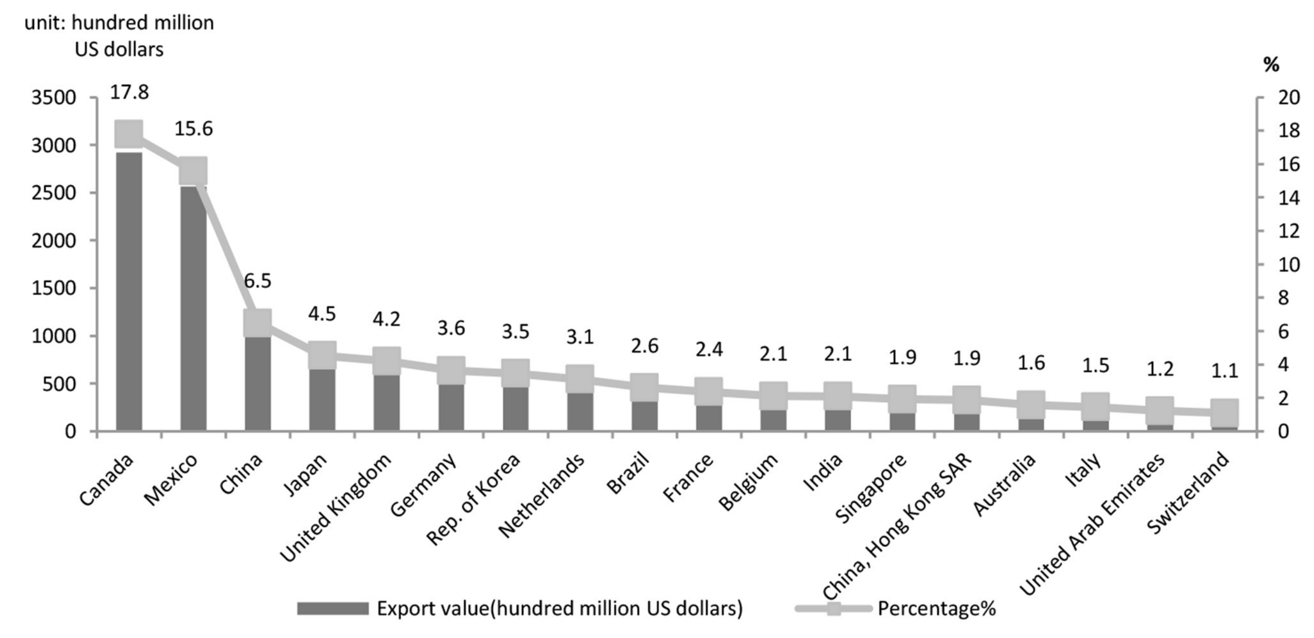

FIGURE 3 | U.S. export partner countries in 2019. Data source: WITS.

production network is followed by GVCs and supply chain reconfiguration that deliver a negative impact on international trade (32). Conversely, the data on the U.S. export quota (**Figure 3**) indicate that in 2019 the U.S. exported 6.5% of its goods to China, its third largest trade partner, larger than the trade partners including the UK, Germany and Brazil which are also hit hard by the pandemic. It is shown in **Figures 2**, **3** that due to the high interdependence between the Chinese economy and the U.S. economy, the worsening of the stagnant U.S. economy and the U.S.–China trade friction wreaks a tremendous impact on the Chinese economy, now deeply integrated in the GVCs.

Second, China remains mired in the mid-and low-end of the GVCs. Hong and Zhong (33) studied participation of multiple countries in the GVCs using the UNCTAD-Eora GVC Database, suggesting that China remains at the lower end (downstream) of GVC participation in regard to division of labor. At present, China ranks on the third of four levels of global manufacturing, a situation supposedly impossible to be fundamentally improved in the short term (**Table 1**).

Third, the pandemic in combination with the U.S.-China trade friction exposes China to the risk of detachment from the GVCs. The outbreak of the pandemic, combined with the U.S.-China trade friction, wreaks a tremendously negative impact on China's value chains and inward/outward FDI. First, as shown in **Figure 4**, the pandemic has brought a negative impact on China in regard to FDI-based GVC participation. Notably, the 1-month-long economic stall in favor of disease control affected the China-based foreign-owned companies to rather great a degree. From January to April, 2020, only a $41.34 billion share of the FDI materialized, dropping by 8.4% year on year. What's more, the OFDI (Outward Foreign Direct Investment) activities of Chinese multinationals are affected by the proliferation and transmission of the pandemic at more than one location across the globe. Investment climate change, factor mobility stagnation, market expectations change, etc. have impeded China's FDI activities. The statistics released by the Ministry of Commerce and the State Administration of Foreign Exchange show that China aggregated $64.17 billion in OFDI from January to July, 2020, a 6.5% year-on-year fall. The amount include a $60.28 non-finance OFDI in 4,625 foreign enterprises in 161 economies around the globe, reflecting a 5.4% fall from the preceding year as well as a hindrance to the Go Global initiative which targets participation in GVC reconfiguration.

TABLE 1 | The four levels of global manufacturing.

Level	Type of manufacturing	Country
1st level	Global technological innovation centers (e.g., the U.S.)	The U.S.
2nd level	High-end manufacturing	EU, Japan, the UK, etc.
3rd level	Mid-and low-end manufacturing	China, Southeast Asia, Brazil, India, etc.
4th level	Natural resource export	OPEC (Organization of the Petroleum Exporting Countries), Africa, Latin America, etc.

Data Source: Minister of IIT Miao Wei's interpretation of Chinese Manufacturing 2025 at the 13th session of the Permanent Committee of the 12th CPPCC (Dec. 9, 2020; https://dy.163.com/article/FDL3M3ST0539AGEJ.html).

We consider the impacts of the Covid-19 pandemic on China's manufacturing sector in GVCs from two perspectives, supply and demand. The first wave of the pandemic exerted remarkable negative impact on China's production network and brought in export slumps. The outbreak of the pandemic in China has caused the postponement of many orders due to closures of logistics services and shutdowns, therefore reducing demand for intermediate goods as well as export to the U.S. and Europe. Manufacturing's GVCs, therefore, have sustained dislocation. The impact of the pandemic on China's industry value added (IVA), fixed investment (FI) and consumer goods retail sales assumes a V-like trend, industry value added slumping by 13.5%, the FI slumping by 24.5% and consumer goods sales slumping by 20.5% (**Figure 5**). The slumps mark the first $6.876 billion trade deficit in history (**Figure 6**). However, the prompt and effective steps taken to contain the virus have resulted in the revival of the production network.

By contrast, the second wave has affected China's foreign trade and its role in GVCs on the demand side. Unlike the 2008 financial tsunami, the COVID-19 pandemic hit China's foreign trade, resulting in not only foreign demand slumps, but also risks of supply chain disruption on the supply side. Besides, the Chinese trade sector is something like post-trade processing which characterizes the commodity structure of both import trade and export trade. In the short run, the impact sustained by

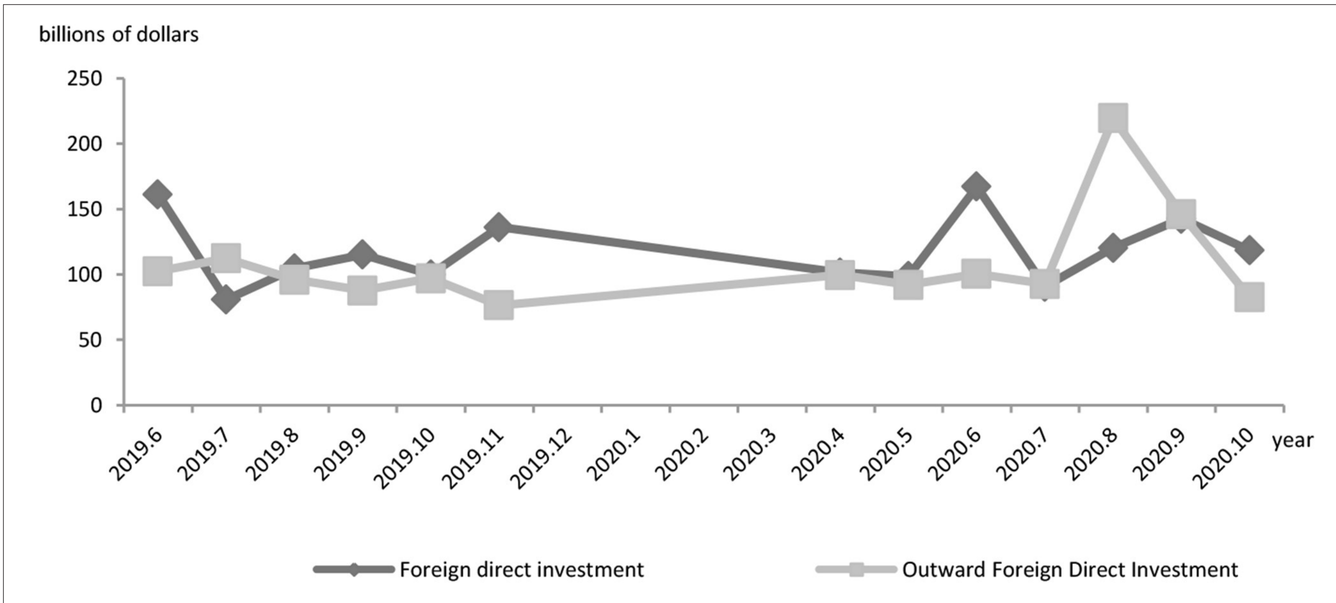

FIGURE 4 | China's foreign direct investment and outward foreign direct investment. Data source: Ministry of Commerce of the people's Republic of China.

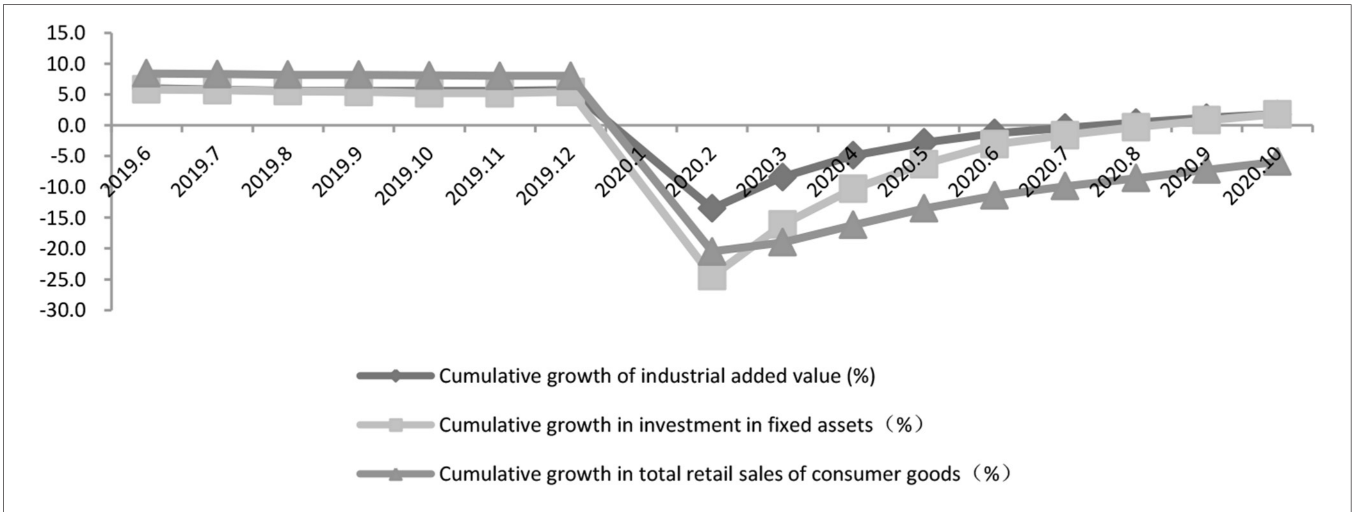

FIGURE 5 | China's industrial value added, investment and social marketing since the outbreak of the COVID-19. Data source: National Bureau of statistics of the People's Republic of China.

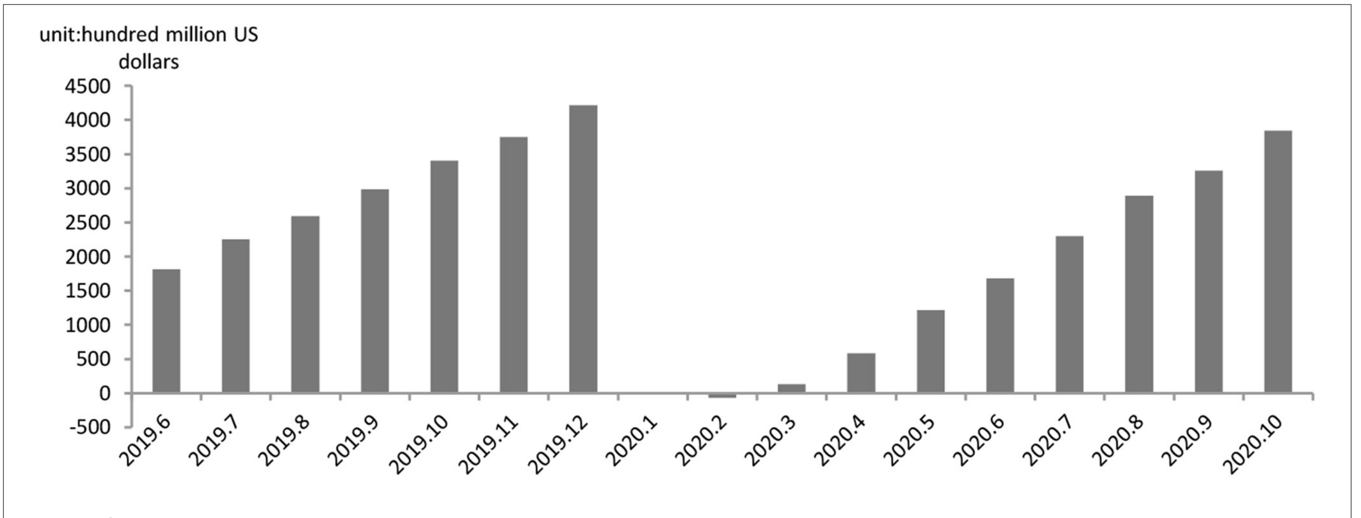

FIGURE 6 | Cumulative value of China's import and export balance. Data source: National Bureau of statistics of the People's Republic of China.

China on export seems to be greater than that on import due to the severity of the pandemic in other countries; in the long run, however, the exposure of the world economy to a long downturn will come with a sharp landslide of foreign demand, impeding intermediate goods import and adding uncertainties to the future trade balance.

The post-pandemic GVCs will have three characteristics in the coming post-pandemic era as the impact of the COVID-19 pandemic on the structure of the Chinese value chains tends to be long and far-reaching. First, they're shortening at an increasingly decelerated pace. Second, geopolitical interests will cause GVC reconfiguration and a shift to security considerations from economic considerations. Third, the GVCs will take a turn to localization and regionalization. The following paragraphs provide more specifics. The combination of the pandemic with the U.S.-China trade dispute shortens the GVCs. According to UNCTAD-Eora GVC Database, the participation of China and the U.S. the GVC had topped before the 2008 financial crisis. Their 2008 GVC participation stood at 61%, 13 percentage points from 1990 (48%). Following the financial crisis, their GVC participation dropped to 57% in 2018 (**Figure 7**).

The radical differences between the U.S. and China in institutions have been driving the trade friction into tariff war (34). A substantive change of the U.S.-China relations has shaken mutual trust. Other major developed economies, under the influence of the U.S. policy change, take actions to reduce their reliance on China's manufacturing sector (35). In the post-pandemic era, it is likely that the major economies make attempt to withdraw their investments in the manufacturing sector of China. As investment withdraw is expected to take place in the post-pandemic era, it's expected that the GVCs will become

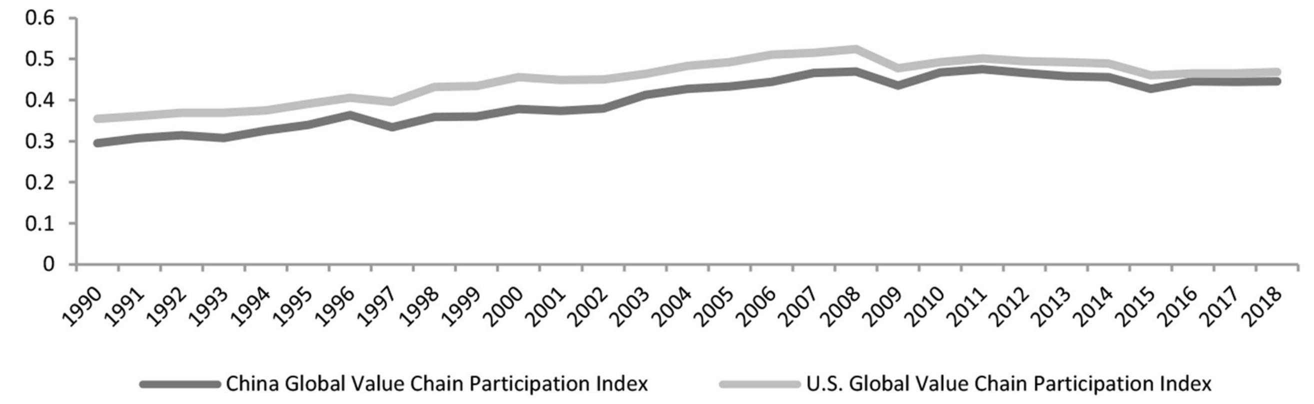

FIGURE 7 | China and U.S. Global value chain participation index. Data source: UNCTAD-Eora GVC.

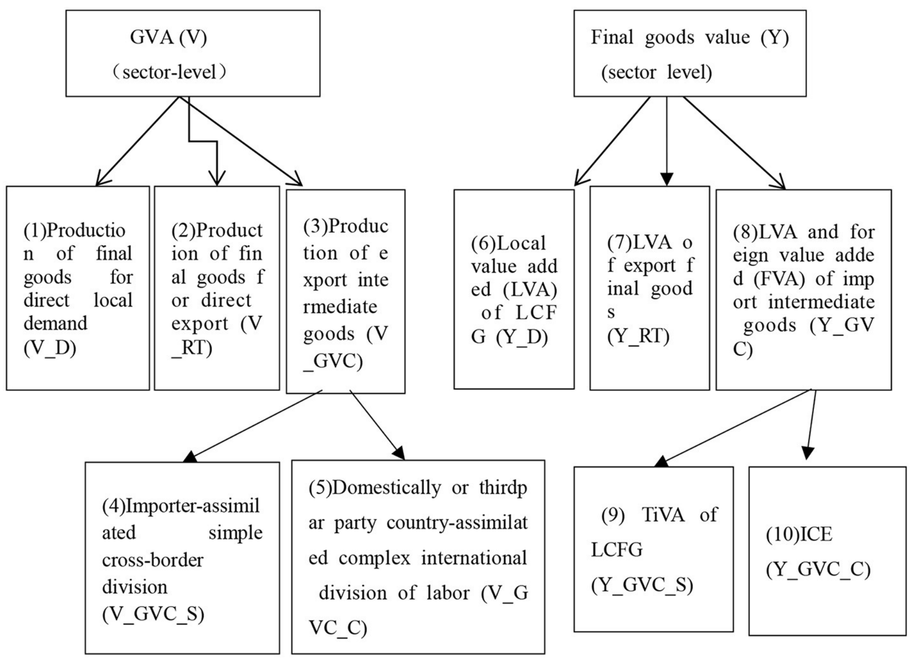

FIGURE 8 | WWYZ decomposition. The left and right drawings show the decomposition of gross value added (GVA) from the perspective of forward industrial linkage and backward industrial linkage, respectively [Source: Wang et al. (31)].

shorter, more scattered and more localized, which makes China exposed to long-term challenges of GVC relocation.

MODELS AND THE INDEX SYSTEM

This part focuses on how to link the GTAP model with the location in division of labor in the GVCs measured based on the TiVA statistical method. Forward GVC participation, backward GVC participation and location in division of labor in the GVCs are constructed to effectively investigate the pandemic's impact on GVC reconfiguration in regard to Chinese manufacturing.

The GTAP model is a global multi-regional computable general equilibrium (CGE) model developed by Purdue University. In regard to application, the database is presented as Eora global multi-region input-output (MRIO) tables with global coverage. The most updated version is GTAP 10 which provides the data about 141 countries and 65 industries, accounting for 98% of the global GDP and 92% of the world's population and covering the world's major economies and segments. Compared with dynamic stochastic general equilibrium (DSGE), the CGE model transmits the external impact through the global multi-region MRIO tables, hence the likeness to the real world. The CGE model finds very wide application in FTAs and government policy simulation. It can be used for the general equilibrium study of such fields as trade, energy, agricultural and tax.

In regard to the division of labor in the international production network, the most common measure of the value chain is the TiVA statistical method which, by combining the traditional Customs statistics with the value added statistics, works out the value added for a single good generated at each stage of the production chain, from raw materials to a final good. Therefore, this paper refers to the decomposition method proposed by Wang et al. (31) and classifies a country's production activities into cross-border non-GVCs and non-cross-border GVCs. At the same time, the paper precisely assesses participation of Chinese manufacturing and its level in division of labor from three perspectives, i.e., forward GVC participation, backward GVC participation and China's level in GVC division of labor.

Wang et al. (31) classified the production activities of a country into purely domestic production activity, traditional international trade, simple GVC activity and complex GVC activity.

$$\begin{aligned}\hat{V}B\hat{Y} &= \hat{V}L\hat{Y}^D + \hat{V}L\hat{Y}^F + \hat{V}LA^F\hat{X} = \hat{V}L\hat{Y}^D + \hat{V}L\hat{Y}^F + \hat{V}LA^F B\hat{Y} \\ &= \hat{V}L\hat{Y}^D + \hat{V}L\hat{Y}^F + \hat{V}LA^F L\hat{Y}^D + \hat{V}LA^F\left(B\hat{Y} - L\hat{Y}^D\right)\end{aligned} \quad (1)$$

Where the sum of the columns indicates the direction of the segment value added of the various countries.

$$va' = \hat{V}BY = \underbrace{\hat{V}LY^D}_{(1)-V\_D} + \underbrace{\hat{V}LY^F}_{(2)-V\_RT} + \underbrace{\hat{V}LA^F LY^D}_{(3a)-V\_GVC\_S} + \underbrace{\hat{V}LA^F\left(BY - LY^D\right)}_{(3b)-V\_GVC\_C} \quad (2)$$

Where the aggregate of the ranks indicates the source of the segment value added of the various countries.

$$Y' = VB\hat{Y} = \underbrace{VL\hat{Y}^D}_{(1)-Y\_D} + \underbrace{VL\hat{Y}^F}_{(2)-Y\_RT} + \underbrace{VLA^F L\hat{Y}^D}_{(3a)-Y\_GVC\_S} + \underbrace{VLA^F(B\hat{Y} - L\hat{Y}^D)}_{(3b)-Y\_GVC\_C} \quad (3)$$

In equation (3), $\underbrace{VL\hat{Y}^D}_{(1)-Y\_D}$ means domestic content of the locally consumed final goods (LCFG), not including foreign value added (FVA); $\underbrace{VL\hat{Y}^F}_{(2)-Y\_RT}$ means domestic content of exports (DCE) which can be seen as traditional trade; $\underbrace{VLA^F L\hat{Y}^D}_{(3a)-Y\_GVC\_S}$ means trade partner-sourced content of LCFG (PLCFG); and $\underbrace{VLA^F\left(B\hat{Y} - L\hat{Y}^D\right)}_{(3b)-Y\_GVC\_C}$ means imports content of exports (ICE). Equation (2) and Equation (3) can be divided into four addends. The first addend on the right of the equation means DVA used to satisfy final domestic demand (FDD; not including FVA), while the second addend means DVA used to satisfy final foreign demand (FFD) and can be seen as traditional trade. Equation (1) and Equation (2) differ in that in the former, $\underbrace{\hat{V}LY^D}_{(1)-V\_D}$ and $\underbrace{\hat{V}LY^F}_{(2)-V\_RT}$ mean the aggregates of value added of the downstream value chain activities of a country's specified sector, and in the latter, $\underbrace{\hat{V}LY^D}_{(1)-V\_D}$ and $\underbrace{\hat{V}LY^F}_{(2)-V\_RT}$ mean the sector's value added which contains value added of all upstream sectors.

Figure 8 shows the decomposition model in detail. Four types of state-sector production activities can be identified from the perspective of whether forward industrial linkage or backward industrial linkage.

The GVC Participation index measures the level of a specified sector of a country in the value chains by calculating the ratio of the sum of indirect value added (IVA) exports and FVA exports, divided by gross exports. Therefore, forward GVC participation and backward GVC participation can be expressed in terms of Equation (4) and Equation (5), respectively.

$$GVCPt_f = \frac{PLv\_GVC\_S}{va'} + \frac{PLv\_GVC\_C}{va'} = \frac{\hat{V}LA^F BY}{va'} \quad (4)$$

$$GVCPt_b = \frac{PLy\_GVC\_S}{Y'} + \frac{PLy\_GVC\_C}{Y'} = \frac{VLA^F B\hat{Y}}{Y'} \quad (5)$$

Forward GVC participation means the GVC-included share of an industry (or sector) of a country or region and reflects the capability of providing intermediate goods for the GVCs. Backward GVC participation means the contribution of domestic and foreign factors of production which participate in global production activities to the final goods value added of the country.

Meanwhile, based on the GVC division of labor method constructed by Koopman et al. (36), the paper measures the level of the division of labor in the GVCs by introducing Equation (4) and Equation (5). See the following equation for details.

$$GVCPS = \ln\left(1 + GVCPt_f\right) \text{-}\ln\left(1 + GVCPt_b\right) \quad (6)$$

Equation (6) presents the level of a specified sector of a country in the GVC division of labor. The higher the level, the closer to the upper-end of the GVCs. Besides, by referring to the methodology of Wang et al. (31), the paper trims the impact of traditional trade and purely domestic production in order to reflect the level of division of labor in the GVCs more precisely.

The standard GTAP model fails to be linked directly with the TiVA decomposition model developed by Wang et al. (31) for several database matching considerations. The first is data form. The GTAP database must be constructed based on the world input-output database (WIOD) tables. An obvious difference of the database from an I-O table is that the former must be leveled and processed in order to be constructed. Considering the difference between the GTAP database and the production decomposition database established by Wang et al. (31), the paper introduces the method developed to convert the GTAP data into the global MRIO tables. The second matching problem is imports distribution. The GTAP model can only simulate the gross trade value of different trade goods at the national level and can't depict in detail the distribution of the imports among different intermediate users and end users in the importing countries.

The database, when decomposed with the KWW method (2017), must depict the distribution proportion of different trade goods of different importing countries. Therefore, the paper introduces fixed proportions, i.e., using distribution coefficient, to the global MRIO model constructed by Johnson and Noguera (37), Meng et al. (38), and Ni and Xia (39), to improve the linkage defect; that is to say, the assumption is that the proportion of an imported good consumed by the different users of a country is equal to the distribution proportion of the production and consumption structure of its domestic counterpart (40).

Considering the inadequacy of current technological and data support, the assumption above is made and the following steps are taken. First of all, use the GTAP model is used for policy simulation for the COVID-19 pandemic. Second, convert the pre-policy and post-policy GTAP simulation results to I-O data in WIOD. Third, based on the TiVA decomposition method proposed by Wang et al. (31), the pre-simulation and post-simulation data in WIOD are decomposed to work out the pre-pandemic and post-pandemic TiVA. Then the policy effect is measured in regard to the impact on China's GVC participation and level of division of labor.

DATABASE AND SCENARIOS

The paper conducts a quantitative analysis based on the GTAP 10 database. The global economy is divided into 141 countries and districts, each having 65 sectors. In order to better simulate the global transmission of the pandemic and measure the impact on GVC reconfiguration at different levels of prevalence, the paper divides the 141 economies into three groups, namely China, developed countries (including the United States, Europe, Japan and South Korea) and other countries, and consolidates the 65 sectors as 46 sectors.

Because the GTAP 10 database takes 2014 as the base period, this paper uses the approaches developed by Walmsley et al. (41) to extend the database to 2020. As a basic solution, the paper introduces the method of Zhou and Zhang (40) to adjust macroeconomic variables (e.g., unskilled & skilled labor, capital, population and GDP) based on CEPII-sourced global forecast data. Notably, the paper adjusts the 2015–2020 data as appropriate in order to ensure data authenticity and database load balancing.

The COVID-19 pandemic broke out first in China, then proliferated to the developed countries and spread increasingly to other countries, including ASEAN countries. In order to systematically simulate the pandemic's impact on GVC participation of the countries and their level of division of labor, the paper the classification approach based on transmission characteristics. Based on the epidemiological theory, Cao et al. (42) characterized the cumulative curve of infection with the logistic curve. The epidemiological study of McKibbin and Fernando (9) assumes that when the pandemic is on a moderate scale, a small scale and a large scale, government spending increase by 0.5, 1.3, and 2.6%, respectively, and that labor supply decreases by 3.4, 7, and 14%. On this basis the paper makes an in-depth computation of national economy fluctuation (the data is provided by National Bureau of Statistics).

Considering the above theory and assumption and the severity of the transmission in the world, four scenarios are established. For the purpose of more credibility and convenience, the paper assumes that the stages of transmission have a deterministic effect on the pandemic's impact on government spending, resident spending and labor supply. Then we use S1, S2, S3, and S4 to represent the simulation results of the above four scenarios

Scenario 1 (S1): The pandemic, in its initial stage, has been relatively prevalent in China, but the government takes effective control measures and prevents it from transmitting to the foreign countries on a large scale.

Scenario 2 (S2): The pandemic begins to transmit to such developed countries as Japan, South Korea, Europe and the U.S. where the pandemic is on a small scale and is more serious than in other countries where the pandemic is on a moderate scale. In China, forceful control measures taken by the government enable the survival of large-scale stage, transforming the pandemic into a small-scale one.

Scenario 3 (S3): In China, the pandemic has been largely brought under control and transforms from a small scale to a moderate scale, while the pandemic has evolved into a full-scale one in such developed economies as Europe and the U.S., entering a large-scale stage; at the same time, the pandemic has transformed from a small scale to a moderate scale.

Scenario 4 (S4): In China the pandemic has been brought under full control. In the developed economies the pandemic has transformed from a large-scale to a small-scale one, while the other countries have entered a large-scale stage.

Besides, in order to ensure model stability and validity, the model should undergo homogeneity & validity testing and calibration. The calibrated model has very good stability and validity, hence its high reliability. Therefore, the paper, based on the calibrated model, further simulates the pandemic's effect on value chain reconfiguration and is linked to the TiVA decomposition model proposed by Wang et al. (31) for an analysis of pandemic's impact on China's GVC participation in GVC reconfiguration.

INTERPRETATION OF SIMULATION RESULTS

The paper simulates and dissects how the likelihood of the spreading COVID-19 pandemic would impact on the world economy. Four scenarios relevant to the four stages of transmission are presented in which the impact on labor supply, consumer spending and fiscal spending is analyzed for the purpose of defining how the pandemic impacts on import & export, trade situation, GDP growth rate and welfare policy. **Table 2** provides more details.

First, the pandemic situation is analyzed in regard to the impact the countries sustain in import & export and trade. There appears to be a major difference among the economies in gross foreign value and trade situation. While we see trade improved in China and the developed countries to some degree, there's a downward trend elsewhere in the world. China has achieved improvements in trade primarily because of the rise in domestic labor cost drives up exports

TABLE 2 | The pandemic's impact on China and other economies.

Scenario	Country	Export changes (%)	Import changes (%)	Net export (million dollars)	Trade situation (%)	GDP growth rate (%)	Social welfare changes (million dollars)
Scenario 1	China	−6.78%	−6.20%	−26798.52	1.34	−4.82	−767011.29
	Developed countries	−0.21	−0.45	19267.29	0.26	0.03	34591.89
	Rest of the world	0.03	−0.52	−8267.73	−0.46	0.02	−29204.68
Scenario 2	China	−4.13	−1.85	−45080.88	1.06	−1.69	−295927.23
	Developed countries	−2.38	−4.32	252729.65	0.25	−4.27	−1851189.20
	Rest of the world	−2.81	−0.97	−97646.85	−0.65	−1.59	−390548.16
Scenario 3	China	−3.88	1.93	−78833.72	1.78	1.63	160086.25
	Developed countries	−3.72	−7.91	619051.44	0.19	−7.58	−3574558.58
	Rest of the world	−5.58	−1.96	−338217.75	−0.93	−3.26	−884977.19
Scenario 4	China	−4.49	2.96	−24992.44	1.35	3.12	348091.56
	Developed countries	−3.369	−4.31	158574.27	0.36	−4.27	−1628015.51
	Rest of the world	−4.51	−6.26	56418.15	−1.01	−6.76	−1857519.26

TABLE 3 | The impact of the pandemic on division of labor in GVC participation of China and its trade partners.

Scenario	Country	Forward GVC participation	Backward GVC participation	GVC division of labor
Scenario 1	The U.S	−1.19%	−1.08%	−0.63%
	Other developed countries	−0.48%	−0.42%	−0.35%
	Rest of the world	−0.02%	−0.12%	0.01%
Scenario 2	The U.S	0.13%	0.81%	−0.36%
	Other developed countries	0.08%	0.32%	−0.09%
	Rest of the world	−0.81%	−0.99%	−0.24%
Scenario 3	The U.S	2.61%	−1.62%	3.79%
	Other developed countries	2.74%	−1.51%	3.43%
	Rest of the world	0.31%	0.16%	0.15%
Scenario 4	The U.S	3.46%	1.27%	2.68%
	Other developed countries	1.79%	0.57%	1.23%
	Rest of the world	2.95%	−2.25%	5.23%

price and therefore trade. The developed countries have also undergone trade improvements to some degree because of price elasticity of exported goods. However, the other countries see trade worsening under the impact of factor price changes.

Second, the pandemic is assessed in regard to its impact on the GDP of the economies. In the context of Scenario 1, the simulation confirms a 4.82% GDP drop. Anyhow, the outbreak of the pandemic in China has no significant impact on the developed countries and other economies, hence a minor spillover effect. In Scenario 3, the outbreak of the disease in the developed economies drives the GDP down by 7.58%, compared with Scenario 4 where the disease drives down the GDP elsewhere in the world by 6.76%.

Table 2 shows in the last column the pandemic's influence on social welfare. Overall, the negative impact of the spreading disease on social welfare .proves to be relatively significant, with China sustaining a loss of around $767 billion in social welfare in Scenario 1, the developed countries sustaining a loss of around $3.57 trillion in Scenario 3, and the other economies sustaining a loss of around $1.86 trillion in Scenario 4.

All the economies, including China, have suffered an economic impact to a varying degree, which is particularly heavy in regard of trade, GDP and social welfare of the developed economies and other economies than China.

The paper measures GVC participation of Chinese manufacturing and the level of division of labor from three perspectives, i.e., forward GVC participation, backward GVC participation and GVC division of labor, based partly on the method of Wang et al. (31). In **Table 3**, the outcome indicates a major difference between China and its various trade partners in regard to GVC participation and level of the division of labor.

In the context of Scenario 1 where the pandemic is prevalent in China, the U.S.–Chinese trade friction combined with the disease results in a great fall in exports to the U.S. and a fall in imports. As China loses the shares of forward participation, backward participation in the U.S. economy and falls in the GVC level of division of labor, part of the low-end manufacturing industry is quickly redirected to the Southeast Asia; at the same time, the U.S. withdraws part of its value chain back out of China.

In Scenario 2, the pandemic has worsened in the developed countries into a small-scale one. While the other countries face

TABLE 4 | The pandemic's impact on different Chinese manufacturing sectors in regard to GVC reconfiguration.

Industry \ variable	Country	Agriculture	Textile	Automotive & parts	Electromechanical equipment	Computer goods	Transport
Forward GVC participation	The U.S	−2.76%	−5.21%	−2.63%	4.36%	4.21%	−5.81%
	Other developed countries	−2.21%	−4.42%	−1.99%	3.51%	3.87%	−4.29%
	Rest of the world	−0.93%	0.56%	−0.83%	2.47%	3.02%	−0.29%
Backward GVC participation	The U.S	−0.13%	−0.82%	−1.65%	−0.61%	−0.68%	−2.92%
	Other developed countries	−2.18%	−3.02%	−1.25%	−0.23%	−0.27%	−2.85%
	Rest of the world	−0.81%	−0.04%	−0.52%	0.61%	0.56%	−0.10%
GVC division of labor	The U.S	−2.63%	−4.32%	−0.78%	4.93%	4.88%	−2.84%
	Other developed countries	−1.98%	−1.31%	−0.73%	3.89%	3.96%	−1.93%
	Rest of the world	−0.53%	0.94%	−0.27%	1.91%	2.24%	0.58%

a moderate-scale stage, forceful containment steps implemented in China alleviate the stress and bring the disease into a small-scale stage. Compared with Scenario 1, the gradually healing Chinese economy climbs up on the GVC level of division of labor, reversing the plummeting trend in both forward GVC participation and backward GVC participation.

In Scenario 3, when the pandemic enters the large-scale prevalent stage in such developed countries as Europe and the U.S. and leads to a stall in economic activities, they turn to China for medical supplies as the Chinese economy already begin gradual recovery. As China resumes trading with the developed economies, e.g., Europe and the U.S., the country's GVC participation level improves in division of labor.

In Scenario 4, China brings the disease under full control, the developed countries enter the small-scale stage and the other countries slide into massive prevalence. In regard to either the developed countries or the other economies, China's forward and backward participation in the GVC division of labor improves to some extent. In the meantime, the prevalence of the pandemic in other countries causes a slump in goods and service purchases by China, therefore resulting in falling backward GVC participation in other economies.

The Impact of Pandemic on Various Sectors in Regard to Value Chain Reconfiguration

This paper is concentrated mainly on how the pandemic affects six sectors of Chinese economy in regard to the GVCs in Scenario 3. The six export sectors include agriculture, textile, automotive & parts, electromechanical equipment, computer goods and transport (**Table 4**). Seen from the perspective of sectoral heterogeneity, the pandemic impacts vary remarkably on different industries in regard to forward and backward GVC participation as well as GVC division of labor. In Scenario 3, the U.S.-led developed economies suffer relatively heavy impacts in terms of GVC participation and level of division of labor. China suffers relatively heavy impacts in agriculture, textile and transport in regard to forward GVC participation, a symbol that compromises the capacity of supply of primary or intermediate goods to other countries. Still, economic resumption drives China to take the lead and contribute to robust growth, which furthers its backward GVC participation.

Overall, the pandemic is proven to reconfigure GVC participation and division of labor. Pretty good disease control policy causes China to be the first of all countries to recover economy, thereby furthering its level of division of labor in GVC participation in regard to in electromechanical equipment, computer goods and other sectors where it commands global competitive advantages.

CONCLUSION AND POLICY ADVICE

The outbreak of the pandemic brings impacts to China's level of division of labor on the GVCs, therefore contributing to China's forward GVC participation and furthering the level of division of Chinese manufacturing on the GVCs, although the impact varies greatly in different economic sectors.

The conclusion proposed in the paper is of great policy concern. First, the Covid-19 should be considered not only as a challenge but also an opportunity to actively promote multilateral interaction and build a regional value chain led by China, Japan and South Korea. China should play a leading role in the negotiations on the Regional Comprehensive Economic Partnership (RCEP), promote the building of a high-quality free trade area, strengthen cooperation with neighboring countries, and put in place a regular dialogue mechanism on supply chain security. At the same time, China should combine global value chain cooperation with the construction of "Belt & Road" Initiative, encouraging involved countries to strengthen the construction of supply chain system. Second, it is pointed out that in-depth structural reform should be carried out and measures taken in an effort to retain the foreign investors. At the present time, the Chinese government has implemented numerous policies to retain the foreign investors and relieve the stress of the pandemic on them. However, the foreign enterprises seek for more fundamental changes in the Chinese market, including more transparency, predictability and equality concerning in regard to regulation procedures. Therefore, more measures should be taken to boost innovation and create a competitive, business-friendly environment. Third, China should take more proactive actions in response to supply chain reconfiguration while implementing the strategy of overseas investment in manufacturing. Based on a short-term perspective, it is vitally important for China to take advantage of the opportunities from global economy recovery. Policies should be made to retain foreign investors in China and stabilize the bilateral trade relations. Based on a long-term perspective, China should make innovations of its own. As the Chinese enterprises improve innovation capability, there will be a downtrend in core technological dependence on the U.S. and an uptrend in delivering goods and services in place of import. At the same time, China should step up efforts to promote M&As and corporate reorganizations as part of the Belt and Road Initiative, add more to the GVCs, and increasingly consolidate the pivotal role of a world-class economy.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found at: https://comtrade.un.org.

AUTHOR CONTRIBUTIONS

YS: conceptualization, methodology, formal analysis, writing—original draft preparation, and funding acquisition. XH: data processing, formal analysis, and writing—original draft preparation. YH: data processing and formal analysis. ZL: conceptualization, project management, writing–review and editing, and funding acquisition. All authors contributed to the article and approved the submitted version.

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REFERENCES

1. OECD. *OECD Economic Outlook*. OECD Publishing, (2020) 2020. doi: 10.1787/39a88ab1-en
2. Antràs P. *De-Globalisation? Global Value Chains in the Post-COVID-19 Age*. Massachusetts, MA: National Bureau of Economic Research (2020). doi: 10.3386/w28115
3. Gozgor G. Robustness of the KOF index of economic globalisation. *World Econ*. (2018) 41:414–30. doi: 10.1111/twec.12546
4. Keogh-Brown MR, Smith RD. The economic impact of SARS: How does the reality match the predictions? *Health Policy*. (2008) 88:110–20. doi: 10.1016/j.healthpol.2008.03.003
5. Verikiosa G, McCaw JM, McVernon J, Anthony H. H1N1 Influenza and the Australian macro-economy. *J Asia Pacif Economy*. (2012) 17:22–51. doi: 10.1080/13547860.2012.639999
6. Bloom DE, Mahal AS. Does the AIDS epidemic threaten economic growth? *J Econo*. (1997) 77:105–24. doi: 10.1016/S0304-4076(96)01808-8
7. Brainerd E, Siegler MV. The Economic Effects of the 1918 Influenza Epidemic. CEPR Discussion Papers. (2003).
8. Prager F, Wei D, Rose A. Total economic consequences of an influenza outbreak in the United States. *Risk Anal*. (2017) 37:4–19 doi: 10.1111/risa.12625
9. McKibbin W, Fernando R. The Global macroeconomic impacts of COVID-19: seven scenarios. *SSRN Electron J*. (2020) 19. doi: 10.2139/ssrn.3547729
10. Alvarez FE, Argente D, Lippi F. *A Simple Planning Problem for Covid-19 Lockdown*. Massachusetts, MA: NBER Working Papers from National Bureau of Economic Research (2020). doi: 10.3386/w26981
11. Jones CJ, Philippon T, Venkateswaran V. *Optimal Mitigation Policies in a Pandemic: Social Distancing and Working from Home*. Massachusetts, MA: NBER Working Papers from National Bureau of Economic Research (2020). doi: 10.3386/w26984
12. Baker SR, Bloom N, Davis SJ, Terry SJ. *COVID-Induced Economic Uncertainty*. Massachusetts, MA: NBER Working Papers from National Bureau of Economic Research (2020). doi: 10.3386/w26983
13. Fornaro L, Wolf M. *Covid-19 Coronavirus and Macroeconomic Policy: Some Analytical Notes*. Economics Working Papers from Barcelona Graduate School of Economics (2020).
14. Shahbaz M, Gozgor G, Adom PK, Hammoudeh S. The technical decomposition of carbon emissions and the concerns about FDI and trade openness effects in the United States. *Int Econ*. (2019) 159:56–73. doi: 10.1016/j.inteco.2019.05.001
15. Dallas MP, Horner R, Li L. The mutual constraints of states and global value chains during COVID-19: The case of personal protective equipment. *World Dev*. (2021) 139:105324. doi: 10.1016/j.worlddev.2020.105324
16. Gereffi G. What does the COVID-19 pandemic teach us about global value chains? The case of medical supplies. *J Int Business Policy*. (2020) 3:287–301. doi: 10.1057/s42214-020-00062-w
17. Gourinchas PO. *Flattening the Pandemic and Recession Curves. In Mitigating the OVID Economic Crisis: Act Fast and Do Whatever*. London: CEPR Press (2020).
18. Baldwin B, DI Mauro BW. *Mitigating the COVID Economic Crisis: Act Fast and Do Whatever It Takes*. London: CEPR Press (2020).
19. Brightman, C. KOA, Treussard J. *Oh My! What's This Stuff Really Worth? Advisors Perspectives*. (2020). Available online at: https://www.Advisorperspectives.com/commentaries (accessed March 5, 2020).
20. Ayitte FK, Ayittey MK, Chiwero NB, Kamasah JS. Economic impacts of Wuhan 2019-nCoV on China and the world.*J Med Virol*. (2020) 92:473–5. doi: 10.1002/jmv.25706
21. Liu ZB. The new trend of economic globalization and the reconstruction of global industrial chain clusters under the COVID-19 pandemic. *Jiangsu Soc Sci*. (2020) 4:16–23. doi: 10.13858/j.cnki.cn32-1312/c.2020.04.001
22. Zhi Y, Luo CY. The impact of COVID-19 pandemic on China economy and its thinking. *Study Exploration*. (2020) 4:99–105.
23. Liu ZB. The impact of COVID-19 epidemic on China's industries: characteristics, risks & policy recommendations. *Southeast Acad Res*. (2020) 3:42–47. doi: 10.13658/j.cnki.sar.2020.03.005
24. Tong JD, Sheng B, Jiang DC, Yan B, Dai JP, Liu C. Global economy amid the COVID-19 outbreak and challenges for China. *Int Econ Rev*. (2020) 3:9–28–4.
25. Wen Y, Zhang T, Du QY. *Quantifying the COVID-19 Economic Impact*. Infinite-Sum Modeling Inc Working Papers (2020). doi: 10.2139/ssrn.3546308
26. Hayakawa K, Mukunoki H. Impacts of Covid-19 on global value chains. *Dev Econ*. (2020). doi: 10.1111/dpr.12539
27. Song Y, Hao F, Hao X, Gozgor G. Economic policy uncertainty, outward foreign direct investments, and green total factor productivity: evidence from firm-level data in China. *Sustainability*. (2021) 13:2339. doi: 10.3390/su13042339

28. Can M, Gozgor G. Effects of export product diversification on quality upgrading: an empirical study. *J Int Trade Econ Dev.* (2018) 27:293–313. doi: 10.1080/09638199.2017.1370006
29. Lin S, Xiao L, Wang X. Does air pollution hinder technological innovation in China? A perspective of innovation value chain. *J Clean Product.* (2021) 278:123326. doi: 10.1016/j.jclepro.2020.123326
30. Zhou XH, Li YZ, Li FY. Assessment and measures of the influence of COVID-19 epidemic on small and medium service enterprises: forecast and analysis based on the optimal regression algorithm model. *Econ Rev.* (2020) 3:101–17. doi: 10.19361/j.er.2020.03.07
31. Wang Z, Wei SJ, Yu X. *Measures of Participation in Global Value Chains and Global Business Cycles.* Massachusetts, MA: NBER Working Papers from National Bureau of Economic Research (2017). doi: 10.3386/w23222
32. Shen GB. The impacts of the COVID-19 pandemic on international trade and reponses to it. *Renming Luntan·Xueshu Qianyan.* (2020) 7:85–90. doi: 10.16619/j.cnki.rmltxsqy.2020.30.005
33. Hong J, Zhong XH. Research on new trends in global value chains in the context of the COVID-19 and Sino-US trade disputes. *Intertrade.* (2020) 9:4–13. doi: 10.14114/j.cnki.itrade.2020.09.002
34. Hong J. An overview of the choice of path for dealing with the escalating sino-US trade friction based on the new characteristics of US trade investigation against China. *Area Stud Glob Dev.* (2019) 3:102–22.
35. Jiang F, Yan QM. A summary of essays on "the impact of the COVID-19 pandemic on China's economy" by scholars of department of economics, Peking university. *Econ Sci.* (2020) 2:130–6.
36. Koopman R, Powers W, Wang Z, Wei SJ. *Give Credit Where Credit is Due: Tracing Value Added in Global Production Chains.* (2010). doi: 10.3386/w16426
37. Johnson RC, Noguera G. Accounting for intermediates: production sharing and trade in value-added. *J Int Econ.* (2012) 86:224–36. doi: 10.1016/j.jinteco.2011.10.003
38. Meng B, Wang Z, Koopman R. How are global value chains fragmented and extended in China's domestic production networks?. *IDE Discussion Papers* (2013).
39. Ni HF, Xia JC. The role of China regions and its changes in the global value chains—based on world input-output model embedded with China regions. *Finance Trade Econ.* (2016) 37:87–101. doi: 10.19795/j.cnki.cn11-1166/f.2016.10.009
40. Zhou LL, Zhang KY. Study of reconstruction of Chinese global value chains participation on COVID-19. *Mod Indust Econ.* (2020) 6:5–15. doi: 10.19313/j.cnki.cn10-1223/f.2020.06.002
41. Walmsley TL, Betina VD, Robert AM. A Base case scenario for dynamic GTAP model.GTAP. *Resource.* (2006) 417:1–14.
42. Cao SL, Feng PH, Shi PP. Study on the epidemic development of COVID-19 in Hubei province by a modified SEIR model. *J Zhejiang University.* (2020) 49:178–84. doi: 10.3785/j.issn.1008-9292.2020.02.05

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Work Resumption Rate and Migrant Workers' Income During the COVID-19 Pandemic

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The COVID-19 public health crisis has quickly led to an economic crisis, impacting many people and businesses in the world. This study examines how the pandemic affects workforces and workers' income. We quantify the impact of staggered resumption of work, after the coronavirus lockdowns, on the migrant workers' income. Using data on population movements of 366 Chinese cities at the daily level from the Baidu Maps-Migration Big Data Platform and historical data on the average monthly income of migrant workers, we find that the average work resumption rate (WRR) during the period of the Chinese Lantern Festival was 25.25%, which was only 30.67% of that in the same matched lunar calendar period in 2019. We then apply Gray Model First Order One Variable [GM (1, 1)] to predict the monthly income of migrant workers during the period of the COVID-19 pandemic. We show that, if without the influence of the COVID-19 pandemic, the average monthly income of migrant workers in 2020 will be expected to increase by 12% compared with 2019. We further conduct scenario analysis and show that the average monthly income of migrant workers in 2020 under the conservative scenario (COS), medium scenario (MES), and worse scenario (WOS) will be predicted to decrease by 2, 21, and 44%, respectively. Through testing, our prediction error is <5%. Our findings will help policymakers to decide when and how they implement a plan to ease the coronavirus lockdown and related financial support policies.

Keywords: COVID-19, migrant worker, work resumption rate, income, scenario analysis

INTRODUCTION

In December 2019, a novel coronavirus disease (COVID-19 for short) appeared in Wuhan, China (1, 2). Then, in early 2020, COVID-19 followed in other parts of the world. As of March 22, 2021, there are approximately 123.87 million confirmed cases of COVID-19 in nearly 200 countries and about 2.73 million people have lost their lives. The effective prevention and control measures of this epidemic should become the top priority of all governments around the world. The Chinese government activated first-level emergency response in order to deal with the outbreak of this epidemic. A series of unprecedented measures, such as city blockade, suspending public transport, imposing gathering and movement restrictions, extended school closures, and factory suspensions, has been implemented rapidly to contain and delay the spread of the COVID-19 (3, 4). China has managed to contain the virus through the use of those draconian control measures, but at a heavy price. The economic fallout from this pandemic is threatening China and global growth and financial stability. Business activity has ground to a halt in most sectors such as aviation, travel, and tourism. Unemployment soars significantly. After months of lockdown in China, the government is slowly easing emergency measures. Industries are allowed to reopen and people are returning to work. But, officials and analysts remain concerned about the negative outlook for China's economic growth in 2020 and in particular about the strain a downturn would have on rural areas and low-income regions. Therefore, it is very important to assess the impact of the COVID-19 on the Chinese labor market and low-income groups, such as migrant workers who most likely lost their jobs during this crisis, in order to provide empirically based implications for government policies that aim to orderly organize workers to resume work and production and guarantee farmers' income after the epidemic alleviates.

According to the National Bureau of Statistics, migrant workers make up about one-third of China's vast workforce. The number of migrant workers reached nearly 291 million in 2019, with 60% of them employed outside the countryside and in cities that may be far away from their official home base (5). Affected by the COVID-19, the Chinese government has taken measures to restrict population mobility (3, 4), and many industries have also been forced to shut down and postpone resumption of work. The outbreak of COVID-19 and the control measures of the Chinese government have put forward higher requirements for the survivability of small- and medium-sized enterprises (SMEs), which are the main carriers of migrant workers. If SMEs go bankrupt, a large number of migrant workers will face the risk of unemployment, thus triggering a social employment crisis and threatening the stability of the entire society.

Moreover, the impact on the income of migrant workers will bring huge pressure to increase farmers' income. In 2019, the per capita disposable income of rural residents in China was $2,322.39. Among wage income, operating income, net property income, and net transfer income, the wage income accounts for the largest proportion, which is 41% (5). Therefore, it is not difficult to infer that the impact of the epidemic on migrant workers will directly affect the farmers' annual income. Secondly, as the main population that flows during the Chinese Spring Festival, migrant workers are affected by factors such as economic conditions, social security, ability of information access, community support, etc., so they are at high risk and highly vulnerable during the epidemic. Compared with public institution staff, they almost have no social security. Once the risk comes, it's even worse. We can foresee that if tens of thousands of migrant workers return to work without any hope, it will not only cause large-scale farmers returning to poverty but also lead to losing a strong support for building a moderately prosperous society in all respects. The consequences could be disastrous.

In China, the employment and income issues of nearly 300 million migrant workers have received considerable attention from government and researchers. China has witnessed deepening reform and a continuous, large-scale exodus of rural labor since the Reform of 1978 (6, 7). Rural labor was gradually showing a trend toward the private sector (8) and trans-regional and urban areas (9, 10). While the labor force was transferred from the countryside to the city, the employment industry of the rural labor force has expanded from agriculture to non-agricultural fields. The non-agricultural employment of agricultural population provided hundreds of millions of labor force for China's economic development and promoted rapid development of the economy (11–15).

The regular mobility of migrant workers', especially seasonal mobility, is an important condition to ensure the full employment. If the mobility is restricted, it is difficult to secure their jobs. Some scholars pointed out that when public emergencies broke out, the flow of migrant workers was mainly restricted by objective factors such as the adjustment of government policies and the adjustment of internal employment plans of the enterprise. At the same time, cost-cutting initiatives such as requiring staff to take unpaid leave, terminating temporary contracts, and stopping all overtime payments were also adopted by enterprises in order to reduce the impact of public emergencies (16, 17). In addition to objective factors such as external policies and internal adjustments of enterprises, the subjective reluctance of farmers to go out is also an important factor affecting work resumption. After the outbreak of public health emergencies, population mobility is restricted, labor input of enterprises is reduced, and both the industry and national economic output will decrease (18–21). Among them, the secondary industry, which is dominated mainly by manufacturing and construction industries (22–24), and the tertiary industry, such as tourism and catering, which absorbs a large amount of rural surplus labors (16, 25–27), have suffered the most obvious impact (28, 29). Furthermore, some scholars have focused their attention on the analysis of factors affecting the employment of migrant workers. Huang et al. (30) found that migrant workers who are older and less educated are more likely to be unemployed, and workers in industry and construction are more likely to be unemployed than workers in the service sector. Wang (31) also pointed out that gender differences would not affect the unemployment of migrant workers but would affect their willingness to move again. It is not difficult to find that when public health emergencies such as the COVID-19 become stable, the resumption of work will be affected by the epidemic prevention and control policies issued by the government, the adjustment of the internal employment plan of enterprises, and the social panic caused by the epidemic.

However, farmers' income is also closely related to their level of education and skills. Wong et al. (32) pointed out that job mobility among migrant workers is very low since the majority of migrant workers are uneducated and do not have special skills. From the perspective of consumption structure, due to the low-income level of migrant workers, the household consumption structure has been dominated by subsistence consumption, household subsidies, and improvement of living conditions (33, 34). Moreover, due to the unique household registration system of China, even if migrant workers have worked in the city for many years, they cannot enjoy the same treatment as urban residents (35, 36), and they may even suffer employment discrimination (32, 37, 38). Compared with the great contribution of migrant workers to urban economic development, the public services and welfare provided by the urban sector to them are very limited. Even if the Chinese government has gradually relaxed the Hukou regulation and instituted a variety of reforms to the household registration system (39), the social, political, and economic disadvantage of migrant workers will not be changed in a short term due to the size of cities and their skills (22, 31, 40). Thus, the risk tolerance of migrant workers is generally weak (33, 40), and it is difficult to withstand the impact of public health emergencies such as COVID-19 with their own strength. Chan (22) also pointed out that migrant workers are extremely vulnerable to external uncertainties (such as the financial crisis), which will result in sudden unemployment and thus impact their income level. Pan et al. (41) believed that COVID-19 has severely affected the famers' wage income and agricultural income, and it may cause about $100 billion in losses.

In conclusion, we can find that the existing research has made some progress in the impact of emergencies such as natural disasters and financial crisis on labor employment and farmers' income. However, there are significant differences between the impact of COVID-19 and the research above. First, earthquake, financial crisis, and other emergencies cannot cause large-scale population mobility restriction. The impact on the employment of labor and the income of migrant workers is shown as local and regional characteristics. Second, most of the existing literature review and summarize the impact of the event on labor employment or farmers' income after the event. There are few papers that, when the incident occurs, based on the development of the epidemic situation and the level of policy response, promptly measure its impact on the return of labor to work and the income of migrant workers.

In order to evaluate the impact of the COVID-19 on the Chinese labor market and the income of migrant workers who are in a highly vulnerable situation, we obtain the migration data of 366 prefecture-level cities and municipalities directly under the central government from the Baidu migration map in 2019 and 2020 by using the web crawler technology. We then calculated the work resumption rate (i.e., WRR) of migrant workers without COVID-19 in 2019 and with COVID-19 in 2020. Furthermore, we evaluated the impact of the COVID-19 on migrant workers. On this basis, according to the emergency response level of the COVID-19, the average monthly income of migrant workers under conservative, medium, and worse scenarios has been predicted by using the scenario analysis method. We also compared the forecast results with the actual income data of migrant workers in order to test the robustness. Finally, this paper provided countermeasures and suggestions for the labor force to return to work after the epidemic alleviates. Our result shows that the migrant workers' income will increase by 12% compared with 2019 if there is no outbreak of the COVID-19 pandemic. The average monthly income of migrant workers will be slightly affected by the epidemic under the conservative scenario (COS) and it is predicted to decrease by 2%. Then, as time passed, the impact of COVID-19 on migrant workers' income will gradually increase if migrant workers still cannot return to work. Also, their average monthly income is predicted to decrease by 21 and 44% under the medium scenario (MES) and worse scenario (WOS), respectively. The contributions of this paper are as follows: First, we successfully predicted the migrant workers' income in 2020, which are not affected by the COVID-19 with a small sample size by using the Gray Model First Order One Variable [GM (1, 1)] method. Second, we realized the prediction of the impact of restrictions on population flow due to emergencies on migrant workers' income. Third, our model can effectively predict the impact of COVID-19 on migrant workers' income by comparing with the official data published by the National Bureau of Statistics, and it can be used for reference by other countries.

The structure of this paper is organized as follows: The Methodology section introduces the methodology. The Empirical Analysis and Discussions section gives the empirical analysis. The Conclusion and Policy Implications section is the conclusion and policy implications.

METHODOLOGY

In this section, this paper introduced the modeling process of COVID-19 impact on return to work of China's rural labor and migrant workers' income. Firstly, this paper selected the two time points of the Chinese Lunar New Year and the Lantern Festival to calculate the WRR according to the Baidu migration daily data. Secondly, according to the historical data, this paper predicted the average monthly income of migrant workers in 2020 under the inertial scenario (INS) (without the impact of the COVID-19) by using the GM (1, 1) method. Finally, by using the scenario analysis method, this paper predicted the average monthly income of migrant workers in three scenarios: conservative scenario (COS), medium scenario (MES), and worse scenario (WOS).

The Impact of the COVID-19 on the Return to Work of China's Rural Labor

According to the traditional customs of China, people need to take a bus from the work site to their hometown and get together with their families for the Spring Festival. After that, they can return to work, and most schools begin classes after the Lantern Festival (the 15th day of the first month of the lunar year). Therefore, this paper can select the Spring Festival and the Lantern Festival as two dividing points. By using data from the Baidu migration map, the city's daily population immigration and emigration data can be obtained (42). Then, we can obtain the WRR for each city. Since the outbreak of the COVID-19 occurred in late January 2020, and January 25 is the Spring Festival, we can use the data of a city's moving-out population before the Spring Festival as the data of labor returning home and the data of the city's moving-in population during the Spring Festival to the Lantern Festival as the data of returning workers.

The ratio of returning to work in this city during the period of Chunyun[1] can be approximated.

Let $\underset{t_1 \to t_2}{r_{in}} = \sum_{i=1}^{m} \underset{t_1 \to t_2}{r_{i,in}}$ be the sum of population immigration indexes of all cities in a certain region in the period from t_1 to t_2. $\underset{t'_1 \to t'_2}{r_{out}} = \sum_{i=1}^{n} \underset{t'_1 \to t'_2}{r_{i,out}}$ denotes the sum of population emigration indexes of all cities in the period from t'_1 to t'_2. $\underset{t_1 \to t_2}{r_{i,in}}$ is the population immigration index of the i^{th} city in the period from t_1 to t_2. $\underset{t'_1 \to t'_2}{r_{i,out}}$ is the population emigration index of the i^{th} city in the period from t'_1 to t'_2. The WRR r can be given by

$$r = \frac{\underset{t_1 \to t_2}{r_{in}}}{\underset{t'_1 \to t'_2}{r_{out}}} = \frac{\sum_{i=1}^{m} \underset{t_1 \to t_2}{r_{i,in}}}{\sum_{i=1}^{n} \underset{t'_1 \to t'_2}{r_{i,out}}} \tag{1}$$

where, Equation (1) is the ratio of the population immigration index r_{in} in the period from t_1 to t_2 and the population emigration index r_{out} in the period from t'_1 to t'_2. It can be used to calculate the WRR. The WRR of the same city in 2019 and 2020 can be used to compare the impact of COVID-19 on workers returning to work. At the same time, we can also make a horizontal comparison between different cities in the same period to find out the difference of impact of the COVID-19 on different cities' WRR.

It should be pointed out that Equation (1) satisfies two basic assumptions. Assumption 1: the demographic structure has not changed much within the selected period. Assumption 2: the purpose of population mobility is relatively single. At present, both of the two hypotheses are established in China. From January 2020 to March 2020, China's population structure does not change much. In addition, China has to experience the Chunyun during the Spring Festival every year. That is to say, people return to their hometown from the city where they work to celebrate the Chinese New Year and then return to the city after the New Year. Therefore, the purpose of population mobility is relatively single. Especially, after the outbreak of the COVID-19, China has taken very strict measures to restrict population mobility, and unnecessary business trips, family visits, and students' return to school have been temporarily banned before the end of February. Then, the main purpose of large-scale population mobility is to return to work.

The Prediction of the Impact of the COVID-19 on the Income of Migrant Workers

Firstly, we provided the definitions of migrant workers and the average monthly income of migrant workers. Migrant workers refer to the workers who are employed outside their villages and towns for more than 6 months in the year and those who do non-agricultural work in or outside their villages and towns for more than 6 months (5). The average monthly income of migrant workers refers to the average monthly monetary wage of each migrant worker in a certain period. Then, this paper analyzed the impact of the COVID-19 on the income of migrant workers from two aspects. On the one hand, the history data of the migrant workers' income was used to predict the migrant workers' income in 2020. Because the income of migrant workers is not affected by the COVID-19 under this scenario, this paper called it as the prediction of migrant workers' income under the inertia scenario (INS). On the other hand, according to the impact of the epidemic on migrant workers' working time, we considered three scenarios, namely, conservative scenario (COS), medium scenario (MES), and worse scenario (WOS), and predicted the average monthly income of migrant workers in different scenarios.

The Prediction Model of Migrant Workers' Income in INS

In the prediction, we found that the sample size of the average monthly income of migrant workers was small. It is due to the annual data of the average monthly income of migrant workers published by the National Bureau of Statistics since 2009. This is consistent with the property of the GM (1, 1) method that can get the high prediction accuracy for the uncertain system with a small sample and poor information (43, 44). A multistep approach for using GM (1, 1) to predict the average monthly income of migrant workers is now presented.

Step 1: the raw data accumulation of monthly average income of migrant workers X_t.

Let $X_0\ (t)$ be the average monthly income of migrant workers in the tth year and $t = 1, 2, \ldots, n$. Given the original data series of monthly average income of migrant workers $X_0 = \{X_0\ (1), X_0\ (2), \ldots, X_0\ (n)\}$, the X_0 is accumulated to generate the series X_1.

$$X_1 = \{X_1(1), X_1(2), \ldots, X_1(n)\} \tag{2}$$

Where $X_1(t) = \sum_{i=1}^{t} X_0(i)$

Step 2: establish the data matrix B and series Y_n

$$B = \begin{bmatrix} -0.5(X_1(1) + X_1(2)) & 1 \\ \ldots \quad \ldots & \ldots \quad \ldots \\ -0.5(X_1(n-1) + X_1(n)) & 1 \end{bmatrix} \tag{3}$$

$$Y_n = \begin{bmatrix} X_0(2) \\ \ldots \\ X_0(n) \end{bmatrix} \tag{4}$$

Step 3: calculate parameters a and u of the GM (1, 1) model

$$\begin{bmatrix} a \\ u \end{bmatrix} = \left(B^T B\right)^{-1} B^T Y_n \tag{5}$$

where, B^T is the transpose matrix of B and $(B^T B)^{-1}$ is the inverse matrix of $B^T B$ in Equation (5).

[1]The Ministry of Transport of the People's Republic of China announces the specific time of the Chunyun every year. Generally, the Chunyun lasts for 40 days. The Chunyun in 2019 starts from January 21 to March 1, and the Chunyun in 2020 starts from January 10 to February 18 (http://www.mot.gov.cn/difangxinwen/xxlb_fabu/fbpd_hubei/201901/t20190118_3158463.html; http://www.mot.gov.cn/difangxinwen/xxlb_fabu/fbpd_guangdong/201912/t20191227_3314427.html).

TABLE 1 | The average monthly income of migrant workers under different scenarios.

Scenario category	Definition	Prediction of the average monthly income of migrant workers X_0 (*t*)
Scenario 1: conservative scenario (COS)	Affected by the NCP, migrant workers cannot go out to work for 1–2 months, which has a slight impact on farmers' income.	Based on the prediction of the average monthly income $X_0(t)$ of migrant workers by the GM (1, 1) method in the INS, the income of migrant workers under the slight impact is as follows: $X_0(t)_{COS} = X_0(t) \times (12 - a)/12$.
Scenario 2: medium scenario (MES)	Affected by the NCP, migrant workers cannot go out to work for 3–4 months, which has a moderate impact on farmers' income.	Based on the prediction of the average monthly income of migrant workers $X_0(t)$ by the GM (1, 1), the income of migrant workers under the moderate impact is as follows: $X_0(t)_{MES} = X_0(t) \times (12 - b)/12$.
Scenario 3: worse scenario (WOS)	Affected by the NCP, migrant workers cannot go out to work for half a year, which has a serious impact on farmers' income.	Based on the prediction of the average monthly income of migrant workers $X_0(t)$ by the GM (1, 1), the income of migrant workers under the serious impact is as follows: $X_0(t)_{WOS} = X_0(t) \times (12 - c)/12$.

Step 4: calculate the cumulative generation predicted value $\hat{X}_1(t)$ of the average monthly income of migrant workers in the *t*th year. It can be given by

$$\hat{X}_1(t) = \left[X_0(1) - \frac{u}{a}\right] e^{-a(t-1)} + \frac{u}{a} \tag{6}$$

In Equation (6), $X_0(1)$ is the first data in the original data series X_0. Substituting $t = 1, 2, \ldots, n$ into Equation (6), respectively, we can get the cumulative generation predicted value $\hat{X}_1(1)$, $\hat{X}_1(2)$, $\ldots$, $\hat{X}_1(n)$ of the average monthly income of migrant workers.

Step 5: the accumulated predicted value $\hat{X}_1(t)$ is used to calculate the predicted value $\hat{X}_0(t)$ of the average monthly income of migrant workers in the *t*th year. That is

$$\hat{X}_0(t) = \hat{X}_1(t) - \hat{X}_1(t-1) \tag{7}$$

Step 6: calculate the average error δ

By comparing the predicted income $\hat{X}_0(t)$ of migrant workers with the real income $X_0(t)$, the average error rate $\delta = \frac{1}{n}\sum_{t=1}^{n}\frac{\left|\hat{X}_0(t)\text{-}X_0(t)\right|}{X_0(t)}$ of the GM (1, 1) model can be calculated. If $\delta < 5\%$, we can use Equation (7) to predict the average monthly income of migrant workers in 2020. Otherwise, the model needs to be readjusted.

Income Prediction of Migrant Workers Based on Scenario Analysis

Combining the emergency response level of Chinese public health emergencies (special major class-I, major class-II, larger class-III, and general class-IV) with the scenario analysis method (45, 46), we can divide the impact of the epidemic on migrant workers into three scenarios.

Conservative Scenario

Affected by restrictions on population mobility caused by the COVID-19, farmers cannot go out to work for 1–2 months under COS. At this time, we suppose a is the number of months when farmers cannot go out to work under the COS. Then, the monthly average income $X_0(t)_{\mathrm{COS}}$ of migrant workers under COS can be given by $X_0(t)_{\mathrm{COS}} = X_0(t) \times (12 - a)/12$.

Medium Scenario

Affected by restrictions on population mobility caused by the COVID-19, farmers cannot go out to work for 3–4 months under the MES. We suppose b is the number of months when farmers cannot go out to work under the MES. Then, the monthly average income of migrant workers under MES can be obtained by $X_0(t)_{\mathrm{MES}} = X_0(t) \times (12 - b)/12$.

Worse Scenario

Affected by restrictions on population mobility caused by COVID-19, farmers cannot go out to work for at least half a year under the WOS. We suppose c is the number of months when farmers cannot go out to work under the WOS. Then, the monthly average income of migrant workers under WOS is $X_0(t)_{\mathrm{WOS}} = X_0(t) \times (12 - c)/12$. The predictions of the average monthly income of migrant workers under different scenarios are shown in **Table 1**.

By comparing the average monthly income of migrant workers in 2020 calculated by three scenarios with the actual monthly income of migrant workers in 2019, we can analyze the impact of the COVID-19 on the income of migrant workers. Furthermore, it provides data support and suggestions for the Chinese and local governments to issue policies to return to work and protect farmers' income.

It is worth noting that due to the different policies and prevention efforts of COVID-19, the epidemic situation varies from country to country. The setting of different scenarios is the anticipation of the epidemic situation in the country. Thus, the duration of different scenarios, i.e., the range and value of parameters a, b, and c, can be changed in other countries.

EMPIRICAL ANALYSIS AND DISCUSSIONS

Evaluation of the Impact of the COVID-19 on the Return to Work

Data

In order to compare the impact of the COVID-19 on the return to work of China's rural labor, we used the Baidu migration map (42) to obtain the data of population migration in and out of 366 cities in mainland China before and after the Spring Festival in 2020, as well as the matched data from the same lunar calendar period in 2019. These 366 cities include four municipalities (i.e., Beijing, Tianjin, Shanghai, and Chongqing) and another 334 prefectural-level cities and 28 county-level cities directly administered by the provinces.[2]

Since the outbreak of the COVID-19 in China started in Wuhan on January 23, 2020, we obtained the data of population immigration and emigration of 366 cities in China from January 10 (the start date of the Chunyun) to March 1, 2020. At the same time, in order to compare the impact of the COVID-19 on the return to work of China's rural labor in various cities in China, we obtained the migration data of 366 cities across China from January 21 (the start date of the Chunyun) to February 19 (the Lantern Festival) in 2019.

Calculation of the Impact of COVID-19 on the Return to Work of Rural Labor

First, this paper compared the impact of the COVID-19 on the return to work of China's rural labor by using the migration data on the Lantern Festival in 2019 and 2020. January 25, 2020 is the Spring Festival of the Chinese lunar calendar, February 8, 2020 is the Lantern Festival, and the Chunyun starts from January 10, 2020. Taking the sum of the migration out data before the Spring Festival from January 10 to January 24, 2020 as the denominator of Equation (1) and taking the migration in data from January 25 to February 8, 2020, the Spring Festival to the Lantern Festival, as the numerator of Equation (1), we can calculate the WRR of 366 cities as of February 8, 2020 (Chinese Lantern Festival), as shown in **Table 2**. It can be found that the average WRR of 366 cities at the end of February 8, 2020 was 25.25%.

Similarly, February 5, 2019 is the Spring Festival of the Chinese lunar calendar. February 19, 2019 is the Lantern Festival, and the Chunyun of 2019 starts from January 21, 2019. Taking the sum of the migration out data from January 21, 2019 to February 4, 2019 as the denominator of Equation (1) and taking the migration in data from February 5, 2019 to February 19, 2019 as the numerator of Equation (1), the WRR of 366 cities as of February 19, 2019 (Chinese Lantern Festival) can be obtained, as shown in the last column of **Table 2**. The average WRR of 366 cities as of February 19, 2019 was 82.34%. We found that the average WRR of China in 2020 was only 30.67% of that in the same period affected by COVID-19. We have also performed T-test for the difference of the mean value of 2019 and 2020 in order to ensure whether there is a difference between the WRR in 2019 and 2020. The result shows that the difference between the WRR in 2019 and 2020 is significant. As a large number of migrant workers cannot return to employment according to the original plan, China's large- and medium-sized enterprises have suffered a tremendous shock. Under the condition that the population mobility is restricted and the WRR is insufficient, most enterprises' existing orders are likely to be delayed. The costs of employees' wages, equipment maintenance, plant depreciation, etc. remain unchanged. Therefore, the normal operation of enterprises is under great pressure.

Second, with the effective control of the COVID-19, the president Xi Jinping, who hosted a meeting on February 12th, asked to conduct classified guidance to promote the work resumption in an orderly way under the premise of ensuring the epidemic prevention work (47). **Figure 1** shows the correspondence between the Chinese lunar calendar and the Gregorian calendar and the dates of fundamental events. **Figure 2** shows the changing trend of average WRR in China from January 1 to February 8 based on the Chinese lunar calendar in 2019 and 2020. It is obvious that the curve in 2020 after the Spring Festival is much lower than that in 2019 because of the COVID-19 pandemic. Also, the average WRR in 2020 was prone to a gradual escalation from January 25, 2020 to March 1, 2020, and it has exceeded 60%, reaching 66.17% by March 1, 2020.

Third, the WRRs of 31 provinces in mainland China on February 8 and March 1 are shown in **Table 3**, and the corresponding regional distribution is shown in **Figures 3**, **4**. Combining **Table 3** with **Figures 3**, **4**, we can find that the WRR of Zhejiang Province is the lowest in China, only 11.48%. Hubei Province, as the worst hit area of the COVID-19, has only 11.65% of the WRR. The reason is that Zhejiang province, as a major province of demanding for labor in China, mainly gets labor from Hubei, Jiangsu, Anhui, Jiangxi, and other neighboring provinces (calculated by the Baidu migration data). After the outbreak of COVID-19, the number of confirmed cases in Zhejiang has been ranked among the top five in China. Before the work resumption policy has been announced on February 10th, Zhejiang strictly implemented the policy of personnel control and enterprise shutdown, with a low WRR. Except for Hubei and Zhejiang, the WRR of Fujian and Xinjiang is also <20%, lower than the average

TABLE 2 | WRR of 366 cities in China (Feb. 8, 2020 and Feb. 19, 2019).

No.	City	WRR-2020		WRR-2019
1	Beijing	28.18%		70.63%
2	Tianjin	27.65%		71.01%
3	Shanghai	29.21%		66.19%
4	Chongqing	41.51%		100.00%
5	Shijiazhuang	19.45%		74.93%
6	Tangshan	20.20%		64.53%
7	Qinhuangdao	24.68%		76.95%
8	Handan	21.19%		70.80%
9	Xingtai	15.88%		68.86%
10	Baoding	15.12%		68.05%
…	…	…		…
363	Tiemenguan	27.84%		65.92%
364	Shuanhe	23.25%		69.65%
365	Kekedala	23.69%		74.01%
366	Kunyu	26.43%		56.41%
T-value			−65.314	
			(0.000)	
Average WRR		25.25%		82.34%

This table shows the comparison of the work resumption rate (WRR) of 366 cities in China on February 19, 2019 and February 8, 2020 (i.e., Chinese Lantern Festival). For the WRR-2019, t_1 is February 5, 2019 and t_2 is February 19, 2019; t'_1 is January 21, 2019 and t'_2 is February 4, 2019. For the WRR-2020, t_1 is January 25, 2020 and t_2 is February 8, 2020; t'_1 is January 10, 2020 and t'_2 is January 24, 2020.

[2]See https://en.wikipedia.org/wiki/Administrative_divisions_of_China, for more information on administrative divisions of the Republic of China.

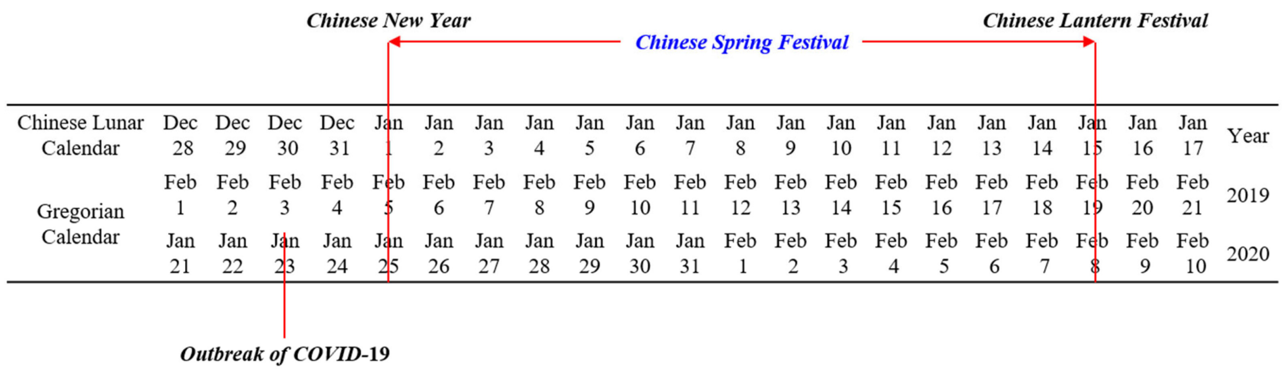

FIGURE 1 | Dates of fundamental events.

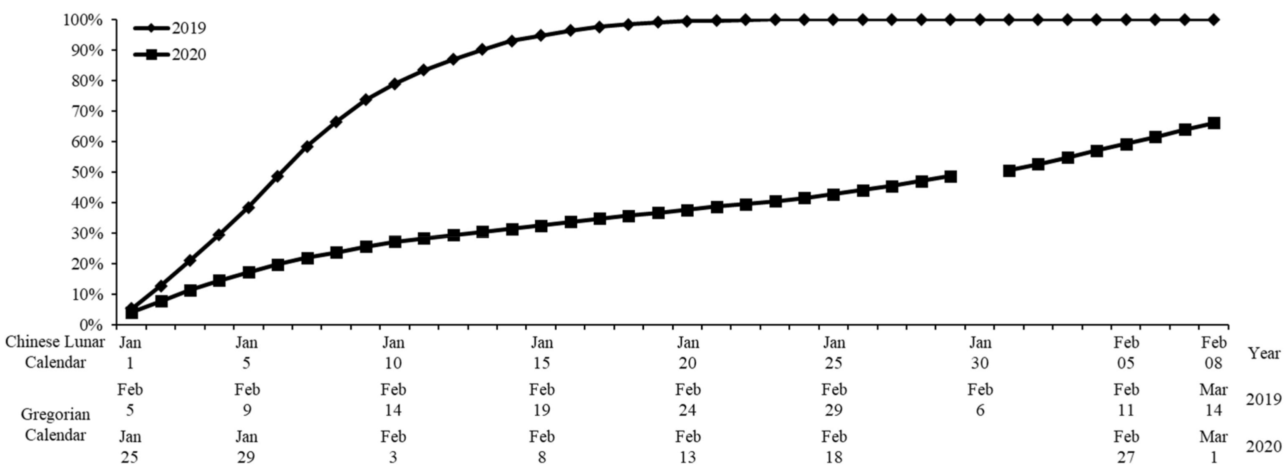

FIGURE 2 | The trend of work resumption rate (WRR) in China. This figure plots the WRR in China from January 1 to February 8 based on the Chinese lunar calendar in 2019 and 2020. For WRR in 2019, t_1 is February 5, 2019 and t_2 are the dates from February 5 to March 14, 2019 corresponding to the horizontal axis; t'_1 is January 21, 2019 and t'_2 is February 5, 2019. For WRR in 2020, t_1 is January 25, 2020 and t_2 are the dates from January 25 to March 1, 2020 corresponding to the horizontal axis; t'_1 is January 10, 2020 and t'_2 is January 24, 2020. It is important to note that since 2020 is a leap year, there are only 29 days in January when we adopt the lunar calendar.

WRR. The WRR of Sichuan, Hunan, Guizhou, and Chongqing is more than 35%, which is higher than the average WRR. The reason is that Sichuan, as a province close to Hubei and with a small number of COVID-19 confirmed case, issued policies for the full resumption of material production enterprises for epidemic prevention and control as early as January 30. Hunan, Guizhou, and Chongqing also issued relevant policies in late January or early February. Driven by these policies, workers actively returned to work. Therefore, the WRR of the above four provinces are higher.

With a large number of medical workers and rescue materials rushing to Hubei, COVID-19 in China has been effectively controlled. On March 1st, most provinces began to implement the policy of work resumption. The WRR of Zhejiang Province reached to 49.55%. At the same time, because Wuhan was still the worst hit area of the COVID-19, and still took measures of city blockade, there were not many migrant workers who could successfully return to work through the "Green Channel." The WRR of Hubei Province was 22.40%, which was higher than that on February 8, but still the lowest province in China.

In addition, we found that the WRR in Beijing, Tianjin, and Shanghai was lower than the average over the same period. The first reason is that Beijing, Tianjin, and Shanghai, as the main labor-importing cities, have a large number of returned workers, so the duration is relatively long. The second reason is that Beijing, Tianjin, and Shanghai strictly control the input personnel and implement the orderly return-to-work policy by stages and batches, resulting in the work resumption rate lower than the average in the short term. We believe that with the gradual improvement of the epidemic situation, the WRR will be significantly increased in provinces other than Hubei, which is the worst-affected area.

TABLE 3 | WRR of 31 provinces on February 8, 2020 and March 1, 2020.

No.	Province	WRR on Feb 8 (%)	WRR on Mar 1 (%)
1	Beijing	28.18	49.08
2	Tianjin	27.65	54.97
3	Shanghai	29.21	56.29
4	Chongqing	41.51	73.02
5	Hebei	28.51	58.31
6	Shanxi	32.37	79.89
7	Inner Mongolia	34.81	73.84
8	Liaoning	42.30	75.39
9	Jilin	48.09	77.13
10	Heilongjiang	45.60	63.19
11	Jiangsu	23.72	57.40
12	Zhejiang	11.48	49.55
13	Anhui	40.92	78.14
14	Fujian	19.31	51.71
15	Jiangxi	34.04	78.55
16	Shandong	26.36	59.29
17	Henan	34.79	70.55
18	Hubei	11.65	22.40
19	Hunan	37.96	83.48
20	Guangdong	23.46	64.69
21	Guangxi	42.91	94.07
22	Hainan	25.48	45.85
23	Sichuan	46.48	77.94
24	Guizhou	45.22	100.00
25	Yunnan	38.30	85.90
26	Tibet	21.27	52.23
27	Shaanxi	30.48	63.61
28	Gansu	44.17	88.10
29	Qinghai	38.50	76.98
30	Ningxia	32.28	63.54
31	Xinjiang	19.43	26.17

This table shows the comparison of the work resumption rate (WRR) of 31 provinces in China on February 8, 2020 (i.e., Chinese Lantern Festival) and March 1, 2020. For the WRR on February 8, t_1 is January 25, 2020 and t_2 is February 8, 2020; t'_1 is January 10, 2020 and t'_2 is January 24, 2020. For the WRR on March 1, t_1 is January 25, 2020 and t_2 is March 1, 2020; t'_1 is January 10, 2020 and t'_2 is January 24, 2020.

Prediction of Migrant Workers' Income in 2020 Under the Impact of COVID-19

Prediction of Migrant Workers' Income in 2020 Under the Inertia Scenario

The average monthly income data of migrant workers from 2009 to 2019 in the second column of **Table 4** was from the income statistics of migrant workers of the China National Bureau of Statistics. Substituting the data in the second column into Equations (2)–(7), the predicted income of migrant workers can be calculated by using the GM (1, 1) model, as shown in the last column of **Table 4**. Thus, the average error rate δ of the GM (1, 1) model could be obtained. $\delta = \frac{1}{11}\sum_{t=1}^{11}\frac{\left|\hat{X}_0(t)-X_0(t)\right|}{X_0(t)} = \frac{1}{11} \times \left(\frac{|207.44-207.44|}{207.44} + \cdots + \frac{|593.52-574.33|}{574.33}\right) = 4.05\%$ That is to say, the accuracy of the GM (1, 1) model in predicting the average monthly income of migrant workers was 95.95%. According to the criteria of the *Prediction of Migrant Workers' Income in 2020 Under the Inertia Scenario* section above, $\delta = 4.05\% < 5\%$, which means that the GM (1, 1) model can be used to predict the income of migrant workers. By using Equation (7), we can get the prediction value X_0 (2020) = 644.34. It can be seen that the average monthly income of migrant workers in 2020 is expected to increase by 12% compared with that in 2019 without the impact of the COVID-19, as shown in the first line of **Table 5**.

Prediction of Migrant Workers' Income in 2020 Under Different Scenarios

This paper predicted the average monthly income of migrant workers in 2020 under the conservative scenario (COS). In this scenario, migrant workers cannot go out to work for 1–2 months, and the parameter belongs to the interval (1, 2). Assuming a = 1.5, the predicted income of migrant workers under COS can be obtained as follows: $X_0(2020)\text{COS} = X_0(2020) \times (12 - a)/12 = 644.34 \times (12 - 1.5)/12 = 563.80$. Similarly, we can calculate the average monthly income of migrant workers in 2020 under the medium scenario (MES) and worse scenario (WOS), as shown in **Table 5**.

It can be seen from **Table 5** that the average monthly income of migrant workers will show a downward trend with the increase of the duration of COVID-19 and the strengthening of restrictions on population mobility. The greater the impact of COVID-19 on the economy and society is, the greater the decrease in migrant workers' income compared with 2019 would be. In the conservative scenario, the predicted average monthly income of migrant workers in 2020 will decrease by 2% compared with that in 2019, and the impact of COVID-19 on migrant workers' income is relatively small (see **Table 5**). Since the outbreak of COVID-19, the Chinese government has realized the effective administration during the epidemic through the classification of risk levels of each province and has taken quite strict prevention and control measures. It is not allowed to leave or go to the high-risk regions, but it is allowed to leave or go to the middle- or low-risk regions with the pass certificate issued by the local government. The epidemic is expected to be controlled within 1–2 months in the COS, and it can be sure that there will not be as many high-risk regions under the influence of the epidemic. Compared with the huge base of migrant workers in China, the proportion of migrant workers in high-risk regions is relatively small. In addition, the minimum living guarantee of migrant workers has been provided by the government since the epidemic. Thus, in the conservative scenario, the impact of COVID-19 on migrant workers' income is slight.

In medium scenario, migrant workers cannot go out to work for 3–4 months. Then, their average monthly income will be greatly impacted, with a decrease of about 21% compared with that in 2019. In worse scenario, migrant workers cannot go out to work for nearly half a year. Then, their average monthly income will be hugely impacted, with a decrease of about 44% compared with that in 2019. In this situation, the epidemic will have a huge impact on migrant workers' income. The government should issue emergency rescue measures to ensure the basic livelihood of farmers.

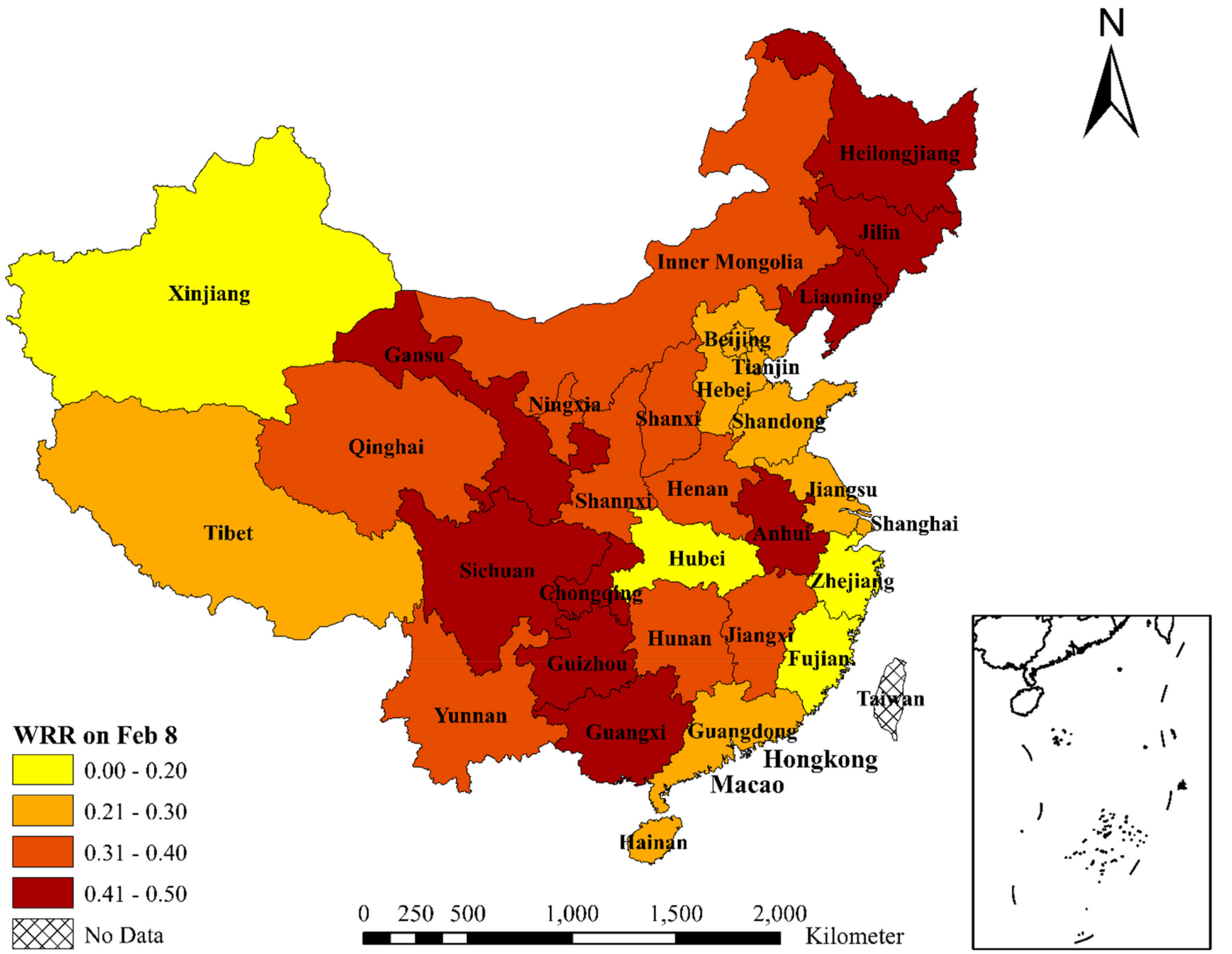

FIGURE 3 | WRR of 31 Chinese provinces on February 8, 2020. This figure shows the work resumption rate (WRR) of 31 provinces in China on February 8, 2020 (i.e., Chinese Lantern Festival). For WRR on Feb 8, t_1 is January 25, 2020 and t_2 is February 8, 2020; t'_1 is January 10, 2020 and t'_2 is January 24, 2020.

According to the National Bureau of Statistics (48), the average monthly income of migrant workers in 2020 was $590.27. In early April 2020, the pandemic has been most effectively controlled in China, and various industries have resumed work in an orderly manner; thus, it is applicable to scenario 1. Since the NBS gives the annual data, the average monthly income of migrant workers in 2020 is larger than that in April, 2020. In scenario 1, we predicted that the average monthly income of migrant workers would be $563.8, and the statistical error is (590.27 − 563.80)/590.27 = 4.49%<5%, which means that our results are robustness.

CONCLUSION AND POLICY IMPLICATIONS

Conclusion

In the context of the global outbreak of the COVID-19, it is very important to evaluate the impact of the epidemic on the return to work of rural labor and low-income groups' income such as migrant workers. It is essential to organize the labor force to return to work in an orderly manner and ensure the basic life security of low-income groups after the epidemic is stable. Based on the data of immigration and emigration of Baidu, this paper calculated the WRR of 366 Chinese cities in 2019 and 2020, respectively. According to the impact of the epidemic on migrant workers' working time, we considered three scenarios, conservative scenario (COS), medium scenario (MES), and worse scenario (WOS), and predicted the average monthly income of migrant workers in different scenarios. The results can be summarized in the following three aspects.

First, affected by the COVID-19, the average WRR was 25.25% as of February 8, 2020, which was only 30.67% of that in the same period of 2019. Since China implemented the policy of promoting to return to work, the average WRR has nearly doubled from 25.25% on February 8 to 66.17% on March 1st.

Second, the inter-provincial differences in WRR were obvious. Hubei Province, as the worst-hit area, had the lowest WRR in China. Affected by the COVID-19, the WRR in Beijing, Tianjin,

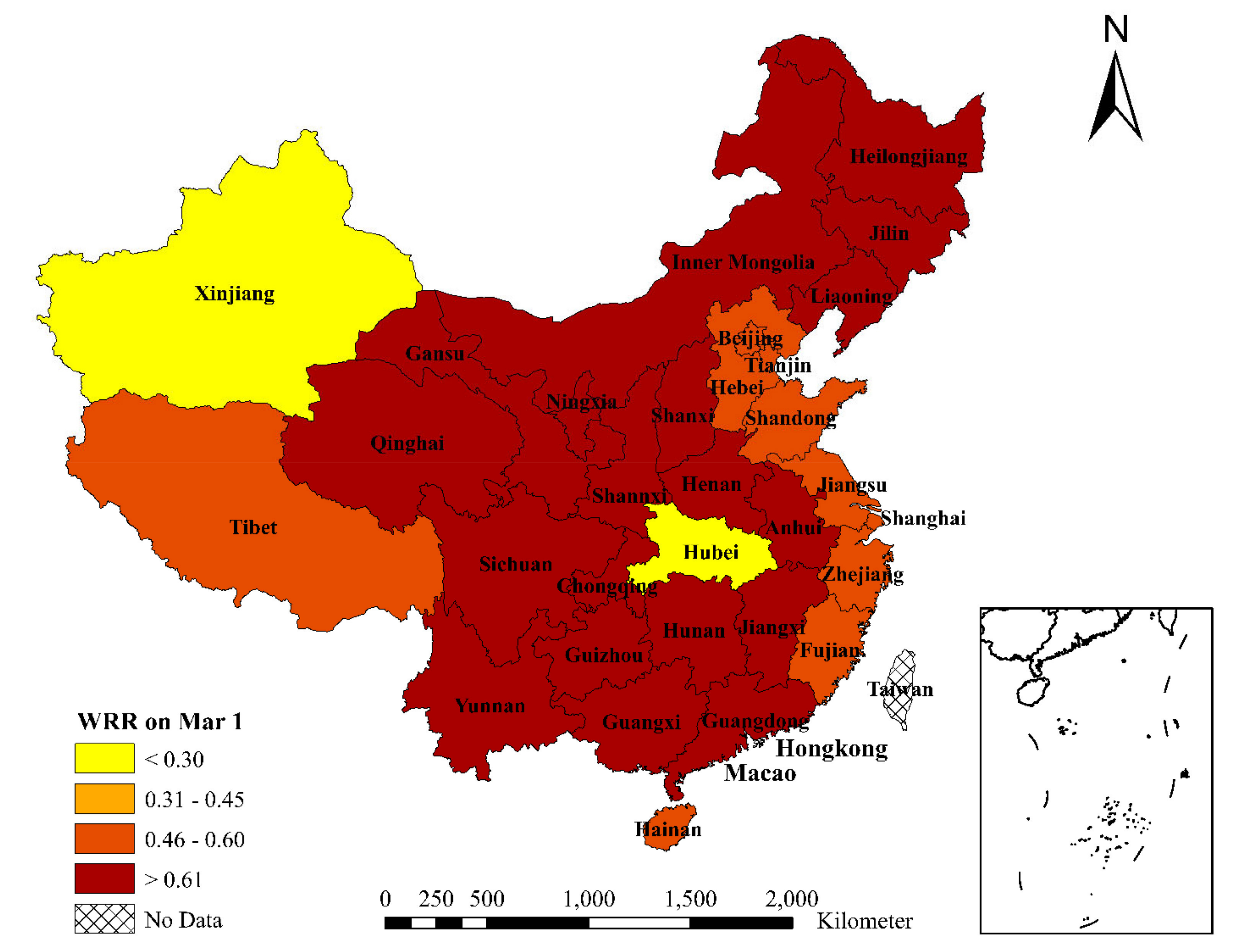

FIGURE 4 | WRR of 31 Chinese provinces on March 1, 2020. This figure shows the work resumption rate (WRR) of 31 provinces in China on March 1, 2020. For WRR on March 1, t_1 is January 25, 2020 and t_2 is March 1, 2020; t'_1 is January 10, 2020 and t'_2 is January 24, 2020.

Shanghai, Zhejiang, and other major labor-importing provinces were lower than the average level. As the key provinces of medical material production guarantee, Sichuan, Chongqing, Hunan, and Guizhou provinces near Hubei implemented the policy of returning to work earlier, and the WRR were relatively high.

Third, without the impact of the epidemic, the average monthly income of migrant workers in 2020 was expected to increase by 12% compared with that in 2019. With the increase of the duration of the COVID-19 and the strengthening of the government's restrictions on population mobility, the monthly average income of migrant workers will show a downward trend. Specifically, in COS that migrant workers cannot go out to work for 1–2 months, the average monthly income of migrant workers in 2020 will decrease by 2% compared with that in 2019, and the impact of the COVID-19 on migrant workers' income is relatively small. In MES that migrant workers cannot go out to work for 3–4 months, their average monthly income will be greatly impacted, with a decrease of about 21% compared with that in 2019. In WOS that migrant workers cannot go out to work for nearly half a year, their average monthly income will be hugely impacted, with a decrease of about 44% compared with that in 2019. By comparing with the data published by the National Bureau of Statistics, we found that the accuracy of our forecast is relatively high.

Policy Implications

China has achieved a staged victory in the prevention and control of the COVID-19, and various regions have begun to resume work in an orderly manner. However, the epidemic situation is still very serious in other countries around the world such as the United States, India, Brazil, and so on. With the gradual improvement of the epidemic prevention and control in China, the experience in work resumption of China will provide an important reference for other countries in the world to formulate or adjust epidemic prevention and control measures and work resumption policies.

TABLE 4 | The average monthly income of migrant workers (dollar).

Year	The average monthly income of migrant workers	The predicted value of income
2009	207.44	207.44
2010	249.65	288.73
2011	317.24	328.53
2012	362.77	364.93
2013	421.27	403.81
2014	466.24	441.99
2015	493.23	473.24
2016	493.05	481.75
2017	516.16	514.52
2018	562.31	569.93
2019	574.33	593.52

TABLE 5 | Prediction of monthly average income of migrant workers in different scenarios.

Scenario type	Predict of average monthly income of migrant workers in 2020 (dollar)	Income change rate compared to 2019 (%)
Inertial scenario (INS)	644.34	12
Conservative scenario (COS)	563.80	−2
Medium scenario (MES)	456.41	−21
Worse scenario (WOS)	322.17	−44

First, on the premise that the epidemic situation has been effectively controlled and the safety of returning to work is guaranteed, migrant workers can be organized to return to work in batches and in an orderly manner. Migrant workers should be guaranteed to return safely to work in batches and in concentration under measures such as gradually restoring road transport and opening a special railway line for them. As for the difficulties of returning to work caused by information asymmetry, local governments can use the Internet, big data, and other means to accurately connect the health status, labor skills, and the direction of intention of migrant workers with the employment demands of enterprises. The mutual recognition mechanism of health inspection for migrant workers in the inflow and outflow areas should also be adopted. We must ensure that migrant workers are allowed to go "from home to car, from car to their factory" and then to achieve a by-batch and orderly resumption.

Second, the government should strengthen employment guidance and psychological counseling for migrant workers in medium and worse scenario of the epidemic and high-risk areas, and the migrant workers should also be encouraged to find jobs nearby and locally. The local government should organize farmers to participate in online skills training and study while they are at home in order to improve their abilities. It should also be considered to increase financial investment to support migrant workers who return to their hometown to start their own businesses. Local government should also organize the spring plowing for migrant workers who are temporarily unable to return to work and make full use of public welfare position to provide migrant workers with more local employment opportunities.

Third, the central government should step up efforts to provide assistance and social security for the livelihood of low-income people such as migrant workers. The specific measures are to pay attention to the basic living security of vulnerable groups, including the families of migrant workers, and to include qualified people into the scope of social assistance. The "gradual withdrawal of subsistence allowances" mechanism should be adopted to encourage capable people to work actively and start their own businesses. For families endangering their basic survival, emergency assistance can be provided through living materials assistance, interest-free or low-interest loans, and so on to support them through their difficulties. In addition, the government should increase the subsidies for medical expenses of migrant workers' families and other difficult families and reduce the risk of poverty caused by illness in low-income families during the epidemic.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: http://qianxi.baidu.com/.

AUTHOR CONTRIBUTIONS

JL and BS wrote this paper. NC, BW, and FO reviewed and improved this article. JL, BC, and BS discussed and analyzed the empirical results. All authors have read and agreed to the published version of this manuscript.

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REFERENCES

1. Chan JFW, Yuan S, Kok KH, To KKW, Chu H, Yang J, et al. A familial cluster of pneumonia associated with the 2019 novel coronavirus indicating person-to-person transmission: a study of a family cluster. *Lancet.* (2020) 395:514–23. doi: 10.1016/S0140-6736(20)30154-9
2. Russell TW, Wu JT, Clifford S, Edmunds WJ, Kucharski AJ, Jit M. Effect of internationally imported cases on internal spread of COVID-19: a mathematical modelling study. *Lancet Public Health.* (2021) 6:e12–20. doi: 10.1016/S2468-2667(20)30263-2
3. Buckley C, May T. *Effects of Coronavirus Begin Echoing Far from Wuhan Epicenter.* (2020). Available online at: https://www.nytimes.com/2020/01/25/world/asia/china-wuhan-coronavirus.html (accessed January 28, 2020).
4. Hu C, Xiao L, Zhu H, Zhu H, Liu L. Correlation between local air temperature and the COVID-19 pandemic in Hubei, China. *Front Public Health.* (2021) 8:1032. doi: 10.3389/fpubh.2020.604870
5. National Bureau of Statistics (NBS). *Statistical Communiqué of the People's Republic of China on the 2019 National Economic and Social Development.* (2020). Available online at: http://www.stats.gov.cn/tjsj/zxfb/202002/t20200228_1728913.html (accessed April 11, 2020).
6. Su Y, Tesfazion P, Zhao Z. Where are the migrants from? Inter- vs. intra-provincial rural-urban migration in China. *China Econ Rev*. (2018) 47:142–55. doi: 10.1016/j.chieco.2017.09.004
7. Zhao H., Liu N, Wang, J. Effects of human capital difference on migration destination preference of rural floating population in China. *J Asia Pacific Econ.* (2019) 24:595–617. doi: 10.1080/13547860.2019.1641356
8. Hao L, Liang Y. The spatial and career mobility of China's urban and rural labor force. *Manag Org Rev*. (2015) 12:135–58. doi: 10.1017/mor.2015.35
9. Cai Y. China's new demographic reality: learning from the 2010 census. *Populat Dev Rev.* (2014) 39:371–96. doi: 10.1111/j.1728-4457.2013.00608.x
10. Yu J, Shen K, Liu D. Rural-urban migration, substitutability of human capital and city productivity: evidence from China. *Rev Dev Econ.* (2015) 19:877–91. doi: 10.1111/rode.12178
11. Li P, Li W. Economic status and social attitudes of migrant workers in China. *China World Econ.* (2007) 15:1–16. doi: 10.1111/j.1749-124X.2007.00072.x
12. Cai F. The great exodus: how agricultural surplus laborers have been transferred and reallocated in China's reform period? *China Agric Econ Rev.* (2017) 10:3–15. doi: 10.1108/CAER-10-2017-0178
13. Hao P, Tang S. Migration destinations in the urban hierarchy in China: evidence from Jiangsu. *Populat Space Place.* (2018) 24:e2083. doi: 10.1002/psp.2083
14. Wu J, Yu Z, Wei Y, Yang L. Changing distribution of migrant population and its influencing factors in-urban China: economic transition, public policy, and amenities. *Habitat Int.* (2019) 94:102063. doi: 10.1016/j.habitatint.2019.102063
15. Zhao Q, Bao HX, Zhang Z. Off-farm employment and agricultural land use efficiency in China. *Land Use Policy.* (2021) 101:105097. doi: 10.1016/j.landusepol.2020.105097
16. Pine R, McKercher B. The impact of SARS on Hong Kong's tourism industry. *Int J Contemp Hosp Manag.* (2004) 16:139–43. doi: 10.1108/09596110410520034
17. Lee GOM, Warner M. The impact of SARS on China's human resources: implications for the labor market and level of unemployment in the service sector in Beijing, Guangzhou and Shanghai. *Int J Hum Resource Manag.* (2006) 17:860–80. doi: 10.1080/09585190600640919
18. Jia W, Liu X. How much did the return of rural migrant labor affect China's national economy? *China Agric Econ Rev*. (2014) 6:38–54. doi: 10.1108/CAER-02-2012-0016
19. Cai F, Wang D, Zhang H. Employment effectiveness of China's economic stimulus package. *China World Econ.* (2010) 18:33–46. doi: 10.1111/j.1749-124X.2010.01179.x
20. Liu X, Lam R, Schipke A, Shen G. A generalized Okun's Law: uncovering the myth of China's labor market resilience. *Rev Dev Econ.* (2018) 22:1195–216. doi: 10.1111/rode.12379
21. McKibbin W, Femando R. The global macroeconomic impacts of COVID-19: seven scenarios. *Asian Econ Papers.* (2020). doi: 10.1162/asep_a_00796. [Epub ahead of print].
22. Chan K. The global financial crisis and migrant workers in China: 'There is no future as a labourer; returning to the village has no meaning'. *Int J Urban Region Res.* (2010) 34:659–77. doi: 10.1111/j.1468-2427.2010.00987.x
23. Zhi H, Huang Z, Huang J, Rozelle SD, Mason AD. Impact of the global financial crisis in rural China: gender, off-farm employment, and wages. *Feminist Econ.* (2013) 19:238–66. doi: 10.1080/13545701.2013.809137
24. Zhao H, Zhao H, Guo S, Li F, Hu Y. The impact of financial crisis on electricity demand: a case study of North China. *Energies.* (2016) 9:250. doi: 10.3390/en9040250
25. Guang L, Zheng, L. Migration as the second-best option: local power and off-farm employment. *China Q.* (2005) 181:22–45. doi: 10.1017/S0305741005000020
26. Li S, Blake A, Cooper C. China's tourism in a global financial crisis: a computable general equilibrium approach. *Curr Issues Tour.* (2010) 13:435–53. doi: 10.1080/13683500.2010.491899
27. Hoque A, Shikha F, Hasanat M, Arif I, Hamid A. The effect of coronavirus (COVID-19) in the tourism industry in China. *Asian J Multidiscip Stud.* (2020) 3:52–8. Available online at: https://asianjournal.org/online/index.php/ajms/article/view/213/96
28. Liang Y, Cao R. Employment assistance policies of Chinese government play positive roles! The impact of post-earthquake employment assistance policies on the health-related quality of life of Chinese earthquake populations. *Soc Indicat Res.* (2015) 120:835–57. doi: 10.1007/s11205-014-0620-z
29. Škare M, Soriano DR, Porada-Rochoń M. Impact of COVID-19 on the travel and tourism industry. *Technol Forecast Soc Change.* (2021) 163:120469. doi: 10.1016/j.techfore.2020.120469
30. Huang J, Zhi H, Huang Z, Rozelle S, Giles J. The impact of the global financial crisis on off-farm employment and earnings in rural China. *World Dev*. (2011) 39:797–807. doi: 10.1016/j.worlddev.2010.09.017
31. Wang M. Impact of the global economic crisis on China's migrant workers: a survey of 2,700 in 2009. *Eurasian Geogr Econ.* (2010) 51:218–35. doi: 10.2747/1539-7216.51.2.218
32. Wong D, Li C, Song H. Rural migrant workers in urban China: living a marginalised life. *Int J Soc Welfare.* (2007) 16:32–40. doi: 10.1111/j.1468-2397.2007.00475.x
33. Cao G, Li K, Wang R, Liu T. Consumption structure of migrant worker families in China. *China World Econ.* (2017) 25:1–21. doi: 10.1111/cwe.12203
34. Gu H., Liu Z, Shen T. Spatial pattern and determinants of migrant workers' interprovincial hukou transfer intention in China: evidence from a national migrant population dynamic monitoring survey in 2016. *Populat Space Place.* (2020) 26:e2250. doi: 10.1002/psp.2250
35. Cai F, Chan K. The global economic crisis and unemployment in China. *Eurasian Geogr Econ.* (2009) 50:513–31. doi: 10.2747/1539-7216.50.5.513
36. de Brauw A. China on the move: migration, the state, and the household. *J Region Sci.* (2010) 50:797–8. doi: 10.1111/j.1467-9787.2010.00688_12.x
37. Huang X, Sheng P, Shui A. Labour market outcomes and migration: evidence from China. *Appl Econ Lett*. (2020) 27:1596–601. doi: 10.1080/13504851.2019.1705236
38. Zheng R, Mei L, Guo Y, Zhen S, Fu Z. How do city-specific factors affect migrant integration in China? A study based on a hierarchical linear model of migrants and cities. *PLoS ONE.* (2021) 16:e0244665. doi: 10.1371/journal.pone.0244665
39. Chan K, Buckingham W. Is China abolishing the Hukou system? *China Q.* (2008) 195:582–606. doi: 10.1017/S0305741008000787
40. Zhang K, Chen C, Ding J, Zhang Z. China's hukou system and city economic growth: from the aspect of rural-urban migration. *China Agric Econ Rev.* (2019) 12:140–57. doi: 10.1108/CAER-03-2019-0057
41. Pan D, Yang J, Zhou G, Kong F. The influence of COVID-19 on agricultural economy and emergency mitigation measures in China: a text mining analysis. *PLoS ONE.* (2020) 15:e0241167. doi: 10.1371/journal.pone.0241167
42. Baidu. *Baidu Migration Map (Baidu), Migration-in and Migration-Out Data.* (2020). Available online at: http://qianxi.baidu.com (accessed March 2, 2020).
43. Wang Z, Li Q, Pei L. A seasonal GM(1,1) model for forecasting the electricity consumption of the primary economic sectors. *Energy.* (2018) 154:522–34. doi: 10.1016/j.energy.2018.04.155
44. Wang Z, Li D, Zheng H. Model comparison of GM(1,1) and DGM(1,1) based on Monte-Carlo simulation. *Phys A Stat Mech Appl.* (2020) 542:123341. doi: 10.1016/j.physa.2019.123341

45. Chi G, Du Y, Shi B. Path selection of industrial dust emissions of green city. *J Syst Eng.* (2014) 29:309–14. doi: 10.13383/j.cnki.jse.2014.03.019
46. Duan H, Wang S, Yang C. Coronavirus: limit economic damage. *Nature*. (2020) 578:515. doi: 10.1038/d41586-020-00522-6
47. Central People's Government of the People's Republic of China (CPGPRC). *President Xi Hosted the Meeting of the Standing Committee of the Political Bureau of the CPC Central Committee, and Analyzed the Epidemic Situation and Strengthened Prevention and Control Work.* (2020). Available online at: http://www.gov.cn/xinwen/2020-02/12/content_5477883.htm (accessed April 12, 2020).
48. National Bureau of Statistics (NBS). *Statistical Communiqué of the People's Republic of China on the 2020 National Economic and Social Development.* (2021). Available online at: http://www.stats.gov.cn/english/PressRelease/202102/t20210228_1814177.html (accessed February 28, 2021).

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Empirical Examination on the Drivers of the U.S. Equity Returns in the During the COVID-19 Crisis

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This study investigates the drivers of the Standard & Poor's (S&P) 500 equity returns during the COVID-19 crisis era. The paper considers various determinants of the equity returns from December 31, 2019, to February 19, 2021. It is observed that the United States Dollar (USD) and the volatility indices (VIX) negatively affect the S&P 500 equity returns. However, the newspaper-based infectious disease "equity market volatility tracker" is positively associated with the stock market returns. These results are robust to consider both the ordinary least squares (OLS) and the least angle regression (LARS) estimators.

Keywords: COVID-19 pandemic, stock market returns, US dollar index, volatility index, infectious disease, equity market volatility tracker, least angle regression

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INTRODUCTION

The COVID-19 pandemic has increased the level of uncertainty in every aspect of financial markets, including oil markets (1), commodity markets (2, 3), financial markets (4), energy markets (5), gold markets (6), and stock markets (7–12). Especially after the World Health Organization (WHO) declaration, which states that the COVID-19 pandemic is a global pandemic and will affect millions of people, the United States (U.S.) stock market crashed in March 2020. The S&P 500 equity index has decreased almost 5%, and the Dow-Jones index crashed almost 3,000 points on March 11, 2020. This event was the greatest decline of the U.S. stock markets since Black Monday in 1987 (13, 14).

In an influential paper, Baker et al. (9) show that the COVID-19 crisis causes an unprecedented shock on the U.S. stock markets compared to other pandemics, such as the Spanish flu, Ebola, bird flu, and swine flu. Toda (12) also introduces a susceptible-infected-recovered (SIR) model to estimate the transmission rate of the COVID-19 across the countries. The author also introduces an asset pricing model to predict the stock prices and concludes that the stock market temporarily decreases by 50% in the benchmark scenario. Still, there will be a W-shaped stock market performance in the forthcoming years. Our paper extends this evidence to until mid-February 2021.

Given these backdrops, this research aims to examine the determinants of the U.S. stock returns during the COVID-19 crisis era. We focus on the Standard & Poor's (S&P) 500 daily equity returns from December 31, 2019, to February 19, 2021. Following previous papers, we use the gold returns and crude oil returns to capture the hedging and portfolio diversification purposes in the financial markets (6, 11). We also include the United States Dollar (USD)'s real value to capture the monetary policy's effects on the stock market returns (15–17). We then add the volatility index (VIX) and the newspaper-based infectious disease equity market volatility tracker (EMVT-ID), which contain useful information for modeling stock market returns (18–21).

Although several studies have examined the determinants of the stock market returns in the previous empirical literature, to the best of our knowledge, this is the first research in the literature to examine the determinants of the U.S. stock market returns using a kernel-based estimator. For this purpose, we use the least angle regression (LARS) method of Efron et al. (22) to check the ordinary least squares (OLS) findings' robustness. We find that the USD and the VIX negatively affect the S&P 500 equity returns. However, the newspaper-based EMVT-infectious disease is positively associated with the stock market returns. These results are robust to consider both the OLS and the LARS estimators.

The structure of the remaining parts of the paper is defined as follows. Section Literature Review briefly reviews the previous papers on the determinants of the stock market returns during the COVID-19. Section Empirical Model, Data, and Estimation Methods explains the empirical model, the data, and the estimation procedures. Section Empirical Results reports the empirical results for the OLS estimations with the robust standard errors. Section Robustness Checks discusses various robustness checks, including the LARS estimations' findings with the robust standard errors for different models and periods. Section Concluding Remarks provides the concluding remarks.

LITERATURE REVIEW

Previous studies examine the determinants of the stock market returns and the stock market price volatility during the COVID-19 era. For instance, Baker et al. (9) consider text-mining approaches to measures the volatility in daily stock market returns to 1900 and the stock market volatility back to 1985. The authors show that there is an unprecedented stock market reaction to the COVID-19 crisis. Alfaro et al. (7) also show that the unexpected changes in the COVID-19 spread indicators can successfully predict the U.S. stock returns using the real-time dataset. Ashraf (8) uses the daily datasets on the COVID-19 confirmed cases and the COVID-19-related deaths to predict the stock market in 64 countries from January 22, 2020, to April 17, 2020. The author observes that the COVID-19 confirmed cases negatively affect the stock market returns. The impact is higher in the COVID-19 confirmed cases than the COVID-19-related deaths. Finally, the results indicate that the negative market reaction to the COVID-19 confirmed cases persists between 40 and 60 days.

Bai et al. (18) use the EMVT-ID to examine the effects of pandemics on stock markets' price volatility in China, Japan, the United Kingdom, and the U.S. for the period from January 2005 to April 2020. The authors observe that a higher level of the EMVT-ID increases the stock market volatility values with a 24-month lag. At this stage, the EMVT-ID provides the smallest impact on the Chinese stock market's price volatility values. Mazur et al. (13) examine the U.S. stock market performance in the market crash of March 2020 due to the COVID-19 shocks. The authors observed significant differences and asymmetries among the stock performances at the sectoral level. Shahzad et al. (23) also confirm this evidence by using the quantile return spillover method. Sharif et al. (11) investigate the causal relationships among the COVID-19 pandemic, economic policy uncertainty, geopolitical risks, oil price, and the U.S. stock market. The wavelet-based approaches' results indicate that the COVID-19 pandemic indicator has a higher impact on the indices of geopolitical risks and economic policy uncertainty than the U.S. stock market returns. Finally, Wang et al. (14) also show that the VIX has the strongest predictive ability for forecasting the futures price volatility in several stock markets during the COVID-19 crisis. The results are robust to consider different volatility methods and to focus on different subsamples. Singh et al. (24) also conclude that there is a temporary negative impact of the COVID-19, and the recovery of stock markets in the G-20 economies started after 60 days from the first shock.

Our previous empirical paper review shows that the COVID-19-related shocks negatively affect stock markets in developed economies. However, the effect is temporary. We also observe that there is no paper in the literature to use the kernel-based estimators. We fill this gap by implementing the LARS estimator.

EMPIRICAL MODEL, DATA, AND ESTIMATION METHODS

Empirical Model and Data

We estimate the following model to examine the determinants of the Standard & Poor's (S&P) 500 equity returns:

$$lnr\_S\&P500_t = \alpha_0 + \alpha_1 X_t + \varepsilon_t \tag{1}$$

In Equation (1), $lnr < uscore > S\&P500_t$ is the S&P 500 equity index's natural logarithmic (log) returns. The data are obtained from St. Louis FED (25). Following previous literature, we focus on various determinants of the S&P 500 equity index, which are represented by X_t. The first indicator is the gold log returns (Fixing Price 3:00 p.m., London Time, in London Bullion Market, based in the USD), and the related data are downloaded by St. Louis FED (26). The second variable is the Brent crude oil log returns, and the related data are obtained from St. Louis FED (27). The third indicator is the trade weighted USD index log returns, and the related data are downloaded by St. Louis FED (27). Note that a higher level of this index means that there is an appreciation in the USD. The fourth indicator is the Chicago Board Options Exchange (CBOE) volatility index (VIX), and the data are obtained from St. Louis FED (27). The VIX measures the market expectation of 3-month volatility conveyed by the S&P 500 stock index option prices. A higher level of the VIX implies that there are higher uncertainty expectations in the U.S. stock markets.

Finally, we use the level change of the newspaper-based Infectious Disease Equity Market Volatility Tracker (EMVT-ID) provided by Baker et al. (28), and the related data are accessed by St. Louis FED (27). The daily frequency data available are from January 1985 up to now. Baker et al. (28) define four terms with their variants to construct the EMVT-ID:

E: {"economic", "economy", "financial"},
M: {"stock market", "equity", "equities", "Standard and Poor's"},
V: {"volatility", "volatile", "uncertain", "uncertainty", "risk", "risky"},

TABLE 1 | Descriptive statistics (December 31, 2019–February 19, 2021).

Indicator	Definition	Data source	Mean	Std. dev.	Min.	Max.	Obs.
S&P 500 equity index	Log returns	St. Louis FED (25)	0.00068	0.210	−0.127	0.089	276
Gold price	Log returns	St. Louis FED (26)	0.00055	0.122	−0.054	0.067	276
Oil price	Log returns	St. Louis FED (27)	−0.00027	0.069	−0.643	0.412	276
U.S. dollar index	Log returns	St. Louis FED (30)	−0.00008	0.003	−0.019	0.019	276
Volatility index	Log returns	St. Louis FED (31)	0.00170	0.093	−0.266	0.480	276
Infectious disease EMVT	Change	St. Louis FED (32)	0.07608	8.787	−30.33	30.26	276

TABLE 2 | Correlation matrix (December 31, 2019–February 19, 2021).

Indicator	The S&P 500 returns	Gold returns	Oil returns	USD returns	VIX returns	ΔEMVT-ID
The S&P 500 returns	1.000	–	–	–	–	–
Gold returns	0.166	1.000	–	–	–	–
Oil returns	0.345	0.0843	1.000	–	–	–
USD returns	−0.399	−0.245	−0.220	1.000	–	–
VIX returns	−0.705	−0.016	−0.266	0.2477	1.000	–
ΔEMVT-ID	0.016	−0.152	−0.030	0.0577	0.0429	1.000

ID: {“epidemic”, “pandemic”, “virus”, “flu”, “disease”, “coronavirus”, “MERS”, “SARS”, “Ebola”, “H5N1”, “H1N1”}.

Then, Baker et al. (28) provide text mining on daily newspaper articles to check whether there is at least one term in each of *E*, *M*, *V*, and *ID* in almost 3,000 United States newspapers. After this, the share of raw EMV-ID articles is calculated in all articles in a given day. Finally, the raw index is rescaled by matching the VIX level between 1990 and 2016 and the overall EMV index (29). Thus, the EMV-ID tracker has been introduced as the ID-EMV articles' ratio to the total EMV articles. Note that a higher level of the index indicates a higher level of pandemic uncertainty in the financial markets (9). Refer to https://www.policyuncertainty.com/infectious_EMV.html for the details of the EMVT-ID index.

Our data focus on the COVID-19 era, i.e., it captures the daily frequency data from December 31, 2019, to February 19, 2021. The period is selected because of data availability. Therefore, we have 276 daily observations. The selection of the period is due to the starting date of the COVID-19 pandemic across the globe. Brief descriptive statistics are provided in **Table 1**.

Table 1 indicates the positive returns in the S&P 500 equity index and gold market on average. There are negative returns in the crude oil market on average and the USD index, which shows the USD's depreciation. There are positive returns in the uncertainty indices, such as the VIX and the EMVT-ID. In terms of the price volatility, the S&P equity 500 index has a higher standard deviation than the gold and crude oil markets over the period under concern.

Furthermore, the pairwise correlation matrix for the empirical analysis indicators is reported in **Table 2** over the period under concern.

Table 2 shows positive correlations between the S&P 500 equity returns and gold returns, and crude oil returns. The correlations between the S&P 500 equity returns and the USD and the VIX returns are negative. The change in the EMVT-ID is positively related to the S&P equity 500, the USD, and the VIX returns. Simultaneously, gold and crude oil returns are negatively correlated with the change in the EMVT-ID. There are also mixed correlations among the gold, crude oil, and USD returns.

Estimation Methods

We consider the OLS method to estimate the empirical model in Equation (1). It is important to note that we confirm the stationarity of all indicators by implementing unit root tests. We do not report the related results to save space due to the limited pages. We also implement the LARS method of Efron et al. (22) to check OLS findings' robustness. The LARS is a model-building algorithm that models parsimony and prediction accuracy. This estimation procedure is simpler than the least absolute shrinkage and selection operator (LASSO) and the forward stage-wise regression (FSR). Refer to Efron et al. (22) and Mander (33) for the LARS estimation method's details.

EMPIRICAL RESULTS

The OLS estimations' findings with the robust standard errors for Equation (1) are provided in **Table 3**.

Column (1) in **Table 3** reports the results for the model with the gold returns. The results indicate that the gold returns are positively related to the S&P 500 equity returns. Column (2) in **Table 3** provides the model's findings with the gold and crude oil returns. The findings show that both the gold and crude oil returns are positively related to the S&P 500 equity returns. Column (3) in **Table 3** reports the model's results with the gold, crude oil, and USD index returns. The results show that both the gold and crude oil returns are positively associated with the S&P 500 equity returns. However, the USD index returns are negatively related to the S&P 500 equity returns. It is important to note that the gold returns coefficient is statistically insignificant, which means that gold's impact on the S&P 500 equity returns is not robust to include additional controls. Column (4) in **Table 3** provides the model's results with the gold, crude oil, USD index, and VIX returns. The findings state that both gold and crude oil returns are positively related to the S&P 500 equity returns. However, the USD index and VIX returns are negatively associated with the S&P 500 equity returns. Note that all coefficients are statistically significant.

TABLE 3 | Results of the OLS estimations.

Indicator	(1)	(2)	(3)	(4)	(5)
Gold (Log returns)	0.286*** (0.102)	0.238** (0.097)	0.110 (0.094)	0.168** (0.070)	0.187*** (0.070)
Oil (Log returns)	–	0.101*** (0.017)	0.081*** (0.016)	0.039*** (0.012)	0.039*** (0.012)
U.S. dollar index (log returns)	–	–	−1.762*** (0.304)	−1.046*** (0.231)	−1.050*** (0.230)
Volatility Index (log returns)	–	–	–	−0.140*** (0.010)	−0.141*** (0.010)
Infectious disease EMVT (change)	–	–	–	–	0.017* (0.009)
Adjusted R-squared	0.0242	0.1321	0.2243	0.5705	0.5744
Observations	276	276	276	276	276

The dependent variable is the S&P 500 equity index log returns. Constant term is included. The robust standard errors are in ().
$^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

TABLE 4 | Results of the LARS estimations.

Indicator	(1)	(2)	(3)	(4)	(5)
Gold (log returns)	0.028 (0.035)	0.005 (0.081)	0.049 (0.081)	0.003 (0.071)	0.024 (0.063)
Oil (log returns)	–	0.079*** (0.020)	0.061*** (0.019)	0.031 (0.023)	0.025 (0.020)
U.S. dollar index (log returns)	–	–	−0.643** (0.265)	−0.496** (0.238)	−0.456** (0.215)
Volatility Index (log returns)	–	–	–	−0.104*** (0.011)	−0.102*** (0.009)
Infectious disease EMVT (change)	–	–	–	–	0.020** (0.008)
Adjusted R-squared	0.0059	0.0878	0.1336	0.6455	0.7197
Observations	276	276	276	276	276

The dependent variable is the S&P 500 equity index log returns. Constant term is included. The robust standard errors are in ().
$^{***}p < 0.01$, $^{**}p < 0.05$.

Finally, Column (5) in **Table 3** reports the findings for the model with the gold, crude oil, USD index, and VIX returns and the change in EMVT-ID. The results show that the gold returns, the crude oil returns, and the changes in the EMVT-ID are positively related to the S&P 500 equity returns. However, the USD index and VIX returns negatively affect the S&P 500 equity returns. Again, all coefficients are statistically significant.

We also find the adjusted R-squared as 0.5744, which means that the gold, crude oil, USD index, and VIX returns and the changes in the infectious disease EMVT explain 57.44% of the S&P 500 equity returns. Overall, the OLS estimations' findings indicate that the crude oil returns and the changes in the infectious disease EMVT positively affect the S&P 500 equity returns. In contrast, the USD index and VIX returns are negatively related to the S&P 500 equity returns. The average coefficients of the crude oil, USD index, and VIX returns and the infectious disease EMVT are calculated as 0.065, −1.286, −0.140, and 0.017, respectively.

ROBUSTNESS CHECKS

The LARS Estimations

The LARS estimations with the robust standard errors for Equation (1) are reported in **Table 4**.

Column (1) of **Table 4** provides the findings for the basic model with the gold returns. The results indicate that the gold returns are positively associated with the S&P 500 equity returns. However, its coefficient is not statistically significant. Column (2) in **Table 4** indicates the model's results with the gold and crude oil returns. The results show that both the gold and crude oil returns are positively associated with the S&P 500 equity returns. However, the coefficient of the gold returns is statistically insignificant. Column (3) in **Table 4** presents the model's findings with the gold, crude oil, and USD index returns. The results show that both the gold and crude oil returns are positively related to the S&P 500 equity returns. Besides, the USD index returns negatively affect the S&P 500 equity returns. At this point, the coefficient of the gold returns is not statistically significant. Column (4) in **Table 4** provides the model's findings with the gold, crude oil, USD index, and VIX returns. The findings illustrate that both the gold and crude oil returns are positively related to the S&P 500 equity returns. However, their coefficients are not statistically significant, which means that the effects of the gold and crude oil returns on the stock market returns are not robust to consider different models and different estimators. At this stage, the USD index and VIX returns negatively affect the S&P 500 equity returns, and their effects are statistically significant at the 5% level at least.

Finally, Column (5) in **Table 4** provides the results for the model with the gold, crude oil, USD index, and VIX returns and the change in infectious disease EMVT. The findings are that both the gold and crude oil returns and the changes in the infectious disease EMVT are positively related to the S&P 500 equity returns. However, merely the coefficient of the infectious disease EMVT is statistically significant at the 5% level.

TABLE 5 | Results of the LARS estimations (lagged model).

Indicator	(1)	(2)	(3)	(4)	(5)
Lagged gold (log returns)	0.119 (0.102)	0.074 (0.097)	0.046 (0.094)	0.071 (0.069)	0.028 (0.069)
Lagged oil (log returns)	–	0.093*** (0.016)	0.074*** (0.015)	0.031*** (0.011)	0.034*** (0.011)
Lagged U.S. dollar index (log returns)	–	–	−1.663*** (0.287)	−0.983*** (0.217)	−0.989*** (0.215)
Lagged volatility index (log returns)	–	–	–	−0.133*** (0.009)	−0.134*** (0.008)
Lagged infectious disease EMVT (Change)	–	–	–	–	0.023*** (0.008)
Adjusted R-squared	0.0049	0.1133	0.2018	0.5623	0.5714
Observations	275	275	275	275	275

The dependent variable is the S&P 500 equity index log returns. Constant term is included. The robust standard errors are in ().
****$p < 0.01$.*

TABLE 6 | Results of the LARS estimations: April 15, 2020–February 19, 2021 (lagged model).

Indicator	(1)	(2)	(3)	(4)	(5)
Lagged gold (log returns)	0.080 (0.086)	0.084 (0.086)	0.021 (0.018)	0.048 (0.075)	0.025 (0.015)
Lagged oil (log returns)	–	0.023*** (0.008)	0.033*** (0.009)	0.032*** (0.010)	0.038*** (0.010)
Lagged U.S. dollar index (log returns)	–	–	−0.557*** (0.189)	−0.492*** (0.183)	−0.517*** (0.201)
Lagged volatility index (log returns)	–	–	–	−0.134*** (0.015)	−0.131*** (0.014)
Lagged infectious disease EMVT (Change)	–	–	–	–	0.024*** (0.009)
Adjusted R-squared	0.0042	0.1224	0.1554	0.3173	0.3362
Observations	205	205	205	205	205

The dependent variable is the S&P 500 equity index log returns. Constant term is included. The robust standard errors are in ().
****$p < 0.01$.*

Furthermore, the USD index and VIX returns are negatively associated with the S&P 500 equity returns. Similarly, the related coefficients are statistically significant at the 5% level at least.

We also obtain the adjusted R-squared as 0.7197, implying that the gold, crude oil, USD index returns, and VIX returns and the changes in the infectious disease EMVT explain 71.97% of the S&P 500 equity returns. The adjusted R-squared of the LARS estimations is significantly higher than that of the OLS estimations. In short, the results of the LARS estimations show that the changes in the infectious disease EMVT positively affect the S&P 500 equity returns. However, the USD index and VIX returns are negatively associated with the S&P 500 equity returns. The average coefficients of the USD index returns, the VIX returns, and the change in the infectious disease EMVT are found as −0.531, −0.103, and 0.020, respectively.

The LARS Estimations With Lagged Model

We have also considered the lagged indicators for the gold, crude oil, USD index, and VIX returns and the change in infectious disease EMVT. The related results are provided in **Table 5**.

Column (1) of **Table 5** shows the results for the simple model with the lagged gold returns. The results show that the lagged gold returns are positively related to the S&P 500 equity returns. However, its coefficient is not statistically significant. Column (2) in **Table 5** states the model's findings with the lagged gold and lagged crude oil returns. The results indicate that both the lagged hold and lagged crude oil returns are positively associated with the S&P 500 equity returns. However, the coefficient of the lagged gold returns is statistically insignificant. Column (3) in **Table 5** demonstrates the model's results with the lagged gold, lagged crude oil, and lagged USD index returns. The findings indicate that both the lagged gold and lagged crude oil returns are positively associated with the S&P 500 equity returns. Besides, the lagged USD index returns negatively affect the S&P 500 equity returns. At this point, the coefficient of the gold returns is not statistically significant. Column (4) in **Table 5** reports the model's findings with the lagged gold, lagged crude oil, lagged USD index, and lagged VIX returns. The results show that both the lagged gold and lagged crude oil returns are positively associated with the S&P 500 equity returns. However, the coefficient of the lagged gold returns is not statistically significant. At this point, the lagged USD index and lagged VIX returns negatively affect the S&P 500 equity returns, and their effects are statistically significant at the 1% level.

Finally, Column (5) in **Table 5** demonstrates the findings for the model with the lagged gold, lagged crude oil, lagged USD index, and lagged VIX returns and the lagged change in the infectious disease EMVT. The findings are that the lagged gold and lagged crude oil returns and the lagged changes in the infectious disease EMVT are positively associated with the S&P 500 equity returns. The coefficients of the lagged infectious disease EMVT and the lagged crude oil returns are statistically significant at the 1% level. At this stage, the lagged USD index and lagged VIX returns are negatively associated with the S&P 500 equity returns. Similarly, the related coefficients are statistically significant at the 1% level.

We also observe the adjusted R-squared as 0.5714, implying that the lagged gold, lagged crude oil, lagged USD index, and lagged VIX returns and the lagged changes in the infectious disease EMVT explain 57.14% of the S&P 500 equity returns.

Overall, the LARS estimations' findings with the lagged model indicate that the lagged changes in the infectious disease EMVT and the lagged crude oil positively affect the S&P 500 equity returns. However, the lagged USD index and lagged VIX returns are negatively related to the S&P 500 equity returns. The average coefficients of the lagged USD index returns, the lagged VIX returns, and the lagged change in the infectious disease EMVT are obtained as −1.211, −0.133, and 0.023, respectively. These results are in line with the benchmark LARS estimations in **Table 4** and Column 5.

The LARS Estimations for the Subperiods

We also provide additional robustness checks. We have analyzed the results in various subperiods. At this stage, we follow the break dates in Dong et al. (34) and Zhang et al. (35). On March 13, 2020, there is the declaration of a national emergency. On March 27, 2020, the Coronavirus Aid, Relief, and Economic Security (CARES) was enacted. The stimulus package started on April 15, 2020. Therefore, we focus on the period from April 15, 2020, to February 19, 2021. These findings are reported in **Table 6**.

Column (1) of **Table 6** indicates the findings for the basic model with the lagged gold returns. The findings demonstrate that the lagged gold returns are positively related to the S&P 500 equity returns. However, its coefficient is insignificant. Column (2) in **Table 6** reports the findings with the lagged gold and lagged crude oil returns. The findings indicate that both the lagged gold and lagged crude oil returns are positively related to the S&P 500 equity returns. However, the coefficient of the lagged gold returns is not statistically significant. Column (3) in **Table 6** indicates the model's results with the lagged gold, lagged crude oil, and lagged USD index returns. The results show that both the lagged gold and lagged crude oil returns are positively related to the S&P 500 equity returns. Besides, the lagged USD index returns negatively affect the S&P 500 equity returns. At this stage, the coefficient of the gold returns is statistically insignificant. Column (4) in **Table 6** provides the model's results with the lagged gold, lagged crude oil, lagged USD index, and lagged VIX returns. The findings indicate that both the lagged gold and lagged crude oil returns are positively related to the S&P 500 equity returns. However, the coefficient of the lagged gold returns is statistically insignificant. Here, the lagged USD index and lagged VIX returns negatively affect the S&P 500 equity returns, and their effects are statistically significant at the 1% level.

Finally, Column (5) in **Table 6** reports the results for the model with the lagged gold, lagged crude oil, lagged USD index, and lagged VIX returns and the lagged change in the infectious disease EMVT. The results are that both the lagged gold and lagged crude oil returns and the lagged changes in the infectious disease EMVT are positively related to the S&P 500 equity returns. The coefficients of the lagged infectious disease EMVT and the lagged crude oil returns are statistically significant at the 1% level. Here, the lagged USD index and lagged VIX returns negatively affect the S&P 500 equity returns. Similarly, the related coefficients are statistically significant at the 1% level.

We also observe the adjusted R-squared as 0.3362, implying that the lagged gold, lagged crude oil, lagged USD index, and lagged VIX returns and the lagged changes in the infectious disease EMVT explain 33.62% of the S&P 500 equity returns. Overall, the LARS estimations' results with the lagged model on subperiod show that the lagged changes in the infectious disease EMVT and the lagged crude oil positively affect the S&P 500 equity returns. However, the lagged USD index and lagged VIX returns are negatively associated with the S&P 500 equity returns. The average coefficients of the lagged USD index returns, the lagged VIX returns, and the lagged change in the infectious disease EMVT are obtained as −0.522, −0.132, and 0.024, respectively. These findings are in line with the benchmark LARS estimations in **Table 4** and Column 5.

CONCLUDING REMARKS

This study examines the S&P 500 equity index returns determinants from December 31, 2019, to February 19, 2021. The empirical results show that the USD and the VIX are negatively associated with the S&P 500 equity index returns. However, the newspaper-based infectious disease "equity market volatility tracker" positively affects the S&P 500 equity index returns. These results are robust to estimate both the OLS and the LARS method of Efron et al. (22). Future papers in this subject can focus on other financial assets, including cryptocurrencies, for investigating the determinants of financial assets' returns and the price volatility.

Given that our findings are limited with the daily-frequency data, particularly, intraday data can provide additional findings for the effects of the COVID-19-related uncertainties on cryptocurrencies and financial markets. Following Sharif et al. (11), we suggest that the index of geopolitical risks be included in a future study. Geopolitical risks can divert people's attention from the government's ineffective response to the COVID-19 pandemic, and therefore, they can negatively affect the stock market performance.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: https://fred.stlouisfed.org/series.

AUTHOR CONTRIBUTIONS

QW: writing original draft and estimations. MB: writing original draft. MH: data collection and reviewing the original draft. All authors contributed to the article and approved the submitted version.

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REFERENCES

1. Gil-Alana LA, Monge M. Crude oil prices and COVID-19: persistence of the shock. *Energy Res Lett.* (2020) 1:13200. doi: 10.46557/001c.13200
2. Bakas D, Triantafyllou A. Commodity price volatility and the economic uncertainty of pandemics. *Econ Lett.* (2020) 193:109283. doi: 10.1016/j.econlet.2020.109283
3. Huang J, Li Y, Zhang H, Chen J. The effects of uncertainty measures on commodity prices from a time-varying perspective. *Int Rev Econ Finance.* (2021) 71:100–14. doi: 10.1016/j.iref.2020.09.001
4. Albulescu CT. COVID-19 and the United States financial markets' volatility. *Finance Res Lett.* (2021) 38:101699. doi: 10.1016/j.frl.2020.101699
5. Salisu AA, Adediran I. Uncertainty due to infectious diseases and energy market volatility. *Energy Res Lett.* (2020) 1:14185. doi: 10.46557/001c.14185
6. Salisu AA, Vo XV, Lawal A. Hedging oil price risk with gold during COVID-19 pandemic. *Resources Policy.* (2021) 70:101897. doi: 10.1016/j.resourpol.2020.101897
7. Alfaro L, Chari A, Greenland AN, Schott PK. *Aggregate and Firm-level Stock Returns during Pandemics, in Real Time. National Bureau of Economic Research (NBER) Working Paper, No. 26950*. (2020) Cambridge, MA: NBER.
8. Ashraf BN. Stock markets' reaction to COVID-19: cases or fatalities? *Res Int Bus Finance.* (2020) 54:101249. doi: 10.1016/j.ribaf.2020.101249
9. Baker SR, Bloom N, Davis SJ, Kost KJ, Sammon MC, Viratyosin T. The unprecedented stock market reaction to COVID-19. *Rev Asset Pricing Stud.* (2020) 10:705–41. doi: 10.3386/w26945
10. Gormsen NJ, Koijen RS. Coronavirus: impact on stock prices and growth expectations. *Rev Asset Pricing Stud.* (2020) 10:574–97. doi: 10.1093/rapstu/raaa013
11. Sharif A, Aloui C, Yarovaya L. COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: fresh evidence from the wavelet-based approach. *Int Rev Financial Anal.* (2020) 70:101496. doi: 10.1016/j.irfa.2020.101496
12. Toda AA. Susceptible-infected-recovered (SIR) dynamics of covid-19 and economic impact. *Covid Econ Vetted Real Time Papers.* (2020) 1:43–63.
13. Mazur M, Dang M, Vega M. COVID-19 and the March 2020 stock market crash. Evidence from S&P1500. *Finance Res Lett.* (2021) 38:101690. doi: 10.1016/j.frl.2020.101690
14. Wang J, Lu X, He F, Ma F. Which popular predictor is more useful to forecast international stock markets during the coronavirus pandemic: VIX vs EPU? *Int Rev Finan Anal.* (2020) 72:101596. doi: 10.1016/j.irfa.2020.101596
15. An L, Wynne M, Zhang R. *Shock-Dependent Exchange Rate Pass-Through: Evidence Based on a Narrative Sign Approach. Available at SSRN. No*. 3480284. Amsterdam: Elsevier (2020).
16. Bruno V, Shin HS. Capital flows and the risk-taking channel of monetary policy. *J Monet Econ.* (2015) 71:119–32. doi: 10.1016/j.jmoneco.2014.11.011
17. Zhang R. *News Shocks and the Effects of Monetary Policy. Available at SSRN, No. 3348466*. Amsterdam: Elsevier (2019).
18. Bai L, Wei Y, Wei G, Li X, Zhang S. Infectious disease pandemic and permanent volatility of international stock markets: a long-term perspective. *Finance Res Lett*. (2021) 40:101709. doi: 10.1016/j.frl.2020.101709
19. Bekaert G, Hoerova M. The VIX, the variance premium and stock market volatility. *J Econometr.* (2014) 183:181–92. doi: 10.1016/j.jeconom.2014.05.008
20. Brogaard J, Detzel A. The asset-pricing implications of government economic policy uncertainty. *Manag Sci.* (2015) 61:3–18. doi: 10.1287/mnsc.2014.2044
21. Liu L, Zhang T. Economic policy uncertainty and stock market volatility. *Finance Res Lett.* (2015) 15:99–105. doi: 10.1016/j.frl.2015.08.009
22. Efron B, Hastie T, Johnstone I, Tibshirani R. Least angle regression. *Annal Stat.* (2004) 32:407–99. doi: 10.1214/009053604000000067
23. Shahzad SJH, Bouri E, Kristoufek L, Saeed T. Impact of the COVID-19 outbreak on the US equity sectors: evidence from quantile return spillovers. *Financial Innovat.* (2021) 7:1–23. doi: 10.1186/s40854-021-00228-2
24. Singh B, Dhall R, Narang S, Rawat S. The outbreak of COVID-19 and stock market responses: an event study and panel data analysis for G-20 countries. *Global Bus Rev*. (2021). doi: 10.1177/0972150920957274
25. St Louis FED. *S&P 500 Series*. St. Louis, MO: St. Louis FED (2021). Available online at: https://fred.stlouisfed.org/series/SP500 (accessed February 15, 2021).
26. St Louis FED. *Gold Fixing Price 3:00 PM. (London Time) in London Bullion Market, Based in U.S. Dollars*. St. Louis, MO: St. Louis FED (2021). Available online at: https://fred.stlouisfed.org/series/GOLDPMGBD228NLBM (accessed February 15, 2021).
27. St Louis FED. *Crude Oil Prices: Brent – Europe*. St. Louis, MO: St. Louis FED (2021). Available online at: https://fred.stlouisfed.org/series/DCOILBRENTEU (accessed February 15, 2021).
28. Baker SR, Bloom N, Davis SJ, Kost KJ. *Policy News and Stock Market Volatility. National Bureau of Economic Research (NBER) Working Paper, No.* (2019) Cambridge, MA: NBER.
29. Balke NS, Fulmer M, Zhang R. Incorporating the Beige book into a quantitative index of economic activity. *J Forecast.* (2017) 36:497–514. doi: 10.1002/for.2450
30. St Louis FED. *Trade Weighted U.S. Dollar Index: Broad, Goods and Services*. St. Louis, MO: St. Louis FED (2021). Available online at: https://fred.stlouisfed.org/series/DTWEXBGS (accessed February 15, 2021).
31. St Louis FED. *CBOE Volatility Index: VIX*. St. Louis, MO: St. Louis FED (2021). Available online at: https://fred.stlouisfed.org/series/VIXCLS (accessed February 15, 2021).
32. St Louis FED. *Equity Market Volatility: Infectious Disease Tracker*. St. Louis, MO: St. Louis FED (2021). Available online at: https://fred.stlouisfed.org/series/INFECTDISEMVTRACKD (accessed February 15, 2021).
33. Mander A. *LARS: Stata Module to Perform Least Angle Regression. Statistical Software Components, S456860*, Boston, MA: Boston College Department of Economics (2006).
34. Dong D, Gozgor G, Lu Z, Yan C. Personal consumption in the United States during the COVID-19 crisis. *Appl Econ.* (2021) 53:1311–6. doi: 10.1080/00036846.2020.1828808
35. Zhang X, Gozgor G, Lu Z, Zhang J. Employment hysteresis in the United States during the COVID-19 pandemic. *Econ Res Ekonomska IstraŽivanja.* (2021) 34:1–13. doi: 10.1080/1331677X.2021.1875253

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Pandemics and Income Inequality: What Do the Data Tell for the Globalization Era?

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This paper empirically investigates the effects of pandemics uncertainty on income inequality We consider a new measure of pandemics uncertainty, the World Pandemic Discussion Index (WPDI), and the post-tax (net) Gini coefficient We focus on the panel data of 141 countries from 1996 to 2020. The results from the Feasible General Least Squares estimations indicate that the WPDI is negatively related to income inequality in 107 non-OECD countries. However, the WPDI is positively associated with income inequality in 34 OECD economies. This evidence remains robust when considering different models, including several controls, and implementing various sensitivity analyses.

Keywords: COVID-19 crisis, pandemics uncertainty, World Pandemic Discussion Index, WPDI, Income inequality, Feasible General Least Squares estimations

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INTRODUCTION

The COVID-19 pandemic again shows us that there can be widespread negative economic effects of a global pandemic (1–3). At this stage, there are various papers on how the COVID-19 pandemic has affected economic and financial indicators. For example, Bakas and Triantafyllou (4) observe that the COVID-19 pandemic has increased commodity price volatility. Chakrabarty and Roy (5) show the positive effects of the COVID-19 pandemic on fiscal stimulus. Gupta et al. (6) state that the COVID-19 pandemic has slowed down the world's macroeconomic activity. Wu (7) indicates that the pandemics-related uncertainty has negatively affected household consumption across the countries.

On the other hand, the COVID-19 pandemic is expected to significantly affect income inequality (8). There are various indicators to determine income inequality, including demographics, economic performance, globalization, government policies, institutions' quality, and labor market regulations (especially unions) [see e.g., (9–16)]. Given these backdrops, this paper aims to investigate the effects of pandemics uncertainty (measured by the World Pandemic Discussion Index-WPDI) and the income inequality [measured by the post-tax (net) Gini coefficient] in the panel dataset of 141 countries from 1996 to 2020.

There are various channels (hypotheses) on how pandemics can affect income inequality. The impact can be positive or negative. The first channel is the direct effect on the mortality rate. The Spanish Flu in 1918 mostly affected young men, and there was a direct impact of this pandemic on labor supply and labor income (1). However, the pandemics in the 21st century, including the COVID-19, have mostly affected older people. Therefore, there are negligible impacts of these pandemics on labor income. The first channel of pandemics can decrease income inequality in developing economies.

The second channel is the decline of households' income and the rise of precautionary savings. According to World Bank (17), the lock-down policies and the isolation measures during the COVID-19 pandemic caused a decline in the households' income. This issue leads to lower household consumption and increased precautionary savings. Wu (7) also confirms this hypothesis by showing that pandemics have reduced household consumption in the panel data of 138 countries from 1996 to 2017. Note that an increase in the precautionary savings can also hurt returns on the capital (3, 18), affecting income inequality. The second channel of pandemics can also reduce income inequality in developing economies.

The third channel is fiscal policy. During the COVID-19 crisis, governments introduced fiscal stimulus packages to increase their credibility and to mitigate the pandemics' negative effects on households and the real economy (19). However, these fiscal stimulus packages will lead to a rise in public debts or tax rates in the forthcoming years. Indeed, previous papers have shown that the tax policies' changes or rising public debts significantly affect income inequality (14, 20, 21). The third channel of pandemics can increase income inequality in developed economies.

However, some developed countries, such as Japan, have considerably high public debts to keep public policies associated with a social-democratic welfare state. Many countries have resources to provide credit, minimum income and social welfare policies. The experiences in China and Vietnam, i.e., the systems of market socialism, characterized by the combination of market freedom in some markets and central planning state, have generated successful results for the pandemics. Overall, there are mainstream economic hypotheses and heterodox neo-Keynesian economics to analyze the effects of pandemics on income inequality.

We hypothesize that there are negative effects of pandemics on income inequality in developing economies; ceteris paribus, the impact is positive in developed countries according to the three channels.

There are a few papers in the literature on how pandemics have affected income inequality. For instance, Sayed and Peng (22) use the Fixed-effects and the Augmented Mean Group estimators to examine pandemics' effects on income inequality globally (mainly based on France, Germany, the United Kingdom, and the United States) from 1915 to 2017. The authors find that there is a suppressing impact of pandemics on income inequality. However, the channels on how pandemics can decrease income inequality remain unclear. Galletta and Giommoni (8) find that the Spanish flu pandemic in 1918 significantly and persistently increased the income inequality in the Italian municipalities. This evidence comes from the issue that there is a significant decline in poor people's income share. However, Alfani (23) and Alfani and Ammannati (24) observe that the 14th-century Black Death plague decreased the Italian regions' income inequality in the following centuries. There is also mixed evidence on the effects of different pandemics on income inequality in the Italian regions during the different pandemics. Using the unbalanced panel dataset of 175 countries from 1961 to 2017; Furceri et al. (25) find that pandemics have caused an increase in the Gini coefficient and higher-income deciles' income shares. Furceri et al.'s (25) approach is based on the shocks of dummy variables for pandemics. Our paper uses the WPDI; therefore, we can measure and compare the uncertainty due to the pandemic's magnitude over time across the countries.

We attempt to contribute to the related empirical literature by investigating the effects of pandemics uncertainty on income inequality. Our paper examines the effects of pandemics uncertainty, measured by a new index, so-called WPDI, and the income inequality, measured by the post-tax Gini coefficient, in the panel data of 141 countries over the period 1996–2020. The WPDI indicator is based on country reports, focusing on pandemic-related events, policy uncertainty, and policy implications on pandemics. The WPDI indicator is similar to business cycle fluctuations, and it has a significant impact on income via pandemic-related uncertainty shocks (26). Therefore, we suggest that the WPDI should have similar income effects with the uncertainty mechanism is valid in the previous literature [see e.g., (27–31)].

At this point, we contribute to the current empirical literature on the relationship between pandemics and inequality by addressing several issues. First, we use different models to tackle potential reverse causality. There are several findings to observe the opposite direction in the COVID-19 era, i.e., inequality affects the virus's spread. According to Ahmed et al. (32), poor people lack access to health services, and they are vulnerable during times of economic crisis. Simultaneously, the less-educated workers have fewer remote works opportunities (33). Therefore, poor workers should go to their work, usually by the public transport system, increasing the virus transmission. Overall, the virus can spread at a higher level in countries where income inequality is a serious problem, such as the United States (34). By using the lagged right-side variables, we address a possible reverse causality issue. Note that the pandemic-related events and pandemics uncertainty is purely exogenous (26). In other words, the WPDI will not theoretically be affected by income inequality.

Secondly, there could be omitted variable bias given that the determinants of income inequality are complex. This paper includes various control variables to capture the effects of demographics, globalization, government size, institutions' quality, labor market conditions, and macroeconomic conditions on income inequality.

Thirdly, we split the countries as the OECD and the non-OECD countries to address the countries' case at different economic development stages. This empirical examination has been very useful since we have observed the mixed effects of pandemics on income inequality in different countries.

Finally, we implement various sensitivity analyses to check the robustness of the findings. For instance, we exclude the countries with extreme inequality levels and extreme uncertainty related to the pandemics. Thus, we show that outliers do not drive the results. Besides, we exclude the countries in different regions, such as East Asia (where the pandemic has been under control since the very begging) and Latin America (it has been the most fragile region regarding the new type of coronavirus). Our results indicate that the WPDI is negatively related to income inequality in 107 non-OECD countries. However, the WPDI is positively associated with income inequality in 34 OECD economies from 1996 to 2020.

The rest of the paper is organized as follows. Section Empirical Model, Methodology, and Data describes the data and empirical models and explains the estimation procedures. Section Empirical Results presents the empirical findings. Section Robustness Checks provides the robustness checks. Section Conclusion concludes.

EMPIRICAL MODEL, METHODOLOGY, AND DATA

Empirical Model and Estimation Procedure

We estimate the following equations:

$$Inequality_{i,t} = \alpha_0 + \alpha_1\ WPDI_{i,t} + \alpha_2\ X_{i,t} + \ \vartheta_t + \vartheta_i + \varepsilon_{i,t} \quad (1)$$

$$Inequality_{i,t} = \beta_0 + \beta_1\ WPDI_{i,t-1} + \beta_2\ X_{i,t} + \ \vartheta_t + \vartheta_i + \varepsilon_{i,t} \quad (2)$$

$$Inequality_{i,t} = \gamma_0 + \gamma_1\ WPDI_{i,t} + \gamma_2\ X_{i,t-1} + \ \vartheta_t + \vartheta_i + \varepsilon_{i,t} \quad (3)$$

$$Inequality_{i,t} = \delta_0 + \delta_1\ WPDI_{i,t-1} + \delta_2\ X_{i,t-1} + \ \vartheta_t + \vartheta_i + \varepsilon_{i,t} \quad (4)$$

In Equations from (1) to (4), $Inequality_{i,t}$ is the current income inequality, based on the Gini index for the post-tax income levels in country *i* at time *t*. $WPDI_{i,t}$ and $WPDI_{i,t-1}$ are the current and the lagged World Pandemic Discussion Index in country *i* at time *t* and *t-k*. $X_{i,t}$ and $X_{i,t-1}$ are current and the lagged vector of controls. Finally, ϑ_t, ϑ_i, and $\varepsilon_{i,t}$ indicate "time random-effects," "country random-effects," and the "error term," respectively. We hypothesize that there are negative effects of pandemics on income inequality in developing economies; ceteris paribus, the impact is positive in developed countries according to the three channels discussed in the introduction.

We estimate these equations using the Feasible General Least Squares (FGLS), the common estimator in the empirical literature [see, e.g., (7, 35–37)].

Data

Our dataset includes the annual frequency panel data from 1996 to 2020 in 141 countries. Note that the WPDI data are available until 2020Q4. Still, the inequality and other measures data are merely available until 2019 at best. Therefore, we use the forecast values of the income inequality and other indicators to capture the effects of the COVID-19 pandemic in 2020. Since we aim to focus on the countries at different development stages, we also split the countries as the non-OECD economies (107 countries) and OECD economies (34 countries) in the dataset. We use the annual-frequency data to capture the effects of business cycles on income inequality. We report a list of countries in our dataset in **Appendix**. Specifically, we consider the following variables in the estimations.

Dependent Variable

Following previous papers [e.g., (25)], we use the post-tax (net) Gini coefficients to measure income inequality. It is an index from 0 to 100. We obtain the related data from the Standardized World Income Inequality Database (SWIID) (version 9.1) of Solt (38).

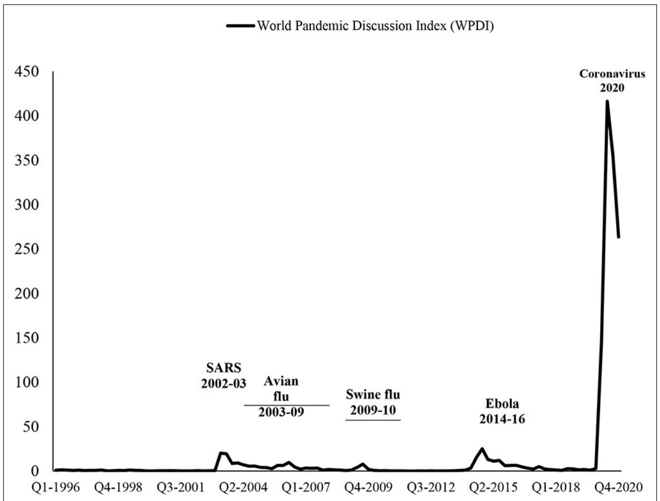

FIGURE 1 | World Pandemic Discussion Index (WPDI) (1996–2020). Data Source: Ahir et al. (26): https://worlduncertaintyindex.com/data/.

World Pandemic Discussion Index

Our research's novelty is that to use a new pandemics uncertainty measure, so-called the WPDI (26). This indicator is based on the text-mining of the country reports in the Economist Intelligence Unit (EIU). At this stage, we focus on the country-level indices on the discussion about pandemics. These indices are constructed by counting the number of times a word related to pandemics is mentioned in the EUI country reports. Ahir et al. (26) consider the following keywords in the EUI country reports: Severe Acute Respiratory Syndrome, SARS, Avian Flu, H5N1, Swine Flu, H1N1, Middle East Respiratory Syndrome, MERS, Bird Flu, Ebola, Coronavirus, COVID-19, Influenza, H1V1, World Health Organization, and WHO. These indices are the percent of the words related to the above pandemics-related words in the EIU country reports, multiplied by 1,000. A greater value means greater discussion, thus uncertainty about pandemics (26). For details, refer to https://worlduncertaintyindex.com/data/. We expect that there can be negative effects of pandemics on income inequality in developing economies; however, the impact should be positive in developed countries according to the three channels discussed in the introduction.

The sample considered in our paper starts in 1996. Some events, such as the Severe Acute Respiratory Syndrome (SARS) in 2002–2003, Avian Flu (H5N1) in 2003–2009, Swine Flu (H1N1) in 2009–2010, Middle East Respiratory Syndrome (MERS) in 2014–2020, Bird Flu in 2013–2017, Ebola in 2014–2016, Coronavirus (COVID-19) in 2020-ongoing, lead to rising pandemics-related uncertainty in the globe, as it is presented in **Figure 1**.

Figure 1 indicates that the WPDI has little trend; until the COVID-19, it does not change significantly over time. However, **Figure 1** provides the WPDI at the global level. There are significant variations in the level of the WPDI across the countries, given that most of these pandemics remain at the regional level rather than the global level. It is also important to note that the WPDI is driven by fully unpredictable shocks, significantly affecting income inequality. For instance, Gupta et al. (6) find that increases in the global pandemics-related uncertainty index are related to the future slowdowns in the global gross domestic product (GDP) growth. Therefore, the WPDI should also be a leading countercyclical variable, affecting income inequality across the countries. Therefore, we also use the lagged WDPI to avoid a possible issue the reverse causality. Furthermore, we observe no reverse causality issue when we run a formal test of panel causality.

Control Variables

Following the empirical approach in Gozgor and Ranjan (12), we include the per capita GDP in the constant $ prices to capture income level and the age-dependency ratio (% of working-age population) to control demographics and trans-generational spillover of the income. According to the Kuznets Curve hypothesis (13), the per capita income decreases income inequality in developed countries (OECD countries in our case). It increases income inequality in developing countries (non-OECD countries in our case). The age dependency ratio should be positively related to income inequality since this issue hurts wealth distribution against poor people. These data come from the World Development Indicators dataset in World Bank (39).

We also add various additional controls to check the robustness of the benchmark findings. As additional controls, we first use the total unemployment rate to control macroeconomic conditions. We expect that unemployment is positively related to income inequality.

Secondly, we consider total population (in logarithmic form) and the urban population relative to total population to capture the effects of demographics on the cross-country differences in income inequality. Generally, total population and urban populations increase income inequality due to the spatial concentration of economic activities.

Thirdly, we add female labor force participation rate and labor market regulations (an index from 0 to 10) to control labor market indicators in the estimations. All of these indicators are obtained from World Bank (39), except for the labor market regulations index, which is obtained from the Economic Freedom of the World Dataset (version 2020), provided by Gwartney et al. (40). Female labor force participation should be negatively linked to income inequality. Freer labor market regulations can increase income inequality, according to the previous empirical papers.

Fourthly, we include control variables to capture government size in the economy via the index from 1 to 10 and the share of transfer and subsidies relative to the GDP. We obtain these data from Gwartney et al. (40). Higher transfers and subsidies are expected to decrease income inequality.

Fifthly, pandemics can affect income inequality through globalization level channels, which may escalate to the pandemics-related uncertainty (41) or directly affect income inequality (12). At this stage, we add the revised version of the KOF indices of globalization (version 2020) for the KOF overall globalization index, introduced by Gygli et al. (42). For the details of the KOF indices of globalization, also refer to Gozgor (43), Dreher (44), and Potrafke (45). Globalization can increase income inequality since it promotes capital gains and decreases the relative income of labor (12).

Sixthly, we control institutions' quality since formal institutions can change the effects of pandemics shocks on income inequality (25). Therefore, we use the democracy/autocracy spectrum, measured by the Revised Combined Polity Score (Polity2) (an index from −10 to +10). These data are obtained from the Polity V Annual Time Series, introduced by Marshall and Gurr (46). Higher quality of institutions can increase the power of the welfare state; thus, it should decrease income inequality.

Finally, details of the variables and a summary of descriptive statistics are provided in **Table 1**.

EMPIRICAL RESULTS

Results of the Model With Non-lagged Controls

Table 2 provides the results of the FGLS estimations for the models in Equations (1, 2) from 1996 to 2020. The dependent variable is the post-tax Gini coefficient.

In the entire sample, the estimated coefficients of the current WPDI and the lagged WPDI are −0.010 and −0.006, respectively. However, only the current WPDI is statistically significant at the 5% level (see Columns 1 and 2, **Table 2**). The findings for 107 non-OECD countries are reported in Columns 3 and 4, while the results for 34 OECD countries are provided in Columns 5 and 6. The effect of the WPDI on income inequality is also adverse in non-OECD countries. Similarly, only the coefficient of the current WPDI is statistically significant at the 5% level.

Interestingly, the impact of the WPDI on income inequality is positive in the OECD countries, and both the estimated coefficients of the current WPDI and the lagged WPDI are statistically significant at the 1% level. This evidence shows that pandemics-related uncertainty has different effects on income inequality in developed countries to developing countries. The negative impact of pandemics-uncertainty shocks on income inequality can also be related to informal income sources in developing countries. Developing countries' income may not be sensitive to the uncertainty, which is measured by the WPDI.

When we analyze the controls, the per capita GDP is positively related to income inequality in the non-OECD countries. However, the per capita income is negatively associated with income inequality in the OECD countries and the entire sample. This evidence is consistent with the Kuznets Curve discussions, indicating a positive relationship between per capita income and income inequality at the first economic development stage. The income inequality will be decreased as per capita income increases (13). Besides, the age dependency ratio positively affects income inequality in all groups of countries. All of the related coefficients are statistically significant at the 1% level. Finally, the Wald test statistics show that the models are valid ($p < 0.001$).

Results of the Model With Lagged Controls

Table 3 reports the FGLS estimations' findings for the models in Equations (3, 4) from 1996 to 2020. Again, the dependent variable is the post-tax Gini coefficient.

The Wald test statistics show that all models are valid ($p < 0.001$). In the entire panel data sample, the estimated coefficients of the current WPDI and the lagged WPDI are

TABLE 1 | Descriptive statistics.

Indicator	Definition	Data source	Mean	Standard deviation	Minimum	Maximum	Obs.
Post-tax Gini coefficient	Index from 0 to 100	(38)	39.10	8.578	22.11	67.55	2,857
World Pandemic Discussion Index	Index	(26)	3.036	17.55	0.000	438.9	3,408
Per capita GDP (constant US$)	Logarithmic form	(39)	8.340	1.545	5.233	11.43	3,377
Age dependency ratio	% of Working-age population	(39)	63.59	19.58	15.74	114.2	3,400
Female labor force participation rate	% of female population ages 15+	(39)	51.74	16.45	5.831	87.68	3,408
Total population	Logarithmic form	(39)	16.44	1.351	13.16	21.05	3,400
Total unemployment rate	% of total labor force	(39)	7.761	6.029	0.090	37.98	3,408
Urban population	% of total population	(39)	56.38	22.92	7.410	100.0	3,400
Transfers and subsidies	Share of GDP	(40)	9.064	7.835	0.000	34.10	2,643
Government size	Index from 0 to 10	(40)	6.504	1.427	0.120	9.510	3,113
Labor market regulation	Index from 0 to 10	(40)	6.107	1.436	2.100	9.730	2,565
Overall globalization	Index from 0 to 100	(42)	59.06	15.93	22.53	90.98	3,266
Democracy/autocracy spectrum	Index from −10 to 10	(46)	3.635	6.301	−10.00	10.00	3,216

TABLE 2 | Feasible General Least Squares (FGLS) (non-lagged controls) (1996–2020).

Sample	All countries	All countries	Non-OECD	Non-OECD	OECD	OECD
Regressor	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Log per capita GDP$_t$	−1.951*** (0.048)	−1.998*** (0.048)	2.307*** (0.051)	2.278*** (0.051)	−6.133*** (0.187)	−6.275*** (0.180)
Age Dependency$_t$	0.092*** (0.003)	0.087*** (0.003)	0.214*** (0.003)	0.213*** (0.003)	0.355*** (0.022)	0.360*** (0.022)
WPDI$_t$	−0.010** (0.004)	–	−0.002** (0.001)	–	0.069*** (0.020)	–
WPDI$_{t-1}$	–	−0.006 (0.004)	–	−0.002 (0.001)	–	0.070*** (0.020)
Intercept	49.48*** (0.608)	50.24*** (0.612)	9.612*** (0.573)	9.970*** (0.582)	76.55*** (2.291)	77.86*** (2.219)
Observation	2,801	2,669	1,991	1,889	810	780
Countries	141	141	107	107	34	34
Wald Test [Probability]	10,285*** [0.000]	9,845*** [0.000]	5,529*** [0.000]	5,464*** [0.000]	1,370*** [0.000]	1,505*** [0.000]

*The dependent variable is the post-tax Gini coefficient$_t$. The standard errors are in (). ***$p < 0.01$ and **$p < 0.05$.*

TABLE 3 | Feasible General Least Squares (FGLS) estimations (lagged controls) (1996–2020).

Sample	All countries	All countries	Non-OECD	Non-OECD	OECD	OECD
Regressor	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Log per capita GDP$_{t-1}$	−1.864*** (0.048)	−1.861*** (0.048)	2.265*** (0.052)	2.265*** (0.053)	−6.057*** (0.189)	−6.062*** (0.189)
Age Dependency$_{t-1}$	0.100*** (0.003)	0.100*** (0.004)	0.211*** (0.003)	0.211*** (0.003)	0.375*** (0.022)	0.375*** (0.023)
WPDI$_t$	−0.009** (0.004)	–	−0.004*** (0.001)	–	0.067*** (0.020)	–
WPDI$_{t-1}$	–	−0.006 (0.004)	–	−0.003** (0.001)	–	0.068*** (0.020)
Intercept	48.27*** (0.612)	48.23*** (0.612)	10.09*** (0.594)	10.08*** (0.598)	74.83*** (2.358)	74.84*** (2.359)
Observation	2,669	2,669	1,889	1,889	780	780
Countries	141	141	107	107	34	34
Wald Test [Probability]	10,059*** [0.000]	10,018*** [0.000]	5,230*** [0.000]	5,217*** [0.000]	1,365*** [0.000]	1,370*** [0.000]

*The dependent variable is the post-tax Gini coefficient$_t$. The standard errors are in (). ***$p < 0.01$ and **$p < 0.05$.*

−0.009 and −0.007, respectively. At this point, the current WPDI is significant at the 5% level (see Column 1, **Table 3**). Similarly, the results for 107 non-OECD countries are provided in Columns 3 and 4, while the findings for 34 OECD countries are reported in Columns 5 and 6. The WPDI significantly decreases the income inequality in the non-OECD countries, and the related coefficients are statistically significant at the 5% level at least.

Furthermore, the effect of the WPDI on income inequality is positive in the OECD countries. Note that the estimated coefficients of the current WPDI and the lagged WPDI are statistically significant at the 1% level. This evidence confirms the previous findings in **Table 3**; that is, pandemics-related uncertainty has different effects on income inequality in developed and developing countries.

TABLE 4 | Feasible General Least Squares (FGLS) estimations (all countries) (1996–2020).

Sample	All countries	All countries	All countries	All countries	All countries	All countries	All countries	All countries	All countries
Regressor	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Log per capita GDP$_{t-1}$	−1.912*** (0.044)	−1.978*** (0.045)	−1.786*** (0.040)	−2.251*** (0.052)	−0.175** (0.069)	−1.766*** (0.058)	−2.759*** (0.044)	−0.660*** (0.005)	−2.137*** (0.047)
Age dependency$_{t-1}$	0.107*** (0.003)	0.087*** (0.003)	0.116*** (0.003)	0.213*** (0.003)	0.070*** (0.004)	0.124*** (0.005)	0.072*** (0.004)	0.081*** (0.003)	0.101*** (0.004)
WPDI$_t$	−0.009** (0.004)	−0.009*** (0.003)	−0.008** (0.003)	−0.010** (0.004)	−0.011*** (0.003)	−0.015*** (0.005)	−0.008** (0.003)	−0.006** (0.003)	−0.013*** (0.003)
Female labor force participation$_{t-1}$	−0.031*** (0.003)	–	–	–	–	–	–	–	–
Log total population$_{t-1}$	–	0.317*** (0.022)	–	–	–	–	–	–	–
Unemployment rate$_{t-1}$	–	–	0.259*** (0.009)	–	–	–	–	–	–
Urban population$_{t-1}$	–	–	–	0.100*** (0.003)	–	–	–	–	–
Transfers and subsidies$_{t-1}$	–	–	–	–	−0.651*** (0.009)	–	–	–	–
Government Size Index$_{t-1}$	–	–	–	–	–	1.313*** (0.047)	–	–	–
Labor market regulation$_{t-1}$	–	–	–	–	–	–	0.206*** (0.030)	–	–
Overall globalization$_{t-1}$	–	–	–	–	–	–	–	0.142*** (0.005)	–
Democracy/autocracy spectrum$_{t-1}$	–	–	–	–	–	–	–	–	−0.127*** (0.010)
Observation	2,669	2,669	2,669	2,669	2,183	2,567	2,102	2,669	2,591
Countries	141	141	141	141	128	138	132	141	139
Wald Test [Probability]	11,126*** [0.000]	14,157*** [0.000]	11,409*** [0.000]	18,966*** [0.000]	13,739*** [0.000]	8,052*** [0.000]	12,943*** [0.000]	12,974*** [0.000]	10,149*** [0.000]

*The dependent variable is the post-tax Gini coefficient$_t$. Intercept is included. The standard errors are in (). ***$p < 0.01$ and **$p < 0.05$.*

TABLE 5 | Feasible General Least Squares (FGLS) estimations (non-OECD countries) (1996–2020).

Sample	Non-OECD	Non-OECD	Non-OECD	Non-OECD	Non-OECD	Non-OECD	Non-OECD	Non-OECD	Non-OECD
Regressor	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Log Per Capita GDP$_{t-1}$	2.352*** (0.060)	2.267*** (0.051)	2.292*** (0.055)	2.335*** (0.052)	2.425*** (0.081)	2.506*** (0.048)	2.089*** (0.071)	2.022*** (0.057)	2.601*** (0.061)
Age Dependency$_{t-1}$	0.194*** (0.003)	0.213*** (0.003)	0.225*** (0.003)	0.219*** (0.003)	0.192*** (0.004)	0.240*** (0.003)	0.216*** (0.004)	0.229*** (0.003)	0.241*** (0.003)
WPDI$_t$	−0.003*** (0.001)	−0.003*** (0.001)	−0.003*** (0.001)	−0.003*** (0.001)	−0.012*** (0.002)	−0.006*** (0.002)	−0.006*** (0.002)	−0.003*** (0.001)	−0.004** (0.002)
Female labor force participation$_{t-1}$	−0.059*** (0.003)	–	–	–	–	–	–	–	–
Log total population$_{t-1}$	–	0.125*** (0.026)	–	–	–	–	–	–	–
Unemployment rate$_{t-1}$	–	–	0.086*** (0.008)	–	–	–	–	–	–
Urban population$_{t-1}$	–	–	–	0.065*** (0.004)	–	–	–	–	–
Transfers and subsidies$_{t-1}$	–	–	–	–	−0.415*** (0.017)	–	–	–	–
Government Size Index$_{t-1}$	–	–	–	–	–	0.578*** (0.032)	–	–	–
Labor market regulation$_{t-1}$	–	–	–	–	–	–	0.244*** (0.033)	–	–
Overall globalization$_{t-1}$	–	–	–	–	–	–	–	0.058*** (0.005)	–
Democracy/autocracy spectrum$_{t-1}$	–	–	–	–	–	–	–	–	−0.325*** (0.010)
Observation	1,889	1,889	1,889	1,889	1,446	1,826	1,373	1,889	1,850
Countries	107	107	107	107	94	104	98	107	105
Wald Test [Probability]	4,781*** [0.000]	5,331*** [0.000]	4,171*** [0.000]	5,303*** [0.000]	3,911*** [0.000]	7,162*** [0.000]	4,912*** [0.000]	4,690*** [0.000]	6,889*** [0.000]

*The dependent variable is the post-tax Gini coefficient$_t$. Intercept is included. The standard errors are in (). ***$p < 0.01$ and **$p < 0.05$.*

TABLE 6 | Feasible General Least Squares (FGLS) estimations (OECD countries) (1996–2020).

Sample	OECD	OECD	OECD	OECD	OECD	OECD	OECD	OECD	OECD
Regressor	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Log per capita GDP$_{t-1}$	−5.571*** (0.220)	−5.329*** (0.138)	−6.696*** (0.195)	−6.287*** (0.162)	−3.264*** (0.155)	−4.030*** (0.150)	−6.316*** (0.168)	−3.297*** (0.295)	−5.453*** (0.198)
Age dependency$_{t-1}$	0.361*** (0.021)	0.379*** (0.015)	0.379*** (0.021)	0.263*** (0.023)	0.413*** (0.017)	0.388*** (0.016)	0.395*** (0.018)	0.287*** (0.023)	0.318*** (0.024)
WPDI$_t$	0.072*** (0.021)	0.046*** (0.017)	0.048*** (0.018)	0.035** (0.017)	0.009*** (0.003)	0.028** (0.014)	0.021** (0.009)	0.025*** (0.008)	0.075*** (0.020)
Female labor force participation$_{t-1}$	−0.061*** (0.015)	–	–	–	–	–	–	–	–
Log total population$_{t-1}$	–	2.017*** (0.069)	–	–	–	–	–	–	–
Unemployment rate$_{t-1}$	–	–	0.198*** (0.026)	–	–	–	–	–	–
Urban population$_{t-1}$	–	–	–	0.109*** (0.012)	–	–	–	–	–
Transfers and subsidies$_{t-1}$	–	–	–	–	−0.480*** (0.012)	–	–	–	–
Government Size Index$_{t-1}$	–	–	–	–	–	3.392*** (0.080)	–	–	–
Labor market regulation$_{t-1}$	–	–	–	–	–	–	0.774*** (0.051)	–	–
Overall globalization$_{t-1}$	–	–	–	–	–	–	–	0.259*** (0.020)	–
Democracy/autocracy spectrum$_{t-1}$	–	–	–	–	–	–	–	–	−0.501*** (0.079)
Observation	780	780	780	780	737	741	729	780	741
Countries	34	34	34	34	34	34	34	34	34
Wald Test [Probability]	1,496*** [0.000]	5,056*** [0.000]	1,565*** [0.000]	1,448*** [0.000]	2,110*** [0.000]	4,024*** [0.000]	2,341*** [0.000]	1,373*** [0.000]	1,420*** [0.000]

*The dependent variable is the post-tax Gini coefficient$_t$. Intercept is included. The standard errors are in (). ***$p < 0.01$ and **$p < 0.05$.*

Looking at the control variables, we observe that the per capita GDP is positively associated with income inequality in non-OECD countries. However, the per capita income is negatively related to the income inequality in the OECD economies and the full sample. Again, this evidence is consistent with the Kuznets Curve hypothesis. Furthermore, the age dependency ratio increases the income inequality in all countries, and this evidence is also in line with the theoretical expectations. These coefficients are statistically significant at the 1% level.

ROBUSTNESS CHECKS

Robustness to the Inclusion of Other Controls

Tables 4–6 report the findings of robustness to the inclusion of several additional controls for the lagged control model with the current WUI in Equation (3) for the post-tax income inequality using the data from 1996 to 2020 in all countries, non-OECD economies, and OECD economies.

Each additional control variable discussed in the Data section is included individually in the FGLS estimations. **Tables 4–6** provide the estimated coefficient on the current WPDI. All results are in line with the benchmark estimations, and they are robust to the inclusion of nine additional control variables.

In the entire sample and the non-OECD countries' case, there are negative impacts of the WPDI on income inequality. The positive impact of the WPDI remains statistically significant in the case of the OECD countries.

More importantly, additional controls for potentially determining the after-tax income inequality, such as economic performance, labor market conditions, government size, globalization, and institutional quality, do not affect the statistical significance of the WPDI. Note that the importance of poverty is indirectly evaluated by the total unemployment rate, transfers and subsidies, and the high relevance of GDP per capita with these results. This evidence supports our main hypothesis that there are negative effects of pandemics on income inequality in developing economies, but the impact is positive in developed countries.

Sensitivity Analyses

Table 7 provides the results of robustness checks by excluding the outliers from the dataset. Again, we consider the FGLS estimations of the lagged control model with the current WUI in Equation (3) for the post-tax income inequality using the data from 1996 to 2020.

Firstly, we exclude the extreme observations of the post-tax income inequality and the WPDI. Following Jha and Gozgor (47), extreme observation is defined as the values as more than two standard deviations away from the average. The results are robust to the exclusion of the extreme observations. Secondly, we individually exclude the observations of the Latin American and the Caribbean (LAC) as well as East Asian countries. We observe the baseline findings are robust to these sensitivity analyses. We conclude that observations from

TABLE 7 | Sensitivity Analyses of the Feasible General Least Squares (FGLS) estimations (lagged controls) (1996–2019).

Excluding	Indicator	All countries	Non-OECD	OECD
Extreme observations of dependent variable	$WPDI_t$	−0.009*** (0.003)	−0.005*** (0.001)	0.071*** (0.017)
Extreme observations of $WPDI_t$	$WPDI_t$	−0.008*** (0.003)	−0.005*** (0.002)	0.070*** (0.024)
LAC economies	$WPDI_t$	−0.010** (0.004)	−0.004*** (0.001)	0.057** (0.023)
East Asia economies	$WPDI_t$	−0.011*** (0.004)	−0.003*** (0.001)	0.055*** (0.019)

*The dependent variable is the post-tax Gini coefficient$_t$. The standard errors are in (). ***$p < 0.01$ and **$p < 0.05$.*

specific regions and extreme observations did not drive the baseline results.

Overall, various robustness checks confirm that pandemics uncertainty decreases the income inequality in the non-OECD countries, but it increases the income inequality in the OECD countries.

CONCLUSION

This paper contributes to the literature by analyzing the effects of pandemics-related uncertainty on income inequality. We use a novel indicator of uncertainty—the World Pandemic Discussion Index (WPDI), introduced by Ahir et al. (26). This indicator is based on international discussions to measure the level of uncertainty related to pandemics at the country level. We find robust evidence that increases in the WPDI decrease the post-tax Gini coefficient in 107 non-OECD countries from 1996 to 2020. However, the FGLS estimations' findings indicate that the WPDI is positively associated with income inequality in 34 OECD countries. This finding is in line with Galletta and Giommoni (8) and Furceri et al. (25). Note that the evidence from Galletta and Giommoni (8) is based on the 1918 Influenza Pandemic and the case of Italy. We have enhanced their findings to 34 OECD economies and the globalization era (1996–2020). Furceri et al.'s (25) data is based on the unbalanced panel of 175 countries from 1961 to 2017. However, their method is based on the shocks of dummy variables for pandemics. We use the WPDI; therefore, we measure and compare the uncertainty due to the pandemic's magnitude over time across different countries.

Overall, our findings indicate that pandemics uncertainty is a significant determinant of income inequality, even though various macroeconomic variables and institutional quality controls are included. Furthermore, the findings suggest that pandemics have different effects on developed economies compared to developing economies. This evidence can be related to different business cycles, and it is in line with the results of the recent paper by Furceri et al. (25).

Finally, we need to enhance our knowledge on income inequality determinants considering the periods of uncertainty. Pandemics turned mandatory social isolation measures, which contributed to coming to an end several enterprises. However, it is important to note that our paper's findings are limited to the macro-level data. More precisely, identifying the exact mechanism relating pandemics-related uncertainty to income inequality requires research with the micro-level data. Thus, we can understand how an increase in pandemics uncertainty affects individual changes in income. At this stage, one can focus on the surveys or micro-level data further to understand the effects of pandemics uncertainty on income inequality. A Principal Component Analysis or the Bayesian Average techniques can be implemented for control variables' selection. Therefore, future studies can use micro-level data and different methods to capture the COVID-19 pandemic era in different countries to verify or reject our results.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: https://worlduncertaintyindex.com/data.

AUTHOR CONTRIBUTIONS

TC: conceptualization, supervision, and writing-original draft preparation. GG: data curation, software, investigation, and writing-original draft preparation. CK: methodology, writing – reviewing and editing, and visualization. All authors contributed to the article and approved the submitted version.

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REFERENCES

1. Barro RJ, Ursúa JF, Weng J. The coronavirus and the great influenza pandemic: lessons from the "Spanish Flu" for the coronavirus's potential effects on mortality and economic activity. In: *National Bureau of Economic Research (NBER) Working Paper, No. 26866.* Cambridge, MA: NBER (2020).
2. Eichenbaum MS, Rebelo S, Trabandt M. The macroeconomics of epidemics. In: *National Bureau of Economic Research (NBER) Working Paper, No. 26882.* Cambridge, MA: NBER (2020).
3. Jordà Ò, Singh SR, Taylor AM. Longer-run Economic Consequences of Pandemics. *Covid Econ Vetted Real Time Pap.* (2020) 1:1–15. doi: 10.3386/w26934

4. Bakas D, Triantafyllou A. Commodity price volatility and the economic uncertainty of pandemics. *Econ Lett.* (2020) 193:109283. doi: 10.1016/j.econlet.2020.109283
5. Chakrabarty HS, Roy RP. Pandemic uncertainties and fiscal procyclicality: a dynamic non-linear approach. *Int Rev Econ Finan.* (2021) 72:664–71. doi: 10.1016/j.iref.2020.12.027
6. Gupta R, Sheng X, Balcilar M, Ji Q. Time-varying impact of pandemics on global output growth. *Finan Res Lett.* (2021). doi: 10.1016/j.frl.2020.101823. [Epub ahead of print].
7. Wu S. Effects of pandemics-related uncertainty on household consumption: evidence from the cross-country data. *Front Public Health.* (2020) 8:798. doi: 10.3389/fpubh.2020.615344
8. Galletta S, Giommoni T. The effect of the 1918 influenza pandemic on income inequality: evidence from Italy. *Covid Econ Vetted Real Time Pap.* (2020) 33:73–109. doi: 10.2139/ssrn.3634793
9. Acemoglu D. Technical change, inequality, and the labor market. *J Econ Lit.* (2002) 40:7–72. doi: 10.1257/jel.40.1.7
10. Atkinson AB. *Inequality: What Can Be Done?* Cambridge, MA: Harvard University Press (2015).
11. Atkinson AB, Piketty T, Saez E. Top incomes in the long run of history. *J Econ Lit.* (2011) 49:3–71. doi: 10.1257/jel.49.1.3
12. Gozgor G, Ranjan P. Globalisation, inequality and redistribution: theory and evidence. *World Econ.* (2017) 40:2704–51. doi: 10.1111/twec.12518
13. Kuznets S. Economic growth and income inequality. *Am Econ Rev.* (1955) 45:1–28.
14. Piketty T. About capital in the twenty-first century. *Am Econ Rev.* (2015) 105:48–53. doi: 10.1257/aer.p20151060
15. Piketty T, Saez E. Income Inequality in the United States, 1913-1998. *Q J Econ.* (2003) 118:1–41. doi: 10.1162/00335530360535135
16. Piketty T, Saez E. Inequality in the Long run. *Science.* (2014) 344:838–43. doi: 10.1126/science.1251936
17. World Bank. *June 2020 Global Economic Prospects Report*. Washington, DC: World Bank (2020).
18. Karlsson M, Nilsson T, Pichler S. The impact of the 1918 Spanish Flu epidemic on economic performance in Sweden: an investigation into the consequences of an extraordinary mortality shock. *J Health Econ.* (2014) 36:1–19. doi: 10.1016/j.jhealeco.2014.03.005
19. Gozgor G. Global evidence on the determinants of public trust in governments during the COVID-19. *Appl Res Qual Life.* (2021). doi: 10.1007/s11482-020-09902-6. [Epub ahead of print].
20. Milanovic B. *Global Inequality: A New Approach for the Age of Globalization*. Cambridge, MA: Harvard University Press (2016).
21. Piketty T, Zucman G. Capital is back: wealth-income ratios in rich countries 1700-2010. *Q J Econ.* (2014) 129:1255–310. doi: 10.1093/qje/qju018
22. Sayed A, Peng B. Pandemics and income inequality: a historical review. *Covid Econ Vetted Real Time Pap.* (2020) 52:96–117.
23. Alfani G. Economic inequality in Northwestern Italy: a long-term view (Fourteenth to Eighteenth centuries). *J Econ History.* (2015) 75:1058–96. doi: 10.1017/S0022050715001539
24. Alfani G, Ammannati F. Long-term trends in economic inequality: the case of the Florentine State, c. 1300-1800. *Econ History Rev.* (2017) 70:1072–102. doi: 10.1111/ehr.12471
25. Furceri D, Loungani P, Ostry JD, Pizzuto P. Will Covid-19 affect inequality? Evidence from past pandemics. *Covid Econ Vetted Real Time Pap.* (2020) 12:138–57.
26. Ahir H, Bloom N, Furceri D. *World Uncertainty Index*. Mimeo, Stanford, CA: Stanford University (2018).
27. Baker SR, Bloom N, Davis SJ. Measuring economic policy uncertainty. *Q J Econ.* (2016) 131:1593–636. doi: 10.1093/qje/qjw024
28. Bloom N. The impact of uncertainty shocks. *Econometrica.* (2009) 77:623–85. doi: 10.3982/ECTA6248
29. Bloom N. Fluctuations in uncertainty. *J Econ Perspect.* (2014) 28:153–76. doi: 10.1257/jep.28.2.153
30. Bloom N, Floetotto M, Jaimovich N, Saporta-Eksten I, Terry SJ. Really uncertain business cycles. *Econometrica.* (2018) 86:1031–65. doi: 10.3982/ECTA10927
31. Jurado K, Ludvigson SC, Ng S. Measuring uncertainty. *Am Econ Rev.* (2015) 105:1177–216. doi: 10.1257/aer.20131193
32. Ahmed F, Ahmed NE, Pissarides C, Stiglitz J. Why inequality could spread COVID-19? *Lancet Public Health.* (2020) 5:e240. doi: 10.1016/S2468-2667(20)30085-2
33. Adams-Prassl A, Boneva T, Golin M, Rauh C. Inequality in the impact of the coronavirus shock: evidence from real time surveys. *J Public Econ.* (2020) 189:104245. doi: 10.1016/j.jpubeco.2020.104245
34. Galasso V. COVID: not a great equalizer. *CESifo Econ Stud.* (2020) 66:376–93. doi: 10.1093/cesifo/ifaa019
35. Gnangnon SK. Export product diversification and fiscal space volatility in developing countries: exploring the economic growth volatility channel. *Econ Bull.* (2020) 40:1837–54. doi: 10.20944/preprints202009.0603.v1
36. Meinhard S, Portrafke N. The globalization-welfare state nexus reconsidered. *Rev Int Econ.* (2012) 20:271–87. doi: 10.1111/j.1467-9396.2012.01021.x
37. Can M, Gozgor G. Effects of export product diversification on quality upgrading: an empirical study. *J Int Trade and Econ Dev.* (2018) 27:293–313. doi: 10.1080/09638199.2017.1370006
38. Solt F. Measuring income inequality across countries and over time: the standardized world income inequality database. *Soc Sci Q.* (2020) 101:1183–9. doi: 10.1111/ssqu.12795
39. World Bank. *World Development Indicators Dataset*. Washington, DC: World Bank (2021).
40. Gwartney J, Lawson R, Hall J. *Economic Freedom of the World 2020 Annual Report*. Vancouver: Fraser Institute (2020).
41. Antràs P, Redding SJ, Rossi-Hansberg E. Globalization and pandemics. In: *National Bureau of Economic Research (NBER) Working Paper, No. 27840.* Cambridge, MA: NBER (2020).
42. Gygli S, Haelg F, Potrafke N, Sturm, J-E. The KOF Globalisation Index - Revisited. *Rev Int Organ.* (2019) 14:543–74. doi: 10.1007/s11558-019-09344-2
43. Gozgor G. Robustness of the KOF index of economic globalisation. *World Economy.* (2018) 41:414–30. doi: 10.1111/twec.12546
44. Dreher A. Does globalization affect growth? Evidence from a New Index of Globalization. *Appl Econ.* (2006) 38:1091–110. doi: 10.1080/00036840500392078
45. Potrafke N. The evidence on globalisation. *World Econ.* (2015) 38:509–52. doi: 10.1111/twec.12174
46. Marshall MG, Gurr TR. *Polity V Project: Political Regime Characteristics and Transitions, 1800-2018.* Vienna, VA: Center for Systemic Peace (2020).
47. Jha P, Gozgor G. Globalization and taxation: theory and evidence. *Eur J Polit Econ.* (2019) 59:296–315. doi: 10.1016/j.ejpoleco.2019.04.001

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APPENDIX

One hundred and forty-one countries in the dataset.

Afghanistan, Albania, Algeria, Angola, Argentina, Armenia, Australia, Austria, Azerbaijan, Bangladesh, Belarus, Belgium, Benin, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, Burkina Faso, Burundi, Cambodia, Cameroon, Canada, Central African Republic, Chad, Chile, China, Colombia, Congo DR, Congo Republic, Costa Rica, Cote d'Ivoire, Croatia, Czech Republic, Denmark, Dominican Republic, Ecuador, Egypt, El Salvador, Ethiopia, Finland, France, Gabon, Gambia, Georgia Germany, Ghana, Greece, Guatemala, Guinea, Guinea-Bissau, Haiti, Honduras, Hong Kong, Hungary, India, Indonesia, Iran, Iraq, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Korea Republic, Kuwait, Kyrgyz Republic, Laos, Latvia, Lebanon, Lesotho, Liberia, Libya, Lithuania, Madagascar, Malawi, Malaysia, Mali, Mauritania, Mexico, Moldova, Mongolia, Morocco, Mozambique, Myanmar, Namibia, Nepal, Netherlands, New Zealand, Nicaragua, Niger, Nigeria, North Macedonia, Norway, Oman, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Portugal, Qatar, Romania, Russia, Rwanda, Saudi Arabia, Senegal, Sierra Leone, Singapore, Slovak Republic, Slovenia, South Africa, Spain, Sri Lanka, Sudan, Sweden, Switzerland, Tajikistan, Tanzania, Thailand, Togo, Tunisia, Turkey, Turkmenistan, Uganda, Ukraine, United Arab Emirates, United Kingdom, United States, Uruguay, Uzbekistan, Venezuela, Vietnam, Yemen, Zambia, and Zimbabwe.

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Innovation Model of China's High-End Equipment Industry: Do Social Capital and Dynamic Capabilities Matter for the COVID-19 Crisis?

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This paper explores the different model combinations of enterprise innovation in China based on the roles of social capital and dynamic capabilities. We implement Qualitative Comparative Analysis to understand the non-linear asymmetric relationships better. We use the data of 44 Listed Companies in China's high-end equipment manufacturing industry and find that three innovation models (the market-oriented independent innovation, government-supported technological innovation and industry-supported learning innovation models) are valid. Social capital, dynamic capabilities, and intra-industry networks are the main determinants of these innovation models. We also discuss the implications of these innovation dynamics on Chinese enterprises as a way to sustain the economy's high-quality development, including during the era of the COVID-19 pandemic crisis.

Keywords: the COVID-19 crisis, social capital, dynamic capabilities, innovation model, qualitative comparative analysis

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INTRODUCTION

Innovation is becoming an important engine for China's economic growth and social development and is a strong driving force for economic transformation and upgrading. Since the introduction of the innovation-driven development strategy in 2012, there have been remarkable achievements in innovation and development in China, which ranks 14th in the Global Innovation Index. The quantity of researchers, patent citations, and scientific and technological publications is in first place. Although the number of innovations in China has increased substantially, there is still a marked difference compared with other countries like the United States (US), European countries, Japan, South Korea, in terms of quality and innovation, the conversion rate of scientific and technological innovation achievements. Therefore, it is important to study the innovation drivers to improve the innovative willingness and innovation performance. Scholars also argue that social capital an important aspect of the social networks of an individual or organization that can mobilize existing and potential resources or the capability to obtain resources for survival and development, which are important non-market factors (1–3). The proper use of social capital plays an important role in overcoming environmental uncertainty, enhancing competitiveness, promoting new product development and technological innovation, and improving innovation performance (4–6).

However, possessing rich natural resources and social capital does not guarantee good innovation in business practice. The dynamic capability is then considered the key factor, influencing the core competency and improving the innovation performance, which is considered the capability to integrate, establish, and reconstruct internal and external competitiveness in response to environmental change (7). On the other hand, several scholars indicate that enterprises, which obtain a competitive advantage directly, improve enterprise performance through capability. However, some researchers verify that different dynamic capability dimensions play a partial or complete moderating role between and the social capital and performance of an enterprise. The social capital of enterprises positively impacts performance by the mediation of accumulation and dynamic upgrading capability (8, 9).

Scholars empirically analyzed the relationship between social capital, dynamic capability, and innovation performance based on regression methods, by paying attention to the impact of some factors on each other. The relationship between variables could be a non-linear relationship under multiple conditions; even the synergy between the variables is neglected by extant literature. Considering the non-linear relationship, we introduce the qualitative comparative analysis method, Qualitative Comparative Analysis (QCA), into the research to explore the innovation model of enterprises with different combinations of social capital, dynamic capabilities, and innovation performance. At this stage, this research is the first paper to use the QCA method for understanding the non-linear asymmetric relationship to the best of our knowledge.

The rest of the paper is organized as follows. Section Literature Review reviews previous papers on social capital and innovation performance. Section Data and Methodology explains the methodology. Section Empirical Findings discusses the empirical findings. Section Conclusions provides the conclusions.

LITERATURE REVIEW

Social Capital and Innovation Performance

Bourdieu (10) first proposed the concept of social capital from a resource-based view. Social capital is formally defined as a collection of actual or potential resources and is closely related to institutionalized social networks, the definition of which covers the sum of the organization and individual social capital. Nahapiet and Ghoshal (11) were the first scholars to put forward corporate social capital. The authors concluded that corporate social capital facilitates new intellectual capital based on structural, cognitive, and relational dimensions. The *Capability School* approach suggests that social capital is a kind of capability, which is the dynamic process of enterprises and individuals obtaining the necessary development resources by constructing a network of relationships (12, 13).

Research literature on the relationship between social capital and innovation performance in China is also abundant. For instance, Zhang (14) divided the social capital of enterprises into horizontal relational capital, vertical relational capital, and social-relational capital and empirically analyzed external social capital's role in improving technological innovation performance. Dai and Zhu (15) found out that social capital has a significant positive impact on an enterprises' innovation performance, while absorptive capacity moderates the relationship between social capital and innovation performance. Wang and Yang (16) divide social capital into the internal and external capitals of enterprises according to the relational dimension, the structural dimension, and the cognitive dimension. Their empirical results show that external social capital, based on cognitive trust and common language, is conducive to knowledge recognition; external social interaction with common institutions, such as the external social capital dimension. These issues help to acquire knowledge and promote the innovation performance of enterprises through knowledge sharing and application. Internal social capital also contributes to knowledge sharing and application, thereby contributing to its innovation performance. Xiong and Sun (17) show that relation intensity, trust, and sharing goals have a significant positive impact on implicit technical knowledge, while implicit technical knowledge acquisition is positively related to product innovation performance; the effect of social capital on the acquisition of explicit technical knowledge is different.

Meanwhile, explicit technical knowledge on product innovation performance is not obvious, which is recommended to improve relation intensity, trust, and shared goals to promote the performance of enterprise production innovation. Zhu and Wang (18) studied the impact on innovation performance from the perspective of horizontal social capital, vertical social capital, and oblique social capital. In this view, the mediating role of absorptive capacity can strengthen the positive influence of horizontal and vertical social capital on innovation performance. Oblique social capital is also transformed from a U-shaped relationship with innovation performance to a positive correlation because of its mediating role.

By reviewing social capital, we observe that an enterprises' social capital directly or indirectly influences innovation performance. There is a direct or an indirect positive relationship between the social capital dimension and innovation performance. In short, it is suggested that social capital has a significant impact on innovation performance.

Dynamic Capabilities and Innovation Performance

The concept of dynamic capability is the extension of the resource-based view for adapting to rapidly changing environments (18, 19). The firm's resources include tangible and intangible assets where "intangible assets are the ultimate source of sustainable value creation" (20). It is intangible assets such as capacity that can create unique competitive advantages over competitors. Early theory of industrial organization, emphasizes the importance of the external environment, however, simultaneously, the dynamic capability view broke through the limitations of passive adaptation, and looks inside the organization, introducing initiative into strategic organization theory.

Scholars deconstruct the connotation and composition of dynamic capability from a variety of perspectives. Teece et al. (21) consider the dynamic ability to perform various functions and strategic activities. Wang and Ahmed (22) treat dynamic capacities as third-order competencies and an indication of ultimate organizational capability. Resources are identified as the zero-order capability and core capability, respectively, as first-order and second-order in the hierarchy of organizational capabilities. Dynamic capability is of great significance because special skills are needed for successfully transferring this ability (23).

Helfat et al. (23) define dynamic capacity as "the capacity of an organization to create, extend, or modify its resource base purposefully." Güttel and Konlechner (24) explain that dynamic capacity is "the adoption of a firms' resource and capability base in rapidly changing environments." Teece (19) further analyzes dynamic capabilities, outlining that they consist of perceiving opportunity, grasping opportunity, and creating opportunities. Eisenhardt and Martin (25) identified an enterprise's dynamic ability as the process of enterprise integration, acquisition, reconstruction, and the release of resources.

Possessing a variety of resources does not mean building and reconfiguring a resource base according to environmental change, which causes different performance. Many scholars take dynamic capability as a dependent and an intermediate variable. Teece (26) suggest that dynamic capabilities can directly lead to competitive advantage and improve performance in response to rapid environmental changes. Makkone et al. (27) conducted empirical research on companies in the maritime, media, food processing, and other industries. The authors found that dynamic capabilities can increase the proportion of new product sales, reflecting their positive impact on innovation performance. Su and Liu (28) constructed a mechanic model of innovation performance from three dynamic capability dimensions: market perception capability, multi-organization collaborative control capability, and organizational learning absorptive capability. The dynamic capability has a significant effect on product innovation performance through innovation strategy. Wu (29) separates dynamic capability into two dimensions: opportunity recognition and opportunity utilization, and empirically tests the mechanism on innovation performance, which concluded that opportunity utilization positively influences innovation performance, while opportunity utilization partially mediates the relationship between opportunity identification and innovation performance. Sun and Zhang (30) explore the impact of dynamic enterprise capability on innovation performance under the context of internationalization. The results show that dynamic capability can significantly improve innovation performance.

By reviewing dynamic capability research, various arguments about the specific mechanism of dynamic capability on innovation performance dominate the literature. Most scholars find that dynamic capability has a positive effect on the maintenance of competitive advantage. It is conducive to breaking path dependence, causing change, renewal, and enables the redeployment of the resource base in response to environmental changes to improve the innovation performance.

Based on the previous literature, it is clear that social capital and dynamic capacity are of great significance to innovation performance. Therefore, successfully managing social capital and dynamic capacity in different ways is crucial to achieving innovation performance. With this in mind, this study aims to empirically examine a successful innovation model in China's equipment manufacturing industries based on the QCA approach. Following our paper's empirical findings, firms can improve innovation performance by establishing their capital and capacities models, especially for the COVID-19 crisis era.

DATA AND METHODOLOGY

Sample and Data Collection

By accessing the information available from the China Stock Market and Accounting Research (CSMAR) Database, State Intellectual Property Office, and Wanfang Patent Database, we obtained information on 106 listed companies that met the basic criteria. After excluding companies with incomplete data, loss of profits, and ST shares, we selected 44 samples over the period from 2014 to 2018, with a total of 1,320 observations for six variables. The mean of the indices was finally selected spanning 5 years of sample data, aggregately 264 observations.

Table 1 shows the industrial range, operating age, and scale of 44 companies. Samples from intelligent equipment manufacturing account for more than 50%, followed by companies for marine engineering, and finally, one company for satellite manufacturing. All the companies have been in operation for a minimum of 10 years, 61.36% of which have more than 2,000 employees.

Variables and Measures

Social Capital

Adler and Kwon (31) classify social capital into two categories: internal social capital, and external social capital. As discussed by Ma and Li (32) and based on the available data, entrepreneurship embodies political social capital, and business social capital, with ties to industry.

Political social capital was measured by the number of senior executives or government officials or the current or former deputies to the National People's Congress or the Chinese People's Political Consultative Conference (CPPCC). Executives in compliance with political identity were assigned 1 point, otherwise, they received 0. Only the highest administrative level for one person was counted. The aggregate value is the sum of people number with the company's specified identity (32). Government and enterprise relation is used to present political capital in the empirical finding.

Ties with industry were measured by the number of senior executives who joined relevant trade associations. Referring to Zhou and Lin (33), senior executives associated with industry and commerce or various trade associations were assigned 1 point, otherwise, they received 0. It is viewed as industrial relation in the empirical analysis.

Dynamic Capabilities

Teece et al. (7) identify dynamic capability as having the following dimensions: coordination and integration ability, learning ability, and reconfiguration ability. Referring to Sheng and Jiang (34),

TABLE 1 | Descriptive statistics of sample data.

Industry	Number	Percentage (%)	Items	Category	Number	Percentage (%)
Aviation Equipment	3	6.82	Operating age (year)	10–15	7	15.91
Satellite Manufacturing and Application	1	2.27		16–20	18	40.91
Rail Transit Equipment Manufacturing	6	13.64		>20	19	43.18
				Total	44	100
Marine Engineering Equipment Manufacturing	7	15.91	Scale (employee)	2,000≤	17	38.64
Intelligent Equipment Manufacturing	25	56.81		2,000–5,000	14	31.82
Photovoltaic Industry	2	4.55		>5,000	13	29.54
Total	44	100		Total	44	100

coordination and integration ability was measured by the ratio of total asset turnover; according to Zhao et al. (35), learning ability and reconfiguration ability are, respectively, estimated by the proportion of employees with a bachelor degree or above, and the return of assets.

Innovation Performance

This paper's innovation performance was measured by the number of applied patents in nearly 5 years. Technology innovation performance is of great significance to the equipment manufacturing industry. Simultaneously, to better measure the actual innovation ability, we distinguished utility model patents from applied patents and used the number of invention patents to measure the actual innovation ability. We tried to encourage deep insights into the different models, successfully achieving a measure of innovation performance by combining social capital with dynamic capability in the high-end equipment manufacturing industry.

This paper aimed to study the optimal combination of social capital and dynamic capabilities by comparing the innovation performance of different enterprises. The traditional statistical method was based on large sample data and a stochastic model that verified a causal relationship between a relatively small number of variables. However, according to the literature, innovation performance, dynamic capability, and social capital have non-linear asymmetric relationships, meaning the QCA is used as a research tool and is concerned with cross-case concurrency causality. Through configuration analysis, we can effectively solve the asymmetric causality problem. This method identifies the pre-factor configuration with the most explanatory power according to "consistency" and "coverage" parameters (36). The QCA technology is a case-oriented approach and suitable for small sample study, without being affected by the number of research samples.

EMPIRICAL FINDINGS

Sample observations are assigned 0 or 1 according to the relevant threshold. According to the observation above, the average level is given the value of 1, and a value of 0 is assigned to the observation below the average. The related results are shown in **Table 2**.

Variables such as dynamic capabilities, social capital, and invention patents were converted into truth tables based on assignments (see **Table 2**).

In **Table 3**, the original consistency threshold was 0.9, so a configuration with 0.9 or higher consistency was set to 1 in the survival column and 0 for cases where consistency was lower than 0.9. "Standard analysis" was selected, then the pre-factor configuration was identified, the software presents complex solutions, straightforward solutions, and intermediate solutions. While presenting simultaneously simple solutions and intermediate solutions, the pre-factors are the core conditions (expressed by "U" and "∼"). Existing in the intermediate solution but not in the simple solution, the pre-factors are the edge conditions (expressed by "U" and "."). The pre-factor configuration for the innovation output is shown in **Table 3**.

As shown in **Table 4**, the five pre-factor configurations' consistency was above 0.9, indicating that all existing pre-factor combinations meet the consistency criteria' requirement and promote performance innovation output. The sign "." and "∼" indicate that the condition exists, and "U" represents that the condition does not exist.

We combine all the configurations with the core conditions in the complex solution. It is concluded that the three configurations of IC-LC-OC, IC-OC-GR, and LC-IR have more explanatory power with a consistency of 1. The results are shown in **Table 5**. The three coverage of the configurations was 0.458, 0.292 and 0.25, respectively (see **Table 5**). According to the higher-order configuration of the core conditions, the combination of dynamic ability, social capital, and innovation output can be summarized into three models.

The market-oriented independent innovation model, i.e., the IC-LC-OC configuration: The core condition of the configuration were the three elements of the integration and coordination capability, learning capability, and organizational transformation capability, which indicates that high-end equipment manufacturing industry enterprises are more willing to take the initiative if they possess a strong dynamic capability.

TABLE 2 | Pre-due feature selection and assignment.

Factors	Pre-factors	Measurement standards	Assignment
Dynamic capabilities	Coordination and integration capability	Value of “coordination and integration capability” is greater than or equal to the sample median	1
		Value of “coordination and integration capability” is less than the sample median	0
	Learning capability	Value of “learning capability” value is greater than or equal to the sample median	1
		Value of “learning capability” value is less than the sample median	0
	Organizational reconstruction capability	Value of “organization reconstruction capability” is greater than or equal to the sample median	1
		Value of “organizational reconstruction capability” is less than the sample median	0
Social capital	Government-enterprise ties relations	Value of “government-enterprise relations” is above or equal to the sample median	1
		Value of “government-enterprise relations” is less than the sample median	0
	Industrial relations	Value of “industrial relation” is above or equal to the sample median	1
		Value of “Indusrial relation” is less than the sample median	0

TABLE 3 | Truth table.

Dynamic capabilities			Social capital		Quantity	Innovation output (PO)
Integration capability (IC)	Learning capability (LC)	Organizational capability (OC)	Government-enterprise relations (GR)	Industrial relations (IR)		
1	0	1	0	0	4	0
1	0	1	1	0	3	1
1	0	0	1	1	3	0
1	0	0	0	0	2	0
1	1	1	1	0	2	1
1	1	1	0	0	1	1
1	1	0	1	0	1	1
1	0	0	0	1	1	1
1	0	1	0	1	1	0
1	1	1	0	1	1	1
1	0	1	1	1	1	1
1	1	1	1	1	1	1
0	0	0	0	0	5	0
0	0	1	1	1	3	0
0	1	0	0	0	2	0
0	1	0	1	0	2	0
0	0	1	1	0	2	0
0	1	0	0	1	2	1
0	1	1	0	1	2	1
0	0	0	1	1	2	0
0	0	1	0	0	1	0
0	1	0	1	1	1	1
0	1	1	1	1	1	1

The first finding was that enterprises that can integrate and coordinate internal and external resources according to market demand and are more willing to innovate future strategies. Second, enterprises with excellent learning capability can also fully use inner and external knowledge to realize the diversification of explicit knowledge replication and tacit

TABLE 4 | Configuration.

Variable	C1	C2	C3	C4	C5
IC	U	~	~	.	.
LC	~	~		.	U
OC		~	~		U
GR			~	.	U
IR	~			U	~
Consistency	1	1	1	1	1
Raw coverage	0.25	0.2083	0.2917	0.125	0.04167
Solution coverage			0.7083		
Solution consistency			1		

TABLE 5 | Major configurations of innovation output.

Variable	C1	C2	C3
IC	~	~	
LC	~		~
OC	~	~	
GR		~	
IR			~
Consistency	1	1	1
Coverage	0.458	0.2917	0.25

knowledge innovation. The more knowledge the enterprises master, the more conducive they are to fostering innovation. Third, enterprises with stronger organizational transformation ability often take the initiative to carry out technology innovation because they can adjust organizational strategy and development model according to environmental change. This model shows that enterprises with dynamic capability are more willing to adopt the "independent innovation model" to improve the performance of the high-end equipment manufacturing industry.

The government-supported technological innovation model, i.e., the IC-OC-GR configuration: The government-supported technological innovation model's core conditions include integrating and coordinating ability, organizational transforming capability, and the good relationship between government and enterprise. In this model, the government's social relations play a leading role, and the dynamic ability of enterprises takes a back seat. In technological innovation, high-end equipment manufacturing enterprises need a lot of capital and policy support. A good relationship with government agencies is therefore an important means for enterprises to gain a competitive advantage. On the one hand, good government-enterprise relations can increase the probability of obtaining competitive financial subsidies and useful policy information. They can re-integrate resources and even change the organizational structure to meet the requirements of national strategies. Under this circumstance, even without strong learning ability, the enterprise still desires to adopt technology-based innovation to achieve innovation targets.

The industry-supported learning innovation model, i.e., the LC-IR configuration: The configuration's core conditions consist of learning ability and good industrial relations. Industry associations can provide a development platform for equipment manufacturing enterprises with learning ability. It can provide enterprises with information on industry development and market demand and guide enterprises to carry out strategic reforms. It also provides strategic opportunities for enterprises to search the key knowledge of employees, perform technological innovation and achieve cooperation to promote the enterprise's willingness to choose innovation. Knowledge about marketing and distribution channels from industrial associations accelerates the transformation of technology innovation. This model stresses that industrial supports promote enterprise to choose innovation.

CONCLUSIONS

Based on a sample of 44 listed companies in the high-end equipment manufacturing industry, this paper has studied the mechanism of dynamic capability and social capital on technological innovation performance. Findings indicate that market-oriented independent innovation and industry-supported learning innovation models are valid. The results show that the innovation model includes different combinations of dynamic capability and social capital. Equipment manufacturers with good dynamic capabilities tend to choose technology innovation. Dynamic capability means that equipment manufacturing enterprises can integrate and reset internal resources, respond to changes in the external environment, capture and master the outside world's key knowledge and technology by using independent learning ability and learning mechanisms to achieve competitive advantages. Dynamic capability and adaptation to the environment help organizations explore market opportunities and withstand market challenges. Therefore, enterprises take the initiative to engage in technological innovation.

Government support is an important condition for these enterprises to adopt technology-style innovation. As a capital-intensive, technology-intensive, and labor-intensive industry, substantial financial, intellectual, and labor factors are required for industrial development. Maintaining good interaction with government departments helps enterprises access important policy information and preferential policies in a timely manner, and even enables more opportunities to participate in the government's important construction projects, which provides tremendous help for equipment enterprises to cope with uncertainty in the market, effectively improving the willingness to carry out technology-oriented innovation activities. A good industrial platform encourages enterprises to choose a technology-style innovation model. Industry associations, industrial and commercial organizations, and other organizations can provide support during strategic development. The knowledge platform these trade associations offer is very important for enterprises in terms of their learning ability.

The suggested policy implications for the COVID-19 era are, firstly, that equipment manufacturing enterprises need to have a good dynamic capability, as this is an influential factor in actively choosing a model of technical innovation. In addition to external social capital, enterprises also need to enhance their operational capability, increase investment in research and development, improve the efficiency of asset operations and product profitability, and create flexible organizational practices to maximize dynamic capability and adapt to environmental changes. Secondly, the platform role of trade associations promotes equipment enterprises to carry out technological innovation. Completing and improving the functions of industry associations in attracting capital and talents, drawing wisdom, and broadening channels further promotes technological innovation by equipment enterprises. Thirdly, strengthening government guidance and support will encourage enterprises to adopt technological innovation and increase the innovation output. Because of China's current innovation capability and level, the government needs to carry out micro-planning and top-level design to develop the equipment manufacturing industry, guide, and support the innovation activities of enterprises. Building up a good policy environment, constructing intelligent science and technology platforms, implementing key projects in major areas, and promoting industry synergism, science, and research are good measures of enhancing willingness toward innovation. The limitations in this study are that single measures are chosen for each capability, which leads to simplification of the research conclusions and the dichotomy of these observations results ignores other configurations. Further research on the innovation model is needed. At this stage, export quality and export diversification indices can be potential drivers for innovation, as Can and Gozgor discuss (37).

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: https://us.gtadata.com/; https://english.cnipa.gov.cn/; http://www.wanfangdata.com/.

AUTHOR CONTRIBUTIONS

YA wrote the manuscript and data collection. DP wrote the manuscript and estimations. All authors contributed to the article and approved the submitted version.

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REFERENCES

1. Nahapiet J, Ghoshal S. Social capital, intellectual capital and the creation of value in firms. *Acad Manag Best Pap Proc.* (1997) 3:35–9. doi: 10.5465/ambpp.1997.4980592
2. Maurer I, Ebers M. Dynamics of social capital and their performance implications: lessons from biotechnology start-ups. *Administr Sci Q.* (2006) 39:7–32. doi: 10.2189/asqu.51.2.262
3. Leana C, Buren V. Organizational social capital and employ practices. *Acad Manag Rev.* (1999) 24:538–55. doi: 10.5465/amr.1999.2202136
4. Land S. Top management's social capital and learning in new product development and its interaction with external uncertainties. *Indust Mark Manag.* (2011) 41:1–10. doi: 10.1016/j.indmarman.2011.06.007
5. Kaasa A. Effects of different dimensions of Social Capital on Innovative Activity: evidence from Europe at the Regional Level. *Technovation.* (2009) 29:218–33. doi: 10.1016/j.technovation.2008.01.003
6. Wei L, Wei L. Empirical research on the influence of enterprise social capital on technological innovation ability. *Sci Manag.* (2011) 32:35–44.
7. Teece D, Pisano JG, Shuen A. Dynamics capabilities and strategic management. *Strateg Manag J.* (1997) 18:509–33.
8. Gang L, Jing L. Empirical study of the impact of dynamic ability on enterprise performance - based on the perspective of environmental dynamics. *Econ Theory Econ Manag.* (2013) 3:83–94.
9. Junyi D, Shengxu X, Xia W. The impact of SME dynamic capability on innovation performance-regulatory effects based on environmental dynamics. *Sci Technol Manag Res.* (2017) 1:25–9.
10. Bourdieuer P. Le capital social: notes provisoires. *Actes Rec Sci Soc.* (1980) 3:2–3.
11. Nahapiet J, Ghoshal S. Social capital, intellectual capital, and the organizational advantage. *Acad Manage Rev.* (1998) 23:242–66. doi: 10.5465/amr.1998.533225
12. Portes A. Social capital: its origins and applications in modern sociology. *Ann Rev Sociol.* (1998) 24:1–24. doi: 10.1146/annurev.soc.24.1.1
13. Yanjie B, Haixiong Q. The social capital of the enterprise and its efficacy. *Chin Soc Sci.* (2000) 2:87–100.
14. Zhang FH. Empirical research on the relationship between resource acquisition and technological innovation performance. *Sci Res.* (2006) 8:157–62.
15. Dai Y, Zhu GL. Research on social capital and innovation performance with absorptive capacity as moderator - An empirical analysis of Guangdong enterprises. *Soft Sci.* (2011) 25:80–5. doi: 10.3969/j.issn.1001-8409.2011.01.018
16. Wang GS, Yang K. An empirical study of the influence of social capital and absorptive capacity on innovation performance. *Manag Sci.* (2011) 24:23–36. doi: 10.3969/j.issn.1672-0334.2011.05.003
17. Xiong J, Sun DY. A study of the relationship among enterprise social capital, technical knowledge acquisition and product innovation performance. *Manag Rev.*(2017) 29:23–39. doi: 10.14120/j.cnki.cn11-5057/f.2017.05.003
18. Zhu JM, Wang HY. Study on the influence of corporate social capital on innovation performance: Based on the mediation effect of knowledge absorption ability. *Sci Technol Manag Res.* (2017) 16:215–23. doi: 10.3969/j.issn.1000-7695.2017.16.031
19. Teece DJ. Explication dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. *Strateg Manag J.* (2007) 28:1319–50. doi: 10.1002/smj.640
20. Kaplan RS, Norton DP. How strategy maps frame an organization's objectives. *Financial Exec.* (2004) 2:40–5.
21. Teece DJ, Pisano G, Shuen A. Dynamic capabilities and strategic management. *Strateg Manag J.* (1997) 18:509–33.
22. Wang CL, Ahmed PK. Dynamic capabilities: a review and research agenda. *Int J Manag Rev.* (2007) 9:31–51. doi: 10.1111/j.1468-2370.2007.00201.x
23. Helfat CE, Finkelstein S, Mitchell W, Peteraf M, Singh H, Teece D, et al. Dynamic capabilities: understanding strategic change in organizations. *Acad Manage Rev.* (2007) 1:203–7. doi: 10.5465/AMR.2005.15281542

24. Güttel WH, Konlechner SW. Continuously hanging by a thread: Managing contextually ambidextrous organizations. *Schmalenbach Bus Rev*. (2009) 2:140–71. doi: 10.1007/BF03396782
25. Eisenhardt KM, Martin JA. Dynamic capabilities: what are they? *Strateg Manag J*. (2000) 21:1105–21.
26. Teece DJ. Dynamic capabilities: routines versus entrepreneurial action. *J Manag Stud*. (2012) 49:1395–401. doi: 10.1111/j.1467-6486.2012.01080.x
27. Makkone H, Pohjola M, Olkkonen A. Dynamic capabilities and firm performance in a financial crisis. *J Bus Res*. (2014) 67:2707–19. doi: 10.1016/j.jbusres.2013.03.020
28. Su JQ, Liu J. Study on relationship between dynamic capabilities and nnovation performance in complex product systems. *Res Sci Manag*. (2013) 34:79–84. doi: 10.19571/j.cnki.1000-2995.2013.10.010
29. Wu H. The dimension of dynamic capabilities and their impact on innovation performance Second thought on Teeces definition. *Manag Rev*.(2016) 28:76–83. doi: 10.14120/j.cnki.cn11-5057/f.2016.03.008
30. Sun H, Zhang SL. Research on the relationship between dynamic capabilities and firms' innovation performance in the background of internationalization. *Indust Technol Econ*. (2018) 11:35–43. doi: 10.3969/j.issn.1004-910X.2018.11.005
31. Adler PS, Kwon SW. Social capital: prospects for new concept. *Acad Manag Rev*. (2002) 27:17–40. doi: 10.5465/amr.2002.5922314
32. Ma H, Li G. System, social capital and financing constraints of high-tech enterprises-An empirical study based on GEM listed companies. *Stock Market Guide*. (2014) 12:43–7.
33. Zhou L, Lin N. Can social capital improve enterprise in access to venture capital-Based on the evidence of Gem listed company. *Sci Technol Prog Policy*. (2018) 12:84–92. doi: 10.6049/kjjbydc.2017030778
34. Sheng YH, Jiang HQ. Research on the relationship between technology diversification strategy and high-tech enterprise performance under dual characteristics. *J Indust Technol Econ*. (2018) 2:13–21. doi: 10.3969/j.issn.1004|910X.2018.02.002
35. Zhao F, Wang TN, Zhang L. An empirical study on the effect of diversification strategy on firm performance. *China Soft Sci*. (2012) 11:111–22. doi: 10.3969/j.issn.1002-9753.2012.11.011
36. Riewoldt B, Larkin CC, Zhou DY, Yongfa L. *QCA Design Principles and Applications-New Methods Beyond Qualitative and Quantitative Research*. Beijing: China Machine Press (2018).
37. Can M, Gozgor G. Effects of export product diversification on quality upgrading: an empirical study. *J Int Trade Econ Dev*. (2018) 27:293–313. doi: 10.1080/09638199.2017.1370006

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BRIEF RESEARCH REPORT
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The Amplifying Effect of Conflicts on Case Fatality Rate of COVID-19: Evidence From 120 Countries

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Using the COVID-19 database of Johns Hopkins University, this study examines the determinants of the case fatality rate of COVID-19. We consider various potential determinants of the mortality risk of COVID-19 in 120 countries. The Ordinary Least Squares (OLS) and the Kernel-based Regularized Least Squares (KRLS) estimations show that internal and external conflicts are positively related to the case fatality rates. This evidence is robust to the exclusion of countries across different regions. Thus, the evidence indicates that conflict may explain significant differences in the case fatality rate of COVID-19 across countries.

Keywords: COVID-19 pandemic, case fatality rate, mortality risk, armed conflicts, machine learning estimator

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INTRODUCTION

The COVID-19 pandemic has affected every aspect of the economy and society. Since this new type of coronavirus is significantly more fatal than the common flu and is transmittable from one human to another, the pandemic has quickly spread across the globe. In mid-May 2021, there were 168 million infected people and almost 3.4 million had died worldwide (1); however, the case fatality rate (henceforth CFR), i.e., the total deaths relative to total cases, differs across countries. For example, according to the COVID-19 database of Johns Hopkins University provided by Dong et al. (1), on May 15, 2021, there were 33,715,951 COVID-19 cases and 600,147 deaths in the United States, for a CFR of 1.78%. This CFR is lower than the CFR of the world, which was 2.07% on that date. Interestingly, there were 4,450,777 total cases and 127,679 total deaths due to the COVID-19 pandemic in the United Kingdom as of May 15, 2021, with a CFR of 2.86%. The data from the database of Johns Hopkins University, on May 15, 2021, show that the CFR of the top 20 most infected countries in the world has changed from 0.87 (Turkey) to 9.25 (Mexico).

Conflicts are a significant reflection of political instability, which can provide a better ground for COVID-19 transmission. A higher number of infected people implies a higher number of deaths. Conflicts should be positively correlated with less effective testing and tracing policy, meaning that more infection cases might go undetected, biasing the CFR toward higher estimates. Therefore, the CFR might be higher in certain countries despite similar infection dynamics. For instance, internal protests and similar social movement events, such as the 2020 Black Lives Matter protests and the 2021 storming of the United States Capitol Building, can increase the CFR of COVID-19 (2). Conflicts affect CFR because of increased transmission, thereby increasing the death probability (3).

Given this context, this study examines the determinants of CFRs related to COVID-19 across 120 countries. There are previous studies that focused on the determinants of CFRs of COVID-19. For instance, Banik et al. (4) and Khan et al. (5) found that the public health system and age structure are the main determinants of the CFR. Similarly, Moosa and Khatatbeh (6) found that age structure and population density are the main determinants of the CFR. Daw (7) showed that armed conflict is the main determinant of the spread of COVID-19 in Libya, Syria, and Yemen. Elgar et al. (8) indicated that social capital and income inequality are the main drivers of COVID-19 deaths in 84 countries. Finally, Sorci et al. (9) observed that share of the population over 70, income per capita, and democracy influence the CFR of a country.

Unlike previous studies, this study implements the Kernel-based Regularized Least Squares (KRLS) to address potential issues of non-linearity and multicollinearity. In doing so, this study obtains evidence on the direction, sign, and magnitude of the causality between armed conflict and COVID-19. In addition, we observe that conflicts positively affect CFR because of increased transmission and increasing death probability.

The rest of the study is organized as follows. First, the paper explains empirical strategy and data. Then, it discusses empirical results and provides robustness checks and concludes.

EMPIRICAL STRATEGY, ESTIMATION PROCEDURE, AND DATA

The Baseline Empirical Model and Estimation Procedure

This study estimates the following equation:

$$CFR_i = \gamma_0 + \gamma_1 X_i + \varepsilon_{i,t} \tag{1}$$

CFR_i is the case fatality rate in country i; X_i is a vector of control variables, which will be explained accordingly; and ε_i indicates the error term in the estimations. The empirical examination is based on a recently available cross-sectional dataset for 120 countries, and the list of countries in the dataset is provided in **Appendix Table I**. The dataset includes countries at very different developmental stages, explaining cross-country differences in the CFR.

We estimate Equation (1) using the Ordinary Least Squares (OLS) estimator, the traditional method. At this stage, we also consider the KRLS, a machine learning method defined in Hainmueller and Hazlett (10). The KRLS estimator can learn the data to decrease potential misspecification bias. The KRLS method can also solve potential problems of non-linearity and multicollinearity in the OLS estimations (10).

Data

Dependent Variable

The dependent variable is the CFR, and it is calculated as the number of total COVID-19 deaths relative to the number of the total confirmed COVID-19 cases, which is accessed on March 15, 2021. It is the benchmark measure of the fatality rate of the mortality risks of COVID-19 in the empirical epidemiology literature (11). In addition, the CFR shows the likelihood of death in the context of an ongoing infection (12), and the CFR indicator is calculated using the data in Dong et al. (1).

Control Variables

Following previous articles, we focus on various potential drivers of the CFR of COVID-19. Finally, we explain the control variables as follows:

Demographics and Social Networks

The CFR of COVID-19 is highly related to age. Older people are expected to have higher mortality due to the COVID-19. Therefore, the share of people aged 65 and above in the total population and those aged between 0 and 14 in the total population are added. Population density (in logarithmic form) also captures the degree of urbanization and social networks.

Health Capacity, Testing, and Tracking

Health equipment (hospital beds) per 1,000 people and physicians per 1,000 people capture health infrastructure conditions. These indicators are drawn from World Bank data (13). Testing and tracking policies (index from 0 to 5, with a higher level of the index indicating higher quality testing and tracking policies) are determinants of the CFR of COVID-19. This indicator is drawn from the work of Hale et al. (14).

Climate

average temperatures can affect the CFR of COVID-19 if the spread of the virus is similar to that of the seasonal flu. Average temperature data (in degrees Celsius) are downloaded from the website of the World Bank (15).

Economic Structure

The economic complexity index captures the effects of economic development on the CFR (a higher level on the index indicates a higher economic development level). Related data are obtained from Hausmann et al. (16). Following Gozgor and Ranjan (17), the post-tax Gini index of income inequality (index from 0 to 1, with a higher index level indicating greater income inequality) is also included. Related data are obtained from the Standardized World Income Inequality Database (SWIID) (version 9.1) of Solt (18). The index of labor market regulations (index from 0 to 10, with a higher index level indicating greater labor market flexibility) is also included since it captures unemployment payments, minimum wages, and working conditions. These data are downloaded from the economic freedom dataset of Gwartney et al. (19). We suggest that economic structure measured by economic complexity, income inequality, and labor market regulations can affect the CFR of COVID-19.

Globalization

It can affect the CFR of COVID-19 (20). Therefore, the overall KOF globalization index in logarithmic form (index from 0 to 100, with a higher index level indicating greater globalization) is included in the estimations. The data are accessed from the revised KOF globalization dataset of Gygli et al. (21). In addition, refer to Dreher (22) and Gozgor (23) for the methodology used in the KOF globalization indices.

Institutional Quality

Institutions with higher quality can control COVID-19 more efficiently. For this purpose, we use the democracy/autocracy spectrum measured by the Polity2 (index from −10 to 10, with −10 indicating full autocracy and 10 indicating full democracy) is added to the estimations. This indicator is obtained from the Polity V annual time series proposed by Marshall and Gurr (24).

Conflicts and Political Instability

Conflicts are defined by the systematic and sustained use of lethal violence by organized groups that result in at least 500 directly related deaths throughout the episode. Internal and external conflicts are an index from 0 to 14. A higher level of the index indicates heavier armed conflicts. This index captures the events related to international violence, international warfare, international independence war, civil violence, civil warfare, ethnic violence, and ethnic warfare, which can significantly affect the CFR of COVID-19. The related data are obtained from the major episodes of political violence dataset of Marshall (25).

Finally, all indicators and the summary of the descriptive statistics are provided in **Table 1**.

EMPIRICAL FINDINGS AND ROBUSTNESS CHECKS

Ordinary Least Squares and KRLS Findings

Table 2 reports the findings of empirical estimations. Colum (I) provides the results of the OLS estimations, and Column (II) provides the findings of the KRLS estimations. The dependent variable is the CFR in 120 countries in both estimations.

In both the OLS and KRLS estimations, all variables are insignificant except for internal and external conflicts. Specifically, a greater share of people aged 65 and above in the total population increases the CFR. Conversely, a greater share of people aged between 0 and 14 in the total population decreases the CFR as shown in **Table 3**. This evidence is in line with the intuition that COVID-19 mainly kills older people, and young people have a lower CFR (6). Thus, population density is negatively associated with the CFR of COVID-19. In addition, previous studies suggested that population density leads to higher transmission risks of COVID-19 [see (26)]; however, there is mixed evidence on the effects of population density on the CFR

TABLE 2 | Results of Ordinary Least Squares (OLS) and Kernel-based Regularized Least Squares (KRLS) estimations (all countries).

Indicator	OLS (I)	KRLS (II)
Share of population: ages 65 and above	0.075 (0.096)	0.005 (0.006)
Share of population: ages 0–14	−0.020 (0.057)	−0.001 (0.004)
Log population density	−0.197 (0.221)	−0.036 (0.057)
Health equipment	−0.121 (0.146)	−0.010 (0.022)
Physicians	−0.077 (0.285)	−0.018 (0.036)
Average temperatures	−0.003 (0.005)	−0.001 (0.006)
Testing and tracking policies	−0.245 (0.213)	−0.091 (0.058)
Economic complexity	0.529 (0.530)	0.021 (0.055)
Post-tax Gini	0.774 (4.909)	0.004 (0.865)
Labor market regulations	−0.039 (0.209)	−0.046 (0.059)
Log globalization	−5.273 (3.747)	−0.281 (0.246)
Democracy/autocracy spectrum	0.031 (0.056)	0.008 (0.010)
Internal- and external conflicts	0.775*** (0.233)	0.167*** (0.045)
R-squared	0.1819	0.2093
Observations	120	120

*The dependent variable is the case fatality rate (CFR). The robust standard errors are in (). ***p< 0.01.*

TABLE 1 | Descriptive statistics.

Indicator	Definition	Data source	Mean	SD	Min.	Max.	Obs.
Dependent variable: case fatality rate	Level	Dong et al. (1)	2.302	2.801	0.050	28.91	120
Demographics: share of population: ages 65 and above	%	World Bank (13)	9.865	6.570	1.144	27.04	120
Demographics: share of population: ages 0–14	%	World Bank (13)	25.69	10.13	12.33	47.30	120
Social networks: population density	Logarithmic form	World Bank (13)	4.228	1.284	0.683	8.976	120
Health capacity: health equipment: hospital beds	Per 1,000 people	World Bank (13)	3.044	2.540	0.001	13.05	120
Health capacity: physicians	Per 1,000 people	World Bank (13)	2.146	1.603	0.014	7.120	120
Testing and tracking policies	Index from 0 to 5	Hale et al. (14)	3.241	1.276	0.000	5.000	120
Climate: average temperatures	Level in celsius degrees	World Bank (15)	17.14	8.606	−5.350	28.25	120
Economic structure: economic complexity	Level in index	Hausmann et al. (16)	0.021	1.007	−2.008	2.309	120
Economic structure: post-tax Gini	Index from 0 to 1	Solt (18)	0.380	0.075	0.227	0.625	120
Economic structure: labor market regulations	Index from 0 to 10	Gwartney et al. (19)	6.298	1.265	2.24	8.98	120
Globalization: KOF globalization index	Log Index from 0 to 100	Dreher (22) & Gygli et al. (21)	4.201	0.193	3.756	4.508	120
Institutional quality: democracy/autocracy spectrum	Index from −10 to 10	Marshall and Gurr (24)	4.741	5.995	−10.00	10.00	120
Conflicts: sum of internal and external conflicts	Index from 0 to 14	Marshall (25)	0.400	1.140	0.000	6.000	120

TABLE 3 | Sensitivity analyses of the KRLS results.

Sensitivity analysis: excluding Indicator	OECD (I)	Europe (II)	Asia (III)	Africa (IV)	South America (V)	Central & North America (VI)
Share of population: ages 65 and above	0.003 (0.008)	0.005 (0.009)	0.008 (0.044)	0.003 (0.004)	0.005 (0.006)	0.008 (0.015)
Share of population: ages 0–14	−0.002 (0.005)	−0.003 (0.005)	−0.002 (0.003)	−0.002 (0.005)	−0.001 (0.004)	−0.005 (0.011)
Log population density	−0.034 (0.054)	−0.044 (0.051)	−0.004 (0.005)	−0.019 (0.036)	−0.027 (0.059)	−0.006 (0.014)
Health equipment	−0.017 (0.020)	−0.023 (0.021)	−0.002 (0.018)	−0.001 (0.015)	−0.007 (0.023)	−0.002 (0.005)
Physicians	−0.015 (0.035)	−0.013 (0.038)	−0.001 (0.002)	−0.012 (0.028)	−0.023 (0.036)	−0.005 (0.008)
Average temperatures	−0.004 (0.006)	−0.004 (0.008)	−0.001 (0.004)	−0.001 (0.004)	−0.001 (0.007)	−0.001 (0.001)
Testing and tracking policies	−0.072 (0.053)	−0.078 (0.057)	−0.006 (0.005)	−0.049 (0.037)	−0.090 (0.060)	−0.021 (0.014)
Economic complexity	0.024 (0.077)	0.030 (0.064)	0.009 (0.039)	0.011 (0.038)	0.039 (0.056)	0.002 (0.012)
Post-tax Gini	0.457 (1.001)	0.539 (1.160)	0.033 (0.057)	0.287 (0.585)	0.171 (0.910)	0.019 (0.208)
Labor market regulations	−0.040 (0.058)	−0.041 (0.057)	−0.005 (0.004)	−0.016 (0.039)	−0.044 (0.068)	−0.009 (0.015)
Log globalization	−0.473 (0.341)	−0.467 (0.340)	−0.003 (0.016)	−0.224 (0.178)	−0.316 (0.252)	−0.080 (0.057)
Democracy/autocracy spectrum	0.002 (0.011)	0.004 (0.011)	0.002 (0.009)	0.004 (0.005)	0.005 (0.011)	0.001 (0.002)
Internal- and external conflicts	0.153*** (0.041)	0.177*** (0.045)	0.006** (0.002)	0.057** (0.026)	0.194*** (0.048)	0.031*** (0.010)
R-squared	0.1841	0.1846	0.2719	0.1447	0.2296	0.0487
Observations	86	86	85	91	110	108

The dependent variable is the case fatality rate (CFR). The robust standard errors are in ().
****p< 0.01 and **p < 0.05.*

of COVID-19. For instance, Khan et al. (5) show that population density has insignificant effects on the CFR of COVID-19 in countries, particularly those with a lower per capita income, where lockdowns and social distancing have been applied.

Healthcare indicators are also included in both estimations. For example, greater healthcare supplies, higher numbers of physicians, and more robust testing and tracking policies negatively affect the CFR of COVID-19; however, their coefficients are statistically insignificant. These results are in line with previous findings, such as those of Banik et al. (4), Khan et al. (5), Moosa and Khatatbeh (6), and Sorci et al. (9). We also find no evidence of a pattern between the CFR of COVID-19 and average temperatures. Again, this evidence aligns with Jamil et al. (27), implying that COVID-19 does not behave like the seasonal flu.

We observe that economic complexity increases the CFR of COVID-19. Given that economic complexity is highly positively correlated with per capita income, this evidence is in line with findings presented in previous studies. Furthermore, greater income inequality, measured by post-tax Gini coefficients, increases the CFR of COVID-19. Elgar et al. (8) indicated that relative income differences in a country could also affect infectious disease patterns. Indeed, income inequality is a strong indicator of inequality in healthcare access, increasing the CFR of COVID-19. In addition, greater labor market flexibility decreases the CFR of COVID-19. Labor market flexibility is, in general, positively associated with the ease of adopting work-from-home arrangements, which decreases the risks of virus exposure (28). We also find that a higher level of globalization reduces the CFR of COVID-19. It is suggested that globalization leads to higher transmission risks of COVID-19 [refer to, e.g., (9)]; however, globalization (especially social globalization indicators, such as internet access) promotes the effects of lockdowns on the spread of COVID-19. Economic globalization can also promote connection with the rest of the world, resulting in greater information sharing and technology to combat COVID-19 (20). The democracy/autocracy spectrum, measured by the Polity2 index, shows that more democratic societies have higher levels of COVID-19 related CFR. This evidence is in line with Sorci et al. (9). It may be related to the issue that it is more difficult to implement hard lockdowns and social distancing in more democratic societies.

The main finding of this study is that internal and external conflicts are positively related to the CFR of COVID-19. Evidence for this finding is observed when the OLS and the KRLS estimations are utilized. The estimated coefficients of total conflicts are around 0.775 and 0.167 in the OLS and the KRLS estimations. Furthermore, both coefficients are statistically significant at the 1% level. Finally, the R-squared of the KRLS estimations is higher than the OLS estimations. This evidence indicates that the KRLS has more explanatory power than the OLS estimations.

Robustness Checks

Table 3 also provides several sensitivity analyses to check the validity of the baseline KRLS estimations. Specifically, following the spirit of Jha and Gozgor (29), we exclude (i) Organization for Economic Co-operation and Development (OECD) member countries; (ii) European countries; (iii) Asian countries; (iv) African countries; (v) South American counties; (vi) Central and North American countries. The related results are provided in Columns (I), (II), (III), (IV), (V), and (VI) of **Table 3**, respectively.

In all the KRLS estimations, the only statistically significant coefficients are internal and external conflicts. Specifically, the greater the share of the population aged 65 and above the higher the CFR of COVID-19, while the greater the share of the population aged between 0 and 14 the lower the CFR. Population density is negatively related to the CFR of COVID-19. Greater supplies of health equipment, higher numbers of physicians, and more robust testing, and tracking policies negatively affect the CFR of COVID-19. There is no evidence of a pattern between the CFR of COVID-19 and average temperatures. Economic complexity increases the CFR of COVID-19. Income inequality increases the CFR of COVID-19. In addition, a greater labor market flexibility decreases the CFR of COVID-19, and a higher level of globalization reduces the CFR of COVID-19. Finally, the more democratic a society, as measured along the democracy/autocracy spectrum, the higher the CFR of COVID-19.

The main and most robust finding in this study is that internal and external conflicts are associated with the CFR of COVID-19. This evidence is still valid when the countries on different continents are excluded. The estimated coefficients of the internal and external conflicts indicator are between 0.006 and 0.194. Thus, all coefficients are statistically significant at the 5% level at least.

CONCLUSION

This study investigates the potential drivers of the CFR of COVID-19 across 120 countries. The results of the OLS and the KRLS estimators indicate that internal and external conflicts are positively associated with the CFR. Other potential determinants are not robust to different estimators. Our main evidence is robust to excluding countries across regions, i.e., the OECD, Europe, Asia, Africa, South America, and Central and North America. Therefore, we suggest that conflicts are significant factors explaining why there are significant differences in the CFR across developed and developing economies.

Overall, monitoring internal and external conflicts may help identify the CFR of COVID-19. These results suggest that the mortality risk of COVID-19 will increase because of the escalation in conflicts. Our findings are consistent with the recent study by Daw (7) that links higher armed conflict levels to the greater spread of the COVID-19 pandemic in Libya, Syria, and Yemen. Future articles can use different indicators and econometric techniques using survey data to predict the drivers of the spread of the COVID-19 pandemic and the CFR in different countries.

DATA AVAILABILITY STATEMENT

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found in the article/supplementary material.

AUTHOR CONTRIBUTIONS

YZ: writing original draft & methodology. DJ: writing original draft & estimations. GG: writing original draft & data collection. EC: reviewing original draft & project management. All authors contributed to the article and approved the submitted version.

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REFERENCES

1. Dong E, Du H, Gardner L. An interactive web-based dashboard to track COVID-19 in real time. *Lancet Infect Dis.* (2020) 20:533–4. doi: 10.1016/S1473-3099(20)30120-1
2. Neyman G, Dalsey W. Black lives matter protests and COVID-19 cases: relationship in two databases. *J Public Health.* (2021) 43:225–7. doi: 10.1093/pubmed/fdaa212
3. Washington Post. *Storming of Capitol was Textbook Potential Coronavirus Superspreader, Experts Say*. (2021) Available online at: https://www.washingtonpost.com/health/2021/01/08/capitol-coronavirus/ (accessed January 8, 2021).
4. Banik A, Nag T, Chowdhury SR, Chatterjee R. Why do COVID-19 fatality rates differ across countries? An explorative cross-country study based on select indicators. *Global Business Review.* (2020) 21:607–25. doi: 10.1177/0972150920929897
5. Khan JR, Awan N, Islam M, Muurlink O. Healthcare capacity, health expenditure, and civil society as predictors of COVID-19 case fatalities: a global analysis. *Front Public Health.* (2020) 8:347. doi: 10.3389/fpubh.2020.00347
6. Moosa IA, Khatatbeh IN. Robust and fragile determinants of the infection and case fatality rates of covid-19: international cross-sectional evidence. *Appl Econ.* (2021) 53:1225–34. doi: 10.1080/00036846.2020.1827139
7. Daw MA. The impact of armed conflict on the epidemiological situation of coronavirus disease (COVID-19) in Libya, Syria, and Yemen. *Front Public Health.* (2021) 9:667364. doi: 10.3389/fpubh.2021.667364
8. Elgar FJ, Stefaniak A, Wohl MJ. The trouble with trust: time-series analysis of social capital, income inequality, and COVID-19 deaths in 84 countries. *Soc Sci Med.* (2020) 263:113365. doi: 10.1016/j.socscimed.2020.113365
9. Sorci G, Faivre B, Morand S. Explaining among-country variation in COVID-19 case fatality rate. *Sci Rep.* (2020) 10:1–11. doi: 10.1038/s41598-020-75848-2
10. Hainmueller J, Hazlett C. Kernel regularized least squares: reducing misspecification bias with a flexible and interpretable machine learning approach. *Pol Anal.* (2014) 22:143–68. doi: 10.1093/pan/mpt019
11. Soodejani MT, Lotfi MH, Tabatabaei SM. Is case fatality rate an appropriate index to represent the status of case-finding process for COVID-19 in different countries? *Infect Ecol Epidemiol.* (2020) 10:1773733. doi: 10.1080/20008686.2020.1773733
12. Kelly H, Cowling BJ. Case fatality: rate, ratio, or risk? *Epidemiology.* (2013) 24:622–3. doi: 10.1097/EDE.0b013e318296c2b6
13. World Bank. *World Development Indicators Dataset*. Washington, DC: World Bank (2021).
14. Hale T, Noam A, Cameron-Blake E, Hallas L, Kira B, Majumdar S, et al. *Oxford COVID-19 Government Response Tracker*. Oxford: Oxford University, Blavatnik School of Government (2020).
15. World Bank. *Climate Data API*. Washington, DC: World Bank (2021).

16. Hausmann R, Hidalgo CA, Bustos S, Coscia M, Simoes A, Yildirim MA. *The Atlas of Economic Complexity: Mapping Paths to Prosperity*. Cambridge, MA: The MIT Press (2013). doi: 10.7551/mitpress/9647.001.0001
17. Gozgor G, Ranjan P. Globalisation, inequality and redistribution: theory and evidence. *World Econ.* (2017) 40:2704–51. doi: 10.1111/twec.12518
18. Solt F. Measuring income inequality across countries and over time: the standardized world income inequality database. *Soc Sci Q.* (2020) 101:1183–9. doi: 10.1111/ssqu.12795
19. Gwartney J, Lawson R, Hall J. *Economic Freedom of the World 2020 Annual Report*. Vancouver: Fraser Institute (2020).
20. Antràs P, Redding SJ, Rossi-Hansberg E. Globalization and Pandemics. *National Bureau of Economic Research (NBER) Working Paper, No. 27840*. Cambridge, MA: NBER (2020). doi: 10.3386/w27840
21. Gygli S, Haelg F, Potrafke N, Sturm J-E. The KOF globalisation index – revisited. *Rev Int Org.* (2019) 14:543–74. doi: 10.1007/s11558-019-09344-2
22. Dreher A. Does globalization affect growth? Evidence from a new index of globalization. *Appl Econ.* (2006) 38:1091–110. doi: 10.1080/00036840500392078
23. Gozgor G. Robustness of the KOF index of economic globalisation. *World Econ.* (2018) 41:414–30. doi: 10.1111/twec.12546
24. Marshall MG, Gurr TR. *Polity V Project: Political Regime Characteristics and Transitions, 1800–2018*. Vienna, VA: Center for Systemic Peace (2020).
25. Marshall MG. *Major Episodes of Political Violence, 1946–2018*. Vienna, VA: Center for Systemic Peace (2019).
26. Feng S, Shen C, Xia N, Song W, Fan M, Cowling BJ. Rational use of face masks in the COVID-19 pandemic. *Lancet Respir Med.* (2020) 8:434–6. doi: 10.1016/S2213-2600(20)30134-X
27. Jamil T, Alam I, Gojobori T, Duarte CM. No evidence for temperature-dependence of the COVID-19 epidemic. *Front Public Health.* (2020) 8:436. doi: 10.3389/fpubh.2020.00436
28. Bonacini L, Gallo G, Scicchitano S. Working from home and income inequality: risks of a 'New Normal' with COVID-19. *J Popul Econ.* (2021) 34:303–60. doi: 10.1007/s00148-020-00800-7
29. Jha P, Gozgor G. Globalization and taxation: theory and evidence. *Eur J Polit Econ.* (2019) 59:296–315. doi: 10.1016/j.ejpoleco.2019.04.001

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

APPENDIX

Appendix Table A1 | The 120 countries in the dataset.

Albania, Algeria, Angola, Argentina, Australia, Austria, Azerbaijan, Bangladesh, Belarus, Bolivia, Bosnia and Herzegovina, Brazil, Bulgaria, Cambodia, Cameroon, Canada, Chile, China, Colombia, Congo Republic, Costa Rica, Cote d'Ivoire, Croatia, Czech Republic, Denmark, Dominican Republic, Ecuador, Egypt, El Salvador, Estonia, Ethiopia, Finland, France, Gabon, Georgia, Germany, Ghana, Greece, Guatemala, Guinea, Honduras, Hungary, India, Indonesia, Iran, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Korea Republic, Kuwait, Kyrgyzstan, Laos, Latvia, Lebanon, Liberia, Libya, Lithuania, Madagascar, Malawi, Malaysia, Mali, Mauritania, Mauritius, Mexico, Moldova, Mongolia, Morocco, Mozambique, Netherlands, New Zealand, Nicaragua, Nigeria, North Macedonia, Norway, Oman, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Portugal, Qatar, Romania, Russia, Saudi Arabia, Senegal, Serbia, Singapore, Slovakia, Slovenia, South Africa, Spain, Sri Lanka, Sudan, Sweden, Switzerland, Tajikistan, Tanzania, Thailand, Trinidad and Tobago, Tunisia, Turkey, Uganda, Ukraine, United Arab Emirates, United Kingdom, United States, Uruguay, Venezuela, Vietnam, Yemen, Zambia, and Zimbabwe.

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