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Managing climate risk in the global economic system in the post-COVID-19 era

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Managing climate risk in the global economic system in the post-COVID-19 era

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Potential Impacts of Fukushima Nuclear Leakage on China's Carbon Neutrality—an Investigation on Nuclear Power Avoidance and Regional Heterogeneity

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Ten years have passed since the Fukushima nuclear accident, but its impact on the environment and energy consumption structure has continued up to now. This accident delayed the process of China's nuclear power construction and may have a certain potential impact on China's goal of carbon neutrality by 2060. This paper aims to properly understand the negative impact of the Fukushima nuclear leakage on China's nuclear power industry, to reawaken the attention of Chinese academic and governmental departments to nuclear energy, and to explore a reasonable path to achieve carbon neutrality. Based on the idea of a quasi-natural experiment, this paper collected the carbon emissions data of 30 provinces and cities in China from 2000 to 2017, and explored the accident impact and mechanism on carbon emissions in the provinces with nuclear power. The research results showed that the Fukushima nuclear accident had different impacts on China's nuclear power provinces. Due to the large proportion of manufacturing industry and high dependence on energy, the carbon emissions in Jiangsu Province rose after being impacted by the incident, in contrast, the research results in Guangdong and Zhejiang provinces were opposite. Through the mechanism test, it was found that the incident impact had reduced the carbon emissions of Guangdong and Zhejiang by improving the industrial structure and energy efficiency, with the explanation ratios of 10.45 and 15.1%, respectively. Technological innovation had obscured the emission reduction effect of the incident impact, and the innovation driving force for green development in nuclear power base provinces was insufficient. These findings are helpful to analyze the regional layout of China's nuclear power and have implications for achieving carbon neutrality. Finally, this study offers relevant policy recommendations.

Keywords: fukushima nuclear leakage, carbon neutrality, nuclear power avoidance, regional heterogeneity, synthetic control method

INTRODUCTION

In September 2021, under the dual pressure of insufficient power supply and actions to control the total and intensity of energy consumption, Northeastern China experienced widespread power outages, causing huge problems for industrial production and residential life, indicating that China's energy demand and emission reduction targets are in a complex interaction relationship. China needs to find a pathway to meet its continuously expanding energy demand and achieve its carbon neutrality targets. In addition to the divergence from energy demand, China's carbon-neutral goal is facing three challenges: First, some effective policy tools and realization paths are needed. Second, the carbon-neutral target reflects the long-term equilibrium of production activities and the natural environment. This goal cannot be realized with a simple method of total amount control. Almost all of the important economic departments will be involved in the project. At the same time, the negative effect of market competition may be revealed, especially the surge and waste in high-carbon consumer products. Third, the path to carbon neutrality is excessively tilted to exploit clean energy, consequently forming a "limping" development. It may create risks for energy security and energy system optimization, especially taking into account indirect and unstable power generation methods such as wind energy and solar energy. The development of the nuclear power industry can overcome these challenges. Therefore, it can be considered as an option for achieving carbon neutrality.

However, since the Fukushima nuclear accident, the public has become sensitive to the construction of nuclear power plants. The deeper reasons for resident's concerns about nuclear power are their dissatisfaction with untimely information disclosure and imperfect participation mechanisms and the like (Huang et al., 2013). Richard AMeserve, chairman of the *United States Nuclear Regulatory Commissio*n, pointed out that public attitude may determine whether nuclear technology can become a part of energy technology. So, how to coordinate the relationship between nuclear power construction projects and residents has become the key point to nuclear energy development.

Also, influenced by public sentiment, countries that originally worked hard to develop nuclear energy had to face the problem of nuclear power evasion. In which, China had issued countermeasures called *National Four Articles*. It brought the following impacts: 28 nuclear power units, already approved by the *National Development and Reform Commission* and started construction, can continue to be constructed. The construction of 6 nuclear power units, which have obtained the construction permit but have not yet started, had been suspended. 14 units that had been approved to enter the preliminary work cannot continue until the safety planning work was completed. Also, although inland provinces were striving for construction, at least 25 nuclear power plants here run aground. After the accident, the national policy for nuclear power development changed from active development to safe development, indicating that China's nuclear power will shift from high-speed development to slow and steady development. Further, the decreased scale and slowdown of nuclear power development may impact China's carbon neutralization goal in 2060. In the post epidemic period, the use of nuclear energy may change many existing economic behaviors and economic results.

The changed nuclear energy policy also impacted China's energy structure and emission reduction effect. Considering China's commitment to global climate change, if avoid developing nuclear power, accelerating the installed capacity of renewable energy may become a good choice. Economic intuition shows that the proportion of renewable energy in China will rise, accompanied by less total carbon emissions. However, due to the terrain limitation of hydropower and the intermittence of wind energy and solar energy, nuclear energy cannot be fully replaced. This situation urges China to find a new balance between energy policy and environmental protection. Potential impacts like these are a complex matter, whether there exists a relation between the nuclear leakage accident and China's carbon emission needs further investigation.

The possible marginal contributions of this paper are three: First, the SCM used in this paper effectively overcomes the endogeneity of the model and the subjectivity of sample selection, and obtains more accurate estimation results. The robustness of the empirical results was tested by using Permutation Test, Falsification Test, PSM-DID, and controlling other policy influences. Second, this paper examines the impact of the Fukushima nuclear accident on China's nuclear power industry, especially inland nuclear power, and provides early recognition of the possible impact of nuclear accidents on China's carbon neutrality targets. Third, due to the nuclear power industry is related to national strategic security, many data are not available, making it difficult for the relevant literature to validate the model empirically through accurate figures, but only through cases. In addition, most of the research on nuclear power in recent years has been conducted from the legal and regulatory perspectives, and there is very little literature and research results from the economic perspective. This paper fills the relevant research gap and enriches the study of China's nuclear power industry.

LITERATURE REVIEW

Impact of Major Emergency Safety Incidents on Clean Energy

The Fukushima nuclear accident is the biggest nuclear disaster since the Chernobyl nuclear accident in 1986, which once again arouses people's attention to nuclear safety around the world (Butler et al., 2011; Hayashi and Hughes, 2013; Huang et al., 2013; Visschers and Siegrist, 2013), and moral issues related to nuclear safety, such as energy, pollution, environment, and health, have also become hot topics (Butler et al., 2011; Mao et al., 2015; Du et al., 2016).

The first clue is the direct impact of nuclear accidents on the development of nuclear power. After the nuclear accident, some countries changed their nuclear energy development strategy or even gave up nuclear power (Lee and Wang, 2014). Generally speaking, after the accident, the attitudes of various countries towards nuclear power development can be divided into two camps: the nuclear abandonment faction, represented by Japan and Germany, and the nuclear improvement faction, represented by China and the United States (Butler et al., 2011; Joskow and Parsons, 2012; Kim et al., 2013; Ming et al., 2016). Nuclear abandonment refers to achieving the goal of abandoning nuclear energy by gradually reducing the number of nuclear power plants. In contrast, nuclear improvement emphasizes strengthening the rational development and utilization of nuclear energy, thus improving the safety of nuclear power. Some factors, such as the contradiction between the shortage of energy supply and the urgency of energy demand, and the advantages of nuclear power in terms of emission reduction and cost compared with traditional energy, determine that the overall trend of China's nuclear power development will not be reversed after the accident. However, the Fukushima nuclear accident did, to a certain extent, impacted the low-carbonization process of China's established energy structure, and inhibited the development of China's nuclear power. This is reflected in the following aspects: First, the speed of nuclear power development was affected. By the judgment of the *State Grid Energy Research Institute*, slowing down the start-up of nuclear power for 1–2 years will probably reduce the installed capacity by more than 10 million kW in 2020. Second, the shelving of China's inland nuclear power construction plan will affect the development of the central and western regions, which have a large population and are in urgent need of nuclear power (Zhu and Krantzberg, 2014). Third, the slow restart of nuclear power has a greater impact on equipment manufacturers, such as *Dongfang Electric* and *China Yizhong*, by November 2014, they had not even received orders for nuclear power equipment for the second year, which is bound to put pressure on China's subsequent nuclear power construction.

The second clue is the indirect effect of the nuclear accident, which means the impact of the nuclear fear triggered by the nuclear leakage. In general, due to the NIMBY effect, residents living near nuclear power plants have a negative attitude towards nuclear energy (Dan, 2007; Guo and Ren, 2017). This sentiment became more significant after the Fukushima nuclear accident (Kessides, 2012; Srinivasan and Rethinaraj, 2013; Lee and Wang, 2014). According to a survey of 18,787 adults in 24 countries by Laes et al. (2011), 62% of respondents opposed nuclear energy, and 26% reported that the Fukushima accident changed their original views. Among them, the Chinese people's attitude towards nuclear power has changed obviously, and residents around nuclear power plants are generally unwilling to build new nuclear power projects (Huang et al., 2013; Huang et al., 2018).

Under the nuclear fear sentiment, many anti-nuclear demonstrations and mass incidents broke out one after another in China. The nuclear fuel treatment plants in Heshan City, Guangdong Province, Lianyungang Nuclear Cycle Treatment Station Project, and Pengze Nuclear Power Plant Construction Project were all shelved due to opposition from residents. Under this situation, to balance the deviation between the international development trend and the domestic public opinion demand, the government adopted a conservative approach in formulating the nuclear power policy agenda. At present, the fear of nuclear has brought far more losses to China than the nuclear leakage itself.

The third clue is the impact of the Fukushima nuclear accident on the rapid development of other clean energy sources in China. Before this nuclear leakage, scholars were already highly concerned about the development of clean energy, especially solar energy (Du et al., 2014). Studies have shown that more people support renewable energy than nuclear energy (McGowan and Sauter, 2005; Pidgeon et al., 2008). This trend was more obvious after the Fukushima nuclear accident. Research from Wallard et al. (2012) showed that the public prefers renewable energy sources, such as solar energy (97%), wind energy (93%), and hydropower (91%) to nuclear energy (38%). A group of scholars has turned their attention to renewable energy that may replace nuclear energy (Notter, 2015; Sorensen, 2017; Bilgili et al., 2021).

Methods for Evaluating the Impact of Exogenous Incidents

As a natural disaster and exogenous event, the Fukushima nuclear accident had different impacts on China's areas that had built nuclear power plants (Guangdong, Jiangsu, and Zhejiang), and those not. It can be regarded as a natural experiment. To study the impact of Fukushima nuclear accident on regional carbon emissions, we compared the changes of carbon emissions in experimental areas before and after the exogenous shock. However, many factors can affect regional carbon emissions.

A common measurement method to eliminate the general factors affecting regional carbon emissions is the Difference in Difference Method (DID). Its principle is to construct a treatment group with incident influence and a control group not. When studying the influence of exogenous shock effect on the treatment group, the control group naturally becomes a reference. The application of DID must satisfy the randomness hypothesis and the homogeneity hypothesis, in which the randomness hypothesis requires the sample selection to be random, and the homogeneity hypothesis requires the treatment group and the control group to have similar development trends before the implementation of exogenous shocks. But these hypotheses are often difficult to meet.

Compared to DID, the Synthetic Control Method (SCM) proposed by Abadie and Gardeazabal (2003) gives different weights to different control group individuals. Based on these weights, a counterfactual control group of policy intervention individuals is constructed to simulate the characteristics of the treatment group before being affected by a event, and the real treatment group value is compared with the synthetic value to obtain the event effect. SCM uses a data-driven method to give weights to synthetic individuals, and calculates out the contribution of each synthetic individual to the counterfactual control group. It effectively overcomes the subjectivity and endogeneity of sample selection, and makes up for the limitations of DID method in policy evaluation. In recent years, SCM has been applied to policy evaluation research in different fields. For example, Adhikari and Alm (2016) evaluated the economic effects of single tax reform through SCM and Kim and Kim (2016) used it to test the implementation effects of green gas initiative policies implemented in the northeastern United States.

Methodology and Data

Based on the idea of counterfactual analysis, this paper used SCM to analyze the impact of Fukushima nuclear accident on China's nuclear power-owning provinces. The carbon emission (*CE*) index used in this paper was calculated according to energy consumption data and emission factors, following the emission accounting method of the *Intergovernmental Panel on Climate Change* (IPCC). The inventory includes energy-related emissions (17 fossil fuels in 47 fields) and process-related emissions (cement production). The calculation formula is as follows:

$$CE_{ik} = AD_{ik} \times NCV_k \times CC_k \times O_{ik} \tag{1}$$

CE_{ik} refers to carbon dioxide emissions in area i; AD_{ik} is the consumption of fuel in area i; NCV_{ik} refers to the net calorific value, that is, the calorific value generated per unit of fossil fuel combustion. CC_k is CO_2 emissions per unit of net heat generated by fossil fuel k; O_{ik} refers to the oxidation rate of fossil fuels during combustion.

According to existing research, factors such as population size, economic development level, industrial structure, energy intensity, and opening-up level will affect carbon emissions. This paper selected these indicators as control variables, among which the urbanization level is the proportion of the urban population at the end of the year, and the data was taken from the *National Bureau of Statistics*. The level of economic development is expressed by the logarithm of regional GDP per capita. The data was taken from the *National Bureau of Statistics* and deflated with 2000 as the base period. The level of opening to the outside world is the ratio of total exports of domestic destinations and sources of goods to GDP. Import and export data came from the *General Administration of Customs* and was converted by the average exchange rate of RMB against the United States dollar in the current year. Data related to coal consumption and thermal power generation were taken from *China Energy Statistics Yearbook* (2001–2018). The energy intensity is the ratio of 10,000 tons of standard coal to the constant price of 10,000 yuan GDP. The relevant data came from *China Energy Statistics Yearbook* (2001–2018). The industrial structure is the ratio of regional industrial added value to regional GDP, and the data came from *China Statistical Yearbook* (2001–2018). The symbols and meanings of each variable were shown in **Table 1** and **Table 2** includes the descriptive statistics of the main variables.

Impact Effect Evaluation of Fukushima Nuclear Accident

With the different weights of the control group, SCM can minimize the Root Mean Square Prediction Error (RMSPE) of the experimental and synthetic control group before the exogenous event. The fitting of predictive control variables is shown in **Table 3**. It shows that the difference of RMSPE among Guangdong, Jiangsu, and Zhejiang is small, which are all less than 10. The predictive control variables, such as economic development level (*lngdppc*), population size (*lnpop*), urbanization level (*urb*), and industrial structure (*is*) in each area are very close to the real level. Among them, the carbon emissions of the synthetic area in 2000 and 2005 are highly similar to those of the experimental area, indicating that the SCM method in this paper fitted well.

The synthetic regional weights of the experimental provinces were shown in **Table 4**. Synthetic areas of Guangdong Province are Hebei (0.592), Liaoning (0.094), and Shanghai (0.315), indicating that the carbon emissions in Guangdong Province were closest to those in Hebei. Synthetic areas of Jiangsu Province are Liaoning (0.353), Shandong (0.489), and Shanghai (0.158), indicating that the carbon emissions in Shandong were most similar to those in Jiangsu. For Zhejiang, synthetic areas are Fujian (0.162), Henan (0.276), Shandong (0.154), and Shanghai (0.408). The basic situation in Shanghai was closest to Zhejiang.

Taking the time of the Fukushima nuclear accident as a boundary, we divided the sample divided into two parts: the pre-incident period (2000–2010) and the post-incident period (2011–2017). Then, we carried out SCM on three experimental areas with completed nuclear power facilities (Guangdong, Jiangsu, and Zhejiang), and the results were shown in **Figure 1**. Before the Fukushima nuclear accident, the actual carbon emissions of Guangdong, Jiangsu, and Zhejiang provinces generally had a good fit with the synthetic areas. After the incident, the carbon emissions of Guangdong and Zhejiang showed a downward trend, in contrast, Jiangsu showed a significant upward trend. This result is inconsistent with economic intuition: due to other clean energy in China cannot be increased quickly after the nuclear suspension, thermal power naturally became an important energy source to make up the energy gap, carbon emissions in the three provinces will then increase. We realize that this may be an important finding, and in subsequent analyses we will examine the reasons for this anomaly based on regional heterogeneity.

Validity and Robustness Test

A core issue, whether any relationship between Fukushima nuclear leakage and China's carbon emissions exists, needs to be confirmed. Because of losing the supply of nuclear energy, carbon emission increased in Jiangsu is foreseeable. However, carbon emission decreased in Guangdong and Zhejiang may be affected by other factors, for example, the carbon trading pilot policy launched in 2011, and other emission reduction measures implied by regional provinces. In general, carbon emission reduction is a global trend, even if there was no nuclear leakage, China's carbon emissions may present a decline. However, the occurrence of the Fukushima nuclear accident has almost affected all nuclear power countries, especially Japan and Germany, which changed energy strategy for public opinion and energy security. The prospect of China's nuclear power had been doubted by the mass and even some scientists. Some government officials believed China's nuclear power may fall into long-term stagnation. To address possible energy crises and emission reduction pressure, governments that lost nuclear power

TABLE 1 | Main indexes and calculation methods of synthetic control method research.

Variable type	Variable name	Symbol	Definition
Explained variable	Carbon emissions	CE	Calculated based on energy consumption data and emission factors. Unit: million tons
	Economic development level	lngdp	The logarithm of real regional GDP. Unit: 100 million yuan
	Industrial structure	is	The added value of secondary industry/regional GDP.
Control variable	Population size	lnpop	The logarithm of the population at the end of the year. Unit: 10,000 persons
	Coal consumption	lncoal	The logarithm of regional raw coal consumption. Unit: 10,000 tons
	Thermal power generation	lnthe	The logarithm of regional thermal power generation. Unit: 100 million kWh
	Energy intensity	ei	Consumption of standard coal (10,000 tons)/constant price GDP (10,000 yuan)
	Level of opening to the outside world	open	Total regional exports/regional GDP.
	Urbanization level	urb	Year-end urban population/year-end total regional population

TABLE 2 | Descriptive statistics for key indicators.

	(1) N	(2) Mean	(3) Sd	(4) Min	(5) Max
CE	540	236.141	177.377	8.700	842.200
lnthe	540	6.457	0.985	3.262	8.545
lngdppc	540	10.342	1.011	7.923	12.357
lnpop	540	8.155	0.757	6.248	9.321
lncoal	540	8.920	0.954	5.256	10.668
ei	540	1.683	0.933	0.459	7.102
open	540	0.235	0.295	0.008	1.787
is	540	0.463	0.078	0.190	0.615
urb	540	0.498	0.152	0.232	0.896

adopted new energy policies and stricter environmental regulations. Although nuclear power accounts for a small proportion of primary energy, the Fukushima nuclear leakage had a profound impact on regional and even national energy strategies.

To confirm the relationship between the nuclear leakage and China's carbon emissions, as well as test the robustness of the previous research results, we combined with the research experience of Abadie and Gardeazabal (2003), Abadie et al. (2010), and conducted the Permutation Test, Falsification Test, PSM-DID, and a method of controlling other policy impacts.

Permutation Test

The permutation test was used to eliminate the interference of other factors. We assumed all the control group areas had nuclear power and were impacted by the Fukushima nuclear accident in 2011. The synthetic objects are re-constructed through SCM, and compared with the actual carbon emission observations of each region (the impact effect is the difference between the actual observation values and the synthetic values of the region). Then, we got the distribution curves of placebo tests in the control group, and compared them with Guangdong, Jiangsu, and Zhejiang province, respectively. If there was a significant difference in the two kind curves, the exogenous impact significantly affected the real experimental area. Otherwise, further tests are needed.

We had 27 control group areas outside Guangdong, Jiangsu, and Zhejiang provinces. However, if the fitting effect of a certain area is poor (the mean square prediction error MSPE is very large) before the incident, the fitting result is not credible (Abadie et al., 2010). We calculated the MSPE of all areas according to **Eq. 2** in the pre-incident period, in which, y_{1t} is the area treated as an experimental object, $y_{jt,}$ and w^{*} are control group areas and their weights respectively. Finally, areas whose MSPE twice the experimental area before the incident were excluded. The placebo test results of the remained 21 areas were listed in **Figure 2**.

$$\mathrm{MSPE}_{pre} \equiv \frac{1}{T_0}\sum_{t=1}^{T_0}\left(y_{1t}-\sum_{j=2}^{J+1} w_j^{*} y_{jt}\right)^2 \quad (2)$$

As shown in **Figure 2**, before the impact of the exogenous incident, the difference of the curves between the experimental province and other areas was little. But after 2011, the curves of Guangdong and Zhejiang was outside and different from others. If random disposal is given, only a 4.5% probability

TABLE 3 | RMSPE comparison chart.

Area	Prediction quality of applying composite control method before the exogenous event										
	RMSPE	*CE* (2000)	*CE* (2005)	*lngdppc*	*lnpop*	*lncoal*	*lnthe*	*ei*	*is*	*open*	*urb*
Real Guangdong	5.6147	199.60	341.80	10.35	9.15	9.23	7.46	0.95	0.51	1.29	0.60
Synthetic Guangdong		197.67	348.12	10.27	8.40	9.43	6.97	1.76	0.50	0.42	0.54
Real Jiangsu	9.9997	199.40	396.10	10.37	8.94	9.65	7.55	0.99	0.54	0.71	0.51
Synthetic Jiangsu		189.09	395.93	10.30	8.61	9.59	7.14	1.50	0.52	0.41	0.52
Real Zhejiang	4.3937	131.40	255.80	10.46	8.53	9.16	7.04	0.99	0.53	0.69	0.56
Synthetic Zhejiang		132.02	263.40	10.37	8.35	9.08	6.85	1.21	0.50	0.55	0.57

TABLE 4 | Weights of synthetic regions of experimental provinces.

Experimental area	Synthetic region (weight)			
Guangdong	Hebei	0.592	Liaoning	0.094
	Shanghai	0.315		
Jiangsu	Liaoning	0.353	Shandong	0.489
	Shanghai	0.158		
Zhejiang	Fujian	0.162	Henan	0.276
	Shandong	0.154	Shanghai	0.408

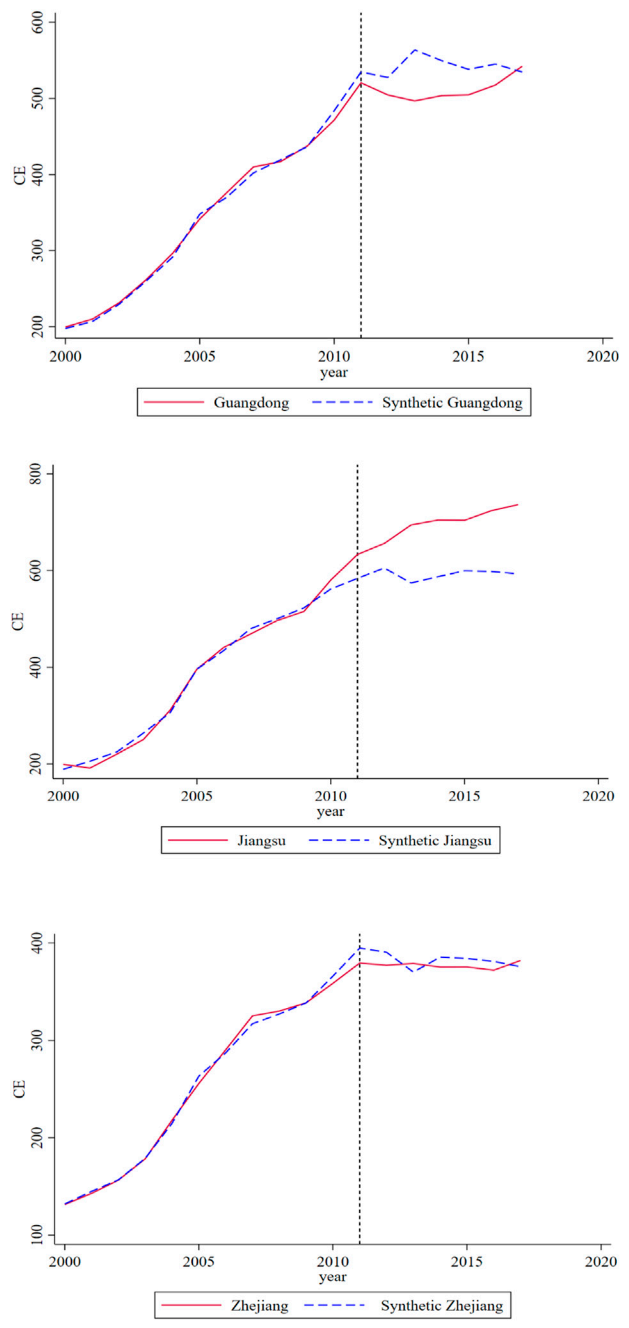

FIGURE 1 | Carbon emissions of experimental provinces and their synthetic control objects **(from top to bottom:** Guangdong, Jiangsu, Zhejiang).

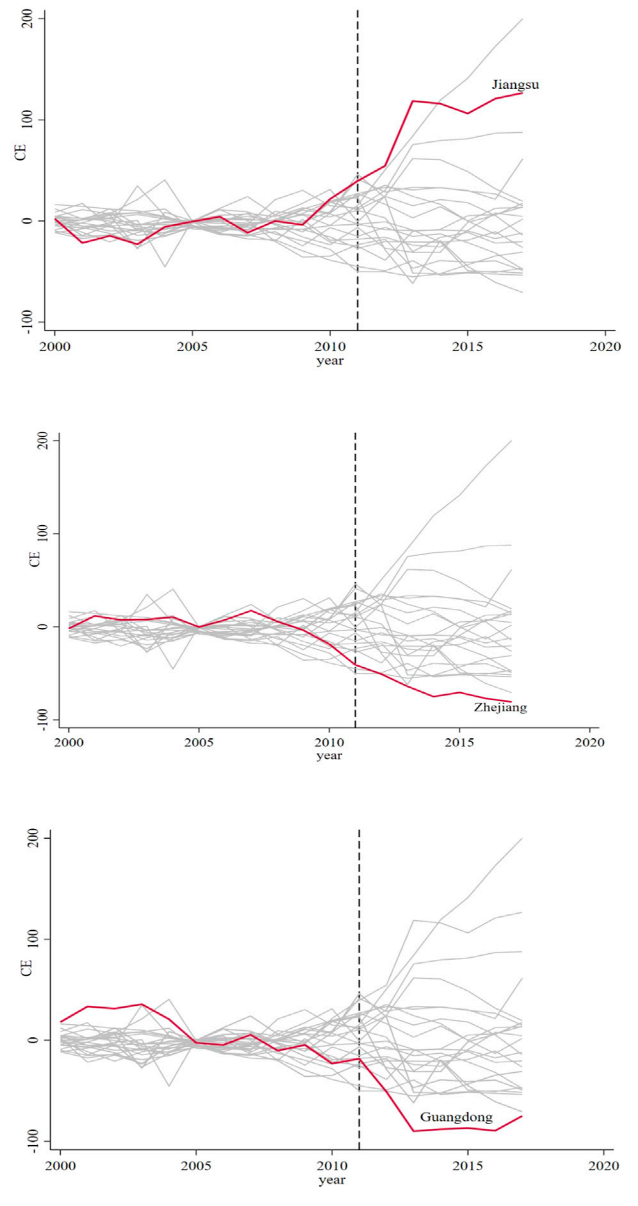

FIGURE 2 | Shock effects of experimental provinces and other regions **(from top to bottom:** Guangdong, Jiangsu, Zhejiang).

that such an impact effect like Guangdong and Zhejiang will occur in other areas.

In contrast, the carbon emissions in Jiangsu kept growing at a high speed after 2011. Until 2013, the curve was located outside other areas, but after that, the curve fell and was surpassed by another one. It was not until 2 years later that the growth rate of Jiangsu's carbon emission decreased. However, on the whole, the curve of Jiangsu Province was located outside other areas. This impact effect was significant at the 5% level.

PSM-DID Robustness Test

Propensity Score Matching (PSM) can overcome the subjectivity in sample selection. The principle is as follows: for the individuals

TABLE 5 | PSM-DID robustness test.

Carbon emissions	Control group before adjustment	Processing group before adjustment	Difference between processing group and control group before adjustment	Adjusted control group	Adjusted processing group	Difference between process group and control group after adjustment	DID test results
Guangdong, Zhejiang	380.758	281.343	–99.415*** (–3.82)	583.877	377.203	–206.674*** (5.4)	–107.259** (2.32)
Jiangsu	379.389	387.23	7.841 (0.27)	542.01	693.247	151.237*** (4.12)	143.396*** (3.05)

*Note: The total number of control group samples in Guangdong and Zhejiang was 207, Jiangsu was 69, and R2 was 0.37 and 0.63 respectively. There are standard errors in parentheses, and ***, **, * represent significant at the level of 1%, 5%, and 10% respectively.*

in the treatment group, finding individuals with similar characteristics in the control group to match. Then the counterfactual results of the control group are estimated by the results of the control group. We selected variables such as economic development level, population size, and industrial structure as matching variables, constructed a logit model, matched samples following the kernel matching principle, and then carried out DID regression. The test results were shown in **Table 5**. The test results were negative in Guangdong and Zhejiang, and the opposite in Jiangsu, but the number of test samples in Jiangsu was small. It may be due to the particularity of Jiangsu's industrial structure, which makes it difficult to find matching samples. On the whole, the research results of PSM-DID are consistent with the previous studies, which proved the robustness of the above research conclusion.

Controlling Other Policy Impacts

In 2011, China launched carbon emission trading pilot projects in Guangdong, Shenzhen, and other places, which may overlap the impact effect of Fukushima incident in terms of carbon emissions. To avoid this interference, we excluded the sample involved in the project and re-conducts the PSM-DID. The results were shown in **Table 6**, the impact effect of the Fukushima nuclear accident was still significant, indicating that the Fukushima nuclear accident has a robust inhibitory effect on carbon emissions in some nuclear power bases in China.

All these results confirmed the Fukushima nuclear accident is an important factor that led to the decrease of carbon emissions in Guangdong and Zhejiang provinces, and the increase of carbon emissions in Jiangsu Province, rather than an accidental and insignificant factor.

An Analysis of the Influence Mechanism of Nuclear Leakage on China's Carbon Emissions

The results of validity and robustness tests confirmed that the Fukushima nuclear leakage affected China's carbon emissions. Furthermore, we were also concerned about the influence mechanism of nuclear leakage on carbon emissions in Guangdong and Zhejiang provinces.

Combined with existing research experience, the government's policies for carbon emission reduction mainly start from three aspects: technological upgrading, optimization of regional pollution level, and energy structure. Consequently, three emission reduction effects: industrial structure effect, technological innovation effect, and energy efficiency effect were generated. Referred to the methods of Wang et al. (2020), we used the intermediary effect test procedure to verify the transmission mechanism of the accident impact on emission reduction. The model is shown as **Eqs. 3–5**. Hausman test results showed that the fixed effect model is more suitable than the random effect model.

$$Y_{it} = \alpha_1 \times D_i \times T_t + \beta_m \sum \times C + \mu_i + \nu_t + \varepsilon_{it} \quad (3)$$

$$M_{it} = \alpha_2 \times D_i \times T_t + \beta_n \sum \times C + \mu_i + \nu_t + \varepsilon_{it} \quad (4)$$

$$Y_{it} = \alpha_3 \times D_i \times T_t + \alpha_4 \times M_{it} + \beta_0 \sum \times C + \mu_i + \nu_t + \varepsilon_{it} \quad (5)$$

Where: D_i is a virtual variable. If region i was affected by nuclear leakage, D_i takes 1, otherwise 0; T denotes the time dummy variable, if $t > 2011$, $T = 1$, otherwise 0. M_{it} represents the intermediary variable of the impact of nuclear leakage. C is all kinds of control variables that affect carbon emissions, including economic development level, urbanization level, etc. u, v represent individual and year fixed effects respectively, controlling individual variables and time variables that may be missed, and ε is error term.

Nuclear Leakage Impact and Industrial Structure

Normally, for regional emission reduction, the regional governments will adjust the industrial structure through a series of environmental regulation tools. China's industrial sector is the main source of carbon emissions. Through a series of policies, governments increased the cost of production factors in industries with high energy consumption, forcing enterprises to reduce the elasticity of resource consumption of their products. Consequently, the development of enterprises was restricted. If enterprises want to survive, they must adjust their production methods and processes to increase the green degree of production. At the same time, industries in low-carbon life were encouraged to develop and expand. These factors drove the adjustment of the regional industrial structure, and the regional carbon emissions were reduced. We used the proportion of the added value of the manufacturing industry to GDP as the proxy variable of the industrial structure. The test results were shown in **Table 7**.

TABLE 6 | Robustness test for controlling other policy impacts.

Carbon emissions	Control group before adjustment	Processing group before adjustment	Difference between processing group and control group before adjustment	Adjusted control group	Adjusted processing group	Difference between process group and control group after adjustment	DID test results
Zhejiang	303.421	247.809	−55.612** (−2.39)	524.858	377.203	−147.655*** (4.75)	−92.043 ** (2.37)

*The total number of control group samples in Guangdong and Zhejiang was 207, Jiangsu was 69, and R^2 was 0.37 and 0.63 respectively. There are standard errors in parentheses, and ***, **, * represent significant at the level of 1, 5, and 10% respectively.*

TABLE 7 | Intermediary test of industrial structure.

	(1) Lnce	(2) is	(3) Lnce
D × T	−0.0821***	−0.0133*	−0.0735***
	(0.0204)	(0.0073)	(0.0192)
is			0.6451***
			(0.1282)
lnpop	−0.5707***	−0.2261***	−0.4248***
	(0.1396)	(0.0358)	(0.1319)
lnthe	0.4533***	0.0517***	0.4199***
	(0.0247)	(0.0087)	(0.0259)
open	0.0268	0.0444***	−0.0019
	(0.0344)	(0.0128)	(0.0336)
urb	0.2443**	0.0720	0.1979*
	(0.1158)	(0.0480)	(0.1029)
Provincial effect	yes	yes	yes
Time effect	yes	yes	yes
_cons	6.7823***	2.0786***	5.4413***
	(1.2157)	(0.3370)	(1.1585)
R^2	0.987	0.835	0.988
N	540	540	540
Sobel-Goodman Mediation Tests			
Sobel		−2.641***	0.0083
Goodman-1(Aroian)	−2.621***	0.0088	
Goodman-2		−2.661***	0.0078

There are standard errors in parentheses, Sobel test reports z value and p *value respectively, and ***, **, * represent significant at 1, 5, and 10% respectively.*

In the table, the coefficient of D × T in the first column is negative, indicating that the loss of the nuclear energy supply, in Guangdong and Zhejiang, failed to increase their carbon emissions, in contrast, their carbon emissions were reduced due to their stricter emission reduction policies. The coefficient of D × T in the second column was also negative, indicating that the industrial structure decreased after the accident. Industrial production is the main source of regional carbon emissions, and industrial governance is the fastest way to reduce carbon emissions. After the Fukushima nuclear accident, to complete the task of reducing emissions, the local governments shifted attention from developing clean energy to changing industrial structure, imposing restrictions on cement, steel, and other industries, forcing these high energy consumption industries to develop in a green way. Owing to Guangdong and Zhejiang provinces had transferred out part high-energy consuming industries, compared with Jiangsu, the proportion and energy dependence of the manufacturing industry were low. As a result, the two provinces can quickly respond to the accident and issue policies to restrict the development of high-energy consuming enterprises, thus realized regional emission reduction.

In contrast, the main source of GDP in Jiangsu was the manufacturing industry with high energy consumption. Higher energy demand will further increase the share of fossil resources in the energy mix (Alvarez-Herranz et al., 2017). Measures to limit energy consumption and reduce emissions do not play well here and are more likely to fall into a high carbon lock-in effect. Cheap and readily available thermal power was used to meet the needs of industry. Statistics from the *National Bureau of Statistics* show that, started from 2011, in all nuclear power base regions, the ratio of the added value of the manufacturing industry to the GDP in Jiangsu was highest. After the nuclear power construction was restarted in 2015, the speed of new nuclear power construction still cannot meet the energy demand of Jiangsu Province.

In the third column, the coefficients of $D \times T$ and *is* are significant, and the direct effect (α_3) and indirect effect ($\alpha_2 \times \alpha_4$) had the same sign. It is worth noting that $|\alpha_1| > |\alpha_3|$, indicating the nuclear leakage impact played a partial intermediary role in reducing regional carbon emissions. We used the Sobel test to analyze the intermediary effect of industrial structure. The results were listed in **Table 7**, which proved that the research results of this intermediary effect are robust. After calculating, the explanation ratio of reduced industrial structure to emission reduction is 10.45%.

Due to a different industrial structure, the Fukushima nuclear accident had a completely different impact on China's provinces with nuclear power.

Nuclear Leakage Impact and Technological Innovation

Technological innovation is another key factor in carbon emission reduction. Appropriate environmental regulations can promote enterprise innovation and improve competitiveness (Porter and Van der Linde, 1995). If the benefits brought by technological innovation are higher than the costs increased by environmental regulation, enterprises will increase investment in green innovation.

When most enterprises realized green production, the regional carbon emission decreased. In general, local governments will allocate carbon emission quotas to enterprises, or levy carbon taxes on enterprises based on certain standards. Environmental protection enterprises take the lead in completing emission reduction tasks and can sell surplus quotas. To avoid buying more carbon emission quotas or paying more carbon taxes, enterprises with high energy consumption and high emissions will increase green investment, so as to improve production methods and reduce carbon emissions. Based on the research experience of Choi and Choi (2021), we selected the natural logarithm of research and experimental development personnel (R&D) to measure the effect of technological innovation (*lntech*). The estimation was based on **Eqs. 3–5**, and the results were listed in **Table 8**.

Table 8 shows that the coefficient of D × T in the first column is negative, indicating that the emission reduction effect from the accident is significant. Similarly, the coefficient of D × T in the second column was also positive, indicating that the nuclear accident impact increased the investment in innovative resources in the regions. In the third column, the coefficient of D × T was negative, but the coefficient of *lntech* was positive, indicating that technological innovation failed to reduce regional emissions. The coefficients of indirect effect and direct effect were different and $|\alpha_1| < |\alpha_3|$. It indicates that the technological innovation was a masking effect in the emission reduction effect, and weakened the effect. Combined with China's actual situation, this unexpected discrepancy may be explained by the lack of enthusiasm for low-carbon innovation among China's high energy consumption and high emission enterprises.

Compared with investing in green innovation, enterprises are more willing to invest to improve productivity (Yang et al., 2017). The improvement of production efficiency can help enterprises to upgrade to the high end of the value chain, and the corresponding benefits can offset the increased cost caused by environmental regulations. The continuous expansion of energy demand from enterprises led to increasing carbon emissions. Therefore, only when enterprise's innovation investment turns to reduce pollution emissions per unit production, realizing the optimization and upgrading of industrial structure, can technological innovation plays a positive role in reducing carbon emissions.

Nuclear Leakage Impact and Energy Efficiency

To reduce the impact of environmental regulation, enterprises will include the increased environmental costs in the production costs. The internalization of enterprise environmental costs leads to the decline of enterprise profit (Copeland and Taylor, 2004). In the long run, if enterprises do not develop green production technology and improve energy efficiency, they may lose competitiveness and be forced to withdraw from the market. We used the ratio of regional GDP (reduced based on 2000) to regional energy consumption (10,000 tons of standard coal) to measure energy efficiency (*ee*). The estimated results were shown in **Table 9**.

TABLE 8 | Technological innovation intermediary test.

	(1) Lnce	(2) Lntech	(3) Lnce
D × T	−0.0956***	0.5651***	−0.1799***
	(0.0234)	(0.0813)	(0.0262)
lntech			0.1492***
			(0.0267)
lnpop	−0.7748***	0.5916***	−0.8631***
	(0.1975)	(0.1981)	(0.1887)
open	0.0608	0.1496	0.0384
	(0.0608)	(0.1099)	(0.0586)
urb	0.3307	0.6882*	0.2280
	(0.2131)	(0.3744)	(0.1717)
Provincial effect	yes	yes	yes
Time effect	yes	yes	yes
_cons	11.2469***	4.8770***	10.5193***
	(1.7053)	(1.7320)	(1.5373)
R^2	0.975	0.976	0.977
N	540	540	540

*There are standard errors in parentheses, and ***, **, * represent significant at 1, 5, and 10%, respectively.*

The test results in **Table 9** shows that after the nuclear accident in 2011, the energy efficiency in Guangdong and Zhejiang had further improved. Energy efficiency played a partial intermediary role in the relationship between the accident impact and the reduced carbon emissions. Sobel test results showed that the research results on the intermediary effect of energy efficiency were stable. After calculation, the explanation ratio of energy efficiency to emission reduction is 15.1%. The improvement of energy efficiency can be reflected by the optimization of energy structure. The *China Energy Statistics Yearbook* showed that, after 2011, the thermal power generation in Jiangsu Province maintained high-speed growth. In contrast, the thermal power generation in Zhejiang and Guangdong slowed down, indicating that the two provinces were trying to find alternative energy sources and reduce their dependence on thermal power. All these show that, to cope with the pressure of carbon emission reduction after the lack of nuclear power, governments of Guangdong and Zhejiang issued a series of policies. The production costs of polluting and high-emission enterprises were increased. To reduce environmental costs, these enterprises gradually improved the energy structure or adopted efficient and energy-saving production methods. As a result, the energy efficiency was improved, industries transformed to green development, and carbon emissions were reduced.

On the whole, the carbon emissions of China's nuclear power base provinces showed a downward trend after the Fukushima nuclear accident. However, the development process of China's nuclear power industry has indeed been delayed. According to the statistics of the *World Nuclear Association*, as of February 2020, there were about 45 nuclear power reactors in operation and 12 under construction in the Chinese mainland. The government's long-term goal was to reach 58 GWe capacity by 2020, with 30 GWe under construction. Judging from this data alone,

TABLE 9 | Energy efficiency intermediary test.

	(1) Lnce	(2) ee	(3) Lnce
D × T	−0.1053***	0.0669***	−0.0894***
	(0.0121)	(0.0207)	(0.0135)
ee			−0.2376**
			(0.1176)
lngdp	0.0916***	0.5277***	0.2170***
	(0.0352)	(0.0324)	(0.0699)
lnthe	0.2140***	0.0543***	0.2269***
	(0.0270)	(0.0208)	(0.0252)
lncoal	0.3714***	−0.4154***	0.2727***
	(0.0319)	(0.0265)	(0.0549)
lnpop	−0.1002	−0.0026	−0.1008
	(0.0784)	(0.0932)	(0.0735)
open	0.0137	−0.0311	0.0063
	(0.0249)	(0.0296)	(0.0243)
urb	0.1090	−0.1374	0.0763
	(0.0915)	(0.0952)	(0.0765)
Provincial effect	yes	yes	yes
Time effect	yes	yes	yes
_cons	0.2769	−0.1534	0.2405
	(0.7817)	(0.9360)	(0.7312)
R^2	0.993	0.942	0.993
N	540	540	540
Sobel-Goodman Mediation Tests			
Sobel		−1.662*	0.0964
Goodman-1(Aroian)	−1.632	0.1027	
Goodman-2		−1.695*	0.0901

There are standard errors in parentheses, Sobel test reports z value and p *value respectively, and ***, **, * represent significant at 1, 5, and 10% respectively.*

China's nuclear power development process has not reached the expected target. As an important part of clean energy, the lagging development of the nuclear power industry will affect the realization of China's carbon neutrality in 2060.

However, the impact of Fukushima nuclear leakage on China's carbon neutrality target goes far beyond these direct impacts. China's central and western regions have a large population and are in urgent need of nuclear power for development. The large energy demand has led to great pressure on carbon emission reduction in Shanxi, Inner Mongolia, Shaanxi, Ningxia, and other central and western regions (Li et al., 2021). The stranding of nuclear power construction projects in the central and western regions, which was caused by the Fukushima nuclear leakage, has not only become an energy bottleneck restricting the development of inland cities, but also hindered the early realization of China's carbon neutrality goal.

Conclusion and Policy Enlightenments

We treated the Fukushima nuclear accident as an exogenous shock, utilized the data of 30 provinces and cities in China from 2000 to 2017, and used the SCM to study the impact of the accident on carbon emissions in nuclear power base provinces. Furthermore, we examined the mediating effect of nuclear leakage on regional carbon emissions reduction from three aspects: industrial structure, technological progress, and energy efficiency. The conclusion of this paper are as follows: 1) After the Fukushima nuclear accident, the nuclear power plants in China's nuclear power-owning provinces (Guangdong, Jiangsu, Zhejiang) were suspended, and the nuclear power gap was filled by thermal power. However, under the pressure of national carbon emission reduction and doubts about nuclear power prospects, these provinces carried out endogenous changes, such as formulating stricter emission reduction policies and a new energy strategy, to reduce carbon emissions. On the whole, the carbon emissions in the three provinces did not rise but fall. However, considering the stranding of inland nuclear power projects, the potential impact of Fukushima nuclear leakage on China's carbon emission reduction may far exceed the direct impact already revealed. 2) Due to heterogeneous industrial structures, the impact of Fukushima nuclear leakage on provinces is different. Jiangsu Province, which had a high industrial structure, increased its demand for thermal power after losing the supply of nuclear power. Contrary to Guangdong and Zhejiang, carbon emissions in Jiangsu increased rapidly after 2011. 3) The emission reduction effect of nuclear leakage, in Guangdong and Zhejiang, was mainly realized through promoting the upgrading of industrial structure and improving energy efficiency, with explanation ratios of 10.45 and 15.1%, respectively. 4) The effect of technological progress on carbon emission reduction is a masking effect. It indicates the innovation driving force of China's green development is insufficient, and enterprises are more willing to put innovation investment into improving enterprise productivity, and make up for the increased environmental costs with the benefits brought by productivity improvement.

Based on these research conclusions of this paper, the following policy suggestions were put forward:

First of all, breaking the NIMBY effect and promoting coastal and inland nuclear power construction. The eastern nuclear power bases need to conduct a dynamic assessment of the safety of nuclear power development and publish the results promptly to improve public acceptance. For the central region in urgent need of nuclear power, the *National Development and Reform Commission* and local governments need to establish inland nuclear power pilot and advance areas after assessing the environment, population distribution, and public acceptance of each region, then promote nuclear power construction inland.

Secondly, realizing a rational industrial layout in China based on regional heterogeneity. Manufacturing costs in the eastern region remain high and the restrictions on resources and the environment are increasingly obvious. So, some industries in the eastern region began to shift to the central and western regions. Guangdong, Zhejiang, and other places have taken the lead. Compared to them, Jiangsu relies much on the manufacturing industry, most of which are labor-intensive and energy-intensive. This development path is unsustainable, so Jiangsu, and other areas similar to it, need to consider industrial transfer and realizing an advanced and green industrial structure. On the other hand, the cost of labor and land factors in central China is low, so under the premise of ecology is not destroyed, they can undertake the transferred high energy consumption enterprises.

Thirdly, adopting appropriate policy tools. Environmental regulation tools, such as environmental standards and emission limits have strong control, in contrast, carbon emission trading and environmental subsidies provide continuous incentives for low-carbon innovation of enterprises. According to the research, environmental regulation can reduce carbon emissions in Guangdong and Zhejiang provinces by improving industrial structure and energy efficiency. However, when it comes to the whole country, it is necessary to consider the regional economic heterogeneity and adopt differentiated environmental regulation. In the eastern developed areas, such as Guangdong and Zhejiang, people have higher demands for green development, so it is suitable to adopt stricter environmental policies like environmental standards and emission limits. For the central and western regions with many resource-intensive industries, the adoption of strict policy may directly curb the lifeblood of regional development. Therefore, incentive policy tools, such as carbon emission trading and environmental subsidies, are suitable choices.

Finally, paying more attention to green innovation. Green innovation technology is an important factor to achieve high-quality development of the regional economy. Ignoring green innovation and focusing only on improving productivity will eventually bring a vicious impact on the environment. The reason for this situation may be that, the short-term income of green investment is not high, and external constraints are not enough to force enterprises to realize low-carbon transformation. Compared with traditional industries, the new energy industry has positive externalities, such as energy security and environmental friendliness, but it also faces the risk of insufficient competitiveness. Therefore, while the government continues to strengthen the environmental regulation on high energy consumption and high emission enterprises, it also needs to subsidize low-carbon development enterprises to enhance their competitiveness. Similarly, to avoid the transformation difficulties caused by high costs, the government needs to use financial tools to help high-energy-consuming enterprises transform into green production.

This paper presents a preliminary analysis of the potential impact of the Fukushima nuclear accident on carbon neutrality in China, but there are shortcomings. The study data in this paper are provincial, but the service area of a nuclear power plant is limited, so a larger study scale may bias the estimation of the impact level. In addition, the impact of the nuclear accident on carbon emissions in inland areas could not be analyzed quantitatively due to limitations in research data and research methods. Finally, now that Japan has decided to discharge its nuclear wastewater into the ocean, the potential impact of a nuclear accident on China goes beyond the nuclear power industry, other industries, such as fishing and mariculture, are likely to be affected by nuclear wastewater. Therefore, future research can be conducted in three aspects. First, based on this study, the scale of studies can be narrowed down to further analyze the impact of nuclear accidents on cities where nuclear power is located, and second, inland areas can be included in the study to explore the heterogeneity of the impact of nuclear accidents on coastal and inland cities. Third, scholars can analyze the impact of the Fukushima nuclear accident on China from multiple perspectives and industries, not just limited to the energy and environmental fields.

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

CL: Conceptualization, Resources, Methodology, Software, Validation, Formal analysis, XY: Writing—original draft, Methodology, Visualization. BL: Investigation, Data curation, ZY: Software, Validation, Writing—review and; editing. LZ: Conceptualization, Project administration, Supervision.

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How Does Land Urbanization Promote CO_2 Emissions Reduction? Evidence From Chinese Prefectural-Level Cities

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The process of land urbanization may result in a great change in land use structure, land use intensity, and efficiency, which could further lead to an increase in carbon dioxide (CO_2) emissions. Despite rich literature on the link between urbanization and CO_2 emissions, the mechanism through which land urbanization promotes CO_2 emissions reductions has not been fully investigated. To address this gap, this study theoretically and empirically explores the mechanism of land urbanization's influence on CO_2 emissions by integrating land use optimization and high-quality industrial development into a unified framework. Firstly, the theoretical mechanism analysis indicates that low-level industrial development and land use management promote the increase of CO_2 emissions per unit of land at the extensive land use stage; however, high-quality industrial development and land use optimization lower CO_2 emissions per unit of land at the intensive land use stage. Subsequently, a STIRPAT model and a spatial adaptive semi-parametric model are employed to verify the relationship between the land urbanization rate and total CO_2 emissions. The results indicate that the land urbanization rate and total CO_2 emissions present an inverted U-shaped relationship. In addition, the mediating mechanism of the advanced industrial structure, CO_2 emissions per unit of GDP, and CO_2 emissions per unit of land, are studied using the mediating effect model. Results indicate that CO_2 emissions reduction can be achieved by promoting the advanced industrial structure, reducing CO_2 emissions per unit of GDP or reducing CO_2 emissions per unit of land. Ultimately, this study showed that the Chinese government may reduce CO_2 emissions by promoting land use structure optimization, land use intensity regulation, land use efficiency improvement, and adjusting energy consumption structure, upgrading industrial structure, and promoting emission efficiency technologies.

Keywords: land urbanization, carbon mitigation, land use optimization, industrial structure adjustment, China

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INTRODUCTION

Urbanization involves an important change: the conversion of large areas of cultivated land into urban land. This process is called "land urbanization" (Zhang and Xu, 2017). China has greatly promoted economic growth through land urbanization and land resource allocation. However, the rapid expansion of urban land can lead to land use/cover change (LUCC), unreasonable land allocation structures, and uncontrolled land development intensity (Yang et al., 2019). Important to note here is that LUCC is the main driving force for carbon storage in terrestrial ecosystems (Chuai et al., 2014). During the process of land urbanization, a large amount of agricultural land is converted into construction land.[1] For instance, the area of urban construction land in China increased from 20,877 km^2 in 1999 to 55,155.5 km^2 in 2017—an increase of 164%. The proportion of secondary industrial land to construction land in China has always been maintained at approximately 20%, which greatly exceeds the international average of 5–8%. In cities with more developed manufacturing industries, such as those in the Pearl River Delta and the Yangtze River Delta, the proportion of secondary industrial land generally exceeds 40%. A high proportion of secondary industrial land leads to slow industrial structure upgrading, unclean energy consumption structures, and low energy efficiency, which cause more carbon emissions (CO_2) to be released into the atmosphere (Zhou et al., 2019b). Furthermore, China's land development intensity also exceeds a reasonable level, and the levels of economically developed cities such as Shanghai and Shenzhen are even close to 50%. Excessive land development intensity seriously impacts the ecosystem's balance, which in turn affects carbon sequestration (Xie et al., 2018; Li et al., 2018). Since unreasonable land urbanization has increased carbon emissions, there is a need to investigate in-depth the mechanism through which land urbanization affects CO_2 emissions. Research on exploring this mechanism is conducive for promoting the coordinated development of urbanization and CO_2 emissions reduction through land use optimization and industrial structure adjustment.

The links between urbanization and CO_2 emissions have recently been extensively investigated by existing research (Lai et al., 2016; Chuai et al., 2016). Previous studies have also addressed multiple effects of different aspects of urbanization, including economic, population, land, and social urbanization, on CO_2 emissions (Zhou et al., 2019a). Generally, previous studies on the relationship between urbanization and carbon emissions focused on four lines. The first line of studies assert that rapid urbanization increases CO_2 emissions both in the short and long-run (Sheng and Guo, 2016), while the second line of studies insist that urbanization can contribute to declines in the carbon emission scale, carbon emissions per capita, and carbon intensity (Yao et al., 2018). The third line of studies supposed that the urbanization exerts no significant effect in the carbon emissions (Rafiq et al., 2016; Behera and Dash, 2017). Finally, the results of the fourth line of studies show an inverted U-shaped relationship between urbanization and CO_2 emissions (Martínez-Zarzoso and Maruotti, 2011; Zhang et al., 2017). Furthermore, a few mediating variables (such as technological progress, industrial structures, energy consumption structure, and foreign direct investment) have also been investigated when analyzing the relationship between urbanization and CO_2 emissions (Wang et al., 2013; Wang et al., 2018b). In addition, certain studies are related to regional and industry-based heterogeneity and spatial spillovers (Zhang et al., 2016; Liu and Liu, 2019). Despite various studies explored the effect of urbanization on CO_2 emissions and the mechanism to achieve the coordination of economic growth and carbon mitigation (Bekun et al., 2019; Bekun et al., 2021a), two limitations continue to restrict our understanding of sustainable development. First, the mechanism of the effect of land urbanization on CO_2 emissions reduction has not yet been thoroughly explored, which limits the possibility to achieve a win-win situation of economic development and carbon mitigation through land use optimization and industrial structure adjustment. Second, previous studies employed parametric econometric models, which may have led to model setting misspecification. To fill these research gaps, this study theoretically explores the mechanism of land urbanization to promote CO_2 emissions reduction, and verifies it empirically by employing a semiparametric model and mediation effect model.

In fact, the impact mechanism of land urbanization on carbon emissions is greatly different from population urbanization or economic urbanization. The urbanization in the existing literature generally refers to population urbanization or economic urbanization. The research from the perspective of population urbanization or economic urbanization is mainly to explore the impact of changes in residential consumption, industrial structure, and technical efficiency on carbon emissions after population or industry agglomeration in cities. It is worth noting that land urbanization is very different from population urbanization. The impact of land urbanization on CO_2 emissions is affected by natural, economic, social, and other factors. On the one hand, in the process of land urbanization, changes in land use types will cause changes in direct carbon emissions. For example, if land is transformed from forest land, wetland, etc. to urban construction land, the carbon emission coefficient will be greatly increased. On the other hand, the land urbanization process will also cause changes in the industrial structure, technical efficiency, energy use efficiency, and carbon emission efficiency by anthropogenic activities carried on the land elements, which in turn affects the level of indirect carbon emissions. Accordingly, it is essential to explore the mechanism of land urbanization affecting CO_2 emissions thoroughly regarding factors such as land use change, and changes in industrial structure and technological efficiency caused by human activities carried on the land elements.

LUCC and anthropogenic activities carried out on land are the two main drivers of terrestrial ecosystem carbon storage. In the process of land use conversion from high to low vegetation biomass, carbon is released into the atmosphere; this affects carbon emission levels (Peters et al., 2019). With the development of land urbanization, more and more cultivated lands, forest lands, and grass lands have been converted to urban construction land; put differently, such lands are converted from carbon sinks to carbon sources (Chuai et al., 2013; Chuai et al., 2014; Chuai et al., 2016). Existing studies have extensively explored the influence of LUCC on CO_2 emissions (Muñoz-Rojas et al., 2011; Chuai et al., 2013; Dang et al., 2014; Chuai et al., 2016; Bossio et al., 2020). However, the impact of effective land use management and industrial structure adjustment on CO_2

[1]The land use structure is calculated according to the proportion of industrial, mining, and storage land in the total land supplied, which is a negative indicator of the land use structure optimization

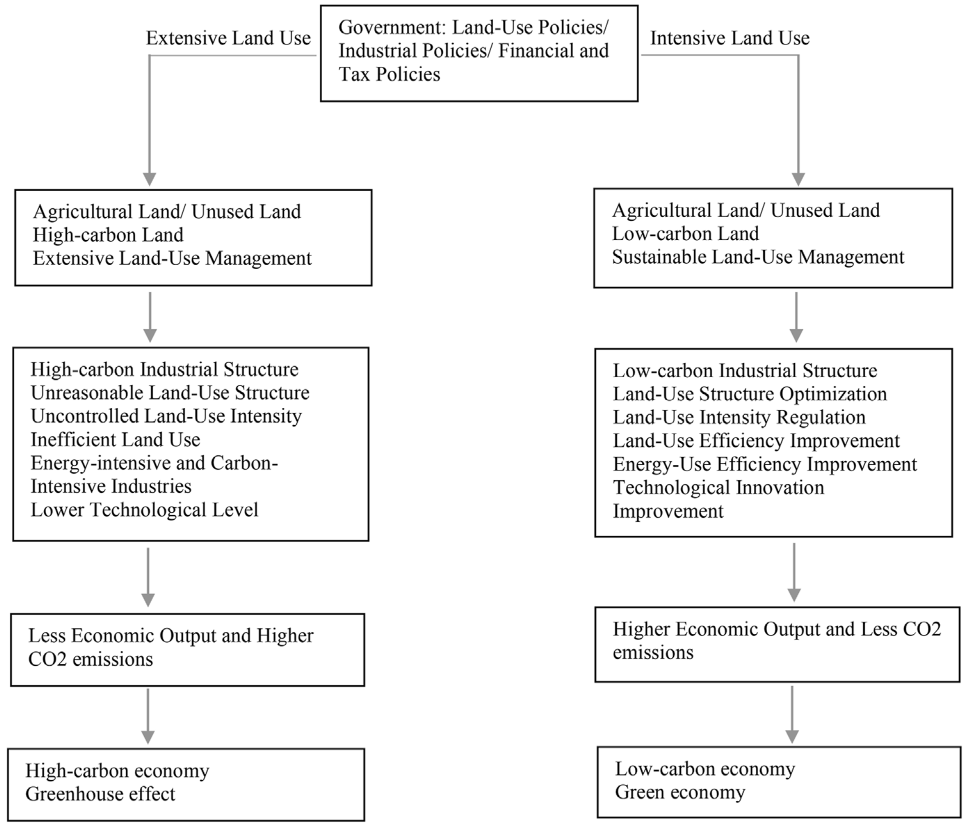

FIGURE 1 | Diagram of the influence mechanism between land urbanization and CO_2 emissions.

emissions reduction has received relatively less attention. Sustainable land use management promotes optimization of land use structure, reasonable control of land use intensity, and improvement of land use efficiency through operating mechanisms, price systems, land ownership systems, and so on (Bateman et al., 2013; Cavender-Bares et al., 2015). Notably, land use structure optimization, land use intensity regulation, and land use efficiency improvement all directly or indirectly affect the carbon emission process and carbon emission level (Cumming et al., 2014; Chen et al., 2020). However, existing research does not integrate these three perspectives and fails to fully explore the internal and mediating mechanisms of land urbanization that reduce CO_2 emissions. Therefore, our study integrates factors such as land use structure optimization, reasonable control of land use intensity, and land use efficiency improvement into a complete theoretical framework to explore the mechanism of land urbanization promoting carbon mitigation. This is exactly where the most important innovation of this study lies.

This study makes two key contributions: First, this study explored in-depth the influential mechanism of land urbanization on CO_2 emissions theoretically by integrating the land use optimization and high-quality industrial development into a unified framework. Second, this study applied a stochastic impact by regression on population, affluence and technology (STIRPAT) model and a spatially adaptive semi-parametric (SASP) model to investigate the relationship between land urbanization and CO_2 emissions to accommodate stochastic factors and spatial heterogeneity. Additionally, this study employed a mediation effect model to investigate the role of advanced industrial structure, CO_2 emissions per unit of GDP, and CO_2 emissions per land regarding land urbanization's effect on total CO_2 emissions.

The rest of this paper is organized as follows. *Section Theory* provides the theoretical analysis, *Section Methods* describes the method, *Section Data* describes the data, *Section Results* presents the empirical results, *Section Discussions* discusses the results, and *Section Conclusion and Policy Recommendations* offers the conclusion.

THEORY

In this section, we adopt the Kaemissions into fours aspects: Landya identity to decompose the driving factors of CO_2 emissions into fours aspects: Land scale, land use structure, land use intensity, and carbon emission intensity (Grossman and Krueger, 1995; Wu et al., 2015). According to a country or region's land use patterns, industrial structure, technological level, government regulation policies, and residents' lifestyles, land urbanization can be roughly divided into two stages:

extensive and intensive modes. This study explores the impact mechanism of land urbanization on CO_2 from two stages: Extensive and intensive land use (**Figure 1**).

Kaya Decomposition to the Driving Factors of Carbon Dioxide Emissions

First, we adopt the Kaya identity to decompose the driving factors of CO_2 emissions into fours aspects: Land scale, land use structure, land use intensity, and carbon emission intensity (Grossman and Krueger, 1995; Wu et al., 2015). The carbon dioxide emissions decomposition model based on land use is presented in **Eq. 1**. The total CO_2 emissions are first decomposed into the carbon emissions of different land use types. Next, CO_2 emissions on each land use type are decomposed into the product of the total land scale, land use structure, land use intensity, and carbon emission intensity. As a result, we are able to decompose carbon emissions per unit of land into the sum of the product of land use structure, land use intensity, and carbon emission intensity for different land use types, as shown in **Eq. 2**.

$$C_t = \sum_{i=1}^{n} C_{it} = \sum_{i=1}^{n} \frac{C_{it}}{GDP_{it}} \cdot \frac{GDP_{it}}{L_{it}} \cdot \frac{L_{it}}{L_t} \cdot L_t \tag{1}$$

$$\frac{C_t}{L_t} = \sum_{i=1}^{n} \frac{C_{it}}{GDP_{it}} \cdot \frac{GDP_{it}}{L_{it}} \cdot \frac{L_{it}}{L_t} = \sum_{i=1}^{n} I_{it} \cdot D_{it} \cdot S_{it} \tag{2}$$

In **Eqs 1**, **2**, C_t is the total CO_2 emissions in period t, C_{it} represents the CO_2 emissions of the i type of land use in period t, L_t is the total area of land in period t, $S_{it} = L_{it}/L_t$ is the area of the i type of land use in the proportion of total land and can be represented as land use structure, $D_{it} = GDP_{it}/L_{it}$ is the economic output of the i type of land use in period t and can be expressed as land use intensity, and $I_{it} = C_{it}/GDP_{it}$ is the CO_2 emissions per unit of GDP for the i type of land use in period t and can be regarded as carbon emission intensity.

To reduce CO_2 emissions per unit of land, it is essential to optimize the land use structure, reduce carbon emission intensity, and regulate the impact of land use intensity on CO_2 emissions according to the carbon emission decomposition model. For the central government and local governments, the impact of land use on CO_2 emissions can be reduced in two ways: 1) by optimizing the structure of spatial land use and 2) by innovating spatial land governance. Notably, CO_2 emissions can be effectively reduced by controlling the expansion of urban construction land and the intensity of land development, compressing the scale and proportion of industrial and mining land, optimizing the structure of construction land, and optimizing the pattern of land development (Sadorsky, 2014). Simultaneously, we can promote the formation of low-carbon development by accelerating the transformation of land use types. The government should promote intensive land use in accordance with the principles of strictly controlling the total amount, revitalizing the inventory, optimizing the structure, and improving efficiency.

Extensive Land Urbanization Stage

When the economy is in the initial stage of urbanization and industrialization, the mode of land urbanization is mainly extensive (Jiang and Lin, 2012; Dong et al., 2019). At this stage, the industrial structure is dominated by high-carbon industries, and the company's technical level and low energy efficiency have led to high carbon emission intensity. Moreover, the government's efforts to reduce carbon emissions are relatively weak, and residents' consumption preferences are not based on low-carbon and energy-saving products (Zhang and Da, 2015). All these factors lead to high levels of carbon emissions.

First, because the economic development stage is still in its infancy and the technical level is relatively not high, companies have mainly invested in high-carbon industries such as energy, power, chemical industry, and construction, thus making it difficult to upgrade and transform the industrial structure (Lu et al., 2019). Furthermore, the limitation of companies' technology level leads to low energy utilization efficiency, which further leads to higher carbon emission intensity, thereby increasing companies' carbon emission level.

Second, the government's efforts to control carbon emission reduction are not effective enough, and reasonable carbon emission control policies have not been issued in neither industrial development nor land use (Yuyin and Jinxi, 2018). On the one hand, local government officials have to vigorously improve local economic performance based on economic performance appraisal and political promotion in the process of industrial development (Liu et al., 2020). From a rational point of view, local officials will not impose strict restrictions on the investment of companies in high-carbon industries, leading to a significant increase in carbon emissions. On the other hand, the government's land use management methods are unreasonable. For example, a large number of low-carbon land, such as forest land and wetland, are converted into urban construction land, leading to a large increase in carbon emissions (Zhang et al., 2020). Since construction land is a net source of carbon emissions, the expansion of urban construction land has led to a surge in carbon emissions (Lai et al., 2016). Furthermore, improper land use management methods lead to a series of problems such as unreasonable land use structure, out of control of land use intensity, and low land use efficiency (Yue et al., 2017). Changes in the land allocation structure alter the carbon emission process and modify the energy consumption structure, thereby impacting the urban carbon emissions level. Excessive land development intensity will destroy the original carbon balance of the biosphere, affect the carbon emission process, and promote the increase of carbon emission levels (Li et al., 2021a). Land use efficiency affects energy use efficiency, which in turn influences the carbon emissions level.

Finally, residents' awareness of energy saving and emission reduction is limited, which has also led to an increase in carbon emission levels to a certain extent. In the absence of publicity and guidance from the government and third-party organizations, residents will not state green, low-carbon and energy-saving products as their main consumer preference, but may instead choose high-carbon products (Rosner et al., 2021).

At the early stage of urbanization and industrialization, local governments are actively attracting investment because of the assessment pressure of economic growth and fiscal revenue. Accordingly, agricultural land or unused land is mainly converted into high-carbon industrial land. The land use structure under land resource allocation leads to the concentration of high-carbon industries, which has undesirable consequences for the carbon cycle in the biosphere system (Chen and Zhao, 2019). Meanwhile, highly energy-intensive, heavily polluting, and carbon-intensive industries form a high-carbon industrial structure dominated by low-end manufacturing industries (Liu et al., 2012; Huang et al., 2018). Moreover, local government land supply strategies and unreasonable land use management often further strengthen the rigidity of the industrial structure and suppress high-carbon to low-carbon industrial structure transformations (Xie et al., 2018; Yang et al., 2018). The unit land output is not relatively high at this stage; here, economic growth occurs at the expense of excessive energy consumption. Energy use efficiency is also low, and carbon intensity is relatively high, which causes a large amount of CO_2 emissions to be released during industrial production (Zhang et al., 2016). At this stage, such highly energy-intensive, carbon-intensive and energy inefficient industrial structures, and unreasonable land use management increase CO_2 emissions per unit of land. Therefore, the CO_2 emissions level from the production process and land use conversion is relatively high during the extensive land use stage (Zhang and Xu, 2017).

Given below is a simple economic model to illustrate the impact of land urbanization on carbon emissions during the extensive land use stage. The input for carbon emission reduction causes a certain loss in economic output, as shown in the production function of **Eq. 3**. More specifically, the production function establishes that economic output Y_t is the function of technology level A_t, capital K_t, energy consumption E_t, and land resources consumption N_t. In addition, $D(EM_t)$ is the output loss function, and EM_t is the CO_2 emissions level.

$$Y_t = (1 - D(EM_t))A_t K_t^{\alpha} E_t^{\beta} N_t^{\gamma} \quad (3)$$

The function of the CO_2 emissions level is shown in **Eq. 4**. CO_2 emissions are mainly caused by energy consumption in industrial production activities and land use changes (such as changes in land types, e.g., forest and grass lands into cultivated land, wet land into construction land, and agricultural land into construction land).

$$EM_t = EM_{ind}(t) + EM_{Land}(t) = B_t E_t^{\rho} + C_t N_t^{\lambda} \quad (4)$$

In **Eq. 4**, EM_t is the CO_2 emissions level; EM_{ind} denotes CO_2 emissions caused by energy consumption in industrial production activities; EM_L and indicates CO_2 emissions caused by land use change; E_t and N_t respectively signify energy and land resource consumption; B_t and C_t respectively signify energy efficiency and land use efficiency; and ρ and λ respectively signify elasticity of energy and land resource.

At the extensive land use stage, the high-carbon industry-based industrial structure, low energy efficiency, and high-carbon intensity increase CO_2 emissions. Meanwhile, the limited land use management level and low land use efficiency also further raise CO_2 emissions (Chuai et al., 2013; Lai et al., 2016). All these factors augment carbon emissions per unit of land during this period.

Intensive Land Urbanization Stage

However, when economic development reaches the stage of high-quality land use, agricultural land is mainly converted into construction land for low-carbon industries. Here, the land-use structure has shifted from low efficiency to high efficiency (Yang et al., 2019). Optimizing the land use structure can promote a low-carbon industrial structure and a clean energy consumption structure (Xu et al., 2018). For our study, it is important to note that a low-carbon industrial structure and a clean energy consumption structure can reduce the negative impact of production processes and land use changes on CO_2 emissions (Huang et al., 2018; Zhou et al., 2019b; Bekun et al., 2021b, 2021c). This effect is reflected in two aspects: 1) the structural optimization effect, that is, a reduction in highly energy-intensive and heavily polluting industries also reduces the degree of human interference in carbon emissions (Li et al., 2017; Zhou et al., 2017) and 2) the technology spillover effect, that is, the development of high-end industries promotes technological progress, which leads to an increase in energy efficiency (Liu et al., 2012; Zhou et al., 2017). As a result, carbon emissions per unit of land declines during this period.

At the stage of high-quality land use, the government implements policies regarding land use and carbon emission reduction to induce enterprises to engage in technological transformation, upgrading, or innovation. The production function for this period is shown in **Eq. 5**. Notably, the technological transformation, upgrading, or innovation activities of enterprises have a spillover effect on economic output.

$$Y_t = \Phi_t A_t K_t^{\alpha} E_t^{\beta} N_t^{\gamma} \quad (5)$$

where Φ_t denotes the spillover effect of technological transformation, upgrading, or innovation.

At this stage, energy and land use efficiency due to the spillover effect of technological innovation increase; thus, the carbon emission level declines. Meanwhile, the sustainable land use management (caused by the policy of the land use regulation) further leads to a decline in carbon emission levels. By formulating reasonable and effective land use regulation policies, the government can promote the land use structure optimization, land use intensity control, land use efficiency improvement to reduce the negative impact of land use on carbon emissions. In addition, the government can also encourage the transformation of residents' consumption to green, low-carbon, and energy-saving products through policy propaganda and guidance, thereby further reducing carbon emissions (Bekun et al., 2021d). The function of CO_2 emissions levels during this period is shown in **Eq. 6**. The low-carbon industrial structure, sustainable land use management, structural optimization effect and the spillover effect of technological innovation ultimately reduce carbon

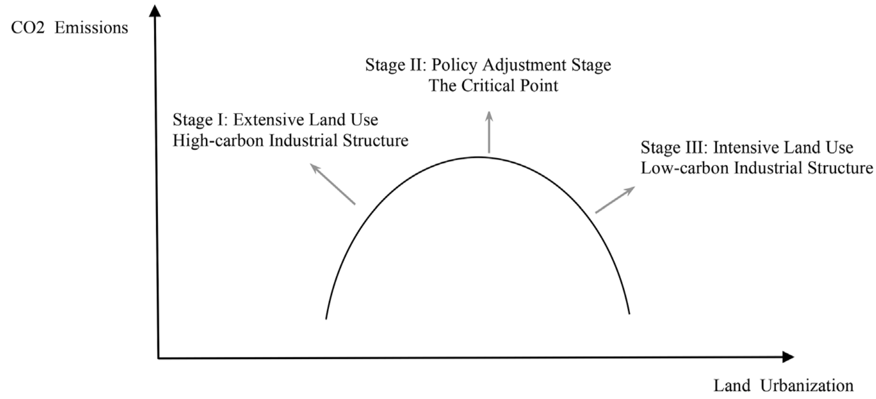

FIGURE 2 | Inverted U-shaped relationship between land urbanization and CO_2 emissions.

emissions, which further lead to a decline in carbon emissions per unit of land during this phase (Poumanyvong and Kaneko, 2010).

$$EM_t = EM_{ind}(t) + EM_{Land}(t) = B_t \frac{E_t^{\rho}}{\Phi_t} + C_t \frac{N_t^{\lambda}}{\Phi_t} \tag{6}$$

An Inverted Relationship Between Land Urbanization and Carbon Emissions

From the above analysis, we hypothesize that an inverted U-shaped relationship exists between land urbanization and carbon emissions (**Figure 2**). The left side of the U-shaped curve (stage I) corresponds to extensive urban land use and high-carbon industrial structure. The right side of the U-shaped curve (stage III) corresponds to intensive urban land use and low-carbon industrial structure. However, there is a policy adjustment stage in the middle (stage II). The Chinese government needs to actively optimize land-use management, adjust environmental regulations, industrial policies, and fiscal and tax policies, so China can quickly enter the third stage of intensive land use and low-carbon industrial structure.

METHODS

Econometric Model: STIRPAT Model

According to the Influence, Population, Affluence, and Technology (IPAT) model proposed by Ehrlich and Holdren (1971), environmental impact is determined by three factors: population (P), affluence (A), and technology (T). Specifically, the IPAT theoretical framework has been widely employed in the research field of environmental assessment (Kassouri et al., 2021). Thereafter, Dietz and Rosa (1997) extended the IPAT framework to include a stochastic component that is called the stochastic IPAT model (STIRPAT) model. According to the STIRPAT model, the effects of human activities on the environment (I) can be showed as the following equation:

$$I_{it} = a_i P_{it}^b A_{it}^c T_{it}^d e_{it} \tag{7}$$

where I_{it} denotes the respective environmental impacts, P_{it} is the population size, A_{it} is the affluence, and T_{it} is the technology level for prefecture-level city i and time period t. a_i is the constant term, and b, c, and d denote the exponents of P, A and T respectively. The variable e_{it} represents the random error term. By taking the logarithms of both sides of **Eq. 7**, a linear equation is obtained:

$$\ln I_{it} = u_i + b \ln P_{it} + c \ln A_{it} + d \ln T_{it} + \varepsilon_{it} \tag{8}$$

Some studies, such as Poumanyvong and Kaneko (2010), Zhang et al. (2017), and Kassouri (2021) added the variable "urbanization" into the STIRPAT model. In this study, we added the variable "land urbanization" into the model following the log-linear version of the STIRPAT model widely used in several previous studies (Poumanyvong and Kaneko, 2010; Kassouri et al., 2021; Kassouri, 2021). The expanded STIRPAT model can be rewritten as follows.

$$\ln C_{it} = u_i + b \ln P_{it} + c \ln A_{it} + d \ln T_{it} + \beta \cdot landrate + \varepsilon_{it} \tag{9}$$

where *landrate* denotes the land urbanization rate. C_{it} is the total carbon emissions for prefecture-level city i and time period t. Since this study also analyzes the impact of land urbanization on the CO_2 emissions of the secondary industry, tertiary industry, energy, and household sectors, C_{it} also represents the CO_2 emissions of these sectors.

Furthermore, to study the nonlinear relationship between land urbanization and CO_2 emissions, a model including a quadratic term of the land urbanization rate is given as follows:

$$\ln C_{it} = u_i + b \ln P_{it} + c \ln A_{it} + d \ln T_{it} + \beta \cdot landrate + \gamma \cdot landrate^2 + \varepsilon_{it} \tag{10}$$

Additionally, we replace the dependent variable "the total carbon emissions (C_{it})" with sectoral CO_2 emissions in **Eq. 10**, including secondary industrial ($C1_{it}$), tertiary industrial ($C2_{it}$), energy ($C3_{it}$), and household ($C4_{it}$) sectors, to investigate the relationship between land urbanization and sectoral CO_2 emissions.

Econometric Model: A Spatially Adaptive Semi-Parametric Model (SASP)

We assume that the variable "land urbanization rate" exists in the above STIRPAT model in the form of a quadratic term. In fact, there may be a misspecification in the model setting. Furthermore, the impact of land urbanization on CO_2 emissions presents spatial heterogeneity and spatial spillover effects (Li et al., 2021b). To avoid model setting misspecification and the curse of dimensionality in the nonparametric model, and to accommodate spatial heterogeneity among different cities, we applied the SASP model to analyze the influential mechanism of land urbanization on CO_2 emissions. The SASP model established in this study is shown below in **Eq. 11** (Ruppert et al., 2003).

$$\ln C_{it} = \beta_0 + \beta_1 \ln P_{it} + \beta_2 \ln A_{it} + \beta_3 \ln T_{it} + f(landrate) + \sum_{k=1}^{K_m} b_k (landrate - \kappa_k^m)_+^p \tag{11}$$

where β_0 is a constant; $\beta_i\,(i = 1, 2, 3)$ are the coefficients for each linear variable; $f(landrate)$ is the non-parametric term; $\kappa_k^m\,(k = 1, 2, \cdots, K_m)$ are knots; K_m is the dimension of knots; $(x_1 - \kappa_k^m)_+^p$ is equal to $(x_1 - \kappa_k^m)^p$ if $(x_1 - \kappa_k^m) > 0$ and b_k is its coefficient; m is the type of knot; and p is the exponential power of the k-th knot.

Empirical Models: Mediation Effect Model

The mediation effect model was used to examine whether Z mediates the effect of X on Y. To test whether the independent variable affects the dependent variable through the mediation variable, the structural equation model can be used for analysis (Gonzalez and Mackinnon, 2016). The specific equations of the mediation effect model are as follows:

$$\ln C_{it} = c \cdot landrate_{it} + \delta Z_{it} + \mu_i + \varepsilon_{it} \tag{12}$$

$$M_{it} = a \cdot landrate_{it} + \delta Z_{it} + \mu_i + \varepsilon_{it} \tag{13}$$

$$\ln C_{it} = c' \cdot landrate_{it} + bM_{it} + \delta Z_{it} + \mu_i + \varepsilon_{it} \tag{14}$$

were M_{it} presents the mediating variables, i.e., advanced industrial structure, CO_2 emissions per unit of GDP or CO_2 emissions per unit of land, Z_{it} indicates the control variables, μ_i signifies the fixed effect, and ε_{it} is the random error term.

In **Eqs 12–14**, if coefficients a, b, and c are all significant and c' is also significant, then there is a partial mediating effect for the mediating variables. Alternatively, if the coefficient c' is not significant, then there is a complete mediating effect for the mediating variables. In **Eqs 12–14**, the mediating effect is identical to indirect effect (ab). The relationship between total effect (c), direct effect (c'), and indirect effect (ab) is as follows (Mackinnon et al., 1995; Yao et al., 2018):

$$c = c' + ab \tag{15}$$

DATA

The research sample of this study included 285 prefecture-level cities in China in 2012 and 2015. CO_2 emissions data consisted of these types: Total CO_2 emissions, CO_2 emissions of secondary industrial, tertiary industrial, energy, and household sectors, CO_2 emissions per unit of GDP, and CO_2 emissions per unit of land. CO_2 emissions data were taken from the 2012 and 2015 Greenhouse Gas Emission Dataset of Chinese Cities established by the China Urban GHG Working Group. The data is based on the Chinese High-Resolution Emission Gridded Database (CHRED 3.0). Notably, this dataset establishes a spatialization bottom-up method based on point emissions sources, line emission sources, and area sources to achieve 1 km of greenhouse gas emission grid data. The advanced industrial structure is calculated according to the method in Chen and Zhao (2019). Land urbanization rate was characterized by the proportion of construction land allocated for urban land area. The data were collected from the China Land and Resource Statistical Yearbook. In addition, data on population, GDP per capita and number of patents granted were also collected from the China City Statistical Yearbook. Descriptive statistics for each variable are presented in **Table 1**.

RESULTS

Empirical Results Between Land Urbanization and Total CO_2 Emissions

Using the STIRPAT and SASP models, the empirical results of land urbanization and total CO_2 emissions are shown in **Table 2**, and the fitting graph of land urbanization and total CO_2 emissions is shown in **Figure 3**. The results in column 1) of **Table 2** are estimated according to the model of **Eq. 9**, while the results in column 2) of **Table 2** are estimated according to the model of **Eq. 10**. The third column in **Table 2** shows the parametric estimation results based on the model of **Eq. 11**, and the non-parametric estimation results of **Eq. 11** are shown in **Figure 3**. The results indicate that the impact of the land urbanization rate on total CO_2 emissions is positive; however, the relationship between land urbanization rate and total carbon emissions presents an inverted U-shaped curve after adding the quadratic term of the land urbanization rate. The results of **Figure 3** show that as the land urbanization rate increases, total carbon emissions also rise, but the speed of increase slows down during the sample period. When the land urbanization rate is relatively low, highly energy-intensive and energy inefficient industrial structures promote the increase in total CO_2 emissions. With the increase in the land urbanization rate, resource and environmental restraints and government regulations promote structural optimization and technology spillover effects. Similarly, the Chinese government could promote land use structure optimization, land use intensity regulation, land use efficiency improvement by optimizing land use regulatory policies to achieve carbon emissions reduction. These effects lead to a decrease in total CO_2 emissions, which is consistent with the results of Martínez-Zarzoso and Maruotti

TABLE 1 | Descriptive statistics of each variable.

Variable	Abbreviation	Unit	Average	Max.	Min.
Total CO_2 emissions	C_{it}	10,000 tons	3,840.42	27,677.32	229.9
CO_2 emissions of secondary industrial sector	$C1_{it}$	10,000 tons	3,010.69	17,518.99	10.1
CO_2 emissions of service sector	$C2_{it}$	10,000 tons	101.41	3,276.29	0.53
CO_2 emissions of energy sector	$C3_{it}$	10,000 tons	3,218.69	22,098.15	165.65
CO_2 emissions of household sector	$C4_{it}$	10,000 tons	105.99	2,146.5	0.71
GDP per capita	A_{it}	yuan	59,370.73	293,346	10,981
Population	P_{it}	10,000 persons	148.23	2,129.09	15.1
Number of patents granted	T_{it}	item	4,243.7	90,298	1
Land urbanization rate	*landrate*	%	8.99	77.32	0.19
Advanced industrial structure	AIS_{it}	none	6.74	7.59	4.76
CO_2 emissions per unit of GDP	CEG_{it}	tons per 10,000 yuan	2.48	25.61	0.16
CO_2 emissions per unit of land	CEN_{it}	tons per square kilometers	4,417.62	43,648.19	39.89

TABLE 2 | Estimating results between land urbanization and total CO_2 emissions based on the parametric and semiparametric model.

Variable	STIRPAT model 1	STIRPAT model 2	SASP model
Population	0.3106*** (0.000)	0.3111*** (0.000)	0.3366*** (0.0000)
GDP per capita	0.5090*** (0.000)	0.4985*** (0.000)	0.5092*** (0.0000)
Technology level	0.0672** (0.023)	0.0623** (0.038)	0.0591** (0.0347)
Land urbanization rate	0.0087*** (0.005)	0.0145** (0.043)	—
Land urbanization rate square	—	−0.0001 (0.370)	—
Constant term	0.3886 (0.549)	0.5033 (0.447)	0.3230 (0.6127)
N	570	570	570
F statistic	82.21	65.9	—
Time effect	yes	yes	—
Individual effect	yes	yes	—
Degree of freedom	—	—	1
Spar Statistics	—	—	51,130
Number of knots	—	—	34

*Note: p-values in the parentheses; ***, **, and * denote statistical significance at the 1, 5, and 10% levels, respectively.*

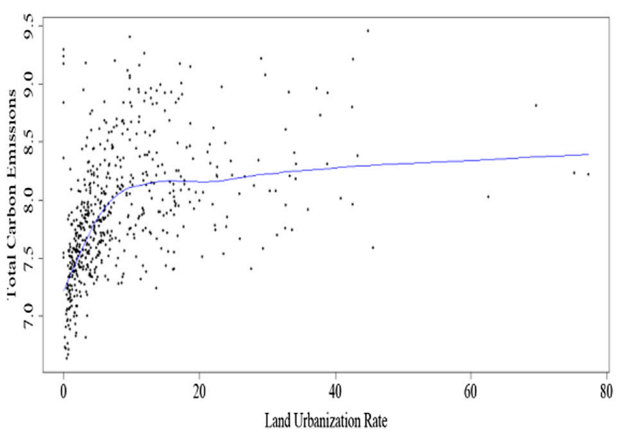

FIGURE 3 | The fitting curve of land urbanization and total CO_2 emissions.

(2011), Yao et al. (2018) and Wang et al. (2021b). The rise in China's CO_2 emissions has slowed down in the current stage. The Chinese government should implement effective policies to promote sustainable land use management, low-carbon industrial structure transformation, energy structure optimization and technological innovation, and enter the win-win phase of land urbanization rate increasement and CO_2 emissions reduction as soon as possible.

Reverse causality and omitted variables could lead to endogeneity between land urbanization and carbon emissions (Zhang et al., 2017; Wang et al., 2021b). To further conduct the robustness check of the benchmark regression results in **Table 3** and resolve the endogeneity problem, we chose the instrumental variables of land urbanization and applied the two-stage least squares (2SLS), generalized moment method (GMM), and limited information maximum likelihood (LIML) methods to perform regression analysis (Xu et al., 2021; Nepal et al., 2021; Safiullah et al., 2021). Following the existing literature, we chose night-time light data, the number of plots of land leasing, and the area of land leasing as the instrumental variables of land urbanization, respectively. The night-time light data were derived from the Visible Infrared Imaging Radiometer Suite sensor on the Suomi NPP satellite, which provides spatially explicit observations of artificial lighting sources across human settlements at night without moonlight (Wang et al., 2018a). The data of the number of plots of land leasing, and the area of land leasing were obtained from the

TABLE 3 | Estimating results between land urbanization and total CO_2 emissions based on the instrumental variable analysis.

Variables	OLS	2SLS	GMM	LIML
Land urbanization rate	0.009***	0.065***	0.069***	0.112***
	(0.003)	(0.019)	(0.018)	(0.034)
Population	0.337***	0.478***	0.467***	0.594***
	(0.052)	(0.080)	(0.079)	(0.124)
GDP per capita	0.509***	0.375***	0.339***	0.265**
	(0.062)	(0.089)	(0.085)	(0.135)
Technology level	0.059**	−0.073	−0.058	−0.183*
	(0.028)	(0.056)	(0.049)	(0.094)
Constant term	0.323	1.545*	1.848**	2.553*
	(0.638)	(0.902)	(0.856)	(1.337)
R^2	0.389	0.007	—	—
N	570	570	570	570

*Note: Standard errors in the parentheses; ***, **, and * denote statistical significance at the 1, 5, and 10% levels, respectively.*

Chinese Land and Resources Yearbook and Chinese Land and Resources Statistical Yearbook. The night-time light data is a good instrumental variable for economic development, including land urbanization (Mellander et al., 2015; Xu et al., 2021). Land leasing scale and area are also reasonable instrumental variables for land urbanization, because they are directly related to land urbanization, but they are also exogenous variables controlled by the Chinese central government. The regression results between land urbanization and total CO_2 emissions based on the instrumental variable analysis are shown in **Table 3**. The results indicate that the impact of land urbanization on the total CO_2 emissions was robust. Land urbanization had positive and significant effects on the total CO_2 emissions in the 2SLS, GMM, and LIML methods, and were consistent with the results of OLS method and **Table 2**.

In order to further analyze which sectors caused the increase in total carbon emissions, we empirically analyzed the relationship between land urbanization and sectoral carbon emissions. The estimated results are shown in **Table 4**. The results indicate that as the land urbanization rate increases, CO_2 emissions of the secondary industrial, tertiary industrial, energy, and household sectors also increase. Moreover, when the land urbanization rate increases by 1%, the increase in CO_2 emissions from the tertiary industrial and household sectors is higher than that in the secondary industrial and energy sectors. This may be caused by the industrial agglomeration effect and the adjustment of energy supply and consumption structure. However, the activities of the tertiary industrial and household sectors are relatively scattered, their green consumption concepts have not been firmly established, and energy-saving products are not widely used. Therefore, the Chinese government must further reduce CO_2 emissions in the secondary industrial and energy sectors. It is also necessary to implement effective policies to promote CO_2 emission reduction in the tertiary industrial and household sectors.

Empirical Results of the Mediating Effect of the Advanced Industrial Structure

To verify whether land urbanization can promote CO_2 emissions reduction through industrial structure optimization, we employed the mediating effect model to perform an empirical analysis. The results of the mediating effect of land urbanization on reducing CO_2 emissions through promoting the advanced industrial structure are shown in **Table 5**.

Table 5 shows that the impact of the land urbanization rate on total CO_2 emissions and on the advanced industrial structure is positive and significant.[1] When land urbanization and the advanced industrial structure are included in a single model, the land urbanization rate's impact on total CO_2 emissions is positive and insignificant, while the advanced industrial structure's effect on total CO_2 emissions is negative and significant. From the mediating effect model, we can conclude that the advanced industrial structure has a complete and negative mediating effect on the land urbanization rate's influence on total CO_2 emissions. As shown in **Table 5**, the mediation effect of the advanced industrial structure is −0.0047 [0.0088*(−0.5356) ≈ −0.0047], indicating that each 1% increase in land urbanization rate can result in 47 tons of carbon emissions because the effect of land urbanization on the advanced industrial structure when other conditions remain unchanged. The findings are in line with previous studies such as Wang et al. (2013) and Wang et al. (2021a), which stated that land urbanization reduced its promotion effect on carbon emissions possibly due to the industrial upgrading, energy consumption transition, and energy efficiency improvement. The impact of the industrial structure on CO_2 emissions is the result of energy use efficiency, energy

TABLE 4 | Estimating results between land urbanization and sectoral CO_2 emissions.

Variables	Secondary industrial sector	Service sector	Energy sector	Household
Population	0.2961*** (0.000)	0.7252*** (0.000)	0.3278*** (0.000)	0.5625*** (0.000)
GDP per capita	0.6481*** (0.000)	0.3947*** (0.000)	0.5769*** (0.000)	−0.2352*** (0.005)
Technology level	0.0488 (0.234)	−0.0666 (0.136)	0.0427 (0.197)	0.0615 (0.119)
Land urbanization rate	0.0097** (0.025)	0.0166*** (0.000)	0.0103*** (0.003)	0.0262*** (0.000)
Constant term	−1.2843 (0.155)	−3.5297*** (0.000)	−0.4981 (0.494)	3.3457*** (0.000)
N	570	570	570	570
F statistic	48.09	49.79	68.72	57.09
Time effect	yes	yes	yes	yes
Individual effect	yes	yes	yes	yes

*Note: p-values in the parentheses; ***, **, and * denote statistical significance at the 1, 5, and 10% levels, respectively.*

TABLE 5 | The mediating effect of the advanced industrial structure.

Variables	Total CO_2 emissions	Advanced industrial structure	Total CO_2 emissions
Land urbanization rate	0.0087*** (0.005) —	0.0088*** (0.000)	0.0136 (0.204) —
Advanced industrial structure	—	—	−0.5356*** (0.000)
Population	0.3111*** (0.000)	−0.0254 (0.252)	0.3247*** (0.000)
GDP per capita	0.5096*** (0.000)	0.1377*** (0.000)	0.4358*** (0.000)
Technology level	0.0677** (0.020)	0.0478*** (0.000)	0.0422 (0.143)
Constant term	0.3773 (0.559)	4.9481*** (0.000)	−2.2727*** (0.005)
F statistics	83.57	53.99	76.07
R^2	0.3746	0.2868	0.4042
Observations	570	570	570
Time effect	yes	yes	yes
Individual effect	yes	yes	yes

*Note: p-values in the parentheses; ***, **, and * denote statistical significance at the 1, 5, and 10% levels, respectively.*

TABLE 6 | The mediating effect of CO_2 emissions per unit of GDP.

Variables	Total CO_2 emissions	CO_2 emissions per unit of GDP	Total CO_2 emissions
Land urbanization rate	0.0087*** (0.005)	−0.00281*** (0.005)	0.0093*** (0.000)
CO_2 emissions per unit of GDP	—	—	0.1974*** (0.000)
Population	0.3111*** (0.000)	—	0.3640*** (0.000)
GDP per capita	0.5096*** (0.000)	—	0.4719*** (0.000)
Technology level	0.0677** (0.020)	—	0.1580*** (0.000)
Constant term	0.3773 (0.559)	2.7508*** (0.000)	−0.5823 (0.233)
F statistics	83.57	7.99	203.25
R^2	0.3746	0.0134	0.6444
Observations	570	570	570
Time effect	yes	yes	yes
Individual effect	yes	yes	yes

*Note: p-values in the parentheses; ***, **, and * denote statistical significance at the 1, 5, and 10% levels, respectively.*

consumption structure, and technological progress, which is complex to a certain extent. With the increasing output value of China's tertiary industry and the improvement in urbanization quality, the demand for energy is decreasing in industrial development (Li et al., 2017). The industrial structure advancement produces a reduced and negative impact on CO_2 emissions, and the optimization and updating of the industrial structure can be regarded as an effective means of lowering CO_2 emissions in China (Wang et al., 2019). Ultimately, this implies that the more the government allocates land indicators to advanced manufacturing, high-tech industries or digital economy, the more it is likely to optimize the land use structure and promote the advanced industrial structure, which can further reduce CO_2 emissions.

Empirical Results of the Mediating Effect of CO_2 Emissions Per Unit of GDP

To verify whether land urbanization can promote CO_2 emissions reduction through lowering CO_2 emissions per GDP, we employed the mediating effect model. The results are shown in **Table 6**.

Table 6 shows that the impact of the land urbanization rate on total carbon dioxide emissions is positive and significant, while its impact on carbon dioxide emissions per GDP is negative and significant. When the land urbanization rate and carbon dioxide emissions per GDP are put in a single model, the land urbanization rate's impact on total carbon emissions is positive and significant, and the effect of carbon dioxide emissions per GDP on total carbon dioxide emissions is also positive and significant. From the mediating effect model, we can conclude that carbon dioxide emissions per GDP has a partial and negative mediating effect on the land urbanization rate's influence on total carbon dioxide emissions. As shown in **Table 6**, the coefficient of total effect c is 0.0087 with a 1% significance level, while the effect of direct effect c' is 0.0093 with a 1% significance level. Accordingly, the mediation effect of CO_2 emissions per unit of GDP is −0.0006 ($-0.00281*0.1974 \approx -0.0006$, and $0.0087 = 0.0093-0.00281*0.1974$), indicating that there is a masking effect of land urbanization on the total carbon emissions. The results are consistent with those of Rafiq et al. (2016), Wang et al. (2019) and Wang et al. (2021b), which insisted that energy consumption structure transformation, energy efficiency improvement, and technological progress brought by land urbanization led to energy intensity and carbon emissions reduction. Ultimately, this implies that in the process of land urbanization, the Chinese government can reduce carbon dioxide emissions per GDP by optimizing the land

TABLE 7 | The mediating effect of CO_2 emissions per land.

Variables	Total CO_2 emissions	CO_2 emissions per land	Total CO_2 emissions
Land urbanization rate	0.0087*** (0.005)	66.9749*** (0.001)	0.0051* (0.077)
CO_2 emissions per land	—	—	5.43*E-05*** (0.000)
Population	0.3111*** (0.000)	879.1059** (0.013)	0.2745*** (0.000)
GDP per capita	0.5096*** (0.000)	2,275.299*** (0.000)	0.3929*** (0.000)
Technology level	0.0677** (0.020)	506.8069*** (0.009)	0.0312 (0.254)
Constant term	0.3773 (0.559)	−28592.5*** (0.000)	1.8705*** (0.003)
F statistics	83.57	42.86	93.60
R^2	0.3746	0.2363	0.4575
Observations	570	570	570
Time effect	yes	yes	yes
Individual effect	yes	yes	yes

Note: p*-values in the parentheses; ***, **, and * denote statistical significance at the 1, 5, and 10% levels, respectively.*

use structure and improving land use efficiency to achieve carbon emissions reduction. To reduce the intensity of carbon emissions per unit of GDP, active measures should be taken from the following three aspects: The first is for the government to take measures to adjust the energy consumption structure, reduce fossil energy consumption, and increase the proportion of clean energy consumption (Zhang et al., 2021). The second is to improve energy efficiency by promoting technological innovation of enterprises and improving the degree of marketization (Chen et al., 2021). The third is to strengthen the guidance of land management policies to promote low-carbon industrial development. For example, local governments restrict the entry of high-carbon industries from land indicators.

Empirical Results of the Mediating Effect of CO_2 Emissions Per Unit of Land

To verify whether land urbanization can promote CO_2 emissions reduction through reducing CO_2 emissions per land, we employed the mediating effect model to perform an empirical analysis. The results of the mediating effect of land urbanization on CO_2 emissions reduction through reducing CO_2 emissions per land are shown in **Table 7**.

Table 7 shows that the impact of land urbanization rate on total CO_2 emissions is positive and significant, and the impact of land urbanization rate on CO_2 emissions per land is positive and significant. When the land urbanization rate and CO_2 emissions per land are put in a single model, the impact of the land urbanization rate on total carbon emissions is positive and significant, and the effect of CO_2 emissions per land on total CO_2 emissions is also positive and significant. From the mediating effect model, we can conclude that CO_2 emissions per land plays a partial and positive mediating effect over the influence of land urbanization rate on total CO_2 emissions. As shown in **Table 7**, the coefficient of total effect c is 0.0087 with a 1% significance level, while the effect of direct effect c' is 0.0051, with a 10% significance level. Accordingly, the mediation effect of CO_2 emissions per unit of land is 0.0036 (66.9749*5.43E-05 $\approx$ 0.0036, and 0.0087 = 0.0051 + 66.9749*5.43E-05), which accounts for 41% of the total effect. The results are in accordance with that of Wang et al. (2021b), which believed that land use efficiency improvement and land use intensity optimization can mitigate the increase in carbon emissions. Ultimately, this implies that in the process of land urbanization, the Chinese government can achieve CO_2 emissions reduction through reducing CO_2 emissions per land. Accordingly, Chinese central and local governments should take effective measures to promote land use optimization and green and low-carbon development. On the one hand, the government should focus on optimizing the structure of construction land and greatly reduce the scale and proportion of secondary industrial and mining land (Liu et al., 2018a). Meanwhile, the government should promote the increase in the scale of forest land and wetland to increase carbon sinks. On the other hand, the government should reasonably control the land development intensity and maintain the carbon balance and sustainability of the biosphere (Wang and Feng, 2015; Guo et al., 2017; Dong et al., 2018). Finally, the government should further improve the efficiency of land use to promote ow-carbon industrial structure transformation, energy structure optimization and technological innovation.

DISCUSSIONS

The increase in urban CO_2 emissions is mainly caused by LUCC and anthropogenic activities (including both production and residential activities). Existing literature has conducted an in-depth examination of CO_2 emissions caused by LUCC, which is the main driving force for carbon storage in terrestrial ecosystems (Chuai et al., 2014). First, LUCC can change vegetation's coverage, biomass, carbon density, and carbon storage, and thus, directly affect CO_2 emissions (Zhu et al., 2019). Second, LUCC also has a profound effect on soil organic carbon (Zhu et al., 2019). Among the main land use types, forest land, wetland, and unused land facilitate net carbon absorption, while cultivated land, grassland, and urban construction land facilitate net carbon emissions. The changes from forest land, wetland, and unused land to other types, and especially alterations to urban construction land, will greatly reduce vegetation biomass and release more carbon into the atmosphere (Houghton, 2003; Bailis and McCarthy, 2011).

With increased development, more and more cultivated land, woodland, and grassland are transformed into urban construction land. Another main driving force for CO_2 emissions is the energy consumption required for production activities on industrial and mining lands, exhaust emissions from transportation lands, and heating in residential areas. The carbon emission intensity of urban construction land is much higher than that of other land types. Among various kinds of construction land, the carbon emission intensity of industrial and mining land is the highest, transportation land is second, and that of urban and rural residential land is the lowest.

This study creatively explores the possibility of synergistic promotion of land urbanization and carbon reduction from the perspective of land use structure optimization, land use intensity regulation, and land use efficiency improvement. More importantly, we found strong evidence to support the environmental Kuznets curve hypothesis between land urbanization and carbon emissions based on land use optimization. In addition, this study provided new insights into the validity of the environmental Kuznets curve hypothesis and focused on how optimized land urbanization can mitigate carbon emissions. China's land is state-owned, and the government controls the land indicators for conversion of agricultural land or unused land to urban construction land. Under this framework, the government can regulate the supply of urban construction land to influence the urban land use structure, and then affect the CO_2 emissions levels through optimization of land use types. Increasing the proportion of land use types with low CO_2 emission intensity is conducive to reducing carbon emission levels. Meanwhile, the government can also promote CO_2 emissions reduction by regulating land use intensity. Excessive land use intensity could disrupt the balance of the atmosphere and biosphere. It could, in turn, affect the impact of ecosystems on carbon sequestration, thereby increasing CO_2 emissions. In addition, the improvement of land use efficiency contributes to reducing CO_2 emissions. The improvement of land use efficiency is reflected in the improvement of technical levels, energy use efficiency, and so on, resulting in the reduction of CO_2 emissions.

It is noteworthy that this study integrated land use optimization and industrial development into a unified framework to analyze the impact of land urbanization on carbon emissions. High-quality land use and land urbanization contribute to declines in the scale of carbon emissions, per capita carbon emissions, and carbon intensity (Yao et al., 2018). The results of this study are consistent with those of Yao et al. (2018), Xie et al. (2018), and Wang et al. (2021a), which showed that reasonable, efficient, and sustainable land urbanization is beneficial for CO_2 emissions reduction. High-quality, and sustainable land urbanization promotes low-carbon development mainly by influencing these mediating variables including industrial structure, energy intensity, energy consumption structure, and technological innovation (Li et al., 2018). More importantly, in the process of land urbanization, the government can promote land use structure optimization, rational land use intensity regulation, land use efficiency improvement by implementing innovative land use policies, which could vigorously promote carbon emissions reduction and low-carbon development.

The government should introduce land policies to promote the optimization of land use structure, land use intensity control, and land use efficiency improvement. First, the government should scientifically formulate spatial land-use planning, with a focus on low-carbon development (Zhang et al., 2018). Indicators such as carbon emissions per unit of land should be included in spatial land-use planning (Wang et al., 2021a). Local governments could control regional land use intensity, optimize land use structure by setting carbon emissions caps, or evaluating energy consumption per unit of industrial land for industrial parks. Second, the Chinese central government should strictly control the land quotas of arable land, forest land, wetland, etc. that are converted into urban construction land. This can promote the optimization of land use structure and reduce the conversion of low-carbon land to high-carbon land. Third, the government should establish a perfect development intensity control system and implement the principle of plot ratio control to restrain the damage of excessive land development intensity to the carbon balance of the biosphere. Finally, local governments should further optimize industrial policies and improve regional land use efficiency. Relevant government departments could conduct performance appraisals on enterprises in the development zone by using indicators such as land use and energy use. In addition, the government could introduce fiscal and tax preferential measures to encourage enterprises to improve their land use and energy use efficiency.

Furthermore, the government should further adjust the energy consumption structure and foster a low-carbon industrial structure, increase the efficiency of energy use, and decrease the intensity of carbon emissions. First, the government should promote energy consumption structure optimization and reducing carbon intensity (Wang et al., 2021a). It should gradually decrease the proportion of high-carbon energy such as coal and coke, and shift away from fossil fuels to renewable low-carbon energy resources such as solar energy, wave energy and wind energy. It also should greatly develop new environment-friendly energy sources to promote the optimization of its energy consumption structure (Wang et al., 2013). At this point, it is also necessary for the government to implement policy measures such as fiscal subsidies and tax incentives to encourage enterprises to optimize their energy consumption structure. Second, the government should pay great attention to upgrading the industrial structure. It will be necessary to optimize the industrial structure, make an appropriate reduction of the secondary industry, greatly develop the tertiary industry, develop the emerging low-carbon industry and boost the upgrade and cluster development of the traditional high energy consumption industry (Wang et al., 2013). Finally, the government should also actively promote technological level advancements and improve carbon emissions efficiency (Wang et al., 2021b). To this end, the government should set target cuts in carbon emissions per unit of GDP. It should also take various measures such as accelerating research and development in low-carbon technology, popularizing new energy-saving products and new technologies, and implementing incentive policies and so on to strengthen energy saving and emission reduction, thus improving energy efficiency (Wang et al., 2013; Wang et al., 2016).

In addition, the government should also make a greater effort to improve the public's awareness of low-carbon technologies, strengthen the generalization of a low-carbon economy, foster low-carbon consumption and green consumption, and encourage households to keep to a sustainable consumption mode (Wang et al., 2013; Liu et al., 2018b). The government can promote low-carbon development by building low carbon eco-cities, encouraging residents to adopt low-carbon lifestyles, including developing low-carbon transportation habits, e.g., green commuting, shared bikes, metro system, electric and hybrid car (Li et al., 2021b). Specifically, evaluation criteria of local government by the central government should be diversified. Economic evaluation can be weakened, and environmental performance, such as green and low-carbon development indicators, can be emphasized accordingly. Eventually, this approach could lead to a decline in the level of carbon emissions per unit of land, thereby achieving a win-win situation through the synergy of land urbanization and carbon emissions reduction.

Although we only use 2 years of cross-section data to form panel data for empirical analysis, our findings will stimulate research on land use to reduce CO_2 emissions and achieve low-carbon development for developing countries. In the future, more micro and high-resolution data can be used to analyze the relationship between land use and CO_2 emissions.

CONCLUSION AND POLICY RECOMMENDATIONS

This study explored the mechanism of land urbanization's effect on CO_2 emissions in China. First, it sought to uncover this mechanism at different stages of economic development. Theoretical analysis showed that at the stage of extensive land use, the energy-intensive industrial structure, low energy use efficiency, low-level of land use management, and low land use efficiency led to an increase in CO_2 emissions per unit of land. However, at the stage of high-quality land use, structural optimization effects, such as an advanced industrial structure and clean energy consumption structure, the spillover effects of technological innovation, and the high-level of land use management caused declines in the CO_2 emissions scale and CO_2 emissions per unit of land. Secondly, a STIRPAT model and a SASP model were used to explore the impact mechanism of land urbanization on CO_2 emissions to accommodate for stochastic factors and spatial heterogeneity among different cities. Meanwhile, the mediating mechanism of the advanced industrial structure, CO_2 emissions per unit of GDP and CO_2 emissions per unit of land was studied using a mediating effect model. The empirical results show that high-quality land use can promote the optimization of land use, thereby reducing carbon emissions per unit of land or carbon emissions per unit of GDP and achieving CO_2 emissions reduction and low-carbon development. Moreover, high-quality land use can achieve CO_2 emissions reduction by promoting the advanced industrial structure. To be sure, the government would do well to work to reduce carbon emissions by optimizing spatial land use regulation and innovating spatial land governance.

There are several actions that can be taken by the government to reduce CO_2 emissions. First, the government should optimize land use structure, rationally control land use intensity, and promote the efficient use of urban construction land by formulating scientific spatial land-use planning and sensible land-use policies. Indicators such as carbon emissions per unit of land could be included in spatial land-use planning. Local governments could set carbon emissions caps, energy consumption caps for enterprises to limit investment in high-carbon industries and promote low-carbon development. Meanwhile, the local governments can further use fiscal and taxation policies to encourage enterprises to improve their technological level, land use efficiency, energy use efficiency, and so on. In addition, the central government should strictly control the land indicators for the conversion of low-carbon land to high-carbon land, establish a perfect land development intensity control system, and implement floor area ratio control. Second, the government should particularly focus on cultivating low-carbon, energy-saving, and environmental protection industries and encourage the development of these industries to promote an advanced industrial structure. Efforts should be made to explore, exploit, and apply renewable, new, and green energy by developing and introducing new energy technologies and environmentally friendly technologies to achieve the targets of carbon mitigation. Finally, the government should also make an effort to increase the public's awareness of low-carbon technologies and encourage the households to adopt a low-carbon consumption mode.

This study takes the first step to investigate the effect of land urbanization on carbon emissions by integrating land use structure optimization, land use intensity regulation, land use efficiency improvement, industrial structural optimization, and carbon efficiency improvement. However, this study still exists some limitations. Due to data limitation, the time-frame for this study was restricted to only 2 years of high-resolution gridded data. The endogeneity in the empirical process needs to be further resolved. In the further studies, with more available high-resolution data, this study can be extended to obtain more information on the relationship between land urbanization and CO_2 emissions. The treatment effect model or the method of randomized control trials could be used to resolve the endogeneity problem of this study in future. Further research regarding the nonlinear relationship between land urbanization and carbon emissions by integrating land use optimization, industrial structure upgrading, and energy use efficiency improvement remains to be done.

DATA AVAILABILITY STATEMENT

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

AUTHOR CONTRIBUTIONS

All authors contributed to the study conception and design. Material preparation, data collection, were performed by MT, and the first draft of the manuscript was written by MT. Data processing and analysis were performed by FH, and the manuscript was reviewed by FH. All authors commented on previous versions of the manuscript. All authors read and approved the manuscript.

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Carbon Emission Trading Scheme, Carbon Emissions Reduction and Spatial Spillover Effects: Quasi-Experimental Evidence From China

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The carbon emission trading scheme (ETS) is an essential policy tool for accomplishing Chinese carbon targets. Based on the Chinese provincial panel data from 2003 to 2019, an empirical study is conducted to measure the effects of carbon emission reduction and spatial spillover effect by adopting the difference-in-differences (DID) model and spatial difference-in-differences (SDID) model. The research findings show that: 1) The ETS effectively reduced the total carbon emissions as well as emissions from coal consumption; 2) such effects come mainly from the reduction of coal consumption and the optimization of energy structure, rather than from technological innovation and optimization of industrial structure in the pilot regions; and 3) the ETS pilot regions have a positive spatial spillover effect on non-pilot regions, indicating the acceleration effect for carbon emission reduction. Geographic proximity makes the spillover effect decrease due to carbon leakage.

Keywords: carbon emission trading scheme, coal removal, spatial spillover effect, carbon emissions reduction effects, SDID

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1 INTRODUCTION

Net zero is a necessary step to mitigate global warming and has become an international consensus. In confronting climate change, the Paris Agreement stipulated objectives to limit the rise of global average temperature within 1.5 and 2°C (UNFCCC, 2015). The Intergovernmental Panel on Climate Change then addressed this act by setting the goal "to achieve global carbon neutrality around 2050, leading to an eventual 1.5°C global warming target by 2100" (IPCC, 2018). However, the published national reduction contributions under the Paris Agreement continue to face challenges in meeting the 1.5°C temperature control target (Duan et al., 2021). Most countries have pledged carbon neutrality targets through legal provisions and policy declarations. As one of the largest energy consumption countries, China signed the Paris Climate Accord and pledged to "peak emission by 2030 and reaching carbon neutral by 2060." However, China's total carbon emissions reached 929 million tons in 2019, approximately one-third of total global emissions, and its coal consumption accounted for nearly 60% of the country's total energy consumption (Wang and Yang, 2021). "Going carbon neutral" in China requires implementation of a combination of policies across the next 4 decades. At the early stages, the focus should be set on achieving optimal energy structures, deepening industrial structural reform, and constructing a green industrial chain (Huang and Zhai, 2021). In mid-to-late stages, attention should be shifted to fossil energy decommissioning and development of technologies related to Carbon Capture and Storage (CCS) (Xu et al., 2021) and Bioenergy Combined with Carbon Capture and Storage (BECCS) (Huang et al., 2020).

The Carbon Emission Trading Scheme (ETS) provides price signals for carbon emission reduction, creates an essential path towards carbon neutrality, and mitigates global warming (Wang et al., 2020). In October 2011, China carried out measures to promote the ETS, authorizing seven provinces and cities to launch pilot projects in carbon emissions trading. In 2021, the long-awaited national carbon emissions trading market was officially launched in China, establishing the world's largest greenhouse gas (GHG) emissions trading market.

Past research focused on the ETS in China through two streams: ex ante analysis and ex post analysis. Ex ante analysis develops Computable General Equilibrium (CGE) models (Lin and Jia, 2018), the Integrated Assessment Model (IAM) (Zhao et al., 2020), or Agent- Based Model (ABM) (Tang et al., 2017) to study the influence of the ETS parameters on emission reduction effect and economic development. Topics discussed involved initial allocation, coverages, reasonable carbon price range, effects on carbon emissions, economic costs, and the interactions between the ETS and other complementing policies (Li et al., 2017; Wu and Li, 2020; Weng et al., 2021). The results of ex ante analysis are potentially affected by multi-parameter settings and model assumptions.

The ex post analysis is focused on assessing operational effectiveness and the impact of such mechanisms based on historical archival data. Most studies concluded that the ETS is an effective policy tool in carbon emissions reduction at provincial, municipal, and corporate levels (Gao et al., 2020; Shen et al., 2020; Zhang W. et al., 2020; Zhang Y. et al., 2020), The emission reduction effect increases annually with the implementation of the policy (Zhang and Zhang, 2019). Some researchers suggest that such action also reduces other pollutants such as PM2.5 and SO_2, promoting China's low-carbon innovation and economic development and finally bringing in more environmental dividends (Feng et al., 2021b; Liu et al., 2021). Wang et al. (2020) adopted the difference-in-differences (DID) model to demonstrate a positive correlation between the ETS and low-carbon economic transformation; however, researchers also argued that the ETS may improve the efficiency of emission reduction, but the actual effect remains relatively weak (Zhu et al., 2020). Due to the immaturity of the regulations and market systems for the ETS pilots (Qi et al., 2021), the ETS market lacks vitality. Such efficiency of emission reduction has slowed (Zhu et al., 2020). Studies on the impact mechanism of the European Union Emissions Trading System (EU ETS) have argued that the EU ETS reduces carbon emissions mainly through technological innovation (Jaraitė and Di Maria, 2012; Calel and Dechezleprêtre, 2016). In a similar scenario, certain Chinese scholars have argued that China's ETS reduces carbon emissions by reducing energy consumption and optimizing energy structure, while the emission reduction effect of technological innovation is not significant (Xuan et al., 2020; Liu et al., 2021).

The emission reduction effects of the pilot regions provide a direct signal and information for the implementation of China's ETS, therefore, this study analyzes the effect of the ETS through six pilot regions. Unlike European countries, coal consumption took a dominating role in the current Chinese energy consumption structure (Wang and Yang, 2021). The ETS will be the main driver in supporting China's carbon neutrality goal. Few studies have analyzed the impact of the ETS on carbon emissions caused by coal consumption, and no empirical evidence has shown the effect and extent of the ETS in coal removal process.

A growing number of studies have focused on the spatial spillover effect and the carbon leakage caused by the ETS. These ex ante analyses were adopted by CGE models or IAM (Antimiani et al., 2016; Yu et al., 2021). Researchers argued that the EU ETS leads to carbon leakage, shifting carbon emissions from regions with strong environmental constraints to those with weak environmental constraints (Paroussos et al., 2015; Böhringer et al., 2017). Similarly, some scholars have demonstrated that carbon leakage is inevitable in China's ETS using CGE model (Tan et al., 2018; Wang et al., 2018), but the simulation results of the ex ante analysis depend heavily on the model setup and the assumptions of the model (Yu et al., 2021). Such methods often underestimate or ignore the efforts of non-pilot regions in carbon emissions reduction.

Empirical analysis on the ex-post spatial spillover effect and carbon leakage are inadequate. As policy implementation increases, more attention has shifted to this area of study. Naegele and Zaklan (2019) find no evidence supporting that the EU ETS leads to carbon leakage based on evidence from European manufacturing development data. Some scholars used the DID model based on the historical data of the ETS pilot regions to test its positive spatial spillover effect. In particular, Liu et al. (2021) adopted the DID model to investigate whether cities adjacent to pilot cities also benefit from the implementation of the ETS and if there is a positive spillover effect of the ETS observed in reducing air pollution. Significantly, Zhou et al. (2020) shows that the ETS can lead to reverse carbon leakage. Pilot regions with larger industries have more industrial transfers in contrast to non-pilot regions, leading to a shift of carbon emissions from non-pilot to pilot regions. However, these empirical findings are far from sufficient to provide ex post data. Local pilots and national carbon markets will co-exist in China with heterogenetic intensity of environmental legislation across regions. Analyzing the existence of a spatial spillover effect of the ETS and the direction of spillover is vital.

As observed, the DID model are widely used to study the emission reduction effect and spatial spillover effect of the ETS, without considering spatial interactions among units. The DID model violates the SUTVA hypothesis of independent and identical distribution, which says one unit should not be affected by the treatment of the other (Cox, 1958; Rosenbaum, 2010), This issue will lead to bias or potential error. Chagas et al. (2016) determined that by performing a treatment group and control group between spatial decomposition, the spatial difference-in-differences (SDID) model was shown to be effective in addressing this challenge, and it is gradually being adopted in the corresponding analyses (Feng et al., 2021a; Yu and Zhang, 2021).

This paper applies both the DID model and SDID model to respond to whether the ETS is effective in the reduction of total carbon emissions and these from carbon emissions. What is the impact of the mechanism? How much is the spatial spillover effect? The main contributions of this research lie in the following three aspects: 1) we analyzed the impact of the ETS on total carbon emissions and those caused by coal consumption, focusing on the effects of the ETS on coal removal; 2) we adopted the DID model to evaluate the emission reduction effect and the impact mechanism of the ETS; 3) we adopted the SDID model to analyze the spatial spillover effect of the policy and its stimulating effect on carbon leakage. The results are more robust and expand the spatial perspective for the study of policy impact effects. The rest of the paper is organized as following: **Section 2** explains the model setup and the selection of variables; **Sections 3**, **4** show the empirical processes and results; and **Section 5** concludes the paper and offers corresponding policy recommendations.

2 MODEL DESIGN AND DATA DESCRIPTION

2.1 Difference-in-Differences Model

The data sample is divided into the treatment and control groups. The treatment group (*Policy = 1*) is made up of the two pilot provinces and four municipalities directly under the central government that implemented the ETS, and the control group (*Policy = 0*) is made up of the non-pilot provinces and autonomous regions. Official approval of the ETS implementation was granted in 2011, and the actual year of implementation was 2013. Therefore, Post-2013 (2013 included) is the policy implementation period (*Post = 1*) and pre-2013 is the non-policy period (*Post = 0*). Therefore, DID estimation is specified as following:

$$Y_{it} = \beta_0 + \beta_1 did_{it} + \alpha_1 X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{1}$$

where Y_{it} is the dependent variable, denoting the total carbon emissions and carbon emissions caused by coal consumption in province i at year t. did_{it} is a cross-term of the pilot policy dummy variable (*Policy*) and the year dummy variable (*Post*). Both dummies are the explanatory variable of the estimation. Its estimated coefficient β_1 indicates the impact of the ETS on both types of carbon emissions. Since the natural logarithm of the dependent variable has been taken, the estimated coefficient β_1 represents the proportional change in carbon emissions before and after 2013 in the provinces and cities with the ETS (experimental group) relative to those without ETS (control group). X_{it} is the set of control variables that may affect CO_2 emissions. μ_i is a province-fixed effect, γ_t is a time-fixed effect, and ε_{it} denotes the random error term.

2.2 Spatial Difference-in-Differences Model

To study spatial spillover effect of ETS, the SDID estimation was carried out using a spatial lag model (SLX) (Chagas et al., 2016). The spatial spillover effect of the ETS can be correctly estimated for both pilot and non-pilot regions. This produces the following SDID specifications:

$$Y_{it} = \beta_0 + \beta_1 did_{it} + +\beta_2 W_{T.T} D_{it} + \beta_3 W_{NT.T} D_{it} + \alpha_1 X_{it} + \alpha_2 W X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{2}$$

where W denotes the spatial weight matrix. $W_{T.T} D_{it}$ denotes the spatial spillover effect within pilot regions, and its estimated coefficient is denoted by β_2. $W_{NT.T} D_{it}$ represents the spatial spillover effect from pilot regions to non-pilot regions, and its estimated coefficient is denoted by β_3. In addition, other parameters are set the same as in **Eq. 1**.

The spatial distance weight matrix W_1 represents the between-region spatial weight effect; to clarify, geographical distance only represents the influence of geographical features and carbon emissions, as the result of human activities have other non-geographical impact factors. Therefore, this paper draws on the method of Li et al. (2010) to establish the economic distance weight matrix W_2. W_2 characterizes the economic distance by the difference of regional GDP per capita, which reflects regions with higher levels of economic development having a stronger influence than those with low level economic development. In addition, to identify carbon leakage from the pilot regions to the adjacent regions, this paper also analysed a local spatial distance weight matrix where 200 km, 300 km, 400 km, and 600 km are the range thresholds analyzed.

2.3 Variables Description

Restricted by data availability of the balance sheets and missing data at the provincial level, this paper focuses on carbon emissions from coal consumption. The sample included data from 29 provinces and municipalities from 2003 to 2019, excluding Hong Kong, Macao, Taiwan, Fujian Province, and Tibet Autonomous Region due to the special research setting. The ETS in Fujian Province was established in 2017, which is different from other pilot regions and the pilot operation period is relatively short, so Fujian Province is excluded from the sample in this paper. Original data were obtained from *China Urban Statistical Yearbook* and *China Energy Statistical Yearbook* from 2004 to 2020.

1) Dependent Variable: Total carbon emissions and those from coal consumption. Based on the energy balance sheets of 29 provinces, the total carbon emissions and those from coal combustion are aggregated by multiplying the amount of energy consumed by the average low level of heat generation, the CO_2 oxidation factor, and the oxidation rate based on varied energy sources. This research excludes the double-counting of consumption during energy conversion. Finally, the two dependent variables are normalized by logarithms and denoted as lnCE and lnCCE, respectively.
2) Treatment Variable (did): an interaction term of the pilot policy dummy variable and the year dummy variable: pilot regions receive valued of 1 during the post-2013 period. Non-pilot regions and those pre-2013 pilot regions receive the value of 0.
3) Control Variables: Based on previous literature, the following variables have been included: Industrialization level (*IL*):

TABLE 1 | Descriptive statistics.

Variable	Mean	SD	Min	Max	Observation
lnCE	9.946	0.825	7.267	11.58	493
lnCCE	9.658	0.972	5.677	11.54	493
Did	0.0850	0.279	0	1	493
IL	45.59	8.445	16.20	61.50	493
SL	43.09	9.490	28.60	83.50	493
lnPGDP	10.29	0.765	8.190	11.91	493
lnPOP	5.420	1.285	2	8.257	493
FDI	0.0230	0.0190	0	0.105	493
IET	0.303	0.380	0.0130	1.721	493
RD	0.0110	0.0230	0	0.164	493
lnCOAL	7.939	0.970	4.171	9.659	493
ES	0.440	0.158	0.0120	0.802	493

share of secondary sector in GDP of each province; economic development level (ln*PGDP*): logarithm of the real GDP of each province (based on 2003) as a share of the total population at the end of the year; Population density (ln*POP*): logarithm of the total population of each province at the end of the year as a proportion of the geographical region of the province; international direct investment (*FDI*): share of foreign direct investment in each province in the GDP of the year; service industry development level (*SL*): share of tertiary industry in the GDP of each province; degree of openness to the world (*IET*): share of the total trade of import and export of each province to the GDP of the year.

4) Mediators: Mediators adopted to study the mechanism of the impact of ETS are shown as follows: industrial structure (*IL*): share of value added of secondary industry in GDP; technological innovation (*RD*): share of R&D expenditures in GDP; energy structure (*ES*); share of coal consumption in total energy consumption; coal consumption (ln*COAL*): logarithm of coal consumption in each province. **Table 1** shows the descriptive statistics.

3 EMPIRICAL RESULTS

3.1 Baseline Regression

The estimated results of ETS abatement effects are shown in **Table 2**; columns 1–2 show the results of the baseline regression of the ETS on total carbon emissions. Column 2 adds the control variables to the baseline model. The results show that the coefficients of *did* in columns 1–2 are negative and statistically significant at the 1% level, suggesting that the ETS has significantly reduced the total carbon emissions. The policy effect is significant. Columns 3–4 show the results of the baseline regression of the ETS on carbon emissions from coal combustion. Column 4 adds control variables to Column 3. The results show that the coefficients of *did* in columns 3–4 are negative and statistically significant at the 5 and 1% levels, respectively. The absolute value of the regression coefficient of *did* in column 4) is larger than the absolute value of the regression coefficient of *did* in column (2). Results suggest that under the ETS, reducing carbon emissions from coal combustion has a larger effect than that of total carbon emissions. Possible explanations might be that most of the pilot firms of the ETS are located in high energy-consuming industries. Coal dominates their energy consumption structure, and these firms prioritize the reduction of carbon emissions by reducing coal consumption. To support this conclusion, we analyzes the effects of ETS on carbon emissions from petroleum and natural gas consumption separately, and the results are shown in **Supplementary Table S1**. The results show that the coefficients of *did* is not significant, indicating that the implementation of ETS does not affect the use of these two energy sources, but has a significant effect on reducing coal consumption; our results provide evidence for the beneficial side of the ETS in the process of coal removal in the pilot regions.

TABLE 2 | The impact of ETS on carbon emissions.

Variables	ln*CE*	ln*CE*	ln*CCE*	ln*CCE*
	(1)	(2)	(3)	(4)
did	−0.263***	−0.282***	−0.575**	−0.488***
	(0.0739)	(0.0772)	(0.263)	(0.152)
Control variables	No	Yes	No	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	493	493	493	493
R-squared	0.808	0.829	0.537	0.571

Robust SE in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

3.2 Parallel Trend Test

DID model is valid only if the parallel trend hypothesis is satisfied. The hypothesis, when satisfied, indicates that the carbon emission trends in the pilot and non-pilot regions are homogeneous. They do not differ significantly before the ETS is implemented, while the emission reduction impact of the ETS only occurs after the policy is implemented. Therefore, this paper establishes a regression model to test the parallel trend hypothesis, and the model structure is shown in :

$$Y_{it} = \beta_0 + \sum_{t=2007}^{2019} \beta_t did_{it} + \alpha_1 X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \quad (3)$$

We set 2013 as the base year. β_t denotes a series of estimates during three periods of time, including 6 years before the base year, the base year itself, and the 6 years after the base year. The regression results are shown in **Figure 1**, and the results of the two dependent variables are shown separately in **Figures 1A,B**. The regression coefficients of *did* before the base year are not significant, suggesting that before the ETS was implemented, no obvious difference in carbon emissions between the pilot and non-pilot regions was observed, satisfying the parallel trend hypothesis. The regression coefficient of *did* is significantly negative from the start of the ETS implementation in the base year, and the emission reduction effect of the ETS gradually increases along with the increases of the implementation year. At the same time, when the ETS was implemented in 2013, the effect of reducing total carbon emissions and carbon emissions from coal combustion was roughly the same. As the policies were implemented over the years, the effect of the ETS on reducing

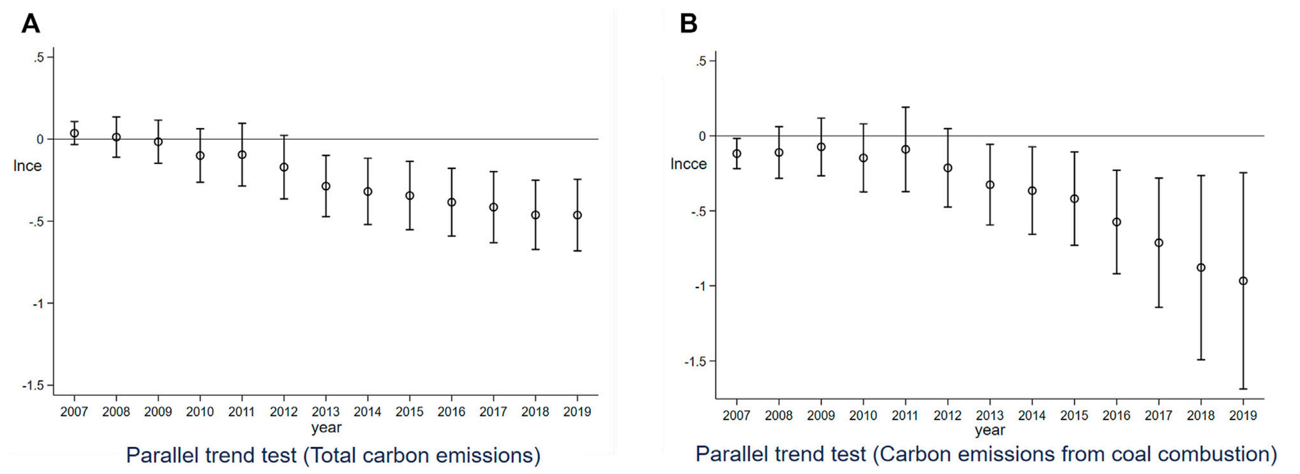

FIGURE 1 | Parallel trend test. **(A)** Parallel trend test (Total carbon emissions). **(B)** Parallel trend test (Carbon emissions from coal combustion).

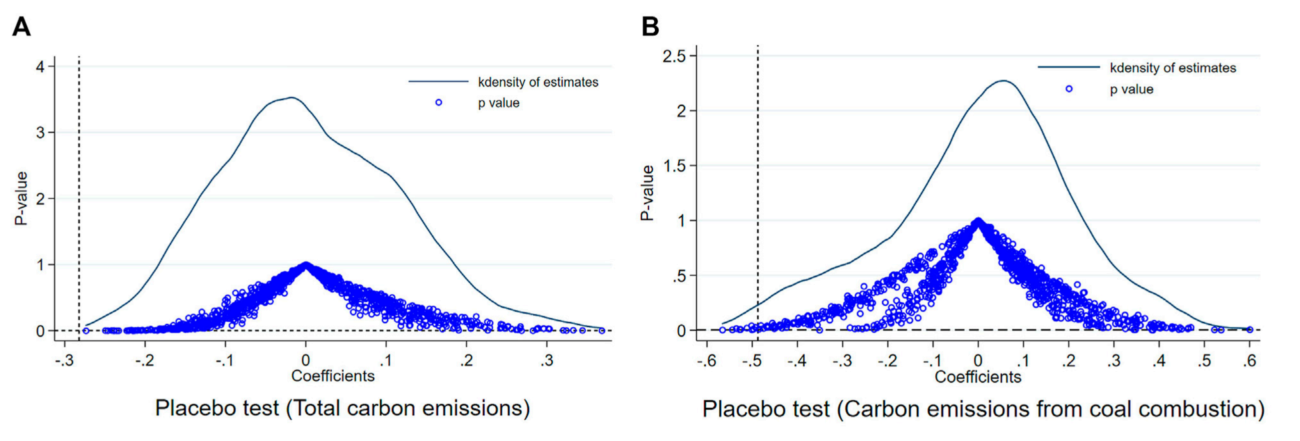

FIGURE 2 | Placebo test. **(A)** Placebo test (Total carbon emissions). **(B)** Placebo test (Carbon emissions from coal combustion).

carbon emissions from coal combustion becomes more obvious, indicating that the ETS has a positive and far-reaching effect on coal removal.

3.3 Placebo Test

Other unobserved regional variables affecting carbon emissions are possible in this study due to data availability issue, and this may result in estimation bias. Therefore, a placebo test needs to be applied to verify whether the omitted and unobserved variables affect the baseline results. The placebo test is adopted to test the robustness of the baseline regression through the random selection of several dummy experimental groups in full samples to perform a regression consistent with the baseline regression (Chetty et al., 2009). Specifically, all samples were sampled 1,000 times in our study. Six regions were randomly selected as the dummy experimental group for each sampling. The rest of the samples were regressed as the control group according to **Eq. 1** to obtain the regression coefficients and p-values.

Figure 2 reports the distribution of regression coefficients, where the *x*-axis represents the regression coefficients from the 1,000 randomly assigned experimental groups of *did*, and the curve is the kernel density distribution of the regression coefficients. The blue dots are the p-values corresponding to the regression coefficients. The red dashed lines present the true regression coefficients with p-values for columns (2) and (4) of **Table 2**, respectively. It is observed that the distribution of the coefficients, estimated based on the random sample, is around 0 with p-values greater than 0.1. The coefficients estimated from the baseline regression are almost independent according to the coefficient distribution. This is in line with Placebo Test's expectation. Thus, the significant abatement impact of the ETS is unlikely to be influenced by unobserved factors, and previous estimation analysis are robust.

3.4 Instrumental Variable Approach

When studying the effect of ETS on CO_2 emissions using DID analysis, the presumed assumption is that the selection process of

TABLE 3 | Regression results of instrumental variable approach.

Variables	IV first stage	IV second stage	
	did	ln*CE*	ln*CCE*
	(1)	(2)	(3)
iv*post	−0.266**		
	(0.111)		
did		−0.835**	−1.455**
		(0.405)	(0.720)
Control variables	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	493	493	493
R-squared	0.534	0.742	0.374
The first stage of F-test	91.99		

*Robust SE in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.*

the ETS pilot regions is random and maintains invariant when changes occur in other potential factors. However, pilot regions are not selected randomly but rather chosen by policy. To prevent the influence of other unobserved potential factors, this paper draws on Tsoutsoura (2011) approach in adopting the instrumental variable approach to address the endogeneity issue of experimental group selection.

Specifically, this paper follows Hering and Poncet (2014) in selecting the ventilation coefficient as an instrumental variable to explain whether a pilot regions has the policy treatment. First, for regions with smaller ventilation coefficients, larger pollutant concentrations are monitored and will incentivize local government to adopt more aggressive and effective environmental regulation policies. This region then gains a better chance to be selected as an ETS pilot. The regression results of the ventilation coefficient and the region selected as a ETS pilot are negatively correlated. Thus, the selection of ventilation coefficient as an instrumental variable satisfies the correlation hypothesis. In addition, because the ventilation coefficient is determined by the meteorological and geographical conditions of each region, it satisfies the exogeneity assumption. In this study, we match the boundary layer height and wind speed information at 10 m height from the ERA dataset of the European Centre for Medium-Range Weather Forecasts to the latitude and longitude of the 29 provinces and cities in the sample. The multiplication of wind speed and boundary layer height for each cell is the circulation coefficient. We then normalized through logarithm of circulation coefficients for 29 sample regions from 2003 to 2019 is selected.

The results of instrumental variable are shown in **Table 3**. Column (1) is listed as the regression results of the first stage: the regression coefficient of the interaction term iv*post is significantly negative at the 5% level, and the F-statistic is greater than the critical value of 10, indicating that the instrumental variable satisfies the correlation condition and there is no weak instrumental variable. In the second-stage regression, the regression coefficient of *did* is still significantly negative, which is consistent with the baseline regression, indicating that after eliminating the endogeneity problem in pilot selection, the ETS can still significantly reduce total carbon emissions and carbon emissions from coal combustion. The previous findings remain robust.

4 FURTHER ANALYSIS

4.1 Analysis of Impact Mechanism

Previous analysis in our study shows that the ETS has had a significant abatement effect on the local pilot. Next, this paper uses a two-stage mediating effect model for validation (Baron and Kenny, 1986) to initially analyze the mechanism of the abatement effect generated by the ETS. The mediating effect model is established as follows:

$$M_{it} = \beta_0 + \beta_1 did_{it} + \alpha_1 X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{4}$$

$$Y_{it} = \beta_0 + \beta_1 did_{it} + \beta_2 M_{it} + \alpha_1 X_{it} + \mu_i + \gamma_t + \varepsilon_{it}, \tag{5}$$

where M denotes the mediators including industrial structure (*IL*), technological innovation (*RD*), energy structure (*ES*), and coal consumption (ln*COAL*). Other model settings are consistent with **Eq. 1**, and the coefficients of the treatment variable *did* in **Eq. 4** and the coefficients of the mediators M in **Eq. 5** are tested. The results are shown in **Table 4**.

The regression coefficients of *did* in columns (1) and (2) in **Table 4** are not significant suggesting the industrial structure and technological innovation in the pilot regions are not affected by the ETS. The mediating effect is tiny. The regression coefficients of *did* in columns (3) and 5) are significantly negative, indicating that the energy structure and the absolute coal consumption in the pilot regions are reduced by the ETS. The second stage estimation of the mediating effect is conducted according to **Eq. 5**, columns (4) and (6) showing that the treatment variable *did* and the mediators *ES* and ln*COAL* are significant, implying that the mediating effect is significant. According to the conclusion, the ETS reduces carbon emissions mainly by reducing the absolute consumption to reach for an optimal energy structure. However, reading an optimal industrial structure is an incremental and lengthy process, and our study had a relatively short window for observation. Although the carbon trading mechanism will reduce the share of traditional industry, such an effect is not significant. Intuitively, the ETS also should boost R&D investment. Research findings also suggest that such an impact is not significant. Technological innovation usually takes more time, and large investments do not always result in the development of effective abatement technologies (Wicki and Hansen, 2019; Zhang Y. J. et al., 2020). At the same time, large investments may increase firms' costs level and reduce firms' market competitiveness.

In summary, the reduction effect of ETS comes mainly from the absolute emission reduction from coal combustion and its share in the energy structure, rather than from the technological innovation and optimization of the industrial structure in the pilot regions.

4.2 Analysis of Spatial Spillover Effect

Based on **Eq. 2**, the SDID model under the spatial distance weight matrix W_1 and economic distance weight matrix W_2. The spatial

TABLE 4 | Impact mechanism analysis.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	IL	*RD*	*ES*	ln*CE*	ln*COAL*	ln*CE*
did	−0.0463	0.00773	−0.0290*	−0.249***	−0.341***	−0.175***
	(0.479)	(0.00722)	(0.0166)	(0.0680)	(0.123)	(0.0504)
ES				1.130***		
				(0.240)		
ln*COAL*						0.315***
						(0.0732)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	493	493	493	493	493	493
R-squared	0.925	0.377	0.642	0.853	0.479	0.879

*Robust SE in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.*

TABLE 5 | The estimation results of the SDID model.

Variables	W_1		W_2	
	ln*CE*	ln*CCE*	ln*CE*	ln*CCE*
	(1)	(2)	(3)	(4)
did	−0.431***	−0.514***	−0.415***	−0.471***
	(0.106)	(0.145)	(0.111)	(0.167)
$W_{T.T}D$	0.187	−0.311	−0.137	−0.922*
	(0.174)	(0.413)	(0.167)	(0.458)
$W_{NT.T}D$	−0.561**	−0.609	−0.480**	−0.652**
	(0.247)	(0.437)	(0.185)	(0.260)
Control variables	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	493	493	493	493
R-squared	0.853	0.707	0.842	0.673

*Robust SE in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.*

influence of the ETS on total carbon emissions and carbon emissions from coal combustion is studied. Results are shown in **Table 5**.

The regression coefficients of *did* are still significantly negative upon consideration of the spatial effect. The absolute values of the regression coefficients of *did* increase with the introduction of spatial control, except for column (4). By comparing the results with those of baseline regression, we can conclude that the DID model has a more significant carbon reduction effect of ETS on local pilot regions after taking into account the spatial influence of policy, which is consistent with previous studies (Chagas et al., 2016; Yu and Zhang, 2021).

ETS has two possible pathways in affecting the non-pilot regions' reduction activities. On one hand, the establishment of the ETS pilot regions is a prelude of the national carbon market, and the non-pilot regions may have realized China's determination to reduce emissions through the implementation of the ETS; thus, the ETS pilot regions could act as role models to stimulate the non-pilot regions' reduction activities. On the other hand, pilot regions could crowd out high emission production activities to non-pilot regions, thus promoting the increase of carbon emissions in these regions. In **Table 5**, the regression coefficient of $W_{T.T}D$ is not significant, except for column (4). Possible explanations include that the ETS pilot regions are dispersed, resulting in less production and economic relations among pilot regions. Pilot regions alone are lack of spatial connectivity. The regression coefficients of $W_{NT.T}D$ are significantly negative except for column (2), suggesting that the ETS can play a role in promoting emission reduction in non-pilot regions. A positive spatial spillover effect is observed. For the non-pilot regions, the role-modeling effect of the ETS pilot regions is greater than that of carbon leakage effects resulting from the effect of crowding out high emission production activities.

To investigate the spatial spillover effect of the ETS on different range regions, the SDID model adopts the local spatial distance weight matrixes. The results are shown in **Table 6**.

The regression coefficients of *did* remain significantly negative. As shown in column (1), the regression coefficient of $W_{NT.T}D$ is positive but not significant within the 200 km range of the pilot regions, which supports that the ETS will increase carbon emissions in the proximity regions with a negative spatial spillover effect. For the neighboring non-carbon pilot regions, the role-modeling effect and economic relation of the ETS pilot have less emission reduction effect than that of carbon leakage effect resulting from the crowding out of production activities. As shown in column (2), the regression coefficient of $W_{NT.T}D$ becomes negative yet insignificant within 300 km of the pilot regions, and the regression coefficient of $W_{NT.T}D$ becomes significantly negative as the range around the pilot regions continues to expand. Evidence suggests that the positive spatial spillover effects become even greater as the geographical range around the pilot regions expands. One potential explanation could be that as physical distance increases, it becomes more difficult to transfer production activities to non-pilot regions, allowing the role-modeling effect of the ETS pilot to dominate non-pilot regions.

TABLE 6 | Estimation results of the SDID model for the pilot covering different ranges.

Variables	W_{200}		W_{300}		W_{400}		W_{600}	
	ln*CE*	ln*CCE*	ln*CE*	ln*CCE*	ln*CE*	ln*CCE*	ln*CE*	ln*CCE*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
did	−0.280***	−0.352***	−0.293***	−0.351***	−0.321***	−0.429***	−0.288***	−0.401***
	(0.0684)	(0.0949)	(0.0689)	(0.0926)	(0.0672)	(0.0906)	(0.0741)	(0.102)
$W_{T,T}D$	0.0958	−0.416	−0.00552	−0.790*	0.0232	−0.694	−0.0831	−0.938*
	(0.0948)	(0.334)	(0.100)	(0.423)	(0.116)	(0.489)	(0.136)	(0.531)
$W_{NT,T}D$	0.00886	0.191	−0.123	−0.166	−0.245***	−0.332***	−0.303**	−0.456***
	(0.118)	(0.286)	(0.0943)	(0.144)	(0.0781)	(0.100)	(0.148)	(0.157)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	493	493	493	493	493	493	493	493
R-squared	0.844	0.665	0.849	0.680	0.858	0.685	0.873	0.696

*Robust SE in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.*

5 DISCUSSION

Based on the panel data of Chinese ETS pilot regions and non-pilot regions from 2003 to 2019, this paper examines the emission reduction effect of the ETS using the DID model. Further analysis on the impact mechanism and spatial spillover effect of the policy is also conducted. The findings are as follows: 1) the ETS can effectively reduce the total carbon emissions and emissions from coal consumption. The relative effect of carbon emissions from coal consumption appears to be better, suggesting an acceleration effect of the ETS in coal removal. 2) China is at the initial stage of moving towards carbon neutrality, and the reduction effect of the ETS comes mainly from the absolute reduction of coal consumption and its share in the energy structure. 3) The ETS has a positive spatial spillover effect, which drives other non-pilot regions to commit to carbon reduction activities through role-modeling effect. The ETS may incentivize pilot regions to crowd out production activities to neighboring non-pilot regions, increased the carbon emissions and thus hindering the carbon reduction process in neighboring regions.

Based on these conclusions, the following recommendations are made. First, China's goal for 2060 carbon neutrality will require the full use of the ETS to reduce emissions and coal removal. With more stringent emission reduction targets, the carbon trading mechanism is to be designed for coverage of a wide range of sources, such as involving sectors and units with a high level of electricity, petroleum and gas consumption. Second, the government should continue to improve the design of the national carbon market. Promote the synergistic development of the local carbon market with the national carbon market to ensure that the ETS can effectively achieve emission reduction effect and positive spatial spillover effect. Then, regional governments should strengthen their interaction and the national carbon market should balance the intensity of the policies of each region to prevent the transfer of high-carbon emitting industries to neighboring regions and thus the occurrence of carbon leakage. Finally, to give the full play to the effect of the carbon market, governments should focus on a high-quality development model and reduce consumption of coal and other energy. Although the reduction emission effect of the ETS does not come from technological innovation and optimization of industrial structure, in order to achieve the long-term goal of carbon neutrality, the government still needs to stimulate the innovation drive of enterprises, encourage the development of low-carbon green technology, improve energy utilization efficiency, and promote industrial structure optimization. Through the above measures, with the support of carbon trading mechanism, the emission reduction effect will be significantly improved.

Restricted to the availability of the data and methods, there are three main limitations in this paper. 1) This paper focuses on the impact of the ETS on emissions from coal consumption, but due to the limitation of coal consumption data, it cannot be studied at the city level. 2) The ETS has synergy effects with various policies, such as the air control policy and the vigorous development of clean energy policy. It is also worthwhile to consider the clean effect of the carbon emission reduction policy upon the removal of the effects of these competing policies. 3) This paper focuses on the carbon emission reduction effect of the ETS and the impact factors but does not further measure the cost of emission reduction policies. Comparative analysis among emission reduction effects and the cost of different carbon markets and the cost of carbon emission reduction of different policies are important research directions for future carbon emission reduction policy analysis.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: www.stats.gov.cn/tjsj/.

AUTHOR CONTRIBUTIONS

ZY: conceptualized the study, analyzed the data and led drafting the manuscript. YY: contributed to the drafting of the manuscript, editing and Supervision QZ: contributed to the drafting of the manuscript and writing-reviewing.

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SUPPLEMENTARY MATERIAL

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Vulnerability Assessment of Climate Change in Vietnam: A Case Study of Binh Chanh District, Ho Chi Minh City

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Climate change poses additional obstacles to poverty eradication and social justice. Rising temperatures, abnormal rainfall increases, storms, floods, and droughts have become more frequent and severe phenomena in Vietnam. This causes serious consequences for the livelihood security of the poor. Binh Chanh district (Ho Chi Minh City) is an area subject to severe risks of climate change in the Mekong River Delta, Vietnam. Here, the low-income groups are the most vulnerable because their adaptive capacity is still limited and low. This study uses the livelihood vulnerability index (LVI) to assess the level of vulnerability to climate change in households and communes in the Binh Chanh district. LVI includes three components: exposure (E), sensitivity (S), and adaptive capacity (AC) based on 23 indicators selected by reviewing the literature and consulting with experts. The article also conducted surveys with 931 households in 16 administrative communes in Binh Chanh for primary data. The research results showed that Tan Kien and An Phu Tay communes have the highest level of vulnerability since they are areas with mainly low-lying terrain and contiguous location rivers; the people in these towns are also vulnerable groups because they do not have a stable source of income, skills, and have low education and experience in climate change adaptation. The study also proposes some solutions to improve the capacity to adapt to climate change of vulnerable communes specifically: 1) creating diversified livelihoods with stable incomes; 2) deploying community-based climate change adaptation models for communes adjacent to rivers; 3) implementing adaptive agriculture and improving social capital for vulnerable households; 4) building resettlement areas for households heavily affected by disasters; and 5) raising awareness among low-income households to respond to natural hazards in the context of climate change.

Keywords: climate change, vulnerability, exposure, sensitivity, LVI, Ho Chi Minh City

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INTRODUCTION

Climate change has impacted so many communities, making them exposed to increasing threats and becoming more vulnerable. In the years to come, climate change will become more apparent and will spell disaster for many communities (IPCC 2007; ADB 2015; UNDRR 2019; World Bank 2020). For effective adaptation planning, scientific analyses of climate change in a macro context are essential (Garschagen 2013; Moe and Pathranarakul 2016; Mojtahedi and Oo, 2017). However, at the local level, it is the analysis and conclusions of regional stakeholders that provide the most relevant information and knowledge (Eakin and Bojorquez, 2008; Adger et al., 2009; Below et al., 2012;

Kootval et al., 2015). Indigenous knowledge is also a reliable source of information, serving as a basis for policymaking and influencing policy. To ensure that development programs reduce people's vulnerability to the effects of climate change, it is imperative that we understand who is vulnerable and why. We must then apply this information to design, implement, monitor, and evaluate activities (Cutter et al., 2003; Ford and Smit 2004; Vincent 2007; Deressa 2010).

Vietnam is one of the five countries most heavily affected by climate change (ADB 2013; ADPC 2021). In Vietnam, Ho Chi Minh City (HCMC) in the Mekong Delta is the economic engine of the country. However, according to the World Bank (2020), this is also the most vulnerable area to climate change due to its natural, economic, and social characteristics (Bubeck et al., 2012; Chau et al., 2013; Hung et al., 2014; Zevenbergen et al., 2018).

Binh Chanh district is a suburban district of HCMC with a convenient river system for agricultural development and waterway traffic. However, due to low-lying terrain, adjacent to large rivers, Binh Chanh is one of the districts at the highest risk of vulnerability to climate change, in which low-income households (poor and near-poor families) are the most affected because they have few resources and conditions to maintain and adapt to climate change (UNDP 2015; World Bank & GFDRR 2018, HCMC People Committee 2020). In recent years, the Binh Chanh district has been heavily affected by natural disasters and sea-level rise. The frequency of heavy rain tends to increase and concentrate in the rainy season, causing flooding and narrowing the arable land; the infrastructure system (production equipment, factories, internal traffic, drainage system, etc.) of industrial zones was heavily flooded, affecting the production process of enterprises. The rising sea level causes salinity in rice-growing areas and aquaculture ponds, leading to large economic damage. In addition, the climate change increases tropical diseases that threaten the people's health (World Bank & GFDRR 2018, HCMC 2020).

To respond to climate change, the Binh Chanh district must conduct adaptation and mitigation actions simultaneously, in which the building capacity to adapt to climate change is the focus. However, the community's ability to adapt to climate change is still limited, in which the ability to adapt to climate change of low-income households is still low, so they are the most vulnerable. Therefore, in order to actively respond to the climate change for households in the Binh Chanh district, the capacity building to adapt to climate change needs to be improved to effectively and promptly respond to the unpredictable changes of climate change.

The objective of this study was to assess the climate change vulnerability of communes in the Binh Chanh district, HCMC, and to evaluate the perception of households on adaptation and response to impacts of climate change, thereby proposing some solutions to improve the awareness and enhance the adaptive capacity to climate change for the district and its communities.

STUDY AREA

Binh Chanh is a rural district located in the southwest of HCMC, Vietnam. It covers an area of 253 km^2. The Bình Chanh district borders the Bình Tân district, Hoc Môn district, and Nha Be district (**Figure 1**). The natural area of the Binh Chanh district is fairly wide and long, of which the agricultural land still occupies a large part. In recent years, many technical and social infrastructure projects have been invested, helping to expand the urban space in the Binh Chanh district, the rural face "changing flesh" day by day. A part of the Binh Chanh district has also become a new urban area in the South of HCMC. Infrastructure, transport network synchronously connected with the central districts of Saigon, and convenient travel and trade make Binh Chanh's population tend to increase rapidly (Binh Chanh District People Committee 2020; HCMC People Committee 2020,World Bank 2020).

Positioned as a gateway to trade with the Mekong Delta, a large economic region in the South, the Binh Chanh district has gradually become a bridge for economic exchange between the Mekong Delta and the southeast economic region key industrial zones. From a district with a large area of agricultural land, the agricultural production reached a significantly higher share in the economic structure than in the inner city districts; Binh Chanh's economic structure has quickly shifted to the industrial group—construction and trade services. With the advantage of a special location in regional linkages and convenient access to 13 provinces and cities of the Mekong Delta, Binh Chanh is a peril-urban district with potential for economic development and is now in the process of industrialization (Bubeck et at. 2012; Chau et al., 2014; Arouri et al., 2015).

The high urbanization rate has made Binh Chanh become one of the high population growth districts in the city. As of 2019, the district had a population of 680,000 with a population density of 2,793 people/km^2. The Binh Chanh district has 16 affiliated commune-level administrative units, including Tan Tuc town (district capital) and 15 communes: an Phu Tay, Binh Chanh, Binh Hung, Binh Loi, Da Phuoc, Hung Long, Le Minh Xuan, Pham Van Hai, Phong Phu, Quy Duc, Tan Kien, Tan Nhut, Tan Quy Tay, Vinh Loc A, and Vinh Loc B (Binh Chanh District People Committee 2020).

During the 2015–2020 period, the district's economy has developed stably, the proportion of industries and services has gradually increased, and the structure of the agricultural sector has shifted toward urban agriculture. In Binh Chanh, rice is the most important crop. It is grown in most of the communes. The other main food crops are maize, potatoes, and nuts. There are also plantations of banana and coconut, and most of them are found in Tan Qui Tay, Binh Loi, and Binh Hung communes. Agriculture is fairly labor-intensive in the district with farming activities being performed manually. During the tenure, the district has maintained an average annual growth rate of 20.5%/year, of which the industry—construction industry—has had a stable growth rate over the years, increasing by 20.9% on average; the trade, service industry has grown quite well, reaching an average of 20.6%/year; the average agricultural sector achieves 5.1%/year (Binh Chanh District People Committee 2020).

In terms of climate change impacts, due to its lowland natural features (nearly 60% of the total area is below the elevation of 1.5 m of sea level) and the terrain being divided by a system of rivers and canals, the Binh Chanh district is heavily affected by climate change. Currently, the district faces frequent flooding problems during the rainy season from June to November and the high tide cycle from September to December every year and the discharge from upstream of the Sai Gon–Dong Nai River. The atrophy of the tidal–rain—flood updated scenario (MONRE 2017) shows that the annual cropland area of the Binh Chanh district that is likely to be deeply flooded is 82.1% total annual acreage of the whole district (**Figure 2**). The flooded area of perennial crops in Binh Chanh is about 3,208 ha (77% total cultivation area). The majority of low-income households in Binh Chanh have their main livelihoods from farming, animal husbandry, and aquaculture and thus are highly vulnerable to bad weather and climate factors (Binh Chanh District People Committee 2020; HCMC People Committee 2020).

METHODOLOGY AND DATA

Approaches to Assess Climate Change Vulnerability

According to IPCC (2012), vulnerability to climate change is defined as "the degree to which a system is susceptible to or unable to cope with the effects of climate change, including climate change and extremes". McCarthy et al. (2001) also identified the three variables needed to assess vulnerability: exposure, sensitivity, and adaptive capacity. Exposure (E) is the nature and extent to which a system is exposed to significant changes in climate. Sensitivity (S) is the degree to which a system is affected either for good or bad by climate-related agents. The adaptive capacity (AC) reflects the ability of a system to adapt to climate change (including extreme events) or to mitigate its potential damage.

$$Vulnerability = f\left(exposure,\ sensitivity,\ adaptive\ capacity\right)$$

Although climate change is a global process, vulnerability is very site-specific (Hassan and Ringler 2009). Many scholars have, therefore, recommended the localized assessment of climate change vulnerability (Vincent 2007; Pandey and Jha, 2012a; Ahsan and Warner, 2014; Bosher et al., 2019). Hahn et al. (2009) and Urothody et al. (2010) recommended testing climate change vulnerability at the community level so that vulnerability of communities within a district or region can be compared. The indicator methods are widely used to assess climate change vulnerability. Because of the simplicity of aggregating indicators to form an index, different vulnerability indexes have been developed (Duriyapong and Nakhapakorn, 2011; Tessema et al., 2013; Wolf et al., 2013; Didar et al., 2015; Seinn et al., 2015).

This study uses the livelihood vulnerability index (LVI) developed by Hahn et al. (2009) for assessing the climate change vulnerability of the communes in Binh Chanh. This index can be estimated using primary data from households and commune levels.

LVI consists of seven main components including the socio-demographic profile (SDP), livelihood strategy (LS), natural hazards (NH), social network (SN), food (F), water (W), and health (H). Each component is composed of several indicators or sub-components. The indicators are standardized as follows:

$$\text{Index } X_{ij} = \left(X_{ij} - \text{Min } X_i\right) \Big/ \left(\text{Max } X_i - \text{Min } X_i\right)$$

Xij: normalized value of the indicator in commune j, Min Xij: minimum actual value of the indicator ij in all communes, and Max Xij: maximum actual value of the indicator ij in all communes.

The LVI uses a balanced weighted average approach where each sub-component contributes equally to the overall index. The LVI was calculated based on the sub-components of each of the major components. The average sub-component can be calculated after each index has been standardized by the following equation:

$$\boldsymbol{M_t} = \frac{\sum_{i=1}^{n} \boldsymbol{indexS_t i}}{\boldsymbol{n}}$$

where Mt represents one of seven main components of LVI for the commune t, index St denotes the subcomponent, index by i and n is the number of sub-components in each major component. After sub-components of the commune t for each of the main components have been deduced, the LVI can be calculated as follows:

$$\boldsymbol{LVI_t} = \frac{\sum_{i=1}^{7} - \boldsymbol{W_{it} M_{it}}}{\sum_{i=1}^{7} - \boldsymbol{W_{it}}}$$

where LVIt is the livelihood vulnerability index for commune t, and i is the index of different households in commune t.

In addition, in this study, we also used an alternative method by IPCC for calculating LVI by combining the components of exposure, sensitivity, and adaptive capacity with the following equation:

$$\mathbf{CF_j} = \frac{\sum_{i-1}^{n} \boldsymbol{W_{mi} M_{ij}}}{\sum_{i-1}^{n} \boldsymbol{W_{mi}}}$$

CF j is contributing the components (exposure, sensitivity, and adaptive capacity) for commune j, Wmi is determined by sub-components setting up the vulnerability component, and Mij is the major component for j commune indexed by i.

LVI-IPCC is calculated by the following formula:

$$LVI - IPCC = (E - AC) \times S$$

where E is the exposure index, AC is the adaptive capacity index, and S is the sensitivity index. LVI-IPCC ranges from −1 to +1, where −1 is the least vulnerable (adaptive capacity is more than exposure), 1 is extremely vulnerable (exposure is higher than the adaptive capacity), and 0 is moderately vulnerable (exposure and adaptive capacity are equal) (Khan 2012; Oo et al., 2018).

Selection of Indicators for Assessing LVI

The study selected a combination of vulnerability indicators that represent the seven components abovementioned from the studies of Hahn et al. (2009), Pandey and Jha (2012b), and Oo et al. (2018). The initial 37 indicators were taken out from these studies. Then, we interviewed experts on vulnerability, climate change, and livelihoods to filter out the most suitable indicators for LVI for the study. The authors consulted 10 experts including management agencies, local leaders, key farmers and NGO project leaders to assess the validity of indicators based on a 5-level Likert scale for each indicator (score 5 is very suitable, and score 1 is not very suitable). The final 23 indicators were chosen by all experts as suitable and very suitable, as follows: socio-demographic profile: household income per month (SDP1), the dependency ratio (SDP2), rate of poor households (SDP3), percentage of households with a head having no secondary school (SDP4), and percentage of households who have the burden of loan (SDP5).

Natural hazard: number of high tides causing flooding in the year (HZ1), percentage of flooded areas (HZ2), percentage of households with family members injured in recent disasters (HZ3), percentage of households reporting loss of livestock due to disaster (HZ4), percentage of households reporting a loss of assets due to disasters (HZ5), and percentage of households reporting not received early warning information (HZ6). Livelihood strategy: percentage of households using the natural resource for livelihood (LS1) and percentage of households dependent solely on agriculture as an income source (LS2).

Social network: number of local civic organizations attended by households (SN1), percentage of households not in receipt of government loans (SN2), and access to information (radio, television, and internet) (SN3).

Food: percentage of households lacking food in the last year (F1).

Water: percentage of households not using clean water (W1), percentage of households that utilize the natural water source (W2), and average for collecting water in a day by households (W3).

Health: percentage of households with a family member having health support from the local government (H1) and average time to the nearest health center (H2).

Data Collection

This study combines qualitative and quantitative data collection methods. From August to October 2021, the research team surveyed households in 16 communes of Binh Chanh to collect data.

The household sample was selected in two phases. First, we implemented a household spatial mapping in all communes. Then, we selected the households in each commune using random sampling based on a list of households provided by 16 communes' People Committee (local government). According to Ho Chi Minh City Statistical Office (2020), 119,298 households are living in 16 studied communes with about 680,000 people (on average, each household has 5.7 people). The study uses the following formula (Creswell 2014) to estimate the number of sampled households:

$$n = \frac{N}{1 + Ne^2}$$

TABLE 1 | Distribution of surveyed households by the communes in the Binh Chanh district.

	Commune	Number of households	Number of households surveyed
1	Tan Tuc	7,135	56
2	An Phu Tay	4,689	37
3	Binh Chanh	4,908	38
4	Binh Hung	6,120	48
5	Binh Loi	10,025	78
6	Da Phuoc	11,567	90
7	Hung Long	9,543	74
8	Le Minh Xuan	8,331	65
9	Pham Van Hai	9,043	71
10	Phong Phu	8,123	63
11	Quy Duc	7,589	59
12	Tan Kien	6,980	54
13	Tân Nhut	7,842	61
14	Tan Quy Tay	5,640	44
15	Vinh Loc A	4,890	38
16	Vinh Loc B	6,873	54
	Total	119,298	931

Source: Original data from the study.

where n is the sample size, N is the total number of households in the population, and e is the accepted errors. With e = 0.05 (the estimated error is 5%) and for a total population, the estimated number of households surveyed to ensure reliability was 931. Thus, 931 households were chosen (0.78% of total households). To ensure the representation, researchers selected 0.78% of households of each commune for the survey (**Table 1**).

In addition, data on flooded areas, inundation depth, and inundation time under exposure component are collected from data of the HCMC Flood Control Center; other data on the sensitivity and adaptive capacity indicator are collected from the data sources of the Statistical Yearbook of the Binh Chanh district in 2019 and 2020.

RESULTS AND DISCUSSION

Overall Results of the Vulnerability Assessment

The results of the vulnerability assessment to climate change for major components of 16 communes in Binh Chanh district and LVIs are presented in **Table 2**. As shown, the normalized value of vulnerability indicators ranges from 0.445 to 0.812. From the result, the studied communes are divided into three groups: the first group is those with high exposure and sensitivity and low adaptive capacity (Da Phuoc, Quy Duc, Hung Long, An Phu Tay, and Tan Kien); the second group is the communes with medium exposure, sensitivity, and adaptive capacity (Tan Qui Tay, Tan Nhat, Tan Tuc, Binh Hung, and Phong Phu); and the third group is the communes with high adaptive capacity and low exposure and sensitivity (Binh Loi, Binh Chanh, Pham Van Hai, Le Minh Xuan, Vinh Loc A, and Vinh Loc B).

The LVI index values are compared for 16 communes of Binh Chanh. Tan Kien is found to be the commune with the highest vulnerability to climate change (score: 0.812), followed by An Phu

TABLE 2 | Livelihood vulnerability index (LVI) of components for the communes of the Binh Chanh district.

Component of the LVI	Vulnerability indicator	*Da Phuoc*	*Pham Van Hai*	*Tan Qui Tay*	*Hung Long*	*Tan Tuc*	*Quy Duc*	*Le Minh Xuan*	*Binh Chanh*	*Tan Kien*	*Tan Nhat*	*Binh Loi*	*Phong Phu*	*An Phu Tay*	*Vinh Loc A*	*Bình Hung*	*Vinh Loc B*
SDC	Household income per month	0.45	0.76	0.45	0.52	0.62	0.37	0.81	0.81	0.69	0.49	0.67	0.75	0.64	0.85	0.67	0.92
	Dependency ratio	0.51	0.69	0.42	0.45	0.6	0.49	0.79	0.78	0.67	0.53	0.72	0.72	0.47	0.81	0.64	0.87
	Rate of poor households	0.37	0.73	0.53	0.39	0.45	0.52	0.78	0.56	0.68	0.59	0.67	0.69	0.61	0.79	0.64	0.85
	Percentage of households with head having no secondary school	0.33	0.81	0.49	0.45	0.47	0.58	0.76	0.68	0.71	0.41	0.78	0.68	0.55	0.86	0.73	0.78
	Percentage of households who have burden of loan	0.32	0.76	0.42	0.32	0.59	0.59	0.87	0.76	0.75	0.5	0.67	0.79	0.45	0.92	0.71	0.86
	AVERAGE	**0.40**	**0.75**	**0.46**	**0.43**	**0.55**	**0.51**	**0.80**	**0.72**	**0.70**	**0.50**	**0.70**	**0.73**	**0.54**	**0.85**	**0.68**	**0.86**
Natural hazards	Number of high tides causing flooding in year	0.62	0.51	0.32	0.61	0.71	0.59	0.45	0.52	0.94	0.45	0.32	0.81	0.79	0.64	0.65	0.72
	Percentage of the flooded area	0.61	0.44	0.44	0.83	0.54	0.79	0.64	0.41	0.85	0.67	0.45	0.67	0.69	0.57	0.77	0.65
	Percentage of households with family members injured in recent disaster	0.75	0.59	0.46	0.78	0.48	0.87	0.71	0.58	0.74	0.45	0.61	0.77	0.93	0.48	0.65	0.78
	Percentage of households reporting loss of livestock due to disaster	0.83	0.53	0.51	0.83	0.61	0.91	0.62	0.41	0.67	0.58	0.34	0.82	0.85	0.69	0.61	0.56
	Percentage of households reporting loss of assets due to disaster	0.72	0.41	0.56	0.67	0.54	0.62	0.42	0.26	0.96	0.32	0.23	0.64	0.77	0.61	0.67	0.67
	Percentage of households reporting not received early warning information	0.68	0.45	0.52	0.62	0.49	0.77	0.53	0.45	0.95	0.57	0.56	0.76	0.83	0.67	0.59	0.73
	AVERAGE	**0.70**	**0.49**	**0.47**	**0.72**	**0.56**	**0.76**	**0.56**	**0.44**	**0.85**	**0.51**	**0.42**	**0.75**	**0.81**	**0.61**	**0.66**	**0.69**
Livelihood strategy	Percentage of households using natural resources for livelihood	0.71	0.51	0.43	0.48	0.61	0.87	0.61	0.48	0.88	0.46	0.31	0.69	0.78	0.61	0.57	0.71
	Percentage of households dependent solely on family farm for food	0.87	0.48	0.57	0.67	0.43	0.71	0.66	0.41	0.76	0.57	0.48	0.78	0.87	0.68	0.73	0.78
	AVERAGE	**0.79**	**0.50**	**0.50**	**0.58**	**0.52**	**0.79**	**0.64**	**0.45**	**0.82**	**0.52**	**0.40**	**0.74**	**0.83**	**0.65**	**0.65**	**0.75**
Social networks	Number of local civic organizations attended by households	0.31	0.69	0.41	0.48	0.61	0.48	0.82	0.69	0.59	0.47	0.65	0.81	0.47	0.86	0.68	0.83
	Percentage of households not in receipt of government loan	0.38	0.78	0.39	0.39	0.62	0.36	0.86	0.74	0.69	0.43	0.81	0.78	0.68	0.87	0.72	0.88
	Percentage of households with no access to information (radio, television, and internet)	0.56	0.79	0.51	0.51	0.59	0.41	0.79	0.73	0.71	0.61	0.69	0.72	0.57	0.78	0.75	0.79
	AVERAGE	**0.42**	**0.75**	**0.44**	**0.46**	**0.61**	**0.42**	**0.82**	**0.72**	**0.66**	**0.50**	**0.72**	**0.77**	**0.57**	**0.84**	**0.72**	**0.83**
Water	Percentage of households not using clean water	0.61	0.44	0.44	0.76	0.54	0.79	0.64	0.47	0.85	0.67	0.45	0.67	0.73	0.57	0.77	0.65
	Percentage of households using natural water source	0.48	0.39	0.51	0.78	0.61	0.69	0.62	0.42	0.71	0.43	0.47	0.74	0.83	0.68	0.69	0.57
	Average time for collecting water in a day by households	0.76	0.48	0.37	0.81	0.55	0.81	0.51	0.33	0.85	0.52	0.41	0.72	0.85	0.52	0.66	0.65
	AVERAGE	**0.62**	**0.44**	**0.44**	**0.78**	**0.57**	**0.76**	**0.59**	**0.41**	**0.80**	**0.54**	**0.44**	**0.71**	**0.80**	**0.59**	**0.71**	**0.62**
Health	Average time to the nearest heath center	0.81	0.52	0.41	0.77	0.49	0.72	0.61	0.45	0.88	0.51	0.37	0.79	0.79	0.53	0.72	0.69
	Percentage of households with family member having health support from the local government	0.72	0.41	0.56	0.67	0.54	0.67	0.42	0.46	0.93	0.37	0.41	0.68	0.77	0.61	0.67	0.75
	AVERAGE	**0.77**	**0.47**	**0.49**	**0.72**	**0.52**	**0.70**	**0.52**	**0.46**	**0.91**	**0.44**	**0.39**	**0.74**	**0.78**	**0.57**	**0.70**	**0.72**

(Continued on following page)

TABLE 2 | (*Continued*) Livelihood vulnerability index (LVI) of components for the communes of the Binh Chanh district.

Component of the LVI	Vulnerability indicator	Da Phuoc	Pham Van Hai	Tan Qui Tay	Hung Long	Tan Tuc	Quy Duc	Le Minh Xuan	Binh Chanh	Tan Kien	Tan Nhat	Binh Loi	Phong Phu	An Phu Tay	Vinh Loc A	Binh Hung	Vinh Loc B
Food	Percentage of households lacking food in the last year	0.62	0.51	0.32	0.81	0.67	0.69	0.49	0.52	0.94	0.45	0.32	0.84	0.91	0.64	0.68	0.72
LVI		0.615	0.557	0.445	0.643	0.569	0.660	0.631	0.529	0.812	0.494	0.484	0.752	0.749	0.677	0.683	0.740
Rank		10	12	16	8	11	7	9	13	1	14	15	2	3	6	5	4

They are average values of the sub component indexes.

Tay (score: 0.752). In contrast, the least vulnerable commune is Tan Qui Tay (score: 0.445).

In terms of the exposure components, the score is highest in the Tan Kien commune (0.85) and the lowest in Binh Loi town (0.42). Tan Kien is also the commune with the highest sensitivity (0.86). This is a riverside commune, heavily affected by inundation and saltwater intrusion, and has many poor households and low socioeconomic conditions, leading to low adaptive capacity. In contrast, the Binh Loi commune is located deep in the mainland and has a fairly flat topography, not adjacent to rivers, so the impact of climate change/flood is not high compared to the communes adjacent to the rivers. In addition, because the income source of the people of Binh Loi commune is stable, their livelihood is less dependent on the climate, so they have the economic potential to purchase equipment and tools to cope with climate change. In terms of adaptive capacity, Da Phuoc commune has the lowest score (0.4), which is the best-adapting capacity town to climate change.

Socio-Demographic Profile

The first component of the LVI conceptual framework is SDP. As indicated in **Table 2**, Vinh Loc B is the most vulnerable town in terms of socioeconomic profile, with an average score of 0.86, followed by Vinh Loc A (0.85). Da Phuoc has the lowest vulnerability in this component (0.32). Zooming into this component, Vinh Loc A has the highest percentage (85%) of household heads with no secondary education, whereas in Tan Qui Tay, this number is only 33%. In fact, in the communes where the education level is low, then levels of formal and informal skills are also low and they affect the score of socio-demography in the studied communes. Also, Vinh Loc B has a higher dependency ratio than Vinh Loc A and Da Phuoc. The findings show that socioeconomic indicators and water and natural disaster indicators are most influential indicators of exposure and sensitivity in Vinh Loc B, Vinh Loc A, and Da Phuoc. This might lead to greater socioeconomic and climate change vulnerability in these communes than in the others. In this research, Hung Long has the lowest water, electricity, and health scores than other towns since this town is now fairly weak in providing clean water, sanitation equipment, health service, and basic infrastructure. In addition, An Phu Tay and Tan Kien have the highest exposure to the impact of natural disasters and climate change in terms of this vulnerability component index. In climatic events, such as the 2018–2019 floods, the agricultural lands in these towns were severely flooded and could not be used for cultivation. After floods, some areas of cultivable land would be lost, and some cannot be restored for planting. In addition, after disasters, households also lost cattle and household assets. Although the local government has worked hard for rehabilitation of the impacted areas, the situation has not fully recovered.

Natural Hazard

Tan Kien is shown as the highest vulnerability town (score: 0.85); the second most vulnerable commune is An Phu Tay, while Binh Loi is the least vulnerable (0.42). The farming households said that the loss of livestock impacted their livelihoods most, even more than assets or housing damages and losses. They also reported that the loss of human livestock is caused by the lack of climate change awareness by the local people and lack of disaster preparedness by the local government, as well as poor restoration and reconstruction processes after hazards. Thus, it is imperative to carry out climate change awareness-raising programs, preventive measures, and climate change adaptation solutions in the district.

Livelihood Strategies

The livelihood strategies of the households in the study area are diverse as the households' knowledge and experience of disaster adaptation are different. Among the study communes, the livelihood index is best at Tan Nhat (0.40) and Binh Chanh (0.45) compared to the other towns. Of all the respondents in An Phu Tay, 78% reported that agriculture is still their main livelihood activity. The farming households say that lack of alternative income chances, especially off-season, is a big constraint for their livelihoods. As a result, the household members have to migrate to cities for jobs; 46.9% of the respondents in An Phu Tay indicated insufficient loan provision by the government. In addition, the lack of infrastructure and accessible markets are also the main challenges for developing households' livelihoods in the study site.

Social Network

With the social network component, Vinh Loc A is the most vulnerable commune (0.84), while Vinh Loc B is the second most vulnerable town (0.83), and Da Phuoc is the least vulnerable commune (0.42). The households in Vinh Loc B town reported having an average of 3.3 local civic organizations to participate by their family, whereas this number for An Qui Tay and Quy Duc are only 2.7 and 2.4, respectively. The households indicated that participating in local organizations is good not only for livelihoods and networks but also for sharing hazard information among the community members and local agencies. A better access to credit and information can be ensured by improving the social capital. Thus, enhancing the social capital and social involvement is important to reduce the risks of disasters for poor households in light of a changing climate.

Water and Health

In terms of water indicators, Tan Kien and An Phu Tay are the most vulnerable towns with a score of 0.8, whereas Binh Chanh is found to be the least vulnerable commune with a score of 0.41. The majority of the households in Tan Kien and An Phu Tay limited access to clean piped water, rather they have to take water from ponds or rain. The average time spent collecting water is maximum at An Phu Tay and Tan Kien (nearly 3 h a day). Water is normally collected by women, and spending more time collecting water might affect the time for the household—caring with females. In addition, the lack of access to clean water would result in water-related illnesses and diseases. Therefore, the farmers reported that improving water management and provision is crucial in the Binh Chanh district.

Two indicators are used to make up the health component ("percentage of households with family members having health support from the local government" and "average time to the nearest health center"). When aggregated, Tan Kien again is found to be the most vulnerable health commune (0.91). The average time for reaching the nearest health center is the highest in this town due to poor infrastructure and communication systems. The poor access to health care services might result in a decrease in public health, hence increasing community vulnerability to natural hazards and climatic events.

Food

Foodstuff is another important item for adaptation to disasters and climatic impacts. These indicators are worse in Tan Kien and Vinh Loc B, whereas tan Qui Tay and Binh Lo have the lowest score (0.32). The survey indicates that farming is the primary profession for households in Binh Chanh. On average, 32.5% of the total households in Binh Chanh rely on non-cash food sources. The local people reported that on average, 2.9 months annually they have to struggle to provide sufficient food for families, especially during the off and inter-cultivation times.

Table 3 represents the vulnerability scores with a ranking according to LVI-IPCC for all communes of the study area. For LVI-IPCC index, the results are fairly consistent where households in Tan Kien and An Phu Tay towns are more vulnerable than those in other communes. This is because households in the three aforementioned communes are more exposed to disasters such as salt intrusion and flood while having low adaptive capacity. This LVI-IPCC index indicates that Vinh Loc A is the least vulnerable commune.

In both LVI assessment approaches, Binh Loi and Tay Qui Tay are the communes least affected by natural hazards and climate change in Binh Chanh. This is because these communes have medium exposure levels and better socioeconomic conditions and adaptive capacity. Among the 16 communes, Tan Kien is the most vulnerable commune with the highest level of exposure to natural disasters while having a low level of adaptive capacity, making this town more vulnerable than the others.

RECOMMENDATIONS TO IMPROVE CLIMATE CHANGE ADAPTATION CAPACITY OF HOUSEHOLDS IN THE BINH CHANH DISTRICT

Based on the abovementioned finding and combined with in-depth interviews relating livelihoods and climate change management stakeholders in Binh Chanh, some recommendations are raised as follows:

First, preparing disaster risk management strategies to reduce exposure, promoting climate change adaptation strategies, and strengthening the adaptive capacity of farm households should be the top priority. The study results show that the lack of households' access to fundamental infrastructure, opportunities for additional income, and sole dependence on agriculture make households more sensitive to

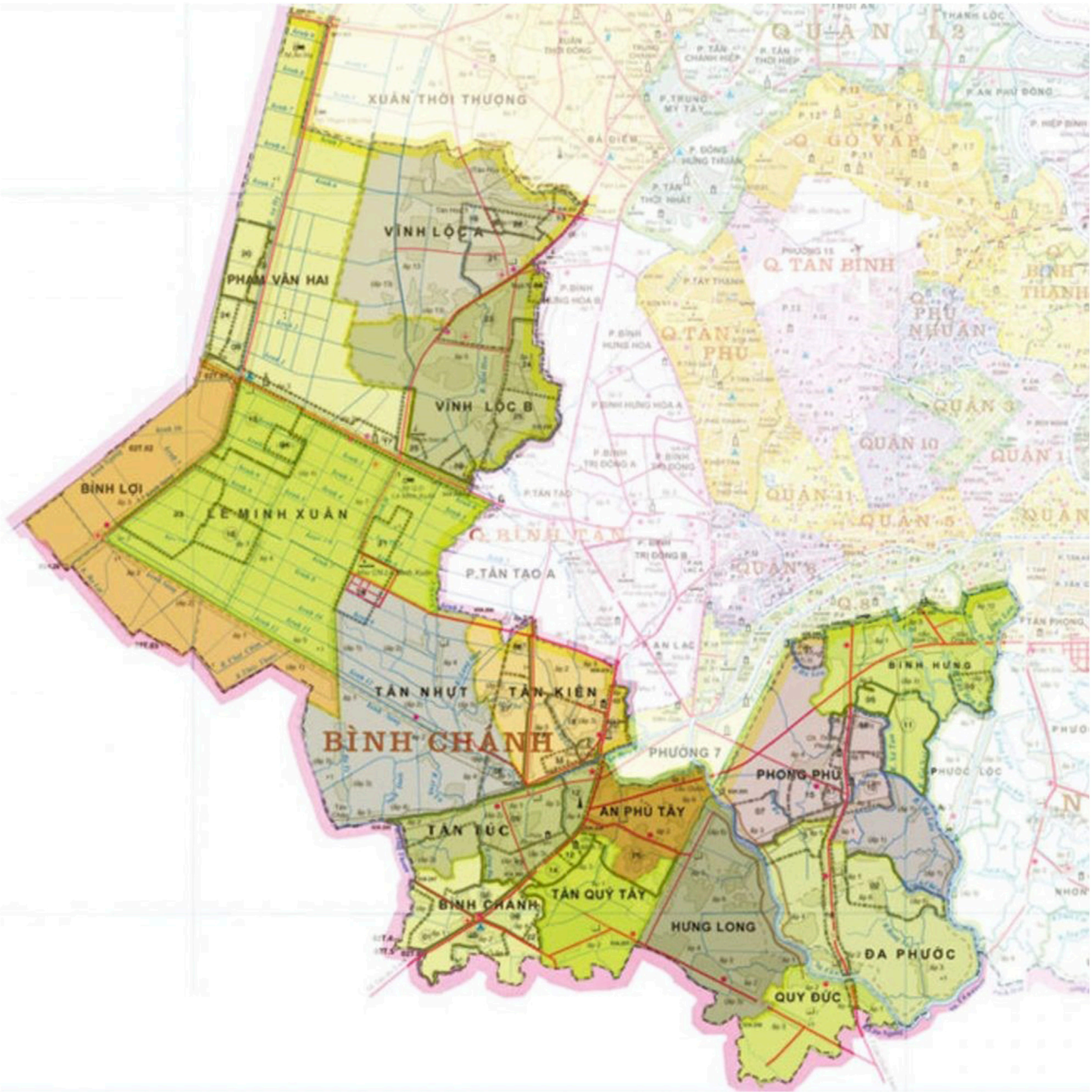

FIGURE 1 | Binh Chanh district location in Ho Chi Minh City.

the impacts of climate change. Thus, their capacity needs to be improved so that they can make choices and turn these choices into actions to respond to climate change/disaster to ensure more stable current and future livelihoods.

Community-based adaptation (CBA) can be a good strategy for climate change management at Binh Chanh. CBA is a critical component of avoidance and management of climate change impacts by local community. It provides information on the potential impacts of CC and mitigation measures with location-specific and community-managed characteristics. CBA also provides information needs that can be replicated in a suitable way acceptable by the local communities (UNDP 2015). For example, in Binh Chanh, converting rice farming to high-tech shrimp farming is a new direction (Le Minh Xuan is the leading commune to deploy an effective high-tech shrimp farming model, which is now being replicated in other communes for development). The shrimp farming model applying high technology in the Le Minh Xuan commune has effectively contributed to changing the community's awareness and income, which improves the capacity to adapt to climate change. In addition, strengthening the capacity and participation of the community, focusing on local response

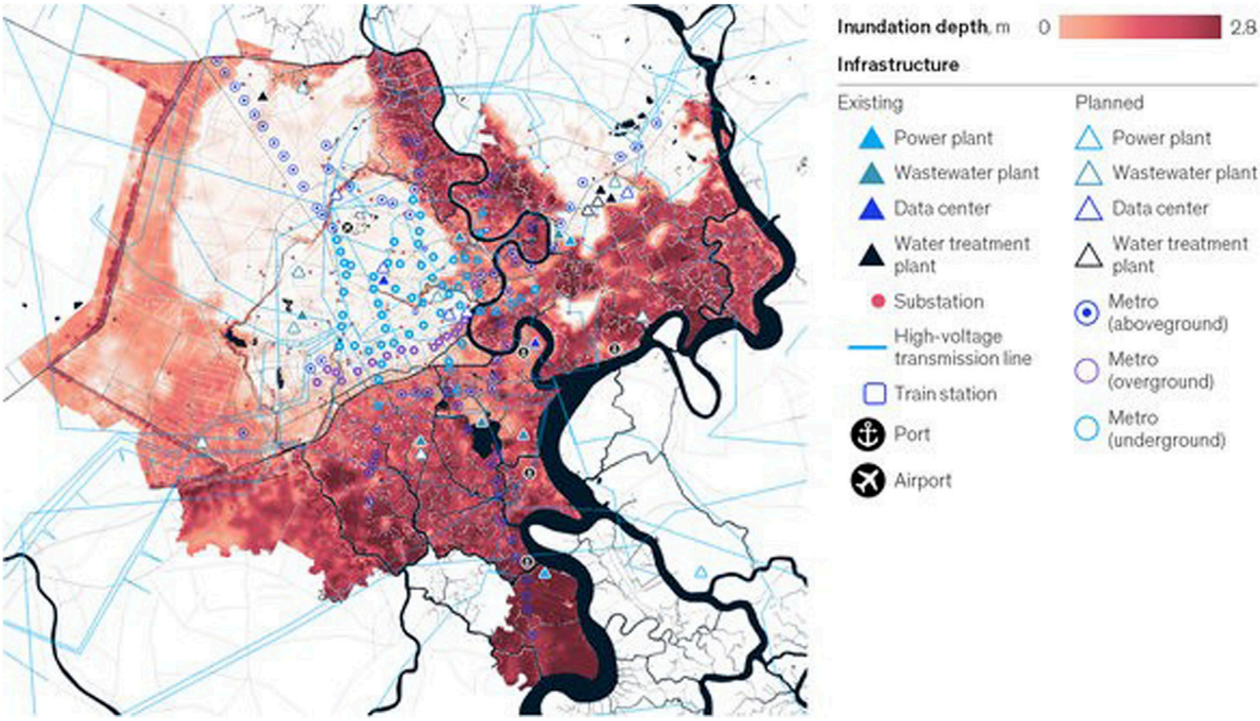

FIGURE 2 | Inundation map of the Binh Chanh district.

TABLE 3 | LVI-IPCC for communes in the Binh Chanh district.

	Commune	Exposure index (E)	Sensitivity index (S)	Capacity index (AC)	LVI- IPCC	Ranking
1	Da Phuoc	0.702	0.694	0.404	0.207	3
2	Pham Van Hai	0.488	0.484	0.751	−0.127	14
3	Tan Qui Tay	0.468	0.453	0.453	0.007	6
4	Hung Long	0.723	0.729	0.439	0.207	4
5	Tan Tuc	0.562	0.573	0.569	−0.004	9
6	Tan Kien	0.758	0.747	0.475	0.211	1
7	Le Minh Xuan	0.562	0.560	0.810	−0.139	15
8	Binh Chanh	0.438	0.441	0.719	−0.124	13
9	Quy Duc	0.852	0.859	0.686	0.143	5
10	Tan Nhat	0.507	0.499	0.504	0.001	7
11	Binh Loi	0.418	0.406	0.708	−0.118	12
12	Phong Phu	0.745	0.743	0.743	0.001	8
13	An Phu Tay	0.810	0.813	0.555	0.207	2
14	Vinh Loc A	0.601	0.612	0.843	−0.148	16
15	Binh Hung	0.657	0.691	0.693	−0.025	10
16	Vinh Loc B	0.685	0.688	0.848	−0.112	11

Source: Original data from the study.

experiences, the role of grassroots mass organizations develop, multiplying traditional models, and experiences in climate change adaptation should also be carried out since the more social capital a household has, the better they can access to a source of information and resource for enhancing the adaptive capacity.

Second, this study has shown that the lack of adaptive capacity of local people (socioeconomic, social networks, and livelihood strategies) is a main cause of climate change vulnerability. Therefore, it would be good if the local governments encourage increased investments in education and income diversification. Moreover, we should develop a micro-finance mechanism for local farmers, providing basic infrastructure, sanitation equipment, clean water, electricity, and setting up more health community centers. In addition, HCMC government managers need to implement a detailed assessment of the impacts of disasters on local livelihoods so that they can design suitable preventive measures aimed at promoting the adaptive capacity and reducing vulnerability to climate change.

Third, this study found that lack of early warning systems and climate information is also a major indicator of climate change vulnerability of households to saltwater intrusion and natural hazards. Therefore, an early warning climate information system should be established in the communes to reduce the potential for loss of property through natural disasters. The localities located adjacent to rivers need to build proper flood control facilities and tidal control infrastructure, including rigid flood control systems (e.g., tidal sluices and flood barriers). Building resettlement areas for households affected by climate change should also be performed. Da Phuoc, An Phu Tay, and Tan Kien communes need to plan resettlement areas for the low-income households living near the banks of rivers and canals that are at the risk of landslides and flooding. At the same time, the commune authorities need to support the jobs and sustainable livelihood transformation solutions (e.g. agricultural and fishery extension services).

Fourth, it is necessary to continue raising public awareness of disaster risk management, specifically the awareness of local authorities and people working in disaster prevention, businesses, and residents with the motto “prevention is key”. This is an important solution to limit risks from natural disasters. Also, it would be good to diversify the forms of training activities, training and drills on natural disaster prevention and control, information, propaganda, communication and knowledge dissemination activities, and organize seminars and conferences to share the lessons learned in disaster prevention. Along with that, HCMC authorities should deploy the acquisition, research, and transfer of information technology and support tools to the vulnerable people, at the same time carrying out natural disaster awareness raising activities in the school system in disaster vulnerable areas.

CONCLUSION

This study examines the vulnerability to climate change of households in the Binh Chanh district in the Mekong River Delta in Vietnam. It estimates the LVI assessment method and compares the vulnerability indexes for 16 communes in the studied district. The indicators of different components show different vulnerability levels for different communes. The LVI and LVI-IPCC indexes indicate that residents in Tan Kien town are the most vulnerable people. This study confirms that farm households that fail to adopt any strategies for adaptation to the impacts of climate change are more vulnerable than adapted households.

The results also indicated that majority of the communes are highly vulnerable with high exposure and sensitivity levels compared to adaptive capacity. The local people still depend much on natural resources for maintaining livelihoods which means that the livelihoods of poor and nearly poor households are regulated by nature. The dependency on primary occupation makes the situation worse. Unskilled citizens have fewer employment opportunities and hence move to other areas for survival. The social ties facilitate local networks and improve support from local associations and government. The impacted people have to live to survive in poor situations by struggling with various natural hazards and lacking the capacity for changing their situation.

If the vulnerable areas get special supports and priorities by enhancing the perception of local households about climate change vulnerability (social, economic, and environmental factors), they can improve their resilience to face the challenges of climate change. This study has proposed some solutions to improve the awareness, adaptive capacity, and response to climate change for impacted households. In addition, this study consults managers and scientists to have a multidimensional view of the capacity to adapt to climate change for local households. The results are intended to provide a database to serve the overall socioeconomic planning and development of the locality toward climate change adaptation. However, this study is limited in terms of spatial investigation, so it is necessary to expand the research area in the future.

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

DT and TD conceived of the presented idea. NH and LH developed the theory and performed the computations. NH verified the analytical methods. DT and TD supervised the findings of this work. All authors discussed the results and contributed to the final manuscript.

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Analysis of Industrial Carbon Transfer in Beijing-Tianjin-Hebei City Cluster and Surrounding Areas

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To achieve the goal of carbon neutrality and win the blue-sky defense battle, the environmental situation in Beijing-Tianjin-Hebei and surrounding areas is still grim, and the optimization of its industrial structure and energy structure is imminent. With the rapid development of interregional trade in intermediate products, carbon emissions are transferred across regions with the trade. Due to the large differences in the technology, industrial structure, and economic development of cities, extending the environmental governance chain of Beijing-Tianjin-Hebei and surrounding areas is indispensable. In this article, based on the interregional input-output tables in 2002, 2007, and 2012, we establish the average propagation length (APL) model and the structural path analysis model Structural Path Analysis model for analyzing the carbon conduction relationship in Beijing-Tianjin-Hebei. And we also compare the situation of the Yangtze River Delta and the Pearl River Delta. The results show that: i) From perspective of the whole urban clusters, Beijing-Tianjin-Hebei has obvious characteristics of coal-fired urban clusters. More than 65% of the carbon-containing resources in Hebei's coal industry are transferred to the electricity and heat industry. In the carbon conduction chain, the carbon emissions caused by electricity and heat industry, which acts as an intermediary, account for more than 85% of the total emissions. ii) From the perspective of industrial structure transfer within the urban clusters, Hebei Province has an important resource support position. Its secondary industry can not only effectively alleviate the shortage of energy supply in other resource provinces, but also has great development potential in the improvement of economic benefits. iii) From the perspective of specific industry sectors, resource provinces such as Shanxi and Inner Mongolia have high carbon emission coefficients in the electricity and heat industry, which is the main reason for the high carbon emissions in the transfer chain.

Keywords: beijing-tianjin-hebei, carbon transfer, coordinated emission reduction, inputoutput, average propagation length model, structural path analysis model

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INTRODUCTION

The Beijing-Tianjin-Hebei regional plan was first proposed by the National Development and Reform Commission in 2004, and the plan involves 11 cities including Beijing, Tianjin and Hebei. It was not until 2011 that the Beijing-Tianjin-Hebei urban clusters included all cities in Hebei Province to achieve integrated and coordinated development. However, since the Beijing-Tianjin-Hebei urban clusters was proposed, its economic contribution has not been outstanding. From 2011 to 2019, the average contribution rate of Beijing-Tianjin-Hebei to economic growth was 7.52%, while the average contribution rates of the Yangtze River Delta and Pearl River Delta were 19.67 and 10.61%, respectively. The insufficiency of Beijing-Tianjin-Hebei economic drive is closely related to the positioning of its urban cluster. Compared with the maintaining growth in the central and eastern regions, Beijing-Tianjin-Hebei, as a new growth pole of the Chinese economy, is more rational in terms of economic growth. In terms of the general development strategy, government emphasizes the transformation of economic mode, improvement of economic quality, and emphasis on energy conservation and emission reduction while maintaining stable growth.

In order to achieve the goal of "stabilizing growth and adjusting structure", energy conservation and emission reduction must be the focus of improving the quality of regional economic growth. The current international situation is becoming more and more complex, China's export-oriented economy has been seriously affected, and the role of the core engine of the regional economy has become increasingly prominent. How to play the role of regional clusters and take into account of their ecological benefits is also the focus and difficulty of future development. In recent years, despite of the positive changes in the coordinated development of Beijing-Tianjin-Hebei, environmental issues have always been a major pain point. Due to the unbalanced regional development, the Beijing-Tianjin-Hebei has obvious urbanization gap. And the influx of population into the economically developed cities, namely Beijing and Tianjin, has caused huge pressure on the two cities' resources, environment, electric power transportation, etc. The positioning and development of Beijing's "Four Centers" faces greater challenges. As the hinterland of Beijing and Tianjin, Hebei's functional status has always been relatively clear, that is, as a resource support area for Beijing-Tianjin-Hebei economic development and an experimental area for industrial transformation and upgrading. However, at present, Hebei Province still has problems such as the insufficient supply of its own energy, unreasonable energy consumption structure, and low energy efficiency. With the proposal of the Beijing-Tianjin-Hebei coordination strategy and the establishment of the Xiongan New Area, higher requirements have been placed on the environmental conditions and pollution emissions of Hebei. Hebei is also facing the dual dilemma of energy conservation, emission reduction, and increased resource use.

How to meet the higher requirements of the national strategy on regional environmental conditions and energy conditions while ensuring the resource needs of economic development in the Beijing-Tianjin-Hebei is the focus of this study. Based on this, we first analyze the Beijing-Tianjin-Hebei urban cluster as a whole, compare the carbon transmission chain and industry linkages in the Yangtze River Delta and the Pearl River Delta, and study the focus of the overall emission reduction of the urban cluster. Secondly, based on the main resource provinces identified by the overall carbon transmission chain of the urban cluster, we further study the carbon transfer of industries in the Beijing-Tianjin-Hebei and other resource provinces. Finally, considering the current situation of insufficient self-sufficiency of some resources and the increasing proportion of external energy in Hebei, we focus on the key industries in Hebei and explore the characteristics of carbon transfer docking with industries in other provinces.

LITERATURE REVIEW

At the end of the 20th century, many scholars studied energy consumption and carbon emissions, and they found that with the increasing frequency of international trade and inter-regional trade, changes in the demand for products or resources often resulted in energy consumption and total carbon emissions in the areas where the resources were provided. Usually, the carbon emission in the consumption area is very small, but the resource supply area is limited by the production technology and cost, and the total carbon emission may be very large (Williams et al., 1987; Xie and Chen, 2007; Zhu et al., 2018). Since then, more and more scholars have carried out a lot of research on the transfer of carbon emissions from domestic and foreign trade.

From the perspective of foreign trade, most scholars mainly focus on global and national alliances to study the impact of carbon transfer. As early as the end of the 20th century, Burniaux and Oliveira Martins (2012) discussed the key mechanisms behind the scale of carbon leakage based on three types of fossil fuels (coal, oil, and low-carbon energy), international trade and capital flows. Subsequently, Baker et al. (2007) used a static equilibrium model to estimate that the carbon leakage in the EU from 1995 to 2005 was generally within 5–20%, but the technology spillover effect in some regions alleviated the "carbon leakage" to a certain extent. Essandoh et al. (2020) studied the relationship between CO_2 and trade in developed and developing countries. The study found that with the increase in trade and foreign direct investment, the emissions were transferred from developed to developing countries. Barker et al. (2007) and Muhammad et al. (2020) verified the conclusion from the perspectives of trade and embodied carbon emissions in the Belt and Road countries and ASEAN five countries, respectively. These findings confirm the long-term and widespread impact of international trade-induced carbon emissions shifts on global carbon emissions totals and patterns.

From a domestic point of view, there are also many scholars taking Chinese provinces and cities as examples to measure the scale of carbon emissions across regions. Feng et al. (2020) studied the implied carbon emissions in China in 2010, and the results showed that the inter-provincial trade increased the national carbon emissions by 247t, and the four trillion stimulus plan promoted a large amount of carbon growth in energy-related trade. Wang and Chen (2016) calculated the amount of pollutant transfer in eight regions in China and pointed out that the phenomenon of implied pollution transfer was detrimental to the interests of late-developing regions. Once the threshold of the ecological environment was exceeded, it would damage the achievement of coordinated regional development. Liao and Xiao (2017) found that there was a phenomenon of carbon emission reduction in the northern and southern coastal areas, while the "carbon leakage" effect was more serious in the southwestern region. Mi et al. (2019) analyzed the carbon emissions of 11 cities in Hebei from the perspective of consumer responsibility, and found that 50% of the carbon emissions in these cities were imported from external regions, and believed that policy cooperation between carbon-consuming and carbon-producing regions should be strengthened to effectively mitigate climate change. Based on the pollutant discharge and development levels of Hebei and Beijing, Zhao and Wu (2020) also found that there was serious transfer pollution in Hebei. Shen and Huang (2015) pointed out that Guangdong was still a "pollution refuge" for international pollution-intensive industries, but with the strengthening of environmental control, pollution-intensive industries have gradually shifted from the Pearl River Delta to non-Pearl River Delta regions. Shao et al. (2020) analyzed the changes and driving forces of carbon emissions on the urban consumption side by taking Shanghai as an example and found that the consumption-based carbon emissions in Shanghai increased by 32.82% since 2007, which was much higher than the production-based carbon emissions, and technological changes had greatly reduced carbon leakage.

The transfer of carbon pollution usually did not only depend on area transfer, but the industrial transfer was the main body of carbon transfer (Liao and Xiao, 2017). Most studies were also based on this, focusing on the carbon ripple effect inside and outside the region, and studying the characteristics of carbon transfer in industries. Wei et al. (2020) quantified the environmental inequality behind regional trade and believed that electricity-related carbon emissions are closely related to more than 40% of China's carbon emissions, and 20–80% of electricity-related carbon emissions in developed provinces and 15–70% of the added value were outsourced to other provinces. Sun et al. (2010) used the IPCC inventory method to explore the carbon footprint characteristics of Chinese foreign trade and domestic industrial sectors, and found that the electricity and heat industry was highly dependent on carbon emissions. The total emissions from the electricity and heat industry, agriculture and manufacturing industry account for more than 80% of the total emissions. Yang (2015) focused on the carbon emissions of 23 industrial sectors in China and found that the carbon transfer between sectors constituted the main part of the complete carbon emissions of the industrial sector. Li J. et al. (2019), Zhang Y. et al. (2016) focused on Beijing-Tianjin-Hebei and pointed out that among the three regions, Hebei was the main energy producer, Beijing and Tianjin were the consumers, and electricity and heat, coal, and aquatic products were the most important high-carbon industries (Shen and Huang, 2015).

To sum up, the articles about carbon pollution transfer and carbon leakage mostly explores international trade, China's inter-provincial and eight major regional levels. There are few research on typical urban clusters (such as Beijing-Tianjin-Hebei and the Yangtze River Delta). Most of the research focused on the direction and total amount of carbon transfer unilaterally in regions and industries, but there were few studies about the dual effects of regions and industries on carbon emissions. Among the research methods, the input-output method could more comprehensively reflect the regional and industrial linkages. However, limited by the data, few studies started from the inter-regional input-output table with multiple industries to screen the key paths of carbon transfer. Thus, we would use the inter-regional input-output table in 2002, 2007, and 2012, focus on the research inside and outside the Beijing-Tianjin-Hebei region, compare the two major urban clusters in the Pearl River Delta and the Yangtze River Delta, study their carbon transfer characteristics and try to give policy recommendations for reducing total regional carbon emissions.

METHODOLOGY

Interregional Input-Output Model

The inter-regional input-output model connects every region's input-output models and systematically reflects the connection of goods and services. Compared with the traditional tabular representation of the input-output relationship between sectors, it divides the input-output table according to the region and industry, and more fully reflects the economic relationship between regions and industries. In the study of the relationship between trade and environmental pollution, through combining the interregional input-output model with relevant data, the interregional input-output model clearly clarifies the resource consumption and pollution transfer problem (Zhang B. et al., 2016).

The basic structure of the input-output table between regions is roughly the same as the general input-output table, but it further divides products and services between regions in the final use and final demand parts. The specific structure is shown in **Supplementary Table S1**:

Average Propagation Lengths

The Average Propagation Lengths (APL) model was proposed by Dietzenbacher and Romero (2007). This model explores the interrelationship between regional sectors from the perspective of the production chain and reveals their inputs sequence of output impacts. We introduce the carbon coefficient into the APL model.

$$L^c = CL = C(I - A)^{-1} = C(I + A + A^2 + \dots) \quad (1)$$

$$G^c = CG = C(I - R)^{-1} = C(I + R + R^2 + \dots) \quad (2)$$

Where C is a diagonal matrix formed by the carbon emission intensity of each industrial sector in each region, and the diagonal element is c_i. A is the direct consumption coefficient matrix, $a_{ij} = \frac{x_{ij}}{x_j}$. R is the direct distribution coefficient matrix, $r_{ij} = \frac{x_{ij}}{x_i}$, and $R = X^{-1}AX$. L^c and G^c are complete carbon consumption coefficient matrix and complete carbon distribution coefficient matrix respectively. L^c reflects the impact of the final demand of an industry in a certain area on the direct or indirect carbon emissions of each unit. **Eq. 1** can also be understood as the emissions caused by an increase in the final demand of the industrial sector by one unit. It means that L^c includes the direct impact on its own department C, the direct impact on all departments CA^2, the indirect impact of the second step CA^3.

Simarly, G^c reflects the impact of the initial investment on the carbon emissions of other industrial sectors by one unit, which can also be decomposed into the initial impact C, which directly affects CR of other sectors. In order to obtain the impact and spread of carbon emissions, we take the impact of each round as a weight, and get the average round, that is, APL. Based on the influencing factors, APL can be divided into backward and forward APL, and the calculation formulas are **3–6**.

$$U_{ij} = \frac{\left(1 \times c_i \times a_{ij} + 2\Sigma c_i a_{ik} a_{kj} + \ldots\right)}{\mathrm{l}^{\mathrm{c}}_{\mathrm{ij}}}, \; i \neq j \tag{3}$$

$$U_{ij} = \frac{\left(1 \times c_i \times a_{ij} + 2\Sigma c_i a_{ik} a_{kj} + \ldots\right)}{\mathrm{l}^{\mathrm{c}}_{\mathrm{ij}} - c_i}, \; i = j \tag{4}$$

$$V_{ij} = \frac{\left(1 \times c_i \times r_{ij} + 2\Sigma c_i r_{ik} r_{kj} + \ldots\right)}{\mathrm{g}^{\mathrm{c}}_{\mathrm{ij}}}, \; i \neq j \tag{5}$$

$$V_{ij} = \frac{\left(1 \times c_i \times r_{ij} + 2\Sigma c_i r_{ik} r_{kj} + \ldots\right)}{\mathrm{g}^{\mathrm{c}}_{\mathrm{ij}} - c_i}, \; i = j \tag{6}$$

c_i is the intensity of carbon emissions. U_{ij} is the backward APL value, which represents the average backward distance of the impact of a change in the final demand of sector j on the carbon emissions of sector i. V_{ij} is the forward APL value, which represents the forward carbon distance of sector j's initial investment to change the impact of one unit on the carbon emissions of industry sector i. The smaller the carbon APL, the stronger the carbon ripple effect between the two sectors. May wish $H = A + 2A^2 + 3A^3 + \ldots = \sum_{n=1}^{\infty} nA^n$, $\bar{H} = R + 2R^2 + 3R^3 + \ldots = \sum_{n=1}^{\infty} nR^n$. Knowing that $R = X^{-1}AX$, $\bar{H} = R(R - I) = X^{-1}L(L - 1)X = X^{-1}HX$, we can get $\overline{h_{ij}} = h_{ij}/x_i$ and $R = X^{-1}AX$, that is $U_{ij} = V_{ij}$. Then the forward APL is equal to the backward APL, collectively called APL (Li Y. et al., 2019).

Before calculating the APL value, in order to screen industries and regions with a greater degree of correlation, it is necessary to calculate the degree of correlation between industries (Ma et al., 2018) as the threshold for carbon chain identification, namely:

$$F = \frac{1}{2}\left(L^c + G^c\right) \tag{7}$$

Structural Path Analysis

Structural Path Analysis (SPA) was proposed by Defourny and Thorbecke (2014). It is mainly based on input-output technology to identify the main production chain and is mostly used for energy, water resources, and other physical quantities in the economy (Lenzen, 2003; Wood and Lenzen, 2003; Peters and Hertwich, 2006).

In the calculation process, the SPA model expands the Leontief inverse matrix by Taylor and multiplies the corresponding carbon intensity coefficient to quantify the direct or indirect carbon conduction effects of other sectors caused by the final demand of the sector and the initial investment. In this way, it clearly reveals the carbon conduction relationship. It is calculated as formula **8**:

$$\hat{S} = C(I - A)^{-1}\hat{F} \tag{8}$$

In **Eq. 8**, S represents the total carbon emissions caused by the path, C represents the diagonal matrix composed of carbon emission intensity vectors and $\hat{F}$ represents the final demand vector. Decomposing **Eq. 8** into conduction paths at all levels can be written as **Eq. 9**:

$$\hat{S} = C\left(I + A + A^2 + A^3 + \ldots\right)\hat{F} \tag{9}$$

In **Eq. 9**, the first $C\hat{F}$ represents the total direct carbon emissions of each sector brought by the final demand, which is called the zero-order effect and $CA\hat{F}$ represents the total indirect carbon emissions brought by the final demand shift, which is called the first-order influence, and so on.

The APL model can effectively identify the main carbon conduction chain, and the SPA model can calculate the carbon emissions in the carbon conduction chain. Therefore, we combine the two models. We use the APL model to identify the carbon conduction chain of high-dimensional data, and obtain the main carbon-sweeping provinces and cities in a certain area and their sequential positions, and then combine formula **9** in the SPA model to obtain the total amount of carbon transfer in each step. The formula for calculating the total amount of carbon transfer in each step is **Eq. 10**.

$$S_{i_n j_n} = C_{i_0} a_{i_0 j_0} \ldots a_{i_n j_n} \widehat{F_{j_n}} \tag{10}$$

In **Eq. 10**, i_n and j_n represent the transfer-in and transfer-out parties in the carbon conduction chain, and i_0 and j_0 represent the initial transfer-in and transfer-out parties in the conduction chain. The absolute amount of specific carbon transfer in the carbon chain can be calculated by **Eq. 10**.

EMPIRICAL ANALYSIS

This paper mainly uses the multi-regional input-output (MIRO) model proposed by Xia and Tang (2017) and Wu et al. (2017), and the regional social accounting matrices (SAMs) of China in 2002, 2007 and 2012. The carbon emission factor is calculated according to the IPCC method based on the energy balance sheet. Subsequently, based on the Average Propagation Length Model (APL) and the Structural Path Analysis Model (SPA), using the IRIO table and the calculated carbon emission coefficients, we first study the overall carbon emissions of the Beijing-Tianjin-Hebei urban clusters and compare it with the Yangtze River Delta and Pearl River Delta. Further, we explore the carbon transfer relationship of the industrial structure in the Beijing-Tianjin-Hebei urban clusters and its surrounding areas. Finally, we study the carbon correlation of major resource transfer industries in the cluster.

Beijing-Tianjin-Hebei Total Carbon Emission and Carbon Emission Coefficient

The proportions of total emissions of the Beijing-Tianjin-Hebei region are shown in **Supplementary Figure S1**. From 2002 to 2012, the total carbon emissions in the Beijing-Tianjin-Hebei region accounts for about 11.03% of the total carbon emissions in 30 provinces and cities across the country. Among the urban clusters, Hebei has the highest total carbon emissions, accounting for 72.15% of the total carbon emissions, while Tianjin and Beijing account for 16.12 and 11.74% respectively. Affected by resource endowment and economic development levels, Hebei undertakes many high-carbon emission industries in Beijing and Tianjin and bears most of the carbon emission pressure. This is the main reason why Hebei's carbon emissions are much higher than the other two places.

To achieve the coordinated development of the Beijing-Tianjin-Hebei, Hebei's resource support is indispensable, but how to reduce the pressure of regional emissions while ensuring the complementarity of its industries is the focus of this study. In this regard, we first compare the industries and carbon emissions of the other two major urban clusters to explore their reference points. Then, we calculate the direct carbon emission coefficients (unit: tCO2/10,000 yuan) of the three industrial sectors in the Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta regions from 2002 to 2012, as shown in **Supplementary Table S2**:

It can be seen from **Supplementary Table S2** that from 2002 to 2012, the carbon emission coefficient of the three major industries in the three major urban clusters in China shows an overall downward trend. Among the three major urban clusters, the secondary industry has the highest carbon emission intensity, followed by the tertiary industry and primary industry. Comparing the three major urban clusters, it can be seen that the three major industries in the Pearl River Delta have relatively low carbon emission coefficient and high efficiency, followed by the Yangtze River Delta and Beijing-Tianjin-Hebei.

In terms of the primary industry, from 2002 to 2012, the proportion of the added value of the primary industry in the three major urban clusters is almost maintained at about 5% of their total added value. The volume of the primary industry in the Beijing-Tianjin-Hebei and Pearl River Delta are similar, and it accounts for 2/3 of the Yangtze River Delta. Due to the strong support for the secondary and tertiary industries in Beijing, Tianjin, and the Pearl River Delta, large amounts of labour and land are separated from agriculture, and the scale of the primary industry is gradually shrinking. However, the agricultural policy support is strong in the Yangtze River Delta, with an annual investment of about 300 million yuan to build farmland infrastructure. And it also develops tourism and other related industries in the corresponding agricultural chain, and the scale of the primary industry is relatively high. Zhang and Wang (2014) mentioned that the scale expansion of the primary industry will accelerate the growth of total carbon emissions at a certain stage, which may be the main reason for the relatively low carbon efficiency of the primary industry in the Yangtze River Delta. As for the Beijing-Tianjin-Hebei and the Pearl River Delta, they are similar in the size of the primary industry, but there is a certain gap in carbon emission efficiency. The main reason is that the added value of the primary industry in the Beijing-Tianjin-Hebei accounts for more than 90%. Compared with the Pearl River Delta, the agricultural industry structure of Hebei is relatively simple, the degree of specialization is not enough, and the rural financial system is relatively backward, resulting in a relatively low carbon emission efficiency.

In terms of the secondary industry, the carbon emission efficiency of Beijing-Tianjin-Hebei is lowest among three clusters. The Pearl River Delta has always been known as the "world's factory", and its labor-intensive manufacturing industry has always occupied an absolute advantage. Limited to the local energy situation, the total carbon emissions of high-carbon industries in the Pearl River Delta, such as coal mining and oil processing, are not high, accounting for only about 5% of the high-carbon industries in the three major urban clusters. And its total added value is relatively low. Additionally, the secondary industry in the Yangtze River Delta strongly leads the economic growth. During the study period, nearly 50% of its economic growth is contributed by industrial growth. Beijing-Tianjin-Hebei is dominated by heavy chemical and capital-intensive industries. It is the industrial base of Chinese heavy chemical industry and equipment manufacturing industry. Most of these industries are carbon-intensive industries. Although the three major urban clusters have different priorities for the development of the secondary industry, the Beijing-Tianjin-Hebei region has the lowest degree of regional cooperation. Hebei, as an important supporting hinterland for agricultural resources and industrial energy in Beijing and Tianjin, has always been in a state of weakness. Lack of industrial supporting service and the weak technical radiation of universities in Beijing and Tianjin are the main reasons for the falling gap.

In terms of the tertiary industry, the carbon emission efficiency of Beijing-Tianjin-Hebei has a slight advantage. The main reason is that 46.9% of the added value of the tertiary industry in Beijing-Tianjin-Hebei from 2002 to 2012 was contributed by Beijing, and Shanghai contributed 25.6% in the Yangtze River Delta. As the center of "scientific and technological innovation", Beijing has 61 colleges and universities, 1/3 of the national scientific research institutions, and the density of technical personnel is the highest in China. The penetration of new technologies into the tertiary industry has significantly improved the technological content of the tertiary industry, and the service methods have become increasingly electronic and low-carbon. However, although Hebei's tertiary industry contributes about 30% to the tertiary industry of the Beijing-Tianjin-Hebei, its carbon emission coefficient is about 1.5 times that of Beijing. Beijing's technological radiation effect on Hebei's tertiary industry is not significant.

Regional Carbon Conduction in Beijing-Tianjin-Hebei

In order to further explore the implied carbon emissions of inter-regional trade, we use the APL model to identify the transfer-in and transfer-out parties in the carbon conduction relationship in Beijing-Tianjin-Hebei through the forward and backward APL values. We take the transfer-in direction of carbon emission as the direction of the arrow, identify the carbon ripple relationship, and calculate the total carbon emissions (tCO_2/10,000 yuan) along the chain based on the carbon chain relationship based on the SPA model. The result is shown in **Supplementary Figure S2**:

It can be seen from **Supplementary Figure S2** that during the study period, the carbon conduction relationship brought about by the foreign trade links between the Beijing-Tianjin-Hebei and other provinces is always relatively stable, and the provinces with the strongest carbon spread are always Shanxi and Inner Mongolia. The carbon chain in the Yangtze River Delta is not stable. Except for the close carbon sweep effect with Anhui, most of the regions in the carbon chain are in flux. The carbon sweep cities in the Pearl River Delta are mainly concentrated in the southwest and southeast.

Using the main related provinces and cities of Beijing-Tianjin-Hebei and other urban clusters revealed in **Supplementary Figure S2**, we study the degree of carbon correlation between these provinces and cities based on the industrial correlation index proposed by Ma et al. (2018). Specific as formula **11**:

$$\xi_{ij} = \frac{\frac{APL_{ij}}{F_{ij}}}{\frac{\overline{APL}}{\bar{F}}} \tag{11}$$

In **Eq. 11**, the APL value measures the economic distance between regions and industries with the average step length of the conduction chain, and the F value can be used to measure the degree of correlation between industries at the same level. The smaller the industry correlation index, the closer the relationship between the region (industry) and other regions (industry) is.

We use 0.05 as the threshold of the industrial correlation index to identify the main related industries of the three major urban clusters. Beijing-Tianjin-Hebei, as a coal-based emission city cluster, also has similar characteristics in its cross-provincial and municipal industry linkages. During the study period, electricity and heat industry in the carbon conduction chain of Beijing-Tianjin-Hebei is the main carrier industry for carbon transfer. For example, during the period from 2002 to 2007, Beijing-Tianjin-Hebei is the carbon transfer-in party of Shanxi, and the main carbon transfer-in industries is electricity and heat. Until 2012, that the transfer industries of Beijing-Tianjin-Hebei changed, which included electric and heat, non-metallic mining and transportation industry. In summary, we further identify the main chains of carbon transfer in Beijing-Tianjin-Hebei and other resource provinces, and calculate that the implied carbon emissions during the transfer of electricity and heat account for more than 85% of the total carbon emissions. Different from the Beijing-Tianjin-Hebei carbon transmission chain, in the Yangtze River Delta, most of the industrial linkages are related to the resource extraction industry and related manufacturing industries, such as metal product manufacturing, boiler manufacturing, motor manufacturing and metallurgical industries. Electricity and heat industry does not play a pivotal role in industry transfer.

In order to further explore the characteristics of the electricity and heat industry in the Beijing-Tianjin-Hebei, we further compare the carbon emission coefficients of the industry in the three major urban clusters. The results show that Beijing-Tianjin-Hebei has obvious characteristics of coal-fired carbon emission urban clusters. The carbon emission coefficients of electricity and heat industry and coal mining industry are not only far higher than other industries in the region, but also significantly higher than the other two major urban clusters. The average carbon emission coefficient of the Beijing-Tianjin-Hebei electric power industry is 18.25tCO2/10,000 yuan, which is about 2 times that of the Pearl River Delta and 2.5 times that of the Yangtze River Delta. In the process of carbon transfer in the coal industry in Hebei, more than 65% of the resources are transferred to the electricity and heat industry in Hebei and then to the electricity and heat industry in Beijing and Tianjin. It is true that the Beijing-Tianjin-Hebei is limited by the input of factors and the consumption structure. Unlike the Yangtze River Delta or the Pearl River Delta, Beijing-Tianjin-Hebei cannot almost completely avoid the intermediary role of electricity and heat from the perspective of carbon transfer. However, it is one of the key points of emission reduction whether to reduce carbon leakage in the electricity and heat industry while ensuring the supply of resources in Beijing and Tianjin. In order to reduce the overall carbon emissions in the region, improving the electric and heating efficiency in the Beijing-Tianjin-Hebei may be a good starting point. The Yangtze River Delta belongs to the East China Power Grid and is one of the models of cross-provincial and cross-regional power cooperation in China. Although it is difficult for Beijing Tianjin Hebei region to realize the mutual assistance and mutual protection of energy similar to the Yangtze River Delta, it is feasible to optimize the power grid structure and develop new energy technologies.

Internal Carbon Conduction Paths in Beijing-Tianjin-Hebei

We aim to further explore the internal correlation of carbon spillover in the three regions of Beijing-Tianjin-Hebei and other provinces with close spillover effects, such as Shanxi, Inner Mongolia, etc. Thus, we consolidated the IRIO table into a whole at the provincial level, set the threshold as 0.1, and take Beijing-Tianjin-Hebei as the center of investment and demand. The relationship between them is identified as shown in **Supplementary Figure S3**:

It can be seen from **Supplementary Figure S3** that the relationship between the transfer-in and transfer-out parties in Beijing-Tianjin-Hebei and other places basically remains unchanged. During the study period, Beijing and Tianjin have been the transfer-in sources of carbon emissions from Hebei, Shanxi, and Inner Mongolia, and Shanxi is mainly the transfer-out party. In terms of the total amount of direct carbon transfer, from 2002 to 2012, the amount of carbon emission transfer in the region continued to increase. The total amount of carbon transfer in Beijing was always the largest, and the total amount transferred from Hebei to Beijing dominated, increasing from 2.26×10^5 t in 2002 to 1.56×10^6 t in 2012.

It can be seen from **Supplementary Figures S2, S3** that the dependence of Beijing-Tianjin-Hebei on resource provinces like Shanxi and Inner Mongolia is strong, and the total amount of carbon transfer within the urban cluster gradually decreases. To further analyze the carbon transfer changes in the industrial structure of the urban clusters, we take Shanxi, Inner Mongolia and Hebei as carbon transfer-out parties, take Beijing and Tianjin as carbon transfer-in parties, and calculate the total carbon transfer changes of the three industries. The calculation formula is **Eq. 12**:

$$\widehat{S_{ij}} = C_i (I - A)^{-1}_{ij} \hat{F}_j \tag{12}$$

Through calculation, it is found that whether it is resource provinces outside the urban cluster (such as Shanxi and Inner Mongolia) or the main energy hinterland within the urban cluster (Hebei), the total carbon transfer-out of the three major industries is basically increasing year by year. The resource status of Hebei Province is also highlighted year by year and the proportion of its total carbon transfer has increased from 47.8% in 2002 to 62.10% in 2012. From the perspective of the structural proportion of industrial carbon transfer, the direct support of the secondary industry in resource provinces to Beijing and Tianjin showed a trend of rising first and then decreasing. The proportion of the secondary industry first increased from 71.73% in 2002 to 81.34% in 2007, and finally fell to 54.81% in 2012. The main reason for the decline in 2012 is that Shanxi has always had a "coal-based" industrial structure (Hu et al., 2016). In 2012, the growth rate of domestic coal demand declined, coal prices plummeted, and most coal enterprises fell into a state of cessation of production. Its economy experienced a "cliff-like" decline (Jiang et al., 2014). But for Hebei, the support structure of its three major industries has been relatively stable, and the proportion of the secondary industry and the tertiary industry has always been about 3:1. And in 2012, although the coal price drop had a greater impact on the coal mining enterprises in Hebei, unlike the overall economic weakness in Shanxi, the coal mining enterprises and power plants in Hebei showed a trend of ebb and flow. The "coal fullness" of power plants in Hebei completely compensated for the reduction in carbon transfer caused by the reduction in the proportion of secondary industries in resource provinces, especially for Shaanxi.

In Summary, it is known that Hebei plays an important role in resource security, and the secondary industry can effectively alleviate the pressure of insufficient supply in resource provinces. So, can the economic benefits of Hebei be improved while ensuring the total supply of resources in Beijing and Tianjin? In response to this problem, we further calculate the carbon productivity of Hebei, that is, the change in value-added per tCO2 emitted (Pan and Zhang, 2011). During the study period, the carbon productivity of the secondary and tertiary industries in Hebei was 6,300 yuan and 48,700 yuan respectively, of which the carbon productivity of the secondary industry was 43.52% lower than the national average, and the tertiary industry was 26.72% higher than the national average. It can be seen that the carbon productivity of the secondary industry in Hebei Province still has a large room for growth. When Hebei meets the energy needs of Beijing and Tianjin, it can improve the economic benefits and achieve the goal of economic growth by optimizing the production structure and energy efficiency of the secondary industry.

Major Industrial Carbon Conduction Paths in Beijing-Tianjin-Hebei

The mismatch between energy pressure and efficiency upgrades in Hebei makes its energy supply more dependent on foreign transfers. From the analysis of carbon transfer inside and outside the Beijing-Tianjin-Hebei urban cluster, we can see that the electricity and heat industry in Hebei Province plays an important intermediary role in the introduction of resources from other provinces. Based on this, we take Hebei electricity and heat as the center to explore the situation of related industries outside the province under the situation of resource transfer.

It can be seen from **Supplementary Figure S4** that when Inner Mongolia, Hebei, and Shanxi transfer carbon resources to Beijing and Tianjin, most of them are transferred through the electricity and heat industry in each province. For example, in 2002, when Hebei metallurgy's resources are transferred to Beijing Metallurgical, it is mainly transferred to Beijing metallurgy through Shanxi electricity and heat industry and Hebei electricity and heat industry, and then Beijing metallurgy is transferred to other industries in the city. Judging from the absolute amount of carbon emissions transferred in each step, the carbon generated by the electricity and heat industries in Inner Mongolia and Shanxi accounts for more than 95% of the entire carbon conduction chain. To further explore the causes of high carbon production in Inner Mongolia and Shanxi, we compare the direct carbon emission coefficients of Beijing-Tianjin-Hebei and major resource provinces such as Shanxi and Inner Mongolia, as shown in **Supplementary Table S3**:

It can be seen from **Supplementary Table S3** that compared with the carbon emission coefficients of the electricity and heat industry in the three places of Beijing, Tianjin and Hebei, Shanxi and Inner Mongolia, especially for Shanxi, are obviously at a higher level. Based on this, it is not difficult to propose that when Beijing-Tianjin-Hebei electricity is transferred out, if the transmission efficiency of the power grid in Shanxi and Inner Mongolia can be optimized to a certain extent, the overall carbon emissions of the region can be reduced. However, as far as the actual situation is concerned, Shanxi has long used coal as its pillar industry. In recent years, the domestic demand for coal, including coal from Shanxi, has not been strong, resulting in greater financial pressure in Shanxi and other places. The upgrading of the structure may lead to a long-term fiscal deficit, which will have a greater negative impact on its economic development (Jiang et al., 2014). Therefore, when reducing the carbon emissions caused by the consumption side in the Beijing-Tianjin-Hebei, it is necessary to include Shanxi, Inner Mongolia and other places into the scope of collaborative governance and share their emission reduction costs.

CONCLUSION

Based on the input-output methodology, the APL model, and the SPA model, combined with the regional input-output tables in 2002, 2007 and 2012, we explore the carbon spillover effect and industrial evolution inside and outside the Beijing-Tianjin-Hebei. The main conclusions drawn are as follows:

First, from the perspective of the internal urban cluster, the electricity and heat industry plays a key role in the main carbon transmission chain, and the carbon emissions brought by it as an intermediary account for more than 85% of the total carbon emissions in the transmission chain. The carbon emission coefficient is relatively high, and the characteristics of coal-fired power are obviously the main characteristics of the electricity and heat structure in the Beijing-Tianjin-Hebei. When considering reducing the total amount of carbon emissions in the region as a whole, due to the limitation of resource endowment, external energy transfer is inevitable, but the development of the power grid in the Yangtze River Delta still has strong reference significance. The Beijing-Tianjin-Hebei, as a national science and innovation base, can make full use of its technological advantages. In terms of new energy development, vigorously developing the abundant wind and solar energy resources in northern Hebei to expand power varieties is essential. In terms of improving energy efficiency, gradually promoting the UHV transmission grid could reduce the coal consumption in Hebei and improve the power receiving capacity outside the area.

Second, from the perspective of the transfer of industrial structure, the secondary industry in Hebei can alleviate the pressure of insufficient supply in resource provinces to a certain extent, and the economic benefits brought about by its emissions have a large room for development. The average carbon productivity of the secondary industry in Hebei is 6,300 yuan, which is only 56.47% of the national average. One of the strategic orientations of Hebei is to ensure the energy supply between Beijing and Tianjin, so given the total amount of resources that Hebei needs to provide to Beijing and Tianjin, its economic benefits still have a lot of room for growth. Therefore, gradually transforming the energy structure dominated by coal, accelerating the development of clean energy, and dealing with "zombie enterprises" in industries such as steel and cement can reduce carbon costs. Increasing carbon productivity could also maximize economic benefits when ensuring resource supply.

Third, from the perspective of major industries, compared with Beijing, Tianjin and Hebei, resource provinces such as Shanxi and Inner Mongolia have high carbon emission coefficients in the electricity and heat industry, which is the main reason for the high carbon emissions in the main transmission chain. Although Hebei has provided energy support for the development of Beijing and Tianjin, the external resource transfer is inevitable. If the total regional carbon emissions are reduced from the perspective of external resource allocation, it is more difficult to rely solely on resource provinces outside the urban cluster, which is likely to lead to conflicts caused by long-term local fiscal deficits. Therefore, when considering the reduction of carbon emissions caused by external resource transfer. Shanxi, Inner Mongolia and other resource provinces should be included in the scope of coordinated governance, and the funds for the implementation of the power transfer strategy should be reasonably apportioned and multi-sourced, and provide them with improved energy efficiency and technical support for clean energy.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: https://www.ceicdata.com/zh-hans/china/energy-balance-sheet Name: Energy Balance Sheet.

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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Research on the Low-Carbon Development Path and Policy Options of China's Transportation Under the Background of Dual Carbon Goals

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Chinese government has proposed ambitious targets to combat climate change. As carbon emissions of China's transportation have been rapidly increasing in past decades, massive efforts for carbon reduction need to be taken by transportation sector. Research on practical action paths for transportation sector's low-carbon development are critical to achieving the Paris Agreement goals and China's "Dual-Carbon" Target. Based on the transportation's historical carbon emissions and the new possible trends in the future, this paper uses a forecast model to predict transportation's carbon emission. Then we adopt a scenario analysis to analyze the total transportation demand in the transportation sector from 2021 to 2060. We quantitatively simulated the emission reduction effects of different policy measures under different scenarios, such as optimization of transportation structure, application of energy-saving and emission-reduction technologies, and new energy vehicles. The results provide paths and measures for the low-carbon development of transportation, and provides policy suggestion for the scientific formulation of the low-carbon development.

Keywords: low carbon transportation, green transportation, development path, scenario analysis, carbon emissions

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1 INTRODUCTION

Global efforts against climate change are currently being strengthened. Numerous nations, including China, have realized that a fair and sustainable development system needs to be established to meet future generations' needs and further contribute to current social and economic developments. With the rapid development of the transportation sector in the world, the proportion of transportation's carbon emissions continued to grow, which has exceeded 25% of the world's total carbon emissions (Liu et al., 2021). In 2020, President Xi Jinping announced that China aimed to peak carbon emissions by 2030 and achieved carbon neutrality by 2060 (so-called "Dual-Carbon" target). The transportation sector, accounting for above 10% of China's total carbon emissions, is estimated to be the hardest sector to reach the peak (He, 2020). According to predictions by the International Energy Agency (IEA), all other sectors in China will peak carbon emission before 2028, while the transportation sector is predicted to reach its peak after 2040 (IEA, 2017). In order to contribute to "Dual-Carbon" target, the efforts to decarbonize the transportation sector need to be strengthened.

With the rapid development of China's economy and society, the turnover of transportation goods has increased significantly. The carbon emissions of transportation increased from 372 million tons in 2005 to 983 million tons in 2020, increased 264%, and the

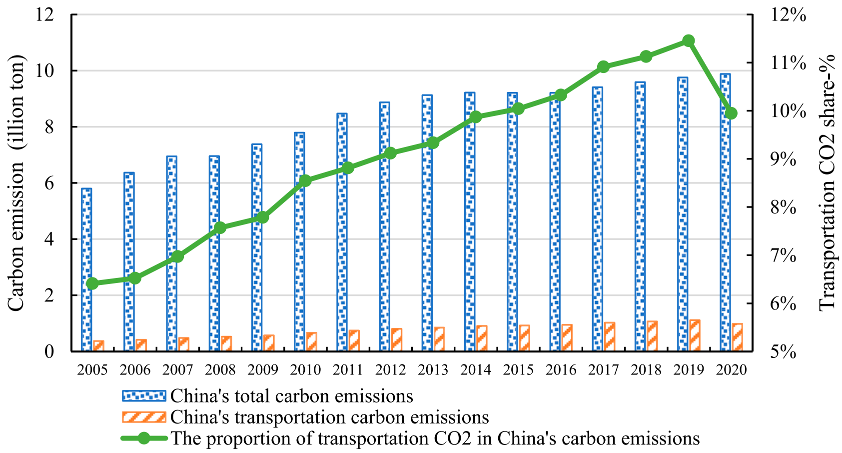

FIGURE 1 | China's transportation carbon emissions.

average annual growth rate reached 6.2%. The carbon emissions' proportion of transportation sector in total China's carbon emission has increased steadily, from 6.4% in 2005 to 9.9% in 2020, as shown in **Figure 1**.

In nowadays, China's transportation sector is still powered by fossil fuel consumption, and the proportion of clean energy use is very low. Transportation sector will face increasingly fierce challenges to meet "Dual-Carbon" target. Firstly, the total demand of transportation will continue to grow, and the whole society will have higher requirements for transportation timeliness, personalization, comfort, which will lead to increasing difficulty in controlling total carbon emissions and carbon intensity of transportation. Secondly, clean energy has not yet formed a large-scale application in the transportation sector, which highly relying on the breakthrough of new energy equipment technology. Thirdly, the emergence of technologies such as autonomous driving, electric vehicles, the application of shared travel will significantly affect and re-shape the transport sector development and emission reduction pathway. The emission growth rate of the transportation sector may will continue to increase, and become the largest contributor to CO2 emissions in China (Tang et al., 2019). As the transportation sector is a fundamental industry for China's economic and social development, reducing emissions is crucial for its long-term decarbonization pathway. However, Therefore, it is necessary to carry out research and implementable policy recommendations on the low-carbon development path of the transportation sector.

Many scholars pay close attention to low-carbon development of transportation research and they mainly focus on two aspects. On one hand, some scholars have studied and identified the influencing factors of China's transportation carbon emissions. Guo and Meng (2019) adopted the LMDI model to analyze the driving factors of carbon emissions from the transportation sector in Beijing-Tianjin-Hebei region. Lv et al. (2019) analyzed the driving factors of China's freight carbon emissions and the impact of urbanization on freight carbon emissions. Xu and Lin (2018) used an econometric model to analyze the driving factors of transportation sector's carbon emissions. The result showed that the main influencing factors included population size, per capita GDP, transportation energy intensity, urbanization level, freight turnover and passenger turnover. Lo et al. (2020) used an econometric model to study the influencing factors of aviation carbon emissions and concluded that aviation fuel prices, flight distance and aircraft type were the main influencing factors. To sum up, most studies at this stage mainly explain the influencing factors of transportation carbon emissions, including the level of economic development, population size, total transportation turnover, urbanization rate, urban space and distribution (Lim et al., 2019), land use (Fei et al., 2009), transportation structure (Hao et al., 2011), transportation efficiency (Talbi, 2017), industrial structure (Wang et al., 2017), scale of private car ownership and fuel prices (Wu et al., 2016), etc., On the other hand, some studies focus on how to achieve carbon emission reduction goal in transportation sector. For example, Acar and Dincer (2020) believed that one of the most effective way to achieve green transportation was replacing traditional fuel vehicles with new energy vehicles. Yang et al. (2017) simulated the carbon emissions of daily travel in Beijing based on the micro-simulation model to evaluate the key low-carbon transportation policies, including public transport improvement, public bicycle policy, energy efficiency improvement policy and electric vehicle promotion policy. The results showed that when the four policies were used together, Beijing's daily travel carbon emissions could be reduced by 43%. Based on the CIAM/NET-Transport model, Tang et al. (2019) simulated China's future carbon emissions path. The results showed that by adopting joint measures, including optimizing transportation structure, improving energy efficiency, promoting alternative fuels can reduce 8447 Mt CO_2 from 2015 to 2050. In general, the existing researches on low-carbon development mainly focus on the influencing factors of transportation carbon emissions and the forecast of future carbon emissions. Few studies have been able to clarify the low-carbon development path of the transportation sector and evaluate the emission reduction effects of different policy measures.

In this paper, we aim to propose a suitable low-carbon development path for China's transportation sector and simulate the effects of diverse policy measures. Overall, three questions are explored in this study: 1) What is the future trend of transportation carbon emissions and when will the China's transportation carbon emissions peak? 2) What will the core indicators associated with energy efficiency and low-carbon transportation (such as electrification rate, green travel ratio, etc.) be at key nodes (peak period, rapid decline period)? 3) How will China's transportation sector achieve more sustainable development and how to develop implementable policy measures? Under the background of national "Dual-Carbon" policies and technologies, we design an Energy and Carbon emission Assessment Scenario model of China's transportation sector to project the carbon emissions to 2060 under different scenarios and provide a roadmap of sustainable low-carbon transport.

The rest of the paper is structured as follows: In **Section 2**, we present the model used in this paper. **Section 3** analyzes future trends and key factors that influence the carbon emissions of China's transportation sector. Then based on these factors, three different emission scenarios for China's transport sector are examined. In **Section 4**, we obtain the carbon emissions of the transportation sector under different scenarios. **Section 5** shows the conclusions and policy recommendations.

2 MATERIALS AND METHODS

2.1 Review of Existing Models

Carbon emissions of transportation sector are mainly mobile source emissions. According to the IPCC Guidelines for National Greenhouse Gas Inventories (Hayama, 2006), mobile source emission accounting methods can be divided into two categories: "top-down" method and "bottom-up" method. The "top-down" model bases on vehicle energy consumption and energy carbon emission conversion factors. The approach has been used in different studies worldwide. Salvatore and Daniela. (2002) applied it to the estimation of carbon emissions from road transport in Italy. Xie and Wang (2011) used the "top-down" model to calculate the carbon emissions of various modes of transportation in China and the carbon emission intensity of major transportation vehicles. The results showed that there was a general downward trend of carbon intensity, and the civil aviation had the largest carbon intensity, while the waterway had the smallest carbon intensity. Cai. (2011a) calculated the carbon emissions of national and regional road transport in 2007 based on the "top-down" model. The results showed that China's road transport carbon emissions in 2007 was 377 million tons, accounting for 86.32% of the carbon emissions in the transportation sector. Chi (2012) calculated the carbon emissions of China's transportation sector from 1991 to 2009 and compared the carbon emissions of various modes of transportation, concluding that the waterway was the transportation mode with the highest carbon emission efficiency from the top-down model.

The "bottom-up"model, first applied in transportation field by Schipper et al. (2000), use the data of different transportation modes' ownership, mileage, and fuel consumption per unit of mileage to calculate transportation's carbon emissions. Li et al. (2018) used the "bottom-up" model to calculate and compare the carbon emissions of four types of public transport (bus, rail transit, taxi and private passenger cars) in urban city and concluded that the annual carbon emissions and carbon intensity of rail transit were the smallest. Chen et al. (2010) calculated the total carbon emissions of transportation sector in Shanghai and compared the carbon emissions of different transportation modes. Cai. (2011b) adopted the "bottom-up" model and calculated carbon emissions of road, railway, air and water transportation of the whole country and each province, the results showed that the road emissions were the largest both in national level and regional level.

2.2 Models in this Paper

Overview, the "top-down" model can well reflect the interrelationship between the transportation system, the energy system, and the economic system. The "bottom-up" model, on the other hand, can describe in detail the energy consumption and carbon emissions of various transport models. Considering that China's transportation demand will grow rapidly, and different policies and technological advances will be used for transportation energy consumption intensity decrease and energy consumption structure improvement, it is difficult to only use top-down or bottom-up models, which needs detailed data. Therefore, in this paper, we apply comprehensive model and scenario design, which simulates the future technological development and analyzes the carbon emissions of different fields of transportation sector in the future. Specifically, we first apply traffic demand model by fully considering the factors that affect the carbon emissions of transportation, to get the traffic activity data. Considering that the passenger transport and freight transport have distinct growth trends, we analyze passenger transport and freight transport separately. Then, according to different modes of transportation we build emission model to calculate transportation's carbon emissions. Detailed classification could be seen in **Figure 2**. Energy application of different modes of transport could be seen in **Supplementary Appendix A1**.

2.2.1 Transportation Demand Model

1) Passenger turnover prediction model

The first sub model simulation is the prediction of total China's passenger turnover. The detailed method is that identifying the major drivers of travel demand and modeling the mathematical relationship between travel demand and these factors.

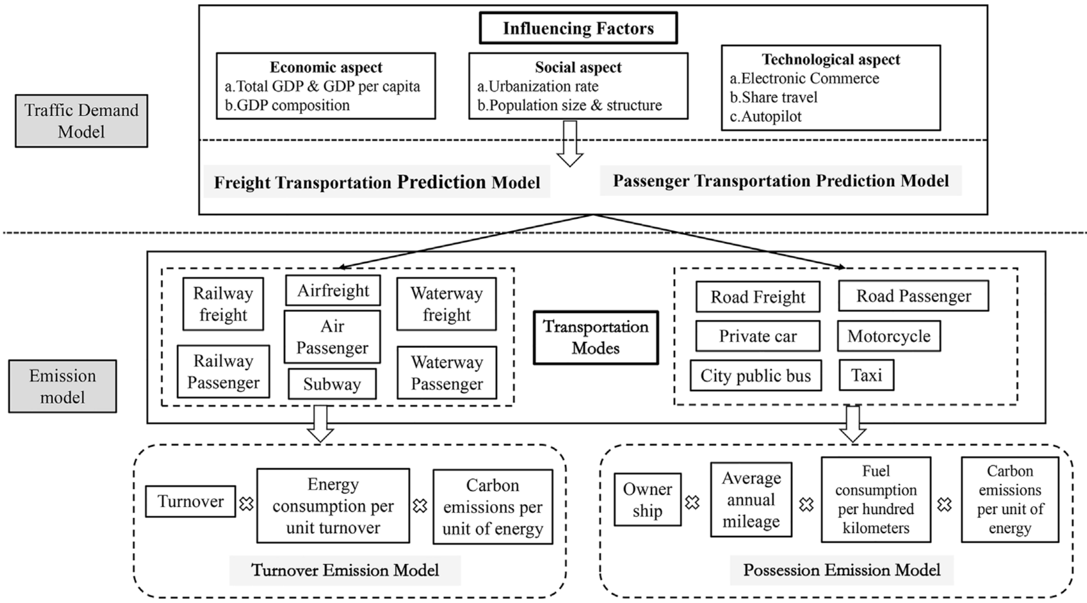

FIGURE 2 | Transport-related carbon emissions calculating model.

We used the cumulative Weibull function to simulate the growth trend of km traveled per capita in China, as **Eq. 1** shows.

$$T_i = T_i^* \times \left(1 + a_i e^{-a x_i} + b_i e^{-b y_i} + c_i e^{-c m_i}\right)$$
$$\text{and } Tu_i = T_i \times Po_i \tag{1}$$

Where, T_i refers to traveled distance per capita in year i, km. T_i^* saturates traveled distance, which is regressed from the historical transport data and economic data in China during 2000 and 2020. x_i refers to GDP per capita in year i. a_i refers to constants for GDP per capita in year i. y_i refers to urbanization rate in year i. b_i refers to constants for urbanization rate in year i. m_i refers to population size in year i. c refers to constants for population size in year i. Tu_i is the turnover of passenger in year i, Po_i is the China's population in year i.

Different passenger transport modes bear different proportions of passenger turnover. Therefore, we apply Kaya model to calculate the passenger turnover of railway, road, aviation and waterway.

$$\begin{cases} T_{ui} \times T_{ai\_share} = T_{ai} \\ T_u i \times T_{ri\_share} = T_{ri} \\ T_u i \times T_{wi\_share} = T_{wi} \\ T_{ui} \times T_{ci\_share} = T_{ci} \\ T_{ui} \times T_{pi\_share} = T_{pi} \\ T_{ui} \times T_{tai\_share} = T_{tai} \\ T_{ui} \times T_{subi\_share} = T_{subi} \\ T_{ui} \times T_{moi\_share} = T_{moi} \\ \sum \begin{matrix} (T_{ti\_share} + T_{ri\_share} + T_{ai\_share} + T_{wi\_share} + T_{ci\_share} \\ + T_{pi\_share} + T_{tai\_share} + T_{subi\_share} + T_{moi\_share}) = 1 \end{matrix} \end{cases} \tag{2}$$

Where, $T_{ai}, T_{ri}, T_{wi}, T_{ci}, T_{pi}, T_{tai}, T_{subi}, T_{moi}$ refer to the passenger turnover of railway, road, water, aviation in intercity passenger transport, and the turnover of city bus, private car, taxi, subway, motorcycle in city passenger transport in year i, respectively. T_{ui} refers to total passenger turnover in year i. T_{ti_share}, T_{ri_share}, T_{ai_share} , T_{wi_share} , T_{ci_share} , T_{pi_share}, T_{tai_share}, T_{subi_share}, T_{moi_share} refer to the proportion of those transport model, which are simulated by cumulative Weibull function. Take T_{ti_share} as an example:

$$T_{ti\_share} = T_{ti-1\_share} \times \left(1 - e^{-x_i^{\gamma}}\right) \tag{3}$$

$$T_{t2020\_share} = \frac{T_{t2020}}{T_{u2020}}, when, i = 2020 \tag{4}$$

Where, T_{ti-1_share} refers to the railway passenger turnover proportion of total passenger transport turnover in the previous of year i. x_i refers to per capita GDP. γ refers to a parameter that determines the shape of curve, which is regressed from the historical transport data and economic data in China during 2005 and 2020. T_{t2020_share} refers to the railway passenger turnover proportion of total passenger transport turnover in 2020. T_{t2020} refers to the railway turnover in the 2020. T_{u2020} refers to the total passenger transport turnover.

The calculation of T_{ri_share}, T_{ai_share} , T_{wi_share} , T_{ci_share} , T_{pi_share}, T_{tai_share}, T_{subi_share}, T_{moi_share} are similar to T_{ti_share}. The difference is that the γ of different modes of transportation is affected by different influence factors.

2) Freight turnover prediction model

The freight turnover prediction model can be expressed as:

$$Tf_i = b_0 + b_1 \times j_i + b_2 \times k_i + b_3 \times m_i + b_4 \times n_i \tag{5}$$

Where, Tf_i represents the turnover of freight in year i. j_i refers to total GDP in year i. k_i refers to population size in year i. m_i refers to urbanization rate in year i. n_i refers to secondary industry added value in year i. b_0, b_1, b_2, b_3, b_4 are undetermined coefficients, which are determined by the least squares method.

Different freight transport modes have different proportions of freight turnover. Therefore, we applied Kaya model to calculate the freight turnover of railway, road, aviation and waterway.

$$\begin{cases} T_{fi} \times T_{fti\_Share} = \mathrm{T}_{fti} \\ T_{fi} \times T_{fri\_Share} = \mathrm{T}_{fri} \\ T_{fi} \times T_{fai\_Share} = \mathrm{T}_{fai} \\ T_{fi} \times T_{fwi\_Share} = \mathrm{T}_{fwi} \\ \sum \left(T_{fti\_Share} + T_{fri\_Share} + T_{fai\_Share} + T_{fwi\_Share} \right) = 1 \end{cases} \tag{6}$$

Where, T_{fti}, T_{fri}, T_{fai}, T_{fwi} respectively represent the freight turnover of railway, road, aviation and waterway in year i. T_{fi} refers to total freight turnover in year i. T_{fti_share}, T_{fri_share}, T_{fai_share}, T_{fwi_share}, refer to the proportion of those transport model, which are simulated by cumulative Weibull function. Take T_{fti_share} as an example:

$$T_{fti\_share} = T_{fti-1\_share} \times \left(1 - e^{-x_{fi}^{\alpha}}\right) \tag{7}$$

$$T_{ft2020\_share} = \frac{T_{ft2020}}{T_{f2020}}, when, i = 2020 \tag{8}$$

Where T_{fti-1_share} refers to the railway turnover proportion of total freight transport turnover in the previous of year i. x_{fi} refers to the total GDP. α refers to a parameter that determines the shape of curve, which is regressed from the historical transport data and economic data in China during 2005 and 2020. T_{ft2020_share} refers to the railway freight turnover proportion of total freight transport turnover in 2020. T_{ft2020} refers to the railway freight turnover in the 2020. T_{f2020} refers to the total freight transport turnover.

The calculation of T_{fri_share}, T_{fai_share} , T_{fwi_share} are similar to T_{fti_share}. The difference is that the α of different modes of transportation is affected by different influence factors.

2.2.2 Carbon Emission Computation Model

According to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories, carbon dioxide emissions from transportation are mobile source emissions. Based on data availability, two methods are used.

1) Turnover emission model

The formula for calculating the carbon emission of the turnover method is as follows:

$$EC_{iz} = \sum_j \left(T_{ijz} \times FT_{ijz} \times e_j \right) \tag{9}$$

where, EC_{iz} represents the carbon emissions of z in year i. z refer to different transportation modes, including railway passenger and freight, air passenger and freight, water passenger and freight, subways. T_{ijk} represents the turnover of different modes z transportation, which is calculated in **Eqs. 2**, **6**. j refers to the type of fuels that z used, which is shown in attachment A1. FT_{ijk} refers to the fuel consumption per turnover. e_j represents the emission factor of j type of fuel, which is shown in attachment A1.

2) Ownership emission model

In this study, City public bus (CBs), Private car (PCs), Motorcycle (Mos), Taxi (Tas), road passenger (Bus), Road freight, which includes: heavy trucks (HTs), medium trucks (MTs), light trucks (LTs), mini vans (MVs), uses the ownership emission model. This bottom-up model is an aggregate time-series model with prediction step of 1 year (Hao et al., 2011). The structure of the model is presented by **Figure 1**.

As shown in **Figure 3**, the numbers of newly registered all the types of vehicles are estimated by using vehicle production, import and export, as **Eq. 10** shows.

$$NV_{i,j,p} = NV_{i-1,j,p} + VR_{i,j,p} - VO_{i,j,p} \tag{10}$$

Where, $NV_{i,j,p}$ refers to the number of j type of fuel of p type of vehicle in year i. p includes: CBs, PCs, Mos, Tas, Bus, HTs, MTs, LTs, MVs. $VR_{i,j,p}$ refers to the newly registered of j type of fuel of p types of vehicles in year i. $VO_{i,j,p}$ refers to the vehicles out of the market.

$$CEV_{i,p} = \sum_j \left(NV_{i,j,p} \times Dis_{i,j,p} \times VFR_{i,j,p} \times e_j \right) \tag{11}$$

Where, $CEV_{i,p}$ refers to the carbon emission of p type of vehicle in year i. $Dis_{i,j,p}$ refers to the distance driven the j type of fuel of p type of vehicle in year i. $VFR_{i,j,p}$ refers to the fuel-consumption rate per 100 km (L/100 km) consumed by the j type of fuel of p type of vehicle in year i. e_j represents the emission factor of j type of fuel.

2.2.3 Data Source

The research scope includes railway, highway and water transport, aviation, pipelines, urban transportation and civil vehicles, etc., mainly the energy consumption of the transportation operation department, excluding the energy consumption of self-provided vehicles of enterprises and institutions.

The turnover data and unit consumption data are mainly from statistical bulletins, including the Statistical Yearbook of the Transportation Industry, the Statistical Bulletin of the Development of the Transportation Industry, the Railway Statistics Bulletin and the Civil Aviation Statistics Bulletin. In addition, the car ownership data is derived from the China City Statistical Yearbook and the China Urban Construction Statistical Yearbook and related research reports.

The energy used by vehicles typically includes gasoline, diesel, kerosene, fuel oil, natural gas, liquefied natural gas, and electricity. According to the General Principles of Comprehensive Energy Consumption (GB/T5892008), China Energy Statistical Yearbook 2016, 2005 China Greenhouse Gas Inventory Research, Provincial Greenhouse

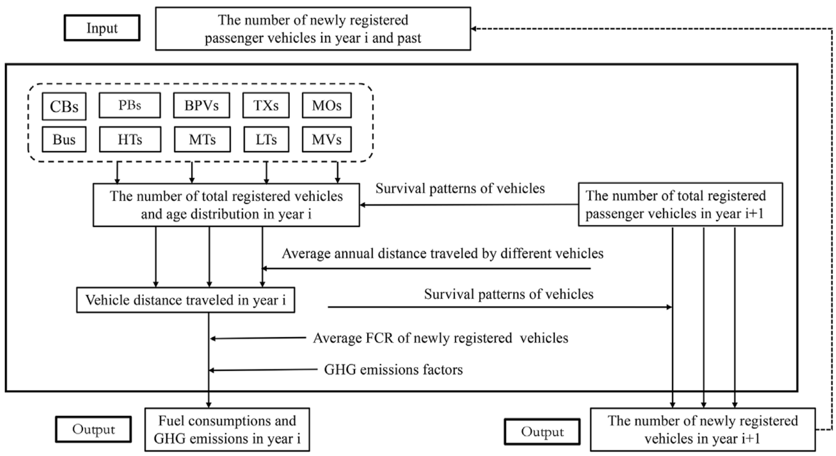

FIGURE 3 | Diagram of ownership model structure.

Gas Inventory Guidelines (Trial), 2006 IPCC National Greenhouse. We calculate the average low calorific value, carbon content per unit calorific value and carbon oxidation rate given in the Gas Inventory Guide and the Guide to the Calculation of Greenhouse Gas Emissions from Source Consumption (version 2.1). The emission factors of diesel, kerosene, fuel oil, natural gas and liquefied natural gas are then obtained according to the standard coal index.

3 SCENARIO DESIGN

3.1 Scenarios Overview

In this study, we set up a baseline scenario, a dual-carbon policy scenario and a radical scenario. We compare the characteristics of the transportation sector at different stages of urbanization at home and abroad, consider the evolution of new technologies in the transportation sector and the implementation of policies, and combine the future social and economic trends of China with the development status of China's transportation system. Combined with China's "Dual-Carbon" target and typical near-zero carbon emission development paths of transportation, the scenarios' parameters are determined.

1) Baseline Scenario

Based on the existing policy measures and technical level, we assume that there will be no major changes or major technological breakthroughs in China's industrial layout, passenger and freight structure, energy efficiency improvements in different transportation modes, and the development of alternative fuel technologies.

2) Dual-carbon policy scenario

Under this scenario, we review the recently issued "dual-carbon" policies and the related China's 14th Five-Year Plan in transportation. The main "dual-carbon" policies include: optimizing the transportation structure, continuous application of energy-saving and emission-reduction technologies, increasing the proportion of green travel, and increasing the penetration rate of new energy vehicles and ships. By summing up these low-carbon policies and measures before 2035, we quantify policy measures into model parameters. In addition, with reference to the results and predictions of some research institutions, the relevant parameters are deduced to 2060.

3) Radical scenario

Based on the dual-carbon policy scenario, we assume that t the application of accelerated emission reduction measures is emphasized, with rapid emission reduction as the primary goal. Specific measures include: intensifying the policies of "transfer from road to railway" and "transfer from road to water", to encourage residents to adopt greener travel modes; to improve the energy consumption efficiency by strengthen the application of "Internet + transportation" and the construction of intelligent transportation; to; to improve the fuel structure by speeding up the elimination of existing and old vehicles and adopting more aggressive measures to improve the penetration rate of new energy vehicles.

3.2 Factors Affecting Transportation Demand

Transportation demand is closely related to macroeconomic and social development indicators such as industrialization, industrial structure and population income levels. According to many studies, there are mainly 13 factors in 4 aspects that affect the transportation demand, including macroeconomic demand factors such as GDP (GDP per capita), industrial structure, urbanization and population; structural factors such as transportation structure adjustment and green travel; energy efficiency improvement factors brought by the application of low-carbon technologies promotion; factors of new energy

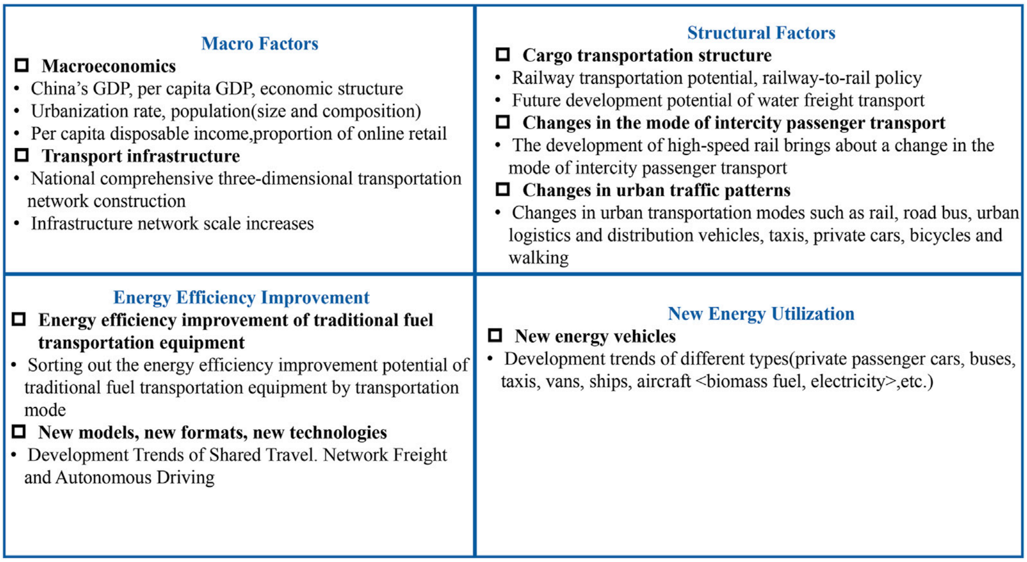

FIGURE 4 | The 13 factors affecting the transportation demand.

transportation equipment application (see **Figure 4**). Detailed scenario parameters could be seen in **Supplementary Appendix A2**.

1) Macro factors

According to the "Outline of the 14th Five-Year Plan (2021–2025) for National Economic and Social Development and Vision 2035 of China" and the World Bank CGE team's forecast of China's economy, China's economy will continue to grow and will basically achieve socialist modernization by 2035. China's economic aggregate and per capita income of urban and rural residents will reach a new level. From 2022 to 2025, it will grow at an average annual rate of 5.2%, and the average annual rate will be 4.4% from 2026 to 2035. By 2035, the per capita GDP of China will reach the level of moderately developed countries, and the middle-income group will expand significantly. China's urbanization rate will increase from 63.89% in 2020 to 65% in 2025 and to around 72% in 2035. According to research forecasts such as the National Population Development Plan (2016–2030) issued by the State Council, China will gradually enter an aging stage by 2030. China's total population was 1.41 billion in 2020 and will peak around 2028, reaching 1.44 billion, and then will drop to 1.401 billion by 2035.

2) Structural factors

The energy consumption intensity of railway freight and waterway freight is 1/7 and 1/9 of that of road freight respectively. Promoting the transfer of bulk cargo and medium and long-distance road freight transport to railway and water transport will be an important measure for green and high-quality development of transportation for a long time in the future. According to the government's requirements on cargo transport structures, it is expected that railway freight volume will increase by 700 million tons and 1.4 billion tons in 2025 and 2030 compared with 2020; inland water freight volume will increase by 500 million tons and 1 billion tons respectively; coastal freight volume will increase by 200 million tons and 500 million tons.

3) Energy efficiency improvement

Advances in energy-saving technologies will further improve the fuel economy of conventional fuel vehicles. There is still room for improvement in the efficiency of gasoline and diesel engines. According to reports such as "Energy-saving and New Energy Vehicle Technology Roadmap 2.0", with the application of lightweight and engine fuel-saving technologies, engine energy efficiency can reach up to 45–50%. With the technical applications such as large-scale ship technology and ship type standardization, the energy efficiency improvement potential of waterway transportation is about 20% as shown in **Table 1**.

Technological advances, such as autonomous driving, can also improve energy efficiency. It is widely believed that the use of autonomous driving technology in public transportation and in specific locations will prevail in the personal passenger vehicle market. According to China's "Technology Roadmap for Energy Saving and New Energy Vehicles", the market share of driver assistance/partially autonomous vehicles will reach 50% by 2030. The market share of fully self-driving vehicles will be nearly 10% by 2035 and will exceed 50% by 2060.

4) New energy Utilization

In 2021, the number of new energy vehicles has reached 7.84 million, accounting for 2.6% of the total vehicles. The annual sales

TABLE 1 | Goals of vehicles on energy saving.

	2025	2030	2035
Private cars	Fuel consumption of traditional energy private car 5.6L/100 km	Fuel consumption of traditional energy private car 4.8L/100 km	Fuel consumption of traditional energy private car 4L/100 km
Commercial vehicles	Fuel consumption of trucks reduces by 8%–10% compared with 2020	Fuel consumption of trucks reduces by 15%–20% compared with 2020	Fuel consumption of trucks reduces by 25%–30% compared with 2020
	Fuel consumption of passenger cars reduces by 10%–15% compared with 2020	Fuel consumption of passenger cars reduces by 20%–25% compared with 2020	Fuel consumption of passenger cars reduces by 30%–35% compared with 2020

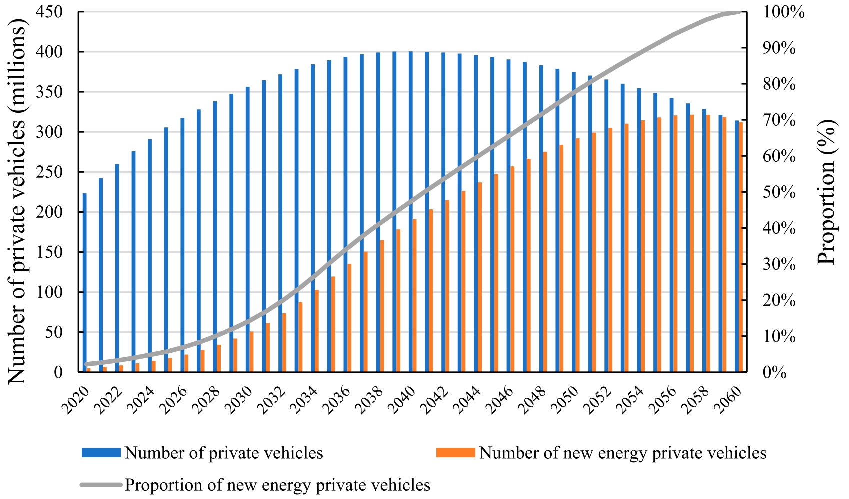

FIGURE 5 | The number and proportion of new energy private vehicles in the future.

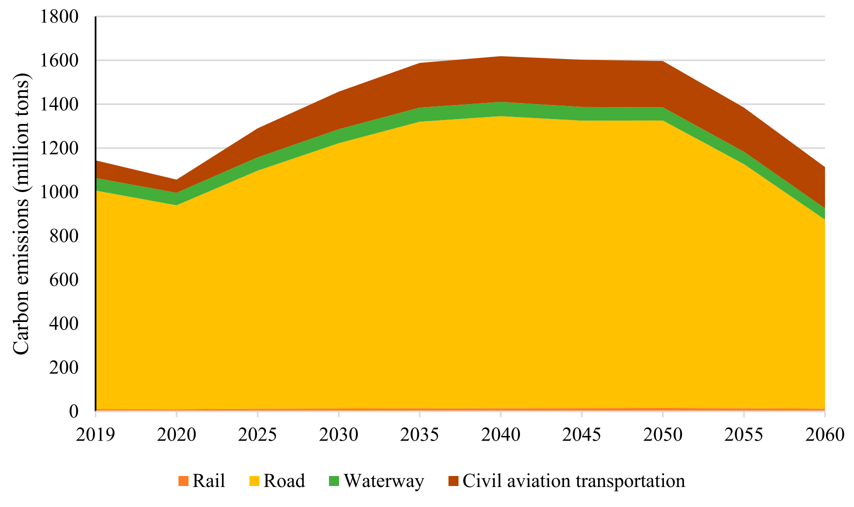

FIGURE 6 | The carbon emissions of transportation under Baseline Scenario.

of new energy vehicles have reached 3.4 million, with a penetration rate of 12.7%. Developing new energy vehicles will still be a key national strategy in the future.

As the new energy vehicles industry enters a period of rapid growth, terminal sales and penetration rates will continue to rise. In accordance with the "New Energy Vehicle Industry Development Plan (2021–2035)", "Carbon Peak Action Plan before 2030", "Energy Saving and New Energy Vehicle Technology Roadmap 2.0", other policy documents and research reports, the sales of new energy vehicles will reach about 20% of the total sales of new vehicles by

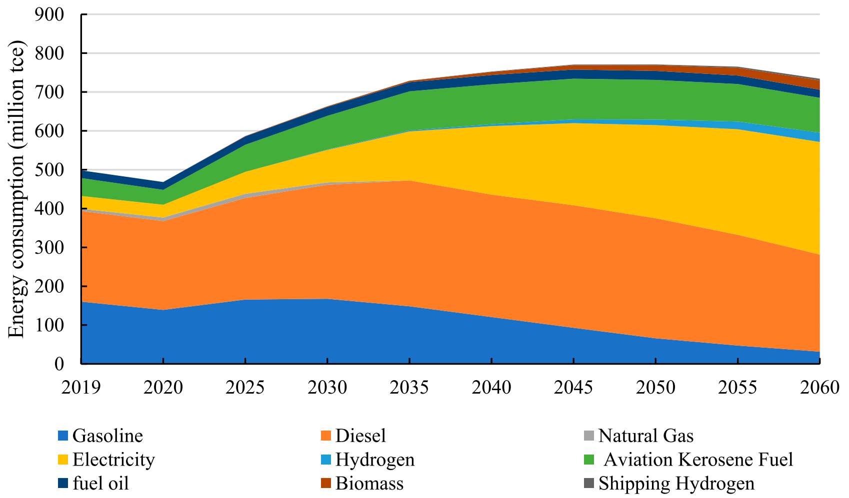

FIGURE 7 | Different fuel consumption trends under the baseline scenario.

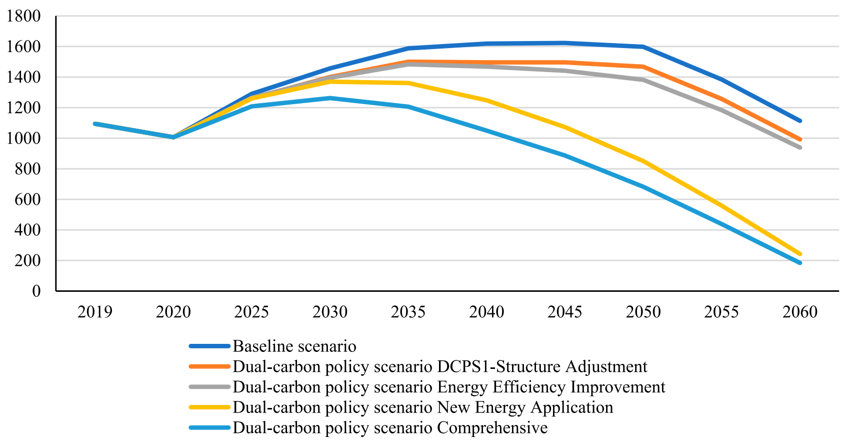

FIGURE 8 | Trends of carbon emissions using different policies and measures under the dual carbon policy scenario.

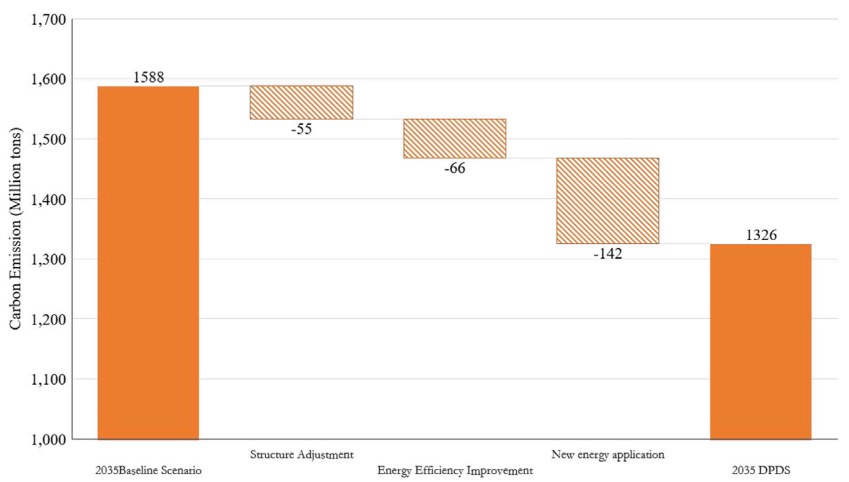

FIGURE 9 | Deconstruction of carbon emissions under the dual carbon policy scenario in 2035.

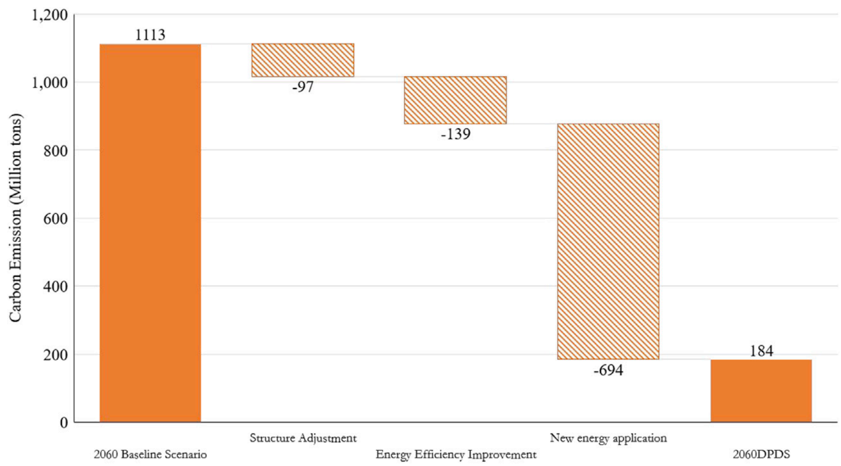

FIGURE 10 | Deconstruction of carbon emissions under the dual carbon policy scenario in 2060.

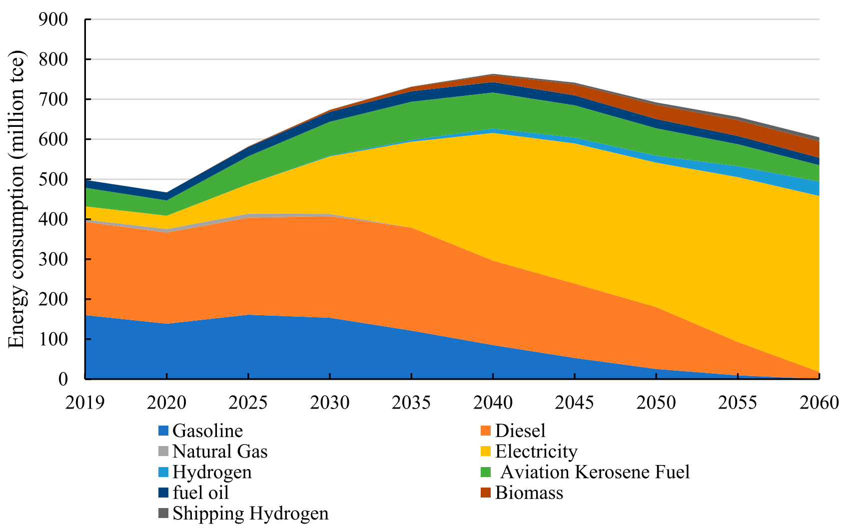

FIGURE 11 | Different fuel consumption trends under the dual carbon policy scenario.

2025, reach 40% by 2030, and will reach 100% in 2045. Based on the vehicle Sale-Ownership prediction model, we obtain the detailed number and proportion of new energy vehicles in China from 2020 to 2060, which are shown in **Figure 5**.

4 RESULTS

4.1 Baseline Scenario

Under the baseline scenario, the penetration rate of new energy vehicles is low, especially in the field of freight transportation, where the proportion of new energy vehicles is only 50% in 2060; the adjustment of the transportation structure is small and the improvement of energy efficiency is limited, resulting in a continuous increase in the total carbon emissions of transportation. The carbon emissions will reach 1.45 billion tons in 2030, peak at 1.62 billion tons in 2045, and drop to 1.13 billion tons in 2060. Road transportation is the most important source of carbon emissions, and the proportion of carbon emissions in the transportation sector will drop from 87% in 2020 to 82.2% in the peak year in 2040, and continue to decline to 77.4% in 2060. The proportion of carbon emissions from aviation transportation will continue to rise, from 7.1% in 2020 to 16.9% in 2060, with an increase of 138%, as shown in **Figure 6**.

In the baseline scenario, traditional fossil fuels are still the main energy sources. By 2040, gasoline, diesel and aviation kerosene will account for 16.1%, 41.9%, and 13.6% of the total transportation energy, respectively. Clean energy such as

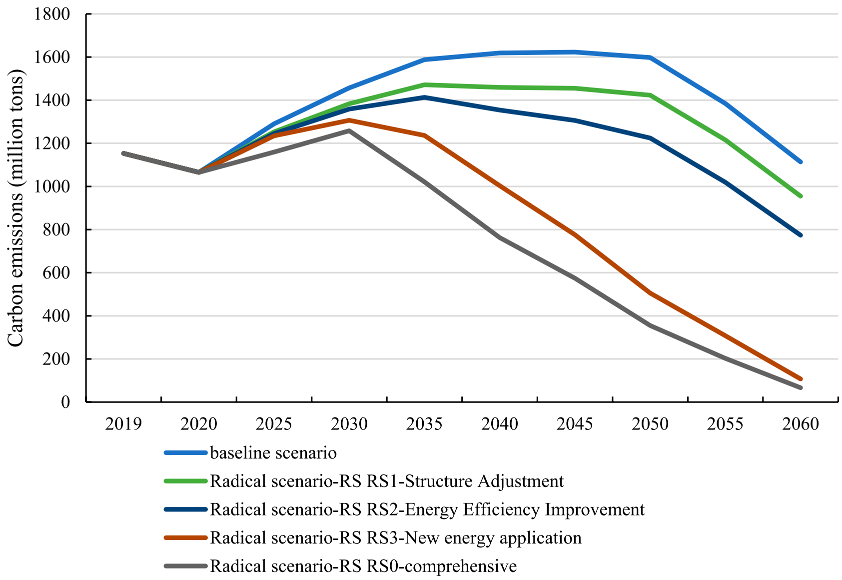

FIGURE 12 | Trends of carbon emissions with different policy measures under the radical scenario.

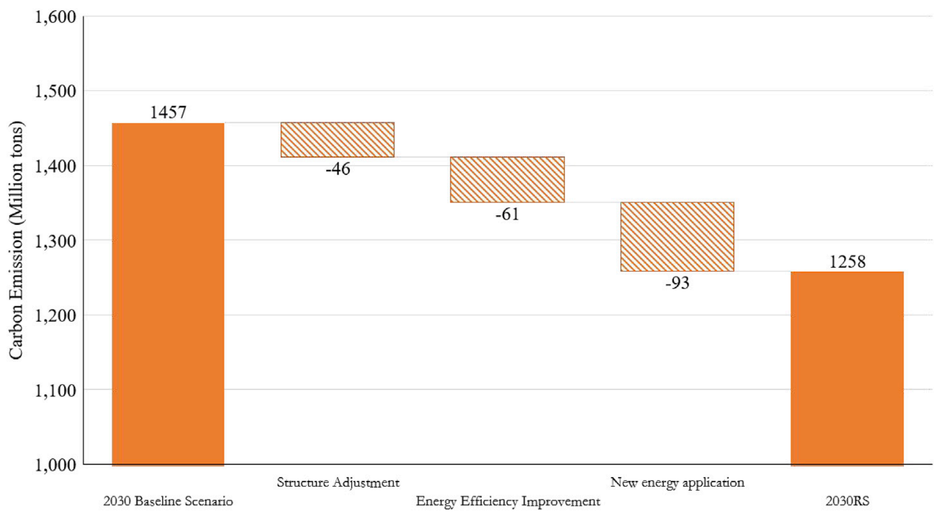

FIGURE 13 | Deconstruction of carbon emissions under the Radical scenario in 2030.

electricity will only account for 24.1%. By 2060, electricity will become the most important transportation energy, accounting for 39.5%, while diesel, aviation kerosene and gasoline will account for 34.1%, 12.2% and 4.3%. Hydrogen will be used to a certain extent, accounting for 3.3% (**Figure 7**).

In general, under the baseline scenario, if effective low-carbon measures are not taken in the transportation sector, it will result in insignificant effects of transferring from road to railway and water transportation and “green travel”, and limited improvement of energy efficiency. The penetration rate of new energy vehicles will not be high, which will lead to the carbon emissions of transportation to be maintained at a high level.

4.2 Dual-Carbon Policy Scenario

Under this scenario, the total carbon emissions from transportation will show a trend of first increasing and then decreasing, reaching a peak around 2035, with a peak carbon emission of 1.33 billion tons. In 2050 and 2060, carbon emissions will drop to 680 million tons and 1.8 billion tons respectively, a decrease of 57.3% and 83.4% respectively compared with the baseline scenario (**Figure 8**).

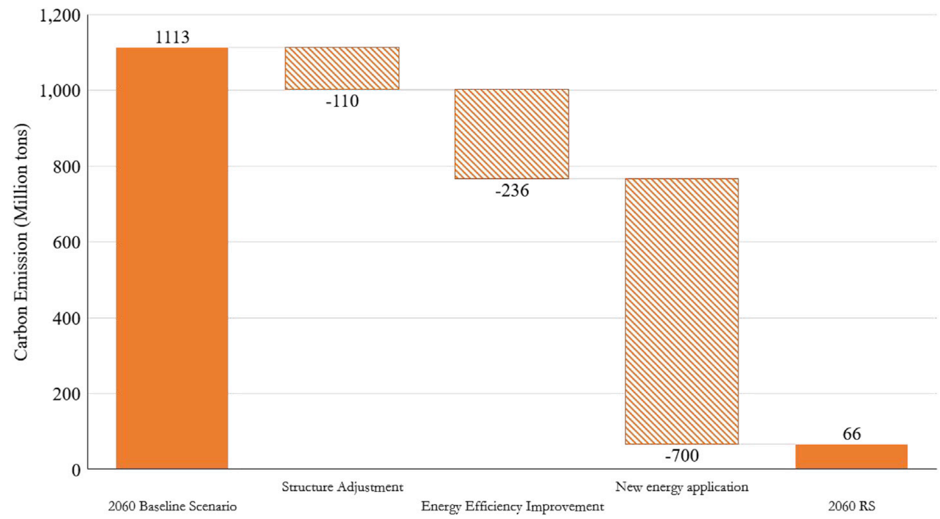

FIGURE 14 | Deconstruction of carbon emissions under the Radical scenario in 2060.

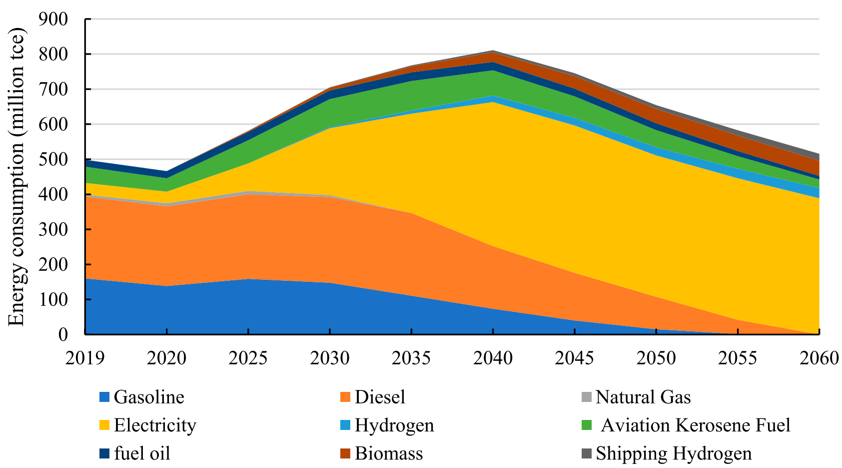

FIGURE 15 | Different fuel consumption trends under the radical scenario.

By 2035, when different policy measures are adopted, as shown in **Figure 9**, the emission reduction effects of the three types of measures, namely, the adjustment of transportation structure, the improvement of energy efficiency, and the application of new energy, will enhance in turn. The emission reductions are 55, 66 and 142 million tons, respectively and will reduce the total emissions by 21%, 25%, and 54% when implementing three different types of measures separately.

As shown in **Figure 10**, by 2060, the reduction effect of transportation structure adjustment and energy efficiency improvement will be further weakened, while the reduction effect of new energy application will be the most prominent. The emission reduction contribution of these three policies accounted for 10%, 15% and 75% respectively when implementing three different types of measures separately.

Under the dual-carbon policy scenario, electricity will gradually become the most important energy source. By 2035, the proportion of gasoline, diesel and aviation kerosene will be 16.6%, 35.2% and 13.1% respectively, and the proportion of clean energy such as electricity will increase to 34.2%. By 2040, electricity will become the main transportation energy, accounting for 41.5% and will continue to increase. By 2060, it will account for 72.8% and the proportion of hydrogen energy and biomass fuel will increase to 5.9% and 6.8% As shown in the **Figure 11**.

4.3 Radical Cenario

Under the radical scenario, the total carbon emissions from transportation are expected to peak around 2030, with peak carbon emissions of 1.26 billion tons, a 22.2% decrease from the peak in the baseline scenario. In 2050, 2055, and 2060, carbon emissions will drop to 350, 190 and 66 million tons, respectively, an 81.3% decline from 2050 to 2060 As shown in **Figure 12**.

In the radical scenario, by 2030, when different policy measures are adopted, as shown in **Figure 13**, it can be seen that the emission reduction effect of the three types of measures, will increase sequentially compared with the baseline, specially, will contribute 0.46, 0.61, and 93 million tons of emission reductions, and the emission reduction contribution ratios are 23%, 31%, and 47%, respectively. Compared with the dual-carbon policy scenario, in the peak emission year of the radical scenario, the contribution rate of new energy applications is slightly smaller. The main reason is that in 2030, the technology of some new energy delivery vehicles is immature and the penetration rate is relatively low.

By 2060, as shown in **Figure 14**, the reduction effect of policies such as transportation structure adjustment and energy efficiency improvement will be further weakened, and the emission reduction effect of new energy application will be the most prominent. The emission reductions are 110, 236, and 700 million tons, accounting for 11%, 23%, and 67% of the emission reduction contribution respectively. Compared with the dual-carbon policy scenario, the contribution of new energy applications in the radical scenario is slightly smaller, and the emission reduction from energy efficiency improvement is larger. The main reason is that in this scenario, in order to speed up the peak emission time of the transportation sector, the application of energy-saving and emission-reduction technologies for traditional fuel vehicles has been accelerated. Compared with the dual-carbon policy scenario, the emission reduction effect of the energy efficiency policy increases by 41.3%.

In the radical scenario, electricity will quickly become the dominant energy source. By 2030, the proportion of gasoline, diesel and aviation kerosene will be 21%, 34.7%, and 11.3%, respectively. The proportion of clean energy such as electricity will increase to 28.6%, and will reach 36.8% in 2035, becoming the most important source of energy consumption. By 2060, the proportion of clean energy will reach 75.4%, and hydrogen energy and biomass fuel will increase to 9.4% and 8.5%, while the traditional fuel will only account for 6.7% as shown in the **Figure 15**.

5 CONCLUSION AND DISCUSSIONS

Based on a scenario analysis of the total transportation demand in the transportation sector from 2020 to 2060, this paper quantitatively simulates the carbon emission reduction effects in the transportation of different policy measures under different scenarios, such as optimization of transportation structure, application of energy-saving and emission-reduction technologies, and new energy applications. The results show that the application of new energy applications and increase in freight efficiency pose the highest potential in reducing emissions in transport sector.

Based on the scenario analysis and results, we put forward several policy recommendations that may contribute to the "Dual-Carbon" target:

First of all, promote the cleanliness and low carbonization of transportation energy systems. Transportation vehicles account for a relatively high proportion of carbon emissions, especially for trucks, which account for more than 50% of carbon emissions in transportation sector. Therefore, it is necessary to promote clean energy vehicles, and take the lead in promoting the realization of fully electrification of urban public transport, and set a timetable for the withdrawal of traditional fossil energy vehicles. The government should continue to support breakthroughs in the research and development of key technologies for low carbonization of transportation equipment, and create a favorable market environment for the application of clean energy equipment through the improvement of systems, standards and norms. The government should also adopt a combination of finance and market policies to reduce new energy application costs and improve electric charging (replacement), hydrogen refueling and maintenance services.

Secondly, encourage green travel. The government and relevant institutions should carry out green transportation missions, strengthen citizens' environmental awareness, and let the residents participate in the construction of green transportation, encourage the public transportation to achieve green and environmental protection. Besides, create a high-quality, fast and diversified urban passenger transportation service system. To make public transport more attractive, it is necessary to promote quality public transportation, further increase the proportion of public transport vehicles in barrier-free cities and improve the passenger comfort, convenience and speed of transportation equipment. The introduction of commercial bus, travel bus, customized bus and other vehicle types will be necessary complements to adapt to increasingly diverse travel needs, making public transport a priority for people to travel, and constantly improve the share of public transport travel. In addition, the incentive of market measures, such as national green travel carbon credit system, should also be implemented. Specially, if residents adopt green travel, they can earn carbon credits, which can obtain corresponding economic benefits in the carbon emissions trading system.

Thirdly, increase the energy efficiency of freight. The government should improve the energy consumption limit standard for transportation vehicles and establish a vehicle carbon emission standard system. Accelerating the elimination of high-consumption and low-efficiency vehicles by economic compensation, strict supervision of excessive emissions, vehicle inspection and maintenance systems. Promoting vehicle energy-saving driving technology and publish best operating practices are also essential. The local government should incorporate energy-saving driving and energy-saving sailing as independent modules into driver (crew) training and examinations. Besides, the government should accelerate the application of smart transportation technologies. Cost-effective and intelligent transportation are key to modern freight logistics. The government and businesses need to improve the organization and intensification level of freight logistics so as to effectively reduce the empty driving rate by promoting the freight network platform and integrating of logistics resources. At the same time, the government could gradually popularize automatic vehicle driving technology and promote intelligent ship driving technology in pilot areas.

DATA AVAILABILITY STATEMENT

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

AUTHOR CONTRIBUTIONS

XW: conceptualized the study, analyzed the data and led drafting the manuscript. YZ: contributed to the drafting of the manuscript. QB: contributed to the data processing and analysis. ZC: contributed to the drafting and editing of the manuscript. BW: contributed to the drafting and reviewing of the manuscript.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2022.905037/full#supplementary-material

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The effects of drought on stock prices: An industry-specific perspective

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In this study, we examine the effect of drought on industry stock prices using a balanced panel of monthly data for 15 industries classified by China Securities Regulatory Commission in 2012. By combining the results of ordinary least squares (OLS) estimation and quantile regression models, we present a comprehensive evaluation of the relationship between drought and industry stock prices. The OLS regression results generally show that drought is negatively correlated with industry stock prices. However, quantile regression reveals that the effect of drought changes from positive to negative from the lowest to the highest stock price quantile. In addition, drought resistance capacity varies by industry. We further use threshold regression to determine the effects of investor sentiment on the relationship between drought and stock prices and identify two different regimes: low sentiment and high sentiment. In the low sentiment regime, drought has a significant negative effect on industry stock prices, while in the high sentiment regime, drought has a significant positive impact on industry stock prices.

KEYWORDS

drought, quantile regression, threshold regression, industry perspective, stock prices

Introduction

The global climate system is undergoing a major change characterized by global warming. Increasing climate change is becoming one of the main drivers of drought, as it speeds up the global water cycle, making wet areas wetter and dry areas drier (Wanders and Wada, 2015). Disintegrated planning, weak governance, and myopic water management can also lead to socioeconomic drought[1]. As a result, water resource management has become more important and difficult. Undoubtedly, a more detailed understanding of the economic impact of drought, including the identification of at-risk industries and the mechanisms contributing to drought hazards, are key steps toward a stronger risk-based approach to drought management. In a relatively efficient market, the

1 Socioeconomic drought refers to conditions whereby the water demand outstrips the supply, leading to societal, economic, and environmental impacts (Hayes et al., 2011; Zseleczky and Yosef, 2014).

impact of a disaster such as drought should be reflected by changes in short-run stock prices, which indicate market views on expected changes in the value of assets (Beatty and Shimshack, 2010; Balvers et al., 2017; Ding et al., 2022). In this study, the effect of drought is approached from the perspective of its effect on industry stock prices.

According to the Chinese Ministry of Water Resources, although China is rich in fresh water resources, its per-capita water resource level is only around a quarter of the global level. Consequently, China is one of 13 countries considered "water-poor" worldwide. This issue is exacerbated by the uneven distribution of China's water resources, which is characterized by greater water availability in southern areas but a higher distribution of cultivated land in northern areas. More than 400 of China's 660 cities face water shortages (i.e., two-thirds of cities have insufficient water supply)[2]. Regions across China exhibit significant cross-sectional variations in climate. Together with regional diversity, climate change has exacerbated the uneven distribution of water resources, thus increasing the disconnect between supply and demand in northern China and perpetuating regional drought in southern China. In addition, China is both a big agricultural country and an industrial country. Agriculture is most vulnerable to drought. Industrial production process is often accompanied by water pollution, which making the problem of drought and its impact more serious. A wrong or lack of intervention is likely to trigger socioeconomic drought. China's geographic vastness, distinct industrial and climatological features provide a unique setting for a study on the economic impact of drought in an Asian country and enable new insights.

Initially, we estimate drought trends using the Palmer Drought Severity Index (PDSI)[3], a widely used resource in climatology studies on drought (Palmer, 1965; Dai, 2011; Trenberth et al., 2014). Our sample comprises the monthly stock return data of 15 industries from 2000 to 2014. We then analyze the effect of drought by industry to account for industry heterogeneity, as this effect depends on both the industry's water demand and the upstream and downstream water demands. From the perspective of the capital market on the economic impact of drought, we successively examine the responses of stock prices in different quantiles and the role of investor sentiment. We mainly use the quantile regression model to study the effect of drought on the conditional distribution of industry stock prices. The weather-related literature reveals that climate factors can affect stock prices by influencing investor sentiment (Kamstra et al., 2000; Hirshleifer and Shumway, 2003; Kamstra et al., 2003; Lu and Chou, 2012; Schmittmann et al., 2015) and that investor sentiment can lead to asymmetric stock price reactions (Chen et al., 2013; Ni et al., 2015). Inspired by this earlier work, we introduce the threshold regression model and find a threshold effect of investor sentiment on the relationship between drought and industry stock prices.

The OLS regression results generally show that drought is negatively correlated with industry stock prices. However, quantile regression reveals that the effect of drought changes from positive to negative from the lowest to the highest stock price quantile. In addition, drought resistance capacity varies by industry. We further use threshold regression to determine the effects of investor sentiment on the relationship between drought and stock prices and identify two different regimes: low sentiment and high sentiment. In the low sentiment regime, drought has a significant negative effect on industry stock prices, while in the high sentiment regime, drought has a significant positive impact on industry stock prices.

This study makes two contributions to the literature. First, by using data from China, a unique setting, to analyze whether and how drought affects stock prices, we contribute to a poorly explored area of research on the effects of climatological factors, climate change, and environmental disasters on economic factors. Second, we present the first industry-wide analysis of the effects of drought on stock prices. Previous studies in this area mainly focus on specific industries, such as agriculture, mining, and real estate (Bonnafous et al., 2017; Farzanegan et al., 2019; Hong et al., 2019), which usually have large water demand and undoubtedly are affected directly by drought. The potential effects of drought on other industries have received little attention. Our study addresses this gap in the literature.

The remainder of this paper is organized as follows. Section 2 describes the channels from drought to industry stock prices. Section 3 presents our data. Section 4 includes an introduction and demonstration of the model and discussion of the empirical results. Section 5 presents the robustness test. The final section contains our concluding remarks.

Why does drought affect industry stock prices?

Drought has direct and indirect economic effects on agriculture and non-agriculture industries through soil moisture, rivers,

2 http://www.ches.org.cn/ches/kpyd/szy/201703/t20170303_879724.htm.

3 The Palmer Drought Index (PDSI) is based on the relationship between water supply and demand. A situation wherein the local water supply falls short of demand is defined as drought; otherwise, it is considered humid. Water supply data are relatively easy to obtain and are usually expressed by precipitation. In contrast, water demand calculations are more complex because they involve the influences of temperature, soil properties, land use, and other factors. To solve this problem, Palmer put forward the concept of "climatically appropriate for existing conditions," defined water demand as "climatically appropriate precipitation," and use the difference between actual precipitation and climatically appropriate precipitation to determine water profit and loss status. The PDSI considers not only the current water supply and demand but also the influence of previous dry and wet conditions and their durations on the current drought situation. Although this index is not perfect, it is the most widely used and readily available resource for climate studies (Alley, 1984).

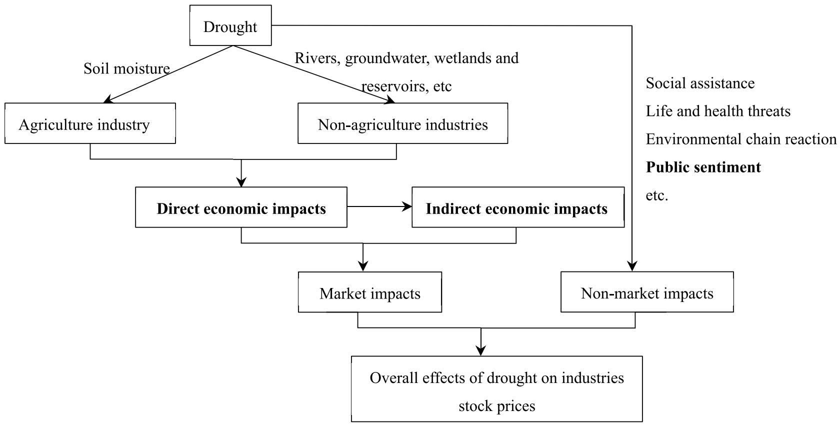

FIGURE 1
An overview of drought effects on industry stock prices.

groundwater, wetlands and reservoirs. In an efficient market, these effects will be reflected in industry stock prices. We call this phenomenon the market impacts of the drought on industry stock prices. From a non-market point of view, government departments and civil society organizations assist affect industries and individuals. For individuals, in addition to the risk of property loss, drought and the environmental chain reaction also brings threats to life and health. These consequences affect investor sentiment, which in turn feeds into risk-taking behavior and stock prices. In short, the effects of drought on industry stock prices can be divided into market and non-market levels. Among them, we focus on two more specific components, the economic impact and investor sentiment. Figure 1 is an overview of drought effects on industries stock prices.

A market-oriented perspective

It is a common practice in the literature to classify the economic effects of natural hazards, including drought into direct and indirect categories (Parker et al., 1987; Cochrane, 2004; Rose, 2004; Van der Veen, 2004). However, a unified and clear definition of the two categories is lacking. Defining the direct effects of drought as physical damage to buildings, crops and natural resources without considering large-scale economic damage does not meet the practical needs of drought economic impact assessment. Therefore, we follow Cochrane (2004), Rose (2004) and Ding et al. (2011) to expand the direct effects of drought to include both physical damage and consequences such as business disruption and unemployment. The indirect impacts are defined as the interaction between industries and the cost of transaction.

For direct effects, agriculture is the most vulnerable industry to drought. Inadequate soil moisture results in crop failure. The economic losses and distribution caused by negative supply shocks of agricultural products depend on the market structure and the supply-demand relations. Farmers can get compensation by buying insurance, or transfer economic losses through high prices. In extreme cases, they can even profit from drought. However, offsets are widespread across vast territories. That is, higher crop prices will attract the inflow of crops from non-arid areas, which curbing local crop prices increase.

Drought also has a direct economic impact on non-agricultural industries by affecting rivers, groundwater, wetlands and reservoirs. Utilities such as water management and water supply need to pay for a balance between supply and demand. In the tourism industry, the development space of forest, grassland, ice and snow, and wetland becomes smaller. The safety and accessibility of the shipping industry are threatened by the drying up of rivers. Other industries are more or less directly affected by drought due to water and environmental needs.

For indirect effects, the direct effects of drought on an industry spread upstream or downstream. In the shipping industry, for example, 2.93 billion tons of goods pass along the Yangtze River in 2019, including large quantities of iron ore, thermal coal and mining and construction materials[4]. Poor transportation of thermal coal will aggravate electricity shortage, while shortages of iron ore and mining materials will affect manufacturing, real estate and mining industries. The increase in raw material prices is expected to pass through the price transfer, but is also likely to cause a decline in income. Any form of economic losses will influence the economic decisions of

4 Website of the Ministry of Transport of the People's Republic of China: https://www.mot.gov.cn/.

market participants in the next stage, thus driving a new round of economic impacts.

A sentiment-oriented perspective

A number of psychological results show that natural disasters have a great influence on sentiment (Nolen-Hoeksema and Morrow, 1991; Krug et al., 1998; Jha et al., 2021). The space-time character of drought should be considered when analyzing its impacts on sentiment. Spatially, drought affects sentiment in arid area and non-arid area through different mechanisms. Direct and indirect gains and losses of assets, as well as life and health crises, may be the main channels through which drought affects the sentiment of arid communities (Bica et al., 2017). Finance can be the savior or the oppressor. Financial Insurance promotes risk-sharing, but insurance contracts and intermediaries are usually designed to prevent subsequent renegotiations (Diamond and Rajan, 2001; Agarwal et al., 2017). When uninsured disasters occur, economic losses are usually concentrated in a small group of people, leading to dissatisfaction and negative emotions (Chetty et al., 2020; Mongey et al., 2021). However, insurance measures may also be ineffective in compensating for property losses and mitigating negative sentiment. Gennaioli et al. (2020) show that insurance claims are often disputed and lead to non-payment or reduced payment. Government aid can act as a backstop and stabilize market sentiment (Jha et al., 2021). In addition, drought may have a positive emotional impact on those who profit from it, such as producers of drought resistance devices and farmers outside the disaster zone.

Social media has changed the way the public engages in disasters and other mass emergencies (Palen and Hughes, 2018). People outside the disaster area can easily communicate sentiment with people in the disaster area through social media, and get witness texts, photos, videos, maps and other information about the disaster. Bica et al. (2017) find that locals are more focused on human suffering and losses, while non-locals are more concerned about recovery and relief efforts. Individual orientations reflected by different positions and concerns produce different sentiments (Bravo-Marquez et al., 2014). Sentiment analysis through machine learning using social media data has become a popular topic in recent years. Yoo et al. (2018) argue that real-time generated content in social media includes information about social issues and events such as natural disasters. They developed the Polaris system to use the real-time information to analyze and predict the emotional trajectories of users. Neppalli et al. (2017) use Twitter data to visualize users' emotions around hurricanes, and then analyze their emotional communication.

From the timeline, public sentiment is evolving at different stages of disaster development. Gruebner et al. (2017) use social media data to surveilla New York population mental health after disasters. They find 24 sentiments spatial clusters. Among them, sadness and disgust are the most prominent sentiments. Anger, confusion, disgust and fear clusters appear pre disaster, surprise is found peri disaster, and sadness emerges post disaster. Han and Wang (2019) use microblog data to analyze people's sentiments during the flood in Shouguang City, China in 2018, and detect nine sentiments. They prove that these sentiments have different time trends.

The psychological literature shows that affective states induce emotional congruence bias in risk decision making, which is expressed as a preference for risk in positive sentiments, and risk aversion in negative sentiments (Yuen and Lee, 2003; Schulreich et al., 2014; Otto et al., 2016). This phenomenon is also fully supported by clinical observations. People with depression tend to ignore the positive aspects, while people with mania tend to ignore the potentially negative consequences of their actions (Beck, 2008; Edition, 2013; Huys et al., 2015). Inspired by this, behavioral economics and finance researchers have identified events that appear to affect asset prices, particularly stock prices, through their impacts on the affective state of investors. Edmans et al. (2007) find a significant stock market decline after soccer losses. Frieder and Subrahmanyam (2004) believe that stock prices are boosted by anticipation and optimism ahead of Patrick's Day and Rosh Hashanah. Lepori (2015) finds that endings of hit teleplay trigger negative emotions in viewers, leading to a drop in stock prices. Saunders (1993) confirms that weather-related sentiment has a significant effect on stock prices. The average stock price on a sunny day is higher than on a cloudy one. Bassi et al. (2013) provide further experimental evidence that sunshine and good weather promote risk-taking through sentiment channel.

In summary, the drought can affect industry stock prices through economic impact and investor sentiment. Given China's vast territory, people's complex positions and emotions, and the complex space-time nature of the drought, we cannot accurately predict the size and direction of drought impacts on industry stock prices. Therefore, it becomes a major problem to be studied in this paper. Another question we are interested in is whether the effects of drought vary depending on investor sentiment.

Data and variables

Sample selection and data sources

Our sample comprises a monthly balanced panel of data from 15 industries classified as follows by the China Securities Regulatory Commission in 2012: agriculture, forestry, animal husbandry, and fishery (AFAHF); mining (Min); manufacturing (Man); electricity, heat, gas, and water production and supply (EHGWPS); construction (Con); wholesale and retail (W&R); transportation, storage, and postal services (TSPS);

accommodation and catering (A&C); information transmission, software, and information technology services (ITS); finance (Fin); real estate (RE); leasing and business services (LBS); water, environment, and public facilities management (WEPFM); culture, sports, and entertainment (CSE); and comprehensive industry (Com). The data span the 2000–2014 period. Economic and financial data are obtained from the China Securities Market and Accounting Research database. As a quantitative measure of drought, PDSI data are taken from the website of the National Center for Atmospheric Research.

Variables

Industry stock return is the dependent variable and drought trend is the independent variable. We first calculate the industry stock return (*Indreturn*) by weighting the monthly stock return of A-share listed companies in a given industry by the circulating market value and subtracting the risk-free interest rate as follows:

$$Indreturn_{it} = \frac{\sum_n w_{nt} r_{nt}}{\sum_n w_{nt}} - R_t \tag{1}$$

where subscripts i, t, and n represent the industry, time, and number of companies in the industry, respectively. w_{nt} is the outstanding market value of stock *n* at time *t-1*. The monthly stock return of each company (r_{it}) is defined as the ratio of the comparable closing price on the last trading day of each month, considering the reinvestment of cash dividends, to the corresponding value of the previous month, minus 1. The risk-free rate (R_t) is based on the 3-month time deposit rate. The industry classification of each company follows the industry classification rules set by the China Securities Regulatory Commission (CSRC) in 2012. We set the following two types of company stock returns as missing values: stocks whose prices rise by 300% or more in 1 month and fall by 50% or more in the next month (rise and then fall), and stocks whose prices have risen by more than 1000% in a month. Finally, all stock prices are winsorized at the 1st and 99th percentiles to reduce the impact of outliers on our results. We focus on A-shares because they account for 99.5% of total market capitalization; in contrast, B-share stocks are small and illiquid. The circulation market value-weighted return heavily weights large and more liquid stocks, which alleviates the disturbance caused by outlying small firms.

As the drought trend (*Trend*) is calculated based on the PDSI index, it is beneficial to understand the ranges and trends of the PDSI values at the sample sites. The PDSI usually falls between −4 and 4; values greater than 0 indicate the degree of moisture, while lower values indicate the degree of dryness. Table 1 presents the correspondence between the PDSI values and drought severity. Figure 2 plots the time series of monthly PDSI values for China from 1930 to 2014 with a fitted trend line. The PDSI fluctuates violently within a range of roughly −6 to 6. The downward-sloping fitted trend line indicates the increasing drought trend in China. The average PDSI from 1930 to 2014 is −1.096, compared with −2.774 during the sample period of 2000–2014; thus, the drought situation in China has changed from slight to moderate drought. Together with the short-term violent fluctuations, these data demonstrate that China is affected by long-term drought and threatened by short-term floods.

We focus on the impact of the long-term drought trend because it has greater economic value and policy guidance implications. Following Hong et al. (2019), we measure *Trend* as

$$PDSI_t = a + bt + cPDSI_{t-1} + \varepsilon. \tag{2}$$

This AR(1) model is augmented with a deterministic time trend *t*. The coefficient *b* of the deterministic time trend is the parameter of interest that captures the long-term drought trend. We define *Trend* as equal to *b*. A smaller value of *Trend* indicates a more serious long-term drought trend. The recursive window method is applied to estimate the above model. $Trend_t$ is estimated using PDSI data from January 1990 to month *t*. In addition to considering the impact of quarterly precipitation differences, we use two alternative measures of drought in the robustness test. One measure is the drought index calculated based using the entire Box–Jenkins iterative process; the other is the lag period drought index.

We introduce some control variables according to the actual situation and the relevant theoretical model. First, we include the 36-month moving average PDSI (*PDSI36*) in the control variables to capture the short-term drought effect. As shown in Figure 2, China faces long-term drought problems but short-term flood hazards.

Our analysis of industry stock prices is based mainly on the Fama–French three-factor model. Therefore, we add the market factor (*RP*), the size factor (*SMB*), and the book-to-market factor (*HML*) to the control variables.

RP is the difference between the monthly A-share market return and the monthly risk-free interest rate. The monthly market return rate is calculated using the weighted average method for the market value of circulation, and cash dividend reinvestment is considered.

SMB is the difference between the monthly returns of a small-cap stock portfolio and a large-cap stock portfolio. Portfolio division is based on the Fama 2 × 3 portfolio division method. The monthly return of the portfolio is calculated using the weighted market value of circulation.

HML is the difference between the monthly returns of a combination of the high book-to-market ratio and the low book-to-market ratio. The portfolio division is based on the

TABLE 1 The correspondence between PDSI values and drought degree.

PDSI value	Drought degree	PDSI value	Drought degree
≤−4	Extreme drought	0.5–1	Initial moisture
−4 to −3	Severe drought	1–2	Slight moisture
−3 to −2	**Moderate drought**	2–3	Moderate moisture
−2 to −1	Slight drought	3–4	Heavy moisture
−1 to −0.5	Initial drought	≥4	Extreme moisture
−0.5 to 0.5	normal		

This table reports the correspondence between PDSI values and drought degree. The bold part shows the drought situation of our sample period.

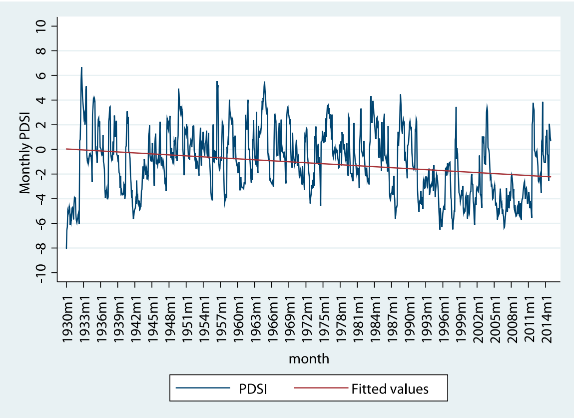

FIGURE 2
Historical PDSI for China. This figure plots the time series of monthly PDSI value for China. The sample period is from January of 1930 to December of 2014. The PDSI value is displayed on the blue line. The red line is the fit line.

Fama 2 × 3 portfolio division method. The monthly return of the portfolio is calculated using the weighted market value of circulation.

Summary statistics

Table 2 describes the statistical results, including the means, medians, standard deviations, skewness, kurtosis, and results of tests of normal distribution and stability. These data are intended to facilitate a preliminary understanding of the properties and distribution of industry stock returns and the key variables used in this study. As shown in Table 2, stock returns in various industries have similar statistical characteristics, and mean industry stock prices and associated SDs fluctuate widely. All of the stock return series are fat-tailed and right-skewed, suggesting asymmetry. The Jarque–Berra test provides further evidence that the stock returns in nearly all industries are not normally distributed. The last column of Table 2 presents the results of the augmented Dickey–Fuller test. All of the time series, including *Trend* and *PDSI36*, are stationary.

Empirical results

Degree and structure of dependence

We use the classical ordinary least-squares (OLS) multiple linear model and quantile regression model to examine the effect of drought on stock prices by industry. The basic model is as follows:

$$y_t = a + bx_t + \varepsilon_t, \tag{3}$$

where y_t represents the industry stock return $(indreturn_t)$ and x_t is a vector consisting of the explanatory variable $(Trend_t)$ and the control variables mentioned above.

The OLS method gives the conditional mean of the target variable as

$$E(y_t|x_t) = a + bx_t. \tag{4}$$

The conditional expectation $E(y_t|x_t)$ indicates the concentrated trend of the conditional distribution of $y_t|x_t$; however, we focus on the influence of $Trend_t$ on the whole conditional distribution of $y_t|x_t$.

Quantile regression, as proposed by Koenker and Bassett (1978), provides comprehensive information about the conditional distribution of $y_t|x_t$. For a given x_t, the conditional quantile function y_t at quantile τ is defined as

$$Q_\tau(y_t|x_t) = a_\tau + b_\tau x_t + F_{\varepsilon_t}^{-1}(\tau), \tag{5}$$

where F_{ε_t} is the distribution function of the error term ε_t. The estimated coefficient $\widehat{b_\tau}$ of the quantile regression is given by the following function:

$$\widehat{b_\tau} = arg \min_{a_\tau, b_\tau \in \mathbb{R}} \sum\nolimits_{t=1}^{T} \rho_\tau(y_t - (a_\tau + b_\tau x_t)), \tag{6}$$

where T is the sample size and ρ_τ is the check function, defined as $\rho_\tau(\varepsilon) = (\tau - 1)\varepsilon$ if $\varepsilon < 0$ and $\rho_\tau(\varepsilon) = \tau\varepsilon$ otherwise. Because the

TABLE 2 Summary statistics.

Industry	*N*	Min	Mean	Med	Max	Std	Skew	Kurt	JB	ADF
AFAHF	180	−0.262	0.015	0.008	0.256	0.097	0.151	3.112	0.780	−2.362***
Min	180	−0.286	0.019	0.011	0.300	0.097	0.214	3.965	8.368**	−4.319***
Man	180	−0.239	0.019	0.020	0.301	0.087	0.078	3.771	4.644*	−3.706***
EHGWPS	180	−0.223	0.014	0.010	0.364	0.087	0.385	4.752	27.462***	−4.216***
Con	180	−0.235	0.014	0.012	0.386	0.098	0.590	4.285	22.845***	−3.139***
W&R	180	−0.250	0.018	0.012	0.323	0.091	0.274	3.720	6.135**	−3.262***
TSPS	180	−0.253	0.013	0.010	0.257	0.083	0.129	3.949	7.257**	−3.759***
A&C	180	−0.297	0.016	0.010	0.295	0.101	0.169	3.151	1.028	−3.148***
ITS	180	−0.256	0.016	0.011	0.358	0.089	0.223	4.452	17.318***	−3.184***
Fin	180	−0.272	0.014	0.008	0.357	0.096	0.559	4.730	31.824***	−3.614***
RE	180	−0.261	0.019	0.011	0.364	0.103	0.529	4.161	18.498***	−4.162***
LBS	180	−0.222	0.018	0.013	0.274	0.090	0.230	3.172	1.805	−4.043***
WEPFM	180	−0.234	0.012	0.006	0.440	0.097	0.798	5.422	63.104***	−3.629***
CSE	180	−0.279	0.019	0.007	0.382	0.115	0.361	3.693	7.518**	−5.549***
Com	180	−0.239	0.016	0.012	0.400	0.098	0.332	3.968	10.328***	−3.766***
Trend	180	−0.378	−0.096	−0.090	0.116	0.115	−0.801	2.936	289.520***	−2.800***
PDSI36	180	−4.578	−3.093	−3.434	−0.279	1.233	0.564	2.064	241.750***	−2.090**

This table reports the summary statistics of each industries' stock returns and drought related indicators, including the means, medians, SDs, skewness, kurtosis, and results of tests of normal distribution and stability. Our sample period is 2000–2014. The 15 industries are Agriculture, forestry, animal husbandry and fishery (AFAHF); Mining (Min); Manufacturing (Man); Electricity, heat, gas and water production and supply (EHGWPS); Construction (Con); Wholesale and retail (W&R); Transportation, storage and postal services (TSPS); Accommodation and catering (A&C); Information transmission, software and information technology services (ITS); Finance (Fin); Real estate (RE); Leasing and business services (LBS); Water, environment and public facilities management (WEPFM); Culture, sports, and entertainment (CSE); Comprehensive industry (Com). JB is the Jarque-Berra test statistic, and the null hypothesis of the test is that variables obey normal distribution. ADF is the augmented Dickey-Fuller test statistic, and the null hypothesis of this test is that unit roots exist. ***, ** and * imply the rejection of the null hypothesis in the case at 1, 5 and 10% levels of significance, respectively.

objective function of quantile regression cannot be differentiated, we usually use the linear programming method to calculate $\widehat{b_\tau}$. Furthermore, we apply a bootstrap method to estimate the quantile regression model, thus avoiding the hypothesis of identically distributed errors and accounting for heteroscedasticity.

Table 3 reports our empirical results. Column (1) presents the results of the OLS estimation and columns (2) to (8) list the results of the quantile regression estimation. For brevity, we report only the coefficients of *Trend*. Notably, the OLS and quantile regression estimations are distinct, with relatively fewer significant values in the OLS regression. We first focus on column (1). Among the 15 coefficients of *Trend*, only one is negative and is not significant. However, 4 of the 14 positive coefficients are significant. Because *Trend* is negatively correlated with the degree of drought, positive coefficients of *Trend* indicate that drought poses downside risks to stock prices in various industries, with significant risks in the AFAHF, Man, Fin, and WEPFM industries. A study by the National Academy of Sciences (1999) classifies the effects of drought as direct, such as "physical destruction of buildings, crops and natural resources," and indirect, such as "consequences of such destruction, such as temporary unemployment and business disruption." The Man, WEPFM, and particularly AFAHF industries have high water demand and are more directly affected by drought (Deschênes and Greenstone, 2007). In contrast, the effect of drought on the Fin industry reflects more indirect costs related to drought-related business disruptions and backward and forward multiplier economic effects, such as non-performing loans.

Quantile regressions can comprehensively reveal the effect of drought on industry stock prices. Columns (2) to (8) of Table 3 reveal that in addition to the four industries listed above, another six industries are affected by drought to various degrees. The strongest effects are observed in the RE and LBS industries, which are both widely associated with other industries. The RE industry is affected by many upstream industries, such as steel, cement, machinery, and home decoration. The LBS industry affects many downstream industries because it includes a wide range of areas, such as business management services, legal consulting, market management, advertising services, conferences and exhibitions, and other business services. As a result, these industries are affected more severely by droughts through subtle, indirect mechanisms involving industrial chains.

Lines 4, 7, and 8 of Table 3 demonstrate that drought does not significantly affect the EHGWPS, TSPS, and A&C industries. This phenomenon may be attributable to various factors, including an active governmental intervention policy and the nature of company ownership. As mentioned above, China's drought problem is local, not global; dry and wet conditions not

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TABLE 3 Coefficients of Trend in OLS and quantile regressions by industry.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	QR05	QR10	QR25	QR50	QR75	QR90	QR95	*N*
AFAHF	**0.073****	**−0.090**	**−0.056**	**0.017**	**0.055****	**0.111****	**0.236*****	**0.308*****	**5**
	(0.035)	**(0.064)**	**(0.045)**	**(0.033)**	**(0.026)**	**(0.045)**	**(0.059)**	**(0.071)**	
Min	0.009	−0.022	−0.028	0.026	0.019	0.002	−0.010	−0.030	0
	(0.032)	(0.043)	(0.040)	(0.033)	(0.042)	(0.055)	(0.068)	(0.103)	
Man	**0.043****	**−0.017**	**0.013**	**0.009**	**0.042***	**0.047****	**0.090*****	**0.110*****	**5**
	(0.018)	**(0.045)**	**(0.033)**	**(0.016)**	**(0.023)**	**(0.020)**	**(0.025)**	**(0.040)**	
EHGWPS	0.019	−0.021	−0.030	−0.015	−0.014	−0.0005	0.086	0.095	0
	(0.032)	(0.050)	(0.046)	(0.037)	(0.031)	(0.042)	(0.074)	(0.073)	
Con	0.056	0.026	−0.054	0.002	0.063*	0.053	0.086	0.078	1
	(0.036)	(0.066)	(0.055)	(0.031)	(0.036)	(0.052)	(0.124)	(0.140)	
W&R	0.018	−0.033	−0.036	−0.005	−0.004	0.044*	0.062	0.070	1
	(0.026)	(0.037)	(0.030)	(0.025)	(0.021)	(0.023)	(0.053)	(0.062)	
TSPS	0.014	−0.092	−0.058	−0.028	−0.010	0.030	0.025	0.075	0
	(0.029)	(0.099)	(0.050)	(0.023)	(0.022)	(0.033)	(0.071)	(0.090)	
A&C	0.019	0.090	−0.003	0.010	0.018	0.029	−0.007	−0.036	0
	(0.033)	(0.065)	(0.042)	(0.040)	(0.033)	(0.055)	(0.088)	(0.091)	
ITS	**0.056**	**−0.017**	**−0.007**	**0.031**	**0.083*****	**0.119****	**0.178***	**−0.027**	**3**
	(0.036)	**(0.047)**	**(0.036)**	**(0.027)**	**(0.031)**	**(0.048)**	**(0.102)**	**(0.187)**	
Fin	**0.054***	**0.092***	**0.063**	**0.080***	**0.074***	**0.015**	**0.013**	**−0.043**	**4**
	(0.030)	**(0.053)**	**(0.061)**	**(0.045)**	**(0.044)**	**(0.049)**	**(0.058)**	**(0.072)**	
RE	**−0.004**	**−0.208*****	**−0.155*****	**−0.090*****	**−0.034**	**0.058**	**0.168****	**0.260*****	**5**
	(0.043)	**(0.055)**	**(0.038)**	**(0.032)**	**(0.031)**	**(0.037)**	**(0.080)**	**(0.096)**	
LBS	**0.029**	**−0.100***	**−0.080***	**−0.031**	**0.021**	**0.095****	**0.157*****	**0.219*****	**5**
	(0.036)	**(0.054)**	**(0.046)**	**(0.040)**	**(0.032)**	**(0.037)**	**(0.057)**	**(0.072)**	
WEPFM	**0.087****	**0.049**	**0.064**	**0.091****	**0.067***	**0.054**	**0.082**	**0.0005**	**3**
	(0.037)	**(0.126)**	**(0.060)**	**(0.044)**	**(0.037)**	**(0.054)**	**(0.112)**	**(0.213)**	
CSE	0.070	0.040	−0.025	0.035	0.060	0.003	0.198	0.396***	1
	(0.059)	(0.122)	(0.093)	(0.060)	(0.052)	(0.096)	(0.132)	(0.145)	
Com	0.033	0.003	0.049	−0.017	0.009	0.041	0.049	0.089	0
	(0.027)	(0.060)	(0.053)	(0.037)	(0.029)	(0.038)	(0.048)	(0.075)	
N	4	3	2	3	6	5	5	5	

This table reports the OLS and quantile regression results of monthly stock returns on the long-term trend of drought by industry. Our sample period is 2000–2014. To save space, we only report the coefficients of *Trend*. From left to right column are the regression results of OLS and quantile regression models on the 5, 10, 25, 50, 75, 90 and 95 quantiles. The rightmost column and the bottom row count the number of significant coefficients by row and column, respectively. The bold part are the industries significantly affected by drought, i.e. there are at least three coefficients of *Trend* are significant in OLS regression and quantile regressions. Numbers in parentheses are standard errors. *, ** and *** denote statistical significance at 10, 5 and 1%, respectively.

only follow an uneven spatial distribution but also a highly variable temporal distribution. To address this long-term imbalance in water resource distribution and complement current resources, the government has developed the South-to-North Water Diversion and West-to-East Electricity Transmission projects. The construction of reservoirs, desalination of seawater, prevention and control of water pollution, and protection of the environment have also effectively enhanced the resilience of these industries to drought. Furthermore, resources considered vital to livelihoods and the economy, such as water, electricity, and transportation, are mostly controlled by the state, and thus the stock prices in these industries are more strongly influenced by national policies. The food industry also is not significantly affected by drought for several reasons. First, the allocation of water resources can alleviate the problem of food production at its source. Second, national grain reserves and imported food supplies can be used as needed to address food shortages. Third, policies to control food prices can prevent excessive inflation.

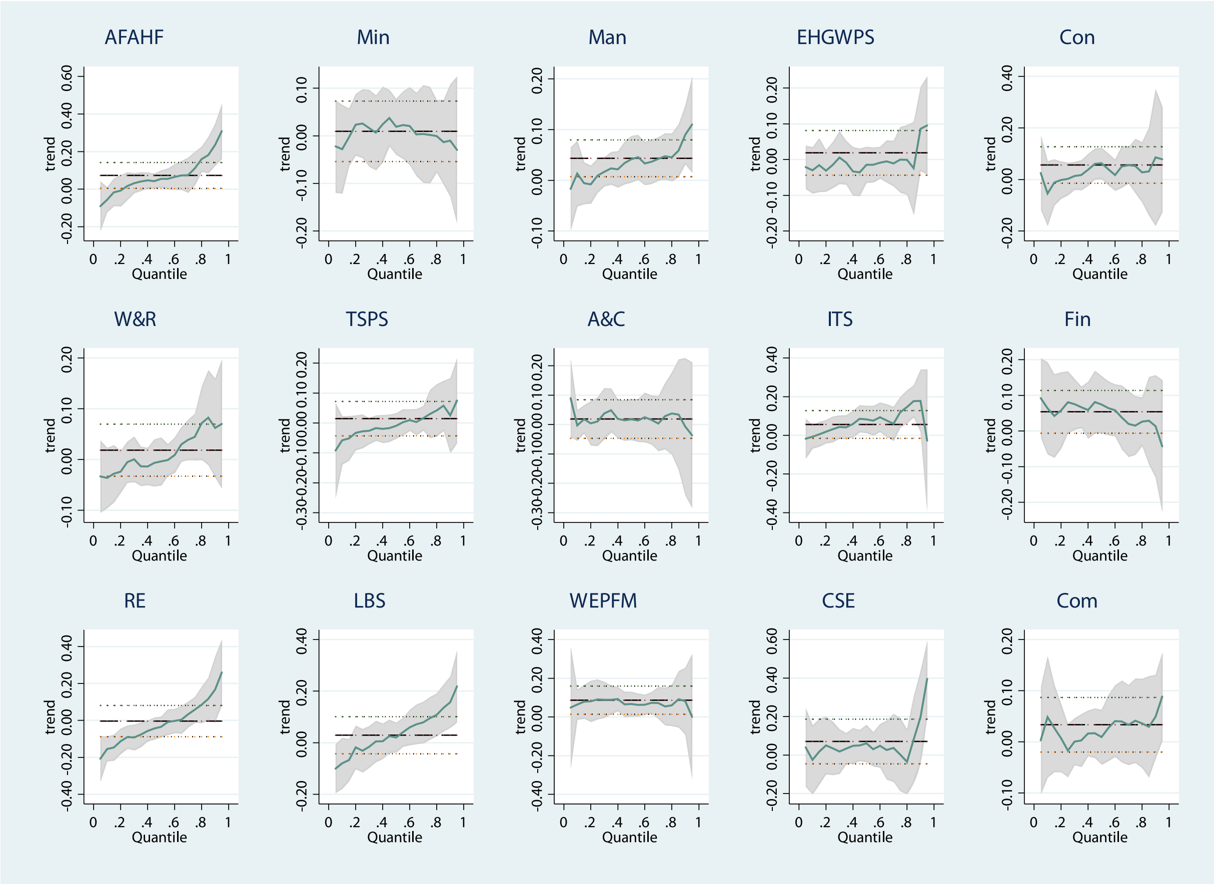

FIGURE 3
Quantile slope coefficients of *Trend*. The blue line is the coefficient values of *Trend*, and the shadow is the corresponding 95% CI. The dotted line is the coefficient value of ordinary least square estimation of *Trend* and its corresponding 95% CI.

The coefficients of *Trend* tend to change from negative to positive from the lowest to the highest stock price quantile. In high quantiles, however, the marginal effect is usually significant. We conclude that co-movement tends to exist in booming markets with high expected returns. A long-term drought trend is not conducive to economic prosperity.

Figure 3 plots changes in the coefficients of *Trend* across quantiles by industry. The 95% confidence interval is indicated by shading. The shift in the basic shape from negative to positive in Figure 3 confirms the overall trend of the coefficients in Table 3. For all industries, the 95% CI widens at both ends of the conditional distribution, indicating that the estimated coefficients are less accurate. The estimated OLS coefficients and 95% CIs (indicated by the dotted line) again demonstrate the superior ability of quantile regression to fully explore the relationship between drought and industry stock prices.

Quantile regression can reveal the effect of drought on the conditional distribution of industrial stock returns. However, a study of the effect of the degree of drought on industrial stock prices is also interesting and can provide more information about the dependence and structure of the relationship between these variables. We build model (7) as follows:

$$\text{Indreturn}_t = \alpha_0 + \beta_1 Trend_t + \beta_2 Dum_t + \boldsymbol{\theta}' \boldsymbol{x}_{it} + \varepsilon_{it}, \qquad (7)$$

where subscript t represents the month and $\boldsymbol{x}_{it}$ represents the control variables, which include $PDSI36_t$, RP_t, SMB_t, and HML_t. Dum_t is a dummy variable that equals 1 when the PDSI of month t is smaller than the mean PDSI of the sample period from January 1990 to month t, and 0 otherwise. Thus, a Dum_t value of 1 represents drought conditions that are more severe than the historical average (i.e., extreme).

Table 4 shows the regression results produced by model (7), classified by industry. In all industries, the coefficients of *Trend* remain positive, again proving that a trend of long-term drought is not conducive to an increase in industry stock prices, as shown in Table 3. However, a discussion of Table 4 should focus on the coefficient estimates of Dum_t, which are negative but not significant in only 2 of 15 industries. In contrast, 6 of the

TABLE 4 The impact of different degrees of drought on industry stock price.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	AFAHF	**Min**	**Man**	**EHGWPS**	**Con**	**W&R**	**TSPS**	**A&C**	**ITS**	**Fin**	**RE**	**LBS**	**WEPFM**	**CSE**	**Com**
Trend	0.079**	0.038	0.061***	0.021	0.082**	0.041	0.029	0.043	0.058	0.052	0.017	0.051	0.092**	0.074	0.032
	(0.037)	(0.034)	(0.019)	(0.034)	(0.038)	(0.027)	(0.031)	(0.035)	(0.039)	(0.032)	(0.046)	(0.039)	(0.040)	(0.063)	(0.029)
Dum	0.004	0.017**	0.010**	0.001	0.015*	0.014**	0.009	0.014*	0.001	−0.001	0.012	0.013*	0.003	0.002	−0.001
	(0.008)	(0.007)	(0.004)	(0.007)	(0.008)	(0.006)	(0.007)	(0.007)	(0.008)	(0.007)	(0.010)	(0.008)	(0.008)	(0.013)	(0.006)
PDSI36	−0.006*	−0.005	−0.004**	−0.002	−0.001	0.001	0.003	0.002	0.001	−0.004	0.002	0.003	−0.003	−0.001	−0.002
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.006)	(0.003)
RP	0.921***	1.091***	0.981***	0.920***	1.035***	0.963***	0.912***	0.941***	0.890***	1.058***	1.099***	0.917***	0.990***	0.939***	1.036***
	(0.041)	(0.037)	(0.021)	(0.037)	(0.042)	(0.030)	(0.034)	(0.039)	(0.043)	(0.036)	(0.050)	(0.043)	(0.044)	(0.070)	(0.032)
SMB	0.741***	−0.343***	0.432***	0.239***	0.296***	0.511***	0.123**	0.859***	0.410***	−0.625***	−0.101	0.309***	0.451***	0.808***	0.631***
	(0.068)	(0.062)	(0.035)	(0.062)	(0.069)	(0.050)	(0.057)	(0.064)	(0.071)	(0.059)	(0.084)	(0.071)	(0.072)	(0.115)	(0.053)
HML	−0.256**	0.092	−0.116**	0.466***	0.278**	−0.234***	0.133	−0.232**	−0.304***	0.047	−0.413***	−0.387***	−0.170	−0.195	−0.175**
	(0.111)	(0.101)	(0.058)	(0.101)	(0.113)	(0.082)	(0.093)	(0.105)	(0.116)	(0.097)	(0.136)	(0.116)	(0.118)	(0.188)	(0.086)
Constant	−0.010	−0.011	−0.004	−0.003	−0.004	0.005	0.010	0.004	0.016*	0.004	0.014	0.017*	−0.001	0.008	0.003
	(0.010)	(0.009)	(0.005)	(0.009)	(0.010)	(0.007)	(0.008)	(0.009)	(0.010)	(0.008)	(0.012)	(0.010)	(0.010)	(0.016)	(0.007)
N	180	180	180	180	180	180	180	180	180	180	180	180	180	180	180
R-squared	0.806	0.841	0.936	0.800	0.801	0.880	0.817	0.838	0.749	0.849	0.742	0.758	0.779	0.606	0.885

This table reports the regression results of different degrees of drought and industry stock prices. Our sample period is 2000–2014. Dum_t is a dummy variable. When the PDSI index of month t is smaller than the mean of PDSI index of the sample period from January 1990 to month t, it is 1, otherwise it is 0. In this way, a value of 1 for Dum_t represents extreme drought conditions that are more severe than the historical average. The last two rows show the goodness of fit and sample size. Numbers in parentheses are SEs. *, ** and *** denote statistical significance at 10, 5 and 1%, respectively.

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13 positive coefficient estimates are significant, corresponding to Min, Man, Con, W&R, A&C, and LBS. These regression results show that extreme drought drives up stock prices in these industries, possibly because of market speculation. The PDSI index trend in Figure 2 suggests that China faces frequent droughts and floods, and extreme droughts usually do not persist. Furthermore, the literature proposes that stock prices have the characteristics of mean reversion (Kim et al., 1991; Barberis et al., 1998; Gropp, 2004). In a drought, industry stock prices fall as climatological conditions worsen. When either drought conditions or stock prices reach a certain threshold, investors expect an immediate reversal and increase their investment, leading to a positive correlation between extreme drought and industry stock prices.

Regimes of investor sentiment

The results of quantile regression show that drought has a complex effect on industry stock returns. This relationship may be affected not only by fundamental factors but also by irrational factors, such as investor sentiment. The signs of the coefficients of *Trend* in each quantile are inconsistent, indicating that the relationship between drought and industry stock returns may be nonlinear due to variable investor sentiment. Therefore, we consider the threshold effect of investor sentiment. To avoid error caused by an artificial division of the investor sentiment interval, we use the threshold panel model developed by Hansen (1999). This model can be used to specify the threshold variable, namely investor sentiment, and endogenously divide the intervals according to the characteristics of the data, allowing a study of the relationship between drought and industry stock returns in different sentiment regimes.

We first focus on a single threshold model and expand it to a multi-threshold model. The single threshold model is set as follows:

$$\begin{aligned}\mathrm{Indreturn}_{\mathrm{it}} = \alpha_{\mathrm{i}} + \boldsymbol{\theta}'\boldsymbol{x}_{it} + \delta_1 \mathrm{Trend}_{\mathrm{t}} \mathrm{I}(\mathrm{TO}_{\mathrm{it}} \le \tau_1) \\ + \delta_2 \mathrm{Trend}_{\mathrm{t}} \mathrm{I}(\mathrm{TO}_{\mathrm{it}} > \tau_1) + \varepsilon_{it}.\end{aligned} \tag{8}$$

Unlike the empirical evidence above, our threshold model (8) is based on panel data of industry stock returns: subscript i represents the various industries and t is the month. $Indreturn_{it}$ and $Trend_t$ remain the dependent and independent variables, respectively. $\boldsymbol{x}_{it}$ represents the control variables, including $PDSI36_t$, RP_t, SMB_t, and HML_t. TO_t is the threshold variable that represents investor sentiment. Following Baker et al. (2012) and Huang et al. (2015), we use the turnover rate to measure investor sentiment, given the positive correlation between these variables. τ_1 is a specific threshold value and $I(\cdot)$ is an indicator function. Finally, α_i reflects the individual effects of the industry, such as the life cycle, location preference, natural ecological attributes, and other unobservable factors. Of these industry effects, the natural ecological attributes are not easily changed in a short time. Some industries exist harmoniously with nature, whereas others inevitably cause harm to the environment. For example, the mining industry tends to pollute water and damage vegetation, thereby increasing the probability of drought. Various government departments have imposed environmental protection requirements on the mining industry. These policies have increased production costs in this industry, which are ultimately reflected in stock prices. To address these variations, we study the threshold effect of investor sentiment using an individual fixed effect model that can control the effects of unobservable factors, such as natural ecological attributes, that are difficult to change in the short term but can affect both drought and stock returns.

To obtain the parameter estimator, we subtract the intra-group mean from each observation to eliminate the individual effect α_i. The transformed model is as follows:

$$\begin{aligned}Indreturn^*_{it} = \delta_1 \mathrm{Trend}^*_t \mathrm{I}(\mathrm{TO}_{\mathrm{it}} \le \tau_1) + \delta_2 \mathrm{Trend}^*_t \mathrm{I}(\mathrm{TO}_{\mathrm{it}} > \tau_1) \\ + \boldsymbol{\theta}'\mathbf{x}^*_{it} + \varepsilon^*_{it}.\end{aligned} \tag{9}$$

Coefficients δ_1 and δ_2 correspond to the different regimes. Given the threshold value τ_1, we can obtain the parameter estimates $\hat{\delta}_1(\tau_1)$ and $\hat{\delta}_2(\tau_1)$ and the residual sum $\mathrm{SSR}(\tau_1)$ of model (9). Finally, by minimizing $\mathrm{SSR}(\tau_1)$, we obtain the estimated value $\hat{\tau}_1$ and parameters $\hat{\delta}_1(\hat{\tau}_1)$ and $\hat{\delta}_2(\hat{\tau}_1)$. Next, we perform two tests to determine whether the threshold effect is significant and whether the estimated threshold value is equal to the actual value. For the first test, the null hypothesis states that there is no threshold effect, H_0: $\delta_1 = \delta_2$, and the corresponding alternative hypothesis is H_1: $\delta_1 \ne \delta_2$. The test statistic is

$$\mathrm{F} = \frac{SSR^* - \mathrm{SSR}(\hat{\tau}_1)}{\hat{\sigma}^2}, \tag{10}$$

where SSR^* is the square sum of the residuals of the model under the null hypothesis. $\hat{\sigma}^2 = \frac{\mathrm{SSR}(\hat{\tau}_1)}{\mathrm{n}(\mathrm{T}-1)}$ is the uniform estimation of the variance of the disturbance term, n is the sample size, and T is the length of time. The larger the value of $SSR^* - \mathrm{SSR}(\hat{\tau}_1)$, the more SSR increases with constraints; further, the likelihood of rejection of the null hypothesis H_0: $\delta_1 = \delta_2$ increases. Under the null hypothesis, the threshold value τ_1 is unrecognizable, so the F statistic has a nonstandard distribution. The bootstrap method can be used to obtain the asymptotic distribution and p value. For the second test, the null hypothesis states that the estimated threshold value is equal to its actual value, H_0: $\hat{\tau}_1 = \tau_0$. The corresponding likelihood ratio test statistic is

$$LR(\tau_1) = \frac{\mathrm{SSR}(\tau_1) - \mathrm{SSR}(\hat{\tau}_1)}{\hat{\sigma}^2}. \tag{11}$$

If $\hat{\tau}_1 = \tau_0$ is true, then the statistic also has a nonstandard distribution. However, its cumulative distribution function is

TABLE 5 Threshold effect test of investor sentiment.

	H0	H1	Fstat	Prob	Crit10	Crit5	Crit1
Full sample	Liner	Single	35.84	0.000	11.677	15.046	21.742
	Single	Double	23.71	0.100	23.542	34.303	55.909
The first subsample	Liner	Single	29.44	0.000	11.107	13.747	22.221
	Single	Double	7.23	0.623	21.153	25.245	38.709
The second subsample	Liner	Single	18.23	0.003	9.593	12.784	16.304
	Single	Double	8.79	0.277	12.311	14.852	20.673

This table reports the threshold effect test results of investor sentiment in three samples. Our sample period is 2000–2014. The full sample is the monthly stock return panel data of 15 industries. The first subsample includes industries significantly affected by drought, i.e. there are at least three coefficients of *Trend* are significant in OLS regression and quantile regression in Table 3. The other industries are included in the second subsample. This table shows the original hypothesis, alternative hypothesis, F statistic, probability value, and critical values at 10, 5 and 1% from left to right columns.

TABLE 6 Threshold regression results of investor sentiment.

	Full sample		The first subsample		The second subsample	
	Liner	Single	Liner	Single	Liner	Single
Trend	0.039***	0.034***	0.048***	0.042***	0.030***	0.024***
	(0.007)	(0.006)	(0.011)	(0.011)	(0.008)	(0.006)
		−0.288***		−0.356**		−0.109***
		(0.075)		(0.097)		(0.029)
PDSI36	−0.002*	−0.0004	−0.002	−0.0001	−0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
RP	0.985***	0.977***	0.984***	0.972***	0.986***	0.965***
	(0.018)	(0.017)	(0.030)	(0.029)	(0.024)	(0.023)
SMB	0.313**	0.304**	0.229	0.215	0.387**	0.383**
	(0.108)	(0.107)	(0.171)	(0.169)	(0.141)	(0.139)
HML	−0.116*	−0.103	−0.243***	−0.225**	−0.005	0.029
	(0.065)	(0.066)	(0.065)	(0.069)	(0.095)	(0.090)
Constant	0.005**	0.007***	0.007	0.010**	0.004	0.009**
	(0.002)	(0.002)	(0.004)	(0.003)	(0.002)	(0.003)
Threshold		**52.3**		**52.0**		**21.9**
95% CI		[50.5, 53.7]		[50.7, 55.6]		[20.6, 22.0]
R^2	0.739	0.743	0.739	0.746	0.743	0.747
N	2700	2700	1260	1260	1440	1440

This table reports the linear and threshold regression results of investor sentiment in three samples. Our sample period is 2000–2014. The full sample is the monthly stock return panel data of 15 industries. The first subsample includes industries significantly affected by drought, i.e. there are at least three coefficients of *Trend* are significant in linear regression and quantile regression in Table 3. The other industries are included in the second subsample. The last four rows show the threshold value, 95% CI of the threshold value, goodness of fit and sample size. Numbers in parentheses are SEs. *, ** and *** denote statistical significance at 10, 5 and 1%, respectively.

$(1 - e^{-x/2})^2$, so its critical value can be calculated directly. The statistic LR can be used to calculate the CI of τ_1. The above model assumes that there is only one investor sentiment threshold. From an econometric perspective, however, there may be multiple thresholds. By assuming a known value of estimated τ_1 in the single threshold model and then searching for τ_2, the single threshold model can be easily extended to a scenario with multiple thresholds.

We also divide the sample according to the empirical results in Table 3 to better test the threshold effect of investor sentiment. We divide the sample using a cut-off value of 3 for the total significant number of *Trend* coefficients in the OLS regression and quantile regression of an industry. Industries with a cut-off value greater than 3 comprise the first sub-sample, which includes AFAHF, Man, ITS, Fin, RE, LBS, and WEPFM. Drought has a significant effect on these industries, and it

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thus increases the probability of observing the threshold effect of investor sentiment. The remaining industries comprise the second sub-sample; here, drought has a lesser effect, so the evidence of a threshold effect of investor sentiment may not be observed. Table 5 presents the *F*-statistics, probability values, and critical values at the 10, 5, and 1% levels for each test of each sample. We use a bootstrap method to calculate the critical *F*-statistic value. The bootstrap number is 300.

In the test of the linear model, the *F*-statistics for the whole sample, the first and the second sub-sample are 35.84, 29.44, and 18.23, each of which rejects the null hypothesis at a 1% level of significance. However, the null hypothesis is not rejected in all samples during the test of the single-threshold model. Therefore, the single-threshold model is suitable for studying the threshold effect of investor sentiment on the relationship between drought and industry stock returns.

To verify the robustness of the results, we present the estimation results for both the linear model and the single-threshold model in Table 6, which also lists the regression results of the full sample and the subsamples. All of the linear models show positive coefficients of *Trend*, again verifying the results of OLS regression for each industry in Table 3. In other words, the correlation between drought and stock prices is generally negative. After the threshold feature is introduced, the SD of the model error decreases and the determinable coefficient increases, indicating that this feature captures at least some of the nonlinear components of the variable relationship. We first focus on the full sample. The estimated threshold value of 52.3 falls within the 95% CI [50.5,53.7], indicating that the estimated threshold value is consistent with the true value. We can sample into a low sentiment regime ($TO \leq 52.3$) and a high sentiment regime ($TO > 52.3$). In the low sentiment regime, the coefficient of *Trend* is 0.034, which means that drought has a significant negative effect on industry stock prices in this regime. This result is consistent with the fact that drought is not conducive to economic development. In the high sentiment regime, the coefficient of *Trend* is −0.288, which is significant at the 1% level. In other words, the effect of the drought on industry stock prices shifts from negative to positive. This phenomenon reflects the irrational or speculative behavior of investors. The regression results in Table 6 are consistent with the findings of research on the effect of investor sentiment on the stock market (Brown and Cliff, 2005; Baker and Wurgler, 2006; Lemmon and Portniaguina, 2006; Kaplanski and Levy, 2010; Mian and Sankaraguruswamy, 2012). Consistently, these studies demonstrate that when investor sentiment is high, investors tend to have a high propensity toward speculation and thus overvalue risky assets such as stocks. The reverse is true during low sentiment periods, as investors' pessimism leads them to undervalue stocks.

The results of regression are the same in the subsamples as in the whole sample. Specifically, as investor sentiment shifts from low to high, the correlation between drought and industry stock prices shifts from negative to positive. The first subsample has a threshold value of 52.0, which is very close to that of the whole sample. Although we also observe a significant threshold effect of investor sentiment in the second subsample, its threshold value of 21.9 is less than half of the corresponding values of the whole sample and the first subsample. Therefore, the effect of drought on industry stock prices is more likely to be distorted by investor sentiment in the second subsample, although we note that the effect of drought on industry stock prices is smaller in the second than in the first subsample. In the low sentiment regime, the coefficients of *Trend* are 0.034, 0.042, and 0.024 in the whole sample, first subsample, and second subsample, respectively. In the high sentiment regime, the coefficient of *Trend* in the second subsample is −0.109, which is approximately half of the corresponding value in the full sample which is −0.288 and one-third of that in the first subsample which is −0.356. These results are consistent with the results of regression in Table 3, which demonstrate drought has a less significant effect on industry stock prices in the second subsample. In summary, the results of regression of the threshold model confirm the influence of the investor sentiment threshold on the relationship between drought and industry stock prices.

Robustness checks

Consideration of differences in quarterly precipitation

China has a pronounced monsoon climate, with seasonal variations in precipitation. According to the China Meteorological data network[5], precipitation is more frequent in the second and third quarters than in the first and fourth quarters. This pattern may affect estimation of the drought trend. To determine whether our regression results are affected by this phenomenon, we add quarter dummy variables to the long-term drought trend measurement model:

$$PDSI_t = a + bt + cPDSI_{t-1} + d_1D_1 + d_2D_2 + d_3D_3 + \varepsilon. \quad (12)$$

This AR(1) model is augmented with a deterministic time trend t and quarter dummies. D_1, D_2, and D_3 are the dummy variables for the first, second, and third quarters, respectively. The coefficient of the deterministic time trend in model (12) is the alternative measure of the long-term drought trend.

Table 7 shows the OLS and quantile regression results of individual industries based on this alternative measure of *Trend*. Again, the OLS regression results show a negative correlation between drought and industry stock prices, and this relationship is significant in four industries, although Fin is replaced with ITS.

5 http://data.cma.cn/.

TABLE 7 Robustness check I: OLS and quantile regressions considering quarterly precipitation difference.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	QR05	QR10	QR25	QR50	QR75	QR90	QR95	*N*
AFAHF	**0.085****	**−0.096**	**−0.059**	**0.025**	**0.061****	**0.124****	**0.208*****	**0.328*****	**5**
	(0.038)	**(0.074)**	**(0.052)**	**(0.038)**	**(0.030)**	**(0.052)**	**(0.063)**	**(0.076)**	
Min	0.016	−0.028	0.004	0.027	0.031	0.002	−0.010	−0.030	0
	(0.035)	(0.050)	(0.045)	(0.037)	(0.044)	(0.062)	(0.067)	(0.110)	
Man	**0.049****	**−0.009**	**0.016**	**0.011**	**0.037**	**0.049****	**0.076*****	**0.112*****	**4**
	(0.020)	**(0.047)**	**(0.036)**	**(0.019)**	**(0.024)**	**(0.023)**	**(0.027)**	**(0.043)**	
EHGWPS	0.021	−0.021	−0.029	−0.017	−0.018	−0.015	0.107	0.100	0
	(0.035)	(0.058)	(0.055)	(0.044)	(0.035)	(0.044)	(0.080)	(0.079)	
Con	0.060	0.030	−0.011	0.005	0.064	0.059	0.081	0.089	0
	(0.039)	(0.072)	(0.064)	(0.034)	(0.041)	(0.064)	(0.141)	(0.159)	
W&R	0.019	−0.034	−0.038	−0.006	−0.005	0.046*	0.067	0.072	1
	(0.028)	(0.039)	(0.034)	(0.028)	(0.024)	(0.025)	(0.058)	(0.071)	
TSPS	0.017	0.157	−0.024	−0.019	−0.011	0.028	0.028	0.083	0
	(0.032)	(0.118)	(0.065)	(0.025)	(0.024)	(0.036)	(0.072)	(0.088)	
A&C	0.014	0.088	−0.006	0.014	0.014	0.008	−0.008	−0.041	0
	(0.036)	(0.071)	(0.042)	(0.044)	(0.039)	(0.061)	(0.098)	(0.098)	
ITS	**0.073***	**−0.017**	**0.010**	**0.037**	**0.088*****	**0.133****	**0.216****	**0.207**	**4**
	(0.040)	**(0.058)**	**(0.042)**	**(0.031)**	**(0.033)**	**(0.055)**	**(0.100)**	**(0.176)**	
Fin	0.045	0.087	0.027	0.067	0.040	−0.013	0.013	−0.053	0
	(0.033)	(0.059)	(0.068)	(0.048)	(0.052)	(0.052)	(0.067)	(0.106)	
RE	**−0.010**	**−0.228*****	**−0.176*****	**−0.118*****	**−0.037**	**0.063**	**0.160***	**0.273****	**5**
	(0.047)	**(0.062)**	**(0.039)**	**(0.033)**	**(0.033)**	**(0.043)**	**(0.086)**	**(0.110)**	
LBS	**0.032**	**−0.102***	**−0.089***	**−0.032**	**0.024**	**0.096****	**0.149****	**0.224*****	**5**
	(0.040)	**(0.061)**	**(0.051)**	**(0.044)**	**(0.036)**	**(0.041)**	**(0.062)**	**(0.080)**	
WEPFM	**0.096****	**0.040**	**0.070**	**0.084***	**0.079****	**0.061**	**0.088**	**0.0005**	**3**
	(0.041)	**(0.126)**	**(0.061)**	**(0.050)**	**(0.040)**	**(0.062)**	**(0.123)**	**(0.196)**	
CSE	0.086	0.047	−0.024	0.039	0.072	0.024	0.250*	0.393***	2
	(0.064)	(0.130)	(0.102)	(0.068)	(0.062)	(0.106)	(0.143)	(0.143)	
Com	0.037	0.003	0.057	−0.019	0.010	0.044	0.084	0.106	0
	(0.030)	(0.063)	(0.060)	(0.040)	(0.031)	(0.039)	(0.051)	(0.079)	
N	4	2	2	2	3	5	6	5	

This table reports the OLS and quantile regression results based on the alternative measure of the long-term trend of drought, which considering quarterly precipitation difference. To save space, we only report the coefficients of Trend. From left to right column are the regression results of OLS model and quantile regression models on the 5, 10, 25, 50, 75, 90 and 95 quantiles. The rightmost column and the bottom row count the number of significant coefficients by row and column, respectively. The bold part are the industries significantly affected by drought, i.e. there are at least three coefficients of *Trend* are significant in OLS regression and quantile regressions. Numbers in parentheses are SEs. *, ** and *** denote statistical significance at 10, 5 and 1%, respectively.

The results of quantile regression demonstrate that more than half of the industries are significantly affected by drought, and this effect is usually positive when stock prices are low and negative when prices are high. The coefficient estimation accuracy is higher at high stock price quantiles. The AFHAF, Man, ITS, RE, and LBS industries are most affected by drought, similar to the results shown in Table 3. In summary, the OLS and quantile regression results are in line with our previous findings.

As shown in Table 8, the results of the threshold effect reveal a single-threshold effect in the whole sample and the first subsample but a double-threshold effect in the second subsample. Table 9 reports both the linear and threshold regression results. The results of linear regression still show a negative correlation of drought with stock prices. No significant changes are observed in the results of threshold regression in either the whole sample or the subsamples. Despite the double-threshold effect in the second subsample, the regression results do not differ substantially from those in Table 6. Specifically, the threshold values in the second subsample are 16.3 and 18.5. At turnover rates higher

TABLE 8 Robustness check I: Threshold effect test of investor sentiment considering quarterly precipitation difference.

	H0	H1	Fstat	Prob	Crit10	Crit5	Crit1
Full sample	Liner	Single	35.84	0.000	11.649	12.986	19.172
	Single	Double	23.71	0.100	23.687	30.644	41.112
The first subsample	Liner	Single	31.73	0.003	12.988	16.581	24.591
	Single	Double	3.09	0.887	19.824	25.362	36.092
The second subsample	Liner	Single	22.04	0.000	10.167	12.127	15.538
	Single	Double	9.27	0.067	8.194	9.659	13.178
	Double	Triple	4.69	0.613	15.707	21.777	31.558

This table reports the threshold effect test results of investor sentiment in three samples based on the alternative measure of the long-term trend of drought. Our sample period is 2000–2014. The full sample is the monthly stock return panel data of 15 industries. The first subsample includes industries significantly affected by drought, i.e. there are at least three coefficients of *Trend* are significant in OLS regression and quantile regression in Table 7. The other industries are included in the second subsample. This table shows the original hypothesis, alternative hypothesis, F statistic, probability value, and critical values at 10, 5 and 1% from left to right columns.

TABLE 9 Robustness check I: Threshold regression results of investor sentiment considering quarterly precipitation difference.

	Full sample		The first subsample		The second subsample		
	Liner	Single	Liner	Single	Liner	Single	Double
Trend	0.039***	0.034***	0.047**	0.040**	0.033***	0.036***	0.033***
	(0.007)	(0.006)	(0.013)	(0.013)	(0.007)	(0.007)	(0.006)
		−0.288***		−0.352**		−0.077**	−0.076**
		(0.075)		(0.107)		(0.033)	(0.033)
							−0.376***
							(0.077)
PDSI36	−0.002*	−0.0005	−0.001	0.0002	−0.002*	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
RP	0.985***	0.977***	0.972***	0.959***	0.994***	0.974***	0.970***
	(0.018)	(0.017)	(0.032)	(0.029)	(0.023)	(0.021)	(0.021)
SMB	0.313**	0.304**	0.371**	0.359**	0.275	0.270	0.266
	(0.108)	(0.107)	(0.113)	(0.108)	(0.168)	(0.168)	(0.167)
HML	−0.116*	−0.103	−0.292***	−0.271***	0.001	0.027	0.030
	(0.065)	(0.066)	(0.050)	(0.060)	(0.084)	(0.080)	(0.081)
Constant	0.005**	0.007***	0.007	0.011**	0.004	0.008**	0.009***
	(0.002)	(0.002)	(0.005)	(0.003)	(0.002)	(0.002)	(0.002)
Threshold		52.3		51.9		16.3	16.3, 18.5
95% CI		[50.5, 53.7]		[50.5,53.2]		[15.0, 16.6]	[14.8,16.6], [18.3,18.7]
R^2	0.739	0.743	0.767	0.776	0.726	0.731	0.732
N	2700	2700	1080	1080	1620	1620	1620

This table reports the linear and threshold regression results of investor sentiment in three samples based on the alternative measure of the long-term trend of drought. Our sample period is 2000–2014. The full sample is the monthly stock return panel data of 15 industries. The first subsample includes industries significantly affected by drought, i.e. there are at least three coefficients of *Trend* are significant in OLS regression and quantile regression in Table 7. The other industries are included in the second subsample. The last four rows show the threshold value, 95% CI of the threshold value, goodness of fit and sample size. Numbers in parentheses are robust SEs. *, ** and *** denote statistical significance at 10, 5 and 1%, respectively.

than 16.3, the impact of drought on stock prices changes from negative to positive, and this positive impact becomes stronger at turnover rates higher than 18.5. Once again, these results demonstrate that the threshold effect of investor sentiment is more likely to distort the relationship between drought and stock prices in the second subsample. A comparison of the subsamples shows that drought has a greater negative effect on the first subsample but nearly identical positive effects on both subsamples, and the second subsample has a significantly lower threshold value. In summary, our main findings are not altered

TABLE 10 Robustness check II: OLS and quantile regressions based on Trend calculated by Box-Jenkins process.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	QR05	QR10	QR25	QR50	QR75	QR90	QR95	*N*
AFAHF	**0.060****	**−0.074**	**−0.043**	**0.006**	**0.046****	**0.090****	**0.171*****	**0.240*****	**5**
	(0.027)	**(0.050)**	**(0.038)**	**(0.028)**	**(0.021)**	**(0.035)**	**(0.044)**	**(0.054)**	
Min	0.015	−0.018	−0.017	0.020	0.023	0.029	−0.005	−0.028	0
	(0.025)	(0.032)	(0.031)	(0.026)	(0.030)	(0.043)	(0.057)	(0.082)	
Man	**0.038*****	**−0.009**	**0.010**	**0.007**	**0.035****	**0.044*****	**0.075*****	**0.090*****	**5**
	(0.014)	**(0.031)**	**(0.025)**	**(0.013)**	**(0.017)**	**(0.015)**	**(0.020)**	**(0.030)**	
EHGWPS	0.014	−0.016	−0.020	−0.016	−0.016	0.004	0.069	0.084	0
	(0.025)	(0.034)	(0.030)	(0.029)	(0.025)	(0.032)	(0.058)	(0.056)	
Con	0.051*	0.020	−0.042	0.002	0.054*	0.051	0.065	0.095	2
	(0.028)	(0.051)	(0.048)	(0.026)	(0.029)	(0.038)	(0.092)	(0.111)	
W&R	0.022	−0.025	−0.020	−0.004	0.002	0.049***	0.050	0.060	1
	(0.020)	(0.028)	(0.025)	(0.020)	(0.017)	(0.017)	(0.039)	(0.049)	
TSPS	0.012	−0.068	−0.048	−0.028	−0.008	0.025	0.057	0.116*	1
	(0.023)	(0.052)	(0.032)	(0.017)	(0.018)	(0.023)	(0.045)	(0.061)	
A&C	0.019	0.080	−0.002	0.008	0.013	0.017	0.010	−0.020	0
	(0.026)	(0.051)	(0.034)	(0.035)	(0.026)	(0.041)	(0.070)	(0.072)	
ITS	**0.046**	**−0.012**	**−0.005**	**0.019**	**0.069*****	**0.097****	**0.132***	**0.134**	**3**
	(0.028)	**(0.036)**	**(0.025)**	**(0.021)**	**(0.024)**	**(0.038)**	**(0.079)**	**(0.150)**	
Fin	**0.046***	**0.070**	**0.053**	**0.063***	**0.059***	**0.016**	**0.010**	**0.004**	**3**
	(0.023)	**(0.045)**	**(0.046)**	**(0.033)**	**(0.034)**	**(0.037)**	**(0.044)**	**(0.058)**	
RE	**0.004**	**−0.159*****	**−0.122*****	**−0.078*****	**−0.017**	**0.044**	**0.124****	**0.203*****	**5**
	(0.033)	**(0.043)**	**(0.032)**	**(0.026)**	**(0.025)**	**(0.030)**	**(0.056)**	**(0.074)**	
LBS	**0.027**	**−0.074***	**−0.062***	**−0.022**	**0.020**	**0.077*****	**0.111****	**0.163*****	**5**
	(0.028)	**(0.042)**	**(0.034)**	**(0.030)**	**(0.025)**	**(0.028)**	**(0.043)**	**(0.050)**	
WEPFM	**0.068****	**0.051**	**0.052**	**0.073****	**0.053***	**0.049**	**0.072**	**0.0003**	**3**
	(0.029)	**(0.120)**	**(0.052)**	**(0.036)**	**(0.029)**	**(0.041)**	**(0.089)**	**(0.182)**	
CSE	0.059	0.030	−0.020	0.031	0.054	0.025	0.193*	0.299***	2
	(0.046)	(0.096)	(0.070)	(0.044)	(0.041)	(0.079)	(0.102)	(0.107)	
Com	0.026	0.002	0.037	−0.014	0.009	0.020	0.052	0.066	0
	(0.021)	(0.045)	(0.039)	(0.028)	(0.025)	(0.031)	(0.036)	(0.049)	
N	5	2	2	3	6	5	6	6	

This table reports the OLS and quantile regression results of monthly stock returns on the long-term trend of drought by industry. Our sample period is 2000–2014. To save space, we only report the coefficients of Trend. From left to right column are the regression results of OLS model and quantile regression models on the 5, 10, 25, 50, 75, 90 and 95 quantiles. The rightmost column and the bottom row count the number of significant coefficients by row and column, respectively. The bold part are the industries significantly affected by drought, i.e. there are at least three coefficients of *Trend* are significant in OLS regression and quantile regressions. Numbers in parentheses are SEs. *, ** and *** denote statistical significance at 10, 5 and 1%, respectively.

by considering the quarterly effects in our calculation of the long-term drought trend.

Alternative drought index

Following the literature, we use *Trend* calculated based on the AR(1) model in our main empirical analysis. To improve robustness, we use the Box–Jenkins process to reselect the model, determine the order, and calculate *Trend*. As PDSI is a stationary time series, we calculate the autocorrelation coefficient and partial autocorrelation coefficient to determine the suitability of the ARMA, AR, and MA models. The autocorrelation coefficient tails off to zero, and the partial autocorrelation coefficient is truncated. Although the third-order partial autocorrelation coefficient is significantly different from zero, values above the third order can be considered equal to zero. Therefore, we extend model (2) to the AR(3) model to recalculate *Trend* and repeat our empirical analysis of the economic impact of drought.

TABLE 11 Robustness check III: OLS and quantile regressions based on $Trend_{t-1}$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	QR05	QR10	QR25	QR50	QR75	QR90	QR95	N
AFAHF	**0.067***	**−0.135****	**−0.068**	**0.009**	**0.057****	**0.072**	**0.201*****	**0.248*****	**5**
	(0.035)	**(0.062)**	**(0.044)**	**(0.035)**	**(0.028)**	**(0.049)**	**(0.061)**	**(0.068)**	
Min	0.008	−0.016	−0.030	0.028	0.020	0.006	−0.008	−0.028	0
	(0.032)	(0.044)	(0.042)	(0.035)	(0.047)	(0.052)	(0.070)	(0.101)	
Man	**0.044****	**−0.012**	**−0.012**	**0.007**	**0.040***	**0.054*****	**0.079*****	**0.113*****	**5**
	(0.018)	**(0.042)**	**(0.033)**	**(0.018)**	**(0.022)**	**(0.019)**	**(0.025)**	**(0.039)**	
EHGWPS	0.016	−0.056	−0.048	−0.023	−0.018	−0.001	0.089	0.079	0
	(0.032)	(0.046)	(0.041)	(0.041)	(0.034)	(0.045)	(0.075)	(0.078)	
Con	0.055	0.027	−0.052	0.003	0.058	0.055	0.085	0.114	0
	(0.036)	(0.059)	(0.051)	(0.029)	(0.036)	(0.047)	(0.119)	(0.141)	
W&R	0.021	−0.030	−0.047	−0.006	−0.004	0.043*	0.053	0.053	1
	(0.025)	(0.040)	(0.032)	(0.024)	(0.021)	(0.022)	(0.049)	(0.057)	
TSPS	0.018	−0.126*	−0.035	−0.034	−0.002	0.031	0.073	0.136*	2
	(0.029)	(0.069)	(0.040)	(0.023)	(0.023)	(0.029)	(0.060)	(0.075)	
A&C	0.029	0.092	−0.003	0.006	0.021	0.050	0.019	−0.034	0
	(0.034)	(0.063)	(0.044)	(0.041)	(0.043)	(0.065)	(0.097)	(0.099)	
ITS	0.048	−0.028	−0.022	0.023	0.083**	0.142***	0.124	−0.037	2
	(0.036)	(0.044)	(0.034)	(0.026)	(0.034)	(0.048)	(0.117)	(0.211)	
Fin	**0.061****	**0.103***	**0.064**	**0.078***	**0.084***	**0.022**	**0.010**	**−0.039**	**4**
	(0.030)	**(0.053)**	**(0.055)**	**(0.042)**	**(0.045)**	**(0.054)**	**(0.067)**	**(0.090)**	
RE	**0.005**	**−0.218*****	**−0.153*****	**−0.099*****	**−0.031**	**0.062***	**0.173****	**0.304*****	**6**
	(0.043)	**(0.060)**	**(0.040)**	**(0.031)**	**(0.031)**	**(0.034)**	**(0.072)**	**(0.101)**	
LBS	**0.020**	**−0.121****	**−0.083***	**−0.044**	**0.017**	**0.093****	**0.068**	**0.230*****	**4**
	(0.035)	(0.056)	(0.046)	(0.041)	(0.034)	(0.041)	(0.057)	(0.082)	
WEPFM	0.073**	0.060	0.069	0.089**	0.053	0.045	0.092	0.0005	2
	(0.037)	(0.127)	(0.066)	(0.043)	(0.037)	(0.050)	(0.121)	(0.226)	
CSE	0.062	0.057	−0.026	0.042	0.055	−0.0002	0.205	0.330**	1
	(0.059)	(0.134)	(0.085)	(0.060)	(0.049)	(0.096)	(0.132)	(0.148)	
Com	0.030	−0.010	0.050	−0.020	0.013	0.036	0.038	0.066	0
	(0.027)	(0.065)	(0.054)	(0.035)	(0.032)	(0.039)	(0.047)	(0.081)	
N	4	5	2	3	4	5	3	6	

This table reports the OLS and quantile regression results of monthly stock returns on the long-term trend of drought lagged one period by industry. Our sample period is 2000–2014. To save space, we only report the coefficients of Trend. From left to right column are the regression results of OLS model and quantile regression models on the 5, 10, 25, 50, 75, 90 and 95 quantiles. The rightmost column and the bottom row count the number of significant coefficients by row and column, respectively. The bold part are the industries significantly affected by drought, i.e. there are at least three coefficients of Trend are significant in OLS regression and quantile regressions. Numbers in parentheses are SEs. *, ** and *** denote statistical significance at 10, 5 and 1%, respectively.

Table 10 presents the results of OLS and quantile regression of the relationship between drought and industry stock prices, which are very close to the results in Table 3. OLS regression reveals a negative effect of drought on industry stock prices. Further consideration of the quantile regression results reveals that for almost all of the industries, the effect of drought shifts from positive to negative with the transition from the low to high quantile and is more significant in the high quantile. This evidence shows that drought is not conducive to economic prosperity and has a negative overall effect on industry stock prices. Individually, OLS regression captures the significant effects of drought on the AFAHF, Man, Fin, and WEPFM industries, while quantile regression further captures the significant effects of drought on the ITS, RE, and LBS industries. These results are consistent with our earlier findings.

It is also interesting to study the delayed response of industry stock prices by directly lagging *Trend* by one period. Here, we replace $Trend_t$ with $Trend_{t-1}$ in model (3). Table 11 reports the results of regression between industry stock returns and the lag *Trend*. A comparison of the regression results in Tables 3, 11 reveals similar responses of industry stock prices to drought in the previous period and in the current period, although drought in the previous period has a relatively smaller and less significant effect on industry stock prices. Out of curiosity, we also examine the effect of monthly changes in *Trend* on industry stock prices. However, our empirical results show that this monthly change has no significant effect on the stock prices of various industries, possibly because monthly variations in the long-term drought trend are too small and difficult to detect (data not shown because of space limitations).

Conclusion

In China, drought is a frequent form of natural disaster characterized by a relative long duration and wide range of effects. Increases in global warming and changes to atmospheric circulation patterns have exacerbated the drought trend in China in recent years. This paper uses the PDSI to examine the effects of long-term drought trends on stock prices in various industries from 2000 to 2014.

The structure and strength of the relationship between drought and stock prices vary according to industry. The results obtained using OLS regression models show that drought generally has a negative correlation with industry stock prices. However, our OLS regression models only identify four industries that are significantly affected by drought. The quantile regression model provides a more comprehensive analysis of the relationship between drought and industry stock prices, revealing that drought significantly affects stock prices in 10 of the 15 studied industries to various degrees. The AFAHF, Man, ITS, Fin, RE, LBS, and WEPFM industries are particularly vulnerable to drought. Furthermore, the effect of drought on industry stock prices shifts from positive to negative as the analysis moves from low to high quantiles and is more significant in the high quantiles latter group. This result indicates that drought is not conducive to economic prosperity.

The results from our threshold model based on panel data show that the effects of drought on industry stock prices vary according to the threshold effect of investor sentiment. In the low sentiment regime, drought is negatively correlated with industry stock prices, whereas in the high sentiment regime, this correlation positive. This pattern suggests that investors are overly cautious or pessimistic during periods of low sentiment period, leading to the undervaluation of stocks, whereas they tend to speculate during periods of high sentiment, leading to the overvaluation of stocks.

Our findings have many implications for policy-makers, practitioners, and academics. First, they confirm the industry-based heterogeneity in the economic effect of drought and the threshold effect of investor sentiment. This confirmation will help the government to guide market investors and formulate drought-response policies for specific industries. Second, our findings may help investors to build portfolios that control their risk of exposure to drought. Third, our results demonstrate the need for more in-depth, detailed studies of the economic effect of drought that combine the effects of different scenarios and other factors, such as industry heterogeneity and investor sentiment.

Although the effects of drought are extensive and complex, research on these effects in the field of economics is still in its infancy. Constrained by the availability of data on drought, this paper mainly studies the economic effect of drought from a capital market perspective, focusing on different quantiles of stock prices and the role of investor sentiment. However, the field of economics still holds considerable scope for drought research. When regional drought data collected over longer time spans and at a higher frequency and greater density become easy to obtain, studies based on panel data and time series data can be carried out smoothly. For example, regional drought indicators can be matched to company addresses, enabling the construction of panel data to study the effect of drought at the firm level. Regarding time series, the overall drought index can be used to study the effects of drought on stock price indexes and commodity futures prices and to predict stock price indexes or inform the construction of commodity futures hedging strategies.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: China Securities Market and Accounting Research database National Center for Atmospheric Research.

Author contributions

All authors contribute equally to the paper.

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.

Publisher's note

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Measuring inclusive green total factor productivity from urban level in China

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Background: Inclusive green development aims to combine economic inclusiveness with greenness, which is an important goal of current economic development for China to achieve common prosperity. Measuring inclusive green total factor productivity (IGTFP) is of great significance for evaluating the quality of inclusive economic growth and accelerating inclusive economic growth.

Method: This study establishes an index evaluation system of IGTFP from four aspects of high quality, efficient, fair, and sustainable development, using super-SBM to measure IGTFP based on panel data of 276 cities in China from 2006 to 2019, and conducts empirical comparative analysis from national central cities, provincial capitals, and ordinary prefecture.

Result: 1) The IGTFP and technical progress rate in the central city and the provincial capital are significantly higher than that of the ordinary prefecture, but there is no significant difference in technical efficiency; the growth rate of IGTFP in the most central city remains around 10%, which is significantly higher in the south than that in the north. 2) According to the index decomposition result, all cities have basically realized the double-line improvement of technological efficiency and technological progress rate, but the technological efficiency is mostly lower than the technological progress rate. 3) From the perspective of economic convergence, only the IGTFP of provincial capitals shows the σ convergence feature, that is, the phenomenon of intra-group convergence; the IGTFP of all cities in three levels shows the β convergence feature, indicating that there is an obvious catch-up phenomenon within the group.

Conclusion: The integration of “technology” and “efficiency” is the main driving force and path to realize the sustainable improvement of IGTFP in cities. Inclusive green growth needs to break “regional boundaries,” including north–south boundaries and urban boundaries.

KEYWORDS

inclusive green total factor productivity, index evaluation system, urban level, super-SBM, economic convergence

Introduction

Common prosperity is the essential requirement of socialism and an essential feature of Chinese-style modernization. Since the 18th National Congress of the Communist Party of China (CPC), China has taken various measures to ensure and improve people's livelihood and achieved comprehensive poverty alleviation in 2020. However, over the past 40 years of reform and opening-up, China's economic development has paid a substantial environmental and social cost. On the one hand, the extensive growth with high input, high consumption, heavy pollution, and low efficiency leads to resource exhaustion, environmental pollution, and ecological destruction. On the other hand, the development opportunities brought by economic growth are not distributed equally among members of the society, and the achievement of growth is not equally distributed, which leads to the widening income gap and the aggravation of social inequality (Wan, 2010). Based on this background, the Chinese government put forward in the "14th Five -Year Plan" that "coordinated development and inclusive growth must be the trend of China's economic and social development." This means that the future of China's economic development should improve the total factor productivity and improve the efficiency of inclusive green growth, and promote inclusive economic development.

Since the Asian Development Bank put forward the concept of inclusive growth in Strategy 2020 in 2008, the academia has not formed a unified definition of inclusive growth. Regarding the theoretical connotation and policy significance of inclusive growth, the research of Sun et al. (2018) shows that the essence of inclusive growth was to reduce the income gap. Rachel thought that inclusive growth should include income growth and welfare growth (Rachel, 2012; World Bank., 2012), while Ali and Son (2007) focused on the opportunity of intergroup welfare access (Ali and Son, 2007). On this basis, some scholars incorporated "green" into the inclusive growth system to comprise inclusive green growth. Similar to inclusive growth, inclusive green growth has not constituted a unified definition. D. Doumbia et al. believed that inclusive green growth should pay attention to current and future generations' welfare growth and intergenerational inheritance when weighing the relationship between economic growth, inclusiveness, and green (Grosse et al., 2008; Dinda, 2014; Doumbia, 2019). Berkhout et al. (2017) show that "inclusive green growth is an economic growth path that aims to reduce regional differences, takes into account ecological environmental protection, and provides more opportunities for poor areas and people" (Hill et al., 2012; Dinda, 2013; Berkhout et al., 2017). By combing through relevant studies on inclusive green growth, we can know that inclusive green growth has not formed a unified concept, but its connotation includes three aspects: economic growth, ecological environmental protection, and social inclusion (Dollar et al., 2014; Ahmad, 2021; Gu et al., 2021; He and Du, 2021). Therefore, the inclusive green growth in our research is an economic development path that takes economic growth as its goal and simultaneously considers ecological environmental protection and social opportunity equity.

Total factor productivity is an important engine of economic growth. The report of the 19th National Congress of the Communist Party of China has made a critical judgment that China's economy has shifted from a high-speed growth stage to a location of high-quality development and put forward urgent requirements for improving total factor productivity. Due to the limited resources and increasingly serious environmental pollution, the concept of green development and sustainable development has attracted people's attention. Resources and the environment are not only endogenous variables that affect economic development, but also rigid constraints that limit the quality of economic development. Compared with the total factor productivity that only considers the expected output, the green total factor productivity that incorporates unexpected output such as pollutant emissions into the indicator system is more comprehensive and objective. Therefore, some scholars (Wang et al., 2019; Song et al., 2020; Wang et al., 2020) have begun to use resource consumption and environmental pollution as measurement indicators and incorporated them into the calculation system of total factor productivity to evaluate industrial development and economic growth. The total factor productivity obtained from this is green total factor productivity.

At the same time, the expansion of the income gap and socially sustainable development poses a severe challenge. On this basis, some scholars (Chen and Qin, 2014; Li and Dong, 2021) have begun to consider the inclusiveness of GTFP. They believe that the government should pay attention to the environmental protection and benefit equity of economic achievements while increasing the TFP. Therefore, IGTFP was proposed. How to realize the common prosperity and realize the harmonious development become the urgent need to solve the strategic problem, inclusive green growth will become a new opportunity, and crack the issue of reasonable measure IGTFP is particularly important.

Compared with the total factor productivity that only considers the expected output, the green total factor productivity that incorporates undesired outputs such as pollutant emissions into the indicator system is more comprehensive and objective. Therefore, many scholars began to use resource consumption and environmental pollution as measurement indicators and incorporated them into the calculation system of total factor productivity to evaluate industrial development and economic growth. The total factor productivity obtained from this is green total factor productivity.

The research on total factor productivity has been relatively complete. Song et al. (2018) studied the traditional total factor productivity and the green total factor productivity with environmental factors, which significantly improved the scientific and accurate estimation of total factor productivity (Chirisa et al., 2016; Song et al., 2018; Cui et al., 2019; Peng et al., 2020). However, China's current development goal is to achieve inclusive economic growth by protecting the environment and saving resources to achieve common prosperity, so social equity is also one of the urgent issues that should be solved. The study of Chen and Qin (2014) shows that the income gap is an undesired output in economic development and incorporated it into the input–output system. However, it only studies the provincial level and does not consider the increasingly severe imbalance in economic development within provinces and among different urban strata. Although Sun et al. (2018) took cities as the research object, they only studied green total factor productivity in the traditional sense and did not involve the fundamental problem of the income gap in the input–output system. The existing measurement methods on inclusive green growth, whether through depicting the opportunity function or building a comprehensive index system, are all essentially measured by a current indicator. It is difficult to judge whether its economic growth is an extensive development with high input and high output or an efficient development with low input and high output. Using super-efficiency SBM to measure inclusive green growth by measuring total factor productivity, on the one hand, we can observe whether China's economic operation keeps efficient development; second, it can analyze whether "inclusive" and "green" achieved at the same time of economic growth (Zhang et al.,2019; Zhu and Azhong., 2018; Sun et al., 2020; Xin et al., 2022).

To sum up, this study first incorporates the income gap as the core concept of inclusive growth. The IGTFP was defined under the new input–output system and was estimated and analyzed based on the super-efficiency SBM model. While observing whether China's economic operation has maintained efficient growth, it also examines whether it has realized "inclusive" and "green," which can scientifically grasp the basis of China's high-quality economic development and promote China's green coordinated development and high quality, balanced development (Parikh, 2014; Chen et al., 2020; Ren et al., 2022). This study empirically investigates the spatial–temporal evolution characteristics of IGTFP growth. It is of great theoretical and practical significance for formulating differentiated regional development policies, realizing coordinated development of economic growth, resource conservation, and environmental protection in various regions of China, and realizing common prosperity.

The marginal contributions of this study are as follows. First, the concept of IGTFP is defined. It is considered that IGTFP is a measurement system about high-quality economic development based on economic growth while including ecological environmental protection and equal distribution of social resources. Second, the income gap index and environmental index are incorporated into the input–output system as "green" and "inclusive" indicators, respectively, to construct the input–output system from the inclusive perspective and carry out positive measurement and analysis of IGTFP based on the city level.

Measurement system of inclusive green total factor productivity

The essence of inclusive green growth is to reduce the gap between the rich and the poor while achieving green economic development and balanced development, and common prosperity (Re and Grosskopf, 2010; Li et al., 2021; Sun et al., 2022). Therefore, based on the connotation of inclusive green growth, in the measurement of IGTFP, based on the measurement system of total factor productivity, this study adds "three industry wastes" and urban–rural income ratio that hinders "green" and "inclusive" (Table 1).

In terms of input factors, this study mainly measures from four dimensions. It includes not only the labor and capital factors that are common in the macro production function, but also the measurement of technology and resources. In the dimension of output factors, in addition to the GROSS regional product, urban and rural residents' income and consumption levels are also included in the expected output. Undesired output includes "three industrial wastes" and the urban–rural income ratio. The total factor productivity is judged to be "green" and "inclusive," respectively.

Input indicators

Labor input

The total number of employed persons represents the labor input of each city, and employed persons include employees of units, individuals, and private enterprises.

Capital input

Fixed capital stock, with 2000 as the base period, is expressed by the perpetual inventory method.

Resource input

The balance between economic development and resource utilization is the primary basis of inclusive economic development (Xin et al., 2021; Zhao et al., 2022). Efficient utilization of resources is an essential symbol of high-quality economic transformation. This study selects the total amount of industrial and agricultural land, power consumption, and water supply as the land, energy, and water resources metrics. Land resources are the necessary conditions for production and the most basic means of

TABLE 1 Input–output system and interpretation.

Indicator type	Indicator meaning		Indicator measuring	Unit
Input	Labor		Total number of employees (Per 10,000 people)	Ten thousand people
	Capital		Fixed capital stock	Ten thousand yuan
	Technology		Public service spending	Billion yuan
			Education expenditure	Billion yuan
			Scientific expenditure	Billion yuan
	Resource	Land Resources	Industrial and agricultural land	Universal
	Energy		Electricity consumption	Billion Kilowa
	Water resource		Total water supply	Billion cubic meters
Output	Expect output		GDP	Ten thousand yuan
	Unexpected output		Industrial waste water emissions	Billion ton
			Industrial waste gas emissions	Billion cubic meters
			Industrial solid waste emissions	Ten thousand tons
			Urban-rural income ratio	%

production. In terms of energy input, this study draws lessons from the practice of Li et al. (2020), taking power consumption as the measurement index of energy input. Water resources are the essential input of economic activities (Li et al., 2020). In this study, the total water supply is selected as the measurement index of water resources.

Technology input

This study adopts public service expenditure, science and technology research expenditure, and education expenditure as the measurement index of expenditure input. Public service expenditure in this study refers to the expenditure part of public finance expenditure except science, technology, and education expenditure, such as medical treatment, pension, housing security, and other related expenditure. Expenditure on public services is the most direct way to increase the well-being of people. And education expenditure is the way to improve the core competitiveness of the next generation in poor areas, to avoid intergenerational transfers of poverty and make economic growth more inclusive; science and technology expenditure can realize green economic development to a certain extent and improve the "green proportion" in total factor productivity.

Output indicators

Expected output

This study selects GDP as the measurement indicator of expected output.

Unexpected output

IGTFP should be "inclusive" based on green total factor productivity. Therefore, this study takes "three industrial wastes" as the unexpected output and incorporates the "urban–rural income ratio," which measures the urban-rural income gap, into the undesired output system. The "three industrial wastes" are industrial waste gas emissions, industrial wastewater, and solid waste emissions, respectively, by sulfur dioxide, industrial smoke, and industrial wastewater emissions. The urban–rural income ratio is the ratio of the per capita disposable income of urban residents to rural residents' per capita net income.

Theoretical models

Based on relative efficiency, the Data Envelopment Analysis (DEA) could use mathematical programming and statistical data to evaluate the relative effectiveness of decision-making units. However, traditional non-parametric DEA measures efficiency from radial and Angle (Wang et al., 2019; Feng et al., 2020; Yang et al., 2022). Therefore, it lacks the slack of considering input and output and cannot distinguish whether multiple decision units are effective or not. Therefore, the accuracy of the efficiency value obtained is difficult to guarantee. However, the SBM model and super-efficiency DEA can directly put the "relaxation" variable into the objective function (Zhou and Wu, 2018; Li et al., 2020). Moreover, it can sort and distinguish multiple decision units. Since the input–output system in this study includes "three industry wastes" and the urban–rural income gap as undesired outputs, this study attempts to use the super-efficiency Slack Based Measure (SBM) model containing undesired outputs to Measure IGTFP of 276 cities in China under the condition of variable returns to scale. There are n DMU (decision units), and each DMU has m kinds of inputs, q_1 expected outputs, and q_2 unexpected outputs. The expression of super-efficiency SBM containing unexpected outputs is as follows:

$$min\delta = \frac{1 + \frac{1}{m}\sum_{i=1}^{m} \frac{S_i^-}{x_{ik}}}{1 - \frac{1}{q^1+q^2}\left(\sum_{r=1}^{q^1} \frac{s_r^+}{y_{rk}} + \sum_{t=1}^{q^2} \frac{s_t^{b-}}{b_{tk}}\right)} \tag{1}$$

$$s.t.\begin{cases} \sum_{i=1, j \neq k}^{n} x_j\lambda_j - s_i^- \leq x_{jk} \\ \sum_{i=1, j \neq k}^{n} y_j\lambda_j - s_r^+ \geq y_{rk} \\ \sum_{i=1, j \neq k}^{n} b_j\lambda_j - s_t^{b-} \leq b_{tk} \\ 1 - \frac{1}{q_1 + q_2}\left(\sum_{r=1}^{q_1} \frac{s_r^+}{y_{rk}} + \sum_{t=1}^{q_2} \frac{s_t^{b-}}{b_{tk}}\right) > 0 \\ \lambda_j, s_i^-, s_r^+, s_t^{b-} \geq 0 \\ i = 1, 2, \cdots, m; r = 1, 2, \cdots, q_1; \\ t = 1, 2, \cdots, q_2; j = 1, 2, \cdots, n; j \neq k. \end{cases} \tag{2}$$

In Eqs. 1, 2 ,δ is the efficiency value, j is the decision-making unit, λ_j is the intensity variable, s represents the relaxation variable of each variable, s_i represents the relaxation variable of input, and s_r and s_t are relaxation variables of expected output and unexpected output, respectively. x represents input (for example, x_{ik} is the input item i of the k^{th} decision unit), y and b represent expected output and unexpected output, respectively, y_{rk} represents the expected output item r of the k^{th} decision unit; b_{tk} represents the undesired output of the t^{th} term of the k^{th} decision unit.

The Inclusive Global Malmquist–Luenberger (IGML) index represents IGTFP, reflecting the efficiency of inclusive and green economic growth with current factor inputs. IGML index also includes the relative relationship between actual production and production frontier as well as the change of production frontier boundary of each DMU. Therefore, it can be decomposed into GTC (Global Technical Change) and GEC (Global Efficiency Change). GEC refers to the change of relative efficiency under the condition of constant return to scale and free disposal of elements. It measures the degree to which the production system catches up with the production possibility boundary from the current period to the next period. If GEC>1, technical efficiency is improved. On the contrary, it means that technical efficiency decreases; GTC represents the change degree of the production technology of the production system from the current period to the next period, that is, the innovation degree of production technology. If GTC>1, it indicates that the production technology has improved. Conversely, explain production technology retreat.

$$\begin{aligned} IGML = GEC \times GTC &= \frac{E^g\left(x^{t+1}, y^{t+1}\right)}{E^g\left(x^t, y^t\right)} \\ &= \frac{E^{t+1}\left(x^{t+1}, y^{t+1}\right)}{E^t\left(x^t, y^t\right)} \times \frac{E^g\left(x^{t+1}, y^{t+1}\right)}{E^{t+1}\left(x^{t+1}, y^{t+1}\right)} \frac{E^t\left(x^t, y^t\right)}{E^g\left(x^t, y^t\right)} \end{aligned} \tag{3}$$

$$GEC = \frac{E^{t+1}\left(x^{t+1}, y^{t+1}\right)}{E^t\left(x^t, y^t\right)} \tag{4}$$

$$GTC = \frac{E^g\left(x^{t+1}, y^{t+1}\right)}{E^{t+1}\left(x^{t+1}, y^{t+1}\right)} \frac{E^t\left(x^t, y^t\right)}{E^g\left(x^t, y^t\right)} \tag{5}$$

In the above formula, x^t represent the input and y^t represent the output value of the evaluated unit in t period, E^g and E^t represent the efficiency value of the global frontier and frontier t period, respectively.

Empirical results

This study takes 276 prefecture-level cities in China as the research object and analyses the IGTFP at the national, regional, and urban levels. The data were obtained from *China Statistical Yearbook*, *China Energy Statistical Yearbook*, and *China Urban Statistical Yearbook* and China Economic Network (Table 1).

General characteristics

The contribution of different urban economic conditions to IGTFP is different. This study takes the proportion of urban GDP in the total urban GDP as the weight and obtains the IGTFP. IGTFP in China basically maintained positive growth from 2006 to 2019 (Figure 1). This shows that China's economic development in recent years has considered both "equity" and "efficiency" to some extent. From the perspective of time, Chinese cities' IGTFP has maintained positive growth during the 11th Five-Year Plan period (2006–2010), except for less than 1 in 2007. The rest showed positive growth; from the decomposition point of view, the rate of technological progress has already exceeded the technical efficiency by the end of the eleventh Five-Year Plan. This indicates that the rate of technological progress has increasingly become the primary driver of IGTFP." During the 12th Five-Year Plan period (2011–2015), the growth of the three indexes showed a relatively stable trend. Although the technical efficiency was lower than 1 in some years, it generally maintained positive growth." IGTFP maintained a high growth level in the first 2 years of the 13th Five-Year Plan period. IGTFP exceeded 1.5 in 2017 and maintained a positive growth trend in the following 2 years, although the growth rate slowed down. In the report to the 19th CPC National Congress in 2017, the CPC Central Committee, for the first time, proposed "establishing and improving the economic system of green, low carbon, and circular development." China has paid more attention to

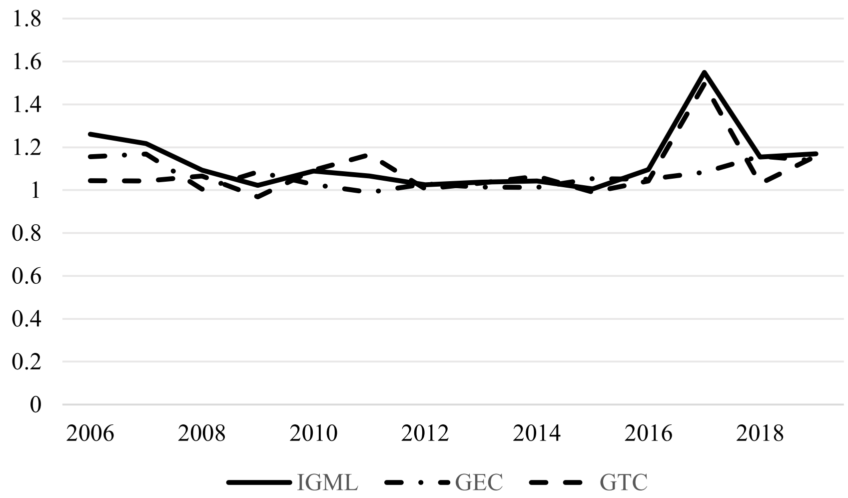

FIGURE 1
National IGTFP and its decomposition.

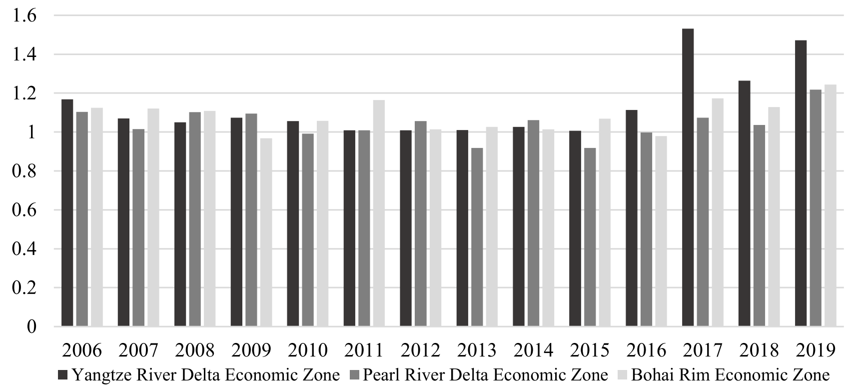

FIGURE 2
IGTFP in three major economic zones.

environmental protection while building a "modern economic system."

Inclusive green total factor productivity in regions

The establishment of national strategic urban agglomeration is an important measure to strengthen the leading role of central cities to surrounding cities, strengthen inter-city cooperation and promote regional integration in China. Yangtze River Delta Economic Zone, Pearl River Delta Economic Zone, and Bohai Rim, as three national strategic city clusters in China, represent the highest level of China's economic development to a large extent and shoulder the responsibility of taking the lead in realizing modernization. Therefore, this study takes the three economic zones as the research object and explores the "inclusiveness" of China's regional economic growth by analyzing their total inclusive factor productivity.

Figure 2 shows IGTFP and fluctuations in the three economic zones. In general, the PEARL River Delta economic zone's IGTFP level is slightly lower than that of the Yangtze River Delta Economic Zone and the Bohai Rim Economic Zone. From 2006 to 2010, the IGTFP of the three economic zones remained the same. Since 2010, the Bohai Rim economic

TABLE 2 Measurement and decomposition of IGTFP.

City category	National central city			Provincial capital city			Ordinary prefecture-level city		
Index category	IGML	GEC	GTC	IGML	GEC	GTC	IGML	GEC	GTC
2006	1.3045	1.2379	1.0538	1.2494	1.2198	1.0242	1.1169	1.1729	0.9523
2007	1.4380	1.1708	1.2282	1.3338	1.3225	1.0085	1.0741	1.1153	0.9631
2008	1.1080	1.0250	1.0810	1.0854	1.0352	1.0486	1.0326	0.9574	1.0785
2009	1.1548	1.1439	1.0096	1.0863	1.0954	0.9917	0.9974	1.0639	0.9375
2010	1.1497	1.0675	1.0770	1.1284	1.0603	1.0643	1.0580	0.9436	1.1212
2011	1.1847	0.9798	1.2091	1.1388	0.9987	1.1404	1.0457	1.0009	1.0502
2012	1.1594	1.0664	1.0873	1.1503	1.1363	1.0123	1.0012	1.0328	0.9694
2013	1.0912	1.0747	1.0153	1.0455	0.9914	1.0837	1.0082	1.0027	1.0054
2014	1.2052	0.9817	1.2276	1.0328	0.9706	1.0640	1.0184	1.0136	1.0047
2015	1.1263	1.0695	1.0530	1.1120	1.0969	1.0138	1.0005	1.0230	0.9780
2016	1.1171	1.0343	1.0800	1.0733	1.0496	1.0465	1.0648	1.0685	1.0012
2017	1.6454	1.1484	1.4328	1.6707	1.0681	1.5642	1.2193	1.0147	1.2017
2018	1.2601	1.2088	1.0424	1.2174	1.1003	1.1064	1.1147	1.0896	1.0231
2019	1.1934	1.0747	1.1105	1.1670	1.1591	1.0068	1.1663	1.0080	1.1570

Zone's IGTFP has been significantly improved, especially in 2011 and 2015. It ranked first among the three economic zones. Since 2016, the inclusive total factor productivity of the Yangtze River Delta Economic Zone and Bohai Rim Economic Zone has gradually opened a gap with that of the Pearl River Delta Economic Zone. From 2017 to 2019, there was a trend of "Yangtze River Delta '>' Bohai Rim '>' Pearl River Delta." The reason for this difference is that there are great differences in the level of economic development between cities in the Pearl River Delta. For example, in 2018, the per capita GDP of the core area of the Pearl River Delta has reached over 100,000 yuan, which has reached the level of high-income countries or regions. For example, the per capita GDP of eastern, western, and northern Guangdong is around 40,000 yuan, far lower than the national average. The low-level cities in the Pearl River Delta economic zone have a relatively low level of professional production technology, and a large number of input production factors cannot get the corresponding except output, while the difference in the level of urban economic development in the Yangtze River Delta is small, and its convenient transportation conditions facilitate the high-frequency technical exchanges between cities, thus promoting the formation of a low input and high-yield industrial chain, It has promoted the overall improvement of inclusive green total factor productivity. As a result, the IGTFP of the PEARL River Delta economic Zone is lower than that of the other two regions.

The IGTFP of the Bohai Rim Economic Zone and the Yangtze River Delta Economic Zone was the same from 2006 to 2017. Only in 2011 and 2015, the Bohai Rim Economic Zone was slightly higher than the Yangtze River Delta Economic Zone. However, from 2016, the inclusive total factor productivity of the Yangtze River Delta economic Zone exceeded that of the other two regions. The reason is that the total economic volume of Shanghai and Zhejiang provinces in the Yangtze River Delta economic zone has declined slightly. Nevertheless, the proportion of Jiangsu province and Anhui province has achieved different rising degrees. The balanced economic development has promoted IGTFP in the Yangtze River Delta region.

Inclusive green total factor productivity in urbans

From the perspective of city classification, the IGTFP of cities of different sizes is different. The specific performance is shown in Table 2. According to the classification of city size, IGTFP showed a phenomenon of "national central city > provincial capital city > prefecture-level city." It indicates that cities' level of economic development and political status positively affects IGTFP to a certain extent. This also confirms the significance of establishing a national central city from the perspective of urban green development. It also shows that China's economic growth still has a certain degree of agglomeration effect. The higher the administrative level of a city, the better it is equipped with transportation and other infrastructure. At the same time, more universities, scientific research talents, and even leading enterprises will gather in this city, thus stimulating the agglomeration effect of urban economic growth.

TABLE 3 National center city.

City	Beijing	Chengdu	Guangzhou	Shanghai	Tianjin	Wuhan	Xi'an	Zhengzhou	Chongqing
IGML	1.2458	1.3146	1.1024	1.1427	1.0970	1.2708	1.2511	1.0826	1.1087
GEC	1.0423	1.1497	1.0368	1.0620	0.9992	1.1063	1.0993	1.0467	1.0708
GTC	1.1952	1.1435	1.0634	1.0518	1.0978	1.1487	1.1380	1.1678	1.0272

From the decomposition results of IGTFP, there is not much difference between the technical efficiency coefficients of the national central city, provincial capital city, and ordinary prefecture-level city, and even the technical efficiency coefficients of the ordinary prefecture-level city exceed that of the provincial capital city and national central city in some years. On the one hand, China's ordinary prefecture-level cities have relatively sufficient land, labor, and other factors of production. On the other hand, the utilization of resources in Chinese cities is relatively complete. The resources of ordinary prefecture-level cities have been brought into full play through policy. However, we can see that the rate of technological progress of ordinary prefecture-level cities is significantly lower than that of provincial capitals and central cities. This is why the IGTFP of ordinary prefecture-level cities is lower than that of national central cities and provincial capitals. It also shows that the production technology of ordinary prefecture-level cities is different from that of national central cities and provincial capital cities. The dividend of the vigorous development of science and technology in China is more applied in major cities.

The national central city is the top-level legal planning in urban and rural planning. It is the overall arrangement of urban development and urban spatial layout, a vital policy basis for actively and steadily promoting urbanization, and the basis for all localities to formulate regional urban system planning and overall urban planning. The development of national central cities has a maximum effect on other cities and even society. Therefore, national central cities' IGTFP is analyzed separately. According to the analysis results in Table 3, the IGTFP of central cities in each country increased from 2006 to 2019. Among them, the geometric mean productivity growth rate of most cities like Chongqing and Beijing reached more than 10%, and five cities like Chongqing, Beijing, Wuhan, Chengdu, and Shanghai even exceeded 14%. The southern cities have comprehensively surpassed the northern cities in terms of region. Among the northern cities, only Beijing and Xi"an have achieved an average growth rate of more than 10%, while all the southern cities have exceeded 10%. This also shows that China's economic development center is still in the south. In the future, more attention should be paid to the economic development of the northern central cities. On the other hand, it also reflects the more stable and "inclusive" development of central cities in the south. The income gap between urban and rural areas in northern China is relatively large, and the "inclusive" level of economic growth is slightly delayed.

From exponential decomposition, all cities have realized the double-line improvement of technological efficiency and progress rate. Although the technical efficiency coefficients of Guangzhou and Tianjin are lower than 1, it also reaches more than 0.99, basically maintaining a stable state. The analysis shows that the technical efficiency coefficients of almost every city are lower than the technological progress rate coefficients. The reason is that China's economy has been growing faster in recent years. The economic growth rate of the country's central cities is leading the country. Large base and resources have been fully utilized, resulting in a slow growth rate of technical efficiency. In recent years, the level of scientific and technological development in China has developed rapidly, and the number of scientific and technological output in China has jumped to the second place in the world. The application of many scientific and technological achievements promotes rapid technological progress in China's production process.

Convergence analysis of inclusive green total factor productivity

In order to further analyze the trend of IGTFP in China, our research uses the σ convergence model and absolute β convergence model to quantitatively study the convergence characteristics of IGTFP. This will provide a more directional reference for promoting China's economy's "green" and "inclusive" development.

σ convergence

The σ convergence reflects the deviation degree of IGTFP of a single city from the overall city level where the city is located. σ convergence of IGTFP means that the divergence of IGTFP among cities tends to decline over time. The convergence model of IGTFP can be expressed as:

$$\sigma_t = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(lns_{it} - \frac{1}{n}\sum_{i=1}^{n}lns_{it}\right)^2} \tag{6}$$

In the above formula, t is the year, i is the city, and n is the number of cities at the corresponding level. $\ln s_{it}$ represents the

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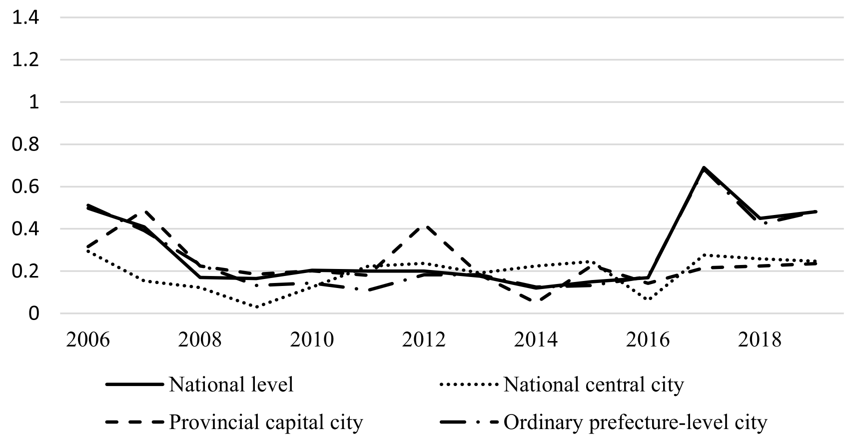

FIGURE 3
σ convergence coefficients.

log value of IGTFP of i city in t year, and σ_t represents the σ convergence test coefficient of IGTFP in t year. If $\sigma_{t+1} < \sigma_t$, there is σ convergence in IGTFP.

According to the national σ convergence coefficients (Figure 3), the σ convergence feature of IGTFP in China is not apparent. Although there were occasional fluctuations, the σ convergence coefficients of IGTFP in national central cities showed a downward trend from 2006 to 2017. However, the overall downward trend is pronounced, indicating that the overall gap between central cities of the country was not large during this period. From 2017 to 2019, the σ convergence coefficients of national central cities increased first and then decreased. The reason is that in 2018, the IGTFP of Wuhan city has been dramatically improved. However, some provinces' green total factor productivity (such as Chongqing) decreased this year, leading to a more extensive convergence coefficients of national central cities this year. Since 2007, the σ convergence coefficients of provincial capital cities have shown a declining trend, indicating that these cities' IGTFP has a particular convergence phenomenon. The σ convergence coefficients of ordinary prefecture-level cities generally decreased first and then increased, indicating a significant difference within this kind of city group. The reason is that the IGML coefficients of some provinces have been lower than 1 since 2015 (for example, the IGTFP of Huludao in 2016 was less than 0.7, while the IGML coefficients of Xuzhou were close to 1.9). The expansion of IGTFP among cities leads to an increase in the σ convergence coefficients of ordinary prefecture-level cities. Therefore, there are still significant differences in IGTFP among cities in China. Except for provincial capital cities, the convergence of other tier cities is not apparent, further indicating significant differences in economic growth efficiency, income gap, and eco-environmental protection intensity.

Absolute β convergence

Absolute β convergence means that cities with low initial IGTFP have a faster growth rate than cities or regions with high IGTFP without considering external factors. And all cities' IGTFP will converge to the same state. Its specific expression is:

$$\frac{(lns_{it} - lns_{i0})}{t} = \alpha + \beta lns_{i0} + \varepsilon_{it} \qquad (7)$$

S_{it} and S_{i0} represent IGTFP of city i in phase t and early stage, respectively, t represents the period. α, β, and ε_{it} represent constant term, absolute β convergence coefficients, and the random error term, respectively. $\beta < 0$ indicates that cities' IGTFP at this level have absolute β convergence, and the larger $|\beta|$ is, the faster the convergence rate is.

Table 4 shows the absolute β convergence coefficients of cities' IGTFP at different levels. From the results, the absolute β convergence coefficients are significantly negative at both the national and each city levels. It indicates that China's IGTFP exists in apparent absolute β convergence. In other words, cities with low inclusive total factor productivity are catching up with cities with high IGTFP. In terms of the convergence rate, the absolute value of the absolute convergence coefficients at all levels shows *national central city > provincial capital city > prefecture-level city*. This indicates that the convergence rate of absolute β convergence in national central cities is significantly faster than others, and further indicates that the higher the city level is, the larger the city size is, the more pronounced the catch-up effect is.

TABLE 4 Absolute β convergence coefficients.

City category	National level	National central city	Provincial capital city	Ordinary prefecture-level city
β	−0.059*** (−5.51)	−0.085** (−2.91)	−0.084*** (−3.62)	−0.060*** (−5.24)
constant	0.042*** (10.62)	0.042*** (8.60)	0.025*** (10.55)	0.045*** (12.97)
F value	26.50	8.47	13.82	27.47

*, **, *** represent a significant level of 10%, 5%, and 1%, which is T value in parentheses.

Conclusion

From the perspective of inclusive green growth, we establish the index evaluation system of inclusive green growth. By using the method of super-SBM, we measure the inclusive green total factor productivity (IGTFP) of China from the city level and explore and analyze the IGTFP index and its decomposition and evolution trend of coefficients of economic convergence. Empirical analysis results are as follows.

First, IGTFP in China has maintained a steady but rising trend both at the national level and at all levels of city, especially after 2008. Second, from the decomposition of IGTFP, there is a positive correlation between the rate of technological progress and the scale of urban development. In addition, the technical efficiency of the country and higher-level cities are generally lower than the rate of technological progress. Third, from the economic region level, the regional development of IGTFP in China is unbalanced. Fourth, the IGTFP of southern cities is significantly higher than that of northern cities, indicating that the southern cities are more substantial than the northern cities in terms of green economic development and social equity. Finally, from the economic convergence, only the IGTFP of provincial capitals shows the σ convergence feature, that is, the phenomenon of intra-group convergence; the IGTFP of all cities in three levels shows the β convergence feature, indicating that cities with a lower level of IGTFP are catching up with that with a higher level.

The policy implications of this study are as follows: first, we should adhere to the concept of inclusive green development and achieve high-quality economic development through energy conservation and emission reduction and promoting social equity. On the one hand, it is necessary to increase investment in enterprise R&D and create a more relaxed R&D environment for enterprises, such as R&D incentives and tax exemptions. On the other hand, we should improve the income distribution system and strengthen the guidance of tertiary distribution on the basis of giving full play to secondary distribution to realize the organic unity of efficiency and fairness. Second, we need to break down the "regional" boundaries including the geographical boundaries (such as the north–south boundary) and the boundaries at the city level, between city scales, and within the economic zone. Third, we should strengthen the core driving function of green technology innovation and progress. The integration of technology and efficiency is the main driving force and path to realize the sustainable improvement of IGTFP in cities. For example, promoting the cooperation between "resource-first" enterprises in underdeveloped cities and "technology-first" enterprises in developed cities, accelerating the upgrading of industrial structure, and realizing the "two-wheel drive" of IGTFP. In addition, cities with low IGTFP can develop rural tourism, e-commerce, and other related industries according to local characteristics, and form an economic form with low input, high output, and lower-income gap with business models such as "New Economy" and "Digital Economy." While promoting rural revitalization, the "digital economy" can also reduce the income gap between urban and rural areas, which can not only promote the improvement of IGTFP level, but also achieve China's common prosperity goal.

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

YG: Data Curation, Formal Analysis and Writing - Original Draft. HW: Conceptualization, Funding Acquisition and Visualization. RG: Resources and Software. DL: Supervision, Validation and Writing - Review & Editing.

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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.

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The casual effect of data production factor adoption on company performance: Empirical evidence from Chinese listed companies with PSM-DID

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The usage of data production factor (DPF) has been extensively studied in academic research and industry. The purpose of this study is to examine the causal effects of DPF adoption on company performance. We firstly provide a measurement of DPF adoption by text mining, which is superior to previous studies that use only single metric. Then, based on PSM-DID method, we use the data of China's listed companies from 2011 to 2019 to identify the causal relationship between data elements adoption and company's performance. We find that the adoption of DPF can significantly increase companies' performance. Further heterogeneity tests show that companies from the service industry and state-owned companies achieve a significant improvement in the performance after adopting DPFs in production. Altogether, this study provides the micro evidence on the relationship between the adoption of DPFs and company performance, providing significant implications for the development of digitalization and intelligence production.

KEYWORDS

data production factor, performance, text mining, PSM-DID, causal effect

1 Introduction

The widespread application and innovation of new-generation information technology have greatly promoted the digital transformation of companies and the reconstruction of productivity and production relations. For the first time, the Fourth Plenary Session of the 19th Central Committee of the Communist Party of China recognized data production factor (DPF) as the seventh production factor, reflecting the important role of data in improving productivity in the context of high-quality development. In April 2020, the State Council of the CPC Central Committee issued a document specifically for production factor market, clearly emphasizing the need to "accelerate the cultivation of DPF market, enhance the value of social data resources, and cultivate new industries, new business models and new modes of the digital economy."

DPF provides the main source of potential for companies to achieve exponential and significant growth. Consequently, companies are gradually increasing their dynamic investments in DPF. The two-way promotion of DPF and companies has enhanced the rate of marketization of DPF and laid the technical foundation for companies to enter the new era of the digital economy. Considering that production factor is a new and powerful resource, there are two major strategic issues that need to be urgently addressed. Is DPF able to create higher value in the process of interaction with traditional production factors, such as labor, capital, land, technology, knowledge, and management? Is DPF conducive to improve the dynamic capability and innovation capacity of companies?

There is already a good number of literatures on the topic of DPF's role in productivity (Evangelista et al., 2012; Enrique et al., 2018). It has been believed that DPF do not act in a single form on economic development, but mainly realize the duty of data empowerment through interaction with traditional production factors. Specifically, DPF do not automatically provide the required information and values without going through appropriate steps, such as data filtering and processing. This means that companies need to use various analytical tools to filter out the useful information contained in data as a scientific basis for decision-making (Baesens et al., 2016). For example, by adopting big data technology in the "precision marketing" strategy, companies can comprehensively grasp consumer demand and market trends in a timelier manner through market analysis, pinpoint the target group of products, and increase marketing interaction (Xue, 2021). The combination of DPF with traditional production factors has shown innovative effects on the development of companies. For instance, when DPF is combined with capital, the increasing investments in R&D lead to a significant increase in the technological innovation of companies. Similarly, a combination with DPF and labors can effectively improve production efficiency. Furthermore, the most significant results are achieved when combining DPF with technology, which can help advance robust technological progress and establish an efficient digital system for companies by taking advantage of the multidimensionality and large capacity of big data (Lin and Meng, 2021). While the accumulation of data capital will further improve data processing efficiency, the combination also increases the overall productivity of companies and boosts economic growth. In summary, DPF provide new resources and strong guarantees for companies to transform and accelerate their adaptation to the era of the digital economy, activate industrial digitization, and promote productivity, innovation, and development.

Recent years have witnessed an increase of literatures concerning the effect of DPF adoption on company performance (Ferreira et al., 2019; Nasiri et al., 2020). The ease of access to DPF is an important reason for the widening gap in size and performance between large- and medium-sized companies (Begenau et al., 2018). The combination of data collected and published by the government and various statistical agencies, as well as companies' own data, enhances the efficiency of companies' decision-making (Hughes-Cromwick and Coronado, 2019). To further evaluate the impact of DPF adoption, some scholars have proposed to open the "black box" of the value realization process and multidimensional value creation mechanism of DPF by establishing the benchmark model of "factor-mechanism-performance," combining its social attributes and dynamic integration theory (Yin et al., 2022). This can provide effective theoretical and practical insights into the sustainable development of companies.

However, the existing literatures on the impact of DPF on company performance is still inadequate. A primary drawback is the lack of comprehensive measurement of DPF adoption. Common measurements include property (Liu et al., 2022), the quality of the corporate website (Bernal et al., 2018), AI related technologies or Big Data analytics. Besides, executives' subjective perception of the technology application is also frequently used, which is measured by questionnaire (Tsou and Chen, 2021; Nasiri et al., 2020). Another shortcoming is that previous literatures have largely failed to focus on causal effects of DPF on company performance. The endogenous issues between company performance and its decision on DPF adoption should not be ignored. In light of this, causal inference methods, such as Difference-In-Difference model (DID), should be used in the empirical studies.

In this paper, we aim to answer the question: does DPF adoption has a positive influence on company performance? Empirical results with 3,233 Chinese listed companies are provided. Compared with previous works, this paper contributes to two points. First, a method for accurately determining whether a company adopts DPF is proposed based on text mining. Second, the adoption of DPF is treated as a quasi-natural experiment, and causal inference is performed through the PSM-DID model to accurately estimate the average gain in performance due to the adoption of DPF. Based on this, the channels of causal effects are further analyzed through heterogeneity analysis of industry and ownership.

The followings are organized as below: Section 2 presents the data sources and indicator settings, Section 3 describes the model setting, Section 4 shows the empirical results, and Section 5 concludes the paper.

2 Data

2.1 Sample and data sources

The initial sample of this paper is all A-share listed companies in the Shanghai and Shenzhen stock markets. The research interval is from 2011 to 2019. Before 2011, there were

TABLE 1 List of keywords for identifying DPFs.

Categories	Keywords
Hardware-facility-supporting DPFs	Internet of Things, cloud computing, edge computing, artificial intelligence, blockchain, data center, big data, data technology, information technology, information system, information software, platform support, database
Technology-supporting DPFs	Data processing, machine learning, cloud technology, data analysis, data transmission, information and intelligent manufacturing, data drive, information and system integration, internet information application, software definition, intelligent leadership
Application of DPFs in industrial development	Digital economy, electronic commerce, digital industrialization, digitalization, company informatization

TABLE 2 Total number of companies using DPFs by year.

Year	Total number of companies that adopt DPFs
2011	270
2012	310
2013	367
2014	389
2015	431
2016	490
2017	550
2018	572
2019	605

more missing values in the data of companies. Due to the outbreak of the COVID-19 pandemic in 2020, which greatly impacted companies, there was a certain incompatibility compared to previous years. After removing sample companies with missing data and stocks with ST label, in short of Special Treatment, we finally obtain a sample of 3,366 companies.

Two sources of data are used in this paper. On the one hand, financial data disclosed by listed companies' annual statements are from the Wind Economic and Financial Database. On the other hand, the Guotaian database provides textual data of companies' basic information, such as company history, main business, technical innovation, and shareholding, which are reported annually.

2.2 Variables

2.2.1 Determination of data production factor adoption

We provide a measurement method of DPF adoption in a two-step process.

2.2.1.1 Step 1: Definition of data production factor

The measurement of DPF adoption in the aspect of company has been little studied. Therefore, the primary aim of this paper is to clarify the definitions of DPF. China's 14th Five-Year Plan highlighted "giving full play to the advantages of massive data and rich application scenarios, promoting the deep integration of digital technology and the real economy and growing new engines of economic development" and discussed the specific path to activate the potential of DPF from three aspects: strengthening the application of key digital technology innovation, accelerating digital industrialization, and promoting industrial digital transformation. Accordingly, this paper defines companies that applying DPF from three perspectives: the supporting hardware facilities, the supporting digital technology, and the application in industrial development. Therefore, a list of keywords was selected according to the above definition.

1) Hardware-facility-supporting DPFs

To improve the complete system and industry chain composed of information collection, mining, analysis, and application, as well as the sharing of DPF, companies should establish a mature new digital infrastructure. Therefore, this paper selected the key terms as the Internet of Things, cloud computing, edge computing, artificial intelligence, blockchain, data center, big data, data technology, information technology, information system, information software, platform support, and database.

2) Technology-supporting DPFs

The existing forms of data elements mostly depend on the development of "big data" and have the characteristics of large flow, diversity, and multiple levels, which are distinctive from traditional data, especially with the role of new media, such as the internet, which expands the channels and scale of data collection, requiring companies to have high data processing and analysis capabilities and to be able to fully exploit the value of data. Based on this, we identified the following keywords: data processing, machine learning, cloud technology, data analysis, data transmission, information and intelligent manufacturing, data drive, information and system integration, internet information application, software definition, and intelligent leadership.

3) Application of DPFs in industrial development

The adoption of DPF has accelerated the upgrading of industrial structures and the transformation of companies. The rise of the digital economy has greatly contributed to the rapid development of online platforms. It is worth mentioning that the labor results of its formation are all digital results. In other words, after being applied to basic industries, such as industry, agriculture, and services, the digital economy has made outstanding contributions to the value of the products created. As such, this paper selected digital economy, electronic commerce, digital industrialization, digitalization, and company informatization as keywords.

The list of keywords in the above three cases is shown in Table 1, with a total of 29 keywords.

2.2.1.2 Step 2: Determination of companies adopting data production factors

We perform a text mining process to determine whether a company adopt DPFs. First, we perform word splitting on the text data of the basic company profile, which is a required disclosure for China's listed companies including the information of company history, main business, technological innovation, shareholding, etc. Then, the keywords contained in Table 1 are automatically checked by computer to see whether it appears in the word splitting results for each company. Further, we manually examine whether the appeared keywords conform to the semantic meaning. For example, the business scope of Company No. 2177 is related to the provision of "digital processing services" and other businesses involved in "data and information processing services." The semantic meaning of the keywords "digital," "data" and "information" here is consistent to our study. Therefore, the company is classified as a data element company. Another example is Company No. 2074, who has a business scope that includes "digital electrical equipment." Since this product is a traditional production equipment, the keyword digitalization here is not in line with the semantic meaning. Therefore, the company is considered as not to adopt DPFs. The year in which the eligible keywords first appear is used as the initial year for adopting DPFs.

Table 2 presents how many companies use data elements as production inputs in each year from 2011 to 2019. In 2011, McKinsey reported that data have swept into every industry and business function and are now an important factor of production, alongside labor and capital (Manyika et al., 2011). Therefore, we consider 2011 as the initial year of our sample. Obviously, the number of companies using DPFs increase more than double in the sample period.

2.2.2 Dependent variable and control variables

To reflect the economic efficiency of companies, this paper selected Earnings Per Share (EPS) as the dependent variable. EPS reflects the after-tax profit created per share and is one of the most important financial indicators of the profitability of listed companies. Generally speaking, the higher the EPS, the better the economic efficiency of the company.

To control for the factors that may trigger changes in the economic efficiency of companies other than the adoption of DPFs, this paper referred to Sheng et al. (2020) and Yang and Yang. (2019) on the factors influencing earnings per share. Details of the control variables are shown in Table 3. Additionally, the effects of province, company ownership, and industry on earnings per share are controlled as the fixed effects.

TABLE 3 Control variables.

Variable	Unit	Meaning	Definition
Gross profit margin (GPM)	%	The percentage of gross profit and sales income (or operating income), in which gross profit is the difference between income and operating costs corresponding to income	(main business income − main business cost)/main business income × 100%
Total assets (TA)	Yuan	All assets owned or controlled by the company	To mitigate the effects of magnitude, take the logarithm of it
Asset-liability ratio (ROL)	%	Total end-of-period liabilities divided by the percentage of total assets, in other words, the ratio of total liabilities to total assets, reflecting how much of total assets are financed through borrowing	Asset-liability ratio = total liabilities/total assets
Net cash flow from operating activities per share of the company (CFPS)	Yuan	The ratio of net cash flow to total equity used to reflect the ability of companies to pay dividends and capital expenditures	Net cash flow/total equity of business activities

TABLE 4 PSM control variables.

Variables	Unit	Meaning	Definition
Company R&D investment intensity (RDIntensity)	%	The proportion of R&D investment in business income reflects the investment in technology R&D	Company R&D investment/company business income
Total company assets (TA)	Yuan	All assets owned or controlled by companies embody the company scale	To mitigate the effect of magnitude, take the logarithm of it
Company operating income (Taking)	Yuan	Income earned by an company in its main business or other business	To mitigate the effect of magnitude, take the logarithm of it
Company net assets per share (NAPS)	Yuan	The ratio of shareholders' equity to total shares; the higher net assets per share, the more value of assets per share owned by shareholders	Total equity/total stock

3 Methodology

3.1 Baseline model

To investigate the effects of adopting DPFs on the growth of economic efficiency, a Difference-In- Difference (DID) method was used. The baseline model is set as follows:

$$EPS_{it} = \beta_0 + \beta_1 DATA_{it} + \beta_2 YEAR_{it} + \beta_3 DATA_i \times YEAR_{it} + \boldsymbol{\theta}^{\mathbf{n}} \mathbf{X}_{i,t-1} + \mu_i + \lambda_i + \eta_i + \varepsilon_{it} \tag{1}$$

The dependent variable EPS_{it} represents earnings per share of the i -th company in year t. $DATA_{it}$ denotes a dummy variable, which takes value of 1 if the i -th company uses DPFs in any year of the sample period; otherwise, it equals to 0. $YEAR_{it}$ denotes the year dummy variable. If the ith company began to use DPFs in year t^*, $YEAR_{it}$ equals to 1 for $t = t^*, \cdots, 2019$. Otherwise, $YEAR_{it}$ is set to 0. The coefficient β_3, which corresponds to the cross term of $DATA_{it} \times YEAR_{it}$, is the focus of this study. If β_3 is significantly positive, it means that the input of DPFs in production improves the EPS of companies. $\boldsymbol{X}$ denotes a set of control variables, including the logarithm of the company's total assets TA, gross sales margin GPM, net cash flow from operating activities per share $CFPS$, and asset-liability ratio ROL To prevent the problem of reverse causality, all the control variables are lagged by one period. In addition, fixed effects of province, ownership, and industry are included, denoted as μ_i, λ_i, and η_i, respectively.

3.2 Propensity score matching

There may be a reverse causal relationship between DPF adoption and a company's economic efficiency; that is, the behavior of a company using data elements in production may have a self-selection effect. The company will decide whether to use DPFs in production according to its own production situation. If we want to identify the causal effect of DPF adoption on the company's economic efficiency, we need to solve the endogenous problem of reverse causality. Therefore, we draw on the practices of Heckman et al. (1998) and Loecker (2007) and use the PSM-DID method to identify the causal effects of DPF adoption on the company's economic efficiency. The PSM-DID method is based on the PSM method. It further differentiates the outcome variable, effectively eliminating the common trend between the treated and control groups. Thus, using the PSM-DID method in analysis can help solve the problems of sample selection bias and reverse causality.

Specifically, we establish a logit model, as shown in Eq. 2, whose dependent variable is $DATA_{it}$ and independent variables are the logarithm of total company assets TA, the intensity of company R&D investment $RDIntensity$, the logarithm of company operating income $Taking$, and company net assets per share $NAPS$ Detailed descriptions of the variables are shown in Table 4. Using this model, the probability of a company using DPFs can be estimated according to its propensity score. And we use the nearest neighbor method with a 1:1 ratio to match a control company for each treatment company.

$$logit\left(DATA_{it}=1\right) = f\left(TA_{i,t-1}, RDIntensity_{i,t-1}, Taking_{i,t-1}, NAPS_{i,t-1}\right) + \varepsilon_{it} \tag{2}$$

A total of 3,323 company samples that adopt DPFs were selected as the treatment group through the company screening method described in the previous section, and 3,184 company samples were selected as the control group through Model (2). Table 5 presents descriptive statistics of the main variables.

TABLE 5 Descriptive statistics of the main variables.

Variables	Average value	Standard deviation	Minimum value	Maximum value
Data dummy variables	0.511	0.500	0.000	1.000
Year dummy variable	0.799	0.401	0.000	1.000
Gross sales margin	29.681	18.267	−62.921	97.957
Net cash flow from operating activities per share	1.230	5.939	−134.039	136.058
Asset liability ratio	36.863	21.281	0.797	169.560
Logarithm of operating income	21.137	1.425	16.075	28.656
R&D investment intensity	0.051	0.059	0.000	0.984
Log of total assets	21.741	1.269	18.067	28.508
Net assets per share	4.412	2.779	−3.856	31.544

TABLE 6 Baseline model results.

Explained variable: Earnings per share (*EPS*)				
Sample interval: 2011–2019				
Explanatory variables	**Coefficient**	**Standard error**	***t*-statistic**	***p*-value**
$DATA_{it} \times YEAR_{it}$	0.076	0.0377	2.02	0.043
$DATA_{it}$	−0.123	0.0462	−2.28	0.023
$log(TA)$	0.022	0.0122	1.84	0.066
GPM	0.006	0.0007	9.24	0.000
$CFPS$	0.017	0.0013	12.99	0.000
ROL	−0.004	0.0006	−6.37	0.000
Wald statistic	435.56	p-value of the Wald test		0.000

TABLE 7 Parallel trend test results.

Processing effects	Coefficient estimates
δ_{-3}	0.0153
δ_{-2}	0.2777
δ_{-1}	−0.344
δ	0.2010
δ_{+1}	0.0667
δ_{+2}	0.0219
δ_{+3}	0.0830*
δ_{+4}	0.1850***

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

4 Results

4.1 Baseline model results

The results of the baseline regression model are shown in Table 6, where the coefficient of the dummy variable cross term DATA × YEAR reflects the net effect of using DPFs on the economic efficiency. The results showed that the coefficient of the cross term was significantly positive, indicating that the companies that adopted DPFs have obtained significant improvements in their earnings per share.

From the regression coefficients of the control variables, the coefficient of total asset size TA was significantly positive, indicating a positive effect of company size on company earnings per share, which is consistent with the analysis of the factors influencing earnings per share conducted by Sheng et al. (2020). The coefficient of gross profit margin GPM was significantly positive, which is consistent with the analysis of Yang and Yang. (2019). The coefficient of net cash flow from operating activities per share $CFPS$ was significantly positive, which is consistent with Song (2019) study on the effect of cash capacity on stock prices. The coefficient of ROL was significantly negative, and the higher the asset–liability ratio of a company, the higher the fixed financial expenses, thus negatively affecting earnings per share, which is consistent with the study by Meng et al. (2018).

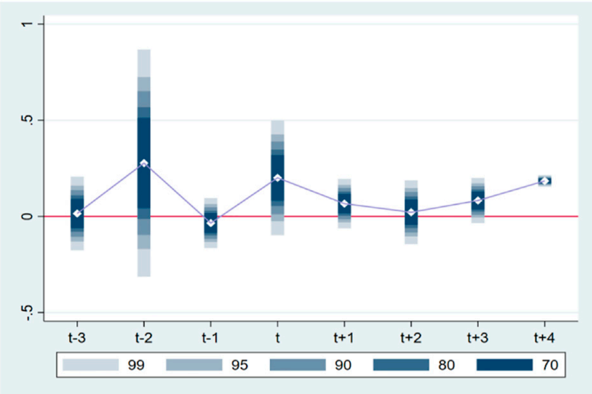

FIGURE 1
Parallel trend test chart.

4.2 Parallel trend test

In the DID model, "parallel trends" is a very important assumption. If the parallel trend assumption holds, then there should be no significant difference between the treatment and control groups before the point at which the company adopts DPFs. The multi-period DID model used in this paper examined the treatment effects before and after the treatment period to test whether the model satisfies the parallel trend assumption. The model was set up as follows.

$$EPS_{it} = \alpha + \sum\nolimits_{\tau=1}^{m} \delta_{-\tau} D_{i,t-\tau} + \delta D_{i,t} + \sum\nolimits_{\tau=1}^{q} \delta_{+\tau} D_{i,t+\tau} + \boldsymbol{\theta}^{\mathbf{n}} \mathbf{X}_{i,t-1} + \mu_i + \lambda_i + \eta_i + \varepsilon_{it} \quad (3)$$

where $D_{i,t}$ is the treatment year dummy variable, which means that it takes value of 1 when year t is the year when the ith company initially adopts DPFs, otherwise it is 0. Similarly, if a company adopts DPFs in period t, the company's $D_{i,t+\tau}$ was 1 when the observation year was $t+\tau$. In the rest of the cases, $D_{i,t+\tau}$ was 0. $\delta_{-\tau}$ and $\delta_{+\tau}$ respectively denote the impact from the τ period before and after the treatment. δ denotes the impact generated in the treatment current period. Therefore, $\delta_{-\tau}$ was the focus of the test, and if it was not significant, it indicates that there was no significant difference between the trends in the control and treatment groups before the treatment, satisfying the parallel trend hypothesis.

This paper examined $m = 3, q = 4$, i.e., three periods before and four periods after treatment. The test results are shown in Table 7, and the parallel trend tests diagram is shown in Figure 1. The coefficients are close to 0 in the three periods before treatment, indicating that the model satisfied the parallel trend hypothesis. The significantly positive coefficients of the third and fourth periods after the treatment confirm that there was a significant positive effect on earnings per share after the adoption of DPFs in the two periods.

4.3 Heterogeneity analysis

4.3.1 Industry heterogeneity analysis

Since there are some differences between technical conditions and economic benefits among different industries,

TABLE 8 Impact of DPF adoption on earnings per share (results of industry heterogeneity model regression).

Dependent variable: Earnings per share (EPS)				
Sample period: 2011–2019				
Industry	**Service industry**		**Industrial sector**	
Explanatory variables	**Coefficient**	***p*-value**	**Coefficient**	***p*-value**
$DATA \times YEAR$	0.110	0.094	0.0460	0.319
$DATA$	−0.885	0.090	−0.1287	0.000
$log(TA)$	0.004	0.860	0.0367	0.013
GPM	0.002	0.200	0.0088	0.000
$CFPS$	0.122	0.000	0.0190	0.000
ROL	−0.002	0.111	−0.0046	0.000
Wald statistic	92.97		398.56	
p-value of the Wald statistic	0.0001		0.0000	
Sample size	4,653		1854	

TABLE 9 Impact of DPF adoption on earnings per share (ownership heterogeneity model with regression results for SOEs and non-SOE classification).

Explained variable: Corporate earnings per share				
Sample interval: 2011–2019				
Ownership	**State-owned companies (SOEs)**		**Non-state-owned companies (nSOEs)**	
Explanatory variables	**Coefficient**	***p*-value**	**Coefficient**	***p*-value**
$DATA \times YEAR$	0.2661	0.001	0.0120	0.782
$DATA$	−0.1412	0.017	−0.1156	0.000
$log(TA)$	0.1008	0.000	−0.0078	0.571
GPM	0.0104	0.000	0.0050	0.000
$CFPS$	0.0127	0.000	0.0176	0.000
ROL	−0.0051	0.000	−0.0031	0.000
Wald statistic	151.6312		370.6134	
p-value of the Wald statistic	0.0000		0.0000	
Sample size	5,191		1,315	

to explore the heterogeneous effect of adopting DPFs on the economic benefits of companies between industries. We divided the sample into two groups, i.e., industrial and service companies, according to the Classification of Industries of National Economy (GB/T 4754-2017), and perform regressions separately. Additionally, the fixed effects of the subsectors are controlled. The regression results of the industry heterogeneity model are shown in Table 8.

In the regression results for the sample of service-sector companies, the coefficients of the dummy variable cross term $DATA \times YEAR$ were significantly positive, and the coefficients of the control variables were consistent with the results of the benchmark model. The process of adopting DPFs in service industry companies is generally to adopt data-related technologies in the traditional service industry and to use data as a production factor to enhance economic benefits for companies through collecting, processing, and analyzing data. Take the traditional commerce service industry as an example. It has been upgraded to e-commerce with the support of computer and internet technologies, and e-commerce platforms have gradually undergone a digital transformation with the development of DPF support technologies, such as cloud computing, big data technology, and deep learning. Furthermore, it has incorporated data as a production factor into production and operations activities. For example, in the traditional business service industry, user demand analysis is often based on the historical experience and business intuition of operators, and its decision-making lack a scientific basis. After the adoption of DPFs, e-commerce platforms could collect user data and analyze user profiles, demand, and other information with the help of data processing technology to promote product sales and enhance the economic efficiency of companies in a targeted manner. For service industry companies, there are two paths for adopting DPFs to improve economic efficiency: direct and indirect. Data information and data analysis technology not only improve the economic efficiency of companies directly by improving product design and optimizing sales channels, but also provide an impetus for strategic planning and business model innovation in the context of big data, which indirectly promotes company economic benefits (Sun, 2018).

In the regression results for industrial companies, the coefficient of the dummy variable cross term $DATA \times YEAR$ was positive but not significant. We speculate that the main reasons come from two aspects, i.e., the intensity of R&D investment on DPF supporting technology, and the imperfect development of DPF markets. First, R&D investment has long been considered important to DPFs. On the one hand, it has been proved there is a threshold effect of the impact of R&D investment intensity on company economic performance (Dai and Cheng, 2013). Specifically, R&D investment intensity can significantly contribute to company performance only when the first threshold value is reached. Since DPF is an emerging concept, the R&D investments of industrial companies engaged in DPF supported technology development may not have yet reached the first threshold value, resulting in insignificant improvement in their economic benefits. On the other hand, Zhao et al. (2012) found that there is a very significant lagged effect of R&D investment on the company performance of listed companies in China, and the most significant lag is 2 years. Second, the imperfect development of the DPF market may also affect the economic efficiency of companies. As an emerging production factor, the market development of DPFs still suffers from unclear data ownership, inconsistent pricing standards, difficulties in data security, and weak data circulation capacity. Limited by the development degree of DPF market, industrial companies adopting DPFs have not yet experienced insignificant improvements in their economic benefits. In summary, the above two points can explain that the adoption of DPFs does not significantly improve the economic performance of industrial companies during the sample period.

4.3.2 Ownership heterogeneity analysis

In the following, we examine the heterogeneity of ownership, mainly caused by varying degrees of influence by macro policies, different channels and management mechanisms for the introduction of new technologies and new elements. We divide the whole sample into two sub-samples, including state-owned companies (SOEs) and non-state-owned companies (nSOEs).

Table 9 shows the regression results of SOEs and nSOEs. Regarding to SOEs, the coefficient of the dummy variable cross term $DATA \times YEAR$ is significantly positive, and the coefficients of the control variables are consistent with the results of the baseline model. There are three main reasons. First, the importance of data as a factor of production is very much valued by top-level design, and one of the important manifestations is that SOEs are vigorously promoting the introduction and application of DPFs. The Action Plan for Promoting the Development of Big Data promulgated by the Fifth Plenary Session of the 18th Central Committee particularly emphasized that SOEs must follow the requirements of the market-oriented allocation of DPFs, strengthen data infrastructure management and data mining applications, use data to improve operational quality and efficiency, accelerate the cultivation of new growth momentum, and win the initiative in competitive development. SOEs have a greater advantage in the implementation of policies and related safeguards, so the adoption of DPFs is more likely to obtain a greater increase in economic efficiency. Second, concerning the lag effects of R&D investment on company performance, Ferreira et al. (2019) found that it is not significant for SOEs, while significant fort nSOEs. Third, SOEs have an advantage over non-SOEs in implementing national policies on DPF and the adoption of DPFs generally occurs earlier. Therefore, the adoption of DPFs has significantly improved the economic efficiency of SOEs during the sample period.

In the regression results for nSOEs, the coefficient of the dummy variable cross term $DATA \times YEAR$ is positive but not significant. Another remarkable difference is that the coefficient of total assets is insignificantly negative. We speculate that a major reason is because these companies experience more uncertainty in the business environment. Since DPF is an emerging concept and the DPF market is not well developed, the stability of the market environment corresponding to DPF still needs to be improved. Moreover, policies related to DPF have only been proposed for a relatively short period, and the stability of related policies remains to be observed. Therefore, nSOEs often have more concerns in the process of adopting DPFs, and thus do not deeply integrate DPFs into the production and operation processes.

5 Concluding remarks

This paper focused on the role of data production factor in the context of the digital economy. We conducted an empirical study to test whether the adoption of DPFs has a significant impact on company performance, which addresses a current concern in economic development.

The study showed that 1) the adoption of DPFs has a positive effect on the earnings per share of companies, which will lead to a significant improvement in company performance; 2) in the study of the heterogeneity of company industries, it was found that the economic efficiency of the service industry companies that adopting DPFs showed a significant improvement, but this could not indicate a significant improvement in the performance of industrial companies; and 3) to analyze the heterogeneity effect of company ownership, this paper divided the sample into SOEs and non-SOEs. From the perspective of the lag in R&D investment on company performance, SOEs have a certain time advantage over non-SOEs in implementing the national policy in DPF, so improvements in SOEs' performance are significant.

Based on the research findings, this paper put forward the following three policy recommendations: 1) Standardize the market for DPF, including the decision mechanism of data value, contribution, and remuneration as well as trading rules, and focus on the integration of data and knowledge management, while establishing and developing a knowledge value-oriented remuneration policy. 2) Vigorously promote the construction of infrastructure technical facilities, such as cloud computing, 5G networks, and distributed data centers, and improve the big data application environment. A large amount of data resources alone is not enough to support the improvement of company performance, and only by strengthening companies' own data analysis capabilities and dynamic innovation capabilities can we achieve scientific decision-making and win in the market competition. 3) Implement various national development policies on DPF, especially for non-SOEs, as the uncertainty of the policy business environment will have a greater impact on the business vitality of companies. Furthermore, because DPF is an emerging concept, their developmental immaturity leads to instability, and adaptability to the market environment still needs to be improved. Therefore, various supporting policies should be improved as soon as possible.

There are three limitations of this study. First, collecting data only from Chinese listed companies may bias the findings and lack generalization. In future studies, more countries and industries should be investigated to enrich the existing theory and practice of data production factor. Second, measuring company performance through only a single metric is not comprehensive enough. Beyond Earnings Per Share (EPS), other performance measurements should be included, such as Tobin's Q and Return on Equity (ROE). Finally, there are some factors that may affect company's digital innovation, such as company's status (Liu et al., 2021) and the attitudes of managers and staff concerning DPF adoption. Future study should consider the mediate effects of these factors.

Data availability statement

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

Author contributions

RG and HW contributed to conception and design of the study. RF organized the database. RF and FL performed the statistical analysis. RF and YR wrote sections of the manuscript. All authors contributed to manuscript revision, read, and approved the submitted version.

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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.

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How to design renewable energy support policies with imperfect carbon pricing?

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Based on the emission trading scheme (ETS), this study built a design framework of renewable energy support policies (RES), which is employed to assess the interaction between RES and ETS. For RES, we consider two policy instruments: feed-in-tariff (FIT) and renewable portfolio standards (RPS). Based on the partial equilibrium model, taking the case of China's electricity market, this study quantitatively discusses the implementation effects of six different policy mix scenarios from three aspects: emission reduction, production of green electricity, and social welfare. According to the results, there were big differences among the implementation effects of different RES instruments based on ETS. The renewable subsidy policy, on the whole, is better than renewable portfolio standards in terms of emission reduction, but worse in terms of improving the production of green electricity. In addition, different from the renewable subsidy policy, the renewable portfolio standards can reduce social welfare. When the emission quota is eased, RES can be implemented to significantly improve social welfare. These simulation results inspire China for the design of effective energy policies.

KEYWORDS

carbon pricing, renewable portfolio standards, social welfare, feed-in tariffs, emission trading scheme

1 Introduction

In recent years, energy shortage and environmental pollution have become increasingly serious, and the energy transition by promoting, developing, and utilizing renewable energy sources has become a consensus and concerted action of the international community (IEA, 2020). However, due to immature technologies and the high cost of renewable energy sources, its market competitiveness is weak. To support the development of the renewable energy industry, many OECD countries have implemented different types of renewable energy support policies. For example, the renewable energy feed-in-tariff (FIT), renewable portfolio standards (RPS), and other policies that can directly stimulate the installed capacity of renewable energy. Different from FIT where a fixed amount of money is paid for each kWh of green electricity, RPS compulsorily stipulates the market share of green electricity in the form of law. Fossil fuel power generation companies can meet RPS by purchasing renewable energy credits (RECs) from the green electricity generation companies or paying heavy fines; thus REC is a policy instrument to implement RPS. Moreover, an emission trading scheme (ETS) is also widely applied. Although it was not specifically designed for renewable energy, it can indirectly stimulate investment in renewable energy by increasing the cost of fossil energy. Since 2013, the Chinese government has formulated a series of policies for the production of green electricity and determined RES as a key component of its development plan (Mischke and Karlsson, 2014; Wang et al., 2014).

Among many renewable energy support policies, FIT is considered to be more effective because it can provide investors with long-term financial stability, but the high cost of subsidies imposes a heavy financial burden on the governments (Zhang et al., 2018). To reduce the aforementioned burden, RPS and REC become alternatives in different jurisdictions (Zhou and Zhao, 2021). Meanwhile, REC can bring economic incentives to cost-effective renewable energy companies, but there is still the risk of price volatility. When the primary goal is reducing emissions, a single RES-E policy (whether FIT or RPS) is always less cost-effective than a carbon pricing policy (Palmer and Burtraw 2005; Fischer and Newell 2008). Some scholars point out that a single policy cannot effectively meet multiple policy goals at the same time (Fischer and Carolyn, 2010). The successful transition to a low-carbon economy depends on the joint effect of low-carbon technology investment and renewable energy development, so it is necessary to adopt policy mixes (Gugler et al., 2021). But due to the volatility and intermittency of RES, these policies may restrain each other to some extent.

To avoid the possible negative effects or to take advantage of the potential synergistic effect of multiple policies, it is necessary to understand how different policy mechanisms interact with each other. In the case of two competing energy sources, which policy can bring more renewable energy investment, lower carbon emissions, and higher social welfare? How does the emission cap in ETS affect the implementation effect of renewable energy support policies? If the goal of the government is to raise the renewable energy share, what does the impact of the subsidy instruments and market mean? However, these issues are seldom talked about in current studies (Kök et al., 2018).

The research objective of this study is to quantify the effectiveness and interaction of ETS and renewable energy support policies. First of all, we built a partial equilibrium model to discuss the interaction mechanisms between ETS and renewable energy support policies. Then, we, combining the theoretical model and numerical model and taking the case of China's electricity market, assessed the performances of different policies in emission reduction, production of green electricity, and social welfare. According to the model result, there were big differences among the implementation effects of different renewable energy support policy instruments based on ETS. The renewable subsidy policy is better than RPS in terms of emission reduction and social welfare, but less effective in terms of improving the production of green electricity.

The rest of this study is organized as follows: the second part introduces the studies on ETS and renewable energy support policies conducted by domestic and foreign scholars. The third part presents the analytical model and describes the supply and demand situation of the electricity market under different policy scenarios as well as the decision-making behavior of two major market players—producers and consumers. The fourth part describes the numerical model and method design. The fifth part discusses the results, and the sixth part draws a conclusion and gives policy implications.

2 Literature review

Domestic and foreign scholars have conducted a series of studies on ETS and renewable energy support policies. First, according to the investigations and research, ETS alone cannot realize the emission reduction and energy objective. Second, we reviewed the necessity, implementation effects, and interactions of the policy mixes.

The economic theory clearly emphasizes that market means should be made full use of to fix a price for social losses caused by greenhouse gas emissions, which will help to stimulate the internalization of externalities of carbon emissions (Pigou, 1920). Therefore, many economists (Branger et al., 2015; Metcalf, 2009) have always considered the emission trading scheme (ETS) as an important emission reduction instrument for a long time, because it can realize emission reduction at the lowest cost. In the real world, however, there are many restrictions on making environmental policies. The economically effective and optimal emission trading market requires a valid high carbon price, which is difficult to realize. This is also proven by the empirical evidence from the EU emission trading market (Perino and Jarke, 2015). The supply–demand imbalance of emission quotas and various uncertainties in the electricity market lead to a low carbon price (Lecuyer and Quirion, 2016). Therefore, ETS alone is not enough to stimulate emission reductions (IEA, 2020). The energy transition requires the deployment of green electricity, but ETS has a limited effect on renewable energy development and cannot provide sufficient incentives for technological innovation. Another reason why ETS is not enough is that ETS is indirect. Firms can also decarbonize by using efficiency measures or switching fuel (e.g., from coal to gas). Firms can even reduce their production to decarbonize, especially under the historical allocation mechanism. On the demand side, many of them only have such measures. For electricity firms, it is the same. Furthermore, under the historical allocation mechanism in ETS, the production reduction of the steel sector can lead to a lower carbon price and reduce the renewable investment in the electricity sector. The experience of the EU tells us that apart from ETS, a specific renewable energy objective is also needed (Schmidt et al., 2012).

To achieve multiple policy goals, it is particularly important to mix ETS and renewable energy support policies (Duan et al., 2018). However, the effect of policy mixes has always been a focus of controversy in academic circles. Many scholars have considered the synergistic effect between ETS and renewable energy support policies and confirmed the importance of policy mixes to achieve desired emission reduction and energy objectives in the most cost-effective manner (Cheng et al., 2016; Fan et al., 2016). Some studies employed the computable general equilibrium model or partial equilibrium model to assess the social and economic impact of policy mixes. For example, some scholars have discussed the interaction between emission cap and REC or the interaction between emission cap and FIT (Böhringer and Behrens, 2015; Jos, 2005). Lots of quantitative studies have shown that although policy mixes can reduce social welfare and cause GDP losses, they can more efficiently reduce the electricity generation from fossil fuels and increase the production of RE, thus promoting the energy transition (Mu et al., 2017; Wu et al., 2017; Wu et al., 2020). There are some similar viewpoints that the policy mixes can help to realize deep decarbonization of energy systems quickly (Hepburn et al., 2020; Rosenbloom et al., 2020).

However, mixed policies may also cause conflicts and even lead to the failure of some policy instruments, thus increasing the social cost of policy implementation. Some scholars pointed out that the impact of renewable energy support policies on ETS should be admitted (Fischer et al., 2010). The implementation of renewable energy support policies can help ETS meet the emission cap and reduce the carbon price, which is thus relatively beneficial to fossil energy. In some studies, it is believed that excessive renewable energy objectives will restrain the demand for carbon emission quotas, thus leading to a low carbon price (Nordhaus, 2011; Berghet al., 2013; Lindberg, 2019). Similarly, the trials of ETS in China also show that the risk of emission quota over-allocation may lead to a drop in carbon price and reduce market efficiency (Wu et al., 2017). Therefore, to achieve climate goals and low-carbon transition, we must fully understand the interaction mechanism between different policies and give play to the advantages of each policy instrument, which is of great significance for China to achieve carbon peak and carbon neutrality.

To sum up, it is necessary and important to study policy mixes, but most of the previous studies focused on quantitative research and ignored the theoretical discussion. Specifically, there is no study on the interaction between China ETS and renewable energy support policies. Based on the partial equilibrium model, this study analyzes how ETS and different renewable energy support policies affect the game behavior of market players. In addition, based on China's electricity market, it simulates CO_2 emissions, production of green electricity, and social welfare under different policy scenarios, which inspires China's design of energy policies.

3 Theoretical model

3.1 Policy description

To explore the interaction mechanism between renewable energy support policies and carbon emission trading, we built a partial equilibrium model and described the supply and demand situation of the electricity market as well as two major market players—producers and consumers—and their decision-making behaviors. The following policies are involved in the model.

An emission trading scheme refers to a mechanism where a certain number of emission credits are assigned to the participants. These credits thus become a commodity, which can be "consumed" by the participants themselves or "traded" with others in the carbon market, which depends on the marginal abatement cost. As a market-driven instrument, it first sets emission caps and then fixes a price for CO_2 produced by burning fossil fuels. Feed-in tariff (FIT), also known as renewable subsidy policy, means that the governments give subsidies for each kWh of electricity to renewable energy power generators (such as PV electricity generators, wind electricity generators, etc.). Many countries have adopted this policy to support and stimulate the green electricity markets at an early stage (such as several member states of the EU, Australia, and several states of the United States). Because high policy cost is needed to implement the renewable subsidy policy, it is not as good as the marketized instruments in the long run and the policy should gradually retreat. To reduce the financial burden caused by subsidies, renewable portfolio standards (RPS) and purchased renewable energy credits (REC) are two alternative market instruments. Green electricity generation companies can make extra profit by selling purchased renewable energy credits.

In the model, the electricity price depends on the supply–demand relationship in the state of equilibrium. ETS can affect the production cost of fossil fuel companies through the carbon price. Renewable energy support policies can change the equilibrium price and production by affecting the electricity generation cost and electricity demand. By comparing the differences among carbon emissions, production of green electricity, and social welfare, we can assess the impact of policies on the economy, environment, and society.

3.2 Behavior of market players

3.2.1 Electricity generators

When fossil fuels are used to generate electricity, pollutants are discharged, leading to environmental externalities. In such a case, the policymakers need to choose the optimal policy instrument to realize the externality, and such intervention is bound to affect other economic agents in the market. The electricity generators are all in pursuit of profit maximization. They will measure the marginal cost and marginal revenue of electricity generation according to policymakers' decisions and then adjust their production $(X_i, i = f, r)$ to ensure their profit maximization.

Suppose that the production cost functions of each technology i are $C_i(X_i), i = f, r$, and it is a continuous convex function (Lecuyer and Quirion, 2016): $C_i^{'}(X_i) = \partial(C_i(X_i))/\partial X_i > 0$ and $C_i^{''}(X_i) = \partial^2(C_i(X_i))/\partial X_i^2 > 0$. Considering the great space change in the availability of wind energy resources and solar energy resources, the sites with the highest resource quality will be used, followed by the sites with the lower quality. The cost function of each technology i is described with the most classical linear quadratic form:

$$C_i(X_i) = a_i X_i^2 + b_i X_i, \quad i = f, r \tag{1}$$

In this function, a_i and b_i are parameters to the cost function of each technology i. The profit of the electricity generator is as follows:

$$\prod\left(p, x_f, x_r, \kappa, \pi, a, b\right) = p \cdot X_f + \pi \cdot X_r - C_{r\&f}\left(X_{r\&f}\right) - \kappa \cdot u \cdot X_f \tag{2}$$

In this function, p stands for electricity price in the market, which is also the marginal revenue of conventional technology companies. π stands for the marginal revenue from the sale of renewable energy, which depends on which renewable energy support policy the regulator chooses. Considering RPS and REC scenarios, $\pi = p + \eta$, in which η stands for renewable energy credits price and endogenously calculated by the following constraint:

$$X_r \geq \gamma \cdot \left(X_f + X_r\right) \perp \eta \geq 0 \tag{3}$$

That requires that a certain share of γ must be from renewable energy sources to form a green certificate equilibrium price η. In the case of the FIT policy, $\pi = S$, in which S stands for tariff level. When ETS is alone, the benefits of renewables just come from electricity price, so $\pi = p$.

In an ETS system, κ stands for the shadow price formed under the constraint of emission cap Ω, and represents the carbon price, which is endogenously determined by the following constraint:

$$\Omega \geq u \cdot X_f \perp \kappa \geq 0 \tag{4}$$

When the emission cap Ω is binding, κ will be positive. When the emission cap Ω is equal to the total amount of CO_2, the emission cap will lose its constraining force and the carbon price $\kappa = 0$.

3.2.2 Consumers

Consumers are always in pursuit of utility maximization, but since China's electricity price is regulated by the government, it can be considered that changes in demand will not lead to significant changes in electricity price. Although the functional relationship between electricity price in the market and electricity demand is not clear, there is still a functional relationship between electricity price in the market p and electricity demand D. We assume that there is a linear relationship between consumer demand D and electricity price in market p in the model (Liu et al., 2019), which is defined as follows:

$$D = B - Ap \tag{5}$$

If the inverse demand function is defined as $p(D)$, the consumer surplus is as follows:

$$CS(\mathrm{p}) = \int_0^q p(x)dx - p \cdot D(p) \tag{6}$$

In this function, x stands for the production of electricity. The consumer surplus function CS is a strictly convex function: $CS' > 0$ and $CS'' > 0$.

3.3 Supply–demand equilibrium model of electricity

First, a perfectly competitive market with symmetric information was assumed in the model (Lecuyer and Quirion, 2016). Second, we considered two technological types of electricity companies i, whose electricity generation is X_i. For conventional energy electricity generation companies, $i = f$ stands for fossil fuel technologies (coal, gas, etc.). For clean-energy electricity generation companies, $i = r$ stands for carbon-free technologies (wind, PV, etc.). Each technology cannot produce more than its available capacity in any period of time (Abrell et al., 2019):

$$\alpha_i \cdot M_i \geq X_i \perp \mu_i \geq 0 \forall i \tag{7}$$

Considering the intermittency of renewable energy resources, the electricity generation from wind and solar energy is greatly affected by weather conditions and geographical location, so α_i is used to measure the availability of renewable energy resources in this study. For conventional technologies, it can also reflect the service condition of electricity generators (there is the possibility of maintenance or downtime). M_i stands for the total existing installed capacity of each energy technology. μ_i is the shadow price of the generating capacity of each technology, which is determined by Eq. 1. If the production is below the capacity limit, the shadow price will be zero $(\mu_i = 0)$; if they are equal, the shadow price will be positive $(\mu_i > 0)$.

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In a perfectly competitive market, no company will be hindered from entering or leaving the market, and no seller or buyer can determine the price, which meets Pareto optimality. In the equilibrium model, the production costs and benefits of electricity generators determine the production of each technology i (Abrell al., 2019). For fossil fuel technologies:

$$C_f\left(X_f\right)/\partial X_f + \kappa + \mu_f \geq p \perp X_f > 0 \tag{8}$$

For carbon-free technologies:

$$C_r\left(X_r\right)/\partial X_r + \mu_r \geq \pi \perp X_r > 0 \tag{9}$$

where $C_i\left(X_i\right)$ stands for the production cost of each technology. When the marginal cost is higher than the marginal revenue, if the company continues the production, it will lead to losses, so $X_i = 0$. When they are equal, the company will increase production, so $X_i > 0$. Meanwhile, the aggregate demand $D$for electricity in the market should be equal to the aggregate supply in any period of time.

$$\sum_i X_i = D \, \forall i \tag{10}$$

3.4 Social welfare maximization

When analyzing the interaction between renewable energy support policies and ETS, we mainly examined the ability to solve the pollutant externalities under two policy scenarios. In a decentralized market economy, the equilibrium decision of energy supply and demand depends on utility maximization for consumers and profit maximization for electricity generators. Therefore, policymakers should focus on social welfare maximization. The social welfare function is as follows (Lecuyer and Quirion, 2016; Abrell et al., 2019):

$$\max_{\Omega,\gamma,s} W = CS(p) + \Pi\left(p, x_f, x_r, \pi, \kappa, \gamma\right) - E\left(x_f\right) - Sub\left(x_r\right) + T\left(x_f\right) \tag{11}$$

$$E\left(x_f\right) = \delta \cdot u \cdot x_f \tag{12}$$

$E\left(x_f\right)$ is the loss function. δ stands for the social cost of carbon, implying the constant marginal loss in a certain period of time. u stands for the carbon intensity of fossil fuels in the power sector (in the model, different coals and natural gases are distinguished).

$$Sub\left(x_r\right) = (\pi - p) \cdot x_r \tag{13}$$

$$T\left(x_f\right) = \kappa \cdot u \cdot x_f \tag{14}$$

$Sub\left(x_r\right)$ is the cost of subsidies, meaning the total cost paid by the governments to the renewable energy producers as subsidies under the scenario of renewable energy support policies. $T\left(x_f\right)$ means that the carbon emission costs paid by fossil energy enterprises are transferred to the government regulatory revenue and then used for redistribution. The last two formulas stand for changes in social welfare under different policy scenarios.

4 Empirical quantitative framework and results

4.1 Description of numerical model

To quantify the implementation effect of the policy mixes, we built a numerical model which was calibrated with data about China's electricity market in 2018. First of all, we found out the differences between different electricity generation technologies i (coal, gas, wind, PV, etc.) including carbon intensity, production cost, installed capacity, and other indicators. Importantly, since China's electricity market is still dominated by coal electricity generation, we further classify coal into coal and coal gangue, so that we can describe policy-induced changes of each technology portfolio on the production and supply sides from the perspective of finer granularity. Then, two renewable energy support policy instruments, renewable subsidy policy and REC, were introduced to the model, and the efforts to implement the policies were also considered. With ETS alone as the benchmark, this study analyzed the effect of policy mixes on social welfare, production of green electricity, and CO_2 emissions.

4.2 Data sources and explanation

Taking the case of China's electricity market in 2018, we conducted an empirical analysis based on the aforementioned theoretical model. In the model, the following parameters are required: α, the availability of renewable energy (wind energy and solar energy) resources which changes over time (Wu et al., 2013; Chang et al., 2014; Yang et al., 2012), and κ_i, the cumulative installed capacity of various energy technologies i (National Energy Commission Administration, 2017). We found that the installed capacity of renewable energy accounted for 20%, but its electricity production only accounted for 8%, which indicates that there is still partial wind and PV curtailment in China, and the availability of renewable energy is low. In combination with the data of α, this study can better describe the heterogeneity and intermittency of renewable energy resources. When calculating the social losses caused by carbon externalities, we got the result by multiplying carbon emissions during electricity production by the social cost of carbon. We got the result of carbon emissions by multiplying the sum of carbon intensity and annual service hours of various conventional technologies by the installed capacity (National Energy

Commission Administration, 2017) (see Supplementary Appendix S1 for other data mentioned in the text).

According to the data about carbon intensity, compared with Germany, the carbon intensity of China's coal electricity plants and the electricity market is dominated by coal electricity in China, which partly contributes to the high ratio of China's carbon emissions over global carbon emissions. Later, we obtained data about China's social cost of carbon (Ricke et al., 2018; Tianet al., 2019). Last, the production cost functions and emission cost functions of various technologies were obtained (Abrell et al., 2019; Liu et al., 2014; Feng et al., 2018). Through the calibration unit, we obtained the electricity demand function (Liu et al., 2019; Lin and Purra, 2019; Pu et al., 2020). The aforementioned data were all calibrated again in the numerical model.

4.3 Design of empirical methods

Based on the partial equilibrium model, we made use of the mixed complementarity formula to describe China's electricity supply–demand market. All nonlinear inequalities can be divided into two kinds: zero profit and market clearing, which form complementary conditions with production X and ω shadow price, respectively. In addition, there is a dynamic game between the two types of competitive companies and policymakers, namely the former pursues profit maximization, while the latter aims to maximize social welfare. In this process, the decision-making variables of the other side need to be taken into account. This is a two-level optimization problem, that is, a low-level constraint set equilibrium problem of maximization objective function. Therefore, we should transform the part of the low-level equilibrium problem into a mixed complementarity problem (MCP). To solve it, we employed the general algebraic modeling system, namely, the path solver in General Algebraic Modeling System (GAMS) software.

In addition, we need to explain some parameters in the model. The emission cap Ω is always an exogenous variable, which should be constantly adjusted during the program run before the optimal solution is found. When policy mixes are implemented, the subsidy S to renewable energy and renewable energy quota γ are also exogenous variables. The optimal value S may fall at any point of the interval 0.05 yuan/kWh–0.5 yuan/kWh, and the optimal value γ may fall at any point of the interval 6%–12%. At this point, we discretize and assign values to Ω, S, and γ at the same time, and the model will constantly be iterated until the optimal solution is found.

4.4 Basic settings of the model

4.4.1 Policy scenarios and benchmark setting

In the empirical analysis, we assessed the interaction between ETS and two alternative renewable energy support policies—purchased renewable energy credits (REC) and renewable subsidy policy. Later, we considered the efforts to implement each renewable energy support policy and divided them into different policy scenarios. The specific scenarios are shown in Table 2. Scenario 1 and Scenario 2 differ in mandatory market share in RPS: S1 = 0.08 and S2 = 0.1. Scenario 3, Scenario 4, and Scenario 5 differ in the amount of policy in renewable subsidy policy: S4 = 0.1, S5 = 0.2, and S6 = 0.3. Moreover, ETS alone is used as the benchmark in this study to compare the different policy scenarios.

4.4.2 Scale setting

As shown in Figures 2, 5, to better show the changes in CO_2 emissions during the implementation of policy mixes compared with those during the implementation of ETS alone, ΔR is defined in this study, which represents emissions during the implementation of ETS alone minus emissions during the implementation of both ETS and renewable subsidy policy. $\Delta R = E_{S3-S5} - E_{S0}$. Similarly, to better show the changes in social welfare during the implementation of policy mixes compared with those during the implementation of ETS alone, ΔW is defined in this study, which represents social welfare during the implementation of both ETS and renewable subsidy policy minus social welfare during the implementation of ETS alone. $\Delta W = W_{S3-S5} - W_{S0}$.

As shown in Figures 1, 3, 4, % is defined in this study, which represents the changing rate of CO_2 emissions, production of green electricity, and social welfare under the policy mix scenarios S1–S5 compared with benchmark scenario S0, namely, $\% = (S_{1-5} - S_0)/S_0$.

5 Analysis of empirical results

5.1 CO_2 emissions

Figure 1 shows the changes in emission reduction in scenarios S1–S5 compared with benchmark scenario S0. According to this figure, we can see that when the emission cap is relatively stringent, implementing ETS and renewable energy support policies at the same time may promote emission reduction more than implementing ETS alone, but the effect varies according to the types of RES and the efforts to implement the policy. The emission reduction effect of implementing renewable subsidy policy (S3–S5) is generally better than that of RPS and RECs (S1, S2), and the greater the subsidy amount and the higher the mandatory market share, the better the emission reduction effect. When the cap is 10 million tons, the emission reduction ratio of S1 and S2 is between 0.9% and 1.3%, while that of S3–S5 is between 1% and 2.8%.

In fact, the subsidies could decrease the carbon price. As shown in Supplementary Table S1, for the same cap, the carbon price decreases with the increase of subsidies. The more

TABLE 1 Variables and parameters in the analysis model.

Variables and parameters in the analysis model	Value	Dimension	Description
x_r	-	MWh	Electricity from renewable sources
x_f	-	MWh	Electricity from fossil fuels
α_i	-	——	Availability of capacity
M_{coal}	1007940	MW	Existing production capacities
M_{gas}	83130	MW	Existing production capacities
M_{wind}	184665	MW	Existing production capacities
M_{pv}	175016	MW	Existing production capacities
$a_{(coal)}$	$3.69*10-^{4}$	MWh^2/RMB	Slope of generation cost functions
$b_{(coal)}$	17.24	MWh/RMB	Slope of generation cost functions
μ_i	-	RMB/MWh	Shadow price of e-generating capacity
p	-	RMB/kWh	Electricity price
κ	-	RMB/ton	CO_2 price
η	-	RMB/MWh	Renewable energy credits price
Ω	8–30	Million tons	Emissions cap
u	-	tCO2/MWh	CO_2 intensity of fossil-based electricity
δ	156	RMB/ton	Social carbon costs
γ	8%–10%	——	Share of RE in total electricity
π	-	RMB/kWh	Effective marginal revenue of renewables
A	-	——	Intercept of demand function
B	-	——	Slope of demand function
S	0.05–0.5	RMB/kWh	Subsidy price

TABLE 2 Policy scenarios.

Scenario	Subsidy (RMB/kWh)	Renewable energy share (γ)
Emission trading scheme only (Benchmark)		
S0	×	×
Emission trading scheme and tradable green certificates		
S1	×	8%
S2	×	10%
Emission trading scheme and renewable subsidy policy		
S3	0.1	×
S4	0.2	×
S5	0.3	×

renewables are deployed, the greater the impact on the carbon price. According to the scenarios of S1–S5, the proportions of renewables in the FIT scenarios are much less than in the RPS scenarios, so the former leads to higher carbon prices than the latter. For example, when the cap = 6 million tons and the tariff is 0.5 RMB, the shares of green electricity are just 2.04%. This is far lower than the green certificate case, which is at least 8.02% under the same cap, see Supplementary Tables S1, S3. The descending carbon price encourages coal-fired generation; therefore, the emission reduction ratio of S1 and S2 is lower than those of the scenarios of S3–S5.

5.1.1 The implementation effect of ETS mixed with FIT

Figure 2 more clearly shows the interaction between renewable subsidy policy and the emission cap. However, whether FIT policies actually contribute to CO_2 reduction when overlapping with an ETS is a question. Under the mixed policy scenario of renewable energy subsidies and carbon market at the same time, through the interaction between subsidy price and emission cap, we find that the results are divided into the following two cases:

On the one hand, when the emission cap of the carbon market is very loose, the carbon price will be much less than the social cost of carbon (SCC) (SCC = 156 RMB/ton, κ = 74.9 RMB/ton), and it is necessary to implement the subsidy policy with a low subsidy level. This is because when the subsidy level is low, the effect of renewables on carbon prices is limited. In addition, low carbon prices cannot or can only trigger a small part of fuel switching between coal and natural gas, and also the renewable energy target cannot be reached. Meanwhile, in such a case, it is necessary to combine the renewable subsidy policy with ETS to

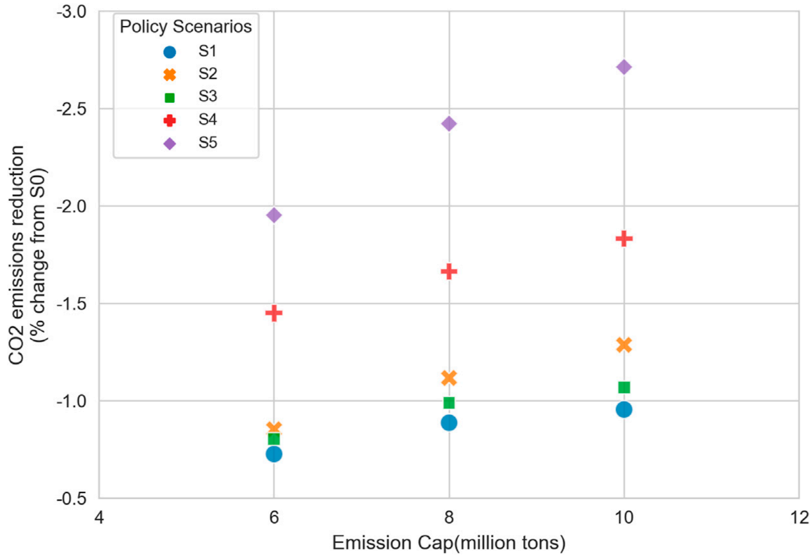

FIGURE 1
CO_2 emissions under different policy scenarios.

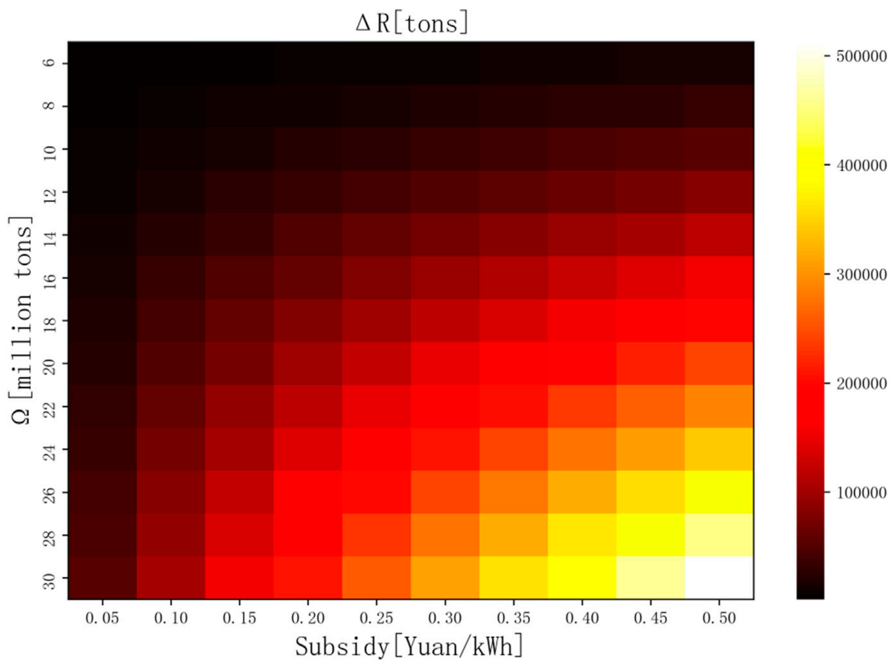

FIGURE 2
Carbon emissions of subsidy and carbon market combination policy.

promote the increase of renewable energy sources, which will achieve emission reduction by a greater order of magnitude.

However, with the high subsidy level combined with the loose emission cap, the situation is unclear. In this situation, the carbon price may be much lower, and high subsidies exacerbate this situation. Since the dirtier coal-fired generation benefits from the carbon price decrease, to maintain the same level of emissions, it must decrease natural gas generation more than

TABLE 3 Electricity generation.

Renewable energy subsidy [RMB/kWh](*S*)		Electricity generation change (%)			
		Coal	Gas	Wind	PV
Cap = 6 million tons					
S3	0.10	−0.303%	+1.161%	+0.567%	+1.463%
S4	0.20	−0.602%	+2.301%	+1.134%	+2.926%
S5	0.30	−0.947%	+3.459%	+1.737%	+4.416%

coal-fired generation. Meanwhile, the emissions may exceed the alternative emission reductions which brought about encouraging renewable deployments. Just as shown in Figure 2, when the cap = 30 million tons, the emission in the case of 0.50 yuan/kWh is surprisingly higher than that of the 0.05 yuan/kWh. Moreover, with the increase in the amount of subsidies, the emission reduction effect will be more significant, but at the same time, it will require greater policy costs.

On the other hand, when the cap is strictly stringent, the carbon price will be approximately equal to 156 RMB/ton. Since implementing ETS alone can achieve the theoretically optimal emission reduction effect, it is unreasonable to implement a subsidy policy at the same time.

5.1.2 The emission reduction path of ETS mixed with FIT

The emission reduction path of scenarios S3–S5 where ETS and FIT are implemented at the same time is shown in Table 3. Under benchmark scenario S0, the production of coal electricity is 17,789.941 TWh, that of natural gas electricity is 6,263.900 TWh, that of wind electricity is 101.627 TWh, and that of photoelectric power is 90.260 TWh. We found two reasons for this:

First, S3–S5 promote fuel conversion among fossil fuels, realizing the transition from high-emission coal electricity generation to natural gas electricity generation. After the introduction of a subsidy policy based on the emission cap control alone, cap = 6 million tons, S = 0.1 RMB/kWh, the terminal demand increases by 0.9%. This part of electricity demand is mainly met by electricity generated from natural gas, supplemented by wind electricity and PV electricity, while the proportion of coal electricity decreases.

Second, S3–S5 promote an increase in the production of renewable energy, so that renewable energy can replace fossil fuels. According to the results of the model, compared with wind electricity, the increase in the production of PV electricity is more significant, which is because the investment in wind electricity generation is larger than that in PV electricity generation. If they are given the same amount of subsidies without considering different renewable energy technologies, the investors may invest more in the PV industry, thus making the proportion of the increase in production of PV electricity larger. For example, when the cap is 6 million tons, as the amount of subsidy gradually increases to 0.3 RMB/kWh from 0.1 RMB/kWh, the proportion of the increase in production of PV electricity becomes 4.416% and that of wind electricity becomes 1.737%. Therefore, when implementing the subsidy policy, the government should take both policy cost and investment benefit into account and implement differentiated subsidies for different renewable energy technologies.

5.1.3 The carbon emissions of ETS mixed with RPS

The performance of the mixed policy of the green certificate and carbon market in carbon emissions are further discussed in the following. As shown in Figure 3, with the increase of the proportion of green electricity, the emission reduction has a fluctuation phenomenon of first decreasing and then increasing, then decreasing and then increasing again. For example, when cap = 6 million tons, when the proportion γ = 16% (see Supplementary Appendix S1 and Table 3), the emission is the lowest, and then increases. This is the very famous phenomenon of “green promotes dirty.” The main reason is that when the renewable energy market share increases, the demand for fossil energy power will decrease, resulting in a decline in fossil energy power generation and carbon emissions (cap = 6 million tons, γ = 10% or 16%) (see Supplementary Appendix S1 and Table 3). However, with the increase in proportion, the demand for carbon emission quotas of fossil energy will be further reduced. See Supplementary Appendix S1, Table 3. At this time, the market carbon price will be reduced (γ=16%, κ = 61.2 RMB/ton) and the power generation cost for coal-fired power enterprises will be reduced, which will seize the fossil energy power market and squeeze cleaner natural gas power generation out of the market. For example, when the renewable energy market share γ = 18%, compared with 16%, coal power increases by 1.6%, natural gas power generation decreases by 3.6%, and the total emissions also increase accordingly (see Supplementary Appendix S1 and Table 3). Therefore, there is a situation where “cleaner power” is replaced by “dirty power”-based market (see Supplementary Appendix S1 and Table 4).

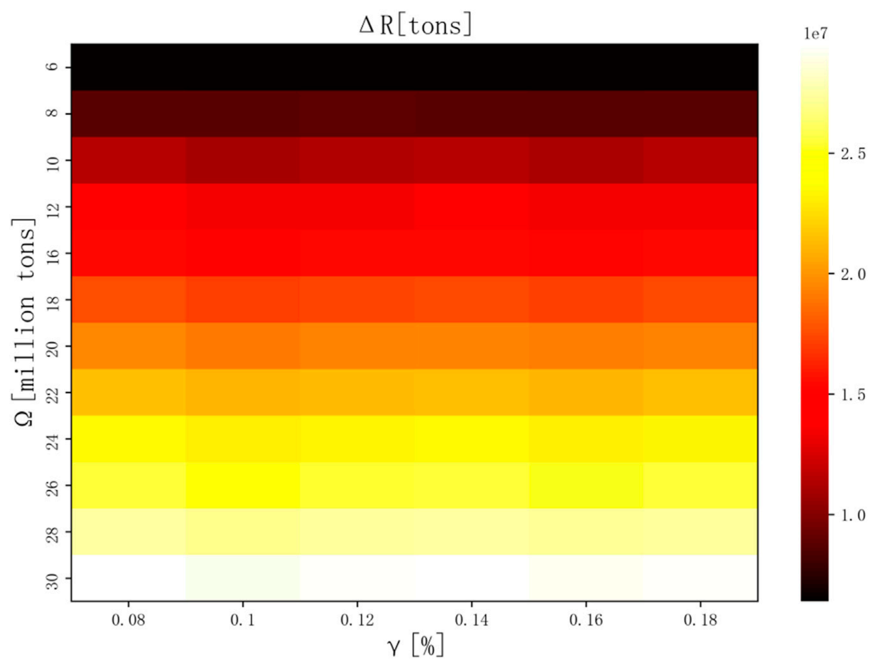

FIGURE 3
Carbon emissions of green credits and carbon market combination policy.

TABLE 4 Comparison of policy scenarios.

Scenario	Carbon price (RMB)	Electricity price (RMB)	Credits price (RMB)
S0	225.8	0.38	
S1	85.6	0.39	1.401
S3	234.3	0.38	

Lastly, we will explain why the emission reduction effect in S1 and S2 are lower than those of S3–S5 on the whole. There might be two reasons: under scenarios S1 and S2, the carbon price is relatively low and the natural gas electricity generation transits to coal electricity generation within the fossil fuels. In some studies, some scholars believe that excessive renewable energy objectives will restrain the demand for carbon emission quotas, thus leading to a low carbon price (Lindberg et al., 2019). This is consistent with the results of the model. As shown in Table 4, the lower case is compared. S0, S1, and S3 deliver similar green electricity generation while leading to quite different carbon prices. For example, the carbon price under scenarios S1 = 85 RMB/ton, far lower than S0 and S3. Moreover, the mandatory renewable energy share will make investors invest in renewable energy electricity generation, which will lead to underinvestment in natural gas electricity generation. However, wind electricity generation and PV electricity generation are intermittent, so backup coal electricity generation units are required for peak-load regulation. At last, the result might be over-reliance on backup (coal-fired) generators (Aflaki and Netessine, 2017), which is consistent with the results of the model. According to the results of the model, when the share of green electricity increased from 10% to 12%, the share of coal electricity increased by 2%.

5.2 Production of green electricity

Figure 4 presents the changes in the production of green electricity under scenarios S1–S5 compared to benchmark scenario S0. We can see that compared with S0, all scenarios S1–S5 can improve the production of green electricity, among which S1 and S2 have better effects. When cap = 10 million tons, increasing proportion under scenarios S1 and S2 ranges from

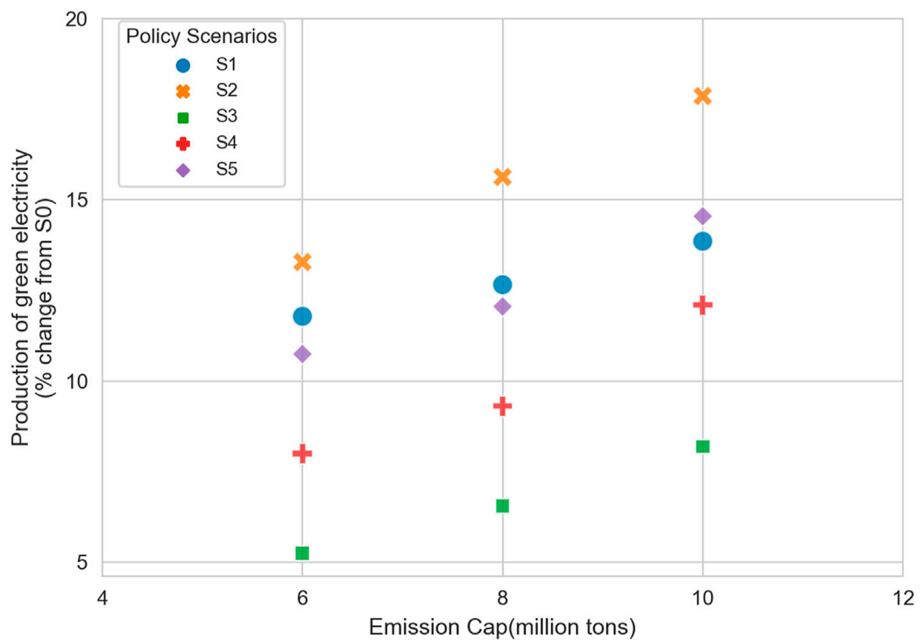

FIGURE 4
Production of green electricity under different policy scenarios.

13% to 18%, while that under scenarios S3–S5 ranges from 8% to 15%. In addition, we can find that S1 and S5 have similar effects on increasing the production of green electricity, but S5 has higher policy costs and cannot solve the long-term incentive problem in the development of the renewable energy industry. Therefore, with a similar effect, REC, as a marketized instrument, maybe a better choice.

First, according to the results of the model, we will analyze the reasons why S1 and S2 can stimulate the increase in the production of green electricity. First, the government stipulates the market share of green electricity, which directly stimulates the investment in RES; as the proportion of γ increases, the share of renewable energy also increases. In the case of cap = 8 million tons, when γ is 0.08, the share of RE is 7.42%; when γ is 0.1, the share of RE is 7.86%. Second, the price of a green certificate can bring extra benefits to renewable energy companies. In the case of cap = 6 million tons, when $\gamma = 0.08$, the quota price is 1.401 RMB/kWh. Since China's quota and green certificate market are still in the early stage, the price of green certificates is low and has volatility risk, but there is still a large space for development.

Second, we will discuss the effect of the interaction between renewable subsidy policy and ETS on the production of green electricity, as shown in Table 3. First, with the same cap, as the amount of subsidy increases, the production of green electricity increases. For example, when cap = 8 million tons, if S increases to 0.5 RMB/kWh from 0.1 RMB/kWh, the shares of green electricity increase by 6.5% and 17.3%, respectively. Since the cost of investment in such renewable energy as wind electricity and PV energy is high, coupled with their natural intermittency and technical thresholds, renewable energy is not very competitive in the electricity market. Nonetheless, the implementation of a renewable subsidy policy can make up for its disadvantage in cost and promote technological innovation. However, the amount of subsidy and the opportunity to retreat should be well grasped. Second, a gradually relaxed cap requirement for ETS that could render the same RPS percentage is correspondingly difficult to achieve. For example, when the RPS percentage requirement is 0.08, if the cap increases to 8 million tons from 6 million tons, the shares of green electricity will decrease by 8.66% and 6.58%, respectively. The scholars believe that raising the carbon price may reduce the overall proportion of green electricity (Aflaki et al., 2017), which is consistent with the result of our model. This means that controlling the emission cap alone can directly stimulate emission reduction, but cannot achieve the goal of renewable energy development. Therefore, to achieve the multiple policy objectives of China, renewable energy support policies must be implemented as supplementary means.

5.3 Social welfare

Figure 5 shows the changes in social welfare of scenarios S1–S5 compared with the benchmark scenario S0. With S0 as the benchmark, scenarios S1 and S2 will reduce social welfare, while scenarios S3–S5 will improve social welfare. In the case of cap = 10 million tons, the social welfare decreases by about 0.0468%–

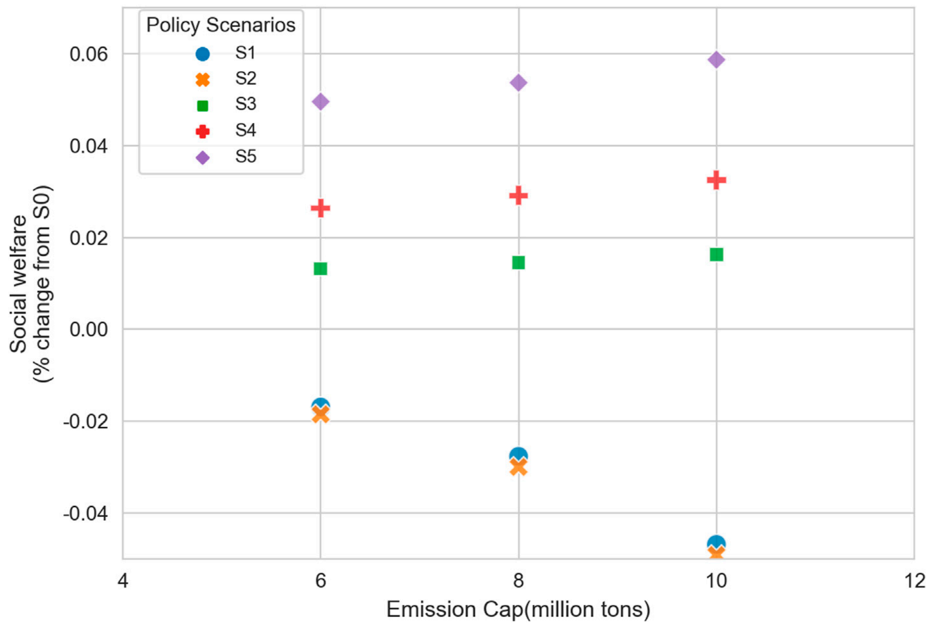

FIGURE 5
Social welfare under different policy scenarios.

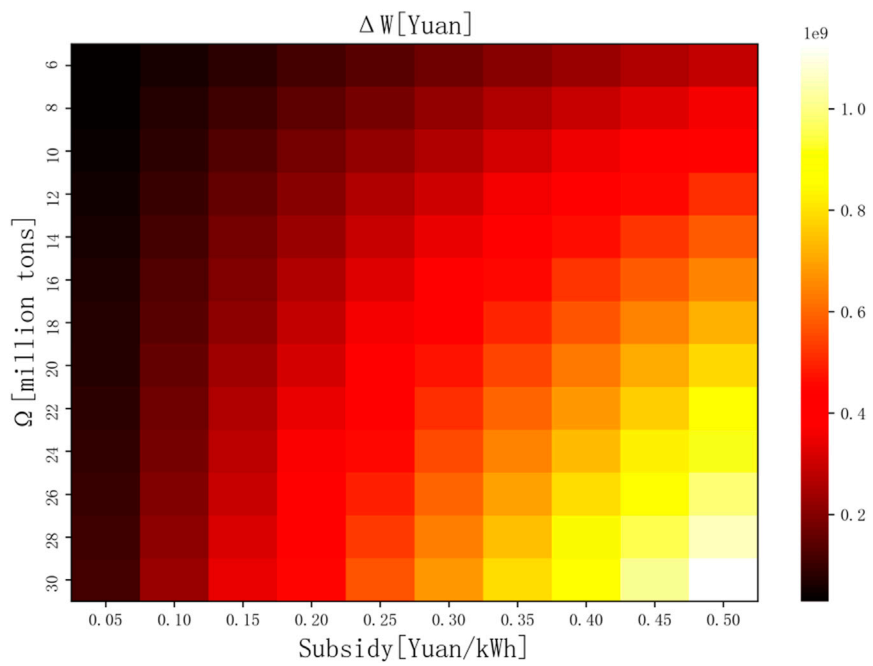

FIGURE 6
Social welfare under subsidy and carbon market combination policy.

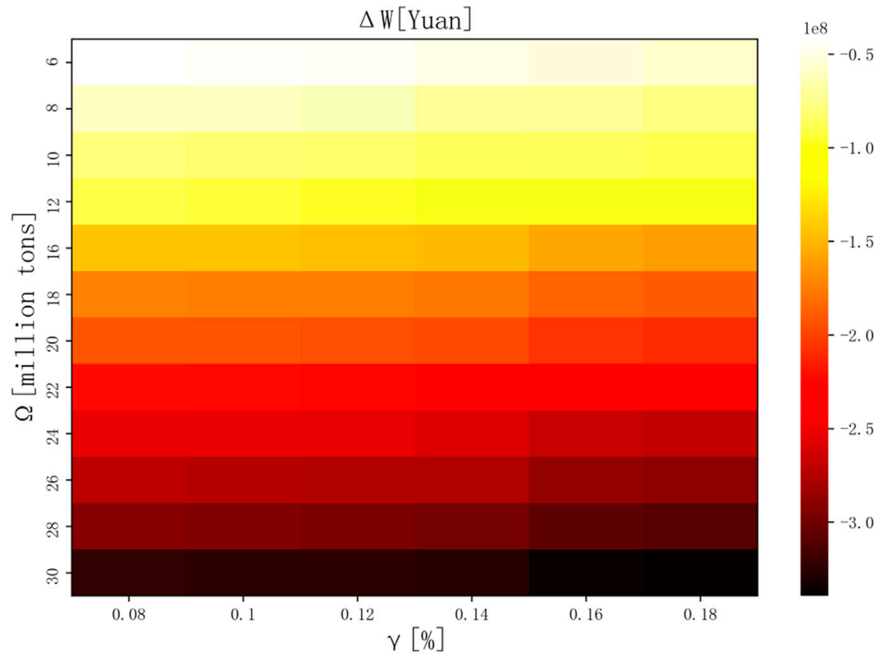

FIGURE 7
Social welfare under green credits and carbon market combination policy.

0.0491% under scenarios S1 and S2, while social welfare increases by 0.0162%–0.0587% under scenarios S3–S5. In the following, we will explain the differences between the two renewable energy support policies according to the results of the model.

First, Figure 6 presents the effect of interaction between renewable subsidy policy and ETS on social welfare. In the practice of China's carbon market, the carbon price is always lower than its theoretical optimal level. When the carbon price is lower than the optimal level, whether the combination of the carbon market and renewable energy support policies is optimal or cost-effective depends on the deviation degree of the carbon price from the optimal level (Abrell et al., 2019). First, when the cap setting is loose, there is an interval of the carbon price and the combination of the carbon market and renewable energy support policies can improve the social welfare, which is consistent with the scholars' conclusion (Abrell et al., 2019). Second, when the cap is set to be valid, the carbon price is close to the social cost of carbon (SCC = 156 RMB/ton). In such a case, it is unnecessary to adopt the renewable subsidy policy at the same time, which can only increase the policy cost. That is because high carbon price has effectively made use of all the emission reduction channels. If subsidies are given to renewable energy technologies in this case, a twist effect will be produced. According to the results of the model, there is an inflection point when the high carbon price is 210 RMB/ton, at which the implementation of subsidy policy will have a negative effect and lead to the situation where the more subsidies are given, the worse the situation will be.

Second, as shown in Figure 7, with the increase of renewable energy market share, γ social welfare is decreasing, which is consistent with the classical economic theory. We find that there is a nonlinear relationship between the increase in proportion and the decrease in welfare. For example, when cap = 6 million tons and the proportion γ = 0.16, social welfare is the most optimal (see Supplementary Appendix S1 and Table 3). The reason for this phenomenon is that with the increase of renewable energy market share, the cost of purchasing green certificates by enterprises increases, and the market electricity price increases. The green certificate price will be transmitted to consumers, resulting in the reduction of consumer surplus, thereby reducing social welfare. In addition, we find that carbon prices and the price of green certificates fluctuate at times. Specifically, the price of green certificates fluctuates greatly. According to the results of the model, the carbon price ranges from 63 RMB/ton to 85 RMB/ton, and the price of green certificates ranges from 0.713 RMB/kWh to 1.401 RMB/kWh. Price volatility has led to fluctuations in the production of electricity from both conventional energy and renewable energy sources.

6 Conclusion and policy implications

6.1 Conclusion

In recent years, policymakers in many countries have begun to implement or seriously consider renewable energy support policies. With the widespread application of renewable energy support policies, the overlap of different policy instruments of RES and ETS may have an important impact on the implementation of regulatory policies. To avoid the possible negative effects or to take advantage of the potential synergistic effect of multiple policies, it is necessary to understand how different policy mechanisms interact with each other.

Based on the aforementioned problems, we, first of all, built a partial equilibrium model to discuss the interaction mechanisms between ETS and renewable energy support policies. Then, we, combining the theoretical model and numerical model and taking the case of China's electricity market in 2018, conducted an empirical analysis and specifically presented the interactions between different policies from three aspects—emission reduction, production of green electricity, and social welfare.

According to the results of the model, there were big differences among the implementation effects of different renewable energy support policy instruments. Based on ETS, the renewable subsidy policy (S3–S5) is better than REC (S1 and S2) in terms of emission reduction, but worse in terms of improving the production of green electricity. In addition, different from the renewable subsidy policy (S3–S5), REC (S1 and S2) can reduce social welfare.

6.2 Policy implications

A renewable subsidy policy is the starting point of the low-carbon transition, but it cannot serve as the core driver for long. Although the policy effect of the renewable subsidy policy completely depends on the government's willingness to reduce emissions, it still faces a large policy cost. According to Figures 2, 5, when the subsidy level is set, the setting of the emission cap should be fully considered, but should not be only based on the investment cost and environmental value of renewable energy sources. In short, the renewable subsidy policy is not a long-term solution and should gradually "retreat." One of the preconditions for subsidy retreat is that the carbon market is efficient. According to the result of the model, when the cap is loose, the carbon price will be much less than the social cost of carbon (SCC = 156 RMB/ton), and it is necessary to implement the subsidy policy. When the carbon market runs effectively, the carbon price will be approximately equal to 156 RMB/ton, it is unnecessary to implement the subsidy policy at the same time. Therefore, to realize subsidy retreat, an effectively running carbon market is needed.

In the trend of subsidy retreat, the country encourages renewable energy enterprises to sell renewable energy green electricity certificates, and the income from it can be used for financial expenditure. According to the result of the model, under scenarios S1 and S5, the effects of increasing the production of green electricity were similar. The income of the renewable energy companies under scenario S1 is approximately equal to the policy cost paid under scenario S5, and at this moment, $\kappa = 85.62$ RMB/ton and $\eta = 1.40$ RMB/kWh. Therefore, it is the core of policy design to gradually improve the carbon market and green certificate market and give full play to the pricing and incentive function of their externalities. In addition, the results of the model show that if the market share goal of green electricity is too radical, there will be a transition from "clean" to "dirty." For example, when the share of green electricity increases from 10% to 12%, the share of coal electricity increases by 2%. Therefore, the government should well grasp the development rhythm of renewable energy and strengthen macro-control with the carbon price and price of green certificates as signals.

Certified emission reduction (CER) is an emerging offset mechanism that can theoretically serve as a complementary instrument to the carbon market. It is a project with certified emission reduction as the main commodity based on the clean development mechanism. In addition, CER can not only further reduce the emission reduction cost of emission reduction entities, but also promote the development of renewable energy. According to the data of the model, it can be inferred that if this market is opened, CER will bring benefits to renewable energy companies that are approximately equal to the amount of subsidy S = 0.15 RMB/kWh, which will thus greatly save the policy cost. Therefore, we believe that the country should open this market and rely on market means to drive China's energy transition.

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

Conceptualization, LL and YW; writing—original draft preparation, XC and WB; writing—review and editing, LL and YW; supervision, LL; project administration, LL; funding acquisition, LL and YW. All authors have read and agreed to the published version of the manuscript.

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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.

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Does digital transformation promote green innovation? A micro-level perspective on the Solow Paradox

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Digitalization and sustainability, as emerging trends, have long attracted both academic and industrial focuses, yet the topic has not been sufficiently investigated at the micro-firm level. Selecting Chinese listed companies from 2010 to 2021 as the research sample and adopting the two-way fixed effects model, the impact of firms' digital transformation on their green innovation as well as the channels and mechanisms involved are investigated. The empirical results show that, firstly, the digital transformation of firms can significantly promote the quality and quantity of their green innovation. Secondly, internal control is a mediating path for digital transformation to promote green innovation, while financing constraints suppress the above effects, and top management team's environmental attention positively moderates the promotion of green innovation by corporate digital transformation. Thirdly, the promotion effects are more pronounced in firms that are state-owned, large-scale, ecologically cost-free, and relatively highly financing constrained. The findings suggest that digital transformation has advantages in revealing the "Solow paradox" that persists in the digital era, and the synergistic development of digitalization and greening at the firm level is realistic and feasible.

KEYWORDS

green innovation (GI), digital transformation (DT), sustainable development, Solow Paradox, mediating effect, suppressing effect, moderating effect

1 Introduction

In the 1970 s, the global ecological environment problems brought about by industrialization became increasingly prominent, and the threat of "the limits to growth" (Meadows, 1972) received extensive academic attention. In this protracted debate, the concept of sustainable development (SD) has become an important milestone and has gradually become an ongoing global initiative. Following the Millennium Development Goals (MDGs), 17 Sustainable Development Goals (SDGs) were adopted at the 2015 UN Sustainable Development Summit, and these globally shared goals and sustainability efforts have played an important role in promoting global sustainable development (ElMassah and Mohieldin, 2020a).

In the overall global effort toward sustainable development, technological change is both the source and solution of many environmental problems related to human activities (Hekkert et al., 2007; ElMassah and Mohieldin, 2020b; Sun and Guo, 2022). On the one hand, digitization can be a disruptive force and negatively affect sustainable development. For instance, 4% of global CO^2 emissions can be attributed to digitization, while global data centers as infrastructure for digital transformation consume about 1% of total global electricity consumption (Masanet et al., 2020). On the other hand, rapid digitalization has also been shown to be associated with less carbon emissions, lower haze concentrations, higher air quality, and a more comprehensive energy system transition (e.g., Wang J. et al., 2022).

Sustainable development and digitalization together are noted as emerging megatrends and lead to paradigm changes in economic and social systems. Government departments and leading companies have begun to focus on integrating environmental sustainability into the digital revolution. However, digitalization, despite the many benefits it can bring to sustainable development, has not yet been fully discussed in academia (George et al., 2020). Existing studies mainly focus on national, regional, and industry levels, while the large lack of data from the firm level hinders the systematic assessment of these impacts (Ghobakhloo et al., 2021).

To fill this gap, this paper aims to establish a dialogue between digitalization and sustainability at the micro-enterprise level. In this vein, the "digital transformation" and "green innovation" of companies become viable indicators to build this bridge. On the one hand, "digital transformation" is an organizational change triggered and shaped by the widespread proliferation of digital technologies and has become a central driver of technological innovation (Berger et al., 2019). Given the consensus on the "digital imperative", the transition to digitalization has become a key strategic decision and an inevitable choice for companies in modern management and information systems upgrading (Bharadwaj et al., 2013). On the other hand, innovation is considered as a vehicle for achieving sustainable development, thus discussing innovation through the lens of sustainability has become an important trend in the field of innovation (Freeman, 1996). "Green innovation", which reflects both ecological and productivity elements and has significant "dual externalities", is an ideal indicator of micro-firms' practice of sustainable development (Sun and Guo, 2022).

A few studies on this micro topic have confirmed that firms' digital transformation can promote their green innovation, and further, factors such as human and financial investment in innovation, government subsidies and taxes, firms' information processing and knowledge integration capabilities, and firms' internal and external costs are considered as intermediate mechanisms by which digital transformation affects their green innovation (e.g., Feng et al., 2022; Sun and Guo, 2022; Xue et al., 2022), and this facilitative effect is heterogeneous across firms. As can be seen, the existing literature partially points out the intermediate mechanisms by which digital transformation affects green innovation, while the moderating role is largely neglected. Therefore, we hope to further explore the channels and mechanisms to provide more micro-level evidence for business managers and policymakers.

Another benefit of this study is that this paper helps to provide evidence to unravel the Solow paradox at the micro-firm level. Solow paradox, also known as the productivity paradox, states that computers are everywhere but are not reflected in productivity (Solow, 1987) and has been widely debated in academia (e.g., Acemoglu et al., 2014). In the digital era, Solow paradox manifests itself in the disproportion between societal investment in digital technologies and the productivity gains resulting from their progress. Possible explanations for this phenomenon have been proposed, with some arguing that the digitization process is still in its early stages and its potential has not yet been fully realized, and others arguing that the social goals undertaken by IDT, such as improving the ecological environment, are not reflected in the statistical indicators, making the output of digitalization underestimated. Therefore, this paper examines the role of digital transformation of micro firms on their green innovation, which would add a footnote to the Solow paradox if positive externalities of digital transformation do exist.

This paper then focuses on the following questions: 1) Can the digital transformation of firms promote their green innovation? 2) If the facilitation effects exist, what are the potential channels and mechanisms involved? 3) Are the effects heterogeneous for firms with different characteristics and features? Furthermore, by examining the above questions, this paper will provide evidence for the unraveling of the Solow paradox in the digital era at the micro-firm level. China is chosen as the research context for this study. As the second largest digital economy after the United States, China is leading the synergistic development of digitization and greening to consolidate its leadership in the digital domain. We examine data for A-share listed companies from 2010 to 2021 and find that firms' digital transformation can promote their green innovation, with internal control and financing constraints as intermediate mechanisms, where the former plays a mediating role while the latter plays a suppressing role. The executive team's environmental attention positively moderates the promotion of green innovation by digital transformation. Moreover, digital transformation promotes better performance of green innovation characterized by double externalities, suggesting that the positive consequences of digital transformation may be reflected beyond productivity, adding new evidence to the Solow paradox.

The possible marginal contributions of this paper are: first, this paper establishes the interaction between digital transformation and sustainable development at the enterprise level from the perspective of green innovation, and the empirical results further support the findings of Sun and Guo (2022), bridging the gap in microscopic research in this area and providing an exegesis for the Solow paradox in the digital era. Second, this paper expands the understanding of the interaction channels and mechanisms between digital transformation and green innovation from the perspective of micro-structured subjects, reveals the path to realize the compatibility between digital and green transformation at the enterprise level, and paves the way for opening the "black box" of digital transformation and green innovation of enterprises. Third, the digital transformation of enterprises with different characteristics and in different contexts elicits heterogeneous green innovation outcomes, and this paper highlights these heterogeneities and examines them through effective empirical means, which further enriches the relevant research.

The rest of the paper is organized as follows: in Section 2, we formulate four hypotheses based on a review of the existing literature and details of the study design, including data sources, sample selection, variable definitions, regression model settings, and descriptive statistics of the variables; in Section 3, the results of our work are presented, including basic regressions, intermediate and moderating effects, endogeneity issues and robustness tests, and heterogeneity analysis. Section 4 discusses the conclusions and implications.

2 Materials and methods

2.1 Theoretical analysis and research hypothesis

2.1.1 Corporate digital transformation and green innovation

Green innovation is considered as technological innovation involving energy saving, pollution prevention, waste recycling, green product design or corporate environmental management (Chen et al., 2006), which can significantly reduce the negative environmental impact in addition to adding value to the firm and its stakeholders. The goal of green innovation is not only to reduce the environmental burden, but to pursue better environmental benefits. The "first mover advantage" that early movers in green innovation may enjoy is tempting, such as demanding higher prices for green products, projecting a green corporate image, and gaining a sustainable competitive advantage (Hart, 1995). Therefore, green innovation is gradually rising as a corporate strategy and is considered as an effective means for firms to gain sustainable competitive advantage in a whole new arena (Taklo et al., 2020).

The importance of green innovation has been widely emphasized in academic studies (e.g., Kunapatarawong and Martínez-Ros, 2016), with the natural resource base view, institutional theory, and stakeholder theory serving as its theoretical cornerstones. Scholars believe that the internal drivers of green innovation mainly include the green orientation of firms, green technological capabilities, green culture and environmental ethics, etc. (e.g., Sharma and Vredenburg, 1998; King and Lenox, 2002), while external factors are reflected in environmental climate, environmental regulation, economic and institutional pressures, government subsidies, green financial policies, stakeholder pressure, etc. (e.g., Wang et al., 2021; Zhang et al., 2019; Chen et al., 2012).

Despite the numerous incentives, there are still many challenges for corporate green innovation. On the one hand, green innovation is characterized by high R&D costs, high risks, and long cost recovery time (e.g., Martínez-Ros and Kunapatarawong, 2019), which may negatively impact short-term economic benefits. Organizations can be skeptical about taking green innovation actions when there is insufficient understanding of green initiatives within the organization, lack of an appropriate organizational culture, or inefficient government support. On the other hand, compared to general technological innovation, green innovation has significant double externalities (Rennings et al., 2006), i.e., the technological efforts of green innovators may be "free-riding" by others, and the social costs of environmental pollution are much higher than the costs borne by polluters. As a result, green innovators may not fully reap the benefits of their innovations, which may inhibit firms' willingness to engage in green innovation.

In this context, digital transformation, spearheaded by the application of digital technologies, may provide support to break the green innovation puzzle. Digital transformation is considered as the process that combines next-generation information and communication technologies to trigger significant changes and drive improvements in the attributes of organizational operations, products, management, business models, production processes, *etc.* In line with the Sustainable Development Goals (SDGs), reducing pollution emissions and implementing green innovations are laudable, and these actions require significant additional management efforts, including redesigning complex processes within companies and developing green capabilities (Kock et al., 2011). Digital transformation of companies requires redefining and redesigning strategic orientations and business processes, and if efforts are made to embed environmental responsibility in this process, it is expected to not only make green innovation less costly and more efficient, but also positively respond to the concerns of internal and external stakeholders and provide them with a considerable level of satisfaction (Miles, 2019).

Currently, digital transformation has become an inevitable requirement for many industries and firms to respond to the call for sustainable development and promote green innovation, as well as an important guarantee for achieving a win-win situation for economic and environmental development (Acemoglu et al., 2012). The digital transformation of firms has brought about the widespread use of digital technologies, which has led to lower information and transaction costs, accelerated the deep integration and sharing of internal and external information and resources, and further alleviated the information asymmetry problem of enterprises. On this basis, the division of labor and green R and D resource allocation of enterprises are also optimized, which empowers innovation activities and further promotes green innovation in enterprises (Li and Shen, 2021; Feng et al., 2022).

The existing normative literature on the relationship between digital transformation and green innovation is relatively limited and focuses on the national, regional, and industry levels. A small number of studies on micro-firms confirm that the application of one of the Frontier technologies, such as manufacturing intelligence, blockchain, and big data, can promote green innovation in enterprises. Moreover, several scholars have also confirmed that digital transformation of firms has a positive impact on their green innovation activities, which helps to enhance their competitive advantage (El-Kassar and Singh, 2018). Regarding the effect of digital transformation on the quantity and quality of green innovation, some studies argue that to seek policy support or financial subsidies with observable innovation output, enterprises may be more inclined to pursue rapid growth in "quantity" of innovation in the short term at the expense of "quality". However, Xiao and Zeng (2022) believe that digital transformation can help mitigate such short-term behavior and facilitate enterprises to strike a balance between "quality" and "quantity" in the pursuit of green innovation. This paper argues that digital transformation, as a systematic and holistic project, contributes to the "quality and quantity" of green innovation and proposes Hypothesis 1.

Hypothesis 1: Digital transformation of enterprises can significantly improve the quality and quantity of their green innovation.

2.1.2 Corporate digitalization, internal control, and green innovation

Internal control is the process of establishing systems, regulations, and control methods in an enterprise to achieve a set of economic and operational objectives, with the aim of improving operational efficiency and achieving corporate strategy (Jensen, 1993). High-quality internal control is the basis for ensuring that business processes are compliant and efficient. According to enterprise risk management theory, internal control is an important guarantee for the implementation of corporate innovation strategies, and its role in promoting corporate innovation has been confirmed by numerous studies (e.g., Hoskisson et al., 2002). In addition, it has been noted that firms' green innovation activities are vulnerable to their level of internal controls (Gordon and Wilford, 2012) and that exposure to poorer governance has a negative impact on green patents (Amore and Bennedsen, 2016).

Digital transformation has brought about the popular application of a new generation of information technology such as artificial intelligence, blockchain, cloud computing and big data, which has greatly improved the digital coverage of key areas and links of enterprise activities, as well as provided technical guarantee and implementation support for the iteration and reshaping of the enterprise internal control system. First, the continuous deepening of digital transformation has introduced the digital model with the characteristics of high efficiency, intelligence and precision into the internal control system of enterprises. The intervention of the digital system has largely reduced the potential risks of fraud and errors brought about by manual operations, making the execution of internal control much more efficient and effective, and reducing supervision costs while improving management efficiency. Second, digital transformation effectively remedies internal control deficiencies, enhances internal control, and improves corporate governance (Skaife et al., 2013), as well as enables greater precision in internal decision making and increased risk assessment and response capabilities. Firms are allowed to pry digital controls to enhance monitoring and supervision of all aspects of green innovation activities (Wang P. et al., 2022), and to pre-empt and mitigate risk potential in green R and D (Gordon & Wilford, 2012), which further stimulates green innovation. Third, good internal controls are strongly associated with better information quality, which can improve information transparency and reduce information asymmetry. External investors have easier access to internal information, which in turn affects the ability of firms to obtain financial support and low-cost financing.

Therefore, when digital transformation leads to improved internal controls, corporate executives tend to be more proactive in taking actions to fulfill social responsibility, such as increasing environmental investment or implementing green innovations to cater to the environmental concerns of their stakeholders. Based on the above analysis, this paper proposes Hypothesis 2.

Hypothesis 2: Digital transformation of enterprises promotes green innovation by improving their internal controls.

2.1.3 Corporate digitalization, financing constraints, and green innovation

In the case of market imperfections such as information asymmetry and agency problems, firms face financial frictions when seeking external financing support, and the phenomenon that external financing is more costly than internal financing is known as financing constraints (Whited and Wu, 2006). Financing constraints are thought to be highly correlated with firms' innovation decisions, innovation capabilities, and innovation outcomes. According to free cash flow theory, tighter financing constraints result in less free cash flow within the firm, alleviating agency problems and prompting firms to make investment decisions that are in the long-term interest, such as boosting R and D investment and developing new products, which has a positive impact on innovation performance. This view is also supported by innovation theory, which suggests that resource constraints force firms to improve the efficiency of their available resources and make optimal investment decisions, thus helping to improve their innovation performance. Conversely, an alternative view is that financing constraints tend to hamper innovation. Resource constraints may limit the advancement of sustainable development, especially given the long payback period, high investment risks and "double externalities" that characterize green innovation, and studies have argued that financing difficulties, as well as perceived financing barriers, can discourage firms from investing in green technologies and green projects.

The influencing factors of financing constraints are mainly studied from the perspectives of government and market. In the context of digital upgrading becoming an unavoidable strategic choice for firms to achieve high-quality development, there are high expectations for digital transformation to ease financing constraints. First, in the Chinese context, the government actively supports firms' digital upgrading initiatives and has introduced a series of policies to provide financial support, which directly enhances firms' ability to access credit financing and alleviates their internal capital pressure (Hinings et al., 2018). Second, digital transformation strengthens enterprises' information processing capabilities and reduces information asymmetry, facilitating interconnection and signaling between enterprises and credit institutions, which in turn alleviates credit resource mismatch and empowers enterprises with financing advantages. Third, digital transformation involves companies leveraging digital technologies to reinvent and reengineer their processes, organizational structures, and business models, thereby enabling them to reduce operational risk, seize growth opportunities and achieve better financial performance, which makes it less of a barrier for companies to seek external financing.

However, the existence of the Solow paradox may make the reality less "ideal". Asongu and Moulin (2016) show that the role of ICTs in facilitating the availability of finance is very limited. On the one hand, digital transformation often implies significant internal resource investment and additional financing needs, which can exacerbate business risks in the short term, while external investors may demand higher returns to address potential risks, resulting in higher financing costs for firms. On the other hand, digital transformation of firms is a systematic change of technology, organization and process, and there is a time lag for its positive effects to appear, especially when "going digital" becomes a trend and enterprises are scrambling to jump on the bandwagon, there will be a "black hole" period with only inputs but no obvious outputs, when the financing constraints faced by enterprises may subsequently increase.

Taken together, the analysis above shows that scholars' views on how digital transformation of firms affects financing constraints and how financing constraints influence green innovation are contradictory. It is affirmed that financing constraints do play an important role in the path of digital transformation affecting green innovation, while the mechanism and direction are not yet fully clear. This paper thus considers financing constraints as an intermediate mechanism by which firms' digital transformation affects their green innovation and proposes Hypothesis 3.

Hypothesis 3: Financing constraints play an intermediate role in the process of digital transformation of enterprises affecting their green innovation.

2.1.4 Corporate digitalization, TMT environmental attention, and green innovation

The upper echelons theory emphasizes the dominance and centrality of the executive team within a firm and suggests that an organization's strategies and behaviors can be viewed as a mapping of the value preferences and psychological perceptions of its top managers (Hambrick and Mason, 1984). Tushman and O'Reilly (2007) believe that only the top management team (TMT) can repeatedly and intentionally coordinate and allocate the assets and resources of the enterprise, as well as put potentially conflicting strategic agendas into action. Furthermore, the attention-based view argues that cognitive factors such as attention, in addition to the personal characteristics of executives, also have an impact on a firm's strategic decisions (Ocasio, 1997). Attention is considered a key ability to sense, identify, and create opportunities (Helfat and Peteraf, 2014), and with top managers' attention being a scarce resource, understanding how the attention of the senior management team is allocated and managed can help explain corporate behavior and decisions (Hambrick and Mason, 1984; Ocasio, 1997).

Studies have concluded that the environmental attention of top managers leads the strategic orientation of firms in terms of environmental protection and green innovation. When top management teams devote more time and effort to ecology-related topics, they are more likely to identify potential opportunities in green innovation, such as government environmental incentives, pricing power for green products, and possible competitive advantages. Therefore, these enterprises possess a stronger willingness for green innovation and tend to develop forward-looking environmental strategies that proactively address environmental issues. Accordingly, some proactive actions may be taken, including developing green products to meet consumer demand, enhancing R and D collaboration on green innovation to share risks, and soliciting government support to offset the cost of green innovation. In contrast, executives who pay less attention to environmental issues or have a negative attitude toward environmental protection may choose to meet only the minimum requirements of relevant environmental regulations (Cordano and Frieze, 2000). During the migration to digitalization, senior management teams with low environmental attention may not purposely allocate resources to green innovation activities, in which case the facilitative effect of digital transformation on green innovation may be significantly diminished. Accordingly, this paper proposes Hypothesis 4:

Hypothesis 4: The role of corporate digitalization in green innovation is more prominent when TMT environmental attention is high.

2.2 Study design

2.2.1 Sample selection and data sources

Our sample combines multiple data sets. We obtained data of A-share listed companies from 2010 to 2021 from China Stock Market and Accounting Research Database (CSMAR). Green patent data is collected from China Research Data Service Platform (CNRDS); Corporate digital transformation and TMT environment attention data are in-scribed through text mining of annual reports of listed companies; Internal control data comes from DIB Internal Control and Risk management database (DIB). Referring to the mainstream literature practice, the raw data are cleaned as follows: 1) samples from the financial industry are excluded; 2) ST and PT companies are excluded; 3) samples with missing regression variables are excluded; 4) observations that do not comply with general accounting standards are excluded, and finally 20,408 sets of observations are obtained. To avoid the impact of extreme values on the regression results, all micro-level continuous variables are winsorized at the 1% level.

2.2.2 Definition of main variables

2.2.2.1 Dependent variables

Green innovation (LNInv, LNInvUti). Patent data are output indicators in innovation activities, and green patents have the inherent advantage of measuring green innovation, such as being widely available and continuously documented across industries and time scales. Given that the patent approval process is cumbersome and time-consuming, and the number of applications is more time-sensitive than the number of grants, this paper selects the number of green patent applications as a proxy variable for green innovation. Specifically, the number of green invention patent applications is used to measure the quality of green innovation (LNInv), and the sum of the number of green invention patent and green utility model patent applications is used to measure the number of green innovation (LNInvUti) (Xiao and Zeng, 2022). The number of green patents is added by one and logarithmically processed due to the right-skewed distribution of the data.

2.2.2.2 Independent variable

Digital transformation (DIG). Drawing on the ideas of Yuan et al. (2021), this paper portrays the level of digital transformation of listed companies based on text analysis methods. Firstly, a dictionary of enterprise digital transformation terms is constructed based on the texts of digital economy-related policies, and 197 key words are obtained by retaining the words that appeared more than 5 times; secondly, text analysis is conducted on the MD&A section of annual reports of listed companies based on machine learning methods, and the frequency of 197 words appeared in the annual reports is counted; finally, the sum of the obtained word frequencies is divided by the length of the MD&A discourse of the annual report of the year and multiplied by 100 (Sun and Guo, 2022), which became the evaluation index of the degree of digital transformation of enterprises (DIG). The higher the index, the higher the degree of digital transformation of the enterprise.

2.2.2.3 Intermediate variables

Internal control (INCON). With reference to existing studies, the "DIB-Chinese listed companies internal control index" is used to reflect the level of internal control of enterprises (Shen et al., 2012). The index is designed based on 11 indicators under the five major objectives of internal control and corrected for internal control deficiencies, with good comprehensiveness and reliability. The larger the index, the higher the quality of internal control.

Financing constraint (SA). This paper adopts the SA index method proposed by Hadlock and Pierce (2010) to measure financing constraints. The SA index is built on two variables with little time variation and strong exogeneity, namely firm size and firm age, and is calculated as follows: SA = -0.737 × Size +0.043 × Size̓2−0.04 × Age, where Size is the natural logarithm of the firm's total assets. In this paper, we use the absolute value of SA index to represent the degree of financing constraint, and the larger the absolute value, the higher the degree of financing constraint.

2.2.2.4 Moderating variable

TMT Environmental attention (EA). The attention-based view holds that attention is mapped onto the lexical language used, that frequently used lexical information reflects attentional focus, and that the frequency of lexical use changes as attention and perception of things change (Sapir, 1944). Therefore, the text data released by listed companies provide a relatively reasonable data source for identifying their TMT attention allocation. According to the China Listed Companies Association, only about 30% of Chinese listed companies have disclosed their social responsibility reports for 2021, and the disclosure behavior itself may imply that these companies have a relatively high level of environmental concern. To avoid sample selection bias, this paper selects the MD&A section of listed companies' annual reports as the material for textual analysis.

The textual analysis method is used to measure TMT environmental attention. Specifically, we sort and summarize the words related to ecology and environmental protection in 500 annual reports, and then supplement their close synonyms with the Chinese Synonyms Dictionary, after which 200 annual reports are randomly selected for verification and 79 keywords are defined. Further, the frequency of TMT environmental attention keywords in the MD&A part of the annual report is counted, and their ratio to the total word frequency of the MD and A text is taken as the TMT environmental attention proxy variable (EA).

2.2.2.5 Control variables

Drawing on previous studies (e.g., Wu et al., 2021; Sun and Guo, 2022), this paper introduces a series of control variables in the regressions, including firm age (Age), firm size (Size), financial leverage (Lev), firm performance (ROA), cash flow (Cash), board size (Board), board independence (Indep), equity concentration (Top1), CEO duality (Dual) and ownership (SOE). In addition, industry (IND) and year (Year) dummy variables are also introduced. The definition and construction of these variables are shown in detail in Table 1.

2.2.3 Empirical model design

2.2.3.1 Basic regression model

First, we use a fixed effects (FE) panel regression to test H1, i.e., whether the digital transformation of firms can promote their green innovation. The fixed effects regression is chosen over the random effects regression based on the Hausman test, which is not detailed here to save space, and the OLS model is:

$$\mathbf{Dev_{i,t}} = \boldsymbol{\alpha_0} + \boldsymbol{\alpha_1}\mathbf{DIG_{i,t}} + \boldsymbol{\alpha_2}\mathbf{CVs_{i,t}} + \mathbf{IND_i} + \mathbf{Year_t} + \boldsymbol{\varepsilon_{i,t}}\,(\mathbf{i} = \mathbf{1}, \ldots, \mathbf{N};\ \mathbf{t} = \mathbf{1}, \ldots, \mathbf{T}) \tag{1}$$

Where i and t stand for enterprise and year respectively. $\mathbf{Dev_{i,t}}$ are explained variables (LNInv and LNInvUti), $\mathbf{DIG_{i,t}}$ are explanatory variables, $\mathbf{CVs_{i,t}}$ represent a set of control variables. Coefficient $\boldsymbol{\alpha_1}$ measures the impact of a firm's level of digital transformation on its green innovation. The model includes industry fixed effects $\mathbf{IND_i}$ and year fixed effects $\mathbf{Year_t}$, while $\boldsymbol{\varepsilon_{i,t}}$ is the random disturbance term.

2.2.3.2 Intermediate effects model

Second, H2 and H3 consider internal control and financing constraints as intermediate variables in the digital transformation of firms affecting their green innovation, and we build the following regressions:

$$\begin{aligned}\mathbf{Dev_{i,t}} &= \boldsymbol{\beta_0} + \boldsymbol{\beta_1}\mathbf{Med_{i,t}} + \boldsymbol{\beta_2}\mathbf{CVs_{i,t}} + \mathbf{IND_i} + \mathbf{Year_t} + \boldsymbol{\varepsilon_{i,t}}\\ \mathbf{Med_{i,t}} &= \boldsymbol{\gamma_0} + \boldsymbol{\gamma_1}\mathbf{DIG_{i,t}} + \boldsymbol{\gamma_2}\mathbf{CVs_{i,t}} + \mathbf{IND_i} + \mathbf{Year_t} + \boldsymbol{\varepsilon_{i,t}}\\ \mathbf{Dev_{i,t}} &= \boldsymbol{\mu_0} + \boldsymbol{\mu_1}\mathbf{DIG_{i,t}} + \boldsymbol{\mu_2}\mathbf{Med_{i,t}} + \boldsymbol{\mu_3}\mathbf{CVs_{i,t}} + \mathbf{IND_i}\\ &\quad + \mathbf{Year_t} + \boldsymbol{\varepsilon_{i,t}}\end{aligned} \tag{2}$$

Where $\mathbf{Med_{i,t}}$ denotes the intermediate variables (internal control and financing constraints).

2.2.3.3 Moderating effects model

Third, H4 proposed TMT environmental attention (EA) as a moderating factor, tested as follows:

$$\begin{aligned}\mathbf{Dev_{i,t}} &= \boldsymbol{\varphi_0} + \boldsymbol{\varphi_1}\mathbf{DIG_{i,t}} + \boldsymbol{\varphi_2}\mathbf{EA_{i,t}} + \boldsymbol{\varphi_3}\,\mathbf{DIG_{i,t}} \times \mathbf{EA_{i,t}} + \boldsymbol{\varphi_4}\mathbf{CVs_{i,t}}\\ &\quad + \mathbf{IND_i} + \mathbf{Year_t} + \boldsymbol{\varepsilon_{i,t}}\end{aligned} \tag{3}$$

Where $\mathbf{EA_{i,t}}$ is the moderator. If H4 is correct, the coefficient $\boldsymbol{\varphi_3}$ will be positively significant.

3 Results

3.1 Correlation analysis

Table 2 reports the variable correlation coefficient matrix. DIG shows a significant positive correlation with LNInv and LNInvUti, which is consistent with. Hypothesis 1 and suggests that the benchmark model is reasonable. DIG is significantly and negatively correlated with Size, Lev, Board and SOE, indicating that smaller, less indebted, smaller board size and non-state-owned enterprises are more likely to implement digital transformation. Correlations between other variables are also plausible. For example, there is a significant positive correlation between Size and Cash, indicating that larger enterprises have stronger cash flow. INCON is significantly and positively correlated with ROA, indicating that firms with better profitability have higher levels of internal control. The multicollinearity test is adopted, and the average VIF value is 1.720, less than the threshold value of 10, which proves that there is

TABLE 1 Variable definitions.

Variable	Name	Explanation	Definition	Data source
Explained variable	LNInvUti	Quantity of Green Innovation	Number of Green Patent Applications	CNRDS
	LNInv	Quality of Green Innovation	Number of Green Invention Patent Applications	CNRDS
Explanatory variable	DIG	Degree of digital transformation	The ratio of word frequency of digital transformation keywords to the length of phrases in the MD&A section	Manual collection
Intermediate variables	INCON	Internal control	Internal Control Index	DIB
	SA	Financing constraints	$\|SA\| = \|- 0.737\times Size + 0.043\times Size^2 - 0.04\times Age\|$	CSMAR
Moderating variable	EA	TMT environmental attention	Ratio of word frequency of TMT environment attention keywords to total word frequency in MD and A section	Manual collection
Control variables	Age	Firm age	The natural logarithm of the difference between the current year and the year of establishment plus 1	CSMAR
	Size	Firm size	The natural logarithm of total assets at the fiscal year end	CSMAR
	Lev	Financial leverage	Total liabilities/total assets	CSMAR
	ROA	Return on assets	The ratio of net income to total assets	CSMAR
	Cash	Cash flow	Monetary fund/total assets	CSMAR
	Board	board size	The natural logarithm of the number of the board of directors plus 1	CSMAR
	Indep	board independence	The ratio the number of independent directors to the number of all directors	CSMAR
	Top1	Largest ownership	Shareholding ratio of the largest shareholder	CSMAR
	Dual	CEO duality	A dummy variable which equals one if the firm's board chair is also its CEO and zero otherwise	CSMAR
	SOE	Ownership	A dummy variable that equals one if a firm is a state-owned enterprise and zero otherwise	CSMAR

no serious multicollinearity problem among the independent variables in the model.

3.2 Descriptive statistics

Table 3 reports the descriptive statistics of the variables. The means of green innovation quality (LNInv) and green innovation quantity (LNInvUti) are 0.7358 and 1.0663, respectively, and the standard deviations are larger than the means, indicating that the level of green innovation varies widely among the sample companies. The mean value of DIG is 0.8810, which is greater than its median value of 0.5114, indicating that more than half of the sample enterprises' digital transformation degree does not reach the mean value, reflecting the limited or relatively low digital transformation degree of Chinese A-share listed companies in general; the standard deviation of DIG (0.9747) is higher than its mean value (0.8810), which indicates that there may be prominent individual or category differences in the degree of digital transformation of the sample companies.

3.3 Benchmark regression results

Table 4 reports the results of the benchmark regressions. When the fixed effects of industry and year are controlled, corporate digital transformation has a significant positive effect on both the quality of green innovation (LNInv) ($\boldsymbol{\alpha_1}$ = 0.096, $p < 0.01$) and the quantity of green innovation (LNInvUti) ($\boldsymbol{\alpha_1}$ = 0.085, $p < 0.01$). After the introduction of control variables, R square of the model becomes larger and the above two coefficients remain significantly positive at the 1% level, which indicates that as the degree of digital transformation of enterprises increases, both the quality and quantity of green innovation have significantly improved. Hypothesis 1 is supported.

3.4 Examination of the intermediate effect of internal control

We test the mediating effect of internal control by Bootstrap method with 5000 repetitions of sampling, and the results are shown in Table 5. At 95% confidence level, the confidence interval of both indirect paths of DIG and LNInv/LNInvUti do not contain zero, which proves the existence of the mediating effect. The direct effects of digital transformation on the quality of green innovation and quantity of green innovation are 0.12165397 ($p < 0.01$), 0.09412338 ($p < 0.01$), respectively. The coefficients of the mediating effect of internal control (INCON) are 0.0011982 ($p < 0.05$) and 0.00116049 ($p < 0.05$), and the percentages of the mediating effect are 0.975% and 1.218%, respectively. The empirical results confirm that internal control (INCON) is a functional channel in the process of digital

TABLE 2 Correlation matrix.

	LNInv	LNInvUti	DIG	INCON	SA	EA	Age	Size	Lev	ROA	Cash	Board	Indep	Dual	Top1	SOE
LNInv	1	0.8957***	0.2785***	0.0715***	-0.0127*	0.2087***	0.0539***	0.3434***	0.0991***	0.0406***	0.0215***	0.0395***	0.0304***	0.0160**	0.0000	0.0395***
LNInvUti	0.9298***	1	0.2806***	0.0642***	-0.0015	0.2598***	0.0590***	0.3601***	0.1129***	0.0336***	0.0270***	0.0394***	0.0211***	0.0112	0.0022	0.0232***
DIG	0.2355***	0.2047***	1	-0.0505***	0.0968***	-0.1168***	0.0639***	-0.0163**	-0.1868***	0.0753***	-0.0065	-0.1302***	0.0541***	0.1609***	-0.1538***	-0.2417***
INCON	0.0995***	0.0893***	-0.0273***	1	-0.1349***	-0.0363***	-0.0746***	0.2304***	0.0486***	0.3951***	0.1693***	0.0946***	-0.0028	-0.0472***	0.1580***	0.1150***
SA	-0.0968***	-0.0828***	0.0792***	-0.1554***	1	0.0298***	0.8807***	0.0653***	0.0080	-0.0130*	0.0016	-0.0155**	-0.0395***	-0.0416***	-0.1259***	0.0479***
EA	0.1984***	0.2551***	-0.1556***	-0.0339***	0.0296***	1	0.0406***	0.1290***	0.1075***	-0.0755***	0.0484***	0.0598***	-0.0452***	-0.0490***	0.0598***	0.0751***
Age	0.0501***	0.0507***	0.0394***	-0.0758***	0.8248***	0.0449***	1	0.1727***	0.1013***	-0.0482***	0.0039	0.0102	-0.0081	-0.0550***	-0.0890***	0.1041***
Size	0.4102***	0.4218***	-0.0388***	0.2482***	-0.0953***	0.1255***	0.1504***	1	0.4635***	0.0226***	0.0693***	0.2205***	0.0079	-0.1244***	0.2279***	0.2754***
Lev	0.1278***	0.1432***	-0.1554***	0.0228***	-0.0178**	0.1150***	0.1110***	0.4576***	1	-0.3717***	-0.1530***	0.1393***	-0.0106	-0.0935***	0.1162***	0.2433***
ROA	0.0245***	0.0186***	-0.0083	0.3849***	-0.0178**	-0.0436***	-0.0496***	0.0608***	-0.3123***	1	0.4099***	0.0241***	-0.0402***	0.0093	0.0908***	-0.0852***
Cash	0.0219***	0.0264***	-0.0265***	0.1507***	0.0007	0.0363***	-0.0004	0.0625***	-0.1661***	0.3882***	1	0.0572***	-0.0207***	-0.0228***	0.1005***	0.0138**
Board	0.0550***	0.0577***	-0.1122***	0.0913***	-0.0258***	0.0549***	0.0136*	0.2419***	0.1475***	0.0430***	0.0522***	1	-0.5384***	-0.1886***	0.0398***	0.2449***
Indep	0.0437***	0.0329***	0.0575***	-0.0032	-0.0589***	-0.0408***	-0.0105	0.0228***	-0.0095	-0.0336***	-0.0143**	-0.5101***	1	0.1032***	0.0177**	-0.0557***
Dual	0.0105	0.0035	0.1485***	-0.0421***	-0.0341***	-0.0481***	-0.0569***	-0.1160***	-0.0921***	-0.0125*	-0.0196***	-0.1807***	0.1094***	1	-0.1021***	-0.2780***
Top1	0.0195***	0.0231***	-0.1595***	0.1516***	-0.1495***	0.0507***	-0.0921***	0.2546***	0.1193***	0.1177***	0.0940***	0.0532***	0.0282***	-0.1054***	1	0.3097***
SOE	0.0614***	0.0447***	-0.1911***	0.1044***	0.0204***	0.0541***	0.1122***	0.2808***	0.2432***	-0.0326***	0.0057	0.2480***	-0.0510***	-0.2780***	0.3064***	1

Notes: ***p < 0.01, **p < 0.05, *p < 0.1. Pearson correlation coefficients are displayed below the diagonal, while the Spearman correlation coefficients are above the diagonal.

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TABLE 3 Descriptive statistics.

VarName	Obs	Mean	SD	Median	Min	Max
LNInv	20,438	0.7358	1.0544	0.0000	0.0000	4.4773
LNInvUti	20,438	1.0663	1.2518	0.6931	0.0000	4.9628
DIG	20,438	0.8810	0.9747	0.5114	0.0000	4.8926
INCON	20,438	656.4738	82.3547	667.0100	306.2400	863.5300
SA	20,438	3.8185	0.2461	3.8263	1.8049	5.1965
EA	20,438	0.0099	0.0109	0.0059	0.0000	0.0577
Age	20,438	2.9249	0.2891	2.9444	2.0794	3.4965
Size	20,438	22.4635	1.2965	22.2958	19.8632	26.3153
Lev	20,438	0.4622	0.1990	0.4629	0.0695	0.8883
ROA	20,438	0.0338	0.0557	0.0317	-0.2157	0.1901
Cash	20,438	0.0455	0.0684	0.0444	-0.1572	0.2406
Board	20,438	2.1439	0.2013	2.1972	1.6094	2.7081
Indep	20,438	0.3747	0.0541	0.3333	0.3333	0.5714
Dual	20,438	0.2277	0.4194	0.0000	0.0000	1.0000
Top1	20,438	33.7319	14.9101	31.3077	8.3218	74.0177
SOE	20,438	0.4406	0.4965	0.0000	0.0000	1.0000

transformation (DIG) for green innovation, validating H2 and answering question 2): corporate digital transformation promotes green innovation by improving the quality of a firm's internal control. In other words, digital transformation of enterprises leverages digital technology to accelerate the standardization and speed up the flow of information, improving the efficiency and agility of all aspects of internal control, effectively preventing and mitigating enterprise risks, and exerting a certain "governance effect", i.e., contributing to the improvement of the quality of internal control. Moreover, higher quality of internal controls increases the transparency of corporate information and exposes companies to greater internal and external scrutiny, which further motivates firms to actively shoulder social responsibility and engage in green innovation activities. Thus, internal controls play a mediating role in the digital transformation of companies to promote their green innovation.

3.5 Examination of the intermediate effect of financing constraints

As mentioned earlier, digital transformation requires firms to redirect and reallocate the investment of financial resources, which will affect their green innovation. Following the suggestion of Jiang (2022), this paper adopts the following steps to test the indirect effects of financing constraints. First, the impact of financing constraints on corporate green innovation is examined, and the results are shown in Table 6. The regression results of financing constraints on the dependent variables (quality and quantity of green innovation) in columns 1) 2) are both significantly negative at the 1% confidence level, i.e., a higher degree of financing constraints inhibits green innovation of enterprises. This result is inextricably linked to the characteristics of green innovation activities such as high investment, long payback period and unpredictable benefits, whose innovation results have the attributes of public goods and can be easily imitated and replicated. When firms are rich in liquidity and redundant resources, they are more inclined to invest in green innovation to gain a differentiated and sustainable competitive advantage; while when financing constraints are high, funds will be prioritized into agendas directly related to the firm's production and operations to cope with current uncertainties, while investments in green innovation activities related to long-term sustainability will be curtailed.

Second, the paper further examines the impact of digital transformation on financing constraints. As shown in columns 3) 4), the regression results of digital transformation on the degree of financing constraints are significantly positive at the 1% confidence level, and the results are still robust when lagging DIG by one period, suggesting that digital transformation exposes firms to a higher degree of financing constraints rather than the "alleviating effect" advocated by some scholars (e.g., Xue et al., 2022). The "Solow paradox" clarifies this result. Firstly, there is a time lag in the effectiveness of digital transformation, and its potential has not been fully realized. In particular, the current digital transformation of the sample firms is generally low, information asymmetry is not significantly reduced, and there is no immediate "profitability effect" in terms of firm performance or growth, and financial institutions often have difficulty in effectively overcoming adverse selection

TABLE 4 Benchmark regression results.

	LNInv		LNInvUti	
	(1)	(2)	(3)	(4)
DIG	0.096***	0.078***	0.085***	0.062***
	(0.016)	(0.016)	(0.018)	(0.017)
Age		-0.230		-0.214
		(0.180)		(0.192)
Size		0.261***		0.330***
		(0.022)		(0.025)
Lev		-0.053		-0.090
		(0.070)		(0.082)
ROA		-0.085		-0.060
		(0.130)		(0.147)
Cash		-0.039		-0.047
		(0.084)		(0.097)
Board		0.035		0.016
		(0.074)		(0.086)
Indep		0.212		0.219
		(0.221)		(0.259)
Dual		0.029		0.012
		(0.021)		(0.024)
Top1		-0.001		-0.001
		(0.001)		(0.001)
SOE		0.080*		0.032
		(0.045)		(0.051)
Year	Yes	Yes	Yes	Yes
IND	Yes	Yes	Yes	Yes
_cons	0.281	-4.909***	0.364*	-6.290***
	(0.171)	(0.699)	(0.201)	(0.761)
N	20,438	20,438	20,438	20,438
r2	0.147	0.172	0.197	0.224
r2_a	0.144	0.168	0.194	0.221

Notes: ***p < 0.01, **p < 0.05, *p < 0.1; The numbers in parentheses are Cluster-robust standard error.

caused by information asymmetry. Secondly, the application of new technologies requires a corresponding "organizational" transformation, which requires a "painful" period of friction, debugging, and integration, during which the implementation of digital transformation may be characterized by increased organizational redundancy rather than output or profitability. Thirdly, digital transformation generates additional financing needs for firms, crowding out their limited funds, which in turn may lead to higher interest costs, thus pushing up the financing constraints of firms. Finally, when digital transformation becomes a "must" and firms rush to this track, it may result in a redistribution of market share rather than a "bigger cake", and the incentive of credit sector to grant "special allowances" is therefore gone. Moreover, the regression results of the control variables show that smaller firms with less adequate cash flow face a higher degree of financing constraints, which supports the scholars' view that large firms rely more on internal funds for innovation while SMEs rely more on exogenous financing and are more likely to face financing constraints (Lei et al., 2022).

TABLE 5 Mediation effect of internal control.

Mediating variables	Explained variables	Effect	Observed Coef	Std. Err	95%CI	
					LLCI	ULCI
INCON	LNInv	Ind_eff	0.0011982	0.00047464	0.0004173	0.0022722
		Dir_eff	0.12165397	0.00971791	0.1033456	0.1411055
	LNInvUti	Ind_eff	0.00116049	0.00052405	0.0002473	0.0023111
		Dir_eff	0.09412338	0.01050338	0.0735492	0.1150003

Notes: ***p < 0.01, **p < 0.05, *p < 0.1; Cluster-robust standard error in parentheses; Ind_eff represents indirect effect, Dir_eff represents direct effect; CI, represents confidence interval; LL, represents lower limit; UL, represents upper limit; Model includes year and industry dummy variables. Sample size: 20,438.

TABLE 6 Intermediate effect of financing constraints.

	(1)	(2)	(3)	(4)	(7)	(8)
	LNInv	LNInvUti	SA	SA	LNInv	LNInvUti
SA	-1.223***	-1.268***			-1.260***	-1.298***
	(0.168)	(0.167)			(0.166)	(0.166)
DIG			0.007***		0.086***	0.071***
			(0.002)		(0.016)	(0.017)
L.DIG				0.010***		
				(0.002)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
IND	Yes	Yes	Yes	Yes	Yes	Yes
_cons	-0.787	-2.008**	3.406***	2.162***	-0.616	-1.868**
	(0.811)	(0.882)	(0.127)	(0.122)	(0.801)	(0.879)
N	20,438.000	20,438.000	20,438.000	16,551.000	20,438.000	20,438.000
r2	0.179	0.231	0.814	0.773	0.182	0.232
r2_a	0.175	0.227	0.813	0.771	0.178	0.229

Notes: ***p < 0.01, **p < 0.05, *p < 0.1; Cluster-robust standard error in parentheses; Model includes year and industry dummy variables. Sample size: 20,438.

Third, financing constraints are added to the regressions, and the results are presented in columns 5) 6). The direct effect coefficients of DIG on the quality and quantity of green innovation are 0.086 ($p < 0.01$) and 0.070 ($p < 0.01$), respectively, which are larger than its total effect of 0.078 ($p < 0.01$) and 0.062 ($p < 0.01$) (see columns 2) 4) of Table 4). In addition, the product of the indirect effect coefficient γ_1 (0.007, $p < 0.01$) and the coefficient μ_2 (-1.260 and -1.298, $p < 0.01$) is negative, in the opposite direction of the direct effect μ_1. According to MacKinnon (2000), the indirect effect of financing constraints on digital transformation and green innovation is the "suppressing effect", which means that financing constraints suppress the effect of digital transformation on green innovation to a certain extent. Specifically, the effect of digital transformation on green innovation is weakened by raising the level of financing constraints. Once the financing constraint is controlled for, the difference in the regression coefficients of digital transformation on green innovation widens. The measured share of the suppressing effect of financing constraints in the path of digital transformation on the quality and quantity of green innovation is 6.370% and 7.587%, respectively. Therefore, H3 passes the test and answers question 2): digital transformation exposes firms to higher financing constraints, and higher levels of financing constraints hinder firms' green innovation efforts, thus showing an overall weakening of the impact of digital transformation on green innovation, a result that reflects the lingering power of the Solow paradox, despite the promising potential and prospects of digital transformation. The positive externalities of digital transformation may be reflected in better environmental performance and higher levels of green innovation, but they do not address the financing constraint.

We note that this empirical finding that digital transformation pushes up firms' financing constraints is not consistent with some existing studies (e.g., Xue et al., 2022), and we dissect the reasons for this may lie in measurement errors and miscalculations. First,

TABLE 7 Moderation effect of TMT environmental attention.

	(1)	(2)
	LNInv	LNInvUti
DIG	0.089***	0.070***
	(0.017)	(0.018)
EA	6.300***	9.200***
	(1.292)	(1.400)
DIG × EA	4.499***	3.854**
	(1.640)	(1.629)
Age	-0.227	-0.211
	(0.180)	(0.191)
Size	0.259***	0.327***
	(0.022)	(0.024)
Lev	-0.055	-0.090
	(0.070)	(0.081)
ROA	-0.094	-0.071
	(0.130)	(0.147)
Cash	-0.044	-0.052
	(0.084)	(0.097)
Board	0.041	0.027
	(0.073)	(0.084)
Indep	0.213	0.224
	(0.219)	(0.256)
Dual	0.028	0.010
	(0.021)	(0.024)
Top1	-0.002	-0.001
	(0.001)	(0.001)
SOE	0.078*	0.029
	(0.044)	(0.051)
_cons	-4.954***	-6.313***
	(0.696)	(0.609)
Year	Yes	Yes
IND	Yes	Yes
N	20,438	20,438
r2	0.175	0.229
r2_a	0.171	0.225

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; Cluster-robust standard error in parentheses; Model includes year and industry dummy variables. Sample size: 20,438.

various measures of the level of digital transformation, such as the proportion of digitization-related intangible assets, the share of IT personnel, IT investment and telecommunication expenditures, and the frequency of digital transformation words, are widely used in a large number of literatures, and scholars have obtained different datasets based on different measures, which in turn have produced different empirical results. Second, financing constraints themselves are difficult to quantify, scholars have used some variables as

TABLE 8 Test results of re-measurement of independent variable.

	LNInv				LNInvUti			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DIG2	0.077***	0.055***			0.069***	0.040***		
	(0.010)	(0.009)			(0.010)	(0.010)		
DIG_ba			0.064***				0.063***	
			(0.015)				(0.017)	
DIG_ap				0.036***				0.019*
				(0.010)				(0.011)
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IND	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
_cons	0.274	-4.728***	-4.844***	-4.862***	0.357*	-6.160***	-6.219***	-6.276***
	(0.172)	(0.703)	(0.704)	(0.704)	(0.204)	(0.763)	(0.763)	(0.764)
N	20,438	20,438	20,438	20,438	20,438	20,438	20,438	20,438
r2	0.149	0.172	0.171	0.170	0.199	0.224	0.224	0.223
r2_a	0.146	0.168	0.167	0.166	0.195	0.221	0.221	0.220

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; Cluster-robust standard error in parentheses; Model includes year and industry dummy variables. Sample size: 20,438.

indicators to measure the degree of corporate financing constraints, and representative indices include FC index, KZ index, SA index and WW index, *etc.*, and the differences of different indices may yield different calculation results. Finally, this paper selects the SA index, which is constructed only by two strongly exogenous variables, namely, firm size and age, to measure financing constraints. However, the SA index calculates a negative value, which has been ignored by some literature, misinterpreting positive effects as negative ones. In this paper, text mining method is used to measure DIG, and the absolute value of SA index is used to represent the degree of financing constraint, which has high credibility. In summary, different measurement approaches may lead to different conclusions, and we believe that the impact of digital transformation on the financing constraints faced by firms is an interesting topic worthy of further exploration and discussion.

3.6 Examination of the moderating effect of TMT environmental attention

Table 7 reports the results of the regression analysis of model 3), with the quality and quantity of green innovation as dependent variables, the coefficients of the cross product term DIG × EA (Interaction term between digital transformation and TMT environmental attention) are 4.499 ($p < 0.01$) and 3.854 ($p < 0.05$), respectively, and are in the same direction as the coefficients of DIG in columns 2) and 4) in Table 4, indicating that TMT environmental attention positively moderates the facilitation of digital transformation on green innovation. The regression results of model 3) are consistent with. Hypothesis 4, which enriches the interpretation of question 2) and further supports the findings of existing studies (e.g., Sun and Guo, 2022). Cognitive factors such as attention have been shown to play an important role in strategic decision making and resource allocation in companies. In particular, the environmental attention of the executive team directs corporate environmental and green actions, and our findings suggest that the role of digital transformation in promoting green innovation is more significant when TMT environmental attention is higher. That is, executive teams with higher environmental attention are more likely to perceive and capture environmental opportunities and tend to allocate more resources to green innovation activities during the digital transformation process, thus achieving better performance in terms of both quality and quantity of green innovation.

3.7 Robustness analysis and endogeneity problem

3.7.1 Re-measurement of digital transformation

Considering that different measurement methods may bring errors, this paper constructs a new digital transformation indicator DIG2 based on the idea of Wu et al. (2021), and then further decomposes the indicator according to two levels, “underlying technology” and “practical application”, and notates them as DIG_ba and DIG_ap, respectively. These indicators are regressed separately according to model 1) and the results are shown in Table 8. After replacing the digital transformation measure and breaking down the dimensions, the coefficient of model 1) remains significantly positive. Specifically, before adding the control variables, the regression coefficients of DIG2 on LNInv, LNInvUti are 0.077 and 0.069 (columns 1) and 5)),

TABLE 9 Test results of two-stage least squares.

	IV = L.DIG			IV = L2.DIG		
	(1)	(2)	(3)	(4)	(5)	(6)
	DIG	LS_LNInv	LS_LNInvUti	DIG	LS_LNInv	LS_LNInvUti
DIG		0.229*** (5.62)	0.175*** (4.00)		0.374*** (3.29)	0.296** (2.46)
IV	0.728*** (74.88)			0.164*** (16.30)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
IND	Yes	Yes	Yes	Yes	Yes	Yes
N	16,345	16,345	16,345	14,014	14,014	14,014
R2		0.145	0.196		0.097	0.173

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; Cluster-robust standard error in parentheses; Model includes year and industry dummy variables. Sample size: 20,438.

respectively; after adding the control variables, the above coefficients are 0.055 and 0.040 (columns 2) and 6)), respectively, both of which are significantly positive at the 1% level. The regression coefficients of digital transformation underlying technology (DIG_ba) on the quality and quantity of green innovation are 0.064 and 0.063 (columns 3) and 7)), respectively, both of which are significantly positive at the 1% level, indicating that the underlying technology of digital transformation (DIG_ba) contributes equally to the quality and quantity of green innovation. The regression coefficients of digital technology application (DIG_ap) on green innovation quality and quantity are 0.036 and 0.019 (columns 4) and 8)), which are significantly positive at the 1% and 10% levels, respectively, indicating that digital technology application (DIG_ap) has a greater contribution to green innovation quality. These results confirm the robustness of the findings of this paper.

3.7.2 Two-stage least squares

The green innovation of enterprises may have prompted the increase of R&D investment and the application of new technologies, which stimulated the improvement of digital transformation level, so the endogeneity problem of reverse causality may exist. Therefore, this paper further uses the two-stage least squares (2SLS) method to mitigate the endogeneity problem. The independent variables are lagged, and the estimated results are shown in Table 9. The first-stage regression coefficients are significantly positive at the 1% level (columns 1) and 4)), and the lagged variables satisfy the correlation condition. Columns 2) and 5) report the results of the second-stage regression of the lagged variables on the quality of green innovation (LNInv), where the regression coefficient of DIG is significantly positive at the 1% level, and columns 3) and 6) report the results of the second-stage regression of the lagged variables on the quantity of green innovation (LNInvUti), where the regression coefficient of DIG is significantly positive at the 1% and 5% levels, respectively. The above results fully demonstrate that the main findings of this paper remain robust and reliable after considering the lagged effect.

3.7.3 Addition of control variables

To mitigate the impact of other potential channels on corporate green innovation, more variables are included in the control variables.

External Environmental Uncertainty (EU). When faced with a highly uncertain external environment, firms may choose to "stay put" and wait for the right opportunity to invest in green innovation, or they may "take a chance" to gain a competitive advantage or external support. Therefore, this paper treats environmental uncertainty (EU) as a control variable, where the EU indicator is constructed by referring to the study of Ghosh and Olsen (2009). The impact of external environmental changes on firms eventually leads to fluctuations in sales revenue or operating performance, so the latter is used to characterize the former (EU), and the measurement process is as follows: 1) The abnormal sales revenue of each sample company for the past 5 years is estimated separately using the following formula: Sale = $\varphi_0+\varphi_1$Year+ε, where Sale is the sales revenue, Year is the annual variable, and the current year is taken as 5, four if last year, and so on, the annual variable is regressed to exclude the change of sales revenue brought by the stable growth of the company, and the residual result obtained from the regression is the abnormal sales revenue; 2) the standard deviation of abnormal sales revenue in the past 5 years is divided by the average value of sales revenue in the past 5 years to obtain the unadjusted environmental uncertainty of the industry; 3) the result of the second step is divided by the industry environmental uncertainty (the median of the non-industry-adjusted environmental uncertainty of all firms in the same industry in the same year) to obtain the industry-adjusted environmental uncertainty (EU). The higher the value, the higher the environmental uncertainty faced by the firm. After including EU in the control variables, the regression results are reported in columns 1) and 5) of Table 10, where the regression coefficient of DIG remains significantly positive.

Government Ecological Attention (GEA). Local governments with higher ecological attention are likely to actively introduce policies that favour green innovation, releasing positive signals

TABLE 10 Test results with added control variables.

	LNInv				LNInvUti			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DIG	0.078***	0.078***	0.077***	0.078***	0.062***	0.062***	0.061***	0.062***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)	(0.017)	(0.017)
EU	-0.005				-0.004			
	(0.006)				(0.007)			
GEA		0.845				2.906		
		(4.355)				(5.202)		
GS			-0.000***				-0.000***	
			(0.000)				(0.000)	
TAX				-0.000				-0.000***
				(0.000)				(0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IND	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
_cons	-4.970***	-4.913***	-4.931***	-4.907***	-6.344***	-6.305***	-6.307***	-6.287***
	(0.696)	(0.699)	(0.698)	(0.699)	(0.758)	(0.760)	(0.760)	(0.760)
N	20,438	20,438	20,438	20,438	20,438	20,438	20,438	20,438
r2	0.172	0.172	0.172	0.172	0.224	0.224	0.225	0.225
r2_a	0.168	0.168	0.168	0.168	0.221	0.221	0.221	0.221

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; Cluster-robust standard error in parentheses; Model includes year and industry dummy variables. Sample size: 20,438.

that prompt local enterprises to undertake green innovation activities. Adopting a text mining approach, we measure the ratio of ecological keyword frequencies to all word frequencies in government work reports as a proxy for the government's ecological attention (GEA) and added it to the control variables. Columns 2) and 6) of Table 10 report the relevant regression results. After controlling for GEA, the regression coefficient of digital transformation (DIG) remains significantly positive.

Government Environmental Subsidies (GS). Studies have shown that policymakers can promote private R&D investments through subsidies. On the one hand, government environmental subsidies can, to some extent, alleviate the financial pressure and compensate for the high costs and risks associated with green innovation in the private sector, and on the other hand, the government may incentivize firms to reduce emissions or enhance green innovation through environmental subsidies. Therefore, the data of government subsidies obtained by listed companies due to their environmental actions are calculated, and government environmental subsidies (GS) are included in the control variables. The results in columns 3) and 7) of Table 10 demonstrate that the regression coefficient of digital transformation remains significantly positive after controlling government environmental subsidies (GS).

Tax Incentives (TAX). Fiscal policy incentives play an important role in the development and diffusion of green innovation, and tax incentives are one of the main instruments of fiscal policy incentives in addition to direct subsidies. Government R&D tax incentives may promote green innovation by firms through direct stimulation or leveraging effects. In this paper, we add tax incentives received by firms (TAX) to the control variables, and as shown in columns 4) and 8) of Table 10, the regression coefficient of digital transformation remains significantly positive when controlling for tax incentives (TAX).

In summary, after multiple robustness and endogeneity treatments, the core findings of this paper remain highly consistent.

3.8 Heterogeneity analysis

In the previous test, this paper examines the impact of corporate digital transformation on green innovation using the full sample, and the results show that corporate digital transformation can significantly improve the quality and quantity of green innovation. However, it is worth noting that the above effects may be asymmetric under different external environments and different corporate attributes. Further, the sample firms are tested by group based on the nature of enterprise ownership, enterprise size, ecological expenditures and financing constraints.

TABLE 11 Heterogeneity test based on property rights.

Variables	LNInv		LNInvUti	
	(1)	(2)	(3)	(4)
	SOEs	Non-SOEs	SOEs	Non-SOEs
DIG	0.131*** (0.016)	0.047*** (0.012)	0.097*** (0.018)	0.038*** (0.013)
Controls	Yes	Yes	Yes	Yes
_cons	0.012 (0.071)	-0.041 (0.085)	-0.009 (0.081)	-0.077 (0.099)
Firm/Year/IND	Yes	Yes	Yes	Yes
N	9,006	11,432	9,006	11,432
Adj.R^2	0.210	0.118	0.261	0.160
p-value	0.048**		0.188	

Note: The inter-group difference *p*-values are used to test the significance of the inter-group "DIG" coefficient differences, which are obtained through Bootstrap 1,000 times.

TABLE 12 Heterogeneity test based on firm size.

Variables	LNInv		LNInvUti	
	(1)	(2)	(3)	(4)
	Large-size	Small-size	Large-size	Small-size
DIG	0.112*** (0.015)	0.046*** (0.011)	0.087*** (0.017)	0.037*** (0.014)
Controls	Yes	Yes	Yes	Yes
_cons	-0.201* (0.115)	-0.035 (0.055)	-0.302** (0.128)	-0.035 (0.066)
Firm/Year/IND	Yes	Yes	Yes	Yes
N	10,219	10,219	10,219	10,219
Adj.R2	0.181	0.108	0.233	0.145
p-value	0.0107**		0.0851*	

Note: The inter-group difference *p*-values are used to test the significance of the inter-group "DIG" coefficient differences, which are obtained through Bootstrap 1,000 times.

3.8.1 Heterogeneity analysis of property rights of enterprises

The impact of digital transformation on green innovation may differ among enterprises with different property rights, so the sample enterprises are grouped according to property rights, and the test results are shown in Table 11. In both groups, the promoting effect of corporate digital transformation on green innovation quality (LNInv) has passed the 1% statistical significance test (Columns 1) and 2)). The *p*-value of the difference between groups is 0.048, indicating that the coefficients are comparable. The coefficient of digital transformation in the group of state-owned enterprises (SOEs) is 0.131, which is higher than that of non-state-owned enterprises (non-SOEs) at 0.047, which means that the promotion effect of digital transformation on the quality of green innovation in SOEs is more significant than that in non-SOEs. Columns 3) and 4) show the regression results of corporate digital transformation on the quantity of green innovation (LNInvUti). Although the coefficient is positive and significant, however, the difference in its coefficient between groups is not significant (p = 0.188) and not comparable, indicating that there is a facilitative effect of corporate digital transformation on green innovation quantity, and there is no significant difference in this effect between state-owned and non-state-owned enterprises.

The reasons for this result are multiple. On the one hand, green innovation quality implies higher technological capacity and correspondingly more investment in R&D resources, while SOEs have natural advantages in terms of strength endowment and resources accessibility due to the endorsement of state credibility, and the government also encourages and guides SOEs to actively implement digital transformation, which in turn facilitates their green innovation. On the other hand, SOEs are held to higher expectations in terms of social responsibility commitment. In the process of digital transformation, SOEs are more motivated to undertake green innovation with high investment and positive externality characteristics in response to the call for green transformation development, and thus their performance in terms of green innovation quality is better than that of non-SOEs. In contrast, the threshold for increasing the quantity of

TABLE 13 Heterogeneity test based on ecological expenditures.

Variables	LNInv		LNInvUti	
	(1)	(2)	(3)	(4)
	EE_Yes	EE _No	EE_Yes	EE _No
DIG	0.027 (0.049)	0.077*** (0.017)	0.021 (0.056)	0.064*** (0.019)
Controls	Yes	Yes	Yes	Yes
_cons	-1.163 (1.775)	-5.407*** (0.775)	-2.666 (2.037)	-6.760*** (0.852)
Firm/Year/IND	Yes	Yes	Yes	Yes
N	3,417	17,021	3,417	17,021
Adj.R2	0.142	0.168	0.216	0.215
p-value	0.024**		0.099*	

Note: The inter-group difference *p*-values are used to test the significance of the inter-group "DIG" coefficient differences, which are obtained through Bootstrap 1,000 times.

green innovation is relatively low, the required resource investment is relatively small, and firms of different ownership that undergo digital transformation can more easily increase their green innovation quantity output. In conclusion, SOEs have stronger strength and incentives to drive green innovation and thus actively undertake social responsibility, as evidenced by higher green innovation quality compared to non-SOEs; while there is no significant difference between SOEs and non-SOEs in terms of green innovation quantity promoted by digital transformation.

3.8.2 Heterogeneity analysis of firm size

To examine the impact of digital transformation on green innovation in enterprises of different sizes, the sample firms are grouped according to the median of their size, and the results are presented in Table 12. In both groups, the coefficients of digital transformation on the quality of green innovation (LNInv) and the quantity of green innovation (LNInvUti) are significantly positive at the 1% level with comparable values (p = 0.0107 and 0.0851, respectively). Specifically, compared with smaller enterprises, digital transformation has a more significant effect on the quality and quantity of green innovation in larger enterprises. On the one hand, this result may be due to the fact that larger enterprises tend to have stronger financial strength and risk resistance, and they have more strength and motivation to actively engage in digital upgrading and thus empower green innovation; on the other hand, large size also implies higher industry status, with significant advantages in seeking external resource support and leading industry development, large enterprises are therefore more likely to take the initiative to seize the opportunities of digital transformation, actively implement green innovation, shape the green image of enterprises and meet the expectations of stakeholders.

3.8.3 Heterogeneity analysis of ecological expenditures

Proactive eco-environmental pollution control and environmental protection investment is also one of the initiatives for enterprises to actively assume environmental responsibility and implement sustainable development strategies. On the one hand, eco-expenditures reflect the subjects' environmental awareness to some extent, and it is inferred that these enterprises may have the willingness to actively carry out green innovation activities; on the other hand, ecological expenditures imply that funds are tied up, which may crowd out funds for green innovation, so firms with eco-expenditures may be associated with lower levels of green innovation. In this paper, the sample firms are divided into two groups for group testing based on the presence or absence of ecological expenditures, and the results are shown in Table 13.

In the group with ecological expenditures, the effect of digital transformation on both green innovation quality (LNInv) and green innovation quantity (LNInvUti) was not significant (columns 1) and 3)); while in the group of firms without ecological expenditures, digital transformation significantly contributed to the improvement of green innovation quality (LNInv) and green innovation quantity (LNInvUti) (columns 2) and 4)). This indicates that firms almost always face resource constraints, and it is often difficult to achieve both "terminal treatment" and "green innovation" at the same time. In the process of digital transformation, when firms invest more resources in direct terminal treatment, digital transformation no longer has a positive effect on green innovation.

3.8.4 Heterogeneity analysis of financing constraints

In this paper, we find that financing constraints suppress the promotion of digital transformation of enterprises for green innovation, and furthermore, we wonder whether there are differences in the aforementioned impact paths when enterprises face different levels of financing constraints. The sample firms are divided into two groups according to the median of financing constraints, and the regression results are shown in Table 14. As can be seen, the coefficients are comparable between the groups at the 1% level (p-values are 0.007 and 0.000, respectively). From columns 1) 2), digital transformation promotes green innovation quality (LNInv) in both the groups with high and low financing constraints, and this boosting effect is more pronounced in the group facing higher financing constraints. According to columns 3) and 4), digital transformation has a significant enhancement effect on

TABLE 14 Heterogeneity test based on financing constraints.

Variables	LNInv		LNInvUti	
	(1)	(2)	(3)	(4)
	SA_high	SA_low	SA_high	SA_low
DIG	0.097*** (0.025)	0.050** (0.023)	0.098*** (0.026)	0.037 (0.025)
Controls	Yes	Yes	Yes	Yes
_cons	-3.057* (1.602)	-3.140** (1.283)	-5.297*** (1.741)	-3.997*** (1.415)
Firm/Year/IND	Yes	Yes	Yes	Yes
N	10,219	10,219	10,219	10,219
Adj.R2	0.148	0.168	0.203	0.212
p-value	0.007***		0.000***	

Note: The inter-group difference *p*-values are used to test the significance of the inter-group "DIG" coefficient differences, which are obtained through Bootstrap 1,000 times.

the quantity of green innovation (LNInvUti) in the group with high financing constraints, while this effect is not significant in the group with low financing constraints. This result supports the idea of innovation theory that when firms face higher levels of financing constraints, limited financial resources leave firms with fewer options and instead stimulate their creativity. Under such circumstances, firms are more motivated to maximize their available resources, make the best investment decisions, and actively seize potential opportunities for green innovation, which leads to better performance in terms of quality and quantity of green innovation.

4 Discussion

To establish an interaction on the synergistic development of digitalization and greening at the micro level, this paper examines the impact of firms' digital transformation on their green innovation by constructing a two-way fixed-effect model, and explores the role of internal control, financing constraints and TMT environmental attention in this impact path. The main findings are as follows: 1) Digital transformation of firms has a significant positive impact on promoting both the quality and quantity of their green innovation, and this finding still holds after multiple robustness tests, which provides a theoretical basis for achieving the synergistic development of digital transformation and green sustainability at the firm level; 2) Digital transformation can improve the level of internal control of firms, thus positively influencing the quality and quantity of green innovation; digital transformation may raise the financing constraint faced by firms, thus suppressing the promotion effect of digital transformation on green innovation; the effect of digital transformation on green innovation is more pronounced when TMT environmental attention is high; 3) Heterogeneity analysis shows that the impact of digital transformation on green innovation is more effective among state-owned enterprises, large-scale enterprises, enterprises without ecological expenditures, and enterprises with higher financing constraints.

4.1 Theoretical contributions

This study makes several theoretical contributions to the existing literature. Firstly, this study echoes the call of the academia to establish an interaction between the two tides of digitalization and sustainable development (Luo et al., 2022), builds a bridge between the interaction of digital transformation and green innovation at the micro-firm level, provides a systematic review of the literature on the topic, and further expands the determinants of green innovation in firms. Secondly, this paper helps to open the "black box" of the process of digital transformation empowering green innovation (Sun and Guo, 2022), finding that internal control is the mediating path of digital transformation promoting green innovation, while financing constraints suppress the impact, besides, TMT's environmental attention positively moderates the contribution of corporate digital transformation to green innovation. The study of these channels and mechanisms enriches existing theoretical studies on the impact of digital transformation and provides new perspectives. Thirdly, this paper uses Chinese listed companies as the research sample to analyze the heterogeneity and dissect the potential causes in terms of ownership, firm size, ecological expenditures, and financing constraints, enriching the existing research.

In addition, this study also provides empirical evidence to reveal the Solow paradox in the era of digital economy from a microscopic perspective. On the one hand, we find that digital transformation of firms can promote green innovation characterized by double externalities, i.e., although digital transformation does not initially aim to reduce environmental burdens, it does generate positive environmental benefits, suggesting that digital transformation generates benefits beyond productivity, adding micro-level evidence to the Solow paradox in the digital era. On the other hand, digital technologies are expected to fundamentally reshape business strategies, business processes, corporate capabilities, products and services, as well as expand relationships among focal companies in business networks (Bharadwaj et al., 2013), however, the manifestation of these effects requires a long period of exploration, debugging and integration. Overall, most enterprises are still in the initial stage of digital transformation, and the potential positive effects of digital transformation have not yet been fully revealed, as evidenced by the fact that the initial investment in digital transformation is much higher than its visible benefits; meanwhile, the high failure rate of digital transformation makes the future benefits highly uncertain. In this context, the credit sector demands higher risk premiums, which exposes firms to a higher degree of financing constraints when seeking external financial support for their digital initiatives. At this stage, IT inputs are not significantly reflected in productivity, and higher inputs and relatively lower outputs make external financing more costly for firms, which may in turn discourage firms' willingness to undertake digital transformation, and firms remain plagued by the Solow paradox.

4.2 Managerial implications

This paper provides some enlightenment for policy making. Firstly, the government should strengthen the construction of digital infrastructure, create the foundation conditions for the wide application of digital technology and the value mining of data elements, consolidate the empowerment base for enterprises to grasp digital opportunities and implement digital transformation. Secondly, the government should flexibly adopt measures such as government subsidies and tax incentives to increase financial support for enterprises' digital upgrading actions, and financial institutions should be supervised to moderately lower the financing threshold to mobilize enterprises' willingness to shift to digitalization and greening. Thirdly, the government should recognize the positive externalities of corporate digital transformation and create a supportive macro environment through multi-level institutional arrangements. The asymmetry of the benefits of green innovation brought by digital transformation is noteworthy, and more preferential treatment for non-state enterprises and SMEs should be considered in the formulation of relevant support policies to improve the overall efficiency of green innovation.

Business entities can also draw inspiration from this paper. First, enterprises should raise the awareness of digital transformation opportunities, take the initiative to assess the gap between strategic objectives and the current situation, actively employ external supportive conditions and environment to take digital actions, promote the deep integration of cutting-edge technologies and business, thus improving their digital transformation level. Second, enterprises should be keenly aware of the positive impacts of digital transformation, such as efficiency gains, cost reductions, reduced information asymmetry, and improved quality of internal controls, and release these positive signals externally to respond to stakeholder concerns and project a corporate image that espouses sustainability and creates conditions for securing external resources. Third, the allocation of attention by the executive team on environmental issues has a significant impact on the quality and quantity performance of green innovation. As green development is expected to shape a firm's green image and gain a sustainable competitive advantage, enterprises should keep track of the latest trends and relevant policy support of the government on environmental protection, and ensure that their executive teams allocate sufficient attention to environmental issues through various means.

5 Conclusion

Digitalization-led green sustainability is attracting widespread attention. Focusing on China's practice of promoting synergistic digitalization and greening, this paper examines the potential impact of corporate digital transformation on contributing to sustainable development through the lens of green innovation. The findings further support the study by Sun and Guo (2022), which clarifies the advantageous role of digital transformation in elucidating the "Solow paradox" in the digital economy and reveals compatible paths for corporate digital transformation and green innovation. Our study provides inspiration for policy makers, academics, and practitioners, broadens feasible pathways for common global challenges and opportunities, and provides empirical references for different countries and regions in developing synergistic strategies for digital transformation and green sustainability.

Several limitations deserve mention. First, the measurement of corporate digital transformation is a long-standing challenge (Yuan et al., 2021). This paper uses a textual analysis approach to portray it and further distinguish it from perspectives of underlying technologies and practical applications, however, such a division is still relatively rough and subjective, and more efforts are needed in future research. Second, green innovation is a comprehensive concept that contains different dimensions such as green product innovation and green process innovation (Chen et al., 2006), green innovation input and green innovation output (e.g., Zhao et al., 2021), green technology innovation and green management innovation (e.g., Shu et al., 2014), etc. This paper uses green patent outputs to portray green innovation, and future research could delineate green innovation in more detail and further investigate the heterogeneous impact that digital transformation may have on it. Third, there may be multiple pathways through which a firm's digital transformation affects its green innovation. This study explores the role played by internal control and financing constraints, and the study of the channels and mechanisms involved still needs to be further expanded. Finally, this study takes China as the research context, while firms in different countries and regions are at different stages of the digital revolution, it is worthwhile to examine in depth whether the promotion effect of corporate digital transformation on green innovation is prevalent, what are the boundary conditions for the occurrence of this impact, and what kind of heterogeneity exists among firms with different characteristics, etc.

Data availability statement

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

Author contributions

YS and MH conceived the study; YS and MH collected the data; MH developed the analyses with input from YS; all authors contributed to writing and revisions. All authors approved this final manuscript.

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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.

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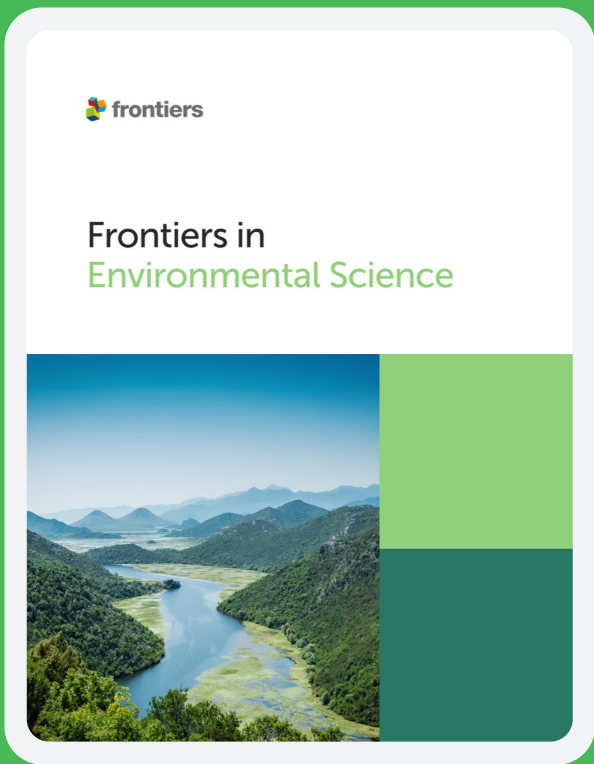

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