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Advances in co-benefits of climate change mitigation

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ORIGINAL RESEARCH
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One Fee, Two Reductions: The Double Abatement Effect of Pollutant Discharge Fees on Industrial Pollution and Carbon Emissions

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Formulating policies under the dual policy objectives of environmental protection and carbon neutrality in China is essential. This paper utilizes enterprise-level data to construct a panel model. Our empirical test indicates that increasing China's pollutant discharge fee can effectively reduce industrial pollutants, including wastewater and exhaust gas. The empirical results indicate that in terms of enterprises, pollutant discharge fees can not only directly reduce carbon emissions but also indirectly by reducing coal assumption. This paper also constructs a threshold model of the carbon emission reduction effect of population size. It has been proved that when the population size does not exceed the threshold, the utility of the pollutant discharge fee is apparent. According to this study's heterogeneity test, the carbon emission reduction effect of the pollutant discharge fee is more evident in large- and medium-sized enterprises and heavy pollution enterprises.

Keywords: pollutant discharge fee, industrial pollution, carbon emission, panel regression, mediation effect, threshold effect

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1 INTRODUCTION

The economic growth and human activities continue to expand carbon emissions, increasing the risk of environmental deterioration. Many researchers have begun to emphasize the importance of the carbon neutrality (Ji et al., 2021). Since the 2015 Paris Agreement, various member countries of the United Nations Climate Change Conference (21st Conference of the Parties, or COP21) are working on policies and strategies to control the problem of carbon dioxide (CO_2) emissions (Zhang and Wang, 2017). Sustainable environmental development is becoming a global consensus. Many countries strive to develop policies to control environmental degradation and reduce environmental pollution.

Among many environmental regulations in China, the pollutant discharge fee has an extensive history. At the corporate level, the most common way to protect the environment is to charge pollutant discharge fees. This paper establishes a model of pollutant discharge fees and other variables to explore the impact of charges on industrial pollutants and carbon emissions. The Chinese government promulgated the regulation for pollutant discharge fees in 1979. But there are two

Abbreviations: COP21, 21st Conference of the Parties; CO_2, Carbon Dioxide; APEC, Asia-Pacific Economic Cooperation; DID, Difference-in-Difference; PM2.5, Fine Particulate Matter; GHG, Greenhouse Gas; GDP, Gross Domestic Product; AESPF, Annual Environmental Survey of Polluting Firms; ASIF, Annual Survey of Industrial Firms; NBSC, National Bureau of Statistics of China problems, lack of motivation for corporate pollution control and significant differences in charging standards in different areas. In 2003, the Chinese government issued the second edition of the regulation and implemented it at the end of 2017. However, as the environment is a non-exclusive public good, many enterprises did not pay the fee as stipulated, leading to low resource allocation efficiency and environmental problems (Hu et al., 2020; Li et al., 2021).

The purpose of charging the pollutant discharge fee is to reduce pollutant emissions. There is evidence demonstrates that it does achieve this purpose. However, it is unclear whether the policy's implementation has played an important role in reducing carbon emissions. To fill this gap, this paper establishes a panel regression model and analyzes the role of pollutant discharge fees. We find that pollutant discharge fees also can reduce carbon emissions. With different population sizes, the carbon emission reduction effect of pollutant discharge fees is different. Further, the type and scale of enterprises also affect the emission reduction effect of the fees.

In addition to the direct effect, we also find that pollutant discharge fees can indirectly influence carbon emissions by reducing the use of coal. The consumption of fossil fuels such as coal is an important source of CO_2. China's current industrial sector requires coal to operate power plants, steel plants, and chemical plants and create electricity, steel, ammonia, methanol, urea, and agricultural fertilizer (Jia and Lin, 2021). Coal is China's major energy source and the most prominent contributor to the country's GHG emissions. The Chinese government attaches great importance to reducing GHG emissions. Energy conservation and emission reduction is the most critical step for China to address global climate change and other environmental issues in the present and future (Zhou et al., 2020). Reducing carbon emissions also have a positive impact on the Chinese government's proposal at the 75th UN General Assembly to achieve carbon neutrality by 2060.

Amid a critical time of global warming, it is effective for China to adopt new policies to reduce carbon emissions, but this will have significant costs. Utilizing existing systems to achieve the goal of reducing carbon emissions is a more efficient approach. In theory, there is a large overlap between the sources of environmental pollutants and CO_2 emissions. This paper uses data at the enterprise level to provide empirical evidence that there is also a negative correlation between the number of emission fees and carbon emissions.

This article provides the following contributions to the existing literature. First, in terms of this paper's research perspective, the pollutant discharge fee is a considerable part of Chinese environmental protection law. Charging for polluters is also a common practice throughout the world. Such regulation is of great significance for reducing environmental pollution and improving environmental quality (Wang et al., 2014a). Studying the actual emission reduction effect of the pollutant discharge fee has great reference value for decision makers to establish more suitable regulatory policies. However, the existing research only focuses on the promoting effect of pollutant discharge fees on environmental pollution, air pollution, and exhaust emission. Few literatures mentioned the effect of this policy on carbon emissions. This paper fills this research gap and studies the dual function of the pollutant discharge fee in China. While having a great inhibitory effect on air pollutants, the pollutant discharge fee also has a significant abatement effect on carbon emissions. Second, from the perspective of research objects, rather than the studying the impact of policies at the provincial or macro level, this paper quantitatively studies the reverse relationship between pollutant discharge fees and carbon emissions at the enterprise level to study the impact of Chinese government procurement of coal substitutions.

The remainder of this study is arranged as follows: **Section 2** presents the related literature review and hypotheses. **Section 3** describes the data and methodology. **Section 4** discusses the empirical results. **Section 5** carries out the heterogeneity analysis. The last section concludes.

2 LITERATURE

Since Arthur C. Pigou first proposed environmental tax in his externality theory, academia has not reached a unified conclusion on the governance effect of environmental tax. China adheres to the policy of the pollutant discharge fee, while other countries implement the environmental tax. Previous studies mainly focus on the role of environmental tax. Many literatures can prove that the implementation of environmental tax has the effects of reducing industrial pollution, strengthening green economies, and inhibiting environmental degradation (Lin and Li, 2011). used the Differences-in-Differences (DID) model to comprehensively evaluate the impact of carbon tax on environmental governance in five Nordic countries (Denmark, Finland, Sweden, the Netherlands, and Norway) and found that environmental taxes had a negative effect on CO_2 emissions in Finland. However, this effect was weak in the other four countries. For the first time (Han and Li, 2020), quantified the impact of environmental taxes on the PM2.5 emissions in China's provinces and noted that clean air policies and environmental taxes could significantly reduce its pollution (Chien et al., 2021). Also proved that environmental taxes and ecological innovation have a positive impact on reducing carbon emissions and haze formation in Asian countries.

There is substantial evidence in various countries that charging taxes is an effective means of reducing environmental damage (Meng et al., 2013). Collated data and noted that carbon taxes can effectively reduce CO_2 emissions. For example, Australia has imposed environmental taxes since 2012 to meet Copenhagen targets for its CO_2 emission reductions. In Europe and China, environmental taxes also have a negative impact on GHG emissions (Yang et al., 2014; Onofrei et al., 2017), indicating that environmental taxes have an important role in reducing environmental pollution (Vallés-Giménez and Zárate-Marco, 2020). Reported that the GHG emissions in Spain are spatially dependent, spatially persistent and temporally. In this case, taxes that aim at reducing emissions have a slight inhibiting effect. However, sometimes environmental taxes have a negative impact on economic development (Floros and Vlachou, 2005). Assessed the impact of environmental tax and found that carbon tax in the

Greek manufacturing industry has been an effective environmental policy to alleviate global warming. But it has proved to be expensive and detrimental to the economic development (Gao and Chen, 2002; Lu et al., 2010). Also illustrated that the implementation of environmental taxes in China will reduce carbon emissions while it may have a negative impact on the country's economy.

Implementing environmental tax has the function of strengthening a green economy. As mentioned for China (Li et al., 2021), explained that the use of environmental taxes and regulatory supervision by relevant institutions can promote the use of green technologies and reduce industrial pollution. More stringent environmental taxes can encourage enterprises to reduce emissions, and there is an inverted U-shaped relationship between industrial pollution reduction and environmental tax rate (Cheng and Li, 2022). Proved that the industrial green total factor productivity (GTFP) increases significantly by increasing the standard pollutant discharge fee. Their conclusion remains valid after alleviating endogenous problems and conducting robustness tests. Increasing environmental costs can promote industrial green growth and improve the level of green technology innovation, which can better transform the mode of a country's economic growth and achieve green industry development. The relationship between environmental taxes and green technology innovation is achieved through incentives for environmental regulatory instruments (Anthony et al., 2011; Jaffe et al., 2002). Some countries are improving green information systems, strengthening internal environmental management (Khan and Yu, 2020), and developing green practices (Khan et al., 2020) and green financial intermediary channels to achieve a zero-carbon economy (Umar et al., 2021).

In addition, environmental taxes affect the choice of pollutant products in the decision-making process, creating incentives to reduce high-pollution products and improve environmental quality (Elkins and Baker, 2002; Niu et al., 2018; He et al., 2019). In other words, environmental taxes correct environmental problems (such as pollution), in whole or in part, by increasing incentives for alternative behaviors. Environmental taxes can increase environmental investment and reduce air pollution emissions. Moreover, according to the idea of asylum tax, in complete competition, the optimal environmental tax can offset the gap between private costs and social costs. These findings suggest that well-designed environmental taxes may be an effective policy tool for the internalization of environmental costs. Threshold regression results have highlighted that there is an optimal tax rate for green technology innovation (Wang and Yu, 2021), However, it is important that China's current environmental tax rate is lower than this tax rate.

World economic and finance development has an important impact on the emission of CO_2 (Xiang et al., 2021; Ren et al., 2022a; Yin et al., 2022). Economic development is inseparable from the demand for resources. Increased demand for resources puts increasing pressure on the natural environment. One of the increasing pressures on the natural environment is that there are more carbon emissions, haze pollution, and unhealthy byproducts produced by different activities (Malghani, 2021), and the increase in economic development leads to more carbon emissions, especially in countries such as China and India (Ran et al., 2021). Except for the economic situation, coal prices can largely affect the use of coal, which are affected by many factors (Ren et al., 2021b). Proposes two new methods to evaluate the predictability of a large group of factors on carbon futures returns.

China's economic growth has been accompanied by substantial energy consumption, surpassing the energy consumption of the United States for the first time in 2010. Furthermore, the annual report of China's energy development illustrated that the renewable energy in China satisfies for only a small proportion of total energy consumption (accounting for 13% in 2016). Conversely, coal (characterized as a high-carbon, high-pollution, and high-emission energy source) represented a large proportion of the total energy consumption (61.8%), while oil and gas accounted for 18.3% and 6.4%, respectively. In addition, there are distinct differences in the energy consumption patterns between China and the world's major developed countries and its energy consumption intensity is significantly higher than that of developed countries. Reliance on coal as a fuel for production is likely to cause higher carbon emissions. This paper verifies whether the increase in pollutant discharge fees can reduce the use of coal, the main contributor to greenhouse gases, and further reduce carbon emissions.

How to mitigate carbon emissions is a hot topic in recent years. There are many direct and indirect factors that affect corporate carbon emissions. For example, relying on fossil fuels for production produces a large amount of carbon dioxide, which puts a certain pressure on the global environment. In addition, increased national climate risk will also promote the carbon emissions of enterprises (Ren et al., 2021).

Meanwhile, researchers work to find ways to reduce carbon emissions. For example, increasing the use of renewable energy can effectively alleviate environmental pressure (Dong et al., 2020). Environmental innovation is also considered one of the critical tools for reducing CO_2 emissions (Cws et al., 2020; Umar et al., 2020). Fostering a migration from traditional energy to renewable energy is not only environmental-friendly but also crucial for steady development of society and economy (Ayres et al., 2013; Wang et al., 2014b). For government policy, mandatory environmental regulation and soft policies directly or indirectly reduce carbon emissions. In addition, some researchers point out that China's energy development will have a significant impact on its economic growth (Li et al., 2017; Xie et al., 2018).

Few studies have investigated the quantitative impact of environmental tax on carbon emissions. Some scholars believe that environmental tax will lead to environmental deterioration (Asmi et al., 2019). However, another school believes that environmental taxes help reduce carbon emissions (Thi et al., 2020). Studied the relationship between environmental taxes, natural resource consumption taxes, and carbon emissions from 2001 to 2018, and the multivariate analysis indicated that the increased environmental taxes can lead to Vietnam's CO_2

emissions reducing. Other studies have indicated that environmental taxes can reduce CO_2 emissions at a higher level worldwide (Wolde-Rufael and Mulat-Weldemeskel, 2021). Collected data on aggregate environmental taxes, energy taxes, and environmental policies in seven emerging countries from 1994 to 2005 and tested the green dividend hypothesis, proving that aggregate environmental taxes and energy taxes improved the environmental quality of these countries.

Environmental taxes may reduce carbon emissions through a variety of ways. Environmental taxes may lead to technological upgrades, potentially combatting the problems associated with high emissions (Borozan, 2019). Ulucak et al. (2020) believed that environmental taxes can achieve the non-linear impact on carbon emissions by improving innovation and energy efficiency. The marginal impact of environmental taxes on natural resource rents and renewable energy consumption rises in a statistically significant manner with increasing tax levels, further affecting carbon emissions. Raising environmental taxes can also have a negative impact on the consumption of traditional energy sources such as coal, indirectly reducing carbon emissions (Martins et al., 2021).

Many environmental tax studies have involved industrial pollution to measure environmental quality, yet rarely involve resource utilization, such as ecological footprint (Ac and Acar, 2018; Sun et al., 2020). Studies have reported that environmental tax can reduce water pollution (Higano et al., 2020), solid waste (Prats et al., 2020), and resource consumption (Söderholm, 2011).

3 METHODOLOGY AND DATA

3.1 Panel Regression Model

In the research method, we use panel regression with time and individual fixed effects. The original intention for the establishment of the pollutant discharge fee was to reduce industrial pollution, so we first explored the direct emission reduction effect of the pollutant discharge fee on waste gas and wastewater. In addition, we regressed CO_2 data to estimate whether this policy has an impact on CO_2 emissions. The baseline measurement model is as follows:

$$w\_gas_{it} = \alpha_1 + \beta_1 fee_{it} + \gamma_1 X_{it} + \mu_t + \eta_i + \varepsilon_{\text{it}} \tag{1}$$

$$w\_water_{it} = \alpha_2 + \beta_2 fee_{it} + \gamma_2 X_{it} + \mu_t + \eta_i + \varepsilon_{\text{it}} \tag{2}$$

$$CO_{2_{it}} = \alpha_3 + \beta_3 fee_{it} + \gamma_3 X_{it} + \mu_t + \eta_i + \varepsilon_{\text{it}} \tag{3}$$

Where i and t denote enterprise and year, respectively, w_gas_{it}, w_water_{it}, and $CO_{2_{it}}$ severally represent industrial waste gas emissions and water emissions and CO_2 emissions, which are calculated by the natural logarithm of CO_2 emissions plus one from industrial enterprises. fee_{it} is the natural logarithm of emission fee for a specific enterprise in a given year. X_{it} is a vector of control variables (Xing et al., 2020), including corporate financial leverage, return on assets, proportion of management expenses, regional per capita GDP, and export value (if the export value is greater than one, the value is one; otherwise, it is zero). ε_{it} is the error term.

3.2 Mediation Effect Model

This study assessed the direct and indirect effects of pollutant discharge fees on carbon emissions by utilizing a mediating effect model. Higher environmental taxes can reduce the use of fossil fuels, such as coal (Murray and Brian, 2015), by promoting green technology and improving the quality of green investment (Lambertini et al., 2020) as well as competitiveness of renewable energy technologies (Wesseh and Lin, 2019). Simultaneously, changes in coal consumption will affect CO_2 emissions in the short and long term (Martins et al., 2021). We speculated that the pollutant discharge fee system can reduce carbon emissions by reducing the use of coal, so our mechanism analysis addressed coal consumption as an intermediary variable. We adopted the following regression model:

$$coal_{it} = \xi + \zeta fee_{it} + \varsigma X_{it} + \mu_t + \eta_i + \varepsilon_{\text{it}} \tag{4}$$

$$CO_{2_{it}} = \alpha + \beta fee_{it} + \theta coal_{it} + \gamma X_{it} + \mu_t + \eta_i + \varepsilon_{\text{it}} \tag{5}$$

Here, i and t denote enterprise and year. $coal_{it}$ and $CO_{2_{it}}$ represent the coal consumption intensity and CO_2 emissions, respectively. fee_{it} refers to the emission fee for a specific enterprise in a given year. X_{it} is a vector of control variables. ε_{it} is the error term.

3.3 Threshold Effect Model

The panel regression model only verifies the existence of a carbon emission reduction effect caused by the pollutant discharge fee, but whether there are other factors, such as population, that affect the carbon emission reduction effect (Wang et al., 2022). Believed that the multi-center structure of urban agglomeration would produce large amounts of carbon emissions (Fan et al., 2021; Wang and Wang, 2021). Indicated that there is a non-linear relationship between aging populations and carbon emissions. However, we believed that different population sizes also have an impact on the CO_2 emission reduction effect. Due to the differences in geographical location, economic foundation, and construction conditions, the population size of cities in China vary. If the urban population size is larger than the population capacity, it indicates that the urban population has caused great pressure, or even damage, to the environment, which is not conducive to the green development of these urban environments. In this case, we speculated that the carbon emission reduction effect of the pollutant discharge fee may be heterogeneous with different population sizes, that is, the impact of urban population size on carbon emissions may have a threshold effect. According to the threshold model constructed by (Hansen, 1999), we constructed the threshold regression model explaining the non-linear influence of population size on CO_2 emissions from pollution charges. In this study, the single-threshold econometric model was as follows:

$$CO_{2_{it}} = \alpha_0 + \beta_1 fee_{it} I(pop \le \gamma) + \beta_2 fee_{it} I(pop > \gamma) + \theta' X_{it} + \mu_t + \eta_i + \varepsilon_{\text{it}} \tag{6}$$

TABLE 1 | Definitions of variables.

	Variable name	Variable symbol	Definitions of variables
Dependent Variables	co2	CO_2 emission	Log (1 + CO_2), where CO_2 is converted from standard coal, the conversion formula is:CO_2 = standard coal*0.714*2.492
	w_gas	industrial waste gas emissions	Total industrial waste gas emissions million standard cubic meters/10000
	w_water	industrial wastewater emissions	Industrial wastewater emissions tonnes/10000
Independent Variable	fee	Pollutant discharge fee	Natural logarithm of emission fee
Control Variables	roa	rate of return on assets	Operating profit/Total assets
	lev	financial leverage	Total liabilities/Total assets
	admin	Proportion of management costs	Ratio of management expenses to sales income of main products
	export	Whether the enterprise has export behavior	0–1 dummy variable, if export value >0, export value is 1, otherwise 0
	lpgdp	Regional per capita GDP	Natural logarithm of per capita GDP in the province where the enterprise is located
Mediator	coal	Coal consumption intensity	Coal consumption amount (million tons)
Threshold Variable	pop	population size	Natural logarithm of end-of-year population in cities where the enterprises is located

In addition to the previously mentioned variables, pop is the population size, the natural logarithm of an urban population at the end of the year. $I(\cdot)$ represents the indication function, which is determined by the threshold variable, pop, and threshold value, γ. The number of thresholds is determined by the significance of F-statistics. μ_t and η_i represent the provincial fixed effect and year fixed effect, respectively, and ε_{it} is the error term.

3.4 Data Sources

The data on firms' pollution emissions comes from Annual Environmental Survey of Polluting Firms (AESPF), which was established by the Ministry of Ecology and Environment (formerly known as the Ministry of Environmental Protection) in the 1980s to record environmental pollution and emission reduction in China. AESPF provides information on corporate environmental performance, including emissions of major pollutants, pollution treatment equipment, and energy consumption. The CO_2 emission data was converted from standard coal data.

Corporate financial control variables (such as asset-liability ratio, corporate scale, corporate age, and enterprise import and export data) are derived from the Annual Survey of Industrial Firms (ASIF), which is one of the most comprehensive and widely used Chinese firm-level dataset maintained by the National Bureau of Statistics of China (NBSC). The ASIF dataset covers all state-owned industrial firms and non-state-owned industrial firms with annual sales above 5 million RMB in China. It contains detailed financial and characteristic information about each firm. The gross domestic product per capita and urban population at the end of the year in the province where the enterprise is located are based on data from the NBSC. We matched the above data according to the enterprise name and the enterprise code and received 178,473 pieces of data. The following table indicates how the study variables are defined (**Table 1**).

TABLE 2 | Descriptive statistics.

Variable	Obs	Mean	Sd	Min	p50	Max
co2	210454	6.356	3.623	0.000	7.320	16.534
fee	469632	11.212	0.647	8.799	11.393	12.227
roa	418667	0.112	0.213	−0.220	0.042	0.989
Lev	418790	0.575	0.287	0.029	0.583	1.539
admin	418375	0.060	0.069	0.001	0.039	0.534
export	469632	0.557	0.497	0.000	1.000	1.000
lpgdp	469632	10.278	0.567	8.346	10.37	11.230
coal	223207	0.028	0.212	0.000	0.001	13.879
pop	442289	6.057	0.576	1.596	6.135	7.088

TABLE 3 | Full sample regression results.

Variables	(1)	(2)
	w_gas	w_water
Fee	−0.2092**	−1.2978**
	(−2.39)	(−1.97)
roa	−2.1065***	−12.6835***
	(−18.59)	(−19.69)
Lev	−0.1966**	2.0711***
	(−2.12)	(3.69)
admin	−3.6420***	−8.1654***
	(−10.51)	(−3.71)
export	1.1967***	7.5602***
	(11.77)	(15.98)
lpgdp	0.4531	−2.7303
	(0.79)	(−1.46)
Constant	−3.0304	60.7645**
	(−0.50)	(2.47)
Time Effect	YES	YES
Industry Effect	YES	YES
Local Effect	YES	YES
Cluster at Firm	YES	YES
Observations	204,321	351,386
R-squared	0.125	0.105

, **, and * indicate significance at 10%, 5% and 1% level, respectively.*

TABLE 4 | Full sample regression results.

Variables	(1)	(2)	(3)	(4)
	CO_2	CO_2	CO_2	CO_2
fee	−0.0797***	−0.0244*	−0.2232***	−0.2232***
	(−6.74)	(−1.88)	(−5.20)	(−6.13)
roa		0.0332	−0.1616***	-0.1616***
		(0.82)	(−3.99)	(−3.12)
Lev		0.6576***	0.4346***	0.4346***
		(23.05)	(15.82)	(11.18)
admin		−0.8590***	−1.2152***	−1.2152***
		(−7.32)	(−11.06)	(−7.94)
export		−0.0630***	0.1014***	0.1014***
		(−2.87)	(4.87)	(3.37)
lpgdp			−1.5757***	−1.5757***
			(−8.27)	(−8.18)
Constant	5.8197***	4.8855***	24.1222***	24.1222***
	(42.87)	(32.49)	(11.77)	(11.58)
Time Fixed-effect	YES	YES	YES	YES
Industry Fixed-effect	YES	YES	YES	YES
Location Fixed-effect	NO	NO	YES	YES
Cluster at Firm	NO	NO	NO	YES
Observations	210,454	178,473	178,473	178,473
R-squared	0.191	0.204	0.268	0.268

, **, and * indicate significance at 10%, 5% and 1% level, respectively.*

TABLE 5 | mediating effect analysis.

Variables	(1)	(2)	(3)
	CO_2	Coal	CO_2
fee	−0.2232***	−0.0056***	−0.2079***
	(−6.13)	(−3.06)	(−5.74)
coal			2.2418***
			(8.28)
roa	−0.1616***	−0.0114***	−0.1405***
	(−3.12)	(−5.91)	(−2.73)
Lev	0.4346***	−0.0003	0.4374***
	(11.18)	(−0.22)	(11.37)
admin	−1.2152***	−0.0734***	−1.0639***
	(−7.94)	(−11.95)	(−6.97)
export	0.1014***	0.0270***	0.0426
	(3.37)	(6.32)	(1.45)
lpgdp	−1.5757***	−0.0335*	−1.4805***
	(−8.18)	(−1.94)	(−7.75)
Constant	24.1222***	0.4045**	22.9801***
	(11.58)	(2.16)	(11.10)
Time Fixed-effect	YES	YES	YES
Industry Fixed-effect	YES	YES	YES
Location Fixed-effect	YES	YES	YES
Cluster at Firm	YES	YES	YES
Observations	178,473	188,948	178,429
R-squared	0.268	0.095	0.283

, **, and * indicate significance at 10%, 5% and 1% level, respectively.*

4 EMPIRICAL ANALYSIS AND DISCUSSION

4.1 Panel Regression Results

The summary statistics of variables such as CO_2 emissions, pollutant discharge fees and coal consumption intensity are exhibited in **Table 2**.

Before investigating the carbon reduction effect of the pollutant discharge fee, we examined its impact on industrial pollutant discharges. The quantities of industrial waste gas and wastewater were regressed on the number of pollutant discharge fees paid and other control variables. The results are reported in **Table 3**. The results prove that this policy has a significant inhibiting effect on industrial waste gas and wastewater emissions at the level of 5%. It proves that the increase of the pollutant discharge fee can promote enterprises to optimize their energy structure independently and replace traditional fossil fuels with clean energy to reduce the emissions of polluting exhaust and wastewater. The original intention of pollutant discharge fee system is to reduce emissions of pollutant, and the results illustrate that this system is effect. This paper attempts to explore whether the pollutant discharge fee has other effects in addition to inhibiting industrial pollution. Furthermore, we hope to explore whether the pollutant discharge fee is conducive to reducing enterprise carbon emissions.

All columns in **Table 4** present basic estimated results of the models with the original data, including firm fixed effects and year fixed effects. In column (1), the coefficient value is −0.0797 which is significant and negative. This result indicates that higher pollution charges will reduce CO_2 emissions, while the effect decreases slightly as more corporate-level covariates are included in the regression. As for other control variables, we can see that rate of return, proportion of management costs, and regional per capita GDP are all important negative factors affecting CO_2 emissions at the corporate level, while financial leverage has positive effects.

TABLE 6 | Test for multiple thresholds.

Threshold	RSS	MSE	F-stat	Prob
Single	4.73e + 04	1.5107	288.58	0.0000
Double	4.71e + 04	1.5040	137.80	0.1167

4.2 Mediation Effect Result

We used the stepwise regression coefficient method to verify the negative mediating effect of coal consumption intensity for CO_2 emissions. **Table 5** indicates that when there is no mediating effect, the coefficient is apparent, which explains the direct negative effect of pollutant discharge fees on CO_2 emissions. When there is a mediator, the indirect impact of pollutant discharge fees on carbon emissions through coal consumption should also be considered. The pollutant discharge fee reduces the use of coal to the level of 1%, and coal consumption can significantly increase CO_2 emissions. The coefficient was 2.2418, which concludes that coal consumption has a partial mediating effect on CO_2 emissions.

4.3 Threshold Effect Result

According to the threshold model constructed by urban population size, the single-threshold test results are clear, while the model rejects the double-threshold hypothesis as shown in **Table 6**. So the effectiveness of pollutant discharge fees in carbon emission reduction is only applicable to the single-threshold hypothesis

TABLE 7 | Threshold effect test results.

Variables	(1)
	CO_2
Roa	0.1615**
	(2.14)
Lev	−0.0297
	(−0.53)
Admin	−0.3495
	(−1.47)
Export	−0.0525**
	(−1.99)
Lpgdp	0.6543***
	(15.65)
0b._cat#c.fee	−0.1260***
	(−3.13)
1._cat#c.fee	0.0522
	(1.41)
Constant	0.9180**
	(2.32)
Observations	31,332
R-squared	0.032
Number of firm	5,222

*, **, and *** indicate significance at 10%, 5% and 1% level, respectively.

TABLE 8 | Heterogeneity—enterprise scale.

Variables	(1)	(2)	(3)
	Large scale	Middle scale	Small scale
	CO_2	CO_2	CO_2
fee	−0.8704*	−1.4262***	0.0404
	(−1.85)	(−9.48)	(0.99)
roa	−2.2226***	−0.0141	0.0622
	(−2.82)	(−0.10)	(1.19)
Lev	1.0432***	0.5609***	0.4057***
	(2.94)	(5.89)	(10.30)
admin	−0.5013	−1.1205***	−1.2194***
	(−0.36)	(−3.15)	(−7.91)
export	0.1245	−0.2732***	−0.2915***
	(0.74)	(−4.98)	(−8.70)
lpgdp	−7.6053***	−3.2042***	−1.7953***
	(−4.18)	(−6.04)	(−8.82)
Constant	94.6390***	53.6197***	23.6125***
	(5.03)	(9.61)	(11.31)
Time Effect	YES	YES	YES
Industry Effect	YES	YES	YES
Local Effect	YES	YES	YES
Cluster at Firm	YES	YES	YES
Observations	4,712	36,347	137,414
R-squared	0.414	0.334	0.261

*, **, and *** indicate significance at 10%, 5% and 1% level, respectively.

of population size. According to **Table 7**, we found that when the population size is below the threshold value of 4.9577, the pollutant discharge fee has a significantly negative effect on CO_2 emissions. When the threshold value is 4.9577–5.8875, the coefficient changes from negative to positive, but the effect is not noticeable. It is shown that when the population does not reach the first threshold, the increase in pollutant discharge fees is significantly conducive to the reduction of carbon emissions. However, after exceeding the threshold, the increase in pollutant discharge fees will increase carbon emissions and cause certain damage to the environment. The population size of a city should be controlled within a certain range. Currently, the inhibitory effect of this policy on carbon emissions is effective. Unrestrained population expansion will not only impose a substantial burden on the environment itself but also weaken the energy saving and emission reduction effect of environmental protection policies, such as emission fee policies.

5 HETEROGENEOUS ANALYSIS

5.1 Enterprise Scale

We divided the enterprise scale into three categories (large, medium, and small) and then completed regression respective to each category to observe whether the CO_2 emission level of enterprises of different scales is affected by variables such as the pollutant discharge fee. For large-scale enterprises, the pollutant discharge fee has a significant inhibitory effect on carbon emissions at the level of 10%, and the return on assets and financial leverage of enterprises have significant positive and negative effects on carbon emissions, respectively. For medium-sized enterprises, the suppressive effect of the increase of the pollutant discharge fee on carbon emissions is significant at the 1% level, while it is not significant for small enterprises. It is necessary to strengthen the supervision of large- and medium-sized enterprises' emission payments and continue the innovation to create useful policies for small-sized enterprises. The results in **Table 8** illustrate that pollutant discharge fees are beneficial to environmental protection and effectively reduce the carbon emissions of large- and medium-sized enterprises.

TABLE 9 | Heterogeneity—Light/heavy industries.

Variables	(1)	(2)
	Light industry	Heavy industry
	CO_2	CO_2
Fee	−0.0450	−0.2606*
	(−1.03)	(−1.91)
Roa	−0.2067***	−0.1409
	(−3.76)	(−1.40)
Lev	0.4747***	0.3198***
	(11.45)	(4.83)
Admin	−1.7168***	−0.0096
	(−10.57)	(−0.04)
Export	−0.0298	0.3556***
	(−0.89)	(6.74)
Lpgdp	−2.0821***	1.0328
	(−10.35)	(1.10)
Constant	27.6884***	−1.7550
	(12.83)	(−0.18)
Time Effect	YES	YES
Industry Effect	YES	YES
Local Effect	YES	YES
Cluster at Firm	YES	YES
Observations	128,829	49,644
R-squared	0.259	0.299

*, **, and *** indicate significance at 10%, 5% and 1% level, respectively.

5.2 Light and Heavy Industries

Statistics indicate that between 2005 and 2019, the average ratio of the Chinese heavy industry's CO_2 emissions to the total CO_2 emissions was about 55%. The heavy industry is the pillar of the Chinese national economy (Xu and Lin, 2020). In the early development stages, broad economic growth spurred rapid growth in the industry, accompanied by high levels of CO_2 emissions (Zhang and Ma, 2020). Statistics demonstrate that between 2005 and 2019, China's heavy industry CO_2 emissions accounted for an average of about 55% of the country's total CO_2 emissions.

To observe the role of the pollutant discharge fee more specifically, we categorized enterprises as part of the light industry or heavy industry. Empirical test proves that the pollutant discharge fee has a significant inhibitory effect on the carbon emissions of heavy industry. For light industry, the coefficient of pollutant discharge fees is negative, but insignificant. The heavy industry does more harm to the environment than the light industry, so it is acceptable that the effect of the pollutant discharge fee on the heavy industry is greater than that of the light industry. **Table 9** demonstrates that the pollutant discharge fee can significantly reduce carbon emissions from heavy industry enterprises.

6 CONCLUSION

Based on the enterprise pollution emission data and financial data, this paper analyzes whether the increase in pollutant discharge fees can reduce industrial pollution. Furtherly, whether it can achieve the purpose of reducing carbon emissions. We established a panel model with time fixed effects and individual fixed effects. The empirical analysis shows that the increase of pollutant discharge fees is useful for companies to increase the use of clean energy, and ultimately achieve the purpose of reducing waste water and waste gas. Meanwhile, by promoting the optimization of the energy structure of enterprises, the increase in pollutant discharge fees can also reduce carbon emissions. With the addition of more corporate variables, pollutant discharge fees continue to maintain a restraining effect on carbon emissions. In addition to the direct impact, pollutant discharge fees can also indirectly reduce carbon emissions. The increase in pollutant discharge fees is conducive to promoting the improvement of green technology and improving the competitiveness of renewable energy, thereby reducing the use of fossil fuels such as coal. The reduction of coal use can reduce CO_2 emissions. Therefore, we believe that the increase in pollutant discharge fees can further reduce carbon emissions by inhibiting the use of coal (i.e., the main contributor of China's greenhouse gases). We also established a threshold model and found that when the urban population is within a certain scale, the inhibitory effect of sewage charges is more significant.

From a national perspective, China should be attentive to its environmental protection efforts while promoting economic development and weigh its speed of economic development with its status quo of environmental governance. The pollutant discharge fee system is not only a mandatory environmental law but also a driver for economic development in the Chinese market, supporting enterprises to reduce the intensity of coal use, encouraging the use of clean energy, and promoting technological innovation and environmental awareness. The Chinese government should introduce mature regulatory policies as well as improve the regulatory system to implement these policies. Simultaneously, researchers should recognize that population size has a certain impact on the effectiveness of environmental protection measures and population size should be controlled as reasonably possible to prevent it from exceeding the threshold to weaken the effect of the country's emission policy.

As mentioned for the enterprises, improving the use of clean gas can reduce CO_2 emissions and reduce harmful gas emissions to improve the environment, thereby reducing the amount of emission fees, achieving the goal of energy structure optimization in the short term, and establishing a more comprehensive carbon neutralization in the long term. While achieving economic goals, the government should continually have a global view and strengthen technological innovations to optimize enterprise energy structures. Enterprises should be environmentally conscious and bear its corresponding social responsibility, comply with the market and government forces, and enhance the competitiveness of their respective markets. Enterprises should also improve their production technology, reduce industrial pollution, reduce energy supplies using coal as fuel for product production, and increase the use of clean energies, such as natural gas, to effectively reduce carbon emissions.

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

ZW: methodology, writing—review and editing, validation, resources, and data curation. LY: methodology, software, resources and visualization. MZ: data curation, supervision and investigation. YX: formal analysis, writing—review and editing, and project administration. XL: data curation, formal analysis and data curation. YW: resources, software, and visualization. ZX: conceptualization, supervision, funding acquisition and writing original draft. All authors: contributed to the article and approved the submitted version.

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REFERENCES

Aşıcı, A. A., and Acar, S. (2018). How Does Environmental Regulation Affect Production Location of Non-carbon Ecological Footprint? *J. Clean. Prod.* 178, 927–936. doi:10.1016/j.jclepro.2018.01.030

Asmi, F., Anwar, M. A., Zhou, R., Wang, D., Sajjad, A., Powe, D. N., et al. (2019). Social Aspects of 'climate Change Communication' in the 21st Century: a Bibliometric View. *J. Environ. Plan. Manag.* 62 (4), 2393–2417. doi:10.1080/09640568.2018.1541171

Ayres, R. U., van den Bergh, J. C. J. M., Lindenberger, D., and Warr, B. (2013). The Underestimated Contribution of Energy to Economic Growth. *Struct. Change Econ. Dyn.* 27, 79–88. doi:10.1016/j.strueco.2013.07.004

Borozan, D. (2019). Unveiling the Heterogeneous Effect of Energy Taxes and Income on Residential Energy Consumption. *Energy Policy* 129, 13–22. doi:10.1016/j.enpol.2019.01.069

Cheng, Z., and Li, X. (2022). Do raising Environmental Costs Promote Industrial Green Growth? A Quasi-Natural Experiment Based on the Policy of Raising Standard Sewage Charges. *J. Clean. Prod.* 343, 131004. doi:10.1016/j.jclepro.2022.131004

Chien, F., Sadiq, M., Nawaz, M. A., Hussain, M. S., Tran, T. D., and Le Thanh, T. (2021). A Step toward Reducing Air Pollution in Top Asian Economies: The Role of Green Energy, Eco-Innovation, and Environmental Taxes. *J. Environ. Manag.* 297, 113420. doi:10.1016/j.jenvman.2021.113420

Cws, A., Bn, B., Xfs, C., Jpl, D., and Zj, E. (2020). Trade and Technological Innovation: The Catalysts for Climate Change and Way Forward for COP21. *J. Environ. Manag.* 269, 774. doi:10.1016/j.jenvman.2020.110774

Dong, K., Dong, X., and Jiang, Q. (2020). How Renewable Energy Consumption Lower Global CO_2 Emissions? Evidence from Countries with Different Income Levels. *World Econ.* 43, 1665–1698. doi:10.1111/twec.12898

Elkins, P., and Baker, T. (2002). Carbon Taxes and Carbon Emissions Trading. *J. Econ. Surv.* 15 (3), 325–376. doi:10.1111/1467-6419.00142

Fan, J., Zhou, L., Zhang, Y., Shao, S., and Ma, M. (2021). How Does Population Aging Affect Household Carbon Emissions? Evidence from Chinese Urban and Rural Areas. *Energy Econ.* 100, 105356. doi:10.1016/j.eneco.2021.105356

Floros, N., and Vlachou, A. (2005). Energy Demand and Energy-Related CO_2 Emissions in Greek Manufacturing: Assessing the Impact of a Carbon Tax. *Energy Econ.* 27, 387–413. doi:10.1016/j.eneco.2004.12.006

Han, F., and Li, J. (2020). Assessing Impacts and Determinants of China's Environmental Protection Tax on Improving Air Quality at Provincial Level Based on Bayesian Statistics. *J. Environ. Manag.* 271, 111017. doi:10.1016/j.jenvman.2020.111017

Hansen, B. E. (1999). Threshold Effects in Non-dynamic Panels: Estimation, Testing, and Inference. *J. Econ.*. doi:10.1016/S0304-4076(99)00025-1

He, P., Ning, J., Yu, Z., Xiong, H., Shen, H., and Jin, H. (2019). Can Environmental Tax Policy Really Help to Reduce Pollutant Emissions? an Empirical Study of a Panel ARDL Model Based on OECD Countries and China. *Sustainability* 11, 4384. doi:10.3390/su11164384

Heyes, A., and Kapur, S. (2011). Regulatory Attitudes and Environmental Innovation in a Model Combining Internal and External R&D. *J. Environ. Econ. Manag.* 61, 327–340. doi:10.1016/j.jeem.2010.12.003

Higano, Y., Shen, Z., and Mizunoya, T. (2020). Analysis of Spatial Effects of Environmental Taxes on Water Pollution in China's Taihu Basin. *Innovations Urban Regional Syst.*, 417–441. doi:10.1007/978-3-030-43694-0_19

Hu, B., Dong, H., Jiang, P., and Zhu, J. (2020). Analysis of the Applicable Rate of Environmental Tax through Different Tax Rate Scenarios in China. *Sustainability* 12. doi:10.3390/su12104233

Jaffe, A. B., Newell, R. G., and Stavins, R. N. (2002). Environmental Policy and Technological Change. *Environ. Resour. Econ.* 22, 41–70. doi:10.1023/A:1015519401088

Ji, X., Zhang, Y., Mirza, N., Umar, M., and Rizvi, S. K. A. (2021). The Impact of Carbon Neutrality on the Investment Performance: Evidence from the Equity Mutual Funds in BRICS. *J. Environ. Manag.* 297, 113228. doi:10.1016/j.jenvman.2021.113228

Jia, Z. J., and Lin, B. Q. (2021). How to Achieve the First Step of the Carbon-Neutrality 2060 Target in China: The Coal Substitution Perspective. *Energy* 233, 14. doi:10.1016/j.energy.2021.121179

Khan, S. A. R., and Yu, Z. (2020). Assessing the Eco-Environmental Performance: an PLS-SEM Approach with Practice-Based View. *Int. J. Logist.* 24, 1–19. doi:10.1080/13675567.2020.1754773

Khan, S. A. R., Yu, Z., Sharif, A., and Golpîra, H. (2020). Determinants of Economic Growth and Environmental Sustainability in South Asian Association for Regional Cooperation: Evidence from Panel ARDL. *Environ. Sci. Pollut. Res.* 27, 45675–45687. doi:10.1007/s11356-020-10410-1

Lambertini, L., Pignataro, G., and Tampieri, A. (2020). The Effects of Environmental Quality Misperception on Investments and Regulation. *Int. J. Prod. Econ.* 225, 107579. doi:10.1016/j.ijpe.2019.107579

Li, G., Liu, W., Wang, Z., and Liu, M. (2017). An Empirical Examination of Energy Consumption, Behavioral Intention, and Situational Factors: Evidence from Beijing. *Ann. Oper. Res.* 255, 507–524. doi:10.1007/s10479-016-2202-8

Li, P., Lin, Z., Du, H., Feng, T., and Zuo, J. (2021). Do environmental Taxes Reduce Air Pollution? Evidence from Fossil-Fuel Power Plants in China. *J. Environ. Manag.* 295, 113112. doi:10.1016/j.jenvman.2021.113112

Lin, B., and Li, X. (2011). The Effect of Carbon Tax on Per Capita CO_2 Emissions. *Energy Policy* 39, 5137–5146. doi:10.1016/j.enpol.2011.05.050

Lu, C., Tong, Q., and Liu, X. (2010). The Impacts of Carbon Tax and Complementary Policies on Chinese Economy. *Energy Policy* 38, 7278–7285. doi:10.1016/j.enpol.2010.07.055

Martins, T., Barreto, A. C., Souza, F. M., and Souza, A. M. (2021). Fossil Fuels Consumption and Carbon Dioxide Emissions in G7 Countries: Empirical Evidence from ARDL Bounds Testing Approach. *Environ. Pollut.* 291, 118093. doi:10.1016/j.envpol.2021.118093

Meng, S., Siriwardana, M., and Mcneill, J. (2013). The Environmental and Economic Impact of the Carbon Tax in Australia. *Environ. Resour. Econ.* 54, 313–332. doi:10.1007/s10640-012-9600-4

Murray, B. (2015). British Columbia's Revenue-Neutral Carbon Tax: A Review of the Latest "grand Experiment" in Environmental Policy. *Energy Policy* 86, 674–683. doi:10.1016/j.enpol.2015.08.011

Nawaz, M. A., Hussain, M. S., Kamran, H. W., Ehsanullah, S., Maheen, R., and Shair, F. (2021). Trilemma Association of Energy Consumption, Carbon Emission, and Economic Growth of BRICS and OECD Regions: Quantile Regression Estimation. *Environ. Sci. Pollut. Res.* 28, 16014–16028. doi:10.1007/s11356-020-11823-8

Niu, T., Yao, X., Shao, S., Li, D., and Wang, W. (2018). Environmental Tax Shocks and Carbon Emissions: An Estimated DSGE Model. *Struct. Change Econ. Dyn.* 47, 9–17. doi:10.1016/j.strueco.2018.06.005

Onofrei, M., Vintila, G., Dascalu, E. D., Roman, A., and Firtescu, B.-N. (2017). The Impact of Environmental Tax Reform on Greenhouse Gas Emissions: Empirical Evidence from European Countries. *Environ. Eng. Manag. J.* 16, 2843–2849. doi:10.30638/eemj.2017.293

Prats, G. M., Álvarez García, Y. I., Hernández, F. S., and Zamora, D. T. (2020). Environmental Taxes. Its Influence on Solid Waste in Mexico. *J. Environ. Manag. Tour.* 11, 755–762. doi:10.14505//jemt.v11.3(43).29

Ran, T. A., Mu, A., An, A., and Ur, B. (2021). The Dynamic Effect of Eco-Innovation and Environmental Taxes on Carbon Neutrality Target in Emerging Seven (E7) Economies - ScienceDirect. *J. Environ. Manag.* 299, 113525. doi:10.1016/j.jenvman.2021.113525

Ren, X., Cheng, C., Wang, Z., Yan, C., and Welford, R. (2021). Spillover and Dynamic Effects of Energy Transition and Economic Growth on Carbon Dioxide Emissions for the European union: a Dynamic Spatial Panel Model. *Sustain. Dev.* 29 (1), 228–242. doi:10.1002/sd.2144

Ren, X., Duan, K., Tao, L., Shi, Y., Yan, C., Tol, R., et al. (2022a). Carbon Prices Forecasting in Quantiles. *Energy Econ.* 108, 105862. doi:10.1016/j.eneco.2022.105862

Ren, X., Li, Y., Shahbaz, M., Dong, K., and Lu, Z. (2022b). Climate Risk and Corporate Environmental Performance: Empirical Evidence from china. *Sustain. Prod. Consum.* 30, 467–477. doi:10.1016/j.spc.2021.12.023

Söderholm, P. (2011). Taxing Virgin Natural Resources: Lessons from Aggregates Taxation in Europe. *Resour. Conservation Recycl.* 55, 911–922. doi:10.1016/j.resconrec.2011.05.011

Sun, Y., Mao, X., Liu, G., Yin, X., and Zhao, Y. (2020). Modelling the Effects of Energy Taxes on Ecological Footprint Transfers in China's Foreign Trade. *Ecol. Model.* 431, 109200. doi:10.1016/j.ecolmodel.2020.109200

Thi, H. D., Thi, K., Phuong, D. L., Thu, V. P., and Minh, C. (2020). Impact of Environmental Tax Collection on CO_2 Emission in Vietnam. *Int. J. Energy Econ. Policy 10* 10 (6), 299–304. doi:10.32479/ijeep.10153

Ulucak, R., DanishKassouri, Y., and Kassouri, Y. (2020). An Assessment of the Environmental Sustainability Corridor: Investigating the Non-linear Effects of Environmental Taxation on CO_2 Emissions. *Sustain. Dev.* 28, 1010–1018. doi:10.1002/sd.2057

Umar, M., Ji, X., Kirikkaleli, D., Shahbaz, M., and Zhou, X. (2020). Environmental Cost of Natural Resources Utilization and Economic Growth: Can China Shift Some Burden through Globalization for Sustainable Development?. *Sustainable Development*. doi:10.1002/sd.2116

Umar, M., Ji, X., Mirza, N., and Naqvi, B. (2021). Carbon Neutrality, Bank Lending, and Credit Risk: Evidence from the Eurozone. *J. Environ. Manag.* 296, 113156. doi:10.1016/j.jenvman.2021.113156

Vallés-Giménez, J., and Zárate-Marco, A. (2020). A Dynamic Spatial Panel of Subnational GHG Emissions: Environmental Effectiveness of Emissions Taxes in Spanish Regions. *Sustainability* 12, 872. doi:10.3390/su12072872

Wang, Q., and Wang, L. (2021). The Nonlinear Effects of Population Aging, Industrial Structure, and Urbanization on Carbon Emissions: A Panel Threshold Regression Analysis of 137 Countries. *J. Clean. Prod.* 287, 125381. doi:10.1016/j.jclepro.2020.125381

Wang, Q., Yuan, X., Zuo, J., Mu, R., Zhou, L., and Sun, M. (2014a). Dynamics of Sewage Charge Policies, Environmental Protection Industry and Polluting Enterprises-A Case Study in China. *Sustainability*, 6(8), 4858–4876. doi:10.3390/su6084858

Wang, Z., Feng, C., and Zhang, B. (2014b). An Empirical Analysis of China's Energy Efficiency from Both Static and Dynamic Perspectives. *Energy* 74, 322–330. doi:10.1016/j.energy.2014.06.082

Wang, Y., Niu, Y., Li, M., Yu, Q., and Chen, W. (2022). Spatial Structure and Carbon Emission of Urban Agglomerations: Spatiotemporal Characteristics and Driving Forces, *Sustain. Cities Soc.*, 78, 103600. doi:10.1016/j.scs.2021.103600

Wang, Y., and Yu, L. (2021). Can the Current Environmental Tax Rate Promote Green Technology Innovation? - Evidence from China's Resource-Based Industries. *J. Clean. Prod.* 278, 123443. doi:10.1016/j.jclepro.2020.123443

Wesseh, P. K., and Lin, B. (2019). Environmental Policy and 'double Dividend' in a Transitional Economy. *Energy Policy* 134, 110947. doi:10.1016/j.enpol.2019.110947

Wolde-Rufael, Y., and Mulat-Weldemeskel, E. (2021). Do environmental Taxes and Environmental Stringency Policies Reduce CO_2 Emissions? Evidence from 7 Emerging Economies. *Environ. Sci. Pollut. Res.* 28 (18), 22392–22408. doi:10.1007/s11356-020-11475-8

Xiang, L., Chen, X., Su, S., and Yin, Z. (2021). Time-Varying Impact of Economic Growth on Carbon Emission in BRICS Countries: New Evidence from Wavelet Analysis. *Front. Environ. Sci.* 36, 5149. doi:10.3389/fenvs.2021.715149

Xiao, Z., Yu, L., Liu, Y., Bu, X., and Yin, Z. (2022). Does Green Credit Policy Move the Industrial Firms toward a Greener Future? Evidence from a Quasi-Natural Experiment in China. *Front. Environ. Sci.* 9. doi:10.3389/fenvs.2021.810305

Xie, R., Wang, F., Chevallier, J., Zhu, B., and Zhao, G. (2018). Supply-side Structural Effects of Air Pollutant Emissions in China: A Comparative Analysis. *Struct. Change Econ. Dyn.* 46, 89–95. doi:10.1016/j.strueco.2018.04.005

Xing, C., Zhang, Y., and Wang, Y. (2020). Do Banks Value Green Management in China? the Perspective of the Green Credit Policy. *Finance Res. Lett.* 35. doi:10.1016/j.frl.2020.101601

Xu, B., and Lin, B. (2020). *Investigating Spatial Variability of CO_2 Emissions in Heavy Industry: Evidence from a Geographically Weighted Regression Model*, 112011. Energy Policy.

Yang, M., Fan, Y., Yang, F., and Hu, H. (2014). Regional Disparities in Carbon Dioxide Reduction from China's Uniform Carbon Tax: A Perspective on Interfactor/interfuel Substitution. *Energy* 74, 131–139. doi:10.1016/j.energy.2014.04.056

Yin, Z., Peng, H., Xiao, Z., Fang, F., and Wang, W. (2022). The Carbon Reduction Channel through Which Financing Methods Affect Total Factor Productivity: Mediating Effect Tests from 23 Major Carbon-Emitting Countries. *Environ. Sci. Pollut. Res.*, 1–13. doi:10.1007/s11356-022-19945-x

Zhang, L., and Ma, L. (2020). The Relationship between Industrial Structure and Carbon Intensity at Different Stages of Economic Development: an Analysis Based on a Dynamic Threshold Panel Model. *Environ. Sci. Pollut. Res.* 27, 33321–33338. doi:10.1007/s11356-020-09485-7

Zhang, X., and Wang, Y. (2017). How to Reduce Household Carbon Emissions: A Review of Experience and Policy Design Considerations. *Energy Policy* 102, 116–124. doi:10.1016/j.enpol.2016.12.010

Zhao, G., Zhou, P., and Wen, W. (2021). Feed-in Tariffs, Knowledge Stocks and Renewable Energy Technology Innovation: The Role of Local Government Intervention. *Energy Policy* 156, 112453. doi:10.1016/j.enpol.2021.112453

Zhou, A. T., Hu, J. Y., and Wang, K. (2020). Carbon Emission Assessment and Control Measures for Coal Mining in China. *Environ. Earth Sci.* 79, 15. doi:10.1007/s12665-020-09189-8

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How Does Green Finance Affect CO_2 Emissions? Heterogeneous and Mediation Effects Analysis

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The original intention of green finance advocacy is to provide financing support for energy conservation and emission-reduction activities. In this context, the carbon dioxide (CO_2) emission-reduction effect is worth further discussion. To this end, by gauging the green finance index, we apply the econometric method to evaluate the impact of green finance on CO_2 emissions. We also discuss geographical heterogeneity and the impact mechanism. The main findings imply that: 1) China's implementation of green finance is an effective measure to mitigate greenhouse gas emissions; in other words, green finance in China can effectively reduce CO_2 emissions; 2) both green finance and CO_2 emissions show significant geographical heterogeneity and asymmetry; only in the eastern and central regions, can green finance help alleviate the greenhouse effect; and 3) besides the total effect, green finance can affect the greenhouse effect by promoting the rapid growth of the provincial economy, restraining the improvement of energy efficiency, and accelerating the optimization of the current industrial structure. Following the above three findings, we propose some policy suggestions related to green finance evolution and CO_2 emissions reduction.

Keywords: carbon dioxide (CO_2) emissions, green finance, heterogeneous analysis, mediation effect analysis, China

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HIGHLIGHTS

- ➢ We assess the impact of China's green finance on CO_2 emissions.
- ➢ Both geographic heterogeneity and CO_2 emission asymmetry are explored.
- ➢ This study evaluates how green finance affects CO_2 emissions.
- ➢ Green finance is an effective strategy for solving the greenhouse effect.
- ➢ Green finance in China reduces CO_2 mainly by promoting industrial optimization.

1 INTRODUCTION

With the rise of global temperatures, the frequent occurrence of natural disasters, and global environmental pollution, the issue of climate change has increasingly attracted the attention of scholars around the world (Hulme et al., 2018; Wang et al., 2021a; Zhao et al., 2022a; Ren et al., 2022c; Yan et al., 2022). If left unchecked, carbon dioxide (CO_2) emissions will cause an additional 1–3.7°C increase in global average temperatures by the end of this century, leading to irreversible changes (Dusenge et al., 2019; IPCC, 2022). Accordingly, the United Nations has held several climate change

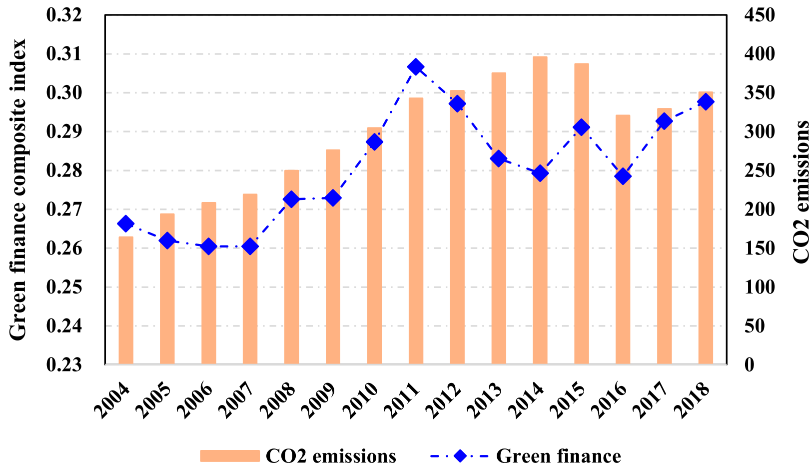

FIGURE 1 | Time trend chart of the average values of CO_2 emissions and green finance.

conferences aimed at cooperating with countries around the world to alleviate the problems caused by climate change and CO_2 emissions. For example, at the COP 26 UN Climate Change Conference, governments committed to phasing out coal-fired power generation, providing a credible guarantee for mitigating global CO_2 emissions (Arora and Mishra, 2021). As the world's largest emission producer, China is also actively seeking ways to reduce CO_2 emissions. China's 14th Five-Year Plan points out that by 2025, energy intensity should be reduced by 13.5%, and non-fossil energy should account for one fifth of primary energy consumption by 2030 (He, 2015; Pan and Dong, 2022), so as to gradually achieve China's worldwide commitment to a zero-carbon target by 2060 (Zhao et al., 2022b).

In order to achieve climate goals, the world needs to transition to a greener, more climate-resilient economy (Ren et al., 2022a), in which green finance will accelerate the construction of greener infrastructure and innovation. In 2012, the China Banking Regulatory Commission released the "Green Credit Guidelines," which established the core framework of the green credit system, and more and more funds are used in terms of low-carbon environmental protection (Yu et al., 2021). In 2015, China became the first country to establish a sound green financial policy system around the world (Lv et al., 2021). The scale of China's green finance market continues to expand (Ren et al., 2022b). In 2018, China issued more than 280 billion yuan of green bonds, and the stock of green bonds is worth close to 600 billion yuan, ranking among the top in the world (PBC, 2019). Therefore, green finance has become the main way for China to deal with climate change and reduce the greenhouse effect. On the one hand, green finance provides financial services for green innovation industries and offers more advanced environmental-protection technologies (Khan et al., 2021). On the other hand, green finance can help mitigate the greenhouse effect by underwriting environmental regulations and environmental directives (Nouira et al., 2016). Statistics published by the International Energy Agency (IEA, 2017) show that green finance will reduce fossil fuel combustion by 26%. However, large-scale inefficient investments caused by green finance should also be taken into account, with the negative effects of climate change (Nawaz et al., 2021). **Figure 1** also presents the average levels of green finance and CO_2 emissions in China, both of which show an increasing trend. Therefore, we urgently need to clarify the role of green finance in addressing the problem of climate change and mitigating CO_2 emissions.

At the same time, there are significant differences in CO_2 emission levels across provinces in China, as shown in **Figure 2**, which has led to different carbon-mitigation policies and the different influences of green finance. Although a few scholars have (explored the nexus between green finance and CO_2 emissions Saeed Meo and Karim, 2022; Xiong and Sun, 2022), there is still insufficient research on the heterogeneity among Chinese provinces. Furthermore, the path through which green finance affects CO_2 emissions is still unclear. Therefore, we put propose to address the following questions: 1) Does green finance help mitigate CO_2 emissions in China? 2) Is green finance affecting CO_2 emissions heterogeneously? 3) What is the impact mechanism between green finance and CO_2 emissions? Based on the panel data of 30 provinces in China from 2004 to 2018, we construct a comprehensive indicator of green finance and assess the impact of green finance on CO_2 emissions in China. We also explore their heterogeneous and mediating effects.

Accordingly, this paper makes the following research contributions. First, we explore the relationship between China's green finance development and CO_2 emissions, which clarifies the direction of China's green finance development and will make the government more confident in investing in green industries. Second, we conduct heterogeneity analyses by geographic position and CO_2 emissions level, which provide more valuable references for regional governments. Third, we innovatively study the

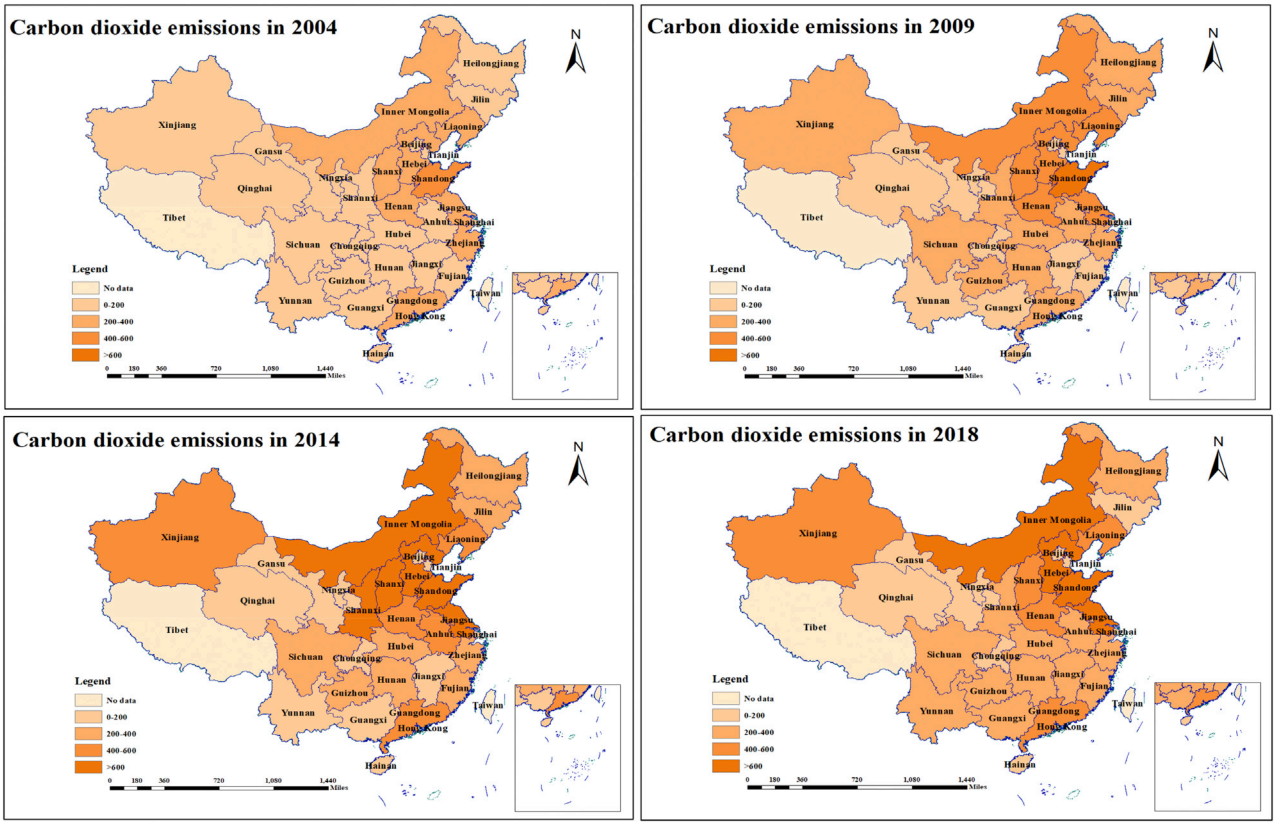

FIGURE 2 | Spatial distribution of CO_2 emissions in selected years.

mediating effect between green finance and CO_2 emissions, which can help governments formulate clearer emission-reduction paths.

The remainder of this paper is organized as follows. The next section is the literature review; **Section 3** represents the econometric methodology and data; **Section 4** discusses the nexus between green finance and CO_2 emissions; in **Section 5**, we analyze the heterogeneity and mediating effect, followed by the conclusion and policy implications in **Section 6**.

2 LITERATURE REVIEW

2.1 An Overview of Green Finance

In 2010, in an attempt to provide financial support for developing countries dealing with climate change, 194 countries established the Green Fund, which is a prototype of the concept of "green finance" (Zhang et al., 2019). Generally speaking, green finance refers to a financial activity that promotes environmental development, improves resource utilization, and responds to climate change (Cui et al., 2020). The green financial market will use various green products as trading platforms, including mainly green credit, green funds, and green derivatives (Taghizadeh-Hesary and Yoshino, 2019). With the severe situation of global climate change in the international community, various governments and scholars have focused on the role of green finance, and carried out large-scale research on this subject.

Constructing and evaluating financial risk indicators accurately are the first concerns of scholars. Some scholars use a single indicator, such as green bonds, as a proxy variable for green finance (Saeed Meo and Karim, 2022). However, a completely green financial system should not only contain a single indicator, but should also be a comprehensive indicator that includes economic reform, economic transformation, and the combination of environmental benefits (Lv et al., 2021). Therefore, Wang et al. (2021b) use the improved fuzzy comprehensive evaluation method combined with the relevant statistical indicators of China's green credit to evaluate the development level of China's green finance. Yang et al. (2021) measure green finance by integrating green credit, green investment, green insurance, green securities, and carbon finance.

Based on the establishment of comprehensive indicators, many scholars have conducted in-depth explorations on the influence of green finance on the global economy and environment (Wang and Zhi, 2016; Li and Gan, 2021; Zhang et al., 2021; Dong et al., 2022). For example, Zhou et al. (2020) point out that green finance can significantly balance the relationship between economic development and environmental quality, and achieve a win-win situation between economic development and the environment. Some scholars have also explored the nexus between green finance and energy security (Sachs et al., 2019a; Sachs et al., 2019b), green finance and non-fossil energy use (Ren et al., 2020), and green finance and energy efficiency (Jin et al., 2021). All of the above studies have shown that green finance supports green and sustainable development and contributes to the progress of the energy system towards a cleaner, more efficient trajectory.

2.2 Studies on the Green Finance-CO_2 Emissions Nexus

Green finance aims to finance green industries, help improve environmental quality, and promote technological innovation in green industries (La Rovere et al., 2018). Therefore, it is not difficult to guess that green finance will have a significant impact on CO_2 emissions. In fact, many scholars have proved the above hypothesis. Globally, Saeed Meo and Karim (2022) study the relationship between green finance and greenhouse gases in major economies that support green finance. Their results show that green finance negatively affects CO_2 emissions. Moreover, from the perspective of a specific country, the nexus between green finance and CO_2 emissions is also a popular subject of research (Xiong and Sun, 2022). For example, Tran (2021) uses multivariate time series analysis to investigate the relationship between green finance and CO_2 emissions in Vietnam. Their results show that there is a one-way causal negative relationship between green investment and CO_2 emissions. In addition, some scholars have explored the sensitivity of CO_2 emissions in a certain industry to green finance. For example, Guo et al. (2022) measure the relationship between green finance and agricultural CO_2 emissions. Their results show that green finance can negatively affect agricultural CO_2 emissions. Gholipour et al. (2022) explore the relationship between green property finance and CO_2 emissions in the construction industry. Their results indicate an obvious negative correlation between the above two factors.

2.3 Literature Gaps

The discussion on green finance has gradually matured in the international community, and research on the green finance-CO_2 emissions nexus has recently emerged. However, we still find knowledge gaps in the existing literature: First, there is no unified standard for measuring green finance, which leads to significant differences in the conclusions of relevant researches on green finance. Second, scholars rarely discuss the nexus between green finance and CO_2 emissions in China. Third, the influence mechanism of green finance on CO_2 emissions is still unclear, and most scholars have failed to show a clearer path for mechanism analysis.

3 EMPIRICAL MODEL AND DATA SOURCES

3.1 Empirical Model

To quantitatively interpret the CO_2 emission reduction effect of green finance development in China, we build an econometric model in the following framework:

$$CO_{2it} = f\left(GFI_{it}, Pgdp_{it}, EE_{it}, ISU_{it}, Tra_{it}, Edu_{it}, Wage_{it}, Gap_{it}\right) \tag{1}$$

where i denotes Chinese 30 provinces, and t refers to the time (2004–2018). CO_2 means the total amount of CO_2 emissions, and *GFI* indicates green finance. *Pgdp*, *EE*, *ISU*, *Tra*, *Edu*, *Wage*, and *Gap* represent economic growth, energy efficiency, industrial structure upgrading, trade openness, education level, wage level, and income inequality, respectively. $f(\cdot)$ is a function.

To effectively address the problems of dimensional inconsistency of the variables and data fluctuation, we apply the natural logarithm of **Eq. 1**, as follows:

$$\ln CO_{2it} = \alpha_0 + \alpha_1 \ln GFI_{it} + \sum_{k=2}^{8} \alpha_k \ln Ctrl_{it} + \eta_t + \nu_i + \varepsilon_{it} \tag{2}$$

where α_0 represents the constant term, η_t refers to the time-specific effect, ν_i denotes the province-specific effect, and ε_{it} indicates the error term. $\alpha_1 - \alpha_8$ are the coefficients that need to be gauged. *Ctrl* refers to the control variables (i.e., *Pgdp*, *EE*, *ISU*, *Tra*, *Edu*, *Wage*, and *Gap*). It is worth noting that the implementation of green finance policies aims to guide financial capital from polluting enterprises or projects to enterprises or projects that actively manage the environment; thus, we expect the coefficient of green finance (i.e., α_1) to be negative.

To address the impact mechanism between green finance and CO_2 emissions, based on the conventional and commonly used theory of three effects of CO_2 emissions proposed by Copeland and Taylor (1994), we choose economic effect, technical effect, and structural effect as mediating variables to further explore whether green finance influences CO_2 emissions by affecting regional economy, technology, and industrial structure. The specific equations of the mediation effect model are constructed as follows:

$$\ln M_{it} = \varphi_0 + \varphi_1 \ln GFI_{it} + \sum_{k=2}^{5} \varphi_k \ln Ctrl_{it} + \eta_t + \nu_i + \varepsilon_{it} \tag{3}$$

$$\ln CO_{2it} = \xi_0 + \xi_1 \ln GFI_{it} + \xi_2 \ln M_{it} + \sum_{k=3}^{6} \xi_k \ln Ctrl_{it} + \eta_t + \nu_i + \varepsilon_{it} \tag{4}$$

where the parameters in front of the variables are estimated coefficients. M in these equations denotes economic effect, technical effect, and structural effect, respectively, which are gauged by economic growth, energy efficiency, and industrial structure upgrading, respectively. In these equations, ξ_1 refers to the direct effect, the product of φ_1 and ξ_2 indicates the mediation effect, and α_1 represents the total effect.

Furthermore, to investigate the asymmetric effect between green finance and CO_2 emissions, we construct the quantile regression model following the estimation framework of Coad and Rao (2006) and Kang et al. (2021):

$$Q_\tau(\ln CO_{2it}) = \phi_{0\tau} + \phi_{1\tau}\ln GFI_{it} + \sum_{k=2}^{8}\phi_{k\tau}Ctrl_{it} + \varepsilon_{it} \quad (5)$$

where the dependent variable $Q_\tau(\ln CO_{2it})$ is the τ^{th} distribution quantile of CO_2 emissions; $\phi_{0\tau}\cdots\phi_{8\tau}$ are the estimated coefficients at quantile τ.

3.2 Variables Setting

3.2.1 Explained Variable

CO_2 emissions (denoted as CO_2). China's official statistics bureau or yearbook currently does not directly publish research data on CO_2 emissions. Generally speaking, most scholars use data on CO_2 emissions caused by fossil energy consumption, which can more accurately assess the greenhouse effect caused by CO_2 emissions (Wang et al., 2021a; Wang et al., 2021b).

3.2.2 Explanatory Variables

Since China put forward the concept of green finance in 2016, many scholars have launched a series of discussions and measures on green finance; however, there is no unified standard for gauging green finance at present. Thus, to effectively assess green finance in China, we refer to the indictor system of Jiang et al. (2020), which consists of three dimensions (i.e., economy, finance, and environment); the specific second-level indicators are listed in **Supplementary Appendix Table S1** in the **Supplementary Appendix S1**. By using the improved entropy method, we gauge the provincial composite index of green finance for the period 2004–2018; the specific calculation steps can refer to the work of Zhao et al. (2021).

On this basis, we further conduct a spatio-temporal analysis on China's green finance. In **Figure 1**, we display the time trend chart of average values of green finance from 2004 to 2018; obviously, before 2011, green finance showed a substantial upward trend and reached its peak in 2011. Thereafter, it gradually declined and then rose slowly between 2016 and 2018. In addition, **Figure 3** presents the spatial pattern of China's green finance in 2004, 2009, 2014, and 2018. These charts imply that green finance shows a wide range of heterogeneous distribution. More specifically, the phenomenon of

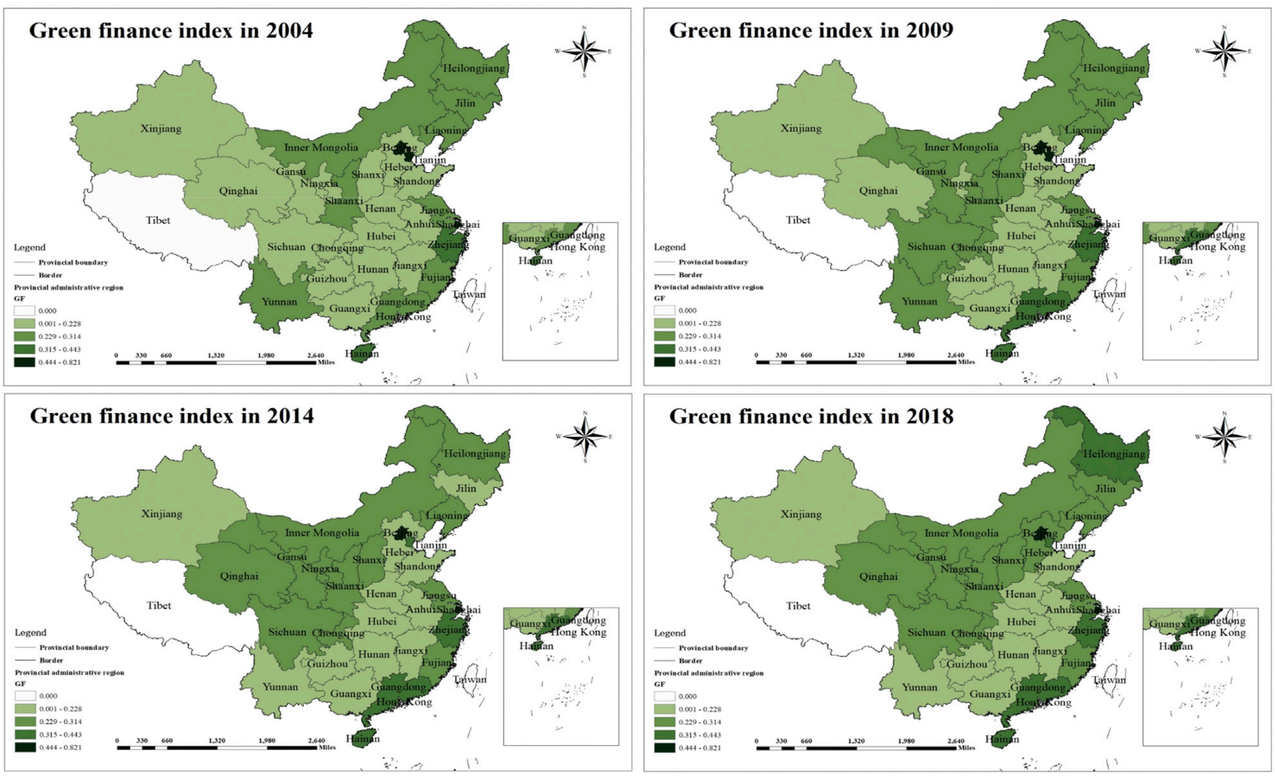

FIGURE 3 | Spatial distribution of the green finance index in selected years.

TABLE 1 | Definitions and descriptive statistics of the selected variables.

Variable	Definitions	Units	Obs	Mean	Std. dev.	Minimum	Maximum
lnCO_2	Total amount of CO_2 emissions	Mt CO_2	450	5.408042	0.8125148	1.757858	7.348459
ln*GFI*	Green finance composite index	—	450	−1.347638	0.367188	−2.031035	−0.197154
ln*Pgdp*	Economic growth assessed by per capita gross domestic product (GDP)	Chinese yuan/ person	450	10.35204	0.6851362	8.370316	11.8509
ln*EE*	Energy efficiency measured by the ratio of GDP to total energy use	%	450	0.0777888	0.5395829	−1.463981	1.428051
ln*ISU*	Industrial structure upgrading measured by the ratio of output value of tertiary industry to GDP	%	450	−0.0600765	0.3731148	−0.699058	1.469621
ln*Tra*	Trade openness gauged by the ratio of total import and export trade to GDP	%	450	−1.662734	0.97987	−4.085905	0.5679131
ln*Edu*	Education level calculated by the ratio of the number of high school students of the total population	%	450	−4.132194	0.3817331	−5.379941	−3.274441
ln*Wage*	Wage level measured by the average wage (yuan) of urban staff and workers on duty	Yuan	450	10.54004	0.5599521	9.380505	11.91734
ln*Gap*	Income inequality measured by the proportion of urban residents' per capita disposable income to rural residents' disposable income	%	450	1.032355	0.1843939	0.6125599	1.560063

Std. dev. refers to standard deviation.

green finance in the Beijing-Tianjin-Hebei region, the Yangtze River Delta, Pearl River Delta, and inland western provinces is obviously better than that in the central region. A possible reason is that the relatively prosperous coastal provinces such as Beijing-Tianjin-Hebei, the Yangtze River Delta, and the Pearl River Delta usually have a sound and complete financial system and relatively frequent financial investment activities. The inner western provinces have a favorable ecological environment despite their relatively backward financial development.

3.2.3 Control Variables

In addition to CO_2 emissions and green finance, we also introduce some control variables which influence the CO_2 emissions. Referring to Bano et al. (2018), Wang and Zhang (2021), and Zhao et al. (2021), we introduce economic growth, energy efficiency, industrial structure upgrading, trade openness, education level, wage level, and income inequality as the determinants of CO_2 emissions.

3.2.4 Mediator Variables

We select three mediator variables, namely economic effect, technical effect, and structural effect. Among them, referring to Zhang et al. (2020), we use the per capita GDP as the proxy variable of economic effect. Referring to Wang et al. (2022), we use the energy efficiency as the proxy variable of technical effect. And referring to Luan et al. (2021), we use the ratio of output value of tertiary industry to GDP as the proxy variable of structural effect. And their definition and units are listed in **Table 1**.

3.3 Data

The explained variable (CO_2 emissions) is obtained from the China Emission Accounts and Datasets (CEADs, 2019). The key explanatory variable (green finance) is calculated by three dimensions—economy, finance, and environment—and the relevant data have been collected from the China Statistical Yearbook (CSY, 2021), the China Regional Financial Operation Report, and the China Environment Statistical Yearbook. Furthermore, CSY (2021) and the China Energy Statistical Yearbook provide the data on the control variables and mediator variables. The specific measures and descriptive statistics of variables used are presented in **Table 1**.

4 EMPIRICAL FINDINGS

4.1 Correlation Check

Before examining the estimated results between green finance and CO_2 emissions, we first check the correlations of all the variables, and present their results in **Table 2**. Except for ln*Tra*, the correlation tests between the other variables and the dependent variable (lnCO_2) are all significant at the 5% significance level, which indicates that the variables selected in this paper are reliable. Moreover, ln*ISU* and ln*Gap* are negatively correlated with the dependent variables, which indicates that industrial upgrading and income inequality may negatively affect CO_2 emissions, but more accurate results require further estimation. In addition, most of the correlation test results between the variables are less than 0.8, which indicates that there is no serious multicollinearity issue between the variables.

4.2 Benchmark Estimates

Next, we examine the correlation between green finance and CO_2 emissions, and show the results in **Table 3**. We apply the feasible generalized least squares (FGLS) method to estimate. FGLS generates estimates that are dependent on the disturbance covariance matrix estimations as well as any estimated autocorrelation parameters (Gulnaz and Manglani, 2022). When the exact form of data heteroskedasticity is known, FGLS is the most suitable model, which is resistant to any type of heteroscedasticity. Also, we set three tests for the FGLS model—the Wald test, the Wooldridge test, and the CD test. Their results show that the null hypotheses are all rejected at the 1% level, indicating that the panel data have groupwise heteroskedasticity, first-order autocorrelation, and cross-sectional dependence (Shahzad et al., 2018). Therefore, the FGLS method can solve the

TABLE 2 | Results of the correlation check.

Variable	lnCO_2	ln*GFI*	ln*Pgdp*	ln*EE*	ln*ISU*	ln*Tra*	ln*Edu*	ln*Wage*	ln*Gap*
lnCO_2	1.0000								
ln*GFI*	−0.1973[a] (0.0000)	1.0000							
ln*Pgdp*	0.3220[a] (0.0000)	0.5548[a] (0.0000)	1.0000						
ln*EE*	0.1370[a] (0.0036)	0.3981[a] (0.0000)	0.7279[a] (0.0000)	1.0000					
ln*ISU*	−0.3259[a] (0.0000)	0.6043[a] (0.0000)	0.3732[a] (0.0000)	0.4090[a] (0.0000)	1.0000				
ln*Tra*	0.0105 (0.8242)	0.6302[a] (0.0000)	0.4160[a] (0.0000)	0.4986[a] (0.0000)	0.3044[a] (0.0000)	1.0000			
ln*Edu*	0.2418[a] (0.0000)	0.4356[a] (0.0000)	0.7428[a] (0.0000)	0.6510[a] (0.0000)	0.2948[a] (0.0000)	0.3634[a] (0.0000)	1.0000		
ln*Wage*	0.2232[a] (0.0000)	0.4125[a] (0.0000)	0.8927[a] (0.0000)	0.6674[a] (0.0000)	0.4757[a] (0.0000)	0.1465[a] (0.0018)	0.6002[a] (0.0000)	1.0000	
ln*Gap*	−0.2417[a] (0.0000)	−0.4019[a] (0.0000)	−0.6999[a] (0.0000)	−0.6058[a] (0.0000)	−0.2408[a] (0.0000)	−0.4941[a] (0.0000)	−0.6753[a] (0.0000)	−0.4824[a] (0.0000)	1.0000

[a]*Refers to* $p < 0.05$.
The data in parentheses denote the p-value of the correlation test.

above problems and obtain unbiased and consistent estimators.

The results of the FGLS method show that the coefficient of green finance is always negative, regardless of whether control variables are added to the model. In other words, green finance negatively affects CO_2 emissions in China. Guo et al. (2022) and Saeed Meo and Karim (2022) also draw the same conclusion by examining the agricultural sector and the top ten economies. Green finance focuses on investment in green-related industries and encourages companies to develop innovative technologies that are conducive to low-carbon energy, such as renewable energy technologies (Saeed Meo and Karim, 2022). China has basically established an overall green financial framework such as green bonds, green insurance, green credit, and so on (Guo et al., 2022). This framework will guide consumers and enterprises to establish the concept of green consumption and reduce the generation of carbon footprint by supporting domestic green-friendly projects (Yang et al., 2021). At the same time, local governments have accelerated the construction of the green financial industry, including establishing green financial reform and innovation pilot zones, accelerating the green transformation of local economies, and providing subsidies for the transformation of high-polluting enterprises, thereby reducing fossil energy consumption and CO_2 emissions (PBC, 2019).

As for the control variables, economic growth effectively promotes CO_2 emissions, which can be attributed to industrial expansion and energy consumption brought about by economic growth. Energy efficiency significantly reduces CO_2 emissions, a fact confirmed in Liu et al. (2019) and He et al. (2021). This is because improved energy efficiency represents advanced technology, which reduces the energy consumption per unit of economic output, thus contributing to the reduction of CO_2 emissions. Industrial structure upgrading has also significantly reduced CO_2 emissions. By guiding the upgrading of strategic emerging industries, China has shifted the country's industrial focus from secondary industry to tertiary industry. The expansion of service industries and high-tech industries has effectively alleviated the large consumption of energy and reduced CO_2 emissions (Wu et al., 2021). Finally, education level and wage level are significant; the former positively promotes CO_2 emissions, while the latter negatively affects CO_2 emissions.

4.3 Robustness Tests

4.3.1 Alternative Estimated Method

In the case of small sample sizes, an econometric model may produce inconsistent estimates; and due to the high correlation among macroeconomic variables, independent variables are correlated with random error terms. Selecting appropriate instrumental variables (IV) can solve the above issues. In general, the IV needs to satisfy the assumption that it should correlate highly with endogenous dependent variables and not correlate with random error terms. Lewbel (2012) constructs IV using heteroscedasticity, and the estimated results are represented in **Table 3**. The test of Hansen J rejects the null hypothesis, and the IV selected in

TABLE 3 | Estimated results of the impact of green finance on CO_2 emissions.

Explained variable: lnCO_2				
Variable	**FGLS estimation**		**IV estimation**	
	No control	**With control**	**No control**	**With control**
ln*GFI*	−0.222[a] (−4.61)	−0.309[a] (−5.13)	−0.437[a] (−5.22)	−1.135[a] (−7.75)
ln*Pgdp*		0.656[a] (6.04)		1.121[a] (7.36)
ln*EE*		−0.477[a] (−5.89)		−0.300[a] (−2.70)
ln*ISU*		−0.238[a] (−4.04)		−0.537[a] (−4.48)
ln*Tra*		0.029 (1.35)		0.123[b] (2.13)
ln*Edu*		0.298[a] (4.39)		0.143 (0.85)
ln*Wage*		−0.678[a] (−5.52)		−0.279 (−1.61)
ln*Gap*		−0.145 (−1.22)		0.263 (1.06)
_Cons	4.477[a] (68.02)	6.040[a] (5.01)	4.820[a] (4.22)	−4.276[a] (−3.03)
Wald test	54,827.47[a]	4,000.05[a]		
Wooldridge test	51.598[a]	53.241[a]		
CD test	48.951[a]	5.121[a]		
Uncen_R^2			0.9788	0.9872
Hansen J			0.000	0.000
Obs.	450	450	450	450

[a]*Refer to statistical significance at the 1% level.*
[b]*Refer to statistical significance at the 5% levels.*
The values in parentheses indicate the t-statistics.

TABLE 4 | Robust results of alternative explained variables.

Variables	**SO_2 emissions**		**COD emissions**	
	No control	**With control**	**No control**	**With control**
ln*GFI*	−0.441[a] (−13.58)	−0.467[a] (−12.24)	−1.162[a] (−30.45)	−1.124[a] (−15.05)
ln*Pgdp*		0.105 (1.60)		0.756[a] (5.58)
ln*EE*		−0.473[a] (−10.03)		0.138 (1.43)
ln*ISU*		−0.225[a] (−5.79)		−0.342[a] (−4.97)
ln*Tra*		−0.039[b] (−2.47)		0.159[a] (6.04)
ln*Edu*		0.239[a] (3.16)		−0.626[a] (−5.56)
ln*Wage*		−0.026 (−0.25)		−1.274[a] (−6.70)
ln*Gap*		0.319[a] (3.27)		0.086 (0.63)
_Cons	12.627[a] (258.92)	12.273[a] (11.31)	9.926[a] (170.17)	12.452[a] (6.58)
Wald test	25,675.53[a]	7,486.61[a]	11,132.35[a]	2,438.48[a]
Wooldridge test	148.157[a]	76.033[a]	66.491[a]	64.367[a]
CD test	60.219[a]	39.564[a]	47.732[a]	21.901[a]
Obs.	420	420	420	420

[a]*Refer to statistical significance at the 1% level.*
[b]*Refer to statistical significance at the 5% levels.*
The values in parentheses indicate the t-statistics.

this method is suitable. The coefficient of green finance is significantly negative, and the benchmark result is robust.

4.3.2 Alternative Explained Variables

Further, we replace the dependent variables with sulfur dioxide (SO_2) emissions and chemical oxygen demand (COD) emissions. Similar to CO_2 emissions, these two pollutants are also the targets of key emission reductions in China (Liu and Wang, 2017); their estimated results are listed in **Table 4**. Green finance negatively affects SO_2 and COD emissions, which is consistent with the results of the benchmark regression. This further confirms the robustness of the benchmark regression results.

5 FURTHER DISCUSSION

5.1 Heterogeneous Analysis

5.1.1 Geographic Heterogeneity

In the last section, we conducted the benchmark regression on the CO_2 emission reduction effect of China's green finance. Notably, the spatial patterns of China's CO_2 emissions and green finance imply significant geographic heterogeneity across different provinces. To this end, in this section, we proceed to investigate the regional heterogeneous effects of green finance on CO_2 emissions by dividing the whole sample into three subsamples—the eastern, central, and western regions. The

TABLE 5 | Estimated results of geographic heterogeneous analysis.

Explained variable: lnCO_2						
Variable	**Eastern region**		**Central region**		**Western region**	
	No Control	**With control**	**No control**	**With control**	**No Control**	**With control**
ln*GFI*	−0.655[a] (−10.45)	−0.619[a] (−5.87)	−0.317[a] (−3.62)	−0.574[a] (−5.42)	0.060 (0.63)	0.205[c] (1.79)
ln*Pgdp*		1.313[a] (6.60)		0.495[a] (3.36)		0.377[b] (2.31)
ln*EE*		−1.620[a] (−9.68)		−1.176[a] (−7.78)		−0.209[b] (−1.96)
ln*ISU*		−0.672[a] (−6.70)		−0.390[a] (−4.04)		−0.011 (−0.09)
ln*Tra*		0.245[a] (4.23)		−0.028 (−0.76)		−0.028 (−0.67)
ln*Edu*		−0.800[a] (−5.36)		−0.586[a] (−3.86)		0.473[b] (2.35)
ln*Wage*		0.097 (0.54)		−0.534 (−1.38)		−0.987[a] (−2.98)
ln*Gap*		0.822[a] (3.44)		0.126 (0.39)		−0.345 (−1.29)
_*Cons*	4.212[a] (60.10)	−14.097[a] (−6.27)	4.561[a] (32.79)	1.163 (0.38)	4.548[a] (31.43)	13.341[a] (3.86)
Wald test	2,755.42[a]	163.79[a]	5,823.61[a]	1,088.07[a]	28,346.64[a]	171.52[a]
Wooldridge test	4.717[c]	7.502[b]	65.677[a]	128.492[a]	194.929[a]	364.818[a]
CD test	19.095[a]	16.682[c]	12.785[a]	1.885[c]	115.572[a]	1.755[c]
Obs.	165	165	120	120	165	165

[a]*Indicate statistical significance at the 1% level.*
[b]*Indicate statistical significance at the 5% levels.*
[c]*Indicate statistical significance at the 10% levels.*
The values in parentheses indicate t-statistics.

specific provinces of these three regions are listed in **Supplementary Appendix Table S2**.

Also using the FGLS technique, we evaluate the CO_2 emission effect of green finance in these three regions, and present the corresponding results in **Table 5**. More specifically, in the eastern region, each 1% increase in green finance will result in a 0.619% reduction in CO_2 emissions. This finding verifies the effective role of green finance popularization in the eastern coastal provinces of China in alleviating the greenhouse effect. The superior geographical location and convenient transportation of our eastern provinces have contributed to the rapid economic growth and basic perfection of financial institutions in this region. In response to the governments' call for environmental protection and the achievement of the provinces' own green and sustainable development, financial institutions have begun to invest their capital in low-carbon technological innovation projects, which is conducive to alleviating the deteriorating ecological environment.

Consistent with the eastern region, the evolution of green finance and CO_2 emissions also shows a significant negative correlation. **Table 5** shows that an increase of green finance by 1% can reduce CO_2 emissions by 0.574%. The CO_2 emission-reduction effect of green finance in the eastern region is significantly better than that in the central region. On the contrary, the widespread advocacy of green finance policies in the western region is not a powerful weapon for mitigating greenhouse gas emissions. The results in **Table 5** illustrate that a 1% increase of green finance can increase CO_2 emissions by 0.205%. As we all know, the rugged geographical location and harsh climate in the western provinces limit population agglomeration and economic evolution, and the scattered pollution and backward economic system hinder the extensive distribution of financial institutions and the continuous perfection of the financial system, which is not conducive to alleviating the greenhouse effect.

5.1.2 Heterogeneity of CO_2 Emissions

In addition to geographical heterogeneity, we further examine the differential causal linkage between green finance and the greenhouse effect under different quantiles of CO_2 emissions. The corresponding results are listed in **Table 6**. Furthermore, this study displays the variation characteristics of green finance and control variables under different quantiles (**Figure 4**).

As this table shows, although under different quantiles, green finance contributes to the mitigation of greenhouse gas emissions, the magnitude of its impact varies. At the 10th quantile of CO_2 emissions, green finance plays the largest role in promoting carbon reduction, followed by the effect in the 25th quantile. This suggests that the carbon reduction effect of green finance is particularly pronounced in regions with relatively low CO_2 emissions. Furthermore, at the 90th and 75th quantiles, we find that the coefficients of green finance are −1.050 and −1.007, respectively, while at the 50th quantile, an increase of green finance by 1% can reduce CO_2 emissions by 0.809%. The above analysis emphasizes that both green finance and CO_2 emissions at the 10th, 25th, 50th, 75th, and 90th quantiles exhibit a U-shaped feature. Actively guiding the green investment of financial institutions is an effective measure to manage the increasingly deteriorating ecological environment.

5.2 Mediating Analysis

In **Section 4**, we perform a systematic analysis on the specific and heterogeneous impacts of green finance on China's greenhouse effect; thus, an interesting question ignites our consideration—through what channels does green finance reduce CO_2 emissions?

TABLE 6 | Estimated results of the heterogeneity of CO_2 emissions.

Explained variable: ln*CO₂*

Variable	Quantiles				
	10th	**25th**	**50th**	**75th**	**90th**
ln*GFI*	−1.463[a] (−5.33)	−1.262[a] (−3.49)	−0.809[a] (−4.37)	−1.007[a] (−11.51)	−1.050[a] (−9.70)
ln*Pgdp*	1.045[a] (2.73)	0.609[c] (1.86)	1.482[a] (6.87)	1.370[a] (10.83)	1.342[a] (9.32)
ln*EE*	0.297 (1.12)	−0.261 (−1.48)	−0.315 (−1.50)	−0.554[a] (−3.56)	−0.783[a] (6.60)
ln*ISU*	−0.544[a] (−3.06)	−0.418[c] (−1.86)	−0.724[a] (−5.05)	−0.608[a] (−5.80)	−0.567[a] (4.00)
ln*Tra*	0.115 (0.88)	0.254[c] (1.65)	0.054 (0.79)	0.053 (1.08)	0.091 (1.53)
ln*Edu*	0.639[b] (2.06)	0.496 (1.15)	−0.519[a] (−2.80)	−0.328[a] (−3.03)	−0.306[b] (−2.55)
ln*Wage*	−0.584 (−1.34)	0.094 (0.28)	−0.471[b] (−2.02)	−0.192 (−0.94)	0.003 (0.01)
ln*Gap*	1.214[c] (1.91)	0.416 (0.82)	0.129 (0.30)	0.179 (0.79)	0.228 (1.62)
_*Cons*	−0.566 (−0.27)	−1.986 (−0.82)	−8.106[a] (−4.21)	−9.111[a] (−6.57)	−10.637[a] (−8.35)

[a]Indicate statistical significance at the 1% level.
[b]Indicate statistical significance at the 5% levels.
[c]Indicate statistical significance at the 10% levels.
The values in parentheses indicate t-statistics.

By employing the Sobel test and bootstrap sampling method simultaneously, we estimate the above three equations, and present the estimated results in **Table 7**. In terms of the economic effect, the value of the Sobel test is 0.153, which is significant at the 1% level. This test underscores the effective mediating role of economic growth. Moreover, from the first three columns of **Table 7**, the coefficients of green finance from column (1) to column (3) are −1.225, 0.095, and −1.377. This implies that while the development of green finance policies in China directly hinders the intensification of the greenhouse effect, it will increase greenhouse gas emissions by facilitating economic growth, and the proportion of total effect that is mediated by economic growth is 12.5%. Green finance policies, while promoting the transfer of investment to environmentally friendly enterprises, also facilitate the corresponding facility construction and productivity improvement, thus boosting economic growth; however, economic growth is highly dependent on fossil fuel burning, thus exacerbating the greenhouse effect. Furthermore, in the bootstrap test, *_bs_1* and *_bs_2* refer to

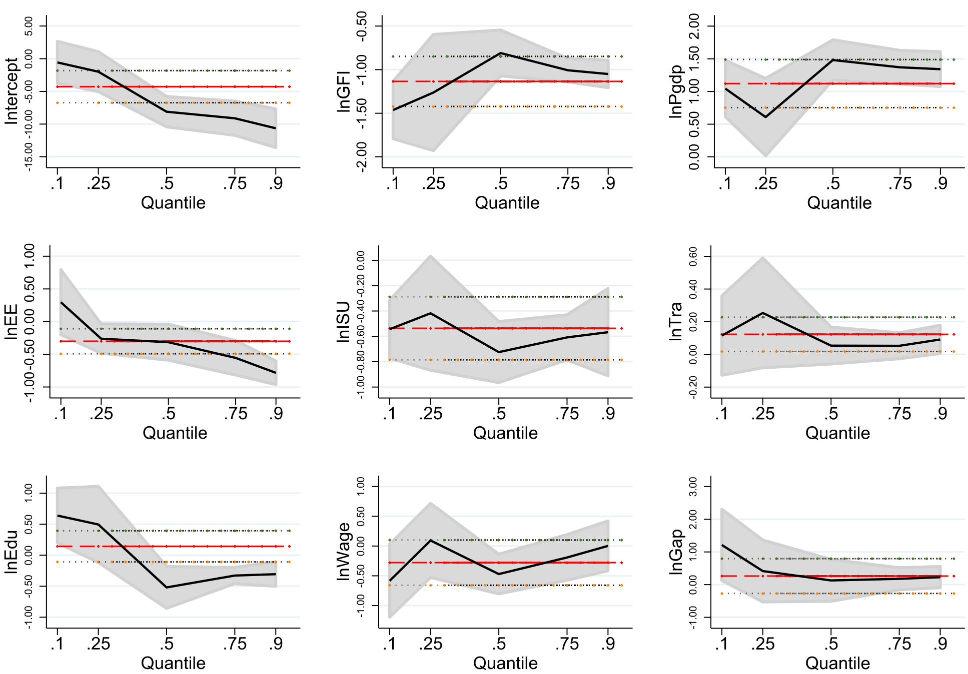

FIGURE 4 | Change in panel quantile regression coefficients. Notes: The *x-axis* represents the conditional quantiles of CO_2 emissions and *y-axis* denotes the coefficient values of various variables. The red line indicates the coefficient values of panel data model with fixed effect.

TABLE 7 | Estimated results of the mediation effects.

Variable	Total effect	Economic effect		Technical effect		Structural effect	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln*GFI*	−1.225[a] (−9.37)	0.095[a] (2.75)	−1.377[a] (−11.52)	−0.335[a] (−5.89)	−1.381[a] (−10.38)	0.553[a] (10.73)	−0.674[a] (−4.99)
ln*Pgdp*			1.608[a] (9.85)				
ln*EE*					−0.467[a] (−4.38)		
ln*ISU*							−0.997[a] (−8.98)
ln*Tra*	0.163[a] (3.28)	0.099[a] (7.52)	0.004 (0.09)	0.247[a] (11.41)	0.279[a] (5.03)	−0.008 (−0.38)	0.156[a] (3.40)
ln*Edu*	0.361[a] (2.71)	0.235[a] (6.70)	−0.017 (−0.13)	0.315[a] (5.42)	0.508[a] (3.77)	−0.092[c] −1.75)	0.270[b] (2.19)
ln*Wage*	0.377[a] (4.63)	0.831[a] (38.78)	−0.960[a] (−6.21)	0.509[a] (14.36)	0.614[a] (6.37)	0.230[a] (7.18)	0.606[a] (7.66)
ln*Gap*	−0.560[b] (−2.06)	−0.720[a] (−10.08)	0.598[b] (2.20)	−0.207[c] (−1.74)	−0.656[b] (−2.46)	0.144 (1.34)	−0.417[c] (−1.67)
_Cons	2.131[c] (1.76)	3.603[a] (11.27)	−3.665[a] (−2.94)	−3.813[a] (−7.21)	0.348 (0.28)	−2.278[a] (−4.77)	−0.140 (−0.12)
Sobel test		0.153[a] (2.65)		0.157[a] (3.51)		−0.551[a] (−6.89)	
Total effect		−1.225[a] (−9.37)		−1.225[a] (−9.37)		−1.225[a] (−9.37)	
Direct effect		−1.377[a] (−11.52)		−1.381[a] (−10.38)		−0.673[a] (−4.99)	
Indirect effect		0.153[a] (2.65)		0.157[a] (3.51)		−0.551[a] (−6.89)	
Proportion of total effect that is mediated		12.5%		12.8%		45.0%	
Bootstrap test							
_bs_1		0.153 (0.032, 0.229)		0.157 (0.071 0.260)		−0.551 (−0.768, −0.367)	
_bs_2		−1.377 (−1.636, −1.123)		−1.381 (−1.663, −1.059)		−0.674 (−0.971, −0.376)	

[a]*Refer to statistical significance at the 1% level.*
[b]*Refer to statistical significance at the 5% levels.*
[c]*Refer to statistical significance at the 10% levels.*
The values in parentheses indicate the t-statistics.

the indirect and direct effects, respectively. And the confidence intervals do not contain 0, which further verifies the reliability of the mediation effect of economic growth on the green finance-CO_2 emissions nexus.

Regarding the technical effect, the value of the Sobel test is 0.157, and is significant at the 1% level; this finding confirms the effectiveness of energy efficiency in affecting the green finance-CO_2 emissions nexus. Specifically, the coefficients of green finance in column (4) and energy efficiency in column (5) are −0.335 and −0.467, respectively. This suggests that the development of green finance cannot enhance energy efficiency and thus reduce greenhouse gas emissions, and the proportion of total effect that is mediated is 12.8%, which is contrary to the findings of Rasoulinezhad and Taghizadeh-Hesary (2022) and Yu et al. (2022). This may be because the implementation of green finance aims to apply economic leverage to guide capital to gradually withdraw from high-energy-consuming enterprises and integrate into energy-saving projects, so as to facilitate the low-carbon allocation of financial resources. However, the ambiguity of credit standards among financial institutions in the early stage of implementation of the policy leads to the phenomenon of "bad money driving out good money" in unfair competition, resulting in an unreasonable layout of green finance and producing the opposite effect on energy efficiency. In addition, a check of the bootstrap test confirms the mediating role of energy efficiency.

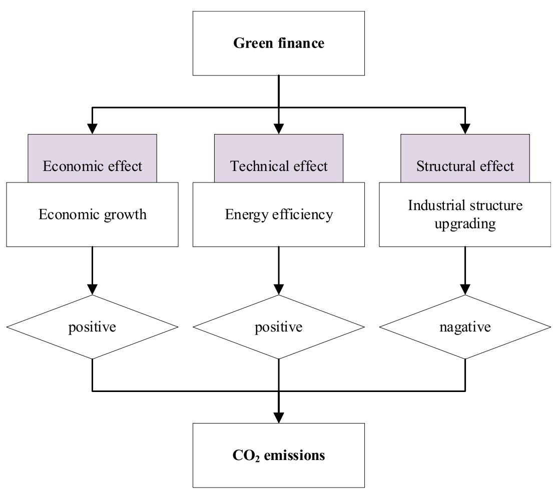

FIGURE 5 | The impact mechanism between green finance and CO_2 emissions.

The Sobel test of the structural effect implies the validity of the mediating role of industrial structure upgrading. To be specific, the coefficients of green finance in column (6) and industrial structure upgrading in column (7) are 0.553 and −0.997, respectively, which suggests that green finance can effectively facilitate the optimization and upgrading of the existing industrial structure, thereby alleviating the greenhouse effect. Moreover, the proportion of total effect that is mediated is 45%. This ratio suggests that industrial structure upgrading has the most obvious mediation effect between green finance and CO_2 emissions. In summary, we can conclude that China's green finance not only directly mitigates CO_2 emissions, but also affects the greenhouse effect by promoting economic growth, restraining energy efficiency improvement, and facilitating industrial structure upgrading. We also draw a mechanism diagram to illustrate the above relationships (**Figure 5**).

6 CONCLUSION AND POLICY IMPLICATIONS

6.1 Conclusion

Based on China's provincial panel dataset from 2004 to 2018, this paper estimates the impact of green finance on CO_2 emissions using the FGLS method, and further explores their heterogeneity and mediating effect. Accordingly, we have drawn the following main conclusion:

1) China's green finance negatively affects CO_2 emissions, which indicates that China's green finance investment is conducive to the country's carbon mitigation process. Moreover, the benchmark regression results pass the robustness test of the alternative estimation method and dependent variables.
2) The results of the heterogeneous analysis suggest that green finance has a heterogeneity impact on China's CO_2 emissions. Specifically, green finance negatively affects CO_2 emissions in eastern and central China; in addition, green finance has a stronger negative impact on CO_2 emissions in regions with a lower level of emissions.
3) The estimated results of the Sobel test and bootstrap test indicate that China's green finance not only helps mitigate the greenhouse effect directly, but also can affect CO_2 emissions by promoting economic growth, inhibiting energy efficiency improvement, and accelerating the optimization and transfer of the current industrial structure.

6.2 Policy Implications

Based on the above three findings, we propose the following policy implications. First, given the negative effect of green finance on the greenhouse effect, it is imperative to strengthen the development of green finance. At present, China's green finance is still in an exploratory stage, so promoting the sustainable and stable development of green finance is crucial. To be more specific, first, local governments should pay attention to comprehensive and specific planning for the overall development of green finance, and establish and improve legal guarantees for green finance. Enterprises that pay attention to environmental protection will be provided with preferential credit or tax policies, and capital will be guided into green financial investment through cooperation between the government and private capital. Second, in addition to government control and guidance, relevant departments should strengthen the supervision of green bonds and improve enterprises' social responsibility in the field of green finance. In addition, environmental protection departments can use advanced technologies such as cloud computing or big data to disclose corporate environmental information and promote timely access and the effective transmission of relevant information by financial institutions. Credit investigation departments should establish an enterprise credit investigation system, and financial institutions should provide timely feedback on green finance-related information to environmental protection departments. Third, comprehensive financial human capital is key to promoting the effective implementation and stable development of green finance. Thus, China should focus on training financial talents, accelerate the transfer and upgrading of intermediate business models, establish scientific talent-training plans, and help employees in the financial industry to carry out financial knowledge training in colleges and universities.

Second, the empirical results of geographic heterogeneity and CO_2 emissions heterogeneity show that provincial governments should introduce or formulate policies and regulations related to green finance or CO_2 emission reduction according to actual local conditions. To be more specific, in the prosperous eastern coastal provinces, especially in specific economic agglomeration areas such as the Beijing-Tianjin-Hebei area, the Yangtze River Delta, and the Pearl River Delta, financial institutions and the policy system are relatively sound. On the basis of the continuous promotion of green finance, the eastern provinces should focus on the agglomeration of technology, human capital, material capital, and public resources, establish financial centers, and give play to their spatial diffusion and radiation functions to drive the rapid evolution of financial institutions in the central and western regions. Provinces in the central region should capitalize on the advantages of the regional economy, actively implement green finance policies, and fully tap the supporting role of green finance in reducing CO_2 emissions. In the economically backward western provinces, the excellent ecological environment in this area should be used to actively exploit the potential role of green finance to overcome obstacles. On the basis of drawing on the advanced experience of green finance in the eastern and central regions, the green credit process and a scheme suitable for local development are being formulated in combination with the actual features of the local region, and the rapid evolution of green finance in the western region will be actively promoted.

Third, the mediation effects of economic, technical, and structural effects imply that the industrial structure optimization effect of green finance has been significantly verified, but its promotion effect on energy efficiency has not been fully explored. Thus, it is vital to further guide and strengthen green finance for investment in tertiary industries with high added value and low pollution. Furthermore, local government should comprehensively determine credit standards to avoid deviations caused by vague and inconsistent investment standards. In addition, financial institutions should strengthen financial investment in enterprises actively engaged in the research and development of green, low-carbon technologies, and provide financial support for environmental protection projects.

DATA AVAILABILITY STATEMENT

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

AUTHOR CONTRIBUTIONS

JW: validation, visualization, writing—original draft, investigation, resources, and data curation. YM: conceptualization, methodology, software, writing—review and editing. All authors contributed to the article and approved the submitted version.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2022.931086/full#supplementary-material

REFERENCES

Arora, N. K., and Mishra, I. (2021). COP26: More Challenges Than Achievements. *Environ. Sustain.* 4, 585–588. doi:10.1007/s42398-021-00212-7

Bano, S., Zhao, Y., Ahmad, A., Wang, S., and Liu, Y. (2018). Identifying the Impacts of Human Capital on Carbon Emissions in Pakistan. *J. Clean. Prod.* 183, 1082–1092. doi:10.1016/j.jclepro.2018.02.008

CEADs (2019). Province CO_2 Emissions Inventory 1997-2019. Avaialable at: https://www.ceads.net/data/province/by_apparent_accounting/.

Coad, A., and Rao, R. (2006). Innovation and Market Value: a Quantile Regression Analysis. *Econ. Bull.* 15, 1–10. Avaialable at: http://www.accessecon.com/pubs/EB/2006/Volume15/EB-06O10012A.pdf.

Copeland, B. R., and Taylor, M. S. (1994). North-south Trade and the Environment. *Q. J. Econ.* 109 (3), 755–787. doi:10.2307/2118421

CSY (2021). National Bureau of Statistics, China Statistical Yearbook 2021. Avaialable at: http://www.stats.gov.cn/tjsj/ndsj/.

Cui, H., Wang, R., and Wang, H. (2020). An Evolutionary Analysis of Green Finance Sustainability Based on Multi-Agent Game. *J. Clean. Prod.* 269, 121799. doi:10.1016/j.jclepro.2020.121799

Dong, K., Taghizadeh-Hesary, F., and Zhao, J. (2022). How Inclusive Financial Development Eradicates Energy Poverty in China? the Role of Technological Innovation. *Energy Econ.* 109, 106007. doi:10.1016/j.eneco.2022.106007

Dusenge, M. E., Duarte, A. G., and Way, D. A. (2019). Plant Carbon Metabolism and Climate Change: Elevated CO2 and Temperature Impacts on Photosynthesis, Photorespiration and Respiration. *New Phytol.* 221, 32–49. doi:10.1111/nph.15283

Gholipour, H. F., Arjomandi, A., and Yam, S. (2022). Green Property Finance and CO2 Emissions in the Building Industry. *Glob. Finance J.* 51, 100696. doi:10.1016/j.gfj.2021.100696

Gulnaz, S., and Manglani, H. (2022). Does Gravity Work in the Context of India and ASEAN Bilateral Trade? an Application of the FGLS Method. *Theor. Appl. Econ.* 29 (1), 143–160.

Guo, L., Zhao, S., Song, Y., Tang, M., and Li, H. (2022). Green Finance, Chemical Fertilizer Use and Carbon Emissions from Agricultural Production. *Agriculture* 12, 313. doi:10.3390/agriculture12030313

He, J.-K. (2015). China's INDC and Non-fossil Energy Development. *Adv. Clim. Change Res.* 6, 210–215. doi:10.1016/j.accre.2015.11.007

He, Y., Fu, F., and Liao, N. (2021). Exploring the Path of Carbon Emissions Reduction in China's Industrial Sector through Energy Efficiency Enhancement Induced by R&D Investment. *Energy* 225, 120208. doi:10.1016/j.energy.2021.120208

Hulme, M., Obermeister, N., Randalls, S., and Borie, M. (2018). Framing the Challenge of Climate Change in Nature and Science Editorials. *Nat. Clim. Change* 8, 515–521. doi:10.1038/s41558-018-0174-1

IEA (2017). Data and Statistics. Avaialable at: https://www.iea.org/.

IPCC (2022). in *Intergovernmental Panel on Climate Change.Climate Change 2022: Impacts, Adaptation and Vulnerability*

Jiang, L., Wang, H., Tong, A., Hu, Z., Duan, H., Zhang, X., et al. (20202020). The Measurement of Green Finance Development Index and its Poverty Reduction Effect: Dynamic Panel Analysis Based on Improved Entropy Method. *Discrete Dyn. Nat. Soc.* 2020, 1–13. doi:10.1155/2020/8851684

Jin, Y., Gao, X., and Wang, M. (2021). The Financing Efficiency of Listed Energy Conservation and Environmental Protection Firms: Evidence and Implications for Green Finance in China. *Energy Policy* 153, 112254. doi:10.1016/j.enpol.2021.112254

Kang, Q., Wu, J., Chen, M., and Jeon, B. (2021). Do Macroprudential Policies Affect the Bank Financing of Firms in China? Evidence from a Quantile Regression Approach. *J. Int. Money Financ.* 115, 102391. doi:10.1016/j.jimonfin.2021.102391

Khan, M. A., Riaz, H., Ahmed, M., and Saeed, A. (2022). Does Green Finance Really Deliver what Is Expected? an Empirical Perspective. *Borsa Istanb. Rev.* 22, 586–593. doi:10.1016/j.bir.2021.07.006

La Rovere, E. L., Grottera, C., and Wills, W. (2018). Overcoming the Financial Barrier to a Low Emission Development Strategy in Brazil. *Int. Econ.* 155, 61–68. doi:10.1016/j.inteco.2017.12.004

Lewbel, A. (2012). Using Heteroscedasticity to Identify and Estimate Mismeasured and Endogenous Regressor Models. *J. Bus. Econ. Statistics* 30, 67–80. doi:10.1080/07350015.2012.643126

Li, C., and Gan, Y. (2021). The Spatial Spillover Effects of Green Finance on Ecological Environment-Empirical Research Based on Spatial Econometric Model. *Environ. Sci. Pollut. Res.* 28, 5651–5665. doi:10.1007/s11356-020-10961-3

Liu, Q., and Wang, Q. (2017). How China Achieved its 11th Five-Year Plan Emissions Reduction Target: A Structural Decomposition Analysis of Industrial SO2 and Chemical Oxygen Demand. *Sci. Total Environ.* 574, 1104–1116. doi:10.1016/j.scitotenv.2016.08.176

Liu, X., Shen, B., Price, L., Hasanbeigi, A., Lu, H., Yu, C., et al. (2019). A Review of International Practices for Energy Efficiency and Carbon Emissions Reduction and Lessons Learned for China. *WIREs Energy Environ.* 8, e342. doi:10.1002/wene.342

Luan, B., Zou, H., Chen, S., and Huang, J. (2021). The Effect of Industrial Structure Adjustment on China's Energy Intensity: Evidence from Linear and Nonlinear Analysis. *Energy* 218, 119517. doi:10.1016/j.energy.2020.119517

Lv, C., Bian, B., Lee, C.-C., and He, Z. (2021). Regional Gap and the Trend of Green Finance Development in China. *Energy Econ.* 102, 105476. doi:10.1016/j.eneco.2021.105476

Nawaz, M. A., Seshadri, U., Kumar, P., Aqdas, R., Patwary, A. K., and Riaz, M. (2021). Nexus between Green Finance and Climate Change Mitigation in N-11 and BRICS Countries: Empirical Estimation through Difference in Differences (DID) Approach. *Environ. Sci. Pollut. Res.* 28, 6504–6519. doi:10.1007/s11356-020-10920-y

Nouira, I., Hammami, R., Frein, Y., and Temponi, C. (2016). Design of Forward Supply Chains: Impact of a Carbon Emissions-Sensitive Demand. *Int. J. Prod. Econ.* 173, 80–98. doi:10.1016/j.ijpe.2015.11.002

Pan, Y., and Dong, F. (2022). Design of Energy Use Rights Trading Policy from the Perspective of Energy Vulnerability. *Energy Policy* 160, 112668. doi:10.1016/j.enpol.2021.112668

PBC (2019). *People's Bank of China*. Avaialable at: http://www.gov.cn/xinwen/2019-11/20/content_5453843.htm.China Green Finance Development Report 2018

Rasoulinezhad, E., and Taghizadeh-Hesary, F. (2022). Role of Green Finance in Improving Energy Efficiency and Renewable Energy Development. *Energy Effic.* 15 (2), 1–12. doi:10.1007/s12053-022-10021-4

Ren, X., Dou, Y., Dong, K., and Li, Y. (2022a). Information Spillover and Market Connectedness: Multi-Scale Quantile-On-Quantile Analysis of the Crude Oil and Carbon Markets. *Appl. Econ.*, 1–21. doi:10.1080/00036846.2022.2030855

Ren, X., Li, Y., Yan, C., Wen, F., and Lu, Z. (2022b). The Interrelationship between the Carbon Market and the Green Bonds Market: Evidence from Wavelet Quantile-On-Quantile Method. *Technol. Forecast. Soc. Change* 179, 121611. doi:10.1016/j.techfore.2022.121611

Ren, X., Shao, Q., and Zhong, R. (2020). Nexus between Green Finance, Non-fossil Energy Use, and Carbon Intensity: Empirical Evidence from China Based on a Vector Error Correction Model. *J. Clean. Prod.* 277, 122844. doi:10.1016/j.jclepro.2020.122844

Ren, X., Tong, Z., Sun, X., and Yan, C. (2022c). Dynamic Impacts of Energy Consumption on Economic Growth in China: Evidence from a Non-parametric Panel Data Model. *Energy Econ.* 107, 105855. doi:10.1016/j.eneco.2022.105855

Sachs, J. D., Woo, W. T., Yoshino, N., and Taghizadeh-Hesary, F. (2019b). Importance of Green Finance for Achieving Sustainable Development Goals and Energy Security. *Handb. green finance Energy Secur. Sustain. Dev.* 10, 1–10. doi:10.1007/978-981-10-8710-3_13-1

Sachs, J., Woo, W. T., Yoshino, N., and Taghizadeh-Hesary, F. (2019a). *Handbook of Green Finance: Energy Security and Sustainable Development*. Springer.

Saeed Meo, M., and Karim, M. Z. A. (2022). The Role of Green Finance in Reducing CO2 Emissions: An Empirical Analysis. *Borsa Istanb. Rev.* 22, 169–178. doi:10.1016/j.bir.2021.03.002

Shahzad, F., Rehman, I. U., Nawaz, F., and Nawab, N. (2018). Does Family Control Explain Why Corporate Social Responsibility Affects Investment Efficiency? *Corp. Soc. Resp. Env. Ma* 25, 880–888. doi:10.1002/csr.1504

Taghizadeh-Hesary, F., and Yoshino, N. (2019). The Way to Induce Private Participation in Green Finance and Investment. *Finance Res. Lett.* 31, 98–103. doi:10.1016/j.frl.2019.04.016

Tran, Q. H. (2021). The Impact of Green Finance, Economic Growth and Energy Usage on CO2 Emission in Vietnam - a Multivariate Time Series Analysis. *Cfri* 12, 280–296. doi:10.1108/CFRI-03-2021-0049

Wang, B., Zhao, J., Dong, K., and Jiang, Q. (2022). High-quality Energy Development in China: Comprehensive Assessment and its Impact on CO2 Emissions. *Energy Econ.* 110, 106027. doi:10.1016/j.eneco.2022.106027

Wang, J., Dong, K., Dong, X., and Jiang, Q. (2021a). Research on the Carbon Emission Effect of the Seven Regions along the Belt and Road-Based on the Spillover and Feedback Effects Model. *J. Clean. Prod.* 319, 128758. doi:10.1016/j.jclepro.2021.128758

Wang, J., Jiang, Q., Dong, X., and Dong, K. (2021b). Decoupling and Decomposition Analysis of Investments and CO2 Emissions in Information and Communication Technology Sector. *Appl. Energy* 302, 117618. doi:10.1016/j.apenergy.2021.117618

Wang, Q., and Zhang, F. (2021). The Effects of Trade Openness on Decoupling Carbon Emissions from Economic Growth - Evidence from 182 Countries. *J. Clean. Prod.* 279, 123838. doi:10.1016/j.jclepro.2020.123838

Wang, X., Wang, X., Ren, X., and Wen, F. (2022c). Can Digital Financial Inclusion Affect CO2 Emissions of China at the Prefecture Level? Evidence from a Spatial Econometric Approach. *Energy Econ.* 109, 105966. doi:10.1016/j.eneco.2022.105966

Wang, X., Zhao, H., and Bi, K. (2021c). The Measurement of Green Finance Index and the Development Forecast of Green Finance in China. *Environ. Ecol. Stat.* 28, 263–285. doi:10.1007/s10651-021-00483-7

Wang, Y., and Zhi, Q. (2016). The Role of Green Finance in Environmental Protection: Two Aspects of Market Mechanism and Policies. *Energy Procedia* 104, 311–316. doi:10.1016/j.egypro.2016.12.053

Wu, L., Sun, L., Qi, P., Ren, X., and Sun, X. (2021). Energy Endowment, Industrial Structure Upgrading, and CO2 Emissions in China: Revisiting Resource Curse in the Context of Carbon Emissions. *Resour. Policy* 74, 102329. doi:10.1016/j.resourpol.2021.102329

Xiong, Q., and Sun, D. (2022). Influence Analysis of Green Finance Development Impact on Carbon Emissions: an Exploratory Study Based on fsQCA. *Environ. Sci. Pollut. Res.* doi:10.1007/s11356-021-18351-z

Yan, D., Ren, X., Zhang, W., Li, Y., and Miao, Y. (2022). Exploring the Real Contribution of Socioeconomic Variation to Urban PM2.5 Pollution: New Evidence from Spatial Heteroscedasticity. *Sci. Total Environ.* 806, 150929. doi:10.1016/j.scitotenv.2021.150929

Yang, Y., Su, X., and Yao, S. (2021). Nexus between Green Finance, Fintech, and High-Quality Economic Development: Empirical Evidence from China. *Resour. Policy* 74, 102445. doi:10.1016/j.resourpol.2021.102445

Yu, C.-H., Wu, X., Zhang, D., Chen, S., and Zhao, J. (2021). Demand for Green Finance: Resolving Financing Constraints on Green Innovation in China. *Energy Policy* 153, 112255. doi:10.1016/j.enpol.2021.112255

Yu, M., Zhou, Q., Cheok, M. Y., Kubiczek, J., and Iqbal, N. (2022). Does Green Finance Improve Energy Efficiency? New Evidence from Developing and Developed Economies. *Econ. Change Restruct.* 55 (1), 485–509. doi:10.1007/s10644-021-09355-3

Zhang, D., Mohsin, M., Rasheed, A. K., Chang, Y., and Taghizadeh-Hesary, F. (2021). Public Spending and Green Economic Growth in BRI Region: Mediating Role of Green Finance. *Energy Policy* 153, 112256. doi:10.1016/j.enpol.2021.112256

Zhang, D., Zhang, Z., and Managi, S. (2019). A Bibliometric Analysis on Green Finance: Current Status, Development, and Future Directions. *Finance Res. Lett.* 29, 425–430. doi:10.1016/j.frl.2019.02.003

Zhang, J., Fan, Z., Chen, Y., Gao, J., and Liu, W. (2020). Decomposition and Decoupling Analysis of Carbon Dioxide Emissions from Economic Growth in the Context of China and the ASEAN Countries. *Sci. Total Environ.* 714, 136649. doi:10.1016/j.scitotenv.2020.136649

Zhao, J., Jiang, Q., Dong, X., Dong, K., and Jiang, H. (2022a). How Does Industrial Structure Adjustment Reduce CO2 Emissions? Spatial and Mediation Effects Analysis for China. *Energy Econ.* 105, 105704. doi:10.1016/j.eneco.2021.105704

Zhao, J., Shahbaz, M., Dong, X., and Dong, K. (2021). How Does Financial Risk Affect Global CO2 Emissions? the Role of Technological Innovation. *Technol. Forecast. Soc. Change* 168, 120751. doi:10.1016/j.techfore.2021.120751

Zhao, X., Ma, X., Chen, B., Shang, Y., and Song, M. (2022b). Challenges toward Carbon Neutrality in China: Strategies and Countermeasures. *Resour. Conservation Recycl.* 176, 105959. doi:10.1016/j.resconrec.2021.105959

Zhou, X., Tang, X., and Zhang, R. (2020). Impact of Green Finance on Economic Development and Environmental Quality: a Study Based on Provincial Panel Data from China. *Environ. Sci. Pollut. Res.* 27, 19915–19932. doi:10.1007/s11356-020-08383-2

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The Pricing of ESG: Evidence From Overnight Return and Intraday Return

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By featuring the link of investor heterogeneity to the persistence of the overnight and intraday components of returns, we examine the ESG–overnight (intraday) alpha relation in the Chinese stock market. The empirical results show that ESG score has a significantly negative effect on the expected stock overnight returns in Fama–MacBeth regression. Consistently, given the biggest market capitalization and the least illiquidity subsamples, the trading strategies by going long (short) the top (bottom) ESG quintile would yield negative profits. In addition, we conduct the implication of the ESG pricing by dividing the full sample into green stock subsample and sin stock subsample, and the empirical results present that the ESG pricing is pervasive of the green-type stocks. These conclusions verify the pricing of ESG and support the conjecture that green stocks have lower expected returns because ESG investors value sustainability.

Keywords: ESG pricing, overnight return, trading strategy, Fama–MacBeth regression, green stock

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INTRODUCTION

Nowadays, the global top-level design policy advocating carbon neutrality makes sustainable investment, an investment approach considering environmental, social, and governance (ESG) factors in portfolio construction and asset management, as well as attractive to scholars, practitioners, policymakers, and regulators. Given that social norms have a great influence on the financial market (Hong and Kacperczyk, 2009), and investors value sustainability (Pástor et al., 2021a; Bauer et al., 2021), it is of great importance to understand the effects of ESG investing on asset price and return.

Actually, ESG is increasingly discussed as a potential alpha signal in academic outlets (Sloan, 1996; Avramov et al., 2021; Gibson et al., 2021; Pedersen et al., 2021). Certain ESG measures predict returns positively, while others predict negatively. For instance, Avramov et al. (2021) confirmed that the average ESG rating negatively predicts the future stock performance only for low-ESG disagreement stocks. Pedersen et al. (2021) proposed an ESG-adjusted capital asset pricing model, showing when ESG raises or lowers the required return. More recently, Pástor et al. (2021b) found that green stocks would outperform brown when there is bad information shock about climate change. Gibson et al. (2021) systematically tested that the second moment of ESG rating has positive consequences for stock return, and they considered that the higher ESG rating disagreement may be perceived as a source of Knightian uncertainty that commands an uncertainty premium.

As one of the largest markets in the world, the China A-shares market has experienced complex changes in recent decades. A great deal of researches focus on Chinese economic and financial phenomenon and have achieved fruitful theoretical and empirical achievements, such as energy finance (Ren et al., 2022; Wen et al., 2021; Zheng et al., 2021; Dai et al., 2021), stock return–risk tradeoff or risk management (Gokmenoglu et al., 2021; Cao et al., 2021; Chen et al., 2022; Dai et al., 2021; Xiao et al., 2021; Wen et al., 2021; Liow et al., 2021; Sikiru et al., 2021; Wen et al., 2021; Umutlu et al., 2021), and financial networks (Cao et al., 2021a; Cao et al., 2021; Wen et al., 2021). The literature has previously identified the pricing of carbon risk and climate risk in China. For example, Ren et al. (2022) evaluated the predictability of a large group of factors on carbon future returns using the quantile-on-quantile method. In addition, Ren et al. (2022) investigated the impact of extreme national climate risk on corporate environmental performance in the context of China. Thus, it can be seen that the evidence associated with the Chinese market can shed new light on the whole world.

China's A-share market has its own characteristics, among which the investor structure and T+1 trading rules are the two most prominent features (Wen et al., 2021; Wen et al., 2021; Chen et al., 2022). With regard to the investor structure, compared to the U.S., there are less institutional investors in the Chinese stock market; thus, the investor sentiment really matters. For example, Li et al. (2021) used the Chinese equity market as the testing venue to explore how investor sentiment affects the immediate reaction of stock prices to earnings news in high- and low-sentiment periods. On the other hand, Qiao and Dam (2020) asserted that "T+1" trading rule prohibits traders from selling the shares they bought on the same day. This restriction leads to a discount on daily opening prices, thus inducing negative overnight returns. In recent years, literature on the components of return, that is, intraday return and overnight return, is widely studied by scholars (Aboody et al., 2018; Lou et al., 2019; Barardehi et al., 2021). Aboody et al. (2018) demonstrate that individual stock overnight returns possess the same characteristics as the investor sentiment; thus, we can use the stock overnight return as the proxy of the investor sentiment at the stock level. Lou et al. (2019) found that, in all cases, profits are either earned entirely overnight (for reversal and a variety of momentum strategies) or entirely intraday, typically with profits of opposite signs across these components.

Moreover, the literature provides evidence that investor heterogeneity can affect asset pricing (Harrison and Kreps, 1978; Constantinides and Duffie, 1996; Boudoukh et al., 2019; Lou et al., 2019). For instance, Lou et al. (2019) confirmed that different types of agents tend to trade at different times during the day, that is, some investors may tend to trade at the morning open, while others may prefer to trade during the rest of the day up to and including the market close, which makes the price movement during the day and at night vary. Also, Boudoukh et al. (2019) and Barardehi et al. (2021) argued that overnight price movements are mainly due to public news, as opposed to the revelation of private information through trading. Consequently, in this study, based on the investor structure, T+1 trading rules, and price movements at night vs. during the day, we empirically analyze the cross-sectional relation between ESG and expected overnight and intraday components of returns in the Chinese stock market. Specifically, our model features the link of investor heterogeneity to the persistence of the overnight and intraday components of returns. In addition, we divide the stocks into green stock subsample and sin stock subsample based on the ESG score to reexamine the cross-sectional ESG–alpha relation. More specifically, we first examine the relation between ESG score and the expected overnight and intraday components of returns in the Chinese stock market. Because the coefficients of ESG score in Fama and MacBeth, (1973) regression of intraday return on the ESG score and Fama–French five-factor ESG score of intraday alpha generated by the zero-cost trading strategy are statistically insignificant, we only report the empirical results of the overnight return. We next zoom in the cross-sectional implication of ESG pricing on green stocks and sin stocks. We define green and sin stocks based on the ESG score, that is, the higher (lower) the ESG score, the greener (sinner) the stock is. More specifically, green (sin) stock subsample is those stocks with ESG scores in the top (bottom) 30%. We state the following hypotheses development:

H1: the ESG score has an asymmetric effect on the components of expected stock return.

H2: firm characteristics matter in the ESG–overnight (intraday) alpha relation.

H3: green stocks would have lower expected returns because ESG investors value sustainability.

The empirical results present that the ESG score has a negative effect on the expected stock overnight returns in Fama–MacBeth regression. In addition, given the biggest market capitalization and the least illiquidity subsamples, the trading strategies by going long (short) the top (bottom) ESG quintile would yield negative profits. These conclusions parallel those of Bauer et al. (2021) and Pástor et al. (2021a), who provided evidence of green assets having lower expected returns. Finally, the implication of the ESG pricing on green stock subsample and sin stock subsample reveals that the ESG pricing is pervasive of the green-type stocks. These conclusions parallel those of Bauer et al. (2021) and Pástor et al. (2021a), who provided evidence of green assets having lower expected returns.

Our contributions are two-fold. First, we contribute to the growing discussion on the cross-sectional pricing of the ESG and sustainable investing. Prior literature documents the overall negative return predictability of the ESG score and emphasizes that responsible investors are in favor of sustainability due to taste of ESG (Fama and French, 2007; Hartzmark, 2019; Fama and French 2015; Pástor et al., 2021a, b; Barber et al., 2021). More specifically, a recent work by Pástor et al. (2021a) used a range of ESG proxies that reflect different clienteles of investors and found that when the economy has many ESG-motivated investors, then high-ESG stocks actually deliver low expected returns because ESG-motivated investors are willing to accept a lower return for a higher ESG portfolio. In contrast to Pedersen et al. (2021), we focus on the link of investor heterogeneity to the persistence of the overnight and intraday components of returns. In all, we offer novel insights into the cross-sectional ESG–overnight (intraday) alpha relation and the pricing of ESG on green stocks and sin stocks.

Second, we contribute to the stream of literature on the pricing of financial anomalies and overnight returns (Avramov and Chordia, 2006; Jacobs, 2015; Aboody et al., 2018; Lou et al., 2019; Hou et al., 2020). Specifically, we study how the ESG score would affect the overnight and intraday components of returns. ESG is a factor related to investors' tastes, while the extant financial anomalies, including trading frictions, momentum, value-versus-growth, and profitability, can be mostly attributed to firm characteristic-related factors

TABLE 1 | Descriptive statistics.

Variable	Observation	Mean	STD	5%	25%	Median	75%	95%
ESG_{score}	3,096	22.385	6.057	15.289	19.008	21.074	23.967	36.580
E_{score}	3,096	11.537	7.315	2.326	6.977	10.078	13.953	28.682
S_{score}	3,096	25.977	8.619	12.281	22.807	22.807	28.070	43.860
G_{score}	3,096	43.852	5.221	33.929	39.286	42.857	48.214	53.571
$R_{close\text{-}to\text{-}close}$	3,096	0.082	0.436	−0.457	−0.228	−0.013	0.301	0.944
$R_{overnight}$	3,096	−0.191	0.225	−0.532	−0.338	−0.204	−0.071	0.193
$R_{intraday}$	3,096	0.417	0.697	−0.289	−0.032	0.219	0.651	1.789
Size	3,096	16.049	1.099	14.324	15.298	15.972	16.705	17.917
BM	3,096	0.696	0.256	0.242	0.504	0.715	0.908	1.071
Illiquidity	3,096	0.035	0.040	0.003	0.010	0.022	0.043	0.114
Turnover	3,096	4.111	3.376	0.674	1.756	3.094	5.316	11.075

This table presents the descriptive statistics of main variables for the sample period from 2011 to 2019. The main variables are environmental, social, and governance score (ESG_{score}*), environmental score (*E_{score}*), social score (*S_{score}*), governance score (*G_{score}*), yearly close-to-close return (*$R_{close\text{-}to\text{-}close}$*), overnight return (*$R_{overnight}$*), intraday return (*$R_{intraday}$*), log market capitalization (*Size*), book-to-market ratio (*BM*), Amihud, (2002) illiquidity (*illiquidity*), and turnover (*Turnover*). The descriptive statistics includes the number of observations, mean, standard deviation (STD), median, and the percentile (5 and 95%) and quartile (25 and 75%) distribution of the variables.*

(Hou et al., 2020). Therefore, our research would shed light on the asset pricing consequence of increasing sustainable investments by responsible investors.

The remainder of this study is organized as follows: **Section 2** describes the data and the calculation of intraday and overnight components of returns. **Section 3** presents the empirical analysis. **Section 4** analyzes the mechanism analysis. **Section 5** discusses the implication of the ESG pricing on green stock subsample and sin stock subsample. Conclusion is given in **Section 6**.

DATA AND DESCRIPTIVE STATISTICS

Data Description

Our sample consists of all listed A-share stocks in China. Daily stock data, Fama–French five factors, turnover, size (market capitalization), BM (book-to-market) ratio, Amihud (2002) illiquidity, and risk-free rate are obtained from the China Stock Market & Accounting Research Database (CSMAR). Individual stocks' environmental, social, and governance score (ESG_{score}), environmental score (E_{score}), social score (S_{score}), and governance score (G_{score}) are obtained from Bloomberg. The sample period is from January 2011 to July 2019.

Calculation of Components of Return

We calculate the intraday and overnight components of firm-level returns according to Lou et al. (2019). Specifically, for each stock *i*, the definition of intraday return is the price appreciation between market open and close of the same day *s*, while the overnight return is the price appreciation between market open price of day *s* and close of the day *s-1*,

$$R^i_{\mathrm{intraday},s} = \frac{P^i_{close,s}}{P^i_{open,s}} - 1, \tag{1}$$

$$R^i_{overnight,s} = \frac{P^i_{open,s}}{P^i_{close,s-1}} - 1. \tag{2}$$

In further research, we calculate intraday return and overnight return for each stock i of each year t by accumulating corresponding daily intraday return and overnight return:

$$R^i_{\mathrm{intraday},t} = \prod_{s\epsilon t}\left(1 + R^i_{\mathrm{intraday},s}\right) - 1, \tag{3}$$

$$R^i_{overnight,t} = \prod_{s\epsilon t}\left(1 + R^i_{overnight,s}\right) - 1. \tag{4}$$

Descriptive Statistics

Table 1 shows the basic descriptive statistics of individual stocks' environmental, social, and governance score (ESG_{score}), environmental score (E_{score}), social score (S_{score}), governance score (G_{score}), yearly close-to-close return ($R_{close\text{-}to\text{-}close}$), overnight return ($R_{overnight}$), intraday return ($R_{intraday}$), log market capitalization (*Size*), book-to-market ratio (*BM*), Amihud (2002) illiquidity (*illiquidity*), and turnover (*Turnover*). On average, there are about 3,096 observations in our sample each year. The average log capitalization of stocks in our sample is 16.049. The mean ESG score is 22.39, and the average components of ESG score including E score, S score, and G score are 11.53, 25.98, and 43.84, respectively. In addition, the average overnight return and intraday return of stocks in our sample are negative (−0.19) and positive (0.41), respectively, which is consistent with previous work by Qiao and Dam, (2020) that has argued that the overnight return is negative due to the "T+1" trading system in the Chinese stock market.

EMPIRICAL ANALYSIS

In this section, using portfolio analysis and Fama–MacBeth regression, we examine the relation between ESG score and subsequent overnight (or intraday) returns in the Chinese stock market. First, we implement the long–short trading strategies to obtain Fama–French (2015) five factors adjusted overnight (intraday) alpha:

$$overnightR_{P,t} - Rf_{P,t} = \alpha_0 + \beta_1 FF5_{P,t} + \varepsilon_{P,t}, \tag{5}$$

TABLE 2 | ESG and overnight return: one-dimensional portfolio sort.

	Average excess return	*Three-factor (FF) alpha*	*Five-factor (FF) alpha*
Low ESG_{score}	−0.2361***	−0.2466***	−0.2192***
2	−0.2116***	−0.2211***	−0.1576***
3	−0.1871***	−0.1966***	−0.1574***
4	−0.2288***	−0.2383***	−0.1763***
High ESG_{score}	−0.1984***	−0.2089***	−0.1523***
High–low	0.0377*** (3.58)	0.0377*** (8.41)	0.0669*** (5.70)

This table reports value-weighted average overnight excess return and Fama–French three-factor and five-factor risk-adjusted portfolio alphas of single-sorted portfolios formed yearly on prior-year ESG_{score}*. The differences in average overnight excess return, three-factor alphas, and five-factor alphas between high and low portfolios are also reported, along with* t*-statistics in parentheses. The* t*-statistics reported in parentheses are based on Newey–West standard errors with 12 lags. The sample period is from 2011 to 2019. *, **, and *** denote significance at 10, 5, and 1%, respectively.*

where the subscript P (p = 1,2,. . .,10) represents the stock portfolio deciles based on the ESG score, $OvernightR_{P,t}$ is the overnight return of the portfolio P, $Rf_{P,t}$ is the risk-free rate, and $FF5_{P,t}$ is the Fama–French five-factor.

Next, we turn to Fama and MacBeth, (1973) regressions to test the cross section of overnight (or intraday) expected return. Based on the works of Dai and Zhu, (2020, 2022), our corresponding Fama–MacBeth regression model is as follows:

$$\begin{aligned} overnightR_{i,t+1} - Rf_{i,t+1} = \alpha_0 + b_1 ESG_{score\, i,t} + b_2 Size_{i,t} + b_3 BM_{i,t} \\ + b_4 Illiquidity_{i,t} + b_5 Turnover_{i,t} \\ + \varepsilon_{i,t}, \end{aligned} \tag{6}$$

where for each stock i, $OvernightR_{i,t+1}$ is the overnight return, $ESG_{score\, i,t}$ is the ESG score, and four firm characteristics are the control variables: market capitalization ($Size_{i,t}$), book-to-market ratio ($BM_{i,t}$), Amihud illiquidity ($Illiquidity_{i,t}$), and turnover ($Turnover_{i,t}$).

Finally, we conduct mechanism tests by conditional two-dimensional portfolio analysis based on the ESG score and the firm characteristics, including market capitalization (Size), book-to-market (BM), and illiquidity of the stocks. Specifically, at the beginning of each year, we first divide stocks into five subsamples based on size, BM, and illiquidity, respectively. Then, in each size or BM or illiquidity subsample, stocks are sorted into quintiles based on their lagged ESG score over the past 1 year.

It is worth noting that we only report the empirical results of the overnight return for the following two reasons: first, the coefficient on intraday return is statistically insignificant in Fama–Macbeth regression. Second, there is no abnormal long–short ESG intraday return: Fama–French five-factor alpha is insignificant.

Environmental, Social, and Governance and Overnight Return: Portfolio Sort

In this section, we first utilize the portfolio analysis to explore whether the ESG score is mispriced. The results are based on value-weighted portfolios. Columns 1–3 of **Table 2** show that the trading portfolios that go long the top ESG score quintile and go short the bottom ESG score quintile could generate statistically

TABLE 3 | ESG and overnight return: Fama–MacBeth regression.

	M1	M2	M3	M4
ESG_{score}	−0.003***			
	(−4.43)			
E_{score}		−0.003***		
		(−3.03)		
S_{score}			−0.001***	
			(−5.59)	
G_{score}				0.000
				(0.12)
Size	0.023***	0.023***	0.020***	0.016***
	(4.15)	(4.04)	(3.85)	(3.38)
BM	0.024	0.024	0.017	0.011
	(0.90)	(0.96)	(0.65)	(0.39)
Turnover	−0.006	−0.006	−0.007	−0.007
	(−1.52)	(−1.50)	(−1.54)	(−1.59)
Illiquidity	−0.950***	−0.930***	−0.992***	−1.012***
	(−4.02)	(−3.85)	(−4.08)	(−4.22)
Intercept	−0.492***	−0.525***	−0.458***	−0.433***
	(−5.57)	(−5.65)	(−5.22)	(−5.52)
Observations	2,677	2,677	2,677	2,677
R2	9.5%	9.6%	9.4%	9.2%

This table shows Fama–MacBeth regression of yearly overnight excess stock returns on ESG score (or E-score or S-score or G-score). The key variables include environmental, social, and governance score (ESG_{score}*), environmental score (*E_{score}*), social score (*S_{score}*), and governance score (*G_{score}*). The control variables are as follows: yearly* Turnover, Size *(market capitalization),* BM *(book-to-market ratio), and Amihud (2002)* illiquidity*. The* t*-statistics reported in parentheses are based on Newey–West standard errors. The panel shows time-series averages of the estimated slope coefficients from the regression.* R^2 *is the time-series average of adjusted R-square in the cross-sectional regression. The sample period is from 2011 to 2019.*

significant positive yearly positive raw overnight return (0.0377, t-statistics of 3.58), Fama–French three-factor overnight alpha (0.0377, t-statistics of 8.41), and Fama–French five-factor overnight alpha (0.0699, t-statistics of 5.70), respectively. This result represents that the higher the ESG score, the lower the expected overnight return. We explain this result from the view of China's unique "T+1" trading rule and investors' taste of ESG. First, Qiao and Dam, (2020) asserted that the "T+1" trading rule prohibits traders from selling the shares they bought on the same day. This restriction leads to a discount on daily opening prices, thus inducing negative overnight return, which could be understood as the illiquidity discount on asset prices (Bian and Sun, 2010). In addition, Pástor et al. (2021a) presented that ESG investors enjoy an "investor surplus": they sacrifice

TABLE 4 | ESG and overnight return: conditional double-sorted portfolio analysis.

Panel A: Double-sorted portfolios based on *Size* and *ESG_{score}*

	Small size	***2***	***3***	***4***	***Large size***
Low ESG$_{score}$	−0.2668***	−0.2819***	−0.1765***	−0.1379***	−0.0732***
2	−0.2647***	−0.2063***	−0.1258***	−0.1121**	−0.0813***
3	−0.2417***	−0.1889***	−0.1371***	−0.1242***	−0.1401***
4	−0.2429***	−0.2187***	−0.2193***	−0.1283***	−0.1143***
*High ESG*score	−0.2535***	−0.2055***	−0.1472***	−0.1589***	−0.1428**
High–low	−0.0073	0.0559**	0.0088	−0.0416	−0.0902**
	(−0.79)	(2.50)	(1.17)	(−1.45)	(−2.38)

Panel B: Double-sorted portfolios based on *BM* and *ESG*$_{score}$

	Low BM	*2*	*3*	*4*	*High BM*
Low ESG$_{score}$	−0.2597***	−0.2378***	−0.2181***	−0.2094***	−0.1101***
2	−0.2362***	−0.1728***	−0.1644***	−0.1936***	−0.0777
3	−0.1729***	−0.1148*	−0.1642***	−0.1969***	−0.1675***
4	−0.1649***	−0.1636***	−0.2028***	−0.184***	−0.0929***
High ESG$_{score}$	−0.2323***	−0.1907***	−0.1363***	−0.1289***	−0.1253***
High–low	0.0068	0.0266	0.0612*	0.0600***	−0.0357*
	(0.64)	(0.85)	(1.86)	(6.60)	(−1.95)

Panel C: Double-sorted portfolios based on *Illiquidity* and *ESG*$_{score}$

	Low illiquidity	*2*	*3*	*4*	*High illiquidity*
Low ESG$_{score}$	−0.1214***	−0.1883***	−0.2084***	−0.1785***	−0.2594***
2	−0.1032***	−0.1254***	−0.1350***	−0.2336***	−0.2280***
3	−0.1093***	−0.1507***	−0.0995***	−0.1557***	−0.2241***
4	−0.1240***	−0.1607***	−0.1974***	−0.2501***	−0.2019***
High ESG$_{score}$	−0.1329**	−0.1924***	−0.1301***	−0.1818***	−0.2239***
High–low	−0.0320**	−0.0247***	0.0577***	−0.0238*	0.0150
	(−2.37)	(−2.90)	(3.21)	(−1.75)	(0.47)

*This table reports Fama–French five-factor risk-adjusted portfolio alphas of double-sorted portfolios. Panel A shows Fama–French five-factor risk-adjusted portfolio alphas of double-sorted portfolios sorted yearly first by prior-year market capitalization (*Size*) and then by prior-year* ESG$_{score}$*. Panel B shows Fama–French five-factor risk-adjusted portfolio alphas of double-sorted portfolios sorted yearly first by the prior-year book-to-market ratio (*BM*) and then by prior-year* ESG$_{score}$*. Panel C shows Fama–French five-factor risk-adjusted portfolio alphas of double-sorted portfolios sorted yearly first by prior-year Amihud (2002) illiquidity (*Illiquidity*) and then by prior-year* ESG$_{score}$*. The differences in average excess return, three-factor alphas, and five-factor alphas between high and low portfolios are also reported, along with* t*-statistic in parentheses. The* t*-statistics reported in parentheses are based on Newey–West standard errors. The sample period is from 2011 to 2019.*

TABLE 5 | Descriptive statistics.

Variable	**Mean**	**STD**	**5%**	**Median**	**95%**	**Observation**
Panel A: Green stock subsample						
ESG_{score}	29.32	6.34	22.73	26.45	43.26	907
E_{score}	18.85	8.89	9.30	15.50	38.76	907
S_{score}	34.26	9.63	22.81	31.58	54.60	907
G_{score}	48.10	5.24	39.29	48.21	57.14	907
$R_{overnight}$	−0.18	0.21	−0.51	-0.19	0.19	907
$R_{intraday}$	0.39	0.64	−0.29	0.21	1.62	907
Panel B: Sin stock subsample						
ESG_{score}	17.12	1.89	13.22	17.36	19.42	960
E_{score}	6.06	2.72	2.33	6.98	10.08	960
S_{score}	19.81	5.05	12.28	22.81	28.07	960
G_{score}	40.84	3.89	33.93	39.29	48.21	960
$R_{overnight}$	−0.21	0.23	−0.55	−0.23	0.17	960
$R_{intraday}$	0.44	0.73	−0.28	0.25	1.86	960

This table presents the descriptive statistics of main variables for the green stock subsample and the sin stock subsample. The sample period is from 2011 to 2019. The main variables are environmental, social, and governance score (ESG_{score}*), environmental score (*E_{score}*), social score (*S_{score}*), governance score (*G_{score}*), yearly overnight return (*$R_{overnight}$*), and intraday return (*$R_{intraday}$*). The descriptive statistics includes the number of observations, mean, standard deviation (STD), median, and the percentile (5 and 95%) and quartile (25 and 75%) distributions of the variables.*

less return than they are willing to in order to hold their desired ESG portfolio. Consequently, we can expect that compared with non-ESG investors, ESG investors do not mind accepting lower liquidity discount, leading to a positive ESG–overnight alpha. In fact, in the next section, we find that illiquidity plays an important role in the sign of ESG–overnight alpha relation.

Environmental, Social, and Governance and Overnight Return: Fama–MacBeth Regressions

Compared to the portfolio sorts, which is a nonparametric method to investigate the relationship between a characteristic and the cross section of average overnight returns with difficulty in controlling for more other characteristics, Fama and MacBeth, (1973) regression is better to avoid measuring problematic partial effects. Columns 1–4 of **Table 3** present the following four Fama–MacBeth regressions forecasting the cross section of overnight return with ESG score and its components E, S, and G. The control variables are the same in the four respective regressions, which are size, book-to-market ratio, illiquidity, and turnover. The results in **Table 3** show that the coefficient of the

TABLE 6 | ESG and overnight return: Fama–MacBeth regression for green stock subsample.

	M1	M2	M3	M4
ESG_{score}	−0.003*			
	(−1.67)			
E_{score}		−0.003***		
		(−2.72)		
S_{score}			−0.000	
			(−0.33)	
G_{score}				−0.000
				(−0.03)
Size	0.001	−0.003	−0.007	−0.005
	(0.07)	(−0.25)	(−0.57)	(−0.47)
BM	0.071**	0.067*	0.054	0.056
	(2.01)	(1.76)	(1.40)	(1.43)
Turnover	−0.007	−0.008	−0.008	−0.006
	(−1.27)	(−1.64)	(−1.45)	(−1.26)
Illiquidity	−1.394**	−1.545***	−1.602**	−1.467***
	(−2.51)	(−2.77)	(−2.39)	(−2.72)
Observations	705	705	705	705
R^2	4.4%	5.6%	4.7%	4.8%

This table shows Fama–MacBeth regression of yearly overnight excess stock returns on lagged firm characteristics. The dependent variable is the overnight excess return in the following year. The key variables include environmental, social, and governance score (ESG_{score}*), environmental score (*E_{score}*), social score (*S_{score}*), and governance score (*G_{score}*). The control variables are as follows:* Turnover *is yearly turnover,* Size *is market capitalization,* BM *is the book-to-market ratio, and* Illiquidity *is Amihud (2002) illiquidity. We divide all stocks into two subsamples, green stocks and sin stocks, based on* ESG_{score}*. These subsamples are composed of the top 30% and bottom 30% stocks sorted by* ESG_{score}*. The* t*-statistics reported in parentheses are based on Newey–West standard errors. The panel shows time-series averages of the estimated slope coefficients from the regression.* R^2 *is the time-series average of adjusted R-square in the cross-sectional regression. The sample period is 2011-2019.*

ESG score is statistically significantly negative, −0.003 (*t*-statistics of −4.43), demonstrating that the firms with higher ESG score will experience a lower expected overnight return. In other words, ESG negatively affects the overnight return, which means investors are willing to accept lower overnight returns for more responsible stocks.

In addition, for other control variables, size is significantly positive (0.023, *t*-statistics of 4.15), indicating that the bigger the size of the firm, the larger the overnight return will be, that is, the opening price of the current day is less discounted than the closing price of the previous day for those larger stocks. The coefficient of BM is positive as well, although statistically insignificant. Meanwhile, the illiquidity is significantly negative (−0.950, *t*-statistics of −4.02), which means that the worse the liquidity, the smaller the overnight return, which is consistent with prior work by Qian and Dam, (2020) which confirms that the unique T+1 trading rule in the Chinese stock market would induce liquidity discount of the overnight return.

Finally, the components of ESG score, E score, and S score are statistically significantly negative as well, −0.003 (*t*-statistics of −3.03) and −0.001 (*t*-statistics of −5.59), respectively, while the coefficient of G-score is insignificantly positive.

To conclude, first, the results of Fama–MacBeth regressions parallel the findings of Pedersen et al. (2021a); they found that the investor demand appears stronger for E, S, and overall ESG score, which could explain the high valuations of stocks that score well on these metrics and the low returns. In addition, it seems that we reach an opposite result with the portfolio analysis and Fama–MacBeth regression. Therefore, in **Section 5**, we will implement the mechanism analysis by classifying two-dimension portfolio sorts based on the ESG score and firm characteristics.

MECHANISM ANALYSIS

In this section, we turn to double-sort portfolio analysis based on three firm characteristics (i.e., stock market capitalization, book-to-market ratio, and illiquidity) and the ESG to reexamine the cross-section expected overnight return. Panels A–C of **Table 4** report the following three double-sort portfolio analyses: a zero-costing trading strategy obtaining abnormal overnight return based on ESG and size, book-to-market ratio, and Amihud illiquidity measures, respectively.

Panel A of **Table 4** presents that the spreads in yearly Fama–French five-factor overnight returns between the top and bottom quintiles become statistically significantly negative (−0.0902, *t*-statistic −2.38) for the biggest size combinations. That is, the positive overnight return is pervasive of the small-median size firms, while it experiences a sharp reversal for big size firms. Overall, size plays a big role in the sign of the abnormal overnight alpha, that is, for big size firms, a contrarian strategy by going long (short) the bottom (top) ESG would earn positive profits, which is consistent with the result of Fama–MacBeth regression.

Similarly, Panel B of **Table 4** presents that the spreads in yearly Fama–French five-factor overnight returns between the top and bottom quintiles become statistically significantly negative (−0.0357, *t*-statistic −1.95) for the highest book-to-market (BM) combinations, while the spreads only remain significantly positive for the median BM quintiles and insignificantly positive for the lowest two BM. That is, the positive overnight return is pervasive of the small-median BM firms, and it experiences a sharp reversal for highest growth-type firms. Overall, the book-to-market ratio also plays a big role in the sign of the abnormal overnight alpha, that is, for top BM growth-type stocks, a contrarian strategy by going long (short) the bottom (top) ESG would earn positive profits.

Finally, Panel C of **Table 4** presents that the spreads in yearly Fama–French five-factor overnight returns between the top and bottom quintiles become statistically significantly negative for the least four illiquidity combinations, while the spread is only insignificantly positive for the most illiquidity quintile. That is, the one-dimensional trading strategy of positive overnight return experiences a sharp reversal for the liquidity stocks. Overall, liquidity also plays a big role in the sign of the abnormal overnight alpha, that is, a contrarian strategy by going long (short) the bottom (top) ESG would earn positive profits.

To conclude, Size, BM, and liquidity play a big role in the sign of the abnormal overnight alpha, which is consistent with the result of Fama–MacBeth regression.

THE IMPLICATION OF ENVIRONMENTAL, SOCIAL, AND GOVERNANCE PRICING

We implement the ESG pricing implication on green stock subsample and sin stock subsample through the portfolio sort and Fama and MacBeth (1973) regressions. Green (Sin) stock subsample are those stocks with ESG scores in the top (bottom) 30%.

Table 5 presents that, compared with sin stock subsample, the mean of ESG score and its components (E-score, S-score, and G-score) are much larger for the green stock subsample. In addition, the average overnight return and intraday return for both green and sin stock subsamples are negative (−0.18 vs. −0.21) and positive (0.39 vs. 0.44), respectively, preliminarily verifying the rationality of featuring the link of investor heterogeneity to the persistence of the overnight and intraday components of returns.

For both sin and green stock subsamples, we only report the results of the overnight return for the following two reasons: first, the coefficients of intraday return are statistically insignificant in Fama and MacBeth, (1973) regressions. Second, Fama–French five-factor ESG score–intraday alphas generated by the trading strategies are insignificant as well.

As seen in column 1 of **Table 6**, for green stock subsample, the coefficient of the ESG score is statistically significantly negative, −0.003, with an associated t-statistics of −1.67. In addition, the coefficient of the E-score is −0.003 (t-statistics of −2.72). These results demonstrate that the firms with higher ESG scores will experience a lower expected overnight return. For other control variables, the coefficient of illiquidity is significantly negative, which is consistent with prior work by Qiao and Dam, (2020) who confirmed that the unique T+1 trading rule would induce liquidity discount of the overnight return.

To summarize, the result parallels that of Pástor et al. (2021a), who argued that preference for holding green stocks negatively affects prices. However, for the sin stock subsample, we find that the coefficients of the ESG score are not statistically significant. Due to space limit, we do not add the tables which report the Fama and MacBeth, (1973) regression and double-sort portfolio analysis for sin stocks.

Next, we turn to a five-by-five conditional double sort based on three firms' characteristics and the ESG. For green stock subsample, Panel A of **Table 7** reports yearly Fama–French five-factor overnight returns for a five-by-five conditional double-sort strategy. Interestingly, we find that the one-

TABLE 7 | ESG and overnight return: conditional double-sorted portfolio analysis for green stock subsample.

Panel A: Double-sorted portfolios based on *Size* and ESG_{score}

	Small size	*2*	*3*	*4*	*Large size*
Low ESG_{score}	−0.2318***	−0.1259***	−0.1174***	−0.1593***	−0.0969***
2	−0.1079***	−0.2249***	−0.1250***	−0.0758*	−0.1727***
3	−0.1752***	−0.1234***	−0.2357***	−0.0747	−0.0532
4	−0.1243***	−0.2224***	−0.1976***	−0.1253***	−0.1794**
High ESG_{score}	−0.2968***	−0.2040***	−0.0582	−0.1839***	−0.2333*
High–low	−0.0856**	−0.1006***	0.0393	−0.0473***	−0.1659**
	(−2.22)	(−3.63)	(0.66)	(−3.75)	(−2.32)

Panel B: Double-sorted portfolios based on *BM* and ESG_{score}

	Low BM	*2*	*3*	*4*	*High BM*
Low ESG_{score}	−0.1901***	−0.1289***	−0.085**	−0.1551***	−0.1108***
2	−0.2124***	−0.2628***	−0.1134**	−0.1191***	−0.0493
3	−0.3106***	−0.1544***	−0.0545**	−0.0589*	−0.1511***
4	−0.2148***	−0.2476***	−0.1903***	−0.0482	−0.1008*
High ESG_{score}	−0.2300***	−0.1530**	−0.1295***	−0.2057**	−0.1078***
High–low	−0.0604	−0.0446	−0.0651	−0.0712	−0.0176
	(−1.02)	(−0.81)	(−0.90)	(−0.68)	(−0.61)

Panel C: Double-sorted portfolios based on *Illiquidity* and ESG_{score}

	Low illiquidity	*2*	*3*	*4*	*High illiquidity*
Low ESG_{score}	−0.1293***	−0.1428***	−0.1019	−0.1773***	−0.1481***
2	−0.1833***	−0.1205***	−0.1886***	−0.2247***	−0.1469***
3	−0.1982***	−0.0295	−0.2227***	−0.0447**	−0.2432***
4	−0.1418***	−0.1424***	−0.0425	−0.2062***	−0.1310***
High ESG_{score}	−0.1334	−0.1055	−0.1200***	−0.2246***	−0.2794***
High–low	−0.0247	0.0198	−0.0387	−0.0684***	−0.1518***
	(−0.27)	(0.67)	(−0.88)	(−2.83)	(−4.39)

This table reports Fama–French five-factor risk-adjusted portfolio alphas of double-sorted portfolios. Panel A shows Fama–French five-factor risk-adjusted portfolio alphas of double-sorted portfolios sorted yearly first by prior-year market capitalization (Size) and then by prior-year ESG_{score}. Panel B shows Fama–French five-factor risk-adjusted portfolio alphas of double-sorted portfolios sorted yearly first by the prior-year book-to-market ratio (BM) and then by prior-year ESG_{score}. Panel C shows Fama–French five-factor risk-adjusted portfolio alphas of double-sorted portfolios sorted yearly first by prior-year Amihud (2002) illiquidity (Illiquidity) and then by prior-year ESG_{score}. The differences in average excess return, three-factor alphas, and five-factor alphas between the high and the low portfolios are also reported, along with t-statistic in parentheses. We divide all stocks into two subsamples, green stocks and sin stocks, based on ESG_{score}. These subsamples are composed of the top 30% and bottom 30% stocks sorted by ESG_{score}. The t-statistics reported in parentheses are based on Newey–West standard errors. The sample period is from 2011 to 2019.

dimensional trading strategy of positive overnight return is pervasive in the median-sized firms and experiences a sharp reversal for other size firms. Overall, size plays a big role in the sign of the abnormal overnight alpha, which is consistent with the result of Fama–MacBeth regression. In addition, for sin stock subsample, we find that the spreads become significantly positive for the biggest size quintile and remains negative for the median and the fourth size quintile.

Panel B of **Table 7** presents the book-to-market ratio, which also plays a role in the sign of the abnormal overnight alpha to some extent for green stocks. In addition, for sin stock subsample, we find that the spreads become significantly positive for the highest BM quintile and remains negative for the second and the median BM quintile.

At last, Panel C of **Table 7** shows that the one-dimensional trading strategy of positive overnight return experiences a sharp reversal for the liquidity stocks. Overall, liquidity also plays a big role in the sign of the abnormal overnight alpha, which is consistent with the result of Fama–MacBeth regression. In addition, for sin stock subsample, we find that the spreads become significantly positive for the least illiquidity quintile and remains negative for the other four illiquidity quintiles.

To summarize, these results confirm that, on the one hand, the size and liquidity are likely to drive the pricing of the ESG for the green stock subsample, and on the other hand, the ESG score is not a pricing factor for the sin stock subsample, and it is the green stocks that contribute to the overnight premium of the ESG score.

CONCLUSION

Whether the price of stocks considering the ESG score has efficiently reflected the market information involves important implications for asset pricing of green finance and carbon finance. While financial economists have long studied the profitability of trading strategies based on the close-to-close return and devoted to the pricing of ESG stocks, we investigate the pricing of ESG based on the relation between ESG score and expected overnight and intraday components of returns in the Chinese stock market.

Our Fama and MacBeth, (1973) cross-sectional regressions present that the coefficient of ESG score is statistically significantly negative, demonstrating that the firms with higher ESG scores will experience a lower expected overnight return. Consistently, conditional double-sort portfolio analysis based on the stock characteristics and ESG score confirms that the contrarian strategies long (short) the bottom (top) ESG would generate five-factor overnight profits per year for the biggest size quintile, the highest book-to-market quintile, and the liquidity quintile. To conclude, the firm characteristics are likely to drive the pricing of the ESG.

In addition, we reexamine the ESG pricing for green stock subsample and sin stock subsample. Overall, the results confirm that the ESG score is not a pricing factor for the sin stock subsample, and it is the green stocks that contribute to the overnight premium of the ESG score. Our mechanism analysis shows that size and illiquidity play a big role in the signs of the abnormal overnight alpha, which indicates that responsible investing may lead some corporates to become greener, and in the long run, ESG investors can also make profits.

Our study has implications of the asset pricing of responsible investing. Specifically, we empirically verify that a stock's environment, social, and governance (ESG) score is beneficial to affecting investor preferences and show the feasibility of responsible investing by using ESG in investing. The main challenge of ESG lies in the absence of a reliable measure of the true ESG performance. We find the ESG scores of the Chinese A-shares stocks are different in different databases, and the database providers do not publish their calculation standards, so we need to cope with incomplete and opaque ESG data. In the future, we can employ the standard deviation of ESG scores from several providers as a proxy for ESG uncertainty and examine the cross-sectional ESG uncertainty–overnight (intraday) alpha relation.

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: XL and YC; Methodology: XL and CY; Software: CY and XL; Validation: XL, CY, and YC; Formal analysis: XL and YC; Investigation: CY and YC; Resources: XL and YC; Data Curation: CY; Writing—Original Draft: XL, CY, and YC; Writing—Review and Editing: XL, YC, and CY; Visualization: CY; Supervision: XL and YC; Project administration: XL and YC; and Funding acquisition: XL.

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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.2022.927420/full#supplementary-material

REFERENCES

Aboody, D., Even-Tov, O., Lehavy, R., and Trueman, B. (2018). Overnight Returns and Firm-specific Investor Sentiment. *J. Financ. Quant. Anal.* 53 (2), 485–505. doi:10.1017/s0022109017000989

Amihud, Y. (2002). Illiquidity and Stock Returns: Cross-Section and Time-Series Effects. *J. Financial Mark.* 5 (1), 31–56. doi:10.1016/s1386-4181(01)00024-6

Avramov, D., Cheng, S., Lioui, A., and Tarelli, A. (2021). Sustainable Investing with ESG Rating Uncertainty. *J. Financial Econ.*.2021. 1. doi:10.1016/j.jfineco.2021.09.009

Avramov, D., and Chordia, T. (2006). Asset Pricing Models and Financial Market Anomalies. *Rev. Financ. Stud.* 19 (3), 1001–1040. doi:10.1093/rfs/hhj025

Barardehi, Y. H., Bernhardt, D., Ruchti, T. G., and Weidenmier, M. (2021). The Night and Day of Amihud's (2002) Liquidity Measure. *Rev. Asset Pricing Stud.* 11 (2), 269–308. doi:10.1093/rapstu/raaa022

Barber, B. M., Morse, A., and Yasuda, A. (2021). Impact Investing. *J. Financial Econ.* 139 (1), 162–185. doi:10.1016/j.jfineco.2020.07.008

Bauer, R., Ruof, T., and Smeets, P. (2021). Get Real! Individuals Prefer More Sustainable Investments. *Rev. Financial Stud.* 34 (8), 3976–4043. doi:10.1093/rfs/hhab037

Bian, J. Z., and Su, T. (2010). The T+1 Trading Rule and the Chinese Warrant Market Premium. *J. Financial Res.* 2010, 143–161. (in Chinese).

Bogousslavsky, V. (2021). The Cross-Section of Intraday and Overnight Returns. *J. Financial Econ.* 141 (1), 172–194. doi:10.1016/j.jfineco.2020.07.020

Boudoukh, J., Feldman, R., Kogan, S., and Richardson, M. (2019). Information, Trading, and Volatility: Evidence from Firm-specific News. *Rev. Financial Stud.* 32 (3), 992–1033. doi:10.1093/rfs/hhy083

Cao, J., Wen, F., and Eugene Stanley, H. (2021). Measuring the Systemic Risk in Indirect Financial Networks. *Eur. J. Finance* 2021, 1–46. doi:10.1080/1351847x.2021.1958244

Cao, J., Wen, F., Stanley, H. E., and Wang, X. (2021). Multilayer Financial Networks and Systemic Importance: Evidence from China. *Int. Rev. Financial Analysis* 78, 101882. doi:10.1016/j.irfa.2021.101882

Cao, J., Wen, F., Zhang, Y., Yin, Z., and Zhang, Y. (2021). Idiosyncratic Volatility and Stock Price Crash Risk: Evidence from China. *Finance Res. Lett.* 2021, 102095.

Chen, R., Wang, Z., Yang, L., Ng, C. T., and Cheng, T. C. E. (2022). A Study on Operational Risk and Credit Portfolio Risk Estimation Using Data Analytics*. *Decis. Sci.* 53 (1), 84–123. doi:10.1111/deci.12473

Chen, R., Xu, G., Xu, F., Jin, C., and Yu, J. (2022). A Clientele Effect in Online Lending Markets: Evidence from the Comovement between Investor Sentiment and Online Lending Rates. *J. Int. Financial Mark. Institutions Money* 76, 101461. doi:10.1016/j.intfin.2021.101461

Constantinides, G. M., and Duffie, D. (1996). Asset Pricing with Heterogeneous Consumers. *J. Political Econ.* 104 (2), 219–240. doi:10.1086/262023

Dai, Z., Kang, J., and Wen, F. (2021). Predicting Stock Returns: a Risk Measurement Perspective. *Int. Rev. Financial Analysis* 74, 101676. doi:10.1016/j.irfa.2021.101676

Dai, Z., Zhou, H., Kang, J., and Wen, F. (2021). The Skewness of Oil Price Returns and Equity Premium Predictability. *Energy Econ.* 94, 105069. doi:10.1016/j.eneco.2020.105069

Dai, Z., and Zhu, H. (2020). Forecasting Stock Market Returns by Combining Sum-Of-The-Parts and Ensemble Empirical Mode Decomposition. *Appl. Econ.* 52 (21), 2309–2323. doi:10.1080/00036846.2019.1688244

Dai, Z., Zhu, H., and Zhang, X. (2022). Dynamic Spillover Effects and Portfolio Strategies between Crude Oil, Gold and Chinese Stock Markets Related to New Energy Vehicle. *Energy Econ.* 109, 105959. doi:10.1016/j.eneco.2022.105959

Fama, E. F., and French, K. R. (2015). A Five-Factor Asset Pricing Model. *J. Financial Econ.* 116 (1), 1–22. doi:10.1016/j.jfineco.2014.10.010

Fama, E. F., and French, K. R. (2007). Disagreement, Tastes, and Asset Prices. *J. Financial Econ.* 83 (3), 667–689. doi:10.1016/j.jfineco.2006.01.003

Fama, E. F., and MacBeth, J. D. (1973). Risk, Return, and Equilibrium: Empirical Tests. *J. Political Econ.* 81 (3), 607–636. doi:10.1086/260061

Gibson Brandon, R., Krueger, P., and Schmidt, P. S. (2021). ESG Rating Disagreement and Stock Returns. *Financial Analysts J.* 77 (4), 104–127. doi:10.1080/0015198x.2021.1963186

Gokmenoglu, K., Eren, B. M., Eren, B. M., and Hesami, S. (2021). Exchange Rates and Stock Markets in Emerging Economies: New Evidence Using the Quantile-On-Quantile Approach. *Quantitative Finance Econ.* 5 (1), 94–110. doi:10.3934/qfe.2021005

Harrison, J. M., and Kreps, D. M. (1978). Speculative Investor Behavior in a Stock Market with Heterogeneous Expectations. *Q. J. Econ.* 92 (2), 323–336. doi:10.2307/1884166

Hartzmark, S. M., and Sussman, A. B. (2019). Do investors Value Sustainability? A Natural Experiment Examining Ranking and Fund Flows. *J. Finance* 74 (6), 2789–2837. doi:10.1111/jofi.12841

Hong, H., and Kacperczyk, M. (2009). The Price of Sin: The Effects of Social Norms on Markets. *J. Financial Econ.* 93 (1), 15–36. doi:10.1016/j.jfineco.2008.09.001

Hou, K., Xue, C., and Zhang, L. (2020). Replicating Anomalies. *Rev. Financial Stud.* 33 (5), 2019–2133. doi:10.1093/rfs/hhy131

Jacobs, H. (2015). What Explains the Dynamics of 100 Anomalies? *J. Bank. Finance* 57, 65–85. doi:10.1016/j.jbankfin.2015.03.006

Li, Z., Tian, M., Ouyang, G., and Wen, F. (2021). Relationship between Investor Sentiment and Earnings News in High and Low Sentiment Periods. *Int. J. Fin. Econ.* 26 (2), 2748–2765. doi:10.1002/ijfe.1931

Liow, K. H., Song, J., Song, J., and Zhou, X. (2021). Volatility Connectedness and Market Dependence across Major Financial Markets in China Economy. *Quantitative Finance Econ.* 5 (3), 397–420. doi:10.3934/qfe.2021018

Lou, D., Polk, C., and Skouras, S. (2019). A Tug of War: Overnight versus Intraday Expected Returns. *J. Financial Econ.* 134 (1), 192–213. doi:10.1016/j.jfineco.2019.03.011

Pástor, L., Stambaugh, R. F., and Taylor, L. A. (2021b). Dissecting Green Returns. *Work. Pap.* 2021, 58.

Pástor, L., Stambaugh, R. F., and Taylor, L. A. (2021a). Sustainable Investing in Equilibrium. *J. Financial Econ.* 142 (2), 550–571.

Pedersen, L. H., Fitzgibbons, S., and Pomorski, L. (2021). Responsible Investing: The ESG-Efficient Frontier. *J. Financial Econ.* 142 (2), 572–597. doi:10.1016/j.jfineco.2020.11.001

Qiao, K., and Dam, L. (2020). The Overnight Return Puzzle and the "T+1" Trading Rule in Chinese Stock Markets. *J. Financial Mark.* 50, 100534. doi:10.1016/j.finmar.2020.100534

Ren, X., Duan, K., Tao, L., Shi, Y., and Yan, C. (2022). Carbon Prices Forecasting in Quantiles. *Energy Econ.* 108, 105862. doi:10.1016/j.eneco.2022.105862

Ren, X., Li, Y., Shahbaz, M., Dong, K., and Lu, Z. (2022). Climate Risk and Corporate Environmental Performance: Empirical Evidence from China. *Sustain. Prod. Consum.* 30, 467–477. doi:10.1016/j.spc.2021.12.023

Ren, X., Tong, Z., Sun, X., and Yan, C. (2022). Dynamic Impacts of Energy Consumption on Economic Growth in China: Evidence from a Non-parametric Panel Data Model. *Energy Econ.* 107, 105855. doi:10.1016/j.eneco.2022.105855

Sikiru, A. A., Salisu, A. A., and Salisu, A. A. (2021). Hedging with Financial Innovations in the Asia-Pacific Markets during the COVID-19 Pandemic: the Role of Precious Metals. *Quantitative Finance Econ.* 5 (2), 352–372. doi:10.3934/qfe.2021016

Sloan, R. G. (1996). Do stock Prices Fully Reflect Information in Accruals and Cash Flows about Future Earnings? *Account. Rev.* 1996, 289–315.

Umutlu, M., and Bengitoz, P. (2020). Return Range and the Cross-Section of Expected Index Returns in International Stock Markets. *Quantitative Finance Econ.* 5 (3), 421–451.

Wen, F., Cao, J., Liu, Z., and Wang, X. (2021). Dynamic Volatility Spillovers and Investment Strategies between the Chinese Stock Market and Commodity Markets. *Int. Rev. Financial Analysis* 76, 101772. doi:10.1016/j.irfa.2021.101772

Wen, F., Li, C., Sha, H., and Shao, L. (2021). How Does Economic Policy Uncertainty Affect Corporate Risk-Taking? Evidence from China. *Finance Res. Lett.* 41, 101840. doi:10.1016/j.frl.2020.101840

Wen, F., Liu, Z., Cao, J., Zhang, Y., and Yin, Z. (2021). Mood Seasonality: Evidence from the Chinese A-Share Market. *Finance Res. Lett.* 2021, 102232.

Wen, F., Yuan, Y., and Zhou, W. X. (2021). Cross-shareholding Networks and Stock Price Synchronicity: Evidence from China. *Int. J. Fin. Econ.* 26 (1), 914–948. doi:10.1002/ijfe.1828

Wen, F., Zhang, K., and Gong, X. (2021). The Effects of Oil Price Shocks on Inflation in the G7 Countries. *North Am. J. Econ. Finance* 57, 101391. doi:10.1016/j.najef.2021.101391

Wen, F., Zou, Q., and Wang, X. (2021). The Contrarian Strategy of Institutional Investors in Chinese Stock Market. *Finance Res. Lett.* 41, 101845. doi:10.1016/j.frl.2020.101845

Xiao, J., Wen, F., Zhao, Y., and Wang, X. (2021). The Role of US Implied Volatility Index in Forecasting Chinese Stock Market Volatility: Evidence from HAR Models. *Int. Rev. Econ. Finance* 74, 311–333. doi:10.1016/j.iref.2021.03.010

Zheng, Y., Zhou, M., and Wen, F. (2021). Asymmetric Effects of Oil Shocks on Carbon Allowance Price: Evidence from China. *Energy Econ.* 97, 105183. doi:10.1016/j.eneco.2021.105183

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Tax Policies of Low Carbon in China: Effectiveness Evaluation, System Design and Prospects

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Fiscal and taxation policy tools play an important role in promoting green and low-carbon development. Based on classical tax theory, including the Potter hypothesis and the environmental Kuznets curve, this paper explores the impact of environmental tax regulation on economic growth and carbon emission reduction. We find that resource tax reform could promote green total factor productivity; however, the ad valorem reform of resource tax does not significantly raise the level of low carbon development. This effect varies among different regions as well as different tax cuts and fee reductions. Fiscal revenue decentralization has a reverse adjustment effect on the impact of resource taxes on green total factor productivity. We conclude that it is necessary to deepen the reform of the fiscal and taxation system to achieve the carbon neutrality and emission peak goal.

Keywords: carbon peak, carbon neutralization, tax reform, low carbon development, resource tax, green total factor productivity

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1 INTRODUCTION

The greenhouse effect represented by carbon dioxide emissions has led to global warming, melting glaciers, rising sea levels, frequent extreme weather and even land desertification, which directly threaten the survival of many species. The 1997 Kyoto Protocol provides for a shared obligation to reduce emissions between developed and developing countries under the principle of "common but differentiated responsibilities." The 2015 Paris Agreement proposes limiting the global average temperature increase to 2°C by the end of the century compared to the industrial era and working toward limiting warming to 1.5°C. In September 2020, President Xi proposed at the 75th session of the UN General Assembly that "China will adopt stronger policies and measures and CO_2 emissions' strive to peak by 2030 and work toward achieving carbon neutrality by 2060." In the process of promoting a green tax system, China's series of tax reforms have already played an important role, such as the change of resource tax from quantity-based to price-based, the introduction of environmental protection tax taking into account the positive incentives for high-quality development and the transformation and upgrading of high-energy-consuming industries, and the adjustment of consumption tax policies for large-emission small cars. A series of tax policy adjustments are constantly releasing positive signals to guide energy conservation and emission reduction. Therefore, to address the shortcomings of the current green tax reform in China and to find an optimal path, it is necessary to realize the vision of "peak carbon and carbon neutral" (hereinafter referred to as the "double carbon" vision) and to promote high-quality economic development, which is also the focus of this paper.

The concept of the "double dividend" was first formalised by Pearce (1991). The first dividend is that environmental taxation policies improve the environment; the second dividend is that environmental taxes improve the efficiency of the tax system and indirectly improve economic efficiency. The environmental Kuznets curve hypothesis suggests that there is an inverted U-shaped relationship between the trend of most pollutants and the trend of per capita national income, which means that the quality of the environment deteriorates with the increase in per capita income during industrialisation and is then treated and improved with a further increase in per capita income. The Porter hypothesis is that environmental regulation can raise the environmental awareness of firms to a certain extent and that firms will have a potential tendency to innovate technologically in the face of pressure from environmental regulation. A sound and effective environmental regulation policy instrument can stimulate technological innovation by firms, increasing productivity through the "innovation compensation effect" and compensating for the cost burden of environmental regulation.

The marginal contributions of this paper include the following: First, the "double dividend" effect of the "double carbon" vision adjustment tax is used as a research perspective to verify the "double dividend" effect and Porter's hypothesis in the context of China's low carbon tax policy. To enhance the contemporary characteristics of traditional theories, green total factor productivity is measured using CO_2 emissions as nondesired output, and the policy effects of resource taxes are tested through fixed effects models, taking full account of the individual characteristics of different low-carbon tax policies. Third, in the context of global warming and the realization of the "double carbon" vision, it is of practical significance to put forward suggestions on resource taxes and environmental protection taxes to improve the green tax system, promote the green transformation of industries and enhance the level of low-carbon development.

The remainder of this paper is organized as follows: **section 2** reviews the relevant literature and proposes our hypothesis; **section 3** introduces the data, variables and empirical methods; **section 4** presents our empirical results; and we conduct a further analysis in **section 5** and conclude in **section 6**.

2 LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 Literature Review

With the definition of the new development concept and the goal of high-quality economic development, the theme of "low carbon" is gradually concerned by more and more scholars, and the research direction and content are increasingly extensive. He et al. (2022a) based on the micro perspective, focused on the ESG performance of enterprises and its impact on enterprise investment risk and manager misconduct while fulfilling environmental responsibilities, and studied the regulatory effect of economic policy uncertainty and corporate social responsibility on Enterprise Green Innovation (He et al., 2020; He et al., 2022b; He et al., 2022c). Ren et al. (2022a) assessed the impact of climate risk on carbon emissions, focusing on the environmental performance of enterprises, and believed that climate risk would promote the carbon emissions of enterprises. In addition, scholars in the field of economics have also updated the measurement methods of indicators such as economic growth and economic development quality in the research process. One of the most important indicators is green total factor productivity (GTFP), which brings ecological and environmental factors into the assessment criteria of economic development quality and pursues the harmonious coexistence of economic growth and resources and the environment. For example, Xiao and You (2021) used the three-stage data envelopment analysis (DEA) method to calculate the green total factor productivity of 30 provinces in China and found that there were significant regional differences in China's green total factor productivity. Feng et al. (2021) also paid attention to the importance of environmental quality to the level of economic development. On the basis of studying the impact of environmental regulation policies on green total factor productivity, they put forward empirical evidence to improve green total factor productivity. In summary, the indicator of green total factor productivity has been widely used in research on the relationship between economic growth and the ecological environment. However, it is worth noting that although the measurement method of green total factor productivity is constantly improving, most scholars still use the emissions of three industrial wastes (waste water, waste gas and solid waste) as the unexpected output, and few scholars have introduced carbon dioxide emissions into the calculation of the model. That is, the "carbon" factor is not fully reflected due to the deficiency of the existing research.

The literature on the influencing factors of low carbon tax policies covers three main areas. First, in terms of the connotation and design of elements of low-carbon tax policy, Nordhaus (2017) define green low-carbon taxation as a tax credit granted to taxpayers who invest in pollution prevention or environmental protection, a tax levied on high-carbon-emitting industries or the use of excess carbon emission rights. Kuninori and Otaki (2016), based on the modified Ramsey optimal tax theory, suggest that carbon tax rates must be proportional to the per capita income and price elasticity of high-carbon products to achieve an effective intertemporal allocation of CO_2 emissions.

Second, in terms of the validation of classical low carbon taxation theory, the first is the "double dividend" effect, which Yuan and Zhang (2021) argue can be achieved by environmental regulation policies that can lead to economic growth and pollution reduction. From an economic perspective, Cao et al. (2021) conduct a multimodel comparison of a carbon tax policy in China and find substantial differences in the change in energy use and economic activity in response to a steadily rising carbon tax. However, there are important similarities. Oladosu and Rose (2007) analyses the local factor growth rate and industrial structure characteristics of the Susquehanna River and concludes that the short-term impact of a carbon tax on regional net output is very small, but the impact on the energy sector is significant. Hao and He (2022) think Green innovation is an important way for firms to achieve both economic benefits and environmental protection in the long term. From a social welfare perspective, Okonkwo (2021), using household survey data for the period 2009–2015, estimates the quadratic almost ideal demand system (QUAIDS) model to obtain elasticities and use them to simulate consumer responses to price changes resulting from carbon taxation. The paper argues that when there is a simultaneous increase in the prices of energy goods, the poorest and middle-income households disproportionately suffer a higher welfare loss compared to the richest households.

Berman and Bui. (2001) use data from the US oil industry and find that environmental supervision leads to an increase in firm productivity. Other scholars oppose Porter's hypothesis. For example, Duan et al. (2021) think thanks to the differences in energy sources and variability over their price distributions, the observed differential in carbon price-response is an indication of non-unique carbon market dynamics. Dension (1981) study of US data from 1972–1975 finds that an increase in the intensity of environmental supervision leads to a decrease in total factor productivity. Du et al. (2021) estimate the heterogeneous impacts of environmental regulation on green technology innovation and industrial structure in 105 Chinese environmental monitoring cities through partially linear functional-coefficient panel models. The results show that when the economic development levels are low, environmental regulation will restrain the development of green technology innovation but have insignificant impacts on the upgrading of industrial structure. Other scholars Rubashkina et al. (2015) examine the "weak" and "strong" versions of the Porter hypothesis using manufacturing in 17 European countries between 1997 and 2009.

Third, in terms of comparing low carbon tax policies with other environmental supervision policies, Pollitt et al. (2014) found that the carbon tax implemented in Japan in 2012 brought about a decline in GDP at the initial stage of reducing conventional energy use, but if combined with flexible adjustments in carbon market pricing and the rational use of related tax revenues, carbon emission reductions and long-term sustainable GDP growth could be achieved. In general, the combination of carbon tax and carbon emission trading framework is worth exploring, which requires us to pay attention to the research on carbon emission trading market while sorting out carbon tax policies. Ren et al. (2022b) used the quantile method to predict the carbon price, and studied the relationship between the carbon market and the green bond market Ren et al. (2022d). Dissou and Karnizova (2016) concludes that the impact of harmful pollution on households and businesses is direct, while carbon emissions are indirect, with no direct impact on economic growth and employment, making low carbon tax policies more effective than mandatory emission reduction measures.

2.2 Hypothesis Development

2.2.1 Reform of the Resource and Environmental Tax

China's low-carbon policy on resources and environmental taxation mainly includes resource taxes, environmental protection taxes and supporting policies. Compared to the resource tax, the environmental protection tax is a "new tax," and since its introduction in 2018, issues such as the application of taxable pollutants and the monitoring and calculation of emissions of taxable pollutants have been clarified. Since its inception in 1984, the resource tax has continued to adjust the levying scope and optimize the tax rate bands to ensure that its functions of adjusting the industrial structure and saving energy and protecting the environment are effectively performed. Since 2010, the ad valorem reform of resource tax by region and by tax item has been gradually promoted, and by 2016, the ad valorem reform of resource tax for all tax items at the national level was achieved.

The environmental effect of the resource tax comes mainly from its price regulation of specific taxable energy sources. The imposition of a resource tax on units and individuals who develop taxable energy increases upstream prices and conducts price transmission, increasing the costs of downstream enterprises and using the increased costs to guide them to adjust their energy consumption structure and increase the proportion of nontaxable energy demanded, thereby achieving the goal of reducing pollutant emissions. At the same time, the adjustment of the energy consumption structure and the innovation and upgrading of production technology caused by the cost effect have further improved the production efficiency of enterprises and finally realized the double improvement of the economy and the environment, that is, the improvement of green total factor productivity. Based on the above analysis, this paper proposes the following research hypothesis.

Hypothesis 1 Resource taxation can regulate the structure of energy consumption and improve green total factor productivity.

2.2.2 Significant Differences in Tax Sources Between Resource Tax Regions

As an important part of China's green tax system, the adjustment of the tax rate and the change in the tax amount can, to a certain extent, reflect China's energy consumption structure and carbon dioxide emissions. As shown in **Figure 1**, since 2014, resource tax revenues in the central and western regions have been significantly higher than those in the eastern regions, with significant differences in tax resources between regions. In addition, as a result of the implementation of the ad valorem resource tax reform for crude oil and natural gas in 2010 and its extension to mineral resources in 2016, with a simultaneous expansion of the scope of tax items, adjustments to elements of the tax regime have led to large fluctuations in the amount of resource tax. Therefore, the following research hypothesis is proposed in this paper.

Hypothesis 2 Resource tax ad valorem reform improves green total factor productivity.

2.2.3 Increasingly Optimized Energy Structure With Arduous Transformation Task

China is in a critical period of economic structure transformation. The corresponding energy production and consumption structure should also shift from traditional nonrenewable energy to renewable energy to promote the low-carbon transformation of the economic structure. On the one hand, low-carbon energy transformation can effectively alleviate energy poverty and is conducive to energy conservation and emission reduction (Dong et al., 2021); On the other hand, the role of energy consumption in promoting economic growth is closely related to the carbon emission reduction target (Ren et al., 2022c). Moreover, changes in energy prices will have a direct impact on carbon prices. As shown in **Figure 2**, from 2011 to 2019, the proportion of raw coal in China's total energy production decreased from 81.9% to 76.2%, and the proportion of coal in total energy consumption decreased from 73.4% to 62.8%. Although both showed a downwards trend year by year, the decline was not

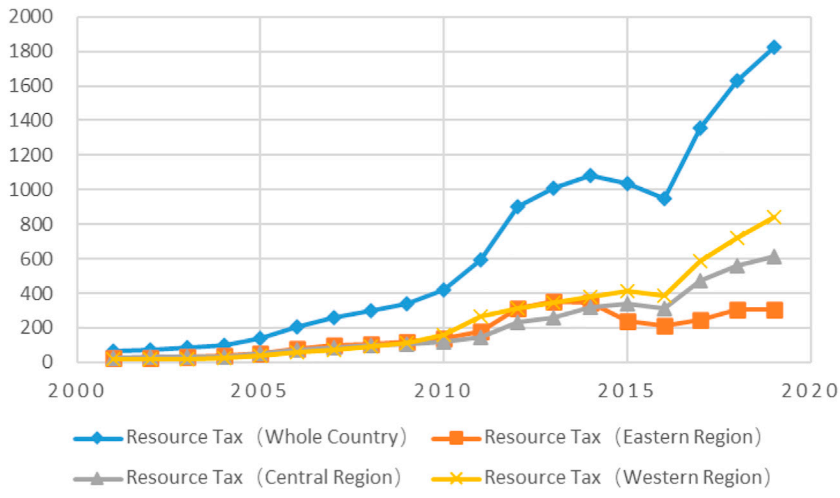

FIGURE 1 | China's resource tax revenues and regional differences.

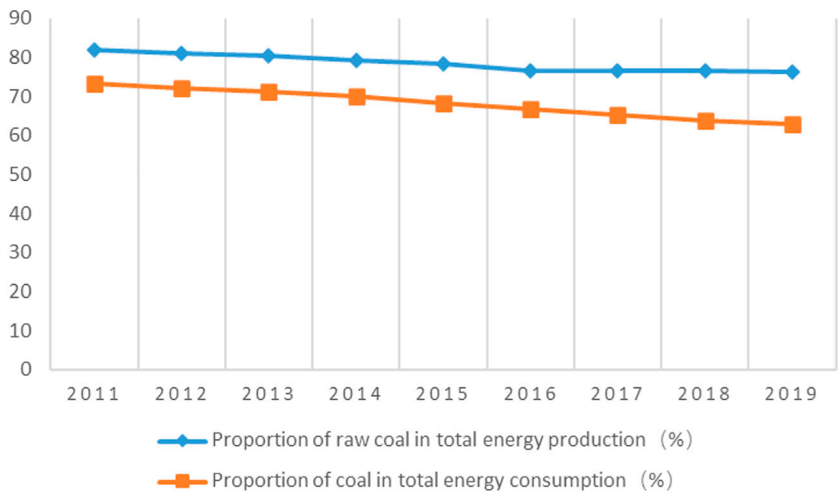

FIGURE 2 | China's energy production/consumption structure.

obvious. On the one hand, it reflected that the task of energy structure transformation and upgrading was still arduous; on the other hand, it also reflected that the current policies and measures to promote energy structure transformation were insufficient. In addition, the transformation of the energy production structure obviously lags behind the transformation of the energy consumption structure, indicating that policy tools such as resource tax acting on the production side need to be further optimized, and the coordination and complementarity between resource tax policy and other fiscal and tax policies, such as tax reduction and fee reduction, need to be further strengthened.

Hypothesis 3 The coordination and complementarity between diversified policy instruments can promote the effect of resource tax policy. Specifically, resource tax policy combined with tax reduction and fee reduction policy can further improve green total factor productivity.

3 RESOURCE TAX REFORM ON LOW CARBON DEVELOPMENT

3.1 Data Sources

The sample interval selected for this paper is 2001–2019, using data from the China Statistical Yearbook, China Taxation Yearbook, China Energy Statistical Yearbook, EPS Global Statistics/Analysis Platform, Wind database and provincial statistical yearbooks. Some of the missing data were filled in using linear interpolation. The descriptive statistical characteristics of the variables are shown in **Table 1**.

TABLE 1 | Descriptive statistical characteristics of variables.

Variables	Sample size	Average value	Standard deviation	Minimum value	Maximum value
GTFP	551	0.9598	0.0830	0.5455	1.8799
Tax	551	21.7926	39.4918	0.0740	383.0339
Reform	551	0.4428	0.4972	0.0000	1.0000
Compete	551	0.0236	0.0208	0.0001	0.1465
Ind	551	1.1480	0.3384	0.1935	2.0228
Gov	551	0.2084	0.0965	0.0772	0.6284
Fd	551	0.0318	0.0264	0.0019	0.1436
Er	551	0.0042	0.0035	0.0002	0.0285
Den	551	343.1315	292.8900	7.2653	1311.8180

TABLE 2 | Measures of green total factor productivity.

Type	Variables	Definition
Input elements	Labor input	Number of people working in society as a whole
	Capital investment	Capital stock calculated using the perpetual inventory method (based on 2000)
	Energy inputs	Total energy consumption
Desired output	Real GDP	Real GDP calculated using 2000 as the base period
Nondesired outputs	Carbon dioxide emissions	emissions by IPCC method

TABLE 3 | Results of green total factor productivity measures.

	2005	2010	2015	2019
Beijing	0.9624	0.9884	0.9731	1.1793
Tianjin	0.9960	0.9004	0.9342	0.7464
Hebei	0.9559	0.9627	0.8971	0.8561
Shanxi	0.9693	0.9718	0.9450	0.9426
Inner Mongolia	0.8749	0.9190	0.9225	0.9576
Liaoning	0.9962	0.9720	0.9874	0.8857
Jilin	0.9618	0.9342	1.0104	0.7682
Heilongjiang	0.9573	0.9650	0.9423	0.8167
Shanghai	0.9994	0.9993	0.9776	1.6655
Jiangsu	0.9460	1.1111	0.9160	1.0406
Zhejiang	0.9169	1.0164	0.9524	1.0277
Anhui	0.9358	0.9778	0.9265	1.1071
Fujian	0.9043	0.9771	0.9594	1.0885
Jiangxi	0.9412	0.9999	0.9270	0.9971
Shandong	0.9221	1.0068	0.9057	0.7895
Henan	0.9679	0.9502	0.9491	1.0722
Hubei	0.9939	0.9737	0.9705	1.0640
Hunan	0.8890	0.9661	0.9700	0.9931
Guangdong	1.1502	1.0279	0.9330	1.1325
Guangxi	0.9183	0.9352	0.9512	0.9439
Hainan	0.9400	0.9814	0.9299	1.0316
Chongqing	1.0164	0.9567	0.9844	1.0559
Sichuan	0.9761	0.9668	0.9720	1.0258
Guizhou	1.0527	0.9785	0.9519	0.9902
Yunnan	0.8502	0.9285	0.9540	1.1497
Shaanxi	1.0069	0.9776	0.8970	0.9497
Gansu	0.9762	0.9852	0.8746	0.9872
Qinghai	0.9517	0.9657	0.8928	0.9779
Ningxia	0.9323	1.0503	0.9385	0.9594
Xinjiang	0.9740	1.0442	0.8559	1.0034

3.2 GTFP Calculation

The dual dividend effect of environmental taxation policies implies that the level of low-carbon development requires that low-carbon taxation policies not only have the carbon emission reduction effect but also contribute to the achievement of economic growth objectives. Therefore, in this paper, to include both CO_2 emissions and the level of economic development in the analytical framework when evaluating the effects of low carbon tax policies, the global Malmquist–Luenberger (GML) index, i.e., green total factor productivity (GTFP), is calculated to represent the level of low carbon development using a nonradial, nonoriented nondesired output SBM model by referring to Tone and Sahoo (2003). As shown in **Table 2**, the input indicators include labor input, capital input and energy input. Considering the availability of data, labor input is represented by the number of employees in society, capital input is represented by the capital stock calculated using the perpetual inventory method, and energy input is represented by total energy consumption. Output indicators include desired output indicators and nondesired output indicators. To eliminate the influence of price factors, this paper takes 2000 as the base period and calculates the real GDP as the desired output indicator, which represents the level of economic development; CO_2 emissions are selected as the nondesired output indicator, and CO_2 emissions are calculated according to the United Nations Intergovernmental Panel on Climate Change (IPCC). emissions are calculated according to the methodology published by the Intergovernmental Panel on Climate Change (IPCC).

Corresponding to the uneven regional distribution of China's population structure, energy structure and industrial structure at this stage, China's green total factor productivity also shows significant regional differences. **Table 3** shows the results of green TFP measurements for 30 provinces, municipalities directly under the Central Government and autonomous regions (hereafter referred to as provinces, excluding Tibet and Hong Kong, Macao and Taiwan in view of the availability of data) in China, which show significant growth, but there are still

TABLE 4 | Definition of variables.

Variable name	Variable symbols	Variable definitions
Green Total Factor Productivity	GTFP	Superefficient SBM-GML method measured
Resource tax	Tax	Resource tax amount
Ad valorem resource tax reform	Reform	Dummy variables
Local competition	Compete	Actual utilization of foreign direct investment/regional GDP
Industrial structure	Ind	Value added in the secondary sector/value added in the tertiary sector
Level of government intervention	Gov	Fiscal expenditure/GDP
Financial decentralization	Fd	Provincial revenue/Central revenue
Environmental regulation	Er	Completed investment in industrial pollution control/industrial added value
Population density	Den	Total population at the end of the year/administrative area

obvious regional differences and optimized space. In 2019, the average green total factor productivity of 30 provinces in China was 1.0068. There were 13 provinces above the average. More than half of the provinces did not reach the average level. Before 2010, the difference in green total factor productivity in the eastern, central and western regions of China was small, but since 2010, the green total factor productivity in the eastern region has been significantly higher than that in the central and western regions, and this gap showed a growing trend.

3.3 Variable Descriptions

(1) Explanatory variables

Green Total Factor Productivity (GTFP): As a measure index of low carbon development, green total factor productivity, as measured by the ultra performance SBM model, captures the "double dividend" of economic growth and environmental protection.

(2) Core explanatory variables

①Resource Tax (Tax): The total resource tax revenue is used as an indicator to measure the resource tax in the green tax system as an example.

②Resource tax ad valorem reform (Reform): Taking the ad valorem reform of resource tax on crude oil and natural gas as an example, a dummy variable is constructed as the measurement index of the ad valorem reform of resource tax. The ad valorem reform of resource tax is carried out in sequence by year and region. Therefore, this paper assigns 0 to the year when the ad valorem reform of resource tax is not carried out in each province and 1 to the year when the ad valorem reform of resource tax has been carried out.

(3) Control variables

To avoid affecting the accuracy of the model regression results due to the omission of important variables, based on the practices of Tu et al. (2019), Yuan and Zhang (2021) and Yang et al. (2022) and combined with the characteristics of the sample data in this paper, local competition (Compete), industrial structure (Ind), the degree of government intervention (Gov), fiscal decentralization (Fd), environmental regulation (Er) and population density (Den) are used as control variables, and the specific definitions of the variables are shown in **Table 4**.

3.4 Model Setting

To study the impact of resource tax and resource tax ad valorem reform on the low carbon development in China and to verify the "double dividend" effect of low carbon tax policy, this paper constructs the following empirical model.

$$GTFP_{it} = \alpha_0 + \beta_1 lnTax_{it} + \beta_2 Reform_{it} + \sum_m \theta_m Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

where $GTFP_{it}$ denotes Green Total Factor Productivity; Tax_{it} denotes total resource tax revenue; $Reform_{it}$ is a dummy variable that takes the value of 1 if the ad valorem resource tax reform on crude oil and natural gas is implemented in year t in province i and 0 otherwise; $Controls_{it}$ is a set of control variables that include other important variables affecting Green Total Factor Productivity; β_1, β_2, and θ_m denote the influence degree of resource tax, resource tax ad valorem reform and control variables on Green Total Factor Productivity, respectively; μ_i denotes individual effects; λ_t denotes time effects; and ε_{it} denotes random errors.

4 EMPIRICAL RESULTS

4.1 Baseline Result

To mitigate heteroskedasticity, the core explanatory variables are treated by logarithm. Meanwhile, to eliminate dimensions, all variables are standardized. Due to the serious lack of data on Shanghai's resource tax revenue, Shanghai was further excluded from the sample interval, and finally, the data of 29 provinces in China were used in the regression model. Considering that low-carbon development means that the proportion of clean energy in the energy structure gradually increases until it finally becomes the main component, the tax system elements of resource tax will change in the process of low-carbon development; that is, the low-carbon development level will have a negative effect on the resource tax, and the endogenous problems that may be caused by this two-way causality will reduce the accuracy of the model regression results. Therefore, in this paper, the 2SLS estimation

TABLE 5 | Empirical regression results.

	(1)	(2)	(3)	(4)
lnTax	0.098*	0.125**	0.097*	0.122**
	(0.05)	(0.05)	(0.05)	(0.05)
Reform			−0.020	−0.017
			(0.02)	(0.02)
Compete		−0.064**		−0.065**
		(0.03)		(0.03)
Ind		0.023		0.025
		(0.02)		(0.02)
Gov		−0.203***		−0.199***
		(0.04)		(0.04)
Fd		0.092		0.096
		(0.08)		(0.08)
Er		0.048**		0.048**
		(0.02)		(0.02)
Den		−0.018		−0.020
		(0.06)		(0.06)
_cons	0.322***	0.364***	0.342***	0.381***
	(0.03)	(0.07)	(0.03)	(0.07)
R2	0.380	0.445	0.383	0.447
Individual effects	YES	YES	YES	YES
Time effects	YES	YES	YES	YES
N	522	522	522	522

*Note: Standard errors in brackets; ***, ** and * denote 1%, 5% and 10% significance levels, respectively.*

method is used to regress model (1), and the lag period of the core explanatory variable is used as the instrumental variable to reduce the interference of endogenous problems on the estimation results. The baseline regression results are shown in **Table 5**. Columns (1) and (2) only test the impact of resource tax on low-carbon development without considering the ad valorem rate reform of resource tax. When controlling the individual fixed effect and time fixed effect at the same time, regardless of whether the control variable is added to the model, the impact coefficient of the resource tax on green total factor productivity is significantly positive, indicating that the collection of resource taxes promotes the improvement of green total factor productivity and effectively promotes the low-carbon transformation of the economy and society. Columns (3) and (4) consider the ad valorem reform of resource tax. The empirical results show that the impact coefficient of resource tax on green total factor productivity is still significantly positive, and the coefficient is basically the same as that when the ad valorem reform of resource tax is not considered; however, there is no significant effect of resource tax ad valorem reform. In other words, the effect of resource tax on green TFP comes from the resource tax itself rather than the event of ad valorem reform. The mechanism of the effect of resource tax on green TFP is that the tax burden on taxpayers will stimulate taxpayers to increase the price of their products, while downstream consumers adjust the structure of energy demand to maximize cost avoidance. Therefore, it is the change in the amount of resource tax that is a direct factor in the impact of resource tax on green total factor productivity.

In terms of control variables, environmental regulation is positively related to green TFP; that is, the means of

TABLE 6 | The test results of VIF.

Variable	lnTax	Reform	Compete	Ind	Gov	Fd	Er	Den
VIF	2.32	2.57	1.51	1.56	2.19	2.07	1.20	2.36

environmental regulation used to control industrial pollution can improve the level of low-carbon development. This is mainly because in the process of industrial development, due to the one-sided pursuit of economic interests and the neglect of environmental protection and resource conservation, the emissions of pollutants such as carbon dioxide are high. Industrial environmental regulation policies can guide the green transformation of industry and increase output value in a more energy-saving and environmentally friendly way. However, local competition and government intervention have an inhibitory effect on green TFP, with blind competition leading to a waste of resources and inefficiency, which is detrimental to the improvement of production and lifestyle, and excessive government intervention affects the effective functioning of the market mechanism, which is not conducive to the improvement of low-carbon development.

4.2 Robustness Tests

To further verify the accuracy of the regression results, this paper first carried out multicollinearity and heteroscedasticity tests. To avoid the model estimation inaccuracy caused by endogenous problems, the difference GMM method and System GMM method were used to re-estimate the model. Then, the robustness test was carried out by adding control variables and modifying the sample interval to exclude the impact of the environmental protection tax.

4.2.1 Multicollinearity and Heteroscedasticity Test

The economic system is a complex and organically connected whole, and many economic things have direct or indirect connections, which means that when building econometric models to analyse the impact effects of economic variables, we should fully consider the correlation between variables and avoid the possible multicollinearity interference between variables to estimate the results of the model. Therefore, before estimating equation (1), this paper first uses the VIF test to judge whether there is multicollinearity in the model. The VIF values of all variables are shown in **Table 6**. The VIF values of all variables are less than 10, which proves that there is no multicollinearity in the model. In addition, to avoid the inaccuracy of the estimation results caused by the heteroscedasticity of the model, the white test method is used to test the heteroscedasticity of the model before the estimation of equation (1). The results show that the p value is equal to $0.735 > 0.1$, and the original assumption of the same variance is accepted, which proves that the model does not have the heteroscedasticity problem.

4.2.2 Endogenetic Test

As mentioned above, there may be a two-way causal relationship between resource tax revenue and green total factor productivity, and the complexity and integrity of

TABLE 7 | The results of the Endogenetic test.

	(1) DIF-GMM	(2) SYS-GMM
lnTax	0.753***	0.143*
	(0.12)	(0.09)
_cons	/	0.236***
		(0.04)
Control variables	YES	YES
Sargan	0.969	0.295
Hansen	0.950	0.112
Individual effects	YES	YES
N	522	551

*Note: Standard errors in brackets; ***, ** and * denote 1%, 5% and 10% significance levels, respectively.*

economic variables also means that there may be missing variables in the process of model construction, which will lead to endogenous problems. The instrumental variable method used in the previous article has reduced the impact of endogenous problems to a certain extent. In this part, the lag order of the core explanatory variable is used as the instrumental variable to build a fixed effect model. The model is estimated by using the difference GMM method and the System GMM method. The estimation results are shown in **Table 7**. Whether using the DIF-GMM method or SYS-GMM method, the coefficients of core explanatory variables are significantly positive; that is, the collection of resource tax can effectively promote the improvement of green total factor productivity. The p values of the Sargan test and Hansen test are greater than 0.1, which proves that the model setting is reasonable and that the instrumental variables are also effective.

4.2.3 Addition of Control Variables

The omission of important variables may lead to endogeneity problems and reduce the credibility of the regression results. For this reason, this paper further adds the degree of openness to the outside world, urbanization rate and fiscal pressure to the set of control variables and reregisters the empirical model. The results are shown in column (1) of **Table 8**. The regression coefficient of the core explanatory variable of resource tax is still significantly positive, again verifying hypothesis 1.

4.2.4 Exclusion of Environmental Protection Tax

The introduction of an environmental protection tax in 2018 is an important part of China's sound green tax system, and the imposition of an environmental protection tax on units emitting taxable pollutants can effectively reduce the emissions of taxable pollutants and improve environmental quality. The tax burden brought by an environmental protection tax is also an important factor influencing taxpayers' behavioral choices. Therefore, this paper modifies the sample interval to 2001–2017 and regresses the empirical model. The results are shown in column (2) of **Table 8**. The variable coefficient indicating the amount of resource tax is still significantly positive, which again verifies the research results of this paper.

4.3 Heterogeneity Analysis

4.3.1 Regional Heterogeneity

In the above analysis, total resource tax revenue, total energy consumption and carbon dioxide emissions all showed significant regional differences, and the impact of resource tax policies on the level of low carbon development in different regions is likely to be heterogeneous as well. For this reason, this paper conducts subsample regressions on the eastern, central and western regions to test regional heterogeneity. As shown in columns (1)–(2) of **Table 9**, resource taxation has a positive impact on green total factor productivity in all regions, which is consistent with the results of the baseline regression, but this impact is not significant in the eastern region, probably because first, the level of low carbon development in the eastern region is inherently higher than that in the central and western regions, which leads to relatively less room for policy regulation; second, the eastern region is mainly the demand side of energy, although its total energy consumption and CO_2 emissions are higher than those of the central and western regions, it does not bear a heavier resource tax burden; third, the eastern region is relatively economically developed and can rely more on technological progress and industrial restructuring to improve

TABLE 8 | Robustness test results.

	(1)	(2)
	Adding control variables	Exclusion of environmental protection tax
lnTax	0.120**	0.126**
	(0.05)	(0.05)
Reform	−0.017	−0.019
	(0.02)	(0.02)
_cons	0.253**	0.333***
	(0.11)	(0.06)
Control variables	YES	YES
R^2	0.460	0.484
Individual effects	YES	YES
Time effects	YES	YES
N	522	464

*Note: Standard errors in brackets; ***, ** and * denote 1%, 5% and 10% significance levels, respectively.*

TABLE 9 | The test results of heterogeneity.

	(1)	(2)	(3)	(4)
	Eastern region	Central and western region	Areas with greater efforts to reduce taxes and fees	Areas with less tax and fee reduction
lnTax	0.087	0.133**	0.128*	0.020
	(0.13)	(0.06)	(0.07)	(0.05)
Reform	−0.049	0.004	−0.013	−0.020
	(0.05)	(0.01)	(0.01)	(0.02)
_cons	0.447***	0.295***	0.344***	0.488***
	(0.11)	(0.05)	(0.08)	(0.07)
Control variables	YES	YES	YES	YES
R2	0.500	0.481	0.566	0.464
Individual effects	YES	YES	YES	YES
Time effects	YES	YES	YES	YES
N	180	342	273	249

*Note: Standard errors in brackets; ***, ** and * denote 1%, 5% and 10% significance levels, respectively.*

environmental quality, and the coordination of multiple policies dilutes the impact of a single policy.

4.3.2 The Influence of Tax Cuts and Fee Reduction on Policy Effect

In recent years, China has vigorously implemented the policy of tax cuts and fee reduction to reduce the burden on enterprises and stimulate the vitality of market players. The policy of tax cuts and fee reduction is an important measure to promote industrial transformation and upgrading and high-quality economic development. It not only effectively promotes employment and scientific and technological innovation but also indirectly promotes the improvement of green and low-carbon development levels while giving play to the innovation incentive effect and structural transformation function. Moreover, as a restrictive tax policy, the resource tax, in the process of guiding the green transformation of enterprises, together with incentive tax preferential policies such as tax reduction and fee reduction, can avoid the excessive tax burden hindering the process of enterprise transformation and upgrading. Based on this, this paper takes the decline rate of tax revenue growth as the measurement index of tax reduction and fee reduction. According to the median value of the index, the sample areas are divided into areas with greater tax reduction and fee reduction and areas with less tax reduction and fee reduction. Regression is carried out by sample. The regression results are shown in columns (3)–(4) of **Table 9**. The impact coefficient of the resource tax on green total factor productivity is still significantly positive in areas with greater tax reduction and fee reduction but not in areas with less tax reduction and fee reduction. This may be because in areas with fewer tax cuts and fee reductions, enterprises bear a heavy tax burden; that is, there is a plan for low-carbon transformation under the guidance of resource taxes, but it cannot be smoothly promoted due to capital constraints. This also fully reflects the necessity of implementing the policy of tax reduction and fee reduction and verifies the establishment of hypothesis 3.

TABLE 10 | Regulatory effect test results.

	(1)	(2)
lnTax	0.173***	0.170**
	(0.07)	(0.07)
Reform		−0.017
		(0.02)
Fd	0.321**	0.323**
	(0.16)	(0.16)
lnTax*Fd	−0.265*	−0.262*
	(0.15)	(0.15)
_cons	0.297***	0.315***
	(0.08)	(0.08)
Control variables	YES	YES
R^2	0.451	0.453
Individual effects	YES	YES
Time effects	YES	YES
N	522	522

*Note: Standard errors in brackets; ***, ** and * denote 1%, 5% and 10% significance levels, respectively.*

5 FURTHER DISCUSSION

Under the background of the tax sharing system, the resource tax, as a kind of central and local shared tax, can balance the relationship between central and local fiscal revenue and expenditure to a certain extent, and it will also be affected by the degree of fiscal revenue decentralization. Therefore, fiscal revenue decentralization may affect the impact of resource taxes on green total factor productivity; that is, fiscal revenue decentralization has a regulatory effect on the impact of resource taxes on low-carbon development. To verify the existence of this regulatory effect, based on equation (1), this part introduces the interaction term of resource tax and fiscal revenue decentralization into the model to test whether fiscal revenue decentralization has a regulatory effect on the impact of resource tax on low-carbon development. The empirical results are shown in **Table 10**. After the introduction of the interactive item, the coefficient of the main effect of resource tax on green total factor productivity is still significantly positive, while the coefficient of the interactive item is significantly negative at the 10% level, which indicates that the decentralization of fiscal revenue will inhibit the positive effect of resource tax on green total factor productivity. This may be because the improvement of the decentralization of fiscal revenue of local governments means that local governments have more self-owned disposable income, and local governments have greater autonomy when coordinating economic activities. Under the action of special administrative systems and officials' promotion incentives, local governments that lack supervision may not consider too many low-carbon factors when allocating resources but focus on realizing explicit economic benefits, thus hindering the improvement of green total factor productivity.

6 CONCLUSION AND POLICY IMPLICATIONS

Green and low-carbon is the inevitable requirement for the transformation of the future economic development mode, and scientific and reasonable low-carbon tax policy is of great significance for the smooth realization of green and low-carbon transformation. This paper first constructs a superefficient SBM model to calculate the green total factor productivity of 30 provinces in China and then uses the panel data of 29 provinces in China from 2001 to 2019 to build a fixed effect model to test the impact of the ad valorem reform of resource tax and resource tax on green total factor productivity. There are obvious regional differences in China's green total factor productivity. The collection of resource tax is conducive to improving green total factor productivity. Compared with the eastern region and the regions with less tax reduction and fee reduction, this effect is more significant in the central and western regions and the regions with more tax reduction and fee reduction. However, the impact of ad valorem resource tax reform on green total factor productivity is not obvious. In addition, fiscal revenue decentralization has a reverse adjustment effect on the impact of resource taxes on green total factor productivity.

To give full play to the dual dividend effect of low-carbon tax policies and successfully achieve the goal of "carbon peaking and carbon neutrality," China should continue to improve the green tax system and strengthen the design of the "double carbon" Vision-regulated taxation system design.

First, we gradually include VOC_S organic gas emissions in the scope of the environmental protection tax. The petrochemical industry is the first sector to be selected for the pilot environmental protection tax "expansion," and the traditional concept of the tax's "revenue raising" function should be appropriately revised in the assessment of VOC_S environmental protection tax collection and management, respecting the inherent regulation law of the tax and avoiding the revenue raising effect as the basis for the assessment. The assessment system should be appropriately designed in line with the VOC emission intensity of major taxpayers.

Second, the restrictive resource tax system for carbon emissions and forest resource development and utilization should be improved. The dual effects of the coal resource tax in terms of energy saving and emission reduction and tax burden fairness should be emphasized; ecological carbon sink resources such as forest grassland and marine blue carbon should be included in the scope of resource taxation; and flexible tax incentives should be implemented for different taxable resource sectors and areas.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: http://olap.epsnet.com.cn EPS global statistical data / analysis platform.

AUTHOR CONTRIBUTIONS

PF, WL, and HL contributed to conception and design of the study. HL organized the database and performed the statistical analysis. PF, WL, HL, and XW wrote the first draft of the manuscript. All authors contributed to manuscript revision, read, and approved the submitted version.

REFERENCES

Berman, E., and Bui, L. T. M. (2001). Environmental Regulation and Productivity: Evidence from Oil Refineries. *Rev. Econ. Statistics* 83 (3), 498–510. doi:10.1162/00346530152480144

Cao, J., Dai, H., Li, S., Guo, C., Ho, M., Cai, W., et al. (2021). The General Equilibrium Impacts of Carbon Tax Policy in China: A Multi-Model Comparison. *Energy Econ.* 99, 105284. doi:10.1016/j.eneco.2021.105284

Dension, E. F. (1981). Accounting for Slower Economic Growth: the United States in the 1970s. *South. Econ. J.* 47 (4), 1191–1193.

Dissou, Y., and Karnizova, L. (2016). Emissions Cap or Emissions Tax? A Multi-Sector Business Cycle Analysis. *J. Environ. Econ. Manag.* 79, 169–188. doi:10.1016/j.jeem.2016.05.002

Dong, K., Ren, X., and Zhao, J. (2021). How Does Low-Carbon Energy Transition Alleviate Energy Poverty in China? A Nonparametric Panel Causality Analysis. *Energy Econ.* 103, 105620. doi:10.1016/j.eneco.2021.105620

Du, K., Cheng, Y., and Yao, X. (2021). Environmental Regulation, Green Technology Innovation, and Industrial Structure Upgrading: The Road to the Green Transformation of Chinese Cities. *Energy Econ.* 98, 105247. doi:10.1016/j.eneco.2021.105247

Duan, K., Ren, X., Shi, Y., Mishra, T., and Yan, C. (2021). The Marginal Impacts of Energy Prices on Carbon Price Variations: Evidence from a Quantile-On-Quantile Approach. *Energy Econ.* 95, 105131. doi:10.1016/j.eneco.2021.105131

Feng, J. Y., Yan, J. J., and Tao, X. (2021). Exposing the Effects of Environmental Regulations on China's Green Total Factor Productivity: Results from Econometrics Analysis and Machine Learning Methods. *Front. Environ. Sci.* 9, 1–12. doi:10.3389/fenvs.2021.779358

Hao, J., and He, F. (2022). Corporate Social Responsibility (CSR) Performance and Green Innovation: Evidence from China. *Finance Res. Lett.* 48, 102889. doi:10.1016/j.frl.2022.102889

He, F., Du, H., and Yu, B. (2022a). Corporate ESG Performance and Manager Misconduct: Evidence from China. *Int. Rev. Financial Analysis* 82, 102201. doi:10.1016/j.irfa.2022.102201

He, F., Feng, Y., and Hao, J. (2022c). Information Disclosure Source, Investors' Searching and Stock Price Crash Risk. *Econ. Lett.* 210, 110202. doi:10.1016/j.econlet.2021.110202

He, F., Ma, Y., and Zhang, X. (2020). How Does Economic Policy Uncertainty Affect Corporate Innovation?-Evidence from China Listed Companies. *Int. Rev. Econ. Finance* 67 (5), 225–239. doi:10.1016/j.iref.2020.01.006

He, F., Qin, S., Liu, Y., and Wu, J. (2022b). CSR and Idiosyncratic Risk: Evidence from ESG Information Disclosure. *Finance Res. Lett.* 49, 102936. doi:10.1016/j.frl.2022.102936

Kuninori, M., and Otaki, M. (2016). Modified Ramsey Rule, Optimal Carbon Tax and Economic Growth. *Atmos. Clim. Sci.* 6 (2), 224–235. doi:10.4236/acs.2016.62019

Nordhaus, W. D. (2017). Revisiting the Social Cost of Carbon. *Proc. Natl. Acad. Sci. U.S.A.* 114 (7), 1518–1523. doi:10.1073/pnas.1609244114

Oladosu, G., and Rose, A. (2007). Income Distribution Impacts of Climate Change Mitigation Policy in the Susquehanna River Basin Economy. *Energy Econ.* 29 (3), 520–544.

Okonkwo, J. U. (2021). Welfare Effects of Carbon Taxation on South African Households. *Energy Econ.* 96, 104903. doi:10.1016/j.eneco.2020.104903

Pearce, D. (1991). The Role of Carbon Taxes in Adjusting to Global Warming. *Econ. J.* 101 (407), 938–948. doi:10.2307/2233865

Pollitt, H., Park, S.-J., Lee, S., and Ueta, K. (2014). An Economic and Environmental Assessment of Future Electricity Generation Mixes in Japan - an Assessment Using the E3MG Macro-Econometric Model. *Energy Policy* 67, 243–254. doi:10.1016/j.enpol.2013.12.018

Ren, X., Duan, K., Tao, L., Shi, Y., and Yan, C. (2022b). Carbon Prices Forecasting in Quantiles. *Energy Econ.* 108, 105862. doi:10.1016/j.eneco.2022.105862

Ren, X., Li, Y., Shahbaz, M., Dong, K., and Lu, Z. (2022a). Climate Risk and Corporate Environmental Performance: Empirical Evidence from China. *Sustain. Prod. Consum.* 30, 467–477. doi:10.1016/j.spc.2021.12.023

Ren, X., Li, Y., Yan, C., Wen, F., and Lu, Z. (2022d). The Interrelationship between the Carbon Market and the Green Bonds Market: Evidence from Wavelet Quantile-On-Quantile Method. *Technol. Forecast. Soc. Change* 179, 121611. doi:10.1016/j.techfore.2022.121611

Ren, X., Tong, Z., Sun, X., and Yan, C. (2022c). Dynamic Impacts of Energy Consumption on Economic Growth in China: Evidence from a Non-parametric Panel Data Model. *Energy Econ.* 107, 105855. doi:10.1016/j.eneco.2022.105855

Rubashkina, Y., Galeotti, M., and Verdolini, E. (2015). Environmental Regulation and Competitiveness: Empirical Evidence on the Porter Hypothesis from European Manufacturing Sectors. *energy Policy* 83, 288–300. doi:10.1016/j.enpol.2015.02.014

Tone, K., and Sahoo, B. K. (2003). Scale, Indivisibilities and Production Function in Data Envelopment Analysis. *Int. J. Prod. Econ.* 84 (2), 165–192. doi:10.1016/s0925-5273(02)00412-7

Tu, Z. G., Zhou, T., and Zhang, N. (2019). Does China's Pollution Levy Standards Reform Promote Green Growth? *Sustainability* 11 (21), 6186. doi:10.3390/su11216186

Xiao, H., and You, J. L. (2021). The Heterogeneous Impacts of Human Capital on Green Total Factor Productivity: Regional Diversity Perspective. *Front. Environ. Sci.* 9, 713562. doi:10.3389/fenvs.2021.713562

Yang, H., Lin, Y., Hu, Y., Liu, X., and Wu, Q. (2022). Influence Mechanism of Industrial Agglomeration and Technological Innovation on Land Granting on Green Total Factor Productivity. *Sustainability* 14 (6), 3331. doi:10.3390/su14063331

Yuan, J., and Zhang, D. (2021). Research on the Impact of Environmental Regulations on Industrial Green Total Factor Productivity: Perspectives on the Changes in the Allocation Ratio of Factors Among Different Industries. *Sustainability* 13 (23), 12947. doi:10.3390/su132312947

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Carbon neutrality cognition, environmental value, and consumption preference of low-carbon products

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It is now the mainstream scientific consensus that carbon emissions cause global climate change. Achieving the goal of China's carbon neutrality is essential for environmental protection and economic sustainable development worldwide. In the above context, this paper aims to explore the carbon neutrality cognition, environmental value, and consumption preference for low-carbon products from the perspective of consumption end. Thus, we built and checked a new conceptual model of consumers' carbon neutrality cognition and the consumption preference for low-carbon products. The TF-IDF algorithm in machine learning was used to confirm the dimensions of carbon neutrality cognition based on text data collected from an academic database CNKI. Then, we used data from a social investigation (N = 405) to test hypotheses and models using bootstrapping and independent sample t-tests. The results showed that altruistic (β = 0.168, 95% CI: [−0.54514, 0.8819]) and egoistic values (β = −0.066, 95% confidence interval [CI]: [−0.6361, 0.6772]) mediated the impact of carbon neutrality cognition on the consumption of low-carbon products, whereas the egoistic value did not (β = −0.066, 95% CI: [−0.6361, 0.6772]). Additionally, based on the characteristics of current Chinese consumers and the market, we argue for two boundary factors: face consciousness and carbon footprint label. The moderation of face consciousness (M_{high} = 5.395 vs. M_{low} = 3.312) and carbon footprint label (M_{with} = 6.394 vs. $M_{without}$ = 5.432) were revealed. The empirical results support our conceptual model, and our findings provide insights to policymakers and enterprises regarding people's carbon neutrality cognition, which will allow them to develop more appropriate policies and sustainable development strategies.

KEYWORDS

carbon neutrality cognition, environmental value, face consciousness, carbon footprint label, machine learning

Introduction

The goal of carbon neutrality is a momentous strategic decision taken by the Chinese government to promote the "green recovery" of the economy after the COVID-19 outbreak, by considering the development concept of "Green water and hills are golden and silver hills," the background of the green transformation and development of the domestic economy and society, and by fully weighing the advantages and disadvantages of the international community in reducing carbon emissions (Wang, 2021). Low-carbon consumption is confronted by vital challenges and opportunities, under the conditions of a "dual circulation" development pattern in which the domestic economic cycle plays a leading role whereas the international economic cycle remains its extension and supplement. In the current context of international and Chinese economic development, carbon reduction is essential for global sustainability.

Specifically, it is not reasonable to focus on large production-based carbon emissions instead of consumption-based carbon emissions. Production-based carbon emissions refer to the amount of CO_2 emitted during the production of products; consumption-based carbon emissions are the amount of CO_2 emitted during the consumption of products. Although these emissions have different sizes, both are essential for carbon reduction. Moreover, carbon emissions from consumption can drive carbon emissions from production. Reducing carbon emissions from consumption can effectively force enterprises to develop technological innovations that reduce carbon emissions from production (Wang, 2015). As a consequence, a low-carbon lifestyle and consumer behavior are indispensable for achieving the goal of carbon neutrality. Thus, consumers' cognition of carbon neutrality, responsibilities, and environmental value are particularly important in the process of daily consumption (Zhuang, 2021).

Research on low-carbon consumption focuses on green consumption, ecological consumption, and prosocial behaviors. However, studies of low-carbon consumption focus on the antecedent that affects the consumers' psychology and behavior related to the consumption of low-carbon products. Prior research reported that environmental literacy includes four aspects: value, responsibility, problem perception, and behavioral skills. Homoplastically, a conceptual model of green consumption behavior with green consumption willingness as the intermediary mechanism was established (Kheiry and Nakhaei, 2012). Six dimensions of environmental emotion have been verified: environmental anxiety, behavioral disgust, behavioral guilt, environmental love, behavioral appreciation, and behavioral pride, based on the two-factor theory hypothesis of affection-behavior (Wang, 2015). Then, the influence mechanism of environmental emotion on consumers' carbon reduction behavior was examined. From the perspective of environmental value, previous studies demonstrated the significant influence of altruistic value and egoistic value on young consumers' willingness to consume organic green food (Yadav, 2016). Analogously, the existing body of research on generation X consumers' ecological purchase behavior suggests that higher consumption preference and willingness to pay a premium are increased by personal, social, and cultural values (Lee and Park, 2018).

Because some Chinese consumers prefer saving face, the face awareness of Chinese consumers has had a positive impact on the purchase intention of green products. Furthermore, the mediation of perceived social value and moderation of use situation, and relative price level were examined (Yu et al., 2019). Specifically, Chinese consumers prefer environmentally friendly products with higher prices if the product is used in a public situation. Currently in China, there are no official laws, regulations, or policies related to carbon footprint labels. Therefore, academic research on carbon footprint labels has mainly focused on the calculation of carbon emissions in carbon footprint labels, the evaluation of accurate measurement methods, and promotion strategies for carbon footprint labels (Wang et al., 2010).

Given the current strategic goal of carbon neutrality, recent Chinese research has investigated the concept of carbon neutrality. These studies analyzed the relationship between carbon neutrality strategies and high-quality development of the domestic economy from a macro perspective to submit proposals to the government and other enterprises. Our literature search found few studies have measured consumers' carbon neutrality cognition from the perspective of micro consumer psychology. Therefore, our research problems were 1) what is the consumers' carbon neutrality cognition? 2) What is the specific relationship between carbon neutrality cognition and consumption preference for low-carbon products? And 3) Are there mediations and boundary conditions between the two? This paper introduces a scheme that solves these problems through social investigation and experimental design. First, consumers' carbon neutrality cognition was identified by social investigation using a questionnaire survey and TF-IDF algorithm in machine learning. Second, the main effect of carbon neutrality cognition on the consumption preference for low-carbon products was explored using linear regression. Third, we considered and checked two boundary conditions of the conceptual framework: face consciousness and carbon footprint label to reveal their moderation roles under a background of Chinese collectivist culture. Finally, we conducted a robustness check of our conceptual model to guarantee the generalizability of the conclusions.

This paper contributes to research on carbon neutrality cognition and carbon footprint label, which has not been considered important and which lacks a national standard in China. In addition, our results indicate that a carbon footprint label can positively promote consumers' consumption preference for low-carbon products, which provides evidence demonstrating the necessity and importance for the government to establish a carbon label institution. Our insights into consumers' carbon neutrality cognition suggest low-carbon consumption can be increased, and that a Chinese carbon neutrality strategy can be achieved as soon as possible from the perspective of the carbon reduction of consumption.

Literature review and hypothesis

Environmental value and consumption preference for low-carbon products

Value is the standard to measure cognition gradually formed by individuals in the process of learning and accumulating experience (Kahle, 1996). Individuals regulate and adjust behaviors through value, and there are differences in value among individuals (Fraj and Martinez, 2006). Simultaneously, value is the standard and viewpoint of individuals to understand and deal with problems. Thus, value is an important factor for individual cognition including the basic viewpoints of the subject towards the object (Arrow, 1951). Undoubtedly, environmental value is also one of the categories of value. According to the classical theory of value-belief-norm, the environmental value is divided into altruistic, egoistic, and ecological values (Stern, 2000). The altruistic value focuses on being considerate of others, whereas in contrast, egoistic value emphasizes thinking for yourself (Hansla et al., 2008). The ecological value promotes the idea that humans belong to the natural environment, and that people should respect and protect nature (Wang and Zhou, 2019). The concept of altruistic behavior has been applied to the research of recycling behavior (Hopper and Nielsen, 1991), energy-saving (Black et al., 1985), and environmental protection political action (Stern and Paul, 1976).

Based on the concept of altruistic behavior, an altruistic value was proposed (Schwartz, 1992). Prior research reported that altruistic value had a remarkable impact on consumers' environmental attitudes, subjective norms, perceived value, and environmental behaviors (The et al., 2017). In addition, the literature indicated that green consumption was increased by altruistic values, because these values are a key factor that guide an individual's moral behavior and significantly affect consumers' attitudes. Driven by altruistic values, consumers prefer environmental-friendly and recyclable products, whereas non-environmental-friendly and non-recyclable products negatively impact consumers' environmental attitudes (Ali et al., 2020). In summary, consumers prefer to make consumption decisions from the perspective of environmental protection rather than only considering ordinary functions of products (Yadav, 2016).

Egoistic value is the judgment standard of positive benefits that are often related to specific behaviors based on the perceived benefits. Previous studies indicated that the correlation between consumers' perceived benefits and purchase intention could be explained by the theory of planned behavior (Ajzen, 1991). Consumers pay more attention to the cost price, discount, and performance of products in the purchase decision process, with less consideration given to the production factors of altruism (Forsythe et al., 2010).

Ecological value emphasizes people's responsibility for the natural environment. The deterioration of the ecological environment requires society to improve the positive awareness of environmental protection; thus, the concepts of ecological consumption and ecological value have been proposed. Ecological value will significantly promote consumers' environmental protection behavior and ecological consumption behavior (Wang and Zhou, 2019). Greater environmental concern and stronger ecological value orientation can promote individuals' pro-environmental behavior and low-carbon behavior, such as turning off the TV standby mode, purchasing less packaged products, using public transportation frequently, and taking short trips by bicycle (Chng and Borzino, 2020). Accordingly, our first two hypotheses are as follows:

H1. : Consumers' consumption preference for low-carbon products is significantly influenced by environmental values, specifically, altruistic values and ecological values that positively influence the consumers' consumption preference for low-carbon products (H1a), whereas egoistic values negatively influence the consumers' consumption preference for low-carbon products (H1b).

Carbon neutrality cognition and environmental value

The concept of carbon neutrality was first proposed by the British company Future Forest.[1] The company advocates residents to purchase carbon credits to neutralize and offset carbon emissions based on the concept of ecological environment protection. At present, carbon neutrality has become one of the most important issues for the international community. Carbon neutrality requires carbon generated by human society during economic development to be offset by forest carbon sinks, energy conservation, emission reduction, and other forms of artificial technology for capture and storage, to achieve zero-emission CO_2 (Kahle, 1996). For instance, commercial building operations with high emission abatement potential are important steps to achieve global carbon neutrality (Xiang

1 The data were collected from the official website of future forest company: https://thefutureforestcompany.com/.

et al., 2022; Zhang et al., 2022). Reducing carbon emissions in the building sector is essential for carbon peak and carbon neutrality (Sun et al., 2022), and mission factors and industrial structures are key to decarbonizing building operations (Xiang et al., 2022).

China has made it clear that it will strive to peak its CO_2 emissions by 2030 and achieve the goal of carbon neutrality by 2060 (Xi, 2020). From the perspective of macro-economic development, under the guidance of the carbon neutrality target, the social responsibility of production enterprises should be implemented from the supply side and the responsibility of consumers should be highlighted to force the transformation and upgrading of energy and industrial structures. From the point of view of microscopic consumption psychology and cognition, the consumers' recognition of carbon neutrality and low-carbon consumption concept will become a new consumption value to form market demand, which will further promote technological innovation, energy conservation, and the carbon reduction of enterprises, which will eliminate enterprises with high energy consumption and high carbon emissions. As a consequence, the importance of consumers' carbon emission reduction and consumers' cognition of carbon neutrality cannot be ignored, when determining the peak CO_2 emissions, and carbon neutrality target schedule and map (Zhuang, 2021).

Prior research suggested that attitude, perception, and belief can guide behavior and preference (Kaplan, 2016). Thus, the consumers' cognition of carbon neutrality has also an impact on the consumption behavior of low-carbon products. Additionally, altruistic and ecological values were closely related to prosocial behavior, environmental protection, and carbon reduction (Chekima et al., 2016). Low-carbon consumption behavior advocates prosocial, low-carbon emission, and green consumption behavior to eliminate consumption pollution and carbon emissions caused by irrational consumption (Yu and Gong, 2015). Other studies demonstrated that people's environmental values will affect ecological consumption behavior through subjective norms, environmental attitudes, and perceived behavior control (Wang and Zhou, 2019). Moreover, altruistic and ecological values will positively affect the consumption behavior of low-carbon products through perceived behavior effectiveness, whereas in contrast, egoistic values have a negative effect on the consumption behavior of low-carbon products (Roos and Hahn, 2018). Therefore, a second hypothesis was proposed as follows:

H2. : Altruistic and egoistic values mediate the impact of carbon neutrality cognition on the consumption of low-carbon products, whereas egoistic values do not.

The mediations of face consciousness and carbon footprint label

Face consciousness based on Chinese society and impression management theory describes the attitude and cognition of others to oneself, which is characterized by social attributes and openness (Yu et al., 2019). Face consciousness mainly includes the expectation of maintaining face, improving face, and avoiding losing face during social activities (Bao et al., 2019). Driven by face consciousness, consumers' psychology and behavior tend to be diversified. If consumers are very concerned about the attitudes and opinions of the people around them, they will have a strong sense of face consciousness and will maintain face by paying attention to the symbolic attributes and social status attributes of products. For instance, luxury consumption is typical face-saving behavior. Luxury products are a symbol of hedonism (Yu et al., 2019) because luxury products can indicate the consumer's great wealth and high social status. The consumption of low-carbon products demonstrates environmental protection and prosocial behavior, and consumers can build a personal reputation by participating in prosocial behavior (Semmann et al., 2005). Compared with general consumption behavior, the consumption of low-carbon products is more related to the social and public interest, which can win the respect and approval of others to increase one's own face (Goh et al., 2021).

Specifically, for consumers with strong face consciousness, prosocial behavior benefits others and themselves. Not all people have a strong face consciousness. When people's ecological value is high, it is still possible to seek a lifestyle that demonstrates social status or identity, and a lifestyle with higher social status is often accompanied by higher energy consumption compared with an ordinary lifestyle. For instance, the consumption of oil resources by the large displacement engines of luxury cars generates a high amount of carbon emissions. From the perspective of egoism, the use of low-carbon products or energy-saving green products will not themselves bring a higher quantity lifestyle, because they are inconsistent with the sufficiency enjoyment motivation advocated by the status-seeking lifestyle (Griskevicius et al., 2010). Therefore, face consciousness and ecological value can have a negative impact on environmental willingness and energy-saving behavior as well as weakening energy-saving and environmental protection behaviors (Wang et al., 2019). Accordingly, a third hypothesis was proposed as follows:

H3. : Face consciousness moderates the impact of environmental values on the consumption of low-carbon products. Under the condition of high face consciousness, the effects of altruistic, egoistic, and ecological values on the consumption preference for low-carbon products is positively moderated by face consciousness (H3a); under

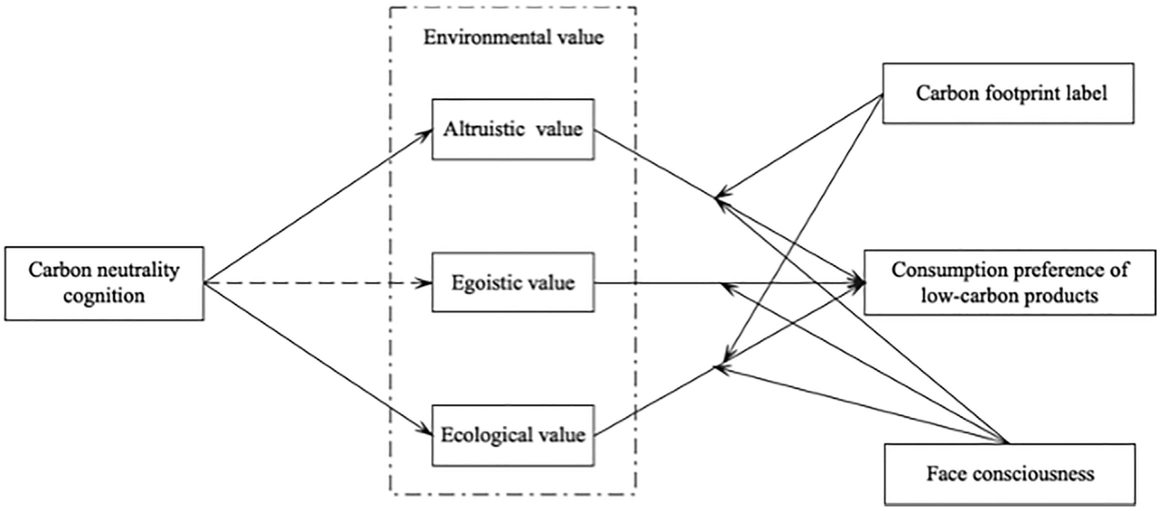

FIGURE 1
Research model framework.

the condition of low face consciousness, the effects of ecological values on the consumption preference for low-carbon products is negatively moderated by face consciousness (H3b). Paradoxically, the moderating effect of face consciousness on altruistic values, egoistic values, and consumption preference for low-carbon products disappears (H3c).

A carbon footprint label attached to packaging provides information related to the product. The CO_2 emission generated during the whole life cycle of the product from production to consumption is marked on the label to inform consumers of the carbon footprint of the product to be purchased (Wang et al., 2010). Previous studies reported the use of carbon footprint labels for products and services increased consumers' attention to carbon emissions (Owususekyere and Jordaan, 2017), and significantly affected consumers' purchase decision behavior (Emberger-Klein and Menrad, 2017), even increasing the willingness to pay a premium for the consumption of low-carbon products (Msl et al., 2019). Simultaneously, the importance of carbon footprint labels on agricultural and pastoral meat products for food consumption carbon reduction was determined by measuring the functional relationship between the forest reduction area and carbon emissions. Producing meat products is related to the cutting down of green vegetation; thus, consumers will consider whether the meat products meet a criterion of low-carbon consumption, which will arouse more attention from consumers to the carbon footprint of the products (Cederberg et al., 2011).

As a consequence, whether the products have a carbon footprint label will affect consumers' consumption behavior of low-carbon products. The carbon footprint label has developed from a public welfare label to information necessary for some developed countries. The carbon footprint label is the embodiment of ecological values in consumption and products. Values related to environmental protection and ecological friendly cultural beliefs can affect consumers' purchase behavior. Therefore, we propose a fourth hypothesis as follows:

H4. : Whether a product has a carbon footprint label moderates the effect of altruistic and ecological value on the consumption preference of low-carbon products. Altruistic and ecological values have a stronger impact on the consumption preference of low-carbon products with a carbon footprint label than without a carbon footprint label (Figure 1).

In summary, current research has predicted technologies and perspectives to achieve carbon neutrality (Wang et al., 2021), and has demonstrated that emission forecasting is vital for policy-making and emission reduction goals globally (Ikram et al., 2021). From the perspectives of macro energy type (Ikram, 2021) and green development (Ikram et al., 2022), carbon reduction and carbon neutrality play important roles in sustainability. Our research focuses more on the micro points of consumers and psychology and contributes to helping governments and enterprises understand people's carbon neutrality cognition, environmental values, and preference for low-carbon consumption.

Methods and materials

Questionnaire design

The questionnaire design included three parts. The first part was the design of the situation of the consumers' consumption preference for low-carbon products. The second part was the measurement design of the variables, including the measurement of six core variables: carbon neutrality cognition, altruistic value, egoistic value, ecological value, face consciousness, and consumption preference for low-carbon products. The last part was the collection of basic demographic information, including sex, age, occupation, and education level.

First, we determined the type of product that was most relevant to carbon neutrality, carbon reduction, and low carbon to achieve a reduction in carbon emissions by daily consumption to design the purchase intention. Prior studies suggested that the greenhouse gas emissions generated by agriculture and animal husbandry accounted for 18% of the global carbon emissions (Pardo et al., 2016), and the carbon emissions generated by breeding were huge because of the large amount of carbon emission equivalents generated by ruminant intestinal fermentation. For example, in South Africa in 2019, agricultural and livestock produced 35.37 million tons of CO_2 (Tongwane and Moeletsi, 2021), and the carbon emissions from the intestinal fermentation of agricultural and livestock accounted for 64.54%. Moreover, the carbon emissions from commercial beef used for market circulation accounted for 50.21%.

With the rapid development of internet communication technology, smartphones have become indispensable communication and entertainment tools in people's daily life with a high penetration rate. According to Apple's official product environment report,[2] one iPhone 12 produces 82 kg of CO_2 during the source material production manufacturing, packaging, use, and recycling. During the product life cycle, carbon emissions from logistic transportation, service, and end-of-life treatment processes account for 2%, 11%, and 1%, respectively. In addition, carbon emissions generated by the production and manufacturing were the largest: 86% (70.52 kg). The carbon emissions of electronic products such as mobile phones cannot be ignored, and these are mainly concentrated in the production and manufacturing processes. One of the industries with the greatest energy saving and emission reduction potential in China is the clothing and textile manufacturing industry, which is expected to reduce the domestic industrial sector's carbon emissions by 28.65% (Li and Xu, 2020). According to estimates by the British Environmental Resources Management Company,[3] a pair of jeans weighing 400 g will produce about 47 kg of carbon emissions over the product life cycle, which is 117.5 times the weight of the product itself. China is a country with a huge population and a large domestic clothing and textile market; therefore, the carbon emissions from the supply and consumption of clothing are high.

Based on the evidence analysis described above, this study used commercial beef, smartphone, and clothing as alternative products in the questionnaire situation design and our preliminary research let participants select the most appropriate stimulus materials. In the preliminary study, participants were asked to look at three pictures showing beef, smartphones, or clothing, with a description of low-carbon products and the carbon emissions generated by each kind of product. Finally, we asked participants the question: "Which type of products in the pictures do you think have more properties and characteristics of low-carbon products?" using the Likert 7-point scale. A total of 148 valid questionnaires were collected, and 47.3% of participants were male. Results demonstrated that the participants were more inclined to choose the mobile phone, which is more appropriate for the properties and characteristics of low-carbon products ($M_{\text{mobile phone}} = 5.232 > M_{\text{beef}} = 4.634 > M_{\text{jeans}} = 4.026$, SD = 1.48).

In the formal questionnaire, a virtual brand of mobile phone (A brand) was used as an experimental stimuli. The materials in the questionnaire are shown in Figure 2, which showed the internal information of the mobile phone system (left of Figure 2) and the external package information (top right of Figure 2) to the participants. The purchase situation was described as: "Beef, clothes, and electronic products we use in daily life. These products will produce certain CO_2 emissions from their production, manufacturing, packaging, and use, which is a challenge for our country to achieve the goal of carbon neutrality strategy in the future. We have the following A brand mobile phone with a low-carbon design concept. Please carefully observe the picture and finish answering." Considering that the popularity and knowledge of carbon footprint labels are low, an explanatory text about carbon footprint labels was added: "Carbon footprint labels are the quantitative index marks of CO_2 emissions generated from the production processes of goods on the product labels."

Data collection

The formal questionnaire for field research was distributed and collected online, and was anonymous. The specific steps of data collection were as follows: 1) Develop an online

2 The data were collected from Apple's official website: https://www.apple.com/environment/pdf/products/iphone/iPhone_12_Pro_PER_Oct2020.pdf.

3 The data were collected from Environmental Resource Management (ERM) of UK: https://www.erm.com/.

FIGURE 2
Design of picture materials in the questionnaire.

questionnaire using Credamo, an online platform, to investigate and generate answer QR codes and links; and 2) Distribute online questionnaires and paper questionnaires randomly and pay ¥ 5 to each participant. Finally, 426 questionnaires were collected, and 405 valid questionnaires were retained. The structural characteristics of the samples are shown in Table 1.

Variable measurements

We explored the dimensions of carbon neutrality cognition accurately from the perspective of academic research. Because 1) the background of this study was based on the strategy of China's current economic situation and need for carbon neutrality, 2) the participants in our social investigation were mainly from China, and 3) we needed consistent participants and questionnaire test items, we chose the China National Knowledge Infrastructure (CNKI) as the text database because of its obvious characteristics of local research in China. We collected 181 Chinese Social Sciences Citation Index (CSSCI) papers from 2011 to 2021 with advanced search keywords including "carbon neutrality," "peak CO_2 emissions," and "zero carbon emission" in the database as source data.

Then, we manually reviewed the titles and abstracts of the papers and eliminated 22 papers that were not associated with carbon neutrality. Finally, 159 papers were retained as source text data. Next, a Word 2 Vector model (Muhammad et al., 2021) was established using the SVM of machine learning and NLP. Homoplastically, TF-IDF was used for keyword calculation and a word frequency statistical algorithm was used to confirm high-frequency words. The collection, cleaning, and processing flow of the paper text data are shown in Figure 3. The visualization of the results of word frequency statistics is shown in Figure 4, where the first 1000 most frequent words are arranged from high to low frequency. The larger the word size in Figure 4, the more times the word appears in the paper text data.

Note: 1) Because our text data set were in Chinese, the results are displayed in Chinese in Figure 4 after running the Python program. 2) Keyword results of original text data are shown inside parentheses in Figure 5, and words outside the parentheses are a Chinese-English translation.

To ensure the accuracy of the high-frequency words, TF-IDF was run in a Python environment to extract the keywords in the paper text data. The basic mathematical derivation of the TF-IDF algorithm was:

$$TF - IDF_{(x)} = TF_{(x)} \cdot IDF_{(x)} \tag{1}$$

TABLE 1 Sample structure characteristics.

Variable	Category	Frequency	Percentage (%)
Sex	Male	186	45.93
	Female	219	54.07
Age (years)	Under 18	17	4.20
	18–24	102	25.19
	25–34	153	37.78
	35–50	114	28.15
	Over 50	19	4.69
Education background	High school and below	65	16.05
	Junior college and equivalent	89	21.98
	Undergraduate course	121	29.88
	Master's degree or above	130	32.10
Occupation	Party and government offices	66	16.30
	Enterprises and public institutions	93	22.96
	Individual business	53	13.09
	Farmers	46	11.36
	Students	62	15.31
	Freelancers	44	10.86
	Retired staff	12	2.96
	Others	29	7.16

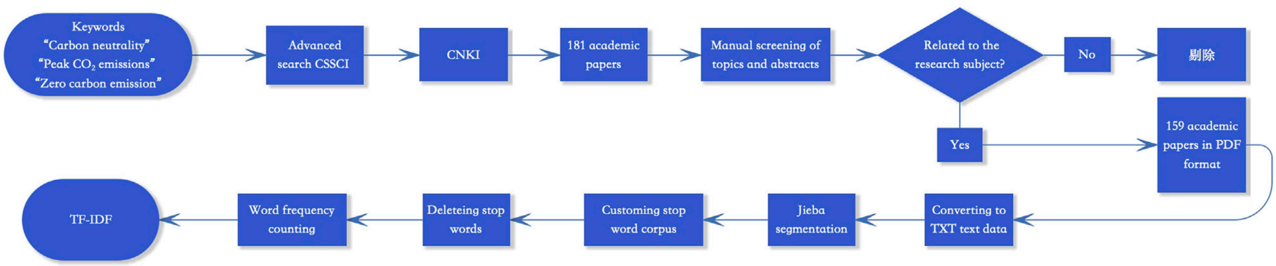

FIGURE 3
Text data collection and cleaning process.

$$\mathrm{TF}_{(x)} = tf_{ij} = \frac{n_{ij}}{\sum_k n_{kj}} \tag{2}$$

$$\mathrm{IDF}_{(x)} = idf_i = \log \frac{|D|}{\left|\{j\colon t_i \epsilon d_j\}\right| + 1} \tag{3}$$

In Formula 2, n_{ij} is the number of occurrences of a word in the text data d_j, and the denominator $\sum_k n_{kj}$ is the sum of the number of occurrences of all words in the text data. In Formula 3, $|D|$ is the total number of words in the text data, and $|\{j\colon t_i \epsilon d_j\}|$ represents the total number of sentences containing a certain word t_i meeting the condition $n_{ij} \neq 0$. In addition, we assigned the denominator to $|\{j\colon t_i \epsilon d_j\}| + 1$ to avoid zero in the denominator because some words did not appear in the text data. Then, the TF-IDF algorithm was run based on Scikit-Learn in Python to extract 20 keywords by setting Top K = 20, and the result is shown in Figure 5.

Based on drawing lessons from previous research on scales of low-carbon awareness (Liu and Ji, 2019), low-carbon cognition (Tang et al., 2018), and environmental

FIGURE 4
Word frequency statistics word cloud label.

sentiment (Wang, 2015), as well as the current study's machine learning quantification of carbon neutrality cognition, nine items for measuring carbon neutrality cognition were adapted and formed. Previous scales were used to measure altruistic values (3 items), egoistic values (3 items), ecological values (5 items) (Wang and Zhou, 2019), and face consciousness (8 items) (Chan et al., 2009). Exploratory factor analysis was conducted on the nine observed variables of carbon neutrality cognition. The results showed that the factor loadings of two observed variables: "Carbon neutrality strategy requires an enhanced forest carbon sink" and "metropolitan area and urban agglomeration play an important role in carbon reduction and emission" were 0.453 and 0.397, respectively, both of which were lower than 0.5. Therefore, these two observed variables were eliminated and seven observed items of latent variables were retained. The above measurement items are shown in detail in Table 2.

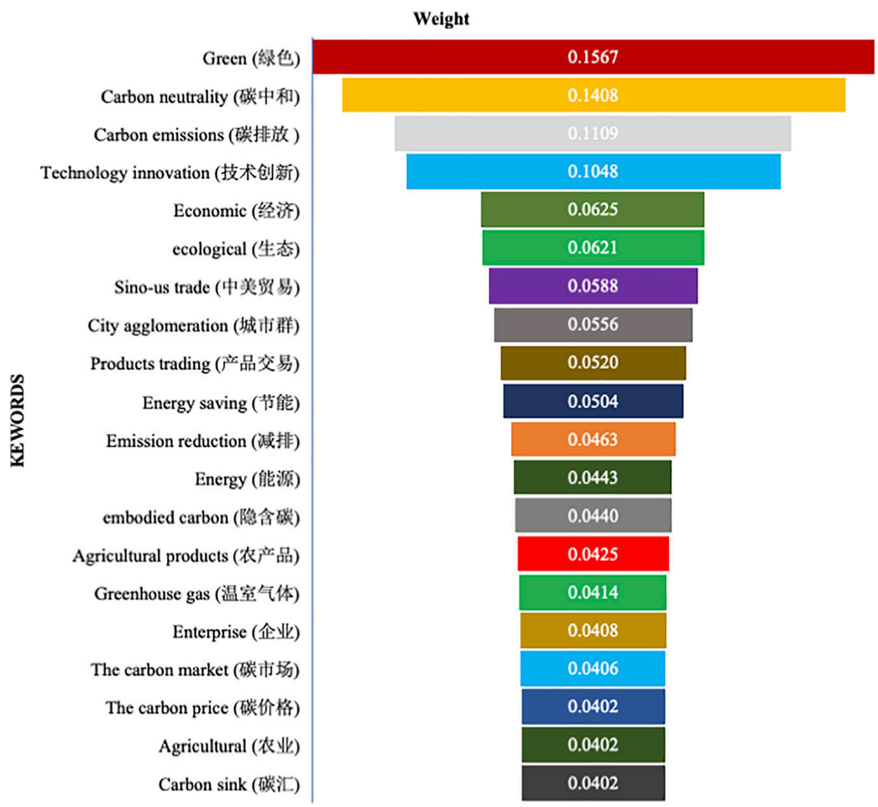

FIGURE 5
Keywords top 20.

Data and results

Tests of reliability and validity

First, the internal consistency method using Cronbach's α was used to test the reliability of the measurement scale. Table 2 shows that each Cronbach's α was in the range of 0.814–0.944. Thus, the internal consistency of each variable was highly reliable, higher than the acceptable value of 0.7 s, and the KMO of the whole scale was 0.822, $p < 0.001$, which indicated that it was a suitable for factor analysis. Six factors with an eigenvalue greater than 1 were extracted, and the accumulated variance contribution rate was 85.28%. The factor loadings were all higher than 0.7; therefore, the research scale had high validity.

Common method deviation test

This paper tested whether the data had common method deviation using program control and statistical control (Podsakoff et al., 2003). The operation of the applied program control was as follows: 1) Disrupting the order of the questionnaire items to prevent the participants from guessing the intention of the items. 2) We promised that the data collected from anonymous questionnaires would only be used for academic research and that we would not collect personal privacy data to ease the concerns of the participants. In addition, the statistical control mainly used correlation analysis. The correlation coefficients of the core variables involved in this paper were all in the range of 0.110–0.575, which are lower than the critical value of 0.9. Therefore, the common method deviation of data was not obvious (Table 3).

Hypothesis test

Multiple regression analysis was conducted for altruistic, egoistic, and ecological values, and the consumption preference of low-carbon products, and sex, age, education background, occupation, aesthetic design, and product familiarity were set as control variables. Model 2 in Table 4 shows that altruistic ($\beta = 0.207$, $p < 0.01$) and ecological values had a positive impact on the consumption preference of low-carbon products ($\beta = 0.615$, $p < 0.01$), whereas egoistic values had a negative impact on the consumption preference of low-carbon products ($\beta = -0.167$, $p < 0.01$).

TABLE 2 Measurement indicators, reliability, and validity of the scale.

Variable	Measuring term	Factor loading	Cronbach's α	KMO	Bartlett Sphericity test
Carbon neutrality cognition	Carbon neutrality requires human society to realize the zero emission of CO_2	0.874	0.892	0.809	Pass
	Under a background of carbon neutrality, it is very important to control and measure the carbon implicit in China-US-trade	0.942			
	Carbon neutrality strategy pays more attention to technological innovation	0.910			
	Carbon neutrality strategy pays more attention to ecological economy	0.893			
	Carbon neutrality emphasizes green energy, energy conservation, and emission reduction	0.730			
	The production and consumption of agricultural products in agricultural activities will produce a large amount of carbon emissions	0.732			
	Carbon neutrality requires enterprises to consider carbon neutrality and carbon price accounting	0.756			
Altruistic value	The pollution problem in one area will affect the health of global residents	0.859	0.814	0.695	Pass
	Environmental pollution in one place will affect the environmental health in surrounding areas	0.833			
	Environmental pollution seriously affects public health	0.810			
Egotistic value	Protecting the environment will reduce employment opportunities	0.798	0.858	0.684	Pass
	The code of conduct to protect the environment limits my personal choices and freedom	0.776			
	Some environmental protection regulations restrict my choices and freedom when I spend money	0.812			
Ecological value	The harm of environmental pollution to human health is more serious than people realize	0.762	0.944	0.727	Pass
	The balance of the natural environment is gradually being broken and will become more serious	0.884			
	The ecological environment is fragile and difficult to repair	0.837			
	Environmental pollution will destroy thousands of living things on the earth	0.945			
	Environmental pollution has caused serious damage to the atmosphere	0.934			
Face consciousness	I care about praise and criticism from others	0.852	0.926	0.755	Pass
	I care about others' attitude towards me	0.848			
	I hate being despised by others	0.887			
	I will be very angry if others are not polite to me	0.778			
	If I am respected, I will be very happy	0.757			
	If I am criticized in public, I will be very sad	0.845			
	I care about my self-image	0.818			
	I care about my social status	0.757			

We set neutrality consciousness as a dependent variable, and altruistic, egoistic, and ecological values as mediating variables, with low-carbon product consumption preference as an independent variable, and sex, age, education, occupation, aesthetic design, and product familiarity as covariant variables. H1 was examined by bootstrapping (Hayes, 2013) in IBM SPSS 22.0 with model 4. The sample size was set at 5000, and the confidence interval was 95%.

Results demonstrate that the direct effect of carbon neutrality cognition on the consumption preference of low-carbon products was not significant (β = 0.168, 95% confidence interval [CI]: [−0.54514, 0.8819], including 0). In contrast, the indirect effect of the altruistic value was significant (β = 0.083, 95% CI: [0.2144, 0.2333], not including 0). Consequently, the altruistic value was a complete mediation of the effect of carbon

TABLE 3 Pearson correlation coefficients among variables and descriptive statistics.

Variable	A	B	C	D	E	F	Mean	Standard deviation	Variance	Maximum	Minimum
A. Carbon neutrality cognition	—						5.422	0.928	0.861	6.810	5.021
B. Altruistic value	0.110**	—					6.286	1.125	1.266	6.933	5.805
C. Egotistic value	0.303	0.395	—				3.538	1.344	1.806	4.920	3.073
D. Ecological value	0.46**	0.142	0.172	—			5.819	0.797	0.635	6.729	5.549
E. Face consciousness	0.299	0.081	−0.186**	0.575**	—		5.196	1.029	1.059	6.381	4.262
F. CPLP	0.187**	0.420*	0.482*	0.146**	0.299**	—	5.81	1.494	2.232	6.487	5.096

Note: N = 405; $^{*}p < 0.05$, $^{**}p < 0.01$.

TABLE 4 Results of multivariate regression analysis.

Variable	Model 1	Model 2
Sex	0.595*	0.467
Age	0.801	0.443
Academic degree	0.299	0.400
Occupation	0.236	0.216
Product aesthetics	0.358	0.233
Product familiarity	−0.112	−0.119
Altruistic value		0.207**
Egoistic value		−0.167**
Ecological value		0.165**
R^2	0.414	0.527
$\triangle R^2$	0.414	0.256
F	10.116*	21.115**

Note: N = 405, $^{*}p < 0.05$, $^{**}p < 0.01$.

neutrality cognition on the consumption preference for low-carbon products. Furthermore, the indirect and direct effects of egoistic values were not significant (β = −0.066, 95% CI: [−0.6361, 0.6772], including 0; β = 0.244, 95% CI: [−0.6766, 1.1610], including 0, respectively). Thus, the egoistic value had no mediating effect on carbon neutrality cognition of the consumption preference for low-carbon products. In addition, the indirect and direct effects of the ecological value were significant (β = 0.223, 95% CI: [0.2776, 0.3533], not including 0; β = 0.154, 95% CI: [0.5375, 0.8453], not including 0, respectively). Thus, the ecological value was a complete mediation of the effect on carbon neutrality cognition of the consumption preference for low-carbon products. In summary, H2 was verified.

To examine H3, the data were divided into two groups according to the mean of the participants' face consciousness: high-face consciousness group (4 ≤ M < 7) and low-face consciousness group (1 ≤ M < 4). Results of the independent-sample t-test indicated there was significant variance of face consciousness between the two groups ($M_{\text{high-face consciousness}}$ = 5.395, $M_{\text{low-face consciousness}}$ = 3.312, t (403) = 3.013, p = 0.015 < 0.05). Results from the high-face consciousness group suggested that face consciousness had a significant moderation effect on the altruistic value (β = 0.412, 95% CI: [1.0290, 0.2058], not including 0), egoistic value (β = 0.806, 95% CI: [0.1596, 1.4531], not including 0), and ecological value (β = 0.481, 95% CI: [0.8130, 0.1497], not including 0) on the consumption preference for low-carbon products. Therefore, H3a was supported. Results from the low-face consciousness group indicated that face consciousness had a significant negative moderation effect on the ecological value (β = −0.927, 95% CI: [−1.6695, −0.11837], not including 0) on the consumption preference for low-carbon products, and H3b was supported. In contrast, the moderating effect of face consciousness on the altruistic value and consumption preference for low-carbon products disappeared (β = 0.038, 95% CI: [−0.4069, 0.1912], including 0), which supports H3c.

When examining H4, the data were divided into two groups: with a carbon footprint label and without a carbon footprint label. Results of the independent-sample t-test (Figure 6) suggested a significant variance ($M_{\text{with carbon footprint label}}$ = 6.394 > $M_{\text{without carbon footprint label}}$ = 5.432, t (403) = 1.357, p = 0.018 < 0.01) in the scores of low-carbon product consumption preference between the two groups. Model 1 was selected for bootstrapping and the sample size was set at 5000 with a CI of 95%. Overall, the effect of the altruistic value on the consumption preference for low-carbon products was moderated by the carbon footprint label (β = 0.203, 95% CI: [0.9462, 0.7468], not including 0). The value of the moderating effect with a carbon footprint label (β = 0.550, 95% CI: [0.3570, 0.4576], not including 0) was larger than that without a carbon footprint label (β = 0.303, 95% CI: [0.0501, 0.9162], not including 0). As consequence, H4 was supported.

Robustness test

When analyzing the moderating effect of face consciousness, this paper divided the data into high and low face consciousness groups for testing. When analyzing the moderating effect of the carbon footprint label, the data were divided into a group with a carbon footprint label and a group without a carbon footprint

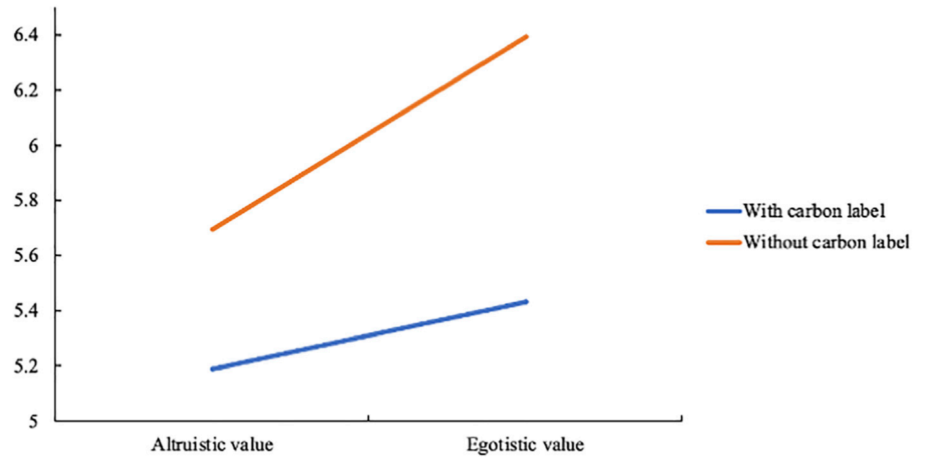

FIGURE 6
Moderating effect of the carbon footprint label.

TABLE 5 Multivariate hierarchical regression results of the robustness test.

Variable		Model 1		Model 2		Model 3		Model 4	
		Coefficient	T	Coefficient	T	Coefficient	T	Coefficient	T
Control variable	Sex								
	Age			0.518	1.241			−0.169	−0.128
	Education background			0.532	1.401			0.534	1.304
	Occupation			0.159	0.876			0.725	1.774
	Product aesthetics			0.126	0.499			0.328	0.871
	Product familiarity			−0.348	−1.767			0.196	1.425
Independent variable	Carbon neutral cognition	0.015**	4.079	0.469**	4.414	0.022**	5.032	0.102**	5.221
Mediating variable	Altruistic value	0.771*	2.797	0.144*	4.285	0.631*	4.992	0.432*	2.965
	Egotistic value	−0.321*	−4.823	−0.061*	−2.369	−0.532*	−2.998	−0.290*	−4.974
	Ecological value	0.156**	7.388	0.299**	14.631	0.214**	9.765	0.293**	16.430
Moderating variable	Face consciousness	0.275**	8.095	0.216**	10.072	0.326**	11.376	0.389**	12.114
	Carbon footprint label	0.643*	6.615	0.316*	4.230	0.701*	1.927	0.396*	5.970

Note: N = 405, *p < 0.05, **p < 0.01.

label. Results (Table 4) suggested that sex significantly affected the consumption preference for low-carbon products when sex is not controlled for ($p < 0.05$). As a result, we regrouped the sample data by sex to test the stability of the hypothetical model and the data results.

In Table 5, model 1 and model 2 are the regression results of subsamples with sex set as male, and model 3 and model 4 are the regression results of sub-samples with sex set as female. Results of the four models indicated that the altruistic value (model 1: $\beta = 0.771$, $t = 2.797$, $p < 0.05$, other models are not listed one by one) and ecological value (model 1: $\beta = 0.156$, $t = 7.388$, $p < 0.01$) had a positive impact on the consumption preference for low-carbon products. In contrast, the egoistic value (model 1: $\beta = -0.321$, $t = -4.823$, $p < 0.05$) negatively influenced the consumption preference for low-carbon products. Therefore, H1a and H1b were supported further.

Further analysis of the mediating and moderating effects demonstrated that the altruistic value ($\beta = 0.193$, 95% CI: [0.2271, 0.8936], not including 0) and ecological value ($\beta = 0.314$, 95% CI: [0.8871, 1.0429], not including 0) were the complete mediators of carbon neutrality cognition on the consumption preference for low-carbon products, but the mediating effect of the egoistic value disappeared ($\beta = -0.034$, 95% CI: [−0.6331, 0.9879], including 0). Thus, H2 was verified further.

Under the condition of high face consciousness, the effects of the altruistic value ($\beta = 0.078$, 95% CI: [0.0199, 0.0785]), egoistic value ($\beta = 0.6174$, 95% CI: [0.4824, 0.6853], not including 0), and ecological value ($\beta = 0.409$, 95% CI: [0.4284, 0.0238], not including 0) on the consumption preference for low-carbon products were positively moderated by face consciousness, and H3a was supported further. Under the condition of low face consciousness, the relationship between the ecological value and consumption preference for low-carbon products was negatively moderated by face consciousness ($\beta = -0.674$, 95% CI: [−6.3894, −2.0728], not including 0), and the moderating effects of face consciousness on the altruistic value ($\beta = 1.583$, 95% CI: [−0.0305, 9.4904], including 0) and egoistic value ($\beta = 4.765$, 95% CI: [−1.4284, 0.0238], including 0) disappeared. Thus, H3a and H3b were supported further. When the product had a carbon footprint label, the altruistic value ($\beta_{\text{with carbon footprint label}} = 1.059 > \beta_{\text{without carbon footprint label}} = 0.365$, $M_{\text{with carbon footprint label}} = 5.436 > M_{\text{without carbon footprint label}} = 4.826$, $p < 0.01$) and ecological value ($\beta_{\text{with carbon footprint label}} = 0.350 > \beta_{\text{without carbon footprint label}} = 0.092$, $M_{\text{with carbon footprint label}} = 6.093 > M_{\text{without carbon footprint label}} = 5.004$, $p < 0.01$) had a greater impact on the consumption preference for low-carbon products. Therefore, H4 was supported further.

In summary, after grouping the samples by sex and further regression testing, the hypotheses were supported further by the empirical data, and the theoretical model framework was robust.

General discussion

Theoretical contributions

Compared with models used in previous research, this paper explored the relationship between carbon neutrality cognition and the consumers' consumption preference for low-carbon products (main effect) for the first time. The results of the main effect were different from previous studies. We also revealed a new mediation mechanism of environmental values that was not considered previously. Furthermore, we considered the new moderating effects of carbon footprint labels and face consciousness to construct a theoretical model. The main conclusions are as follows: 1) Consumers' environmental values will affect their consumption preference for low-carbon products. Specifically, the higher the altruistic value and ecological value, the stronger the consumers' preference for low-carbon products is. However, the egoistic value negatively affected the consumption preference for low-carbon products. 2) Consumers' carbon neutrality cognition will affect the consumption preference for low-carbon products partly through the environmental value. This means that altruistic and ecological values have a mediating role in the impact of carbon neutrality cognition on the consumption preference for low-carbon products (the dashed arrows in Figure 1), whereas the egoistic value does not have a mediating role in the above-mentioned impact relationship. 3) Consumers' high face consciousness positively moderates the effects of the altruistic, egoistic, and ecological values on the consumption preference for low-carbon products. Low face consciousness negatively moderates the effect of the ecological value on the consumption preference for low-carbon products. However, low face consciousness has no moderating effect on the altruistic and egoistic values, or the consumption preference for low-carbon products. 4) Carbon footprint labels moderate the effects of the altruistic and ecological values on the consumption preference for low-carbon products. Compared with the products without carbon footprint labels, the consumers' preference was stronger, and the mediation effect value was larger.

Our results provide compelling evidence that carbon neutrality cognition can influence the consumption preference for low-carbon products under the context of a carbon peak and carbon neutrality strategy. First, this paper contributes to extending research related to carbon neutrality. Generally, carbon neutrality is a national strategic goal at top-level policy design from a macro perspective, which guides economic development and ecological protection. Carbon emissions initiating from consumers upgrade buying cannot be ignored in China, because the output of energy consumption meets the people's growing consumption demand and provides people with high-quality services. Therefore, our research provides insights into people's perception of the carbon neutrality strategy from a micro research perspective. In terms of the breadth of the research, our findings extend the scope of carbon neutrality and environmental values. Second, this study builds a theoretical model of the effect of carbon neutrality cognition on the consumption preference for low-carbon products. Recent research demonstrated that environmental protection concepts, environmental awareness, and demographic factors influenced consumers' ecological and low-carbon consumption behavior. Inspired by these recent studies, we set carbon neutrality cognition as the antecedent factor for low-carbon consumption research and explored the related mechanisms. The mechanism has a clear influence path that can explain the correlation between the psychology of carbon reduction and the preference for low-carbon products. Finally, this study contributes to enhancing our knowledge related to the research of environmental values. The current research on environmental values mainly focuses on environmental awareness, economic consumption values, and functional consumption values. Few studies have investigated the carbon footprint label and face consciousness as moderating variables to determine the boundary conditions of the proposed theoretical model. Our study provides a new framework for future studies to understand carbon reduction at the consumption end and sustainability.

Management implications

The research findings in this paper suggest the following management implications. First, enterprises should pay attention to and have insights into consumers' carbon neutrality cognition so they can guide consumers' environmental values. Under the background of proposing a carbon neutrality target, consumers should be aware of the cognitive level of the significance of carbon reduction and emission reduction to affect their low-carbon consumption behavior accordingly. Thus, enterprises should actively guide consumers to establish higher altruistic and ecological values and guide the consumption concept and motivation for low carbon and zero carbon in product design and marketing activities. Second, firms can stimulate consumers' face consciousness appropriately because this can enhance the consumption preference for low-carbon products. More elements of face consciousness can be added into new products and advertisements. In contrast, the negative effect of ecological values on the consumption preference for low-carbon products caused by low face awareness should be avoided. Third, the relevant Chinese government departments can promote the carbon footprint label through laws, regulations, and policies and use it as an information guide of the products for sale. The carbon footprint label had a significant positive moderating effect on the consumers' consumption preference for low-carbon products. Products with high carbon emissions can be eliminated through the choice of consumers to force enterprises to carry out low carbon technology innovation.

Limitations and future research

First, the main limitation of the current work was that cultural factors were not considered in the model of carbon neutrality cognition and the consumption preference for low-carbon products. Future research could check the universality of the model based on the diversity of consumer cultures. It will also be interesting to explore whether there are new boundary conditions. Second, we used SVM and NLP to deal with text data, and the accuracy of our machine learning models was about 90.34%. Whether there are more appropriate and accurate methods for this type of study should be explored. Thus, future research can build or match a more accurate algorithm to promote the efficiency and accuracy of text data that includes carbon neutrality cognition. Finally, are there any other factors influencing the effect of carbon neutrality cognition on the consumption of low-carbon products? Future research might identify more complicated interactive factors and reveal new influencing mechanisms. We strongly encourage researchers in these topics to move this study forward.

Data availability statement

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

Author contributions

BL: project administration, funding acquisition, project administration, validation, and supervision. YN: conceptualization, methodology, data curation, and writing-original draft preparation. RY: writing—reviewing and editing, software, and investigation. All authors agree to be accountable for the content of the work.

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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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References

Ajzen, I. (1991). The theory of planned behavior. *Organ. Behav. Hum. Decis. process.* 50 (2), 179–211. doi:10.1016/0749-5978(91)90020-T

Ali, F., Ashfaq, M., Begum, S., and Ali, A. (2020). How "Green" thinking and altruism translate into purchasing intentions for electronics products: The intrinsic-extrinsic motivation mechanism. *Sustain. Prod. Consum.* 24, 281–291. doi:10.1016/j.spc.2020.07.013

Arrow, K. J. (1951). Economic welfare theory. (Book reviews: Social choice and individual values). *Sci. Mon.* 73 (5), 327–362.

Bao, Y., Zhou, K., and Su, C. (2019). Face consciousness and risk aversion: Do they affect consumer decision-making? *Psychol. Mark.* 20 (8), 733–755. doi:10.1002/mar.10094

Black, J. S., Stern, P. C., and Elworth, J. T. (1985). Personal and contextual influences on househould energy adaptations. *J. Appl. Psychol.* 70 (1), 3–21. doi:10.1037/0021-9010.70.1.3

Cederberg, C., Persson, U. M., Neovius, K., Molander, S., and Clift, A. R. (2011). Including carbon emissions from deforestation in the carbon footprint of Brazilian beef. *Environ. Sci. Technol.* 45 (5), 1773–1779. doi:10.1021/es103240z

Chan, H., Wan, L. C., and Sin, L. (2009). The contrasting effects of culture on consumer tolerance: Interpersonal face and impersonal fate. *J. Consum. Res.* 36 (2), 292–304. doi:10.1086/597329

Chekima, B., Syed Khalid Wafa, S. A. W., Igau, O. A., Chekima, S., and Sondoh, S. L. (2016). Examining green consumerism motivational drivers: Does premium price and demographics matter to green purchasing? *J. Clean. Prod.* 112, 3436–3450. doi:10.1016/j.jclepro.2015.09.102

Chng, S., and Borzino, N. (2020). Predictors of environmental behaviour: The role of value orientations, environmental concern, and beliefs in Singapore." in *Sustainability and environmental decision making*. Singapore: Sustainable Development. Available at: http://www.researchgate.net/publication/344726835_Predictors_of_Environmental_Behaviour_The_Role_of_Value_Orientations_Environmental_Concern_and_Beliefs_in_Singapore.

Emberger-Klein, A., and Menrad, K. (2017). The effect of information provision on supermarket consumers' use of and preferences for carbon labels in Germany. *J. Clean. Prod.* 172 (PT.1), 253–263. doi:10.1016/j.jclepro.2017.10.105

Forsythe, S., Liu, C., Shannon, D., and Liu, C. G. (2010). Development of a scale to measure the perceived benefits and risks of online shopping. *J. Interact. Mark.* 20 (2), 55–75. doi:10.1002/dir.20061

Fraj, E., and Martinez, E. (2006). Environmental values and lifestyles as determining factors of ecological consumer behaviour: An empirical analysis. *J. Consum. Mark.* 23 (3), 133–144. doi:10.1108/07363760610663295

Goh, I., Pappu, R., and Chien, P. M. (2021). Investigating the impact of perceived nonprofit sponsorship engagement on prosocial behavior. *J. Bus. Res.* 126, 113–125. doi:10.1016/j.jbusres.2020.12.042

Griskevicius, V., Tybur, J. M., and Van den Bergh, B. (2010). Going green to be seen: Status, reputation, and conspicuous conservation. *J. Personality Soc. Psychol.* 98 (3), 392–404. doi:10.1037/a0017346

Hansla, A., Gamble, A., Juliusson, A., and Gärling, T. (2008). Psychological determinants of attitude towards and willingness to pay for green electricity. *Energy Policy* 36 (2), 768–774. doi:10.1016/j.enpol.2007.10.027

Hayes, A. F. (2013). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*. Available at: http://www.researchgate.net/publication/289066201_Introduction_to_Mediation_Moderation_and_Conditional_Process_Analysis_A_Regression-Based_Approach.

Hopper, J. R., and Nielsen, M. C. (1991). Recycling as altruistic behavior. *Environ. Behav.* 23 (2), 195–220. doi:10.1177/0013916591232004

Ikram, M. (2021). Models for predicting non-renewable energy competing with renewable source for sustainable energy development: Case of asia and oceania region. *Glob. J. Flex. Syst. Manag.* 22 (2), 133–160. doi:10.1007/s40171-021-00285-7

Ikram, M., Sroufe, R., Awan, U., and Abid, N. (2022). Enabling progress in developing economies: A novel hybrid decision-making model for green technology planning. *Sustainability* 14 (1), 258. doi:10.3390/su14010258

Ikram, M., Sroufe, R., Zhang, Q., and Ferasso, M. (2021). Assessment and prediction of environmental sustainability: Novel grey models comparative analysis of China vs. the USA. *Environ. Sci. Pollut. Res.* 28 (14), 17891–17912. doi:10.1007/s11356-020-11418-3

Kahle, L. R. (1996). *Social Values and Consumer Behaviour: Research from the List of Values*, Lawrence Erlbaum Associates Publishers. Available at: http://www.researchgate.net/publication/291065231_Social_Values_and_Consumer_Behaviour_Research_from_the_List_of_Values.

Kaplan, S. (2016). Aesthetics, affect, and cognition: Environmental preference from an evolutionary perspective. *Environ. Behav.* 19 (1), 3–32. doi:10.1177/0013916587191001

Kheiry, B., and Nakhaei, A. (2012). *Consumers' green purchase decision: An examination of environmental beliefs, environmental literacy and demographics*. Kuala Lumpur: International Journals of Marketing & Technology. Available at: http://www.indianjournals.com/ijor.aspx?target=ijor:ijmt& volume=2& issue=9& article=012.

Lee, H. J., and Park, S. Y. (2018). Consumer values and green consumption: Implications for marketing strategy and environmental policy. *amj.* 19 (4), 87–114. doi:10.15830/amj.2018.19.4.87

Li, X., and Xu, H. (2020). The energy-conservation and emission-reduction paths of industrial sectors: Evidence from chinas 35 industrial sectors. *Energy Econ.* 86, 104628. doi:10.1016/j.eneco.2019.104628

Liu, W., and Ji, R. (2019). The influence of low-carbon awareness and low carbon lifestyles on consumers' low carbon consumption intention. *Ecol. Econ.* 35 (8), 40

Msl, A., Jv, B., Pvg, A., Mjjm, A., Eo, A., As, A., et al. (2019). Consumers' preferences for freezing of meat to prevent toxoplasmosis– A stated preference approach. *Meat Sci.* 149, 1–8. doi:10.1016/j.meatsci.2018.11.001

Muhammad, P. F., Kusumaningrum, R., and Wibowo, A. (2021). Sentiment analysis using Word2vec and long short-term memory (LSTM) for Indonesian hotel reviews. *Procedia Comput. Sci.* 179 (6), 728–735. doi:10.1016/j.procs.2021.01.061

Pardo, G., Martin-Garcia, I., Arco, A., Ya?Ez-Ruiz, D. R., Moral, R., and Prado, A. D. (2016). Greenhouse-gas mitigation potential of agro-industrial by-products in the diet of dairy goats in Spain: A life-cycle perspective. *Anim. Prod. Sci.* 56 (3), 646–654. doi:10.1071/an15620

Podsakoff, P. M., Mackenzie, S. B., Lee, J. Y., and Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *J. Appl. Psychol.* 88 (5), 879–903. doi:10.1037/0021-9010.88.5.879

Roos, D., and Hahn, R. (2018). Understanding collaborative consumption: An extension of the theory of planned behavior with value-based personal norms. *J. Bus. Ethics* 158, 679–697. doi:10.1007/s10551-017-3675-3

Schwartz, S. H. (1992). Universals in the content and structure of values: Theoretical advances and empirical tests in 20 countries. *Adv. Exp. Soc. Psychol.* Vol. 25, 1–65. doi:10.1016/s0065-2601(08)60281-6Available at: http://www.researchgate.net/publication/304380643_Universals_in_the_content_and_structure_of_values_Theory_and_empirical_tests_in_20_countries

Semmann, D., Krambeck, H. J., and Milinski, M. (2005). Reputation is valuable within and outside one's own social group. *Behav. Ecol. Sociobiol.* 57 (6), 611–616. doi:10.1007/s00265-004-0885-3

Sternand Paul, C. (1976). Effect of incentives and education on resource conservation decisions in a simulated common dilemma. *J. Pers. Soc. Psychol.* 34 (6), 1285–1292. doi:10.1037/0022-3514.34.6.1285

Stern, P. C. (2000). New environmental theories: Toward a coherent theory of environmentally significant behavior. *J. Soc. Issues* 56 (3), 407–424. doi:10.1111/0022-4537.00175

Tang, C., Yu, Y., Yang, C., Zhong, linsheng, and Li, H. (2018). Analysis of tourists' cognition, intention and behavior of low carbon in Zhangjiajie National Forest Park. *J. Arid Land Resour. Environ.* 32 (4), 43–48. doi:10.13448/j.cnki.jalre.2018.105

The, N., Nguyen, A., Lobo, S., and Greenland (2017). The influence of Vietnamese consumers' altruistic values on their purchase of energy efficient appliances. *Asia Pac. J. Mark. Logist.* 29, 759–777. doi:10.1108/APJML-08-2016-0151

Tongwane, M. I., and Moeletsi, M. E. (2021). Provincial cattle carbon emissions from enteric fermentation and manure management in South Africa. *Environ. Res.* 195 (2), 110833. doi:10.1016/j.envres.2021.110833

Wang, F., Harindintwali, J. D., Yuan, Z., Wang, M., Wang, F., Li, S., et al. (2021). Technologies and perspectives for achieving carbon neutrality. *Innovation* 2 (4), 100180. doi:10.1016/j.xinn.2021.100180

Wang, J. (2015). The dimensional structure of environmental emotion and its impact on carbon emission reduction behavior: A two-factor hypothesis of emotion and behavior and its verification. *Manag. World* 12, 82–95. doi:10.19744/j.cnki.11-1235/f.2015.12.008

Wang, L., Wei, F., and Zhang, X. (2019). Why does energy-saving behavior rise and fall? A study on consumer face consciousness in the Chinese context. *J. Bus. Ethics* 160 (2), 499–513. doi:10.1007/s10551-018-3944-9

Wang, R., Sun, Y., Liu, W., and Zhuang, X. (2010). Study on establish carbon label system in ChinaCNKI:SUN:ZGRZ. *China Popul. Resour. Environ.* 20 (2), 9

Wang, S., and Zhou, H. (2019). The influence of environmental values on ecological consumption Behavior: An empirical test based on mediating variables. *Soft Sci.* 33 (10), 50–57. doi:10.13956/j.ss.1001-8409.2019.10.09

Wang, Y. (2021). The tragets of carbon peak and crabon neutralization and Chinese new energy revolution. *Frontiers* 14, 88–96. doi:10.16619/j.cnki.rmltxsqy.2021.14.010

Xi, J. (2020). *Address at the general debate of the seventy-fifth session of the united nations general assembly*. Peking: People's Daily.

Xiang, X., Ma, M., Ma, X., Chen, L., Cai, W., Feng, W., et al. (2022). Historical decarbonization of global commercial building operations in the 21st century. *Appl. Energy* 322, 119401. doi:10.1016/j.apenergy.2022.119401

Xiang, X., Ma, X., Ma, Z., Ma, M., and Cai, W. (2022). Python-LMDI: A tool for index decomposition analysis of building carbon emissions. *Buildings* 12 (1), 83. doi:10.3390/buildings12010083

Yadav, R. (2016). Altruistic or egoistic: Which value promotes organic food consumption among young consumers? A study in the context of a developing nation. *J. Retail. Consumer Serv.* 33, 92–97. doi:10.1016/j.jretconser.2016.08.008

Yu, C., Zhu, X., Wang, X., and Zhang, Y. (2019). Face consciousness and green buying intention: The moderating effect of consumption context and mediating effect of price. *Manag. Rev.* 31 (11), 139–146. doi:10.14120/j.cnki.cn11-5057/f.2019.11.011

Yu, S., and Gong, L. (2015). Analysis of consumption pollution of urban residents based on externality theory. *Macroeconomics* 3, 16. doi:10.16304/j.cnki.11-3952/f.2015.03.016

Zhang, S., Ma, M., Xiang, X., Cai, W., Feng, W., and Ma, Z. (2022). Potential to decarbonize the commercial building operation of the top two emitters by 2060. *Resour. Conservation Recycl.* 185, 106481. doi:10.1016/j.resconrec.2022.106481

Zhuang, G. (2021). Consumer responsibility and policy recommendations under the guidance of carbon neutrality goal. *Frontiers* 14, 62–68. doi:10.16619/j.cnki.rmltxsqy.2021.14.007

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The effect of social capital on the career choice of entrepreneurship or employment in a closed ecosystem

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Restricted by China's "hukou" system, the population in any given area of the country is relatively constant, and its employability and workability are mutually determined, as in a closed ecosystem. Social capital (or "guanxi" in Chinese society) in China has the effects of reducing set-up costs for entrepreneurship or securing the job-seeking for employment. This paper uses equilibrium analysis and makes some modifications to Kihlstrom and Laffont's model to explore career choice mechanisms in China's context. It was found that when social capital only reduces the set-up costs for entrepreneurship, there exists one equilibrium point; individuals with more social capital will choose entrepreneurship, and those with less social capital will be workers or unemployed. When social capital simultaneously reduces the set-up costs for entrepreneurship and secures employment, four equilibrium points appear along with the strength of social capital, and the career options occur in the order of entrepreneurship, employment, entrepreneurship, and unemployment. The findings fill the gap that career choice is mainly determined by an individual's risk-aversion and contribute specifically to China's entrepreneurship and employment selection.

KEYWORDS
equilibrium analysis, social capital, refugee effect, career choice, closed ecosystem

1 Introduction

Since 2014, the Chinese government has adopted mass entrepreneurship and innovation to stimulate sustainable economic growth. Some policies, such as "to encourage entrepreneurship to create more employment opportunities" are widely advocated for the coming years. Known as the two most important types of career choices, entrepreneurship and employment are equally important for China's economic development and social stability. However, the rates of both entrepreneurship and employment in some regions (such as Hunan province and Qinghai province) have not improved significantly even with the support of numerous stimulus policies.

Conversely, low-end entrepreneurship and even unemployment are increasing in some areas, particularly as the COVID-19 pandemic continues.

With contextualization in entrepreneurial studies, social factors such as customs, norms, and connections are involved to explain more specific entrepreneurial problems. In China, social capital, also referred to as "guanxi", a Chinese expression of interpersonal connections, is widely seen in the country's social and economic activities (Park and Luo, 2001; Chen and Chen, 2004; Barbalet, 2018). Its prevalence and increasing significance during China's post-1978 shift toward a market economy has even been reinforced (Bian, 2018), especially in less developed areas (Guo et al., 2018). Taormina and Gao (2010) pointed out that guanxi is a type of dimension for relation study in China's Confucian culture due to its function in reducing exchange costs and facilitating communication when confronted with hindrances from norms or laws. To foster guanxi among individuals, it is necessary to build relationships based on long-term associations and reciprocity (Bian, 2018). In addition to these benefits, social capital in China can also contribute to better trust and bring more implicit resources for newly established companies; it can also reinforce the depth of communication even among business cycles and government agencies as well. For this reason, social capital plays an important role in start-up activities in China (Alistair et al., 2008; Opper et al., 2017; Ju et al., 2019). As concluded by Jing et al. (2018), in rural China, social capital can significantly improve entrepreneurial survival performance and innovative performance. Social capital is not only significant for entrepreneurship but is also important in job seeking and job development (Bian et al., 2012; Chung, 2019), including expanding job market resources, securing job retention, and even facilitating career paths.

China's labor market has another specific characteristic due to the "hukou" system. Hukou is the household registration and residential permission system for China's labor force. Legal hukou has a significant impact on social stratification and mobility in most areas because it implicitly brings with it much social welfare, such as buying houses, entering schools, or even enjoying social security guarantees (Lu, 2008; Chen and Hu 2021). Under the restrictions of hukou, most individuals cannot freely move outside of their permission areas. Entrepreneurial resources, including energy supply, financial support, technology innovation, etc. (Dong et al., 2021; Ren et al., 2022; Wang et al., 2022), are essentially constant and form a closed ecosystem for career choices. Accordingly, individuals may form a closed ecosystem in which entrepreneurship will only digest the labor demand locally (Huang et al., 2010), and those who cannot be digested in the ecosystem will always be left unemployed (Zhang, 2010).

In the classical work of Kihlstrom and Laffont (1979), the career choice of individuals whether to be employed on a salary from a company or to initiate their own start-up (entrepreneurship) can be explained by a labor market equilibrium model (referred to as the K-L model). In the K-L model, is the set of agents who have been identified with $[0, 1]$, and agent has von Neumanna Morgenstern utility function $u(I, \alpha)$, where I represents income. Following this model, it is clear that the first and second derivatives u' and u'' exist and are continuous. For the reason that $u' > 0$ and $u'' < 0$, all agents are risk averse or indifferent to risk. In a competitive market, the model shows that there exists an equilibrium point that separates two career choices: the more risk-averse agents become employees while the less risk-averse agents become entrepreneurs. This pioneering research has inspired numerous discussions around who will preferentially choose a career as an employee and who will prefer to be an entrepreneur (Turro et al., 2016; Parker, 2018; Yang and Wen, 2020; de Blasio et al., 2021), and whether an individual's risk aversity is one of the attributes for selecting entrepreneurship or employment (Choi et al., 2019; Bonilla and Vergara, 2021). Other factors that can affect the choice of career have also been introduced. According to Poschke (2008), the major determinant is education, and he confirmed that in an equilibrium model the level of education determines a U-shaped career choice: the individuals with the lowest and the highest levels of education are more likely to choose entrepreneurship. However, Van der Sluis et al. (2008) reviewed articles related to education and the decision to follow entrepreneurship and found that the impact of education on selecting entrepreneurship is insignificant. Using data from China, Chu and Wen (2019) conducted an empirical study and found that college education decreases self-employed-type entrepreneurial choices but increases boss-type activities. In this case, opportunity entrepreneurship and necessity entrepreneurship have been distinguished in China's context.

Different from the mathematical modeling analysis by Kihlstrom and Laffont (1979) and Poschke (2008), Thurik et al. (2008) adopted an empirical study approach, in which the entire economic system only has agents that comprise employees or entrepreneurs, with each highly impacted by the other. On one hand, when new entrepreneurs are expelled as "refugees" from the employment market, a high unemployment rate will produce a high entrepreneurship rate; on the other hand, when the production function needs more labor input, a high entrepreneurship rate could create more employment demand. Therefore, in the studies by Thurik et al. (2008) and Aubry et al. (2015), career choice is affected by two types of effects: the refugee effect and the entrepreneurial effect. These two effects were verified by Dong et al. (2012), using data from the Chinese mainland.

For the reason that the refugee effect and the entrepreneurial effect cannot be drawn from the K-L model, some detailed career choice situations such as low-end entrepreneurship and unemployment have not been explained. In addition, the K-L model applies to an open system and thus cannot reflect the situation under China's hukou system. Therefore, in this paper the traditional K-L model is modified by adding social capital and confining the scope to a closed ecosystem, to better reflect the reality of China's employment and entrepreneurial choices and also to explore internal relations and career choice mechanisms.

Unlike traditional studies, which have shown that risk aversion is an important factor for career choice, this paper demonstrates that social capital, or guanxi in China's context, is a very important determinant. Whether social capital can reduce the set-up costs for entrepreneurship or secure employment for jobseekers, there will be an equilibrium both for an individual's utility and for the labor market in a closed ecosystem such as that restricted by China's hukou system. The Schumpeter effect and the refugee effect will appear along with the strength of an individual's social capital.

This paper is organized as follows: in Section 1, I introduce the background, some concepts, and the motivation to conduct this study. In Section 2, I describe the basic model based on the K-L model. Section 3 explores the existence and uniqueness of equilibriums of both utilities and labor forces for two kinds of careers. In Section 4, the effects of social capital on this equilibrium are discussed. Section 5 comprises the conclusion and implications of this study.

2 Basic model

The basic model is a modified version of the K-L model. Referring to the K-L model, I assume there is a closed system (in which the population is a constant) with a set of agents (who face career choices in the market) defined by the interval $\alpha \in [0,1]$; a higher value represents a greater aversion to risk. Each agent has an initial physical asset denoted by A and an initial income denoted by $I \in [0,\infty]$, where I is continuous. Any individual α has a von Neumann–Morgenstern utility function $u(I,\alpha)$, so all agents are risk averse or indifferent to risk. Also, assuming the Arrow (1971) and Pratt (1964) absolute risk-aversion measure (see the K-L model) is non-decreasing in α, i.e., if α exceeds β, then:

$$r(I,\alpha) = -u''(I,\alpha)\big/u'(I,\alpha) \geq -u''(I,\beta)\big/u'(I,\beta) = r(I,\beta) \tag{1}$$

for all $I \in [0,+\infty]$.

Additionally, the technology function $y(\cdot)$ is introduced, where $y = g(L,\tilde{x})$ represents the individual entrepreneurship function, y is the output, and L is the labor input (employed by entrepreneurship, no less than 0), $\tilde{x} \in [0,\bar{x}]$ and is independently identically distributed. Note that L is the employed population, and both entrepreneurs and workers are included in $y(\cdot)$, thus in an equilibrium system, the population of workers should equal to the employed workers by all entrepreneurs. Otherwise, there will be surplus population (unemployed or non-employer).

Note that the fostering of social capital requires long-term associations and reciprocity in China and having more connections will reduce the exchange cost. Therefore, for entrepreneurship, the set-up cost function $F(\alpha)$ is negatively correlated with the agent $\alpha \in [0,1]$, where α represents the value of social capital strength.

Also, the technology function of $g(L,x)$ is adopted, in which g is the output and x is the value taken by a nondegenerate random parameter $\tilde{x}$ with the support of $[0,\bar{x}]$, $0 < \bar{x} < +\infty$. The income function for entrepreneurship is therefore defined by:

$$I_E = A + \pi - F(\alpha) \tag{2}$$

Where w is the wage paid for employment; when an entrepreneur α pays the wage w and employs $L(w,\alpha)$ workers, $\pi = g(L,\tilde{x}) - wL$ is the profit obtained by the entrepreneur, but it is random.

The income function for employment can be specified as:

$$I_L = A + w \tag{3}$$

Also, according to agents' utility functions, denoted as $Eu(A + g(L,\tilde{x}) - wL - F(\alpha),\alpha)$ for entrepreneurs and $u(A+w)$ for workers, note that agent αwill choose to be an entrepreneur when:

$$Eu\left(A + g\left(L,\tilde{x}\right) - wL - F(\alpha),\alpha\right) \geq u(A+w) \tag{4}$$

Or he will choose to be a worker (when equality happens, the agent will be indifferent as an entrepreneur or a worker).

As mentioned earlier, in a closed ecosystem, the labor forces will reach equilibrium when the labor market clears. When this happens, the total number of workers demanded by entrepreneurship equals the number supplied by the market, with the equilibrium wage of w^*, and the market can be described as:

$$\int L(w^*,\alpha)d\alpha = 1 - \alpha \tag{5}$$

and $L(w,\alpha) \in [0,\ (A - F(\alpha))/w]$.

3 The existence and uniqueness of equilibrium

Equilibrium analysis is widely used in economics research (Cheng et al., 2021; Duan et al., 2021; Wen et al., 2022). In Sections 3.1 and 3.2, the existence of points where utility and labor market equilibrium is reached will be explored.

3.1 The equilibrium of utility

In Section 2, $Eu(A + g(L,\tilde{x}) - wL - F(\alpha),\alpha) \geq u(A+w)$ was set as the criteria to be an entrepreneur, and the following is to judge whether there exists the certainty equivalent wage w^* which makes agent α indifferent between two careers. So, there is the utility function:

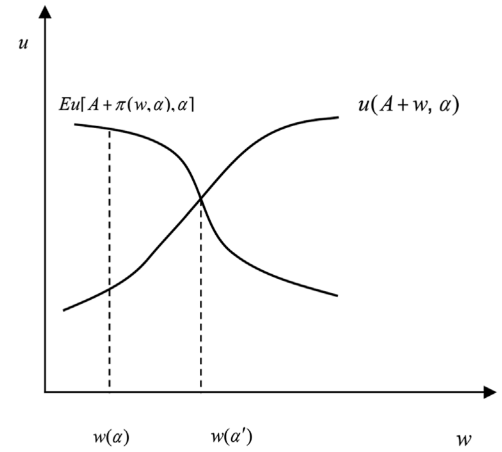

FIGURE 1
Wages under the equilibrium of utility.

$$Eu\Big(A + g\big(L, \tilde{x}\big) - wL - F(\alpha), \alpha\Big) = u(A + w) \tag{6}$$

Which can be rewritten as:

$$P(w) = Eu\Big(A + g\big(L, \tilde{x}\big) - wL - F(\alpha), \alpha\Big) - u(A + w) \tag{7}$$

When $w > w'$, under the precondition of $(A - F(\alpha))/w \geq L \geq 0$and $(A - F(\alpha))/w' \geq L \geq 0$, we have:

$$\begin{aligned} \max Eu\Big(A + g\big(L, \tilde{x}\big) - wL - F(\alpha), \alpha\Big) &\leq \max Eu\Big(A + g\big(L, \tilde{x}\big) \\ &\quad - w'L - F(\alpha), \alpha\Big) \\ &= Eu\Big(A + g\big(L, \tilde{x}\big) - w'L - F(\alpha), \alpha\Big) \end{aligned} \tag{8}$$

Which proves that $P(w)$ is monotonically decreasing.

Also, when $w \to 0$,

$$Eu(A + g(L, x) - wL - F(\alpha), \alpha) - u(A + w, \alpha) > 0 \tag{9}$$

and when $w \to \infty$,

$$g(L, x) - wL - F_E(\alpha) \leq \max g(L, x) \to 0 \tag{10}$$

The intermediate value theorem implies the existence of a positive w^* that satisfies $Eu(A + g(L, \tilde{x}) - wL - F(\alpha), \alpha) = u(A + w)$, and the existence and uniqueness of w^* has verified the monotonicity of $P(w)$. The utility functions for the two parties are illustrated in Figure 1.

Let's move to the variable of social capital in China, or guanxi, which can both facilitate resource acquisition and decrease set-up costs. For any given agent, if they are endowed with less social capital, they will face higher set-up costs, so the expected value from entrepreneurship will decrease. On the other hand, if they, as an entrepreneur, pay higher initial wages to their workers, the expected value will accordingly decrease. For the workers, a higher wage will definitely increase their utility. Reflecting on $Eu(A + g(L, \tilde{x}) - wL - F(\alpha), \alpha)$ and $u(A + w)$, the former expression is decreasing and the latter is increasing, so one w^* will exist that realizes the equilibrium [see Figure 1, intersection at $w(\alpha')$].

Therefore, no matter whether social capital is considered, there exists the certainty equivalent wage w^* which makes agent α indifferent to the choice between entrepreneurship and employment.

3.2 The equilibrium of the labor market

As shown in the basic model, in a closed ecosystem such as that formed by the hukou system, the number of workers demanded by entrepreneurship equals the number supplied by the market, so the market is determined by:

$$\int L(w^*, \alpha) d\alpha = 1 - \alpha \tag{11}$$

I define $(\{\Delta, \Gamma\}, w) = (\{0, \hat{\alpha}^*], (\hat{\alpha}^*, 1], w(\hat{\alpha}^*))$.

For the reason that $L(w, \alpha) > 0$ and when $\hat{\alpha} < \widehat{\alpha'}$ $w(\hat{\alpha}) \geq w(\widehat{\alpha'})$, then:

$$\begin{aligned} \int_0^{\widehat{\alpha'}} L\Big(w\Big(\widehat{\alpha'}\Big), \alpha\Big) d\alpha &= \int_0^{\hat{\alpha}} L\Big(w\Big(\widehat{\alpha'}\Big), \alpha\Big) d\alpha \\ &\quad + \int_{\hat{\alpha}}^{\widehat{\alpha'}} L\Big(w\Big(\widehat{\alpha'}\Big), \alpha\Big) d\alpha > \int_0^{\hat{\alpha}} L(w(\hat{\alpha}), \alpha) d\alpha \end{aligned} \tag{12}$$

Thus, the labor demand $\int_0^{\hat{\alpha}} L(w(\hat{\alpha}), \alpha) d\alpha$ at $w(\hat{\alpha})$ is increasing at $\hat{\alpha}$. From the labor supply at $w(\hat{\alpha})$, $1 - \hat{\alpha}$ is a strictly decreasing function of $\hat{\alpha}$. Therefore, it can be concluded that $\int L(w^*, \alpha) d\alpha = 1 - \alpha$ holds because of increasing $\int_0^{\alpha} L(w^*, \alpha) d\alpha - (1 - \alpha)$ at α, and there exists only one specific $\hat{\alpha}$ that satisfies the equation of $\int L(w^*, \alpha) d\alpha = 1 - \alpha$.

In that case, when social capital is considered and for $Eu(A + g(L, x) - wL - F_E(\alpha), \alpha) - u(A + w - F_L(\alpha))$ is decreasing. Accordingly, there will be $w(\hat{\alpha})$ that satisfies the equations of $\int L(w^*, \alpha) d\alpha = 1 - \alpha$ and $w(\hat{\alpha}) > w(\alpha^*)$. It should also be noted that social capital is set in the interval of $\alpha \in [0, 1]$, where αrepresents the value of social capital strength. Therefore, $\int L(w^*, \alpha) d\alpha = 1 - \alpha$ can be rewritten as $\int_\alpha^1 L(w^*, \alpha) d\alpha = \alpha$ to better describe the situation. For the difference of $w(\hat{\alpha})$ and $w(\alpha^*)$, those with more social capital will choose to be entrepreneurs, while those with less social capital may choose to be workers. Under this situation, the entrepreneurs will employ the number of $L(w(\alpha^*), \alpha)$ workers.

From the labor market analysis, it can be concluded that an equilibrium wage exists that can satisfy the equation of $\int_\alpha^1 L(w^*, \alpha) d\alpha = \alpha$, i.e., the equilibrium of the labor market holds.

4 Results

4.1 The effects of social capital on the equilibrium

As shown in Section 3, when the effects of social capital are ignored, the career choice among individuals is mainly affected by risk aversion, and the equilibriums of both utility and the labor market can be met at a certain wage level. Also from Section 3, we know that when social capital exists, either utility equilibrium or labor market equilibrium could be realized for the given agents, but it remains unknown whether a constant wage exists that can satisfy both types of equilibrium. When social capital is considered, and to explore the equilibrium for utility and labor markets, this discussion is divided into two parts. The first part focuses on the situation in which entrepreneurs are capable of using their social capital to reduce set-up costs, while workers have no effective social capital to safeguard their employment. The second part discusses the situation in which social capital can simultaneously reduce the set-up costs for entrepreneurs and secure employment for workers.

4.2 The effect of social capital on entrepreneurship

In this part, it is assumed that entrepreneurs have social capital while workers have no social capital to secure their jobs. Considering the effects of social capital, for $dr(I)/d(I) < 0 \rightarrow \partial L/\partial\alpha > 0$, the employable capability from entrepreneur agent is correlated with the strength of their social capital and risk-aversion inclination. If an agent has more social capital and is a risk-seeker, they will have a greater intention to hire more workers. Additionally, $dr(I)/d(I) > 0 \rightarrow \partial L/\partial\alpha < 0$ signifies that if an agent is risk averse, their intention to hire workers decreases.

As described in Section 3, when wage $w(\hat{\alpha})$ is the minimum wage and $w(\hat{\alpha}) > w(\alpha^*)$, an entrepreneur cannot support that high level wage, so they will reduce employment. In other words, the wage $w(\hat{\alpha})$ cannot satisfy the labor market equilibrium, which can be expressed as:

$$\int_{\hat{\alpha}}^{1} L(w(\hat{\alpha}),\alpha)d\alpha - \hat{\alpha} < 0 \tag{13}$$

For the difference between actual employment and potential workers, $\hat{e}$ is denoted as the equilibrium employment rate. Therefore, at $\hat{\alpha}$,

$$0 < \hat{e} = \int_{\hat{\alpha}}^{1} L(w(\hat{\alpha}),\alpha)d\alpha \Big/ \hat{\alpha} < 1 \tag{14}$$

When $0 < \hat{e} \le 1$, $1 - \hat{e}$ is the unemployment rate the agents face. An individual who chooses to be a worker will face the utility function $\hat{e}\cdot u(A + w(\hat{\alpha})) + (1-\hat{e})\cdot u(A) < u(A + w(\hat{\alpha}))$, and given that the population is a constant in a closed ecosystem, the worker faces the risk of being unemployed. Accordingly, an entrepreneur faces the utility function of $Eu(A + \tilde{\pi}(w(\hat{\alpha}),\hat{\alpha}) - F(\hat{\alpha})) = u(A + w(\hat{\alpha}))$, which is larger than the utility of being a worker. As a result, it can be concluded that at $w(\hat{\alpha})$, an agent will prefer to be an entrepreneur.

Considering the effects of social capital, I chose the agent $\hat{\alpha} - \varepsilon(\varepsilon \rightarrow 0)$, who faces an employment rate $e(\hat{\alpha} - \varepsilon) = \int_{\hat{\alpha}-\varepsilon}^{1} L(w(\hat{\alpha}),\alpha)d\alpha/(\hat{\alpha} - \varepsilon)$. Obviously,

$$\int_{\hat{\alpha}-\epsilon}^{1} L(w(\hat{\alpha}),\alpha)d\alpha/(\hat{\alpha}-\epsilon) > \int_{\hat{\alpha}}^{1} L(w(\hat{\alpha}),\alpha)d\alpha/(\hat{\alpha}-\epsilon) > \hat{e} \tag{15}$$

holds, indicating that an individual $\hat{\alpha} - \varepsilon$ who chooses to be an entrepreneur will increase the employment rate. Therefore, the expected utility for the worker will be increased accordingly.

I now move on to the discussion of utility for an entrepreneur at a given wage of $w(\hat{\alpha})$.

As indicated in (6), $Eu(A + g(L,x) - wL - F(\hat{\alpha})) = u(A + w(\hat{\alpha}))$ holds, so then:

$$\begin{cases} u(A + w(\hat{\alpha})) > u(A + w(\hat{\alpha}-\epsilon)) \\ u(A + w(\hat{\alpha}-\epsilon)) = Eu\left(A + \tilde{\pi}(w(\hat{\alpha}-\epsilon),\hat{\alpha}-\epsilon) - F(\hat{\alpha}-\epsilon)\right) \\ Eu\left(A + \tilde{\pi}(w(\hat{\alpha}-\epsilon),\hat{\alpha}-\epsilon) - F(\hat{\alpha}-\epsilon)\right) > Eu\left(A + \tilde{\pi}(w(\hat{\alpha}),\hat{\alpha}-\epsilon) - F(\hat{\alpha}-\epsilon)\right) \end{cases} \tag{16}$$

From (16), the agent $\hat{\alpha} - \varepsilon$ as an entrepreneur has lower utility than the agent $\hat{\alpha}$ as an entrepreneur when at a given wage of $w(\hat{\alpha})$. The workers have utility values expressed as $e\cdot u(A + w(\hat{\beta})) + (1-e)\cdot u(A)$, therefore it can be concluded that $\bar{\alpha} < \hat{\alpha}$ exists that satisfies:

$$Eu\left(A + \tilde{\pi}(w(\hat{\alpha}),\bar{\alpha}) - F(\bar{\alpha})\right) = e(\bar{\alpha})u(A + w(\hat{\alpha})) + (1 - e(\bar{\alpha}))\cdot u(A) \tag{17}$$

This indicates that it is indifferent to be an entrepreneur or a worker for any agent $\bar{\alpha}$. Also, it can be found that $e(\bar{\alpha})$ is the employment rate when the employment reaches equilibrium at the minimum wage value of $w(\hat{\alpha})$, and $\alpha^* < \bar{\alpha} < \hat{\alpha}$ is the situation in which more agents will adjust their career choice based on utility value.

Next, $1 - e(\bar{\alpha})$ was set as the risk that an agent faces when they decide to be a worker. For $\alpha^* < \bar{\alpha} < \hat{\alpha}$, it can be divided into two intervals: $[\alpha^*, \bar{\alpha})$and $[\bar{\alpha}, \hat{\alpha}]$.

According to the K-L model, the agents from $[\bar{\alpha}, \hat{\alpha}]$ will be workers. However, in the present model, the agents facing the risk of unemployment $1 - e(\bar{\alpha})$, so they will be excluded from employment and then choose to be entrepreneurs. For the reason that the would-be workers are forced to choose entrepreneurship (or the impact of the unemployment rate on entrepreneurship), they are more similar to refugees from employment markets, so in economics this situation is described as the "refugee effect" (Thurik et al., 2008; Ghavidel et al., 2011). For the interval $[\bar{\alpha}, \hat{\alpha}]$, the number of $\int_{\bar{\alpha}}^{\hat{\alpha}} L(W(\hat{\alpha}),\alpha)d\alpha$ workers will be created, thus

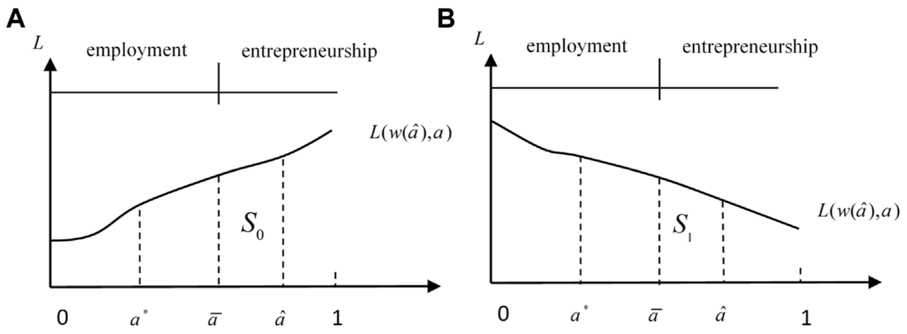

FIGURE 2
The refugee effect and the Schumpeter effect under social capital for entrepreneurship.

the entrepreneurial effect or the Schumpeter effect appears in this situation, by which more innovative entrepreneurship appears to create more job vacancies (Aubry et al., 2015; Ferreira et al., 2017). Both effects are shown in Figure 2, where S_0, S_1 is the number of jobs created by the Schumpeter effect. In Figure 2A, the situation of risk-seeking in relation to income is measured, so $L(w(\hat{\alpha}), \alpha)$ is increasing. In Figure 2B, the situation of risk aversion in relation to income is measured, so $L(w(\hat{\alpha}), \alpha)$ is decreasing. Affected by social capital, agents staying at the interval of $[\bar{\alpha}, 1]$ are entrepreneurs, while individuals staying at the interval of $[0, \bar{\alpha}]$ are workers or unemployed agents. So, a single equilibrium point $\bar{\alpha}$ exists, and this reflects the boundary of the two types of careers.

4.3 The effect of social capital on employment

When social capital as a factor can both decrease the set-up costs for entrepreneurship and secure employment for workers, α can also be used to signify the ability of agents to secure their jobs, i.e., holders of higher α will be preferably employed. With the aid of social capital, the utility of agents from the interval of $[\bar{\alpha}, \hat{\alpha}]$ will be improved, and the former entrepreneurs created by the refugee effect will be substituted by the workers. Less entrepreneurship will lead to less employment requirements, so those agents with lower social capital cannot be sure of getting a job. The term $\alpha' = \hat{\alpha} - \int_{\hat{\alpha}}^{1} L(W(\hat{\alpha}), \alpha)d\alpha$ is used to express those agents who cannot be employed in their one-time career choice, which gives:

$$\int_{\hat{\alpha}}^{1} L(W(\hat{\alpha}), \alpha)d\alpha = \hat{\alpha} - \alpha' > \hat{\alpha} - \bar{\alpha} \tag{18}$$

After the one-time choice, career choices vary in intervals $[0, \alpha']$, $(\alpha', \bar{\alpha}]$, $(\bar{\alpha}, \hat{\alpha}]$, and $(\hat{\alpha}, 1]$. Obviously, the agents that stay at $(\hat{\alpha}, 1]$ will choose entrepreneurship, and they are always risk-takers. Impacted by the Schumpeter effect from $(\hat{\alpha}, 1]$, employment will increase by S_0 presented across the interval $(\alpha', \bar{\alpha}]$, and all agents in this interval have no risk of being a worker due to their higher social capital. However, affected by lower social capital, agents that stay at the interval of $[0, \alpha']$ cannot compete with other agents who have higher social capital, so they must make the next career choice.

Also, given the constant population in a closed ecosystem, the agents in an interval will have three career options. The first is entrepreneurship for a living, also known as necessity entrepreneurship (O'Donnell et al., 2021; Dencker et al., 2021). The second is employment arising from the entrepreneurial effects of the above-mentioned necessity entrepreneurship. The third is unemployment, because the agents have no resources to secure their career.

With regard to the interval of $[0, \alpha']$, if there are no agents engaging in entrepreneurship, there will be no employment. For workers, if their utility is higher than $u(A)$, they will be willing to be employed. Thus, this gives the equilibrium:

$$Eu\Big(A + \tilde{\pi}(w(\hat{\alpha}), \alpha) - F(\alpha)\Big) = u(A) \tag{19}$$

As shown in the proof in 3.1, the intermediate value theorem implies the existence of a positive $\underline{\alpha}$ $(0 < \underline{\alpha} < \alpha')$ that satisfies $Eu(A + \tilde{\pi}(w(\hat{\alpha}), \underline{\alpha}) - F(\underline{\alpha})) = u(A)$. Therefore, in the interval of $(\underline{\alpha}, \alpha')$, all agents will choose entrepreneurship, but this will be confined to necessity entrepreneurship. In this interval, some agents are those who are excluded from the one-time choice. Accordingly, the refugee effect appears in this interval. Also, the necessity entrepreneurship will create $\int_{\underline{\alpha}}^{\alpha'} L(W(\hat{\alpha}), \alpha)d\alpha$ employment.

If agents exist who cannot be employed in the interval of $(\underline{\alpha}, \alpha')$, i.e., when $\int_{\underline{\alpha}}^{\alpha'} L(W(\hat{\alpha}), \alpha)d\alpha < \underline{\alpha}$ holds, then $\widehat{\alpha} = \underline{\alpha} - \int_{\underline{\alpha}}^{\alpha'} L(W(\hat{\alpha}), \alpha)d\alpha$. It can be seen that $\alpha \in [\widehat{\alpha}, \underline{\alpha}]$ are those agents who benefit from the Schumpeter effect and become employed, but the agents $\alpha \in [0, \widehat{\alpha}]$ cannot get employed because of the insufficient social capital in a closed ecosystem.

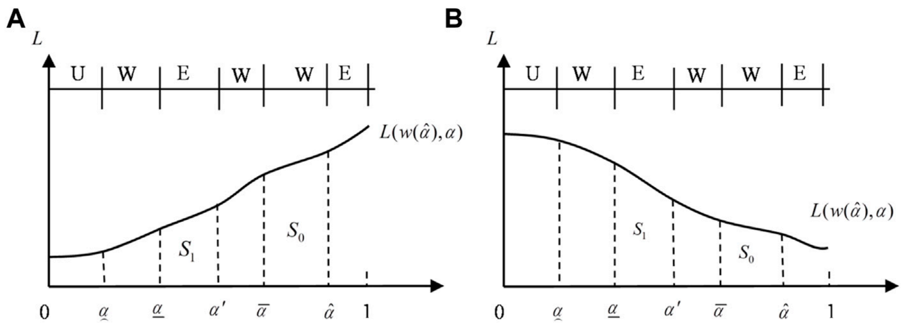

FIGURE 3
Staggered career choices along with the strength of social capital.

This process is also expressed in Figure 3. $L(w(\hat{\alpha}),\alpha)$ is increasing or decreasing depending on an agent's risk-seeking or risk-aversion tendencies (which are shown in Figures 3A,B). If $\hat{\alpha}-\alpha' \geq \hat{\alpha}-\bar{\alpha}$ and $\alpha'-\underline{\alpha} \geq \hat{\alpha}-\bar{\alpha}$, the area of S_1 or $\int_{\underline{\alpha}}^{\alpha'} L(W(\hat{\alpha}),\alpha)d\alpha$ is the employment increased by the interval of $(\underline{\alpha},\alpha']$, and S_0 or $\int_{\bar{\alpha}}^{\hat{\alpha}} L(W(\hat{\alpha}),\alpha)d\alpha$ is the employment increased by the interval of $(\bar{\alpha},\hat{\alpha})$. When $L(w(\hat{\alpha}),\alpha)$ is increasing (Figure 3A), the employment created by the Schumpeter effect from $\alpha \in (\underline{\alpha},\alpha')$ is smaller than the potential employment created by the potential entrepreneurs $\in (\bar{\alpha},\hat{\alpha})$, i.e., the social capital has squeezed employment in this situation. The opposite situation happens when $L(w(\hat{\alpha}),\alpha)$ is increasing, and in this situation, social capital expands employment (see Figure 3B).

From the entire landscape, when social capital can both reduce the set-up costs for entrepreneurship and secure jobs, career choices will be staggered along with the strength of social capital. As shown in Figure 3, $\alpha \in (\hat{\alpha},1]$ and $\alpha \in (\underline{\alpha},\alpha')$ choose entrepreneurship, $\alpha \in (\alpha',\hat{\alpha})$ and $\alpha \in [\widehat{\alpha},\underline{\alpha})$ choose employment, and $\alpha \in [0,\widehat{\alpha})$ will face unemployment. $\hat{\alpha}$, α', $\underline{\alpha}$, and $\widehat{\alpha}$ are equilibrium points.

5 Conclusion and suggestions

This paper describes some modifications to the traditional K-L model, which was then used to explore the mechanism of career choice between entrepreneurship and employment. For the K-L model and some other scholars (Parker, 2018; Choi et al., 2019; Yang and Wen, 2020; Bonilla and Vergara, 2021), as based on the rule of risk aversion for individuals, it was found that a utility equilibrium and a labor equilibrium exists in the market, and agents who are more risk-seeking will prefer to be entrepreneurs, while the more risk-averse will be workers. Similarly, an equilibrium analysis by Posche (2008) confirmed that education is a significant factor in career choice. However, when social capital, or guanxi in China, which is rooted in the country's Confucian culture and widespread in Chinese society, and the hukou system, a type of permission certificate that stops people moving freely around the country, are considered in a K-L model, the equilibrium analysis of career choice will show many differences, as outlined below.

For the prevention of free mobility by hukou, any given area will basically keep a stable population and is always seen as a closed ecosystem where people, no matter entrepreneurs or workers, are interactively digested by each other. When social capital (or guanxi) can only reduce the set-up costs for entrepreneurship but has no effect on workers, there is only one equilibrium point. Holders of greater social capital will choose entrepreneurship, while the holders of lower social capital will choose to be workers or will be unemployed.

When social capital can simultaneously reduce the set-up costs for entrepreneurship and secure workers' jobs, there will be at least four equilibrium points, with a staggered career choice along with the strength of social capital (from highest to lowest) of entrepreneurship, employment, entrepreneurship, and unemployment. This conclusion is different from Dong et al.'s (2021), who suggest that entrepreneurship and employment are dichotomies.

No matter whether social capital can only reduce the set-up costs for entrepreneurs or can both reduce the set-up costs for entrepreneurs and secure jobs for workers, there appears to be a Schumpeter effect through which more employment will be stimulated with incremental entrepreneurship. However, when social capital has the capability of securing jobs, some holders of lower social capital will be excluded from the first employment market and will then have to choose necessity entrepreneurship, so the refugee effect appears. This conclusion is in agreement with the study of Chu and Wen (2019), who stress that education decreases self-employed-type entrepreneurial choices but increases boss-type activities. My explanation is that education is a good channel through which to improve social capital because of its wider social space and stronger relations.

Under both the Schumpeter effect and the refugee effect, some holders of even lower social capital will be squeezed to choose low-end employment or even become unemployed. This could explain why in some less developed areas (such as Hunan province and Qinghai province), where guanxi is more unevenly distributed and the hukou system is even stricter, low-end entrepreneurship and unemployment are common.

These conclusions have many implications, such as the fact that social capital can consolidate both entrepreneurship and employment and improve the quality of career choices; individuals who have weak social capital are more vulnerable in the job market; and that closed ecosystems could result in a precarious employment rate. To smooth the employment market and improve career quality, the following suggestions are made. Noting that guanxi, China's social capital, is always based on long-term associations and reciprocity, individuals should positively expand their social interactions; establish long-term and stable relations with their relatives, classmates, or other peers; and be ready to "pay back" if they are asked for help by other parties. For the government, on one hand noting that nurturing social capital is essential, the government should initiate more educational or professional agencies to accommodate more people to establish or even strengthen their communications; on the other hand, the government should reduce the restrictions arising from the hukou system and open more job markets in different areas to compensate for the weakness of holders of lower social capital and increase the quantity and quality of employment and entrepreneurship.

This paper primarily focuses on the modification of the K-L model, with frequent use of equilibrium analysis. Further empirical research analysis should be conducted to test related conclusions. Here, the understanding of social capital in China is confined to saving costs and securing jobs, but the actual connotations of social capital, or guanxi, are more complicated in China's context. In the future, more mechanisms should be added to the K-L model, to better match reality.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material; any further inquiries can be directed to the corresponding author.

Author contributions

The author confirms being the sole contributor of this work, and has contributed to the conception, model design, mathematical analysis, discussion and conclusion of the study.

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Conflict of interest

The author declares 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

References

Alistair, R., Anderson, Yiu, E., and Lee, C. (2008). From tradition to modern: Attitudes and applications of guanxi in Chinese entrepreneurship. *J. Small Bus. Enterp. Dev.* 15 (4), 775–787. doi:10.1108/14626000810917852

Aubry, M., Bonnet, J., and Renou-Maissant, P. (2015). Entrepreneurship and the business cycle: The "schumpeter" effect versus the "refugee" effect—a French appraisal based on regional data. *Ann. Reg. Sci.* 54 (1), 23–55. doi:10.1007/s00168-014-0645-x

Barbalet, J. (2018). Guanxi as social exchange: Emotions, power and corruption. *Sociology* 52 (5), 934–949. doi:10.1177/0038038517692511

Bian, Y. (2018). The Prevalence and the increasing significance of Guanxi. *China Q.* 235 (3), 597–621. doi:10.1017/s0305741018000541

Bian, Y., Zhang, W., and Chen, C. (2012). A social network model of the job-search process: Testing a relational effect hypothesis. *Chin. J. Sociol.* 32 (3), 24–37.

Bonilla, C. A., and Vergara, M. (2021). Risk aversion, downside risk aversion, and the transition to entrepreneurship. *Theory Decis.* 91 (1), 123–133. doi:10.1007/s11238-020-09786-w

Chen, J., and Hu, M. (2021). City-level hukou-based labor market discrimination and migrant entrepreneurship in China. *Technol. Econ. Dev. Econ.* 27 (5), 1095–1118. doi:10.3846/tede.2021.15006

Chen, X. P., and Chen, C. C. (2004). On the intricacies of the Chinese guanxi: A process model of guanxi development. *Asia Pac. J. Manag.* 21 (3), 305–324. doi:10.1023/b:apjm.0000036465.19102.d5

Cheng, C., Ren, X., Dong, K., Dong, X., and Wang, Z. (2021). How does technological innovation mitigate CO2 emissions in OECD countries? Heterogeneous analysis using panel quantile regression. *J. Environ. Manag.* 280, 111818. doi:10.1016/j.jenvman.2020.111818

Choi, S., Kim, N., and Kim, W. (2019). Are social entrepreneurs more risk-averse? *Appl. Econ. Lett.* 26 (11), 933–937.

Chu, T., and Wen, Q. (2019). Does college education promote entrepreneurship in China? *J. Labor Res.* 40 (4), 463–486. doi:10.1007/s12122-019-09293-0

Chung, H. (2019). How Guanxi networking matters in the relation between market orientation and innovation in Asian emerging economies - the case of markor. *J. Bus. industrial Mark.* 34 (4), 836–849. doi:10.1108/jbim-05-2017-0115

de Blasio, G., De Paola, M., Poy, S., and Scoppa, V. (2021). Massive earthquakes, risk aversion, and entrepreneurship. *Small Bus. Econ.* 57 (1), 295–322. doi:10.1007/s11187-020-00327-x

Dencker, J. C., Bacq, S., Gruber, M., and Haas, M. (2021). Reconceptualizing necessity entrepreneurship: A contextualized framework of entrepreneurial processes under the condition of basic needs. *Acad. Manage. Rev.* 46 (1), 60–79. doi:10.5465/amr.2017.0471

Dong, K., Ren, X., and Zhao, J. (2021). How does low-carbon energy transition alleviate energy poverty in China? A nonparametric panel causality analysis. *Energy Econ.* 103, 105620. doi:10.1016/j.eneco.2021.105620

Dong, Z. Q., Wei, X. H., and Zhang, T. H. (2012). Business start-ups and unemployment: An empirical investigation on refugee effect vs. entrepreneur effect. *Econ. Rev.* 1 (2), 80–87.

Duan, K., Ren, X., Shi, Y., Mishra, T., and Yan, C. (2021). The marginal impacts of energy prices on carbon price variations: Evidence from a quantile-on-quantile approach. *Energy Econ.* 95, 105131. doi:10.1016/j.eneco.2021.105131

Ferreira, J. J., Fayolle, A., Fernandes, C., and Raposo, M. (2017). Effects of Schumpeterian and Kirznerian entrepreneurship on economic growth: Panel data evidence. *Entrepreneursh. Regional Dev.* 29 (1-2), 27–50. doi:10.1080/08985626.2016.1255431

Ghavidel, S., Farjadi, G., and Mohammadpour, A. (2011). The relationship between entrepreneurship and unemployment in developed and developing countries. *Int. J. Econ. Behav. (IJEB)* 1 (1), 71–78.

Guo, Y., Rammal, H. G., Benson, J., Zhu, Y., and Dowling, P. J. (2018). Interpersonal relations in China: Expatriates' perspective on the development and use of guanxi. *Int. Bus. Rev.* 27 (2), 455–464. doi:10.1016/j.ibusrev.2017.09.012

Huang, Y., Guo, F., and Tang, Y. (2010). Hukou status and social exclusion of rural–urban migrants in transitional China. *J. Asian Public Policy* 3 (2), 172–185. doi:10.1080/17516234.2010.501160

Jing, D., Xu, W., and Yu, Z. (2018). Investigation of performance of rural entrepreneurial firms in China: Influence and interaction between renqing relationship and normative experience. *J. Finance Econ.* 2018 (1), 20–32.

Ju, W., Zhou, X., and Wang, S. (2019). The impact of scholars' guanxi networks on entrepreneurial performance—the mediating effect of resource acquisition. *Phys. A Stat. Mech. its Appl.* 521, 9–17. doi:10.1016/j.physa.2019.01.066

Kihlstrom, R., and Laffont, J. (1979). A general equilibrium entrepreneurial theory of firm formation based on risk aversion. *J. Political Econ.* 87, 719–748. doi:10.1086/260790

Lu, Y. (2008). Does hukou still matter? The household registration system and its impact on social stratification and mobility in China. *Soc. Sci. China* 29 (2), 56–75. doi:10.1080/02529200802091250

O'Donnell, P., O'Gorman, C., and Clinton, E. (2021). Rethinking the "necessity" in necessity entrepreneurship. *Acad. Manage. Rev.* 46 (4), 827–830. doi:10.5465/amr.2020.0143

Opper, S., Nee, V., and Holm, H. J. (2017). Risk aversion and guanxi activities: A behavioral analysis of CEOs in China. *Acad. Manage. J.* 60 (4), 1504–1530. doi:10.5465/amj.2015.0355

Park, S. H., and Luo, Y. (2001). Guanxi and organizational dynamics: Organizational networking in Chinese firms. *Strateg. Manag. J.* 22 (5), 455–477. doi:10.1002/smj.167

Parker, S. C. (2018). Entrepreneurship and economic theory. *Oxf. Rev. Econ. Policy* 34 (4), 540–564. doi:10.1093/oxrep/gry013

Poschke, M. (2008). *Who becomes an entrepreneur? Labor market prospects and occupational choice, IZA Discussion Papers, No. 3816*. Bonn: Institute for the Study of Labor (IZA). https://nbn-resolving.de/urn:nbn:de:101:1-20081127397.

Ren, X., Li, Y., Shahbaz, M., Dong, K., and Lu, Z. (2022). Climate risk and corporate environmental performance: Empirical evidence from China. *Sustain. Prod. Consum.* 30, 467–477. doi:10.1016/j.spc.2021.12.023

Taormina, R. J., and Gao, J. H. (2010). A research model for guanxi behavior: Antecedents, measures, and outcomes of Chinese social networking. *Soc. Sci. Res.* 39 (6), 1195–1212. doi:10.1016/j.ssresearch.2010.07.003

Thurik, A. R., Carree, M. A., Stel, A. V., and Audretsch, D. B. (2008). Does self-employment reduce unemployment? *J. Bus. Ventur.* 23 (6), 673–686. doi:10.1016/j.jbusvent.2008.01.007

Turro, A., Alvarez, C., and Urbano, D. (2016). Intrapreneurship in the Spanish context: A regional analysis. *Entrepreneursh. Regional Dev.* 28 (5-6), 380–402. doi:10.1080/08985626.2016.1162850

Van der Sluis, J., Van Praag, M., and Vijverberg, W. (2008). Education and entrepreneurship selection and performance: A review of the empirical literature. *J. Econ. Surv.* 22 (5), 795–841. doi:10.1111/j.1467-6419.2008.00550.x

Wang, X., Wang, X., Ren, X., and Wen, F. (2022). Can digital financial inclusion affect CO2 emissions of China at the prefecture level? Evidence from a spatial econometric approach. *Energy Econ.* 109, 105966. doi:10.1016/j.eneco.2022.105966

Wen, F., Tong, X., and Ren, X. (2022). Gold or Bitcoin, which is the safe haven during the COVID-19 pandemic? *Int. Rev. Financial Analysis* 81, 102121. doi:10.1016/j.irfa.2022.102121

Yang, Z., and Wen, F. (2020). From employees to entrepreneurs: Rural land rental market and the upgrade of rural labor allocation in non-agricultural sectors. *Manag. World* 36 (7), 171–184. (in Chinese).

Zhang, H. (2010). The Hukou system's constraints on migrant workers' job mobility in Chinese cities. *China Econ. Rev.* 21 (1), 51–64. doi:10.1016/j.chieco.2009.10.002

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How substantive corporate social responsibility attributions promote employee work engagement: A triple mediation model

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Increasing evidences suggest that employees exhibit positive attitudinal and behavioral responses when they attribute their company's demonstrations of corporate social responsibility as substantive. However, there has been insufficient investigation into the underlying psychological processes through which substantive corporate social responsibility attributions are associated with work engagement. Based on the model of psychological conditions for engagement, we proposed that attributions of substantive CSR are positively related to work engagement *via* work meaningfulness, psychological safety, and organization-based self-esteem. We collected two-wave time-lagged questionnaire data from 503 fulltime employees in mainland China. Hierarchical regression was conducted to test hypothesized model using SPSS Process macro. Results indicated that substantive corporate social responsibility attributions positively predicted work engagement; work meaningfulness, psychological safety and organization-based self-esteem parallel mediated this relationship. The findings contribute to the literature of well-being related outcomes of corporate social responsibility attributions and help a thorough understanding of antecedents of work engagement. It expands our knowledge of the new mechanisms in the relationship between corporate social responsibility attributions and work engagement. Our findings also could shed lights on the management for employees' work engagement.

KEYWORDS

substantive corporate social responsibility attributions, work engagement, work meaningfulness, psychological safety, organization-based self-esteem

1 Introduction

The rapid economic growth is accompanied with energy consumption and environmental problems (Ren et al., 2022c; Ren et al., 2022d). Increasing environmental problems such as global warming, ozone layer destruction, and depletion, as well as acid rain pose huge challenges to the international community and even humanity (Wang et al., 2022a; Wang et al., 2022b). Meanwhile, poverty is also a social problem that has received wide attention (Dong et al., 2021). More and more corporate stakeholders expect that companies should show corporate social responsibility (CSR) which contributes to society and the environment while achieving profitability (Farooq et al., 2017; Ren et al., 2022b). As key stakeholders, employees have the potential to support, participate in, or even lead CSR initiatives (Farooq et al., 2017).

It has been found that employees' perception of CSR can lead employees' positive outcomes, such as organizational commitment (Edwards and Kudret, 2017), organizational identification (Farooq et al., 2017), task performance (Edwards and Kudret, 2017), and organizational citizenship behavior (OCB, Rupp et al., 2013; Farooq et al., 2017; He et al., 2019). However, Manika et al. (2015) and Newman et al. (2015) found no correlation between CSR perception and OCB. It is possible that employees care more about the motivations behind enterprises' CSR initiatives than the initiatives themselves (Vlachos et al., 2017). Presumably, employees will exhibit more positive attitudinal and behavioral responses if they attribute the CSR practices to motivations that are substantive (efforts to be genuine and other-serving) rather than symbolic (efforts to comply with regulations or greenwash the company's reputation) (Donia et al., 2017; Donia et al., 2019). Prior studies explored the boundary condition played by CSR attributions in the relationship between CSR perception and employee attitudinal and behavioral outcomes (De Roeck and Delobbe, 2012; Gatignon-Turnau and Mignonac, 2015; Lee and Seo, 2017). However, as a subjective reasoning and judgment about the motives behind the enterprise's social responsibility practices, CSR attributions have a potential to impact employees directly (Donia et al., 2017). A limited number of studies have shown a facilitative effect of employees' attributions of substantive CSR on organizational pride (Donia et al., 2019), job satisfaction (Vlachos et al., 2013), and affective commitment (Raub, 2017), but largely ignoring its positive impact on employees' health and well-being (Gond et al., 2017).

Indeed, being a typical and critical form of work-related well-being, work engagement refers to a positive, fulfilling, affective-motivational state (Bakker et al., 2008; Bakker, 2009). Engaged employees are more likely to be psychologically and physically healthy, they have a higher level of energy to fulfill family roles (Eldor, 2016; Knight et al., 2017). Moreover, a meta-analytic review indicated that work engagement was positively associated with task performance (Christian et al., 2011), which can provide enterprises with a competitive advantage (Eldor, 2016). The unique value of work engagement both for employees, enterprises, and families, emphasizes the importance to identify the driving factors of work engagement. Prior studies found that task characteristics (e.g., task significance, Goštautaitė and Bučiūnienė, 2015); leadership (e.g., charismatic leadership, Babcock-Roberson and Strickland, 2010), and dispositional characteristics (e.g., conscientiousness, Furnham et al., 2002) were positively related to work engagement. Scholars called for further investigation of its facilitative factors in addition to these above factors (Christian et al., 2011).

Accordingly, this study fills in these research gaps by empirically investigating whether substantive CSR attributions promote work engagement. We believe that substantive CSR attributions can satisfy employees' various needs (Rupp et al., 2006), which encourages employees to reciprocate with greater engagement. Moreover, it should be noted that the formation of work engagement is a complex psychological process. Kahn (1990) proposed psychological conditions for engagement model (Kahn's model) and indicated that employees could only fully experience work engagement when three psychological conditions were simultaneously presented namely psychological meaning, psychological safety, and psychological resource availability. Kahn's model helps connect a broader work environment and work engagement (Fletcher et al., 2018). According to Kahn's (1990) model, this study aims to further explore the parallel mediating effect played by work meaningfulness, psychological safety, and organization-based self-esteem (OBSE) in the relationship between substantive CSR attributions and work engagement. In line with previous research, work meaningfulness (Roberts and David, 2017; Lin et al., 2020) and psychological safety (Roberts and David, 2017; Lin et al., 2020) correspond to two of the three conditions for engagement in Kahn's (1990) model. Meanwhile, our study proposes that the third antecedent of engagement, psychological resource availability, can be represented by organization-based self-esteem. Furthermore, prior studies demonstrated that employee perceptions of CSR practices as substantive (i.e., genuine and other-serving) were positively associated with increased work meaningfulness (Donia et al., 2019) and psychological safety (Ahmad et al., 2019). In addition, working for a socially responsible enterprise can raise employees' OBSE (Hur et al., 2022). Therefore, according to Kahn's (1990) model, we believe that employees' substantive CSR attributions will give rise to the three psychological antecedents of engagement.

Taken together, this study proposes and tests a triple-mediation model in which attributions of substantive CSR are positively related to work engagement through the three parallel mediators of work meaningfulness, psychological safety and OBSE. This research is important for several reasons. First, by establishing a positive link between substantive CSR attributions and work engagement, this study contributes to the literature on attributions of substantive CSR in relation to employees' well-being and health, specifically their engagement in work. Meanwhile, it also echoes the call to further investigate the driving factors of work engagement and helps a thorough understanding of antecedents of work engagement. Second, this study introduces Kahn's (1990) model of conceptually relevant mediators of this association. It could advance our knowledge of the potential mechanisms by which substantive

CSR attributions enhance work engagement. Lastly, the present study contributes to enriching our theoretical understanding of the facilitator of psychological conditions for engagement, as well as expanding the application scope of this theoretical model. Our findings also could shed lights on the management for employees' work engagement.

2 Theoretical background and hypotheses development

2.1 The psychological conditions for engagement model

The primary tenet of Kahn's (1990) model of psychological conditions for personal engagement at work posits that the degree to which employees engage in their work depends on three psychological conditions. The first is psychological meaningfulness, which represents employees' belief that they receive sufficient returns on the time, energy, and efforts that they invest into their work. The second is psychological safety, which refers to employees' perception that it is safe to fully express themselves at work. The third is psychological resource availability, which can be viewed as employees' sense of possessing sufficient personal resources to fully invest themselves in work. Kahn (1990) further posits that there is a psychological contract between each employee and his or her work role, and the three psychological conditions reflect the logic of that contract. Employees will invest themselves into their work roles when they believe that this contract will bring desired benefits (meaningfulness) and a guarantee of protection (safety); investment also relies on the employee having the resources to fulfill this contract (Kahn, 1990).

Kahn's (1990) model provides an integrated theoretical framework to understand the psychological mechanisms of how substantive CSR attributions are translated to work engagement. Specific to this study, we propose that work meaningfulness represents the degree of meaning stemming from employees' work (Kahn, 1990), which could correspond to psychological meaningfulness (Roberts and David, 2017; Lin et al., 2020). Meanwhile, psychological safety refers to employees' belief that the presentation of genuine self at work will not negatively impact on his or her status or career (Kahn, 1990), we believe that it is consistent with psychological safety (Roberts and David, 2017; Lin et al., 2020). Moreover, we propose that psychological resource availability could be represented by organization-based self-esteem (OBSE). Resources could be defined as anything that individuals perceive as being helpful to achieving their goals, psychological resources are tools that help efficiently deal with job tasks (Halbesleben and Wheeler 2008). Self-esteem is such a typical psychological resource, because self-esteem facilitates individuals to optimize the use of contextual resources, individuals with high self-esteem tend to start a challenging task and are more inclined to actively look for help to finish their task (Hardré, 2003; ten Brummelhuis and Bakker, 2012). Rooted on self-esteem, organization-based self-esteem (OBSE) represents employees' belief that they are important, capable, and competent individuals in their organization (Pierce and Gardner, 2004), which could be viewed as a crucial personal resource.

In addition, according to Kahn (1990), substantive CSR attributions may shape three psychological conditions, which in turn promote work engagement. These three psychological conditions are outcomes of the interaction between employees and working contexts (Kahn 1990). We rely on these three psychological conditions to develop our hypotheses. First, we will adopt the psychological meaningfulness condition to develop the hypothesis about the mediating effect of work meaningfulness. When employees attribute enterprise's CSR actions as substantive, they could integrate the enterprise's ethical policies and actions into their working experiences, and experience that they contribute to a greater purpose (Hulin, 2014). Therefore, they could bring their selves to work for a sense of meaningfulness (i.e., desired benefits). Second, we will employ the psychological safety condition to explain the mediating effect of psychological safety. By creating a safe and supportive working environment (Rupp and Mallory, 2015), substantive CSR attributions could allow employees to feel that they have a safe space (i.e., guarantee of protection) to present their true selves. Third, we will explain the mediating effect of OBSE with the psychological resources availability condition. Working for an enterprise that engaged in substantive CSR activities contributes to improved OBSE, which provides sufficient personal resources for employees to present their self in work.

2.2 Substantive CSR attributions and work engagement

Work engagement represents "a positive work-related state of fulfillment of mind" (Schaufeli et al., 2006, p. 702). We assert that work engagement may be a useful way for employees to reciprocate company's substantive CSR practices. Based on the multiple need model of organizational justice, working for a company with sincere and altruistic CSR practices could satisfy employees' instrumental, relational, and moral needs (Rupp et al., 2006). Meanwhile, according to self-determination theory, Camilleri (2021) proposed that "laudable CSR" practices might satisfy employees' needs of relatedness, competence, and autonomy. Owing to satisfaction of various needs, employees will pay back the costs of the organizations' substantive CSR investments through increased engagement with their work.

Hypothesis 1: Substantive CSR attributions are positively related to work engagement.

2.3 The mediating effect of work meaningfulness

This study believes that work meaningfulness might mediate the promoting effect of substantive CSR attributions on work engagement. Work meaningfulness refers to employees' opinions and beliefs about the importance and value stemming from their work (Rosso et al., 2010).

According to engagement theory, individuals experience meaning at work when an enterprise's ethical policies and actions are integrated into employees' working experience, thereby allowing them to express their concerns for the well-being of society (Rupp and Mallory, 2015). CSR may be an important source of the sense of work meaning (Bauman and Skitka, 2012). Everyone possesses an innate desire for contributing to a greater purpose (Hulin, 2014). Working for companies that practice substantive CSR, employees may perceive that they are also contributing to the greater good of society by being a positive influence on others (Lips-Wiersma and Morris, 2009), hence increasing the meaningfulness they gain from work. It has been argued that employees can derive energy, psychological resilience, sense of meaning, enthusiasm, and inspiration from their company's substantive CSR initiatives (Rich et al., 2010). Therefore, they are more likely to experience work meaningfulness when they attribute CSR initiatives to substantive motivations.

In line with Kahn's (1990) model, the meaning of work is a reward for work, the more meaningful the work is the more employees might believe that they will derive benefits from investing their whole selves into their work (Kahn, 1990; Lin et al., 2020). Meanwhile, work meaningfulness is also a critical aspect of intrinsic motivation of work (Bailey et al., 2019), work meaningfulness fosters employees' dedication to work and enthusiasm about work (Aryee et al., 2012). By contrast, when employees feel their job is not meaningful, they might conclude that investing their personal selves in the job will not be reciprocated by the organization (Kahn, 1990; Lin et al., 2020). Consequently, they are less likely to be engaged with their work. Supporting this, prior studies have found that work meaningfulness positively predicted work engagement (Lips-Wiersma and Morris, 2009; Bauman and Skitka, 2012).

Taken together, we argue that work meaningfulness mediates the positive effect of substantive CSR attributions on work engagement. In line with Kahn's (1990) model, work elements such as CSR are associated with meaningfulness. Substantive CSR attributions could make employees feel that they are valued and important to society. It will lead to an increased sense of meaningfulness, which in turn encourages employees to engage more in their work. Therefore, we hypothesize the following:

Hypothesis 2–1: Substantive CSR attributions are positively related to work meaningfulness.

Hypothesis 2–2: Substantive CSR attributions are positively related to work engagement through increased work meaningfulness.

2.4 The mediating effect of psychological safety

We next argue that psychological safety also mediates the positive influence of substantive CSR attributions on work engagement. Psychological safety refers to employees' belief that the presentations of genuine self at work will not negatively impact on his or her status or career (Kahn, 1990).

It has been argued that enterprises' internal or external practices help shape employees' perception of work safety (Camilleri, 2021). Specific to this study, we assume that enterprises' substantive CSR practices contribute to creating a predictable, consistent, and unambiguous work context, which helps foster psychological safety. CSR attributions provide important information for employees to evaluate the character or nature of their organization (Donia et al., 2019), as well as the work environment. When employees attribute CSR activities as substantive and worthwhile motivations, they could believe that their organizations will continue to invest in those CSR programs in the future. Stable and sustained CSR practices allow employees to more accurately predict their organizations' behavior, and further increase their certainty about the nature of their own relationship with their organizations (Rupp, 2011). In addition, when employees perceive that organizations treat external stakeholders in a fair, moral, and sincere manner, they believe that as internal stakeholders, they will also receive the same treatment and respect (Kim et al., 2021). Prior research suggested that CSR practices that were viewed as genuine and other serving were positively related to psychological safety (Ahmad et al., 2019). In summary, substantive CSR attributions lead employees to view their work environment as predictable, consistent, and clear. In this context, they may feel reassured that displaying their true selves at work will not bring any negative consequences (May et al., 2004). Collectively, substantive CSR attributions are positively related to psychological safety.

Kahn's (1990) model proposes that psychological safety could increase work engagement. Specifically, when employees experience psychological safety, they are more willing to invest themselves in work without fearing negative consequences (May et al., 2004). High psychological safety motivates employees to internalize their work roles into self-concepts, and to express their self-concepts through work (Brown and Leigh, 1996). As consequence, they will actively invest their efforts and energies in work (Amabile, 1983). In contrast, employees with low psychological safety will be less likely to invest themselves in work, because they might worry about the potential social risks resulting from unfiltered self-expression (Kahn, 1990; May et al., 2004). They may even exhibit withdrawal and self-defense behaviors, which could be viewed as a manifestation of low engagement (Kahn, 1990; Lin et al., 2020). Furthermore, a meta-analysis revealed a significant positive association between psychological safety and work engagement (Frazier et al., 2017). Accordingly, it is reasonable to expect that psychological safety is positively associated with work engagement.

We argue that attributions of substantive CSR are positively related to psychological safety, which in turn promotes work engagement. Based on Kahn's (1990) model, a safe, predictable, and consistent social environment facilitates engagement by fostering a sense of psychological safety. In line with this model, substantive CSR attributions help employees believe that their work environment is safe, predictable, and consistent, which makes them feel that they are safe to engage their whole selves in work. Therefore, we propose the following:

Hypothesis 3–1: Substantive CSR attributions are positively related to psychological safety.

Hypothesis 3–2: Substantive CSR attributions are positively related to work engagement through increased psychological safety.

2.5 The mediating effect of organization-based self-esteem

We propose that attributions of substantive CSR could foster employees' OBSE. Employees' moral experiences in work context play an important role in the creation of self-esteem (Collier and Esteban, 2007). Companies may shape a responsible and caring corporate image by practicing CSR in a genuine manner for the well-being of society (Yan et al., 2021). Employees will incorporate this positive corporate reputation into their self-concept, thus maintaining and enhancing positive views about themselves (Paruzel et al., 2020). By comparing the organization to which they belong with other organizations, employees will experience a sense of pride and value as a member of moral organization, which helps to enhanced OBSE (Lin et al., 2012). Moreover, substantive CSR attributions could shape a relationship based on trust between employees and enterprises, employees would perceive being trusted and valued by their enterprises (De los Salmones et al., 2005), which is also beneficial to shape OBSE. Although there was no direct evidence for the positive relationship between substantive CSR attributions and OBSE, prior studies found that CSR was positively related to team self-esteem (Lin et al., 2012) or collective self-esteem (Gao et al., 2018).

According to Kahn's (1990) model, being a form of personal resources, OBSE contributes to an employee's positive experience at work, especially work engagement (Pierce et al., 1989; Xanthopoulou et al., 2009). From the resource perspective, employees with high self-esteem will be more confident that they have sufficient psychological resources to invest themselves in their work (Kahn, 1990; May et al., 2004). A high level of mental resources can be seen as individuals' positive evaluation of their own ability to complete their work (Gao et al., 2018). Employees with high OBSE are more likely to possess feelings of self-efficacy, competence, and confidence that they can complete all of their work tasks successfully (Pierce et al., 1989). As a subjective evaluation of one's competence, OBSE provides psychological resources for employees to be more engaged with their work (Gao et al., 2018). In contrast, employees with low OBSE may perceive that they do not have sufficient psychological resources to satisfy their work demands and obligations, leading to work withdrawal behavior (Kahn, 1990; May et al., 2004). Employees' perception that they do not have sufficient psychological resources to do their job could lead to decreased engagement. Prior research found a positive association between collective self-esteem and work engagement (Gao et al., 2018), providing indirect support for our argument that OBSE could positively predict work engagement.

In summary, we assert that OBSE mediates the positive impact of substantive CSR attributions on work engagement. OBSE is a core resource that represents a response to the interaction between person and environment and plays an important role in influencing one's attitude and behavior in the workplace (Hobfoll and Freedy, 1993; Wang et al., 2020). According to Kahn's (1990) model, attributions of substantive CSR communicate to the employee that they are important, valuable, and competent members of organizations, which in turn enhances their OBSE. Subsequently, increased OBSE provides sufficient psychological resources for employees to invest themselves in work. Thus, we hypothesize the following:

Hypothesis 4–1: Substantive CSR attributions are positively related to organization-based self-esteem.

Hypothesis 4–2: Substantive CSR attributions are positively related to work engagement through increased organization-based self-esteem.

Taken together, the proposed theoretical model was shown in Figure 1.

3 Materials and methods

3.1 Participants and procedure

To minimize common method bias (Podsakoff et al., 2003), data were collected at two time points, 2 months apart, with different questionnaires at each point. Moreover, our questionnaires used different anchor point number and response format which also could restrict CMV by lessening

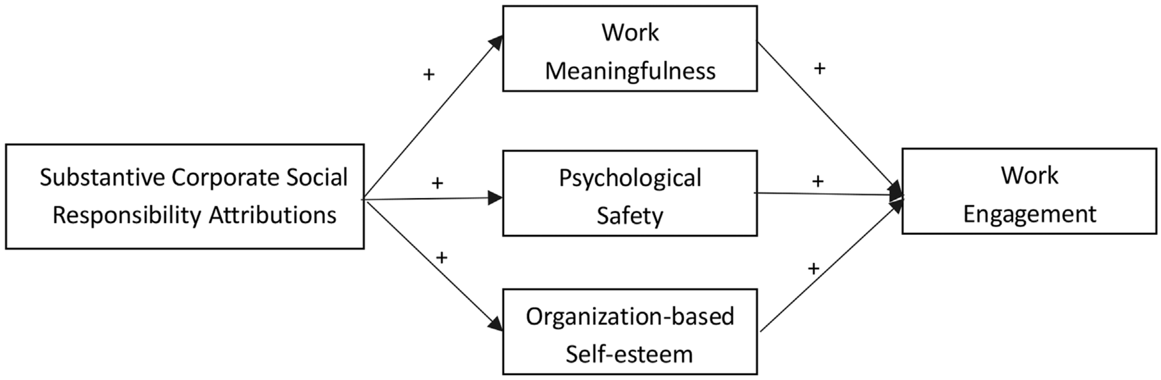

FIGURE 1
Overview of the proposed triple mediation model.

anchoring effects. Additionally, the use of reverse-coded items in questionnaires could diminish response pattern biases, which is a useful tool to constrain CMV.

Participants were full-time employees from central and southern mainland China. They worked in various industries, including finance, manufacturing, mining and smelting, pharmaceuticals, real estate and logistics. With the permission of top management, the employees who volunteered completed the anonymous questionnaires as a group in a conference room at work. Coordinators in each company assigned a unique ID number to each participant to match the questionnaires before the first distribution of questionnaires. Once a participant was finished, they gave the completed questionnaires directly to the researchers. Participants received monetary compensation of about 10 Chinese yuan at each time point.

At the first time point, 936 employees were invited to report their demographic information, their rating of substantive CSR attributions, work meaningfulness, psychological safety, and OBSE. We received 705 valid responses (a valid response rate of 75.32%). Two months later, we distributed questionnaires concerning work engagement to employees who provided valid responses in the first survey. 503 employees returned valid questionnaires resulting in a valid response rate of 71.35%. Among the final sample consisting of 503 participants, 41.90% were female, 58.10% were male; 62.90% held a bachelor's degree or above; and 93.60% were at or below the junior management level. The average age of participants was 35.137 years (SD = 8.180).

3.2 Measures

As all focal variables were measured using scales originally developed in English (Detailed information of used scales would be seen in Table 1), we translated the scales into Chinese by following translation/back translation procedures (Brislin, 1986). To be specific, two PHD students in Human Resource Management independently translated and cross-referenced to generate the first draft of scales' Chinese version. Then, one PH. D student who had studied in United Kingdom was invited to translate them back. The authors and three translators have compared the translated English version with the original version and modified the Chinese version of scales to ensure the conceptual equivalence. Finally, three MBA students revised the Chinese version and generated the final version of questionnaire.

3.2.1 Substantive CSR attributions

In line with Donia et al. (2019), substantive CSR attributions were assessed with the subscale of substantive CSR from Substantive and Symbolic Corporate Social Responsibility (CSR-SS) scale (Donia et al., 2017). This subscale consisted of eight items, and asked employee to indicate the degree to which each of the following statement explains the true motives of their organization to engage in socially responsibility activities, such as environment protection, and participation in local community affairs. This measure used a five-point Likert scale from 1 (*strongly disagree*) to 5 (*strongly agree*). The Cronbach's α of this sub-scale was. 0.854.

3.2.2 Work meaningfulness

We used the five-item scale developed by Bunderson and Thompson (2009). This measure used a seven-point Likert scale, which is ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). The Cronbach's α of this scale was 0.863.

TABLE 1 Measured survey items of variables.

Variable	Sub-dimension	Measured item	Sources
Substantive CSR attributions	/	1. Because it cares about what happens to the community in which it operates (both domestic and internationally, if operating globally). (SCSA1)	Donia et al. (2017)
		2. Because it cares about what happens to external actors it does business/interacts with. (SCSA2)	
		3. Because it wants to help solve problems in the community. (SCSA3)	
		4. Because it has a genuine interest in the welfare of external individuals affected by its practices (i.e. such as the local community in which it operates). (SCSA4)	
		5. Because it feels it is important to help those in need. (SCSA5)	
		6. Because it wants to help external actors it does business/interacts with in any way it can. (SCSA6)	
		7. Because it values a role of interacting with the community. (SCSA7)	
		8. Because it takes on the needs of the community and external individuals as its own. (SCSA8)	
Work meaningfulness	/	1. The work that I do is important. (WMF1)	Bunderson and Thompson (2009)
		2. I have a meaningful job. (WMF2)	
		3. The work that I do makes the world a better place. (WMF3)	
		4. What I do at work makes a difference in the world. (WMF4)	
		5. The work that I do is meaningful. (WMF5)	
Psychological safety	/	1. Members of this team are able to bring up problems and tough issues. (PYS1)	Edmondson (1999)
		2. People on this team sometimes reject others for being different. (PYS2)	
		3. It is difficult to ask other members of this team for help. (PYS3)	
		4. No one on this team would deliberately act in a way that undermines my efforts. (PYS4)	
		5. Working with members of this team, my unique skills and talents are valued and utilized. (PYS5)	
Organization-based self-esteem	/	1. I count around here. (OBSE1)	Pierce et al. (1989)
		2. I am taken seriously. (OBSE2)	
		3. I am important. (OBSE3)	
		4. There is faith in me. (OBSE4)	
		5. I can make a difference. (OBSE5)	
Work engagement	Vigor (WEG1)	1. At my work, I feel bursting with energy	Schaufei et al. (2006)
		2. At my job, I feel strong and vigorous	
		3. When I get up in the morning, I feel like going to work	
		4. I can continue working for very long periods at a time	
		5. At my job, I am very resilient, mentally	
		6. At my work, I always persevere, even when things do not go well	
	Dedication (WEG2)	7. I find the work that I do full of meaning and purpose	
		8. I am enthusiastic about my job	
		9. My job inspires me	
		10. I am proud of the work that I do	
		11. To me, my job is challenging	
	Absorption (WEG3)	12. Time flies when I am working	
		13. When I am working, I forget everything else around me	
		14. I feel happy when I am working intensely	
		15. I am immersed in my work	
		16. I get carried away when I am working	
		17. It is difficult to detach myself from my job	

3.2.3 Psychological safety

The current study assessed psychological safety with Edmondson (1999)'s scale. We selected the five items with the highest factor loadings. This measure used a five-point Likert scale (1 being *strongly disagree*, and 5 being *strongly agree*) and Cronbach's α was 0.773.

3.2.4 Organization-based self-esteem

We employed five items with the highest factor loadings from Pierce et al. (1989)'s scale to measure OBSE. This scale asked respondents to recall the information they received from leader's behavior or attitude, and then rated how much they agree or disagree with following statements. This measure used a five-point Likert scale (1 = *strongly disagree*, 5 = *strongly agree*) and Cronbach's α for this scale was 0.807.

3.2.5 Work engagement

The shortened version of Schaufeli et al.'s (2006) scale includes 17 items to assess three sub-dimensions of work engagement. Participants were asked to indicate how often they feel about their work in certain ways in the past 2 months. If they never had this feeling, marked "0"; if they had this feeling, marked the number (ranging from 1 to 6) that most accurately reflects the frequency. Six items measure the sub-dimension of vigor (α = 0.912). Five items assess the sub-dimension of dedication (α = 0.923). Six items measure the sub-dimension of absorption (α = 0.890). Cronbach's α in the current study was 0.966. Cronbach's α for whole scale was 0.966.

3.2.6 Control Variables

Previous studies found that age, gender, position at work, and education level influenced work engagement (Schaufeli et al., 2006; Halbesleben and Wheeler, 2008). Accordingly, we controlled for these variables to alleviate potential confounding effects of demographic variables. Gender was coded as 0 (female), and 1 (male). Age was measured in years. Position was coded as 1 (non-managerial position), 2 (junior management level), or 3 (middle management level). Education level was coded as 1 (high school degree or below), 2 (junior college/associate degree), 3 (bachelor's degree), or 4 (master's degree or above).

4 Results

4.1 Validity

Using AMOS 24.0, we conducted confirmatory factor analysis (CFA) to examine the appropriateness of our measurement model. Because scales consisting of many items may decrease the ratio of sample size to the number of estimated parameters, and may lead to variables being over-identified (Little et al., 2002), we combined items from each of the subscale of work engagement scale into parcels. Item parceling improves the ratio of participants to parameters modeled (Little et al., 2002). Compared to using individual items, item parceling is thought to be more reliable because it could reveal a larger proportion of true-score variance (Little et al., 2013). The three parcels were made up of the items from the dedication, vigor, and absorption subscales of the work engagement measure. Specifically, we aggregated the items of each subscale by using the mean scores as a single indicator, and then set these indicators to load onto a second order factor representing work engagement.

As shown in Table 2, the five-factor model fitted the data well (χ^2 = 783.911, *df* = 289, CFI = 0.927, TLI = 0.918, RMSEA = 0.058). This model provided a significantly better fit than all other alternative models. Moreover, we calculated the value of standard factor loadings, composite reliability (CR) and average variance extracted (AVE) to further examine convergent validity. The values of factor loadings higher than 0.50, CR greater than 0.60 and AVE exceeding 0.50 could establish convergent validity (Fornell and Larcker, 1981). Results from Table 3 showed that all items' standard factor loadings were ranging from 0.537 to 0.962, which higher than 0.50; the value of focal variable's CR were ranging from 0.770 to 0.963, which exceeding 0.60. We found that several construct's AVE were in the range of 0.402–0.480, which not reaching 0.50. However, it has been suggested that the cutoff point of 0.50 for AVE was too strict, and convergent reliability could be established by CR alone (Malhotra, 2010). Meanwhile, Fornell and Larcker (1981) also posited that when CR value exceeding 0.60, the AVE value of corresponding construct being in the range of 0.40–0.50 was acceptable. Accordingly, the CR value of all focal constructs were greater than 0.700. Taken together, the convergent validity of constructs was acceptable. Furthermore, we found the square roots of the AVE of focal constructs were in the range of 0.634–0.947, which were greater than corresponding inter-construct correlations. Hence, in line with Fornell and Larcker (1981)'s criterion, we believe that the discriminant validity of focal constructs was satisfactory. Moreover, the ratio of HTMT (Heterotrai-monotrait) between focal variables were in the range of 0.369–0.655, which were less than the cutoff 0.85 suggested by Henseler et al. (2015) and providing further support for the establishment of discriminant validity.

4.2 Common method variance

Although we collected different questionnaire data at the two time-points, all variables were assessed by employees' self-reports. This raised the concern of common method variance (CMV). Accordingly, we conducted an unmeasured latent method construct (ULMC) analysis to detect CMV (as shown in Table 2). The difference in CFI (ΔCFI = 0.039) and NFI (ΔNFI = 0.041) between models with and without an unmeasured latent method factor was less than 0.05. These values were below the criterion that prior research has proposed

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TABLE 2 Results of confirmatory factor analysis.

Model	χ^2	*df*	χ^2/df	CFI	TLI	RMSEA
The hypothesized five factor-model (SCSA, WMF, PYS, OBSE, WEG)	783.911	289	2.712	0.927	0.918	0.058
The four-factor model (SCSA + PYS, WMF, OBSE, WEG)	1219.711	293	4.163	0.864	0.849	0.079
The three-factor model (SCSA, WMF + PYS + OBSE, WEG)	1414.748	296	4.780	0.835	0.819	0.087
The two-factor model (SCSA + WMF + PYS + OBSE, WEG)	2125.613	298	7.133	0.731	0.707	0.111
The single factor-model (SCSA + WMF + PYS + OBSE + WEG)	3560.266	299	11.907	0.520	0.479	0.147
Common method factor model (SCSA, WMF, PYS, OBSE, WEG, ULMC)	492.228	263	1.872	0.966	0.958	0.042

Note. SCSA, substantive CSR attributions; WMF, work meaningfulness; PYS, psychological safety; OBSE, Organization-based self-esteem; WEG, work engagement; ULMC, unmeasured latent method construct.

TABLE 3 Results of validity and reliability.

Variable	Item	Factor loadings	CR	AVE	Cronbach's α
Substantive CSR attributions	SCSA1	0.616	0.858	0.431	0.854
	SCSA2	0.621			
	SCSA3	0.706			
	SCSA4	0.740			
	SCSA5	0.667			
	SCSA6	0.684			
	SCSA7	0.655			
	SCSA8	0.544			
Work meaningfulness	WMF1	0.808	0.875	0.588	0.863
	WMF2	0.899			
	WMF3	0.759			
	WMF4	0.537			
	WMF5	0.785			
Psychological safety	PSY1	0.613	0.770	0.402	0.773
	PSY2	0.618			
	PSY3	0.598			
	PSY4	0.643			
	PSY5	0.692			
Organization-based self-esteem	OBSE1	0.663	0.818	0.480	0.807
	OBSE2	0.842			
	OBSE3	0.756			
	OBSE4	0.612			
	OBSE5	0.553			
Work engagement	WEM1	0.962	0.963	0.897	0.966
	WEM2	0.951			
	WEM3	0.929			

Note. CR, composite reliability; AVE, average variance extracted.

to represent a substantial difference between models (Bagozzi and Yi, 1990; Gong et al., 2022), indicating that there was no significant difference between the fit indices of two models. Moreover, the method factor accounted for 22.98% of the total variance, which is lower than the 25% threshold value suggested in prior research (Williams et al., 1989). Taken together, these results indicated that CMV may not cause serious bias in our results.

4.3 Descriptive statistics

The means, standard deviations, and correlations of the studied variable are shown in Table 4. The correlation results of our focal variables provided initial supports for our hypotheses. More detailed information could be seen in Table 4.

TABLE 4 Means, standard deviations, and correlations of studied variables (n = 503).

Variable	*M*	*SD*	1	2	3	4	5	6	7	8
1. Gender	0.581	0.494								
2. Age	35.137	8.180	0.237***							
3. Position	1.610	0.605	0.165***	0.248***						
4. Education	2.581	0.781	−0.111*	−0.395***	0.067					
5. Substantive CSR attributions	3.784	0.377	−0.002	0.055	0.044	−0.012				
6. Work meaningfulness	5.142	0.853	0.111*	0.092*	0.074	−0.012	0.448***			
7. Psychological safety	4.334	0.643	−0.075	−0.054	0.026	0.022	0.355***	0.438***		
8. Organization-based self-esteem	3.256	0.529	0.133***	0.011	0.143**	0.015	0.363***	0.546***	0.448***	
9. Work engagement	4.022	1.128	0.087	0.221***	0.141**	−0.057	0.374***	0.428***	0.315***	0.357***

Note. M, mean; SD, Standard deviation.
*p < 0.05.
**p < 0.01.
***p < 0.001.

TABLE 5 Results of hierarchical regression (n = 503).

Variable	Work meaningfulness		Psychological safety		Organization-based self-esteem		Work engagement			
	Model 1		Model 2		Model 3		Model 4		Model 5	
	B	*SE*	*B*	*SE*	*B*	*SE*	*B*	*SE*	*B*	*SE*
Gender	0.171	0.071	−0.084	0.056	0.139**	0.046	0.079	0.096	0.015	0.092
Age	0.005	0.005	−0.006	0.004	−0.005	0.003	0.025	0.007	0.026***	0.006
Position	0.036	0.059	0.043	0.047	0.108**	0.038	0.137	0.080	0.092	0.076
Education	0.023	0.048	−0.010	0.038	−0.002	0.031	0.026	0.065	0.022	0.061
Substantive CSR attributions	1.009***	0.090	0.610***	0.071	0.509***	0.058	1.082***	0.121	0.555***	0.132
Work meaningfulness									0.279***	0.065
Psychological safety									0.203*	0.080
Organization-based self-esteem									0.239*	0.103
R^2	0.217***		0.136***		0.166***		0.188***		0.285***	

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

4.4 Hypotheses testing

We used SPSS 26.0 to test all hypotheses. Meanwhile, to test our mediation hypotheses, we used bootstrap analysis conducted with the PROCESS macro developed by Hayes (2012) in SPSS 26.0. Hypothesis 1 proposed that substantive CSR attributions positively predicted work engagement. As presented in Table 5, when controlling for gender, age, education and position, substantive CSR attributions positively predicted work engagement (Model 4 in Table 5: B = 1.082, p < 0.001), supporting Hypothesis 1.

TABLE 6 Results of mediation effect analysis (n = 503).

Indirect effect	*Estimate*	*Boot S E*	95% bootstrap CI	
			Lower	Upper
SCSA→ WMF→ WEG	0.282	0.070	0.152	0.427
SCSA→ PYS→ WEG	0.124	0.051	0.033	0.235
SCSA→OBSE→ WEG	0.121	0.055	0.016	0.229

Note. SCSA, Substantive CSR attributions; WMF, work meaningfulness; PYS, psychological safety; OBSE, Organization-based self-esteem; WEG, work engagement.

Hypothesis 2 proposed that work meaningfulness mediated the positive effect of substantive CSR attributions on work engagement. Results showed there was a positive relationship between substantive CSR attributions and work meaningfulness (Model 1 in Table 5: $B = 1.009$, $p < 0.001$), supporting Hypothesis 2–1. Meanwhile, Model 5 showed a positive link between work meaningfulness and work engagement (Model 5 in Table 5: $B = 0.279$, $p < 0.001$). Moreover, Hypothesis 2–2 was also supported, because bootstrapping results shown in Table 6 indicated that substantive CSR attributions had a significant positive indirect effect on work engagement *via* increased work meaningfulness (Table 6: indirect effect = 0.282, Bootstrap SE = 0.070, 95% CI [0.152, 0.427]). Taken together, the results provided full support for Hypothesis about the mediating effect of work meaningfulness in the relationship between substantive CSR attributions and work engagement.

Hypothesis 3 proposed the mediating effect played by psychological safety in the relationship between substantive CSR attributions and work engagement. Hypothesis 3-1 was supported because substantive CSR attributions positively predicted psychological safety (Model 2 in Table 5: $B = 0.610$, $p < 0.001$). Hypothesis 3-2 was also supported, psychological safety was positively associated with work engagement (Model 5 in Table 5: $B = 0.203$, $p < 0.05$), and the bootstrapping results shown in Table 6 confirmed that substantive CSR attributions had a significant positive indirect influence on engagement through increased psychological safety (*indirect effect* = 0.124, *Bootstrap SE* = 0.051, 95% *CI* [0.033, 0.235]).

Hypothesis 4 was that substantive CSR attributions would be positively associated with work engagement *via* OBSE. As shown in Table 5, substantive CSR attributions were positively related to OBSE (Model 3 in Table 5: $B = 0.509$, $p < 0.001$), supporting Hypothesis 4–1. In addition, OBSE was positively connected with work engagement (Model 5 in Table 5: $B = 0.239$, $p < 0.05$), and substantive CSR attributions significantly indirectly promoted work engagement through OBSE (Table 6: *indirect effect* = 0.121, *Bootstrap SE* = 0.055, 95% *CI* [0.016, 0.229]), which supported Hypothesis 4–2. Overall, Hypothesis 4 was fully supported by these results.

5 Discussion

5.1 Theoretical contributions

The theoretical contributions of this study are three-folds. First, the present study reveals that substantive CSR attributions positively predict employees' work engagement which enriches the research of CSR attributions. Prior studies mainly identified employees' CSR attributions as a boundary condition of the impact of CSR on employees (De Roeck and Delobbe, 2012; Gatignon-Turnau and Mignonac, 2015; Lee and Seo, 2017), explorating the inducing role of CSR attributions on employees remains insufficiently (Gond et al., 2017). Although some scholars have preliminarily investigated the facilitative effect of substantive CSR attributions on employees' organizational pride (Donia et al., 2017), affective commitment (Raub, 2017), as well as job satisfaction (Vlachos et al., 2013) which were criterion variables (Chaudhary, 2017), little was known about the relationship between substantive CSR attributions and employee's health-related constructs. Work engagement is a specific measurement indicator of psychological health (Timms et al., 2015), and also provides enterprises with a unique competitive advantage (Eldor, 2016). Our findings help confirm that CSR attributions are beneficial to create win-win situations for the well-being of employees and enterprises.

Second, based on Kahn's (1990) model, this study demonstrates the parallel mediating roles of work meaningfulness, psychological safety, and OBSE in the association between substantive CSR attributions and work engagement. Previous studies explored the direct relationship between CSR attributions and work engagement, but few have investigated the psychological mechanisms underlying this relationship (Chaudhary and Akhouri, 2018). Our study shows that the formation of work engagement is a complex psychological process wherein three psychological conditions (i.e., meaning, safety, and availability) collectively determine the extent to which employees are engaged in their work (Kahn, 1990). As a result, our findings help build a more holistic and accurate framework of the psychological mechanisms through which CSR attributions can promote employees' work engagement.

Third, by introducing Kahn's (1990) model into CSR attributions research, this study expands our knowledge about the antecedents of work engagement. Prior studies mainly found that job characteristics (e.g., task significance, Goštautaitė and Bučiūnienė, 2015); leadership (e.g., charismatic leadership, Babcock-Roberson and Strickland, 2010), and dispositional characteristics (e.g., conscientiousness, Furnham et al., 2002) were positively related to work engagement. Scholars called for further investigate the other potential promoting factors (Christian et al., 2011). In addition to these studies, this study now evidences that work engagement can be predicted by employees' perceptions that their company's CSR initiatives are motivated by genuine, altruistic concerns. Our study also helps expand the potential application of Kahn's (1990) model.

5.2 Managerial implications

The results have several potential practical implications. First, enterprises may benefit from ensuring that employees are convinced of the genuine and sincere motivations behind the CSR initiatives. Organizations could encourage employees to participate in CSR activities in order to increase their understanding and awareness of why the enterprise engage in these CSR practices. In addition, organizations should provide timely and necessary information about their CSR practices to employees, which can help them to perceive those initiatives as substantive (Donia and Sirsly, 2016).

Second, organizations are encouraged to take measures to promote these three crucial antecedents of engagement. To be specific, the perceived meaningfulness of work can be enhanced through such practices as arranging diverse work, giving employees more authority and discretion, and providing timely performance feedback (De Roeck and Maon, 2018). To foster psychological safety, organizations may benefit from relational job design (Grant, 2007) and the construction of relational high-performance working system (Gittell and Douglass, 2012). Organizations could promote OBSE through high job complexity and autonomy design (Lapointe et al., 2011).

5.3 Limitations and future research directions

The present study also has several limitations. First, the present study employed a two-wave time-lagged design, which has certain advantages in mitigating common method bias (Podsakoff et al., 2003). However, we cannot identify the causal directions in our proposed theoretical model. Future studies could apply longitudinal or experimental design to validate the causal directions of interest.

Second, we did not examine any boundary conditions on the effect of substantive CSR attributions on work engagement. CSR attributions have been presented not to have the same effect on all employees (Donia and Sirsly, 2016). Employees with higher moral identity were shown in one study to be more sensitive to the moral cues in the workplace and more responsive to moral issues (Aquino and Reed, 2002). In line with this logic, moral identity motivates employees to feel more appreciative of substantive CSR initiatives (Donia and Sirsly, 2016). As such, we suggest that future studies investigate the boundary condition played by moral identity on the relationships explored in this study.

Third, we conducted this study in only one cultural context of high collectivist orientation which differs from the cultural setting with high individualism orientation (Hofstede, 1993). Therefore, multi-cultural investigations are recommended to examine whether the beneficial effect of substantive CSR attributions on work engagement can be generalized to another cultural context. Moreover, our respondents were limited in five industries which might also constrain the generalizability of findings, and we encourage future research to address this concern by expanding the diversity of industry.

6 Conclusion

In recent years, to address environmental and social issues, increasing enterprises have engaged in CSR activities (Dong et al., 2021; Ren et al., 2022a). As internal stakeholders, Employees are more likely to respond positively to substantive CSR practices (Donia et al., 2019). Several studies found that substantive CSR attributions could motivate positive working perception and attitude (Vlachos et al., 2013; Raub, 2017; Donia et al., 2019), however, little was known about the association between substantive CSR attributions and employees' well-being. Drawing upon Kahn's model of psychological conditions for engagement at work, the present study demonstrated a potential positive influence of employees' attributions of substantive CSR on work engagement. In addition, this positive effect was mediated by three parallel mediators, namely work meaningfulness, psychological safety, and OBSE. These findings extend the current knowledge of the effect of employees' substantive CSR attributions on their well-being and provide an integrative framework for understanding the psychological mechanisms that shape individual positive reactions to CSR practices. The results have significant practical implications for organizations and managers in enhancing employees' work engagement.

Data availability statement

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

Ethics statement

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. The patients/participants provided their written informed consent to participate in this study.

Author contributions

HG and XH contributed to conception and design of the study. AY and XH collected the data. XH performed statistical analysis. HG wrote the first draft of the manuscript. AY and XH contributed to manuscript revision and read the submitted version. All authors contributed to the article 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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References

Ahmad, I., Donia, M. B., and Shahzad, K. (2019). Impact of corporate social responsibility attributions on employees' creative performance: The mediating role of psychological safety. *Ethics Behav.* 29 (6), 490–509. doi:10.1080/10508422.2018.1501566

Amabile, T. M. (1983). The social psychology of creativity: A componential conceptualization. *J. Pers. Soc. Psychol.* 45 (2), 357–376. doi:10.1037/0022-3514.45.2.357

Aquino, K., and Reed, A. (2002). The self-importance of moral identity. *J. Pers. Soc. Psychol.* 83 (6), 1423–1440. doi:10.1037//0022-3514.83.6.1423

Aryee, S., Walumbwa, F. O., Zhou, Q., and Hartnell, C. A. (2012). Transformational leadership, innovative behavior, and task performance: Test of mediation and moderation processes. *Hum. Perform.* 25 (1), 1–25. doi:10.1080/08959285.2011.631648

Babcock-Roberson, M. E., and Strickland, O. J. (2010). The relationship between charismatic leadership, work engagement, and organizational citizenship behaviors. *J. Psychol.* 144 (3), 313–326. doi:10.1080/00223981003648336

Bagozzi, R. P., and Yi, Y. (1990). Assessing method variance in multitrait-multimethod matrices: The case of self-reported affect and perceptions at work. *J. Appl. Psychol.* 75 (5), 547–560. doi:10.1037/0021-9010.75.5.547

Bailey, C., Yeoman, R., Madden, A., Thompson, M., and Kerridge, G. (2019). A review of the empirical literature on meaningful work: Progress and research agenda. *Hum. Resour. Dev. Rev.* 18 (1), 83–113. doi:10.1177/1534484318804653

Bakker, A. B., Schaufeli, W. B., Leiter, M. P., and Taris, T. W. (2008). Work engagement: An emerging concept in occupational health psychology. *Work Stress* 22 (3), 187–200. doi:10.1080/02678370802393649

Bakker, A. (2009). "Building engagement in the workplace," in *The peak performing organization*. Editors J. Burke and C. L. Cooper (Oxon, UK: Routledge), 50–72.

Bauman, C. W., and Skitka, L. J. (2012). Corporate social responsibility as a source of employee satisfaction. *Res. Organ. Behav.* 32, 63–86. doi:10.1016/j.riob.2012.11.002

Brislin, R. W. (1986). "The wording and translation of research instruments," in *Cross-cultural research and methology series*. Editors W. J. Lonner and J. W. Berry (New York, NY: Sage Publications), 137–164.

Brown, S. P., and Leigh, T. W. (1996). A new look at psychological climate and its relationship to job involvement, effort, and performance. *J. Appl. Psychol.* 81 (4), 358–368. doi:10.1037/0021-9010.81.4.358

Bunderson, J. S., and Thompson, J. A. (2009). The call of the wild: Zookeepers, callings, and the double-edged sword of deeply meaningful work. *Adm. Sci. Q.* 54 (1), 32–57. doi:10.2189/asqu.2009.54.1.32

Camilleri, M. A. (2021). The employees' state of mind during COVID-19: A self-determination theory perspective. *Sustainability* 13 (7), 3634. doi:10.3390/su13073634

Chaudhary, R., and Akhouri, A. (2018). Linking corporate social responsibility attributions and creativity: Modeling work engagement as a mediator. *J. Clean. Prod.* 190, 809–821. doi:10.1016/j.jclepro.2018.04.187

Chaudhary, R. (2017). Corporate social responsibility and employee engagement: Can CSR help in redressing the engagement gap? *Soc. Responsib. J.* 13 (2), 323–338. doi:10.1108/SRJ-07-2016-0115

Christian, M. S., Garza, A. S., and Slaughter, J. E. (2011). Work engagement: A quantitative review and test of its relations with task and contextual performance. *Pers. Psychol.* 64 (1), 89–136. doi:10.1111/j.1744-6570.2010.01203.x

Collier, J., and Esteban, R. (2007). Corporate social responsibility and employee commitment. *Bus. Ethics.* 16 (1), 19–33. doi:10.1111/j.1467-8608.2006.00466.x

De los Salmones, M. D. M. G., Crespo, A. H., and del Bosque, I. R. (2005). Influence of corporate social responsibility on loyalty and valuation of services. *J. Bus. Ethics* 61, 369–385. doi:10.1007/s10551-005-5841-2

De Roeck, K., and Delobbe, N. (2012). Do environmental CSR initiatives serve organizations' legitimacy in the oil industry? Exploring employees' reactions through organizational identification theory. *J. Bus. Ethics* 110 (4), 397–412. doi:10.1007/s10551-012-1489-x

De Roeck, K., and Maon, F. (2018). Building the theoretical puzzle of employees' reactions to corporate social responsibility: An integrative conceptual framework and research agenda. *J. Bus. Ethics* 149 (3), 609–625. doi:10.1007/s10551-016-3081-2

Dong, K., Ren, X., and Zhao, J. (2021). How does low-carbon energy transition alleviate energy poverty in China? A nonparametric panel causality analysis. *Energy Econ.* 103, 105620. doi:10.1016/j.eneco.2021.105620

Donia, M. B., Ronen, S., Tetrault Sirsly, C.-A., and Bonaccio, S. (2019). CSR by any other name? The differential impact of substantive and symbolic CSR attributions on employee outcomes. *J. Bus. Ethics* 157 (2), 503–523. doi:10.1007/s10551-017-3673-5

Donia, M. B., and Sirsly, C.-A. T. (2016). Determinants and consequences of employee attributions of corporate social responsibility as substantive or symbolic. *Eur. Manag. J.* 34 (3), 232–242. doi:10.1016/j.emj.2016.02.004

Donia, M. B., Tetrault Sirsly, C. A., and Ronen, S. (2017). Employee attributions of corporate social responsibility as substantive or symbolic: Validation of a measure. *Appl. Psychol.* 66 (1), 103–142. doi:10.1111/apps.12081

Edmondson, A. (1999). Psychological safety and learning behavior in work teams. *Adm. Sci. Q.* 44 (2), 350–383. doi:10.2307/2666999

Edwards, M. R., and Kudret, S. (2017). Multi-foci CSR perceptions, procedural justice and in-role employee performance: The mediating role of commitment and pride. *Hum. Resour. Manag. J.* 27 (1), 169–188. doi:10.1111/1748-8583.12140

Eldor, L. (2016). Work engagement: Toward a general theoretical enriching model. Hum. Resour. *Hum. Resour. Dev. Rev.* 15 (3), 317–339. doi:10.1177/1534484316655666

Farooq, O., Rupp, D. E., and Farooq, M. (2017). The multiple pathways through which internal and external corporate social responsibility influence organizational identification and multifoci outcomes: The moderating role of cultural and social orientations. *Acad. Manage. J.* 60 (3), 954–985. doi:10.5465/amj.2014.0849

Fletcher, L., Bailey, C., and Gilman, M. W. (2018). Fluctuating levels of personal role engagement within the working day: A multilevel study. *Hum. Resour. Manag. J.* 28 (1), 128–147. doi:10.1111/1748-8583.12168

Fornell, C., and Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *J. Mark. Res.* 18, 39–50. doi:10.1177/002224378101800104

Frazier, M. L., Fainshmidt, S., Klinger, R. L., Pezeshkan, A., and Vracheva, V. (2017). Psychological safety: A meta-analytic review and extension. *Pers. Psychol.* 70 (1), 113–165. doi:10.1111/peps.12183

Furnham, A., Petrides, K., Jackson, C., and Cotter, T. (2002). Do personality factors predict job satisfaction? *Pers. Individ. Dif.* 33, 1325–1342. doi:10.1016/S0191-8869(02)00016-8

Gao, Y., Zhang, D., and Huo, Y. (2018). Corporate social responsibility and work engagement: Testing a moderated mediation model. *J. Bus. Psychol.* 33 (5), 661–673. doi:10.1007/s10869-017-9517-6

Gatignon-Turnau, A. L., and Mignonac, K. (2015). Mis)Using employee volunteering for public relations: Implications for corporate volunteers' organizational commitment. *J. Bus. Res.* 68 (1), 7–18. doi:10.1016/j.jbusres.2014.05.013

Gittell, J. H., and Douglass, A. (2012). Relational bureaucracy: Structuring reciprocal relationships into roles. *Acad. Manage. Rev.* 37 (4), 709–733. doi:10.5465/amr.2010.0438

Gond, J. P., El Akremi, A., Swaen, V., and Babu, N. (2017). The psychological microfoundations of corporate social responsibility: A person-centric systematic review. *J. Organ. Behav.* 38 (2), 225–246. doi:10.1002/job.2170

Gong, Y., Li, J., Xie, J., Zhang, L., and Lou, Q. (2022). Will "green" parents have "green" children? The relationship between parents' and early adolescents' green consumption values. *J. Bus. Ethics* 179 (2), 369–385. doi:10.1007/s10551-021-04835-y

Goštautaitė, B., and Bučiūnienė, I. (2015). Work engagement during life-span: The role of interaction outside the organization and task significance. *J. Vocat. Behav.* 89, 109–119. doi:10.1016/j.jvb.2015.05.001

Grant, A. M. (2007). Relational job design and the motivation to make a prosocial difference. *Acad. Manage. Rev.* 32 (2), 393–417. doi:10.5465/amr.2007.24351328

Halbesleben, J. R., and Wheeler, A. R. (2008). The relative roles of engagement and embeddedness in predicting job performance and intention to leave. *Work Stress* 22 (3), 242–256. doi:10.1080/02678370802383962

Hardré, P. L. (2003). Beyond two decades of motivation: A review of the research and practice in instructional design and human performance technology. *Hum. Resour. Dev. Rev.* 2, 54–81. doi:10.1177/1534484303251661

Hayes, A. F. (2012). Process: A versatile computational tool for observed variable mediation, moderation, and conditional process modeling [White paper].

He, J., Zhang, H., and Morrison, A. M. (2019). The impacts of corporate social responsibility on organization citizenship behavior and task performance in hospitality: A sequential mediation model. *Int. J. Contemp. Hosp. Manag.* 31 (6), 2582–2598. doi:10.1108/IJCHM-05-2018-0378

Henseler, J., Ringle, C. M., and Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *J. Acad. Mark. Sci.* 43 (1), 115–135. doi:10.1007/s11747-014-0403-8

Hobfoll, S. E., and Freedy, J. (1993). "Conservation of resources: A general stress theory applied to burnout," in *Professional burnout: Recent developments in theory and research*. Editors W. B. Schaufeli, C. Maslach, and T. Marek (London, UK: Taylor & Francis), 115–129.

Hofstede, G. (1993). Cultural constraints in management theories. *Acad. Manag. Perspect.* 7 (1), 81–94. doi:10.5465/ame.1993.9409142061

Hulin, C. L. (2014). "Work and being: The meanings of work in contemporary society," in *The nature of work: Advances in psychological theory, methods, and practice*. Editors J. K. Ford, J. R. Hollenbeck, and A. M. Ryan (Washington, DC: American Psychological Association), 9–33.

Hur, W. -M., Rhee, S. Y., Lee, E. J., and Park, H. (2022). Corporate social responsibility perceptions and sustainable safety behaviors among frontline employees: The mediating roles of organization-based self-esteem and work engagement. *Corp. Soc. Responsib. Environ. Manag.* 29 (1), 60–70. doi:10.1002/csr.2173

Kahn, W. A. (1990). Psychological conditions of personal engagement and disengagement at work. *Acad. Manage. J.* 33 (4), 692–724. doi:10.5465/256287

Kim, B.-J., Kim, M.-J., and Kim, T.-H. (2021). The power of ethical leadership": The influence of corporate social responsibility on creativity, the mediating function of psychological safety, and the moderating role of ethical leadership. *Int. J. Environ. Res. Public Health* 18 (6), 2968. doi:10.3390/ijerph18062968

Knight, C., Patterson, M., and Dawson, J. (2017). Building work engagement: A systematic review and meta-analysis investigating the effectiveness of work engagement interventions. *J. Organ. Behav.* 38 (6), 792–812. doi:10.1002/job.2167

Lapointe, É., Vandenberghe, C., and Panaccio, A. (2011). Organizational commitment, organization-based self-esteem, emotional exhaustion and turnover: A conservation of resources perspective. *Hum. Relat.* 64 (12), 1609–1631. doi:10.1177/0018726711424229

Lee, S. Y., and Seo, Y. W. (2017). Corporate social responsibility motive attribution by service employees in the parcel logistics industry as a moderator between CSR perception and organizational effectiveness. *Sustainability* 9 (3), 355. doi:10.3390/su9030355

Lin, C. P., Baruch, Y., and Shih, W. C. (2012). Corporate social responsibility and team performance: The mediating role of team efficacy and team self-esteem. *J. Bus. Ethics* 108 (2), 167–180. doi:10.1007/s10551-011-1068-6

Lin, W., Koopmann, J., and Wang, M. (2020). How does workplace helping behavior step up or slack off? Integrating enrichment-based and depletion-based perspectives. *J. Manag.* 46 (3), 385–413. doi:10.1177/0149206318795275

Lips-Wiersma, M., and Morris, L. (2009). Discriminating between 'meaningful work' and the 'management of meaning. *J. Bus. Ethics* 88 (3), 491–511. doi:10.1007/s10551-009-0118-9

Little, T. D., Cunningham, W. A., Shahar, G., and Widaman, K. F. (2002). To parcel or not to parcel: Exploring the question, weighing the merits. *Struct. Equ. Model. A Multidiscip. J.* 9 (2), 151–173. doi:10.1207/S15328007SEM0902_1

Little, T. D., Rhemtulla, M., Gibson, K., and Schoemann, A. M. (2013). Why the items versus parcels controversy needn't be one. *Psychol. Methods* 18 (3), 285–300. doi:10.1037/a0033266

Malhotra, N. K. (2010). *Marketing Research: An Applied Orientation*. Upper Saddle River: Pearson Publishing.

Manika, D., Wells, V. K., Gregory-Smith, D., and Gentry, M. (2015). The impact of individual attitudinal and organisational variables on workplace environmentally friendly behaviours. *J. Bus. Ethics* 126 (4), 663–684. doi:10.1007/s10551-013-1978-6

May, D. R., Gilson, R. L., and Harter, L. M. (2004). The psychological conditions of meaningfulness, safety and availability and the engagement of the human spirit at work. *J. Occup. Organ. Psychol.* 77 (1), 11–37. doi:10.1348/096317904322915892

Newman, A., Nielsen, I., and Miao, Q. (2015). The impact of employee perceptions of organizational corporate social responsibility practices on job performance and organizational citizenship behavior: Evidence from the Chinese private sector. *Int. J. Hum. Resour. Manag.* 26 (9), 1226–1242. doi:10.1080/09585192.2014.934892

Paruzel, A., Danel, M., and Maier, G. W. (2020). Scrutinizing social identity theory in corporate social responsibility: An experimental investigation. *Front. Psychol.* 11, 580620. doi:10.3389/fpsyg.2020.580620

Pierce, J. L., Gardner, D. G., Cummings, L. L., and Dunham, R. B. (1989). Organization-based self-esteem: Construct definition, measurement, and validation. *Acad. Manage. J.* 32 (3), 622–648. doi:10.2307/256437

Pierce, J. L., and Gardner, D. G. (2004). Self-esteem within the work and organizational context: A review of the organization-based self-esteem literature. *J. Manag.* 30 (5), 591–622. doi:10.1016/j.jm.2003.10.001

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., and Podsakoff, N. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *J. Appl. Psychol.* 88 (5), 879–903. doi:10.1037/0021-9010.88.5.879

Raub, S. (2017). When employees walk the company talk: The importance of employee involvement in corporate philanthropy. *Hum. Resour. Manage.* 56 (5), 837–850. doi:10.1002/hrm.21806

Ren, X., Duan, K., Tao, L., Shi, Y., and Yan, C. (2022a). Carbon prices forecasting in quantiles. *Energy Econ.* 108, 105862. doi:10.1016/j.eneco.2022.105862

Ren, X., Li, Y., Qi, Y., and Duan, K. (2022c). Asymmetric effects of decomposed oil-price shocks on the EU carbon market dynamics. *Energy* 254, 124172. doi:10.1016/j.energy.2022.124172

Ren, X., Li, Y., Shahbaz, M., Dong, K., and Lu, Z. (2022b). Climate risk and corporate environmental performance: Empirical evidence from China. *Sustain. Prod. Consum.* 30, 467–477. doi:10.1016/j.spc.2021.12.023

Ren, X., Tong, Z., Sun, X., and Yan, C. (2022d). Dynamic impacts of energy consumption on economic growth in China: Evidence from a non-parametric panel data model. *Energy Econ.* 107, 105855. doi:10.1016/j.eneco.2022.105855

Rich, B. L., Lepine, J. A., and Crawford, E. R. (2010). Job engagement: Antecedents and effects on job performance. *Acad. Manage. J.* 53 (3), 617–635. doi:10.5465/AMJ.2010.51468988

Roberts, J. A., and David, M. E. (2017). Put down your phone and listen to me: How boss phubbing undermines the psychological conditions necessary for employee engagement. *Comput. Hum. Behav.* 75, 206–217. doi:10.1016/j.chb.2017.05.021

Rosso, B. D., Dekas, K. H., and Wrzesniewski, A. (2010). On the meaning of work: A theoretical integration and review. *Res. Organ. Behav.* 30, 91–127. doi:10.1016/j.riob.2010.09.001

Rupp, D. E. (2011). An employee-centered model of organizational justice and social responsibility. *Organ. Psychol. Rev.* 1 (1), 72–94. doi:10.1177/2041386610376255

Rupp, D. E., Ganapathi, J., Aguilera, R. V., and Williams, C. A. (2006). Employee reactions to corporate social responsibility: An organizational justice framework. *J. Organ. Behav.* 27 (4), 537–543. doi:10.1002/job.380

Rupp, D. E., and Mallory, D. B. (2015). Corporate social responsibility: Psychological, person-centric, and progressing. *Annu. Rev. Organ. Psychol. Organ. Behav.* 2 (1), 211–236. doi:10.1146/annurev-orgpsych-032414-111505

Rupp, D. E., Shao, R., Thornton, M. A., and Skarlicki, D. P. (2013). Applicants' and employees' reactions to corporate social responsibility: The moderating effects of first-party justice perceptions and moral identity. *Pers. Psychol.* 66 (4), 895–933. doi:10.1111/peps.12030

Schaufeli, W. B., Bakker, A. B., and Salanova, M. (2006). A resource perspective on the work-home interface: The work-home resources model. *Edu. Psychol. Meas.* 66 (4), 701–716. doi:10.1177/0013164405282471

ten Brummelhuis, L. L., and Bakker, A. B. (2012). A resource perspective on the work–home interface: The work–home resources model. *Am. Psychol.* 67 (7), 545–556. doi:10.1037/a0027974

Timms, C., Brough, P., O'Driscoll, M., Kalliath, T., Siu, O. L., Sit, C., et al. (2015). Flexible work arrangements, work engagement, turnover intentions and psychological health. *Asia Pac. J. Hum. Resour.* 53 (1), 83–103. doi:10.1111/1744-7941.12030

Vlachos, P. A., Panagopoulos, N. G., Bachrach, D. G., and Morgeson, F. P. (2017). The effects of managerial and employee attributions for corporate social responsibility initiatives. *J. Organ. Behav.* 38 (7), 1111–1129. doi:10.1002/job.2189

Vlachos, P. A., Panagopoulos, N. G., and Rapp, A. A. (2013). Feeling good by doing good: Employee CSR-induced attributions, job satisfaction, and the role of charismatic leadership. *J. Bus. Ethics* 118 (3), 577–588. doi:10.1007/S10551-012-1590-1

Wang, X., Guchait, P., and Paşamehmetoğlu, A. (2020). Why should errors be tolerated? Perceived organizational support, organization-based self-esteem and psychological well-being. *Int. J. Contemp. Hosp. M.* 32 (5), 1987–2006. doi:10.1108/IJCHM-10-2019-0869

Wang, X., Li, J., and Ren, X. (2022a). Asymmetric causality of economic policy uncertainty and oil volatility index on time-varying nexus of the clean energy, carbon and green bond. *Int. Rev. Financ. Anal.* 83, 102306. doi:10.1016/j.irfa.2022.102306

Wang, X., Wang, X., Ren, X., and Wen, F. (2022b). Can digital financial inclusion affect CO2 emissions of China at the prefecture level? Evidence from a spatial econometric approach. *Energy Econ.* 109, 105966. doi:10.1016/j.eneco.2022.105966

Williams, L. J., Cote, J. A., and Buckley, M. R. (1989). Lack of method variance in self-reported affect and perceptions at work: Reality or artifact? *J. Appl. Psychol.* 74 (3), 462–468. doi:10.1037/0021-9010.74.3.462

Xanthopoulou, D., Bakker, A. B., Demerouti, E., and Schaufeli, W. B. (2009). Work engagement and financial returns: A diary study on the role of job and personal resources. *J. Occup. Organ. Psychol.* 82 (1), 183–200. doi:10.1348/096317908X285633

Yan, A., Tang, L., and Hao, Y. (2021). Can corporate social responsibility promote employees' taking charge? The mediating role of thriving at work and the moderating role of task significance. *Front. Psychol.* 11, 613676. doi:10.3389/fpsyg.2020.613676

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Carbon risk and return prediction: Evidence from the multi-CNN method

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This paper investigates the carbon risk and its role in stocks' return prediction by identifying the carbon risk information implied in feature engineering. We predict the stock returns with different neural networks, construct the investment portfolio according to the predicted returns and reflect the returns of stocks with different carbon risks through the relevant evaluation of the investment portfolio. Our Multi-CNN method can best collect information on different relationship types and make full use of graph structure data to identify carbon risks. With or without carbon factor, the stock market performance of high-carbon industry is better than that of medium-carbon industry, and the performance of low-carbon industry is the worst. Moreover, our finding is consistent in both Chinese and American markets. Investment should pay attention to carbon risk and requires corresponding carbon risk premium.

KEYWORDS

carbon risk, return prediction, neural network, deep learning, multi-CNN

1 Introduction

As concerns grow over global warming, climate extremes and human-generated carbon dioxide emissions, increasing attention has been paid on carbon issues (Bolton and Kacperczyk, 2021a; Ren et al., 2022a; Ren et al., 2022b). For example, the *Paris Agreement* was adopted at the Paris Climate Change Conference and signed by 195 countries worldwide. From then on, more countries have initiated policy measures to address climate change. Particularly, the Department of Resource Conservation and Environmental Protection issued the *Working Guidance for Carbon Dioxide Peaking and Carbon Neutrality in Full and Faithful Implementation of the New Development Philosophy*[1] on 24 October 2021. These policies enhance the strategic significance to achieve the peak of carbon dioxide emissions and carbon neutrality, which may also impact the performances of carbon-related firms in capital markets. Therefore, a related research question is raised: whether some carbon risk factors are of concern to stock investors. If so, whether these carbon risk factors have important roles in predicting stock returns.

Carbon risk has attracted widespread attention (Görgen et al., 2020; Bolton and Kacperczyk, 2021; Wang et al., 2022a). Extreme climate events, physical risks and environmental regulations caused by carbon emissions may bring risks of low-carbon transition and lead to the revaluation of corporate financial assets (Carney, 2015; Campiglio et al., 2018; Wang et al., 2022b; Dou et al., 2022). Moreover, for companies facing carbon risks, especially fossil fuel-intensive companies, due to factors such as uncertainty in carbon control regulations and fluctuations in carbon prices, future cash flow is extremely unstable (Oestreich & Tsiakas, 2015; Ilhan et al., 2021). They might be very easy to fall into operational difficulties, which in turn affects the expectations on their stock returns. In addition, the stock returns of fossil fuel-intensive companies are also affected by the risk of fossil energy prices and commodity prices (Bolton and Kacperczyk, 2021).

However, it is very difficult to isolate carbon risk, as there are many kinds of characteristic factors that reflect stock information. In this paper, we choose two groups of carbon factors. First, for dominant carbon factors, we consider carbon emissions and crude oil prices, as documented in the literature (Wei Li et al., 2021; Ren X. et al., 2022c). Second, for non-dominant carbon factors that are not directly related to the company's carbon risk, we use fundamental factors and price factors as they reflect the consistency of carbon risk of enterprises with the same degree of relevance to carbon. Accordingly, this paper also sorts all stocks into high-carbon, medium-carbon, and low-carbon industries, in order to distinguishing stocks based on the degree of relevance to carbon issues. In theory, the carbon risk in high-carbon industries might be the highest, followed by that in medium-carbon industries and the lowest in low-carbon industries.

There is a long line of literature on stocks' return predictability, while only a few have considered the roles of carbon risk. In this paper, we assume that adding carbon risk would help to improve the accuracy of predicting stock returns, especially for stocks that are highly relevant with the carbon issues. We analyze individual stock information through feature engineering. Feature engineering plays a decisive role in neural network prediction to some extent. It provides predictable information for subsequent operations, and the richness of information as well as the content of expression play a key role.

This paper mainly contributes to the literature from three perspectives. First, we use a neural network model to find that there is a positive carbon risk premium in the stock market under the nonlinear assumption. Second, we use the Multi-CNN method to selectively gather information on different relationship types, and make full use of graph structure data to identify carbon risks, which gives the best prediction power when compared to other methods. Third, we find a significant strategy for selecting stocks with better performance based on our prediction results, in both Chinese and American markets. In particular, we predict the return and choose the best 100 stocks according to the predicted value to construct investment portfolios. Our portfolios outperform the benchmark portfolios in all cases.

The structure of this paper is as follows. In Section 2 we review related literature. In Section 3, we develop our main model used for prediction. In Section 4, we present our empirical methodologies and conduct robustness tests. Section 5 concludes and puts forward some potential research questions.

2 Literature review

2.1 Carbon risk and return prediction

Carbon risk generally refers to uncertainty risks associated with climate change or the use of fossil fuels (Hoffmann & Busch, 2008). The earliest definition of carbon risk includes three independent parts: regulatory risk, physical risk and business risk (Labatt & White, 2007). For example, the carbon reduction requirements in the Paris Agreement and related climate policies have prevented some traditional energy companies from making full use of existing resources, resulting in a decline in the value of these assets (McGlade & Ekins, 2015), which is a manifestation of regulatory risk. Some scholars also suggest six specific types of carbon risks (Lash & Wellington, 2007), namely regulatory risk, physical risk, reputational risk, legal risk, product and technology risk and supply chain risk. On this basis, related studies have carried out different studies on the connotation of carbon risk according to different focuses (Subramaniam et al., 2015; Gasbarro et al., 2017).

The long-term, structural and systemic effects of low-carbon transition and global warming have profoundly affected the stability of the real economy and financial markets (Svartzman et al., 2021; Dong et al., 2021). Among them, the important channels through which changes in investment decisions caused by carbon risk affect the financial market are mainly reflected in the relationship between carbon risk and stock returns. Therefore, many scholars begin to consider the impact of carbon risk on the stock market, and most of the results show that there is a positive carbon premium in the stock market. That is, investors require the securities issued by carbon emission companies they hold to provide higher expected returns to compensate for higher climate policy risk exposure. For example, Oestreich and Tsiakas (2015) apply the capital asset pricing and Fama-French factor models and use a "dirty" vs. "clean" portfolio approach with data from the German stock market. The abnormal returns (alpha) of the "dirty-minus-clean" portfolios are defined as a carbon premium. Wen et al. (2020), based on the data of 245 companies in Shenzhen Carbon emission rights Pilot Exchange, find that the establishment of carbon emission rights exchange significantly increases the carbon risk premium by using DID model. Bolton & Kacperczyk (2021) find that companies with higher total CO2 emissions have higher stock returns, mainly because investors are already demanding compensation for the carbon risks they face. Related to this, Hsu et al. (2022) look at the effects of environmental pollution on the cross-section of stock returns. They find that highly polluting firms are more exposed to environmental regulation risk and com-mand higher average returns. Kim et al. (2015) and Trinks et al. (2022), based on Korean and global data, show that carbon intensity is positively correlated with a firm's cost of equity capital. However, some scholars have come to the opposite conclusion that there is a negative carbon premium in the stock market, and companies with higher carbon risks have lower expected stock returns. Garvey et al. (2018) find that a portfolio constructed by ranking stocks according to carbon emission intensity can produce positive α. In et al. (2017) similarly points out that the portfolio of long stocks of low carbon emission companies and short stocks of high emission companies will generate positive abnormal returns. Furthermore, Görgen et al. (2020) explores global stock prices and find no evidence of a significant carbon risk premium.

Therefore, it is interesting to investigate whether the carbon risk have impacts on predicting stock returns. If so, would the predictability vary across stocks with different degrees of relevance to the carbon.

2.2 Return prediction methods

Stocks' return prediction is an important research topic. Early studies tend to investigate this topic by using traditional statistical methods, such as linear econometric models. Recently, some scholars start to use nonlinear models (e.g., neural network model). Financial time series are characterized by nonstationarity, nonlinearity, and high noise, and thus it is difficult for traditional statistical models to predict them accurately. Lin et al. (2013) put forward an SVM-based approach with a two-part feature selection and forecasting model, and prove that this method has better generalization ability than traditional methods. Wanjawa and Muchem (2014) propose the use of an Artificial Neural Network that is a feedforward multi-layer perceptron with error backpropagation and this model can better predict the typical stock market. Zhao et al. (2017) add a time weighting function to LSTM, and their result is better than other models. Zhang and Wen (2022) combine CNN and RNN and propose a new architecture-DWNN. The results show that compared with the conventional RNN model, the DWNN model can reduce the mean square error of prediction by 30%. Some other studies also enhance residual error (ER) which is used to extract important information from the shallow layer and migrate it to the deep layer. The neural networks prove robust to this new statistical test and emerge as the best-performing method in terms of predictability (LeippoldWang and Zhou, 2022).

CNN model is also widely used in image recognition. Krizhevsky et al. (2017) develop a new model structure —Alexnet, which greatly reduced the error rate and subverted the image recognition field, in order to enhance the network expression ability and enhance the network level. Szegedy et al. (2015) construct a 22-layer CNN model, which is cascaded by the Inception structure as the basic modules, and each module uses different sizes. The filter is processed in parallel with the maximum pooling, and the number of parameters is reduced by deleting the full connection layer. By constructing a dense block structure to approximate the optimal sparse structure, the performance can be improved without increasing the amount of computation. He et al. (2016) propose a residual network model (ResNet), which effectively solved the problem of gradient disappearance. Currently, convolutional neural network (CNNs) has been introduced into the field of stock performance prediction, which is capable of directly extracting the features of the input without sophisticated preprocessing and can efficiently process various complex data (Krizhevsky et al., 2017; Widiastuti 2019; Chen and Huang, 2018). When grouped according to the degree of carbon risk, combined with the characteristic engineering including dominant and non-dominant carbon factors, it essentially constitutes the relational data similar to the graph structure. The convolutional neural network is very suitable for processing graph structure data (Kim et al., 2019) because of its good fault tolerance, parallel processing ability, and generalization ability. At the same time, convolutional neural networks are widely used in carbon-related problems (Estrada and Pop, 2011; JiZou et al., 2019; ZhaoWang et al., 2019; Zhang and Wen, 2022), indicating that convolutional neural networks can efficiently identify carbon risks and carbon relationships.

Therefore, we also use the Multi-LSTM and CNN-LSTM methods as our baseline methods. However, in order to make full use of the excellent nature of the neural network in forecasting (Rather et al., 2015; Akita et al., 2016; Gao, 2016), we further develop the Multi-CNN approach to improve the accuracy of carbon risk identification and predicting stocks' returns. We predict the rate of return to the screen, reduce the number of stocks and make them appear more obvious agglomeration effect.

3 Model development

3.1 CNN

Convolutional neural network has different layers which could be categorized into the input layer, convolutional layer, fully connected layer, and the output layer.

The convolutional layer is used to do the convolution operation on the data. We posit input of layer l–1 is an $N\times N$ matrix with $F\times F$ convolutional filters. Then, the input of layer l is calculated according to Eq. 1.

$$v_{i,j}^{l} = \delta\left(\sum_{k=0}^{F-1}\sum_{k=0}^{F-1} w_{k,m} V_{i+k,j+m}^{l-1}\right) \tag{1}$$

In the Eq. 1, $v_{i,j}^{l}$ is the value at row i, column j of layer l, $w_{k,m}$ is the weight at row k, column m of filter and δ is the activation function.

ReLu (Eq. 2) is a commonly used nonlinear activation function.

$$f(x) = max(0, x) \tag{2}$$

Fully connected layer is responsible for converting extracted features in the previous layers to the final output. The relation between two successive layers is defined by Eq. 3

$$v_j^i = \delta\left(\sum_k v_k^{j-1} w_{k,i}^{j-1}\right) \tag{3}$$

In Eq. 3, v_j^i is the value of neuron i at the layer j, δ is activation function and weight of connection between neuron k from layer $j-1$ and neuron i from layer j is shown by $w_{k,i}^{j-1}$.

Dropout layer can avoid the model from too much learning of the training data. It discards some data in time to effectively prevent over-fitting.

When we distinguish high-carbon, medium-carbon and low-carbon industries, we automatically cluster the carbon risk information as the first type of information. The dominant carbon factor and the non-dominant carbon factor add two different types of data, and at the same time, the two types can be subdivided into other types of data. For example, the non-dominant carbon factor contains price information and fundamental information. There are relationships among these different types of data, such as subordination between individual stocks and characteristics, subordination between individual stocks and industries, etc. Thus, we innovatively adopt CNN in this paper to solve the estimation difficulty given these complex relationships and graph structure data.

3.2 LSTM

Long Short-Term Memory (LSTM) is first designed for overcoming the back-propagating errors (RumelhartHinton and Williams, 1986). As a special kind of RNN, capable of learning long-term dependencies, LSTM can solve the problem of exploding and vanishing gradient problem for general RNN (Graves 2012).

A typical LSTM cell is composed of an input gate, an output gate, and a forget gate. Each cell has two states, the cell state and the hidden state (Liu and Pun, 2022). The output of LSTM at time t is h_i, which is defined by Eq. 4

$$\boldsymbol{h_i} = \boldsymbol{o_i}^* \tanh(\boldsymbol{c_i}) \tag{4}$$

In the Eq. 4:

$$\boldsymbol{o_t} = \boldsymbol{\sigma}(\boldsymbol{W_o x_t} + \boldsymbol{U_o h_{t-1}} + \boldsymbol{b_o}) \tag{5}$$

$$\boldsymbol{c_t} = \boldsymbol{f_t c_{t-1}} + \boldsymbol{i_t \tilde{c}_t} \tag{6}$$

$$\boldsymbol{f_i} = \boldsymbol{\sigma}\left(\boldsymbol{W_f x_t} + \boldsymbol{U_f h_{t-1}} + \boldsymbol{b_f}\right) \tag{7}$$

$$\boldsymbol{i_t} = \boldsymbol{\sigma}(\boldsymbol{W_i x_t} + \boldsymbol{U_i h_{t-1}} + \boldsymbol{b_i}) \tag{8}$$

$$\boldsymbol{\tilde{c}_t} = \tanh(\boldsymbol{W_c x_t} + \boldsymbol{U_c h_{t-1}}) \tag{9}$$

In the Eq. 5, $\mathbf{o_t}$ is the output of the output gate, $\boldsymbol{\sigma}$ is Sigmoid function, $\boldsymbol{x}_t$ is the input vector at time $\boldsymbol{t}$, $\boldsymbol{h_t}$ is the output of the hidden layer at time $\boldsymbol{t-1}$, and $\mathbf{W}$, $\mathbf{U}$ as well as $\mathbf{b}$ are the weight matrix and offset vector during calculation, respectively. In the Eq. 6, $\mathbf{i_t}$ is the output of the input gate at time $\boldsymbol{t}$. In the Eq. 6, $\mathbf{f_t}$ is the output of the forget gate at time $\boldsymbol{t}$.

3.3 CNN-LSTM

Figure 1 shows the CNN-LSTM structure used in the paper. The data is transmitted *via* the input layer, and the convergence of the network structure is accelerated by Batch Normalization layer, preserving the characteristic skew of the activation function at one and the mean activation average near zero due to normalization. The normalized result is calculated by the 1D convolutional layer and the LSTM layer. To match the size of the input data amount, two operations are performed separately. Following that, part of the data is discarded through the Dropout layer to prevent overfitting. The processing data is flattened and then passed through the fully connected layer (Dense) and the result is finally obtained through the output layer.

3.4 Sliding window

To study the impact of the real stock market, we use the sliding window method (Nair et al., 2010) to simulate the real investment process, as shown in Figure 2. The model performs estimation and prediction within one data window at a time, and after a single completion, lets the data window slide forward to perform the same estimation and prediction operation for the next interval. The sliding window method preserves the time series information within the data and is consistent with reality compared to traditional data set segmentation methods such as the random leave-out method (Li et al., 2017). Within each data window, we divide it into a training interval, a test interval and a validation interval. The training interval is to fit the parameters of the model using the data while the test interval is to test the selection of suitable hyperparameters and then refit the model on the training and validation data once suitable hyperparameters are obtained. Furthermore, the validation interval is to test the out-of-sample prediction of the resulting model.

3.5 Multi-CNN

Finally, based on the models and LSTM approach introduced above, we increase the complexity of the model and develop the Multi-CNN methodology as the main empirical model for our

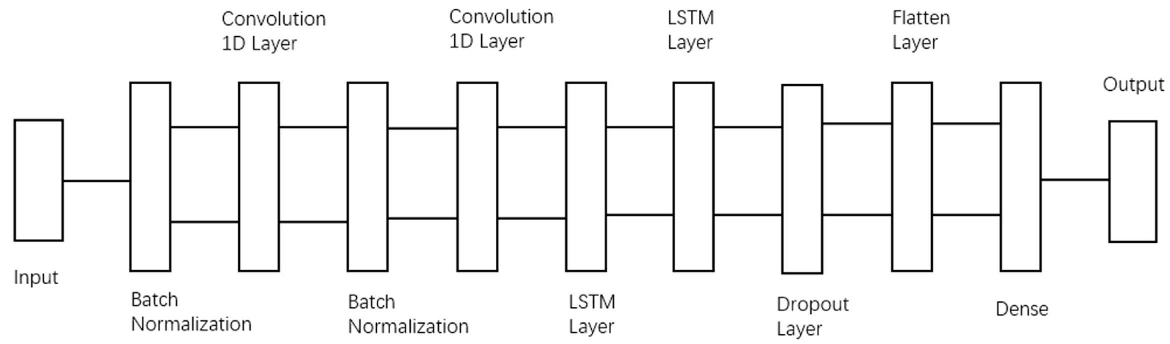

FIGURE 1
CNN-LSTM structure. Note: the data is transmitted *via* the input layer, and the convergence of the network structure is accelerated by Batch Normalization layer. The normalized result is calculated by the 1D convolutional layer and the LSTM layer. Following that, part of the data is discarded through the Dropout layer to prevent overfitting. The processing data is flattened and then passed through the fully connected layer (Dense) and the result is finally obtained through the output layer.

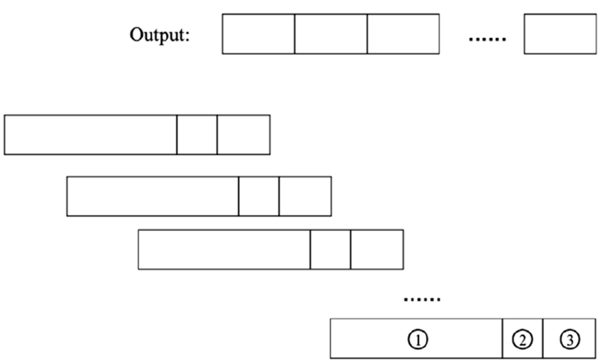

FIGURE 2
Sliding window operation mode. Note: the model performs estimation and prediction within one data window at a time, and after a single completion, lets the data window slide forward to perform the same estimation and prediction operation for the next interval. Within each data window, we divide it into a ① training interval; ② a test interval and a ③ validation interval.

study. Basically, we refer to standard approach in the literature and select Conv1D layers, LSTM layers, Dense layers, Dropout layers, Batch Normalization layers, ReLu activation functions, finding suitable combinations for hyperparameters selection, model estimation, and performance evaluation. It is worth noting that we do not include Conv2D layers, Conv3D layers and Pooling layers in the construction of the model. This is because both layers require the input quantities to be converted to 2D or 3D, which can lose the original 1D data characteristics of the stock data and add a large amount of redundant information creating interference. Although Pooling layers can prevent over-fitting to some extent, they are essentially downscaling and abstraction of visual input objects modelled on the human visual system, which is clearly not applicable to stock data.

Moreover, we do not construct a particularly large set of features, preventing the influence of the carbon factor from being weakened. In addition, on the application of sliding windows, 90% of the first order of all trading day data for 5 years is taken as the training interval each time, and the remaining 10% is the test interval. The test interval is the 1 month of trading day data immediately following this 5-year period. All the neural networks are built using Keras, a high-level API for Tensorflow in Python, and to accomplish the computation of huge amounts of data, we program them on the Linux operating system, using GPU acceleration.

4 Empirical methodology

4.1 Data sample

We obtain Chinese daily quotes data for all A-share stocks listed on the Shanghai and Shenzhen stock exchanges from the Tendency and download carbon-related factors from Wind Database, the largest financial data provider in China. Meanwhile, according to the "*Notice on the Release of Energy Efficiency Benchmarking Levels and Benchmarking Levels in Key Areas of High Energy-Consuming Industries (2021 Edition)*", which defines high energy-consuming industries. All individual stocks are sorted into high-carbon, medium-carbon and low-carbon industries according to the *CSRC Releases Guidance Document on Uncovered Losses of Listed Companies*. Our data sample covers more than 4,600 A-share stocks traded from January 2000 to 2 December018. We also collect the same dimensional data for the US, obtaining daily frequency quotes for all US stocks from the Wharton CRSP database and for the S&P

TABLE 1 Evaluation of prediction accuracy using Multi-LSTM method and CNN-LSTM method with and without carbon factor in feature engineering Note: This table records the values of MSE, RMSE and MAE used to evaluate the prediction accuracy of Multi-LSTM method and CNN-LSTM method. And all, high, mid as well as low represent the full stock, high-carbon, medium-carbon as well as low-carbon sectors respectively. Meanwhile, the values of Chinese market and American market are recorded respectively. Overall, in the case of feature engineering with and without carbon factor, the values of each forecast accuracy assessment indicator in different industries are small, indicating that the methodology has good forecasting effect and high forecast accuracy.

	CNN-LSTM-China			CNN-LSTM-America			Multi-LSTM-China			Multi-LSTM-America		
	MSE	MAE	RMSE	MSE	MAE	RMSE	MSE	MAE	RMSE	MSE	MAE	RMSE
All_non_c_factor	0.0201	0.0009	0.0290	0.0182	0.0008	0.0250	0.0217	0.0010	0.0300	0.0187	0.0008	0.0268
High_non_c_factor	0.0210	0.0009	0.0273	0.0180	0.0007	0.0243	0.0211	0.0009	0.0280	0.0183	0.0008	0.0261
Mid_non_c_factor	0.0210	0.0009	0.0298	0.0191	0.0007	0.0253	0.0215	0.0009	0.0299	0.0189	0.0009	0.0268
Low_non_c_factor	0.0269	0.0012	0.0352	0.0230	0.0093	0.0299	0.0286	0.0014	0.0363	0.0206	0.0012	0.0331
All_c_factor	0.0229	0.0009	0.0329	0.0198	0.0009	0.0298	0.0232	0.0010	0.0319	0.0213	0.0009	0.0284
High_c_factor	0.0204	0.0008	0.0303	0.0183	0.0008	0.0280	0.0218	0.0009	0.0298	0.0217	0.0008	0.0282
Mid_c_factor	0.0201	0.0009	0.0289	0.0194	0.0009	0.0284	0.0228	0.0010	0.0304	0.0208	0.0009	0.0270
Low_c_factor	0.0288	0.0010	0.0314	0.0237	0.0010	0.0335	0.0299	0.0013	0.0354	0.0248	0.0011	0.0332

500, which is set as the benchmark. In distinguishing between high-carbon, medium-carbon and low-carbon industries in US markets, we follow the industry classification of the Wharton database and refer to the definition of high energy-consuming industries by Bolton et al. The final sample of data from the US covers 7,528 stocks traded from January 2000 to December 2018.

For the data processing of the US and Chinese data, we used the same method. We build the pool of stock-level predictive characteristics, which includes 19 characteristics in total, including four carbon-related factors, namely China CO2 emissions, Global CO2 emissions, Futures Settlement Price (continuous): Brent Crude Oil, Futures Settlement Price (continuous): WTI Crude Oil. In terms of data frequency, all 15 stock characteristics are updated daily, 2 crude oil futures prices are daily updated and 2 carbon emissions factors annually. In order to improve the validity of the data, the annual data is converted into daily data.

Machine learning has been proven to be effective in extracting features for prediction in complex and noisy data environments. In order to exploit the potential of the data, enriching the amount of information provided by the limited data available, we process the data slices, not only in terms of the number of factors, but also in terms of the length of the data slices, creating a more complex three-dimensional tensor. For example, the training set shapes for the Chinese and US stock markets from 2014 to 2018 are 3339180*20*19 and 9106633*20*19 respectively.

4.2 Prediction accuracy assessment for baseline methods

The metric for evaluating forecast accuracy is defined as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \tag{10}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \tag{11}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i| \tag{12}$$

where y represents the true return, $\hat{y}$ represents the model predicted return, MSE, RMSE, MAE represent the mean squared error, root mean squared error and mean absolute error of the model respectively. Their statistical values lie between 0 and 1, with smaller data representing better model prediction performance.

We initiate our tests by using some baseline methods such as Multi-LSTM, CNN-LSTM methodologies, as shown in Table 1. Prediction accuracy assessment metric values (MSE, RMSE and MAE) are calculated under the without and with the carbon factor, respectively. The neural network method has similar prediction results for the all-stock, high-carbon and medium-carbon sectors, while the prediction accuracy is poorer for the low-carbon sector. Moreover, the prediction effect of the neural network is less affected by the carbon factor.

In order to more clearly and visibly represent the impact of the inclusion of factors representing the carbon macro environment on the stock market, we conduct an in-depth analysis by constructing a portfolio. For all stocks, we rank their returns over the forecast period. Then, to amplify the impact to get more valuable results, we select the top 100 stocks in terms of forecast returns to build the portfolio for that day and calculate both the true return and the cumulative return of the daily portfolio from January 2005 to December 2018. The SSE is used as a benchmark for the Chinese stock

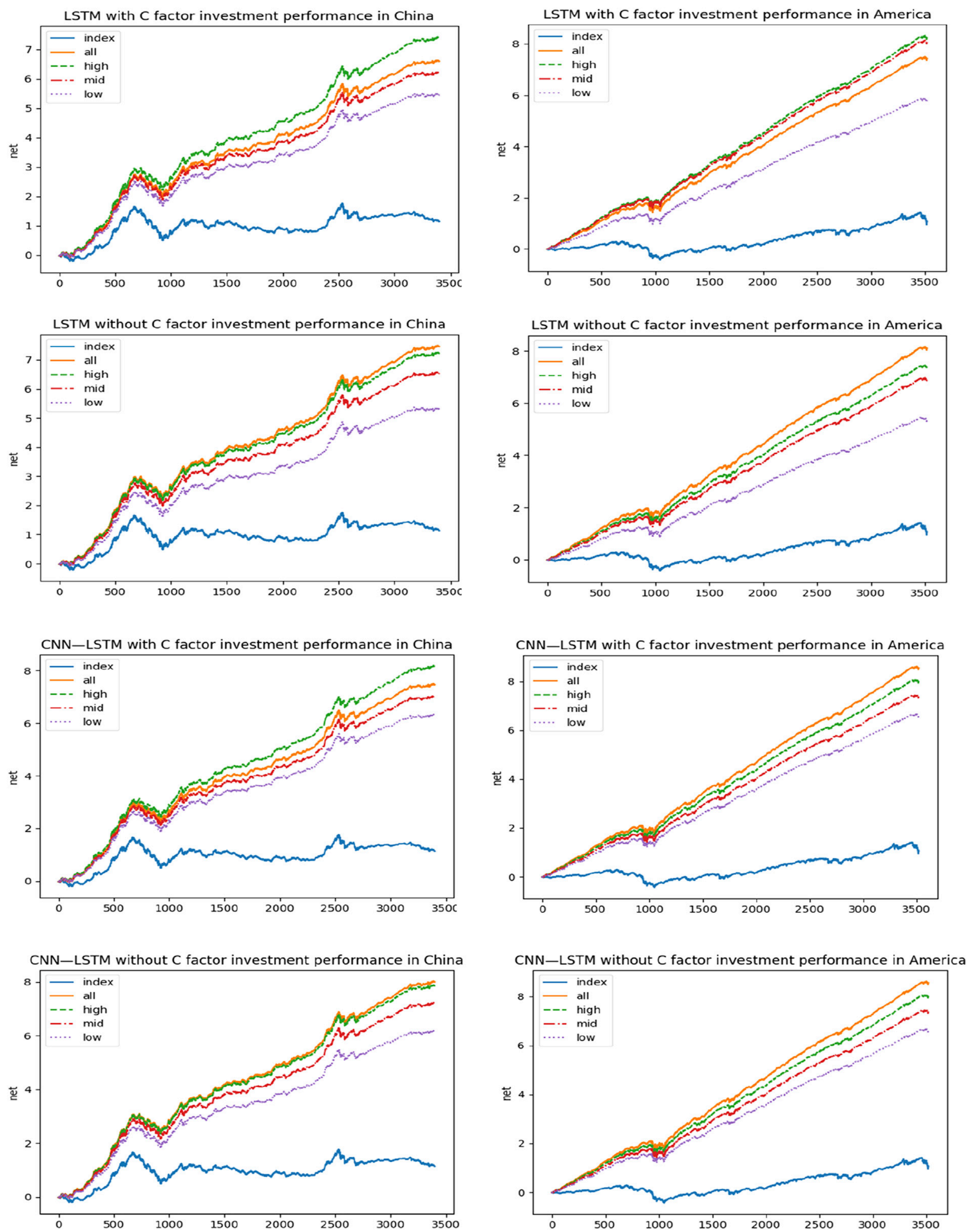

FIGURE 3
Cumulative return rate of portfolio constructed by Multi-LSTM method and CNN-LSTM method. Note: the figure shows the cumulative returns from January 2005 to December 2018 of investment portfolios constructed by China and America through Multi-LSTM method and CNN-LSTM method with and without carbon factors in feature engineering. SSE Composite Index is selected as benchmark in China, while the S&P 500 is selected in America. In the legend, all stands for all stocks, high stands for high-carbon industry, mid stands for medium-carbon industry and low stands for low-carbon industry.

TABLE 2 Evaluation of performance of portfolio using Multi-LSTM method and CNN-LSTM method with and without carbon factor in feature engineering Note: This table records the values of total return, average return, omega ratio, Sharpe ratio and Sortino ratio used to evaluate the performance of portfolio of Multi-LSTM method and CNN-LSTM method. And all, high, mid as well as low represent the full stock, high-carbon, medium-carbon as well as low-carbon sectors respectively. Meanwhile, the values of Chinese market and American market are recorded respectively. And SSE Composite Index is selected as benchmark in China, while the S&P 500 is selected in America. Compared to the benchmark, the five measures of investment performance of the portfolio constructed by this methodology far exceed the benchmark, implying a significantly higher return per unit of risk, which is a positive prediction.

	Non_c_factor_LSTM-China					**Non_c_factor_LSTM-America**				
	Index	**All**	**High**	**Mid**	**Low**	**Index**	**All**	**High**	**Mid**	**Low**
All_return	113.98	745.59	722.45	654.15	530.53	97.05	810.2	738.74	689.77	537.14
Annual_return	8.77	57.35	55.57	50.32	40.81	7.47	62.32	56.83	53.06	41.32
Omega_ratio	1.06	1.44	1.42	1.38	1.32	1.08	1.73	1.67	1.64	1.49
Sharpe_ratio	0.32	2.05	1.99	1.81	1.5	0.37	2.95	2.73	2.58	2.05
Sortino_ratio	0.44	3.02	2.93	2.65	2.16	0.52	4.55	4.17	3.91	3.05
	C_factor_LSTM-China					C_factor_LSTM-America				
	Index	All	High	Mid	Low	Index	All	High	Mid	Low
All_return	113.98	660.17	738.4	619.05	544.39	97.05	743.36	825.36	807.75	580.67
Annual_return	8.77	50.78	56.8	47.62	41.88	7.47	57.18	63.49	62.13	44.67
Omega_ratio	1.06	1.41	1.44	1.36	1.33	1.08	1.73	1.76	1.81	1.55
Sharpe_ratio	0.32	1.87	2.03	1.72	1.54	0.37	2.84	3.03	3.08	2.23
Sortino_ratio	0.44	2.73	3	2.5	2.22	0.52	4.33	4.67	4.74	3.33
	Non_c_factor_CNN-LSTM-China					Non_c_factor_CNN-LSTM-America				
	Index	All	High	Mid	Low	Index	All	High	Mid	Low
All_return	113.98	746.74	816.34	699.9	630.54	97.05	855.79	801.01	738.86	662.21
Annual_return	8.77	57.44	62.8	53.84	48.5	7.47	65.83	61.62	56.84	50.94
Omega_ratio	1.06	1.44	1.5	1.41	1.4	1.08	1.79	1.72	1.68	1.66
Sharpe_ratio	0.32	2.05	2.26	1.94	1.81	0.37	3.14	2.93	2.75	2.58
Sortino_ratio	0.44	3.03	3.36	2.85	2.63	0.52	4.87	4.51	4.2	3.89
	C_factor_CNN-LSTM-China					C_factor_CNN-LSTM-America				
	Index	All	High	Mid	Low	Index	All	High	Mid	Low
All_return	113.98	746.74	816.34	699.9	630.54	97.05	784.77	866.32	738.37	651.21
Annual_return	8.77	57.44	62.8	53.84	48.5	7.47	60.37	66.64	56.8	50.09
Omega_ratio	1.06	1.44	1.5	1.41	1.4	1.08	1.71	1.82	1.68	1.65
Sharpe_ratio	0.32	2.05	2.26	1.94	1.81	0.37	2.88	3.2	2.75	2.54
Sortino_ratio	0.44	3.03	3.36	2.85	2.63	0.52	4.42	4.97	4.2	3.82

market and the S&P 500 is used as a benchmark for the US stock market, and they are used to compare the cumulative returns of the method with and without the carbon factor respectively. Figure 3 shows the cumulative returns of the portfolios constructed under the Multi-LSTM, CNN-LSTM methodologies for both the no-carbon factor and the carbon-containing factor. The portfolio constructed through the neural network approach outperforms and that the carbon factors have a significant impact on portfolio selection. With the addition of the carbon factor, the high carbon sector forecasts improve significantly in these neural network methodologies and the portfolios all achieve good returns. The total return, average return, omega ratio, Sharpe ratio and Sortino ratio of the portfolio, using Multi-LSTM method and CNN-LSTM method, are calculated for further analysis, given in Table 2. In fact, for high carbon sectors, they have higher carbon risk and investors need a higher risk premium to compensate.

4.3 Further evidence from the Multi-CNN methods

Similarly to the tests we have done on the two baseline methods, Table 3 records the MSE, RMSE, MAE values of these prediction accuracy assessment metrics for the Multi-CNN methodology without and with carbon factors separately, where All, High, Mid, and Low represent the all-stock, high-carbon, medium-carbon, and low-carbon sectors, respectively.

Clearly, the Multi-CNN methodology has the smallest MSE, RMSE and MAE values and performs the best, the CNN-LSTM

TABLE 3 Evaluation of prediction accuracy using Multi-CNN method with and without carbon factor in feature engineering Note: This table records the values of MSE, RMSE and MAE used to evaluate the prediction accuracy of Multi-CNN method. And all, high, mid as well as low represent the full stock, high-carbon, medium-carbon as well as low-carbon sectors respectively. Meanwhile, the values of Chinese market and American market are recorded respectively. Overall, in the case of feature engineering with and without carbon factor, the values of each forecast accuracy assessment indicator in different industries are small, indicating that the methodology has good forecasting effect and high forecast accuracy.

	Multi-CNN-China			Multi-CNN-America		
	MSE	MAE	RMSE	MSE	MAE	RMSE
All_non_c_factor	0.0199	0.0008	0.0284	0.0143	0.0007	0.0225
High_non_c_factor	0.0195	0.0008	0.0278	0.0153	0.0006	0.0215
Mid_non_c_factor	0.0198	0.0008	0.0282	0.0157	0.0006	0.0223
Low_non_c_factor	0.0250	0.0012	0.0343	0.0183	0.0009	0.0302
All_c_factor	0.0198	0.0008	0.0283	0.0162	0.0006	0.0242
High_c_factor	0.0193	0.0008	0.0275	0.0161	0.0007	0.0249
Mid_c_factor	0.0197	0.0008	0.0281	0.0167	0.0007	0.0241
Low_c_factor	0.0245	0.0011	0.0338	0.0221	0.0009	0.0290

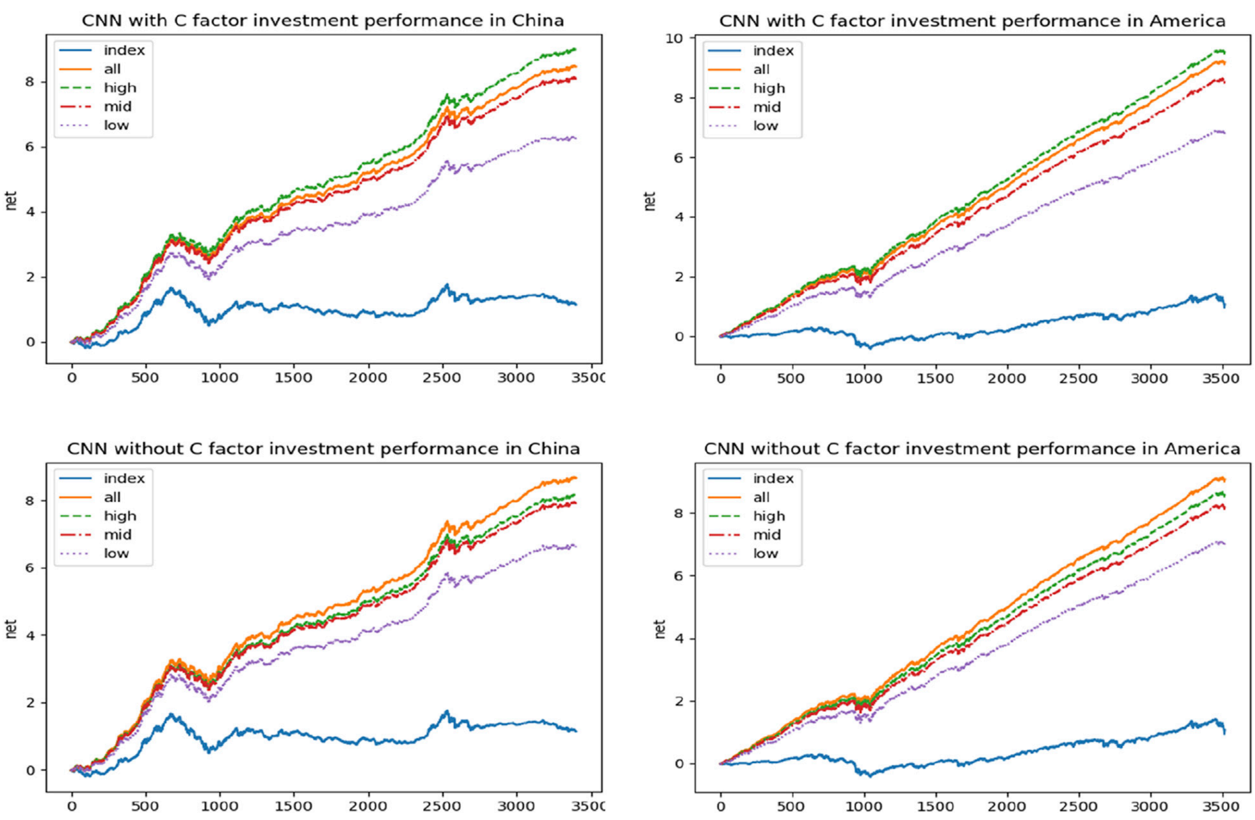

FIGURE 4
Cumulative return rate of portfolio constructed by Multi-CNN method. Note: the figure shows the cumulative returns from January 2005 to December 2018 of investment portfolios constructed by China and America through Multi-CNN method with and without carbon factors in feature engineering. SSE Composite Index is selected as benchmark in China, while the S&P 500 is selected in America. In the legend, all stands for all stocks, high stands for high-carbon industry, mid stands for medium-carbon industry and low stands for low-carbon industry.

TABLE 4 Evaluation of performance of portfolio using Multi-CNN method with and without carbon factor in feature engineering Note: This table records the values of total return, average return, omega ratio, Sharpe ratio and Sortino ratio used to evaluate the performance of portfolio of Multi-CNN method. And all, high, mid as well as low represent the full stock, high-carbon, medium-carbon as well as low-carbon sectors respectively. Meanwhile, the values of Chinese market and American market are recorded respectively. And SSE Composite Index is selected as benchmark in China, while the S&P 500 is selected in America. Compared to the benchmark, the five measures of investment performance of the portfolio constructed by this methodology far exceed the benchmark, implying a significantly higher return per unit of risk, which is a positive prediction.

	Non_c_factor_CNN-China					Non_c_factor_CNN-America				
	Index	All	High	Mid	Low	Index	All	High	Mid	Low
All_return	113.98	864.37	812.68	790.87	663.13	97.05	906.62	859.28	819.21	701.08
Annual_return	8.77	66.49	62.51	60.84	51.01	7.47	69.74	66.10	63.02	53.93
Omega_ratio	1.06	1.51	1.49	1.47	1.38	1.08	1.81	1.81	1.74	1.61
Sharpe_ratio	0.32	2.34	2.25	2.17	1.82	0.37	3.25	3.17	2.99	2.57
Sortino_ratio	0.44	3.50	3.34	3.21	2.66	0.52	5.08	4.93	4.62	3.90

methodology is in the middle and performs the second best, and the Multi-LSTM methodology is the largest and performs the worst, but compared to other traditional methods, the neural network methodologies still perform well in prediction.

In more detail, the values of each forecast accuracy assessment indicator in different industries are small, indicating that the methodology has good forecasting effect and high forecast accuracy. The high prediction accuracy of the Multi-CNN approach also shows that this method is suitable for the graph structure data used in this paper. It has good fault tolerance, parallel processing ability, and self-learning ability. It can deal with the problems of complex environmental information, unclear background knowledge, and unclear reasoning rules, and identify carbon risks efficiently. The close relationship between levels and spatial information makes it especially suitable for the processing and understanding of graph structure data, and it can automatically extract rich related features. From the results, the values of each indicator for the all-stock, high-carbon and medium-carbon sectors are not significantly different, implying that they have similar prediction results, while the values of each indicator for the assessment of prediction accuracy for the low-carbon sector are greater than those of the other groups, implying that the methodology has poorer prediction accuracy for the low-carbon sector. This may be because the small number of stocks in the low carbon sector means that the amount of data is low, which affects the forecasting effect. Following this, the groups with and without the carbon factor are similar in the values of these indicators, with only individual indicator values being smaller in the neural network system with the carbon factor. Thus, the inclusion of the carbon factor or not has no significant effect on the prediction accuracy. In terms of the dimension of prediction accuracy alone, the carbon factor has little influence on the predictive effectiveness of this multi-CNN method.

Furthermore, as illustrated in Figure 4, the cumulative returns of the portfolios constructed through the Multi-CNN methodology all significantly outperform the benchmark, although the downward trend and timing of returns occur roughly in line with the index. This again means that the methodology is not able to select stocks that perform well during a downturn in the stock market, which is not ideal, whereas when the index is running smoothly, the methodology's forecasts are able to successfully select stocks with top real returns, resulting in an increasing cumulative portfolio return.

We can also find that the addition of the carbon factor has a significant impact on sectors with different carbon relevance. A pool of all stocks without the carbon factor has the highest cumulative portfolio returns constructed through the neural network system, followed by high-carbon, medium-carbon and low-carbon sectors in that order. We believe that an all-stock group implies a greater range of selection and a wide variety of stocks covered, which can effectively avoid a collective decline in yield due to an over-concentration of stocks included in the group. And when the carbon factor is added, the cumulative returns of the high carbon sectors increase significantly, outperforming the cumulative returns of the all-equity range constructed portfolios. This reflects the presence of investors demanding a higher risk premium for carbon risk, a phenomenon highlighted by the introduction of the carbon factor.

The total return, average return, omega ratio, Sharpe ratio and Sortino ratio of the portfolio, using Multi-CNN method, are calculated for further analysis, given in Table 4. Compared to the benchmark, the five measures of investment performance of the portfolio constructed by this methodology far exceed the benchmark, implying a significantly higher return per unit of risk, which is a positive prediction. In contrast, we can see that overall investment performance declines with the addition of the carbon factor, possibly because the independent carbon factor changes the stable structure of the neural network's already

15 factors, and is less effective than without the carbon factor in terms of overall input.

5 Conclusion

This paper mainly develops the Multi-CNN method to predict stock returns, dividing all stocks into high-carbon industry, medium-carbon industry and low-carbon industry for their carbon relevance degree. According to the predicted returns, we construct investment portfolios in different industries, and reflect the stock performance of with different carbon relevance. We analyze individual stock information through feature engineering, distinguishing all data between dominant and non-dominant carbon factors. It is found that under the nonlinear hypothesis, the stock market also has a carbon risk premium, and it is a positive carbon risk premium. We find that Multi-CNN methods can selectively collect information on different relationship types and make full use of graph structure data to identify carbon risks. Using Multi-CNN method for return predictions does outperform Multi-LSTM and CNN-LSTM methods.

In the empirical process, some interesting phenomena are found. For example, when the characteristic engineering contains an explicit carbon factor, the investment return of the portfolio formed by stocks selected from high-carbon industries is higher than that of the portfolio formed by stocks selected from all stocks. Theoretically, if the forecast is accurate, the return of the all-stock portfolio should be the highest. Thus, some further studies might be required to explain this phenomenon. Moreover, in reality, carbon risk is not the only influencing factor. Some other factors can be further controlled when studying carbon risk premium, which is reflected in the subdivision of internal stocks in high-carbon, medium-carbon, and low-carbon industries.

Some inspirations are drawn from the above conclusions. It is necessary to continuously improve the efficiency and effectiveness of carbon supervision, form a balanced carbon price signal through market operations, and guide the sustainable development of high-carbon enterprises. In addition, attention should also be paid to the role of laws and regulations in the green transformation of high-carbon enterprises, strengthening the connection between China and the global carbon market, and generating economic and political benefits.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: All A-share stocks listed on the Shanghai and Shenzhen stock exchanges from the Tendency and download carbon-related factors from Wind Database.

Author contributions

JT: Analysis, Software, Writing JL: Methodology, Analysis, Supervision and Writing and Editing.

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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References

Akita, R., Yoshihara, A., Matsubara, T., and Uehara, K. (2016). "Deep learning for stock prediction using numerical and textual information," in 2016 IEEE/ACIS 15th International Conference on Computer and Information Science (ICIS), 1–6. doi:10.1109/ICIS.2016.7550882

Bolton, P., and Kacperczyk, M. (2021). Do investors care about carbon risk? *J. Financial Econ.* 142 (2), 517–549. doi:10.1016/j.jfineco.2021.05.008

Campiglio, E., Dafermos, Y., Monnin, P., Ryan-Collins, J., Schotten, G., and Tanaka, M. (2018). Climate change challenges for central banks and financial regulators. *Nat. Clim. Chang.* 8 (6), 462–468. doi:10.1038/s41558-018-0175-0

Carney, M. (2015). Breaking the tragedy of the horizon–climate change and financial stability. *Speech given A. T. Lloyd's Lond.* 29, 220–230.

Chen, A.-P., and Huang, S.-H. (2018). "Cloning strategies from trading records using agent-based reinforcement learning algorithm," in IEEE International Conference on Agents (ICA), 34–37. doi:10.1109/AGENTS.2018.8460078

Dong, K. Y., Ren, X. H., and Zhao, J. (2021). How does low-carbon energy transition alleviate energy poverty in China? A nonparametric panel causality analysis. *Energy Econ.* 103, 105620. doi:10.1016/j.eneco.2021.105620

Dou, Y., Li, Y. Y., Dong, K. Y., and Ren, X. H. (2022). Dynamic linkages between economic policy uncertainty and the carbon futures market: Does Covid-19 pandemic matter? *Resour. Policy* 75, 102455. doi:10.1016/j.resourpol.2021.102455

Estrada, D., and Pop, E. (2011). Imaging dissipation and hot spots in carbon nanotube network transistors. *Appl. Phys. Lett.* 98, 073102. doi:10.1063/1.3549297

Gao, Q. (2016). *Stock market forecasting using recurrent neural network*. United states: ProQuest Dissertations Publishing.

Garvey, G. T., Iyer, M., and Nash, J. (2018). Carbon footprint and productivity: Does the "E" in ESG capture efficiency as well as environment. *J. Invest. Manag.* 16 (1), 59–69.

Gasbarro, F., Iraldo, F., and Daddi, T. (2017). The drivers of multinational enterprises' climate change strategies: A quantitative study on climate-related risks and opportunities. *J. Clean. Prod.* 160, 8–26. doi:10.1016/j.jclepro.2017.03.018

Görgen, M., Jacob, A., Nerlinger, M., Riordan, R., Rohleder, M., and Wilkens, M. (2020). Carbon risk. *SSRN Electronic Journal*.

Graves, A. (2012). Long short-term memory. *Supervised Sequence Label. Recurr. Neural Netw.* 385, 37–45.

He, K., Zhang, X., Ren, S., and Sun, J. (2016). "Deep residual learning for image recognition," in Proceedings of the IEEE conference on computer vision and pattern recognition, 770–778. doi:10.1109/CVPR.2016.90

Hoffmann, V. H., and Busch, T. (2008). Corporate carbon performance indicators: Carbon intensity, dependency, exposure, and risk. *J. Ind. Ecol.* 12 (4), 505–520. doi:10.1111/j.1530-9290.2008.00066.x

Hsu, P. H., Li, K., and Tsou, C. Y. (2022). The pollution premium. *SSRN J.* doi:10.2139/ssrn.3578215

Ilhan, E., Sautner, Z., and Vilkov, G. (2021). Carbon tail risk. *Rev. Financ. Stud.* 34 (3), 1540–1571. doi:10.1093/rfs/hhaa071

In, S. Y., Park, K. Y., and Monk, A. (2017). Is "being green" rewarded in the market? An empirical investigation of decarbonization risk and stock returns. *Int. Assoc. Energy Econ. Singap. Issue)* 46 (48).

JiZou, Y., He, K., and Zhu, B. (2019). Carbon futures price forecasting based with ARIMA-CNN-LSTM model. *Procedia Comput. Sci.* 162, 33–38. doi:10.1016/j.procs.2019.11.254

Kim, R., So, C. H., Jeong, M., Lee, S., Kim, J., and Kang, J. (2019). *Hats: A hierarchical graph attention network for stock movement prediction*. arXiv preprint arXiv:1908.07999.

Kim, Y. B., An, H. T., and Kim, J. D. (2015). The effect of carbon risk on the cost of equity capital. *J. Clean. Prod.* 93, 279–287. doi:10.1016/j.jclepro.2015.01.006

Krizhevsky, A., Sutskever, I., and Hinton, G. E. (2017). Imagenet classification with deep convolutional neural networks. *Commun. ACM* 60 (6), 84–90. doi:10.1145/3065386

Labatt, S., and White, R. R. (2007). *Carbon finance: The financial implications of climate change*. NewYork: John Wiley & Sons.

Lash, J., and Wellington, F. (2007). Competitive advantage on a warming planet. *Harv. Bus. Rev.* 85 (3), 94–102.

LeippoldWang, Q., and Zhou, W. (2022). Machine learning in the Chinese stock market. *J. Financial Econ.* 145 (2), 64–82. doi:10.1016/j.jfineco.2021.08.017

Li, B., Lin, Y., and Tang, W. X. (2017). ML-TEA: A set of quantitative investment algorithms based on machine learning and technical analysis. *Syst. Eng. Theory Pract.* 37 (5), 1089–1100.

Lin, Y., Guo, H., and Hu, J. (2013). "An SVM-based approach for stock market trend prediction," in The 2013 international joint conference on neural networks (IJCNN), 1–7.

Liu, R., and Pun, C. S. (2022). Machine-learning-enhanced systemic risk measure: A two-step supervised learning approach. *J. Bank. Finance* 136, 106416. doi:10.1016/j.jbankfin.2022.106416

McGlade, C., and Ekins, P. (2015). The geographical distribution of fossil fuels unused when limiting global warming to 2 C. *Nature* 517 (7533), 187–190. doi:10.1038/nature14016

Nair, B. B., Mohandas, V. P., and Sakthivel, N. R. (2010). A decision tree-rough set hybrid system for stock market trend prediction. *Int. J. Comput. Appl.* 6 (9), 1–6. doi:10.5120/1106-1449

Oestreich, A. M., and Tsiakas, I. (2015). Carbon emissions and stock returns: Evidence from the EU emissions trading scheme. *J. Bank. Finance* 58, 294–308. doi:10.1016/j.jbankfin.2015.05.005

Rather, A. M., Agarwal, A., and Sastry, V. N. (2015). Recurrent neural network and a hybrid model for prediction of stock returns. *Expert Syst. Appl.* 42 (6), 3234–3241. doi:10.1016/j.eswa.2014.12.003

Ren, X. H., Duan, K., Tao, L. Z., Shi, Y. K., and Yan, C. (2022b). Carbon prices forecasting in quantiles. *Energy Econ.* 108, 105862. doi:10.1016/j.eneco.2022.105862

Ren, X. H., Li, Y. Y., Qi, Y. S., and Duan, K. (2022a). Asymmetric effects of decomposed oil-price shocks on the EU carbon market dynamics. *Energy* 254 (B), 124172. doi:10.1016/j.energy.2022.124172

Ren, X., Li, Y., Yan, C., Wen, F., and Lu, Z. (2022c). The interrelationship between the carbon market and the green bonds market: Evidence from wavelet quantile-on-quantile method. *Technol. Forecast. Soc. Change* 179, 121611. doi:10.1016/j.techfore.2022.121611

RumelhartHinton, G. E., and Williams, R. J. (1986). Learning representations by back-propagating errors. *Nature* 323 (6088), 533–536. doi:10.1038/323533a0

Subramaniam, N., Wahyuni, D., Cooper, B. J., Leung, P., and Wines, G. (2015). Integration of carbon risks and opportunities in enterprise risk management systems: Evidence from Australian firms. *J. Clean. Prod.* 96, 407–417. doi:10.1016/j.jclepro.2014.02.013

Svartzman, R., Bolton, P., Despres, M., Pereira Da Silva, L. A., and Samama, F. (2021). Central banks, financial stability and policy coordination in the age of climate uncertainty: A three-layered analytical and operational framework. *Clim. Policy* 21 (4), 563–580. doi:10.1080/14693062.2020.1862743

Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., and Rabinovich, A. (2015). "Going deeper with convolutions," in Proceedings of the IEEE conference on computer vision and pattern recognition, 1–9.

Trinks, A., Ibikunle, G., Mulder, M., and Scholtens, B. (2022). Carbon intensity and the cost of equity capital. *Energy J.* 43 (2), 181. doi:10.5547/01956574.43.2.atri

Wang, X., Li, J., and Ren, X. (2022a). Asymmetric causality of economic policy uncertainty and oil volatility index on time-varying nexus of the clean energy, carbon and green bond. *Int. Rev. Financial Analysis* 83, 102306. doi:10.1016/j.irfa.2022.102306

Wang, X., Wang, X., Ren, X., and Wen, F. (2022b). Can digital financial inclusion affect CO2 emissions of China at the prefecture level? Evidence from a spatial econometric approach. *Energy Econ.* 109, 105966. doi:10.1016/j.eneco.2022.105966

Wanjawa, B. W., and Muchemi, L. (2014). *ANN model to predict stock prices at stock exchange markets*.

WeiLi, Y., Ren, X., and Duan, K. (2021). Crude oil price uncertainty and corporate carbon emissions. *Environ. Sci. Pollut. Res.* 29 (2), 2385–2400. doi:10.1007/s11356-021-15837-8

Wen, F., Wu, N., and Gong, X. (2020). China's carbon emissions trading and stock returns. *Energy Econ.* 86, 104627. doi:10.1016/j.eneco.2019.104627

Widiastuti, N. (2019). Convolution neural network for text mining and natural language processing. *IOP Conf. Ser. Mat. Sci. Eng.* 662 (5), 052010. doi:10.1088/1757-899X/662/5/052010

Zhang, F., and Wen, N. (2022). Carbon price forecasting: A novel deep learning approach. *Environ. Sci. Pollut. Res.* 29 (36), 54782–54795. doi:10.1007/s11356-022-19713-x

Zhao, Z., Rao, R., Tu, S., and Shi, J. (2017). "Time-weighted LSTM model with redefined labeling for stock trend prediction," in 2017 IEEE 29th international conference on tools with artificial intelligence (ICTAI), 1210–1217.

ZhaoWang, S., He, F., Zhang, J., Chen, L., Dong, P., Tai, Z., et al. (2019). Hydroxylated carbon nanotube/carbon nitride nanobelt composites with enhanced photooxidation and H2 evolution efficiency. *Carbon* 150, 340–348. doi:10.1016/j.carbon.2019.05.020

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Impact of air quality on enterprise productivity: Evidence from Chinese listed companies

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We provide insights and innovative ideas for China to achieve green development and promote high-quality economic development by studying the impact of air quality on enterprise productivity. This paper uses data from 2008 to 2016 for A-share companies listed on the Shanghai and Shenzhen stock markets, as well as the levels of particulate matter under 2.5 μm in diameter for 214 major Chinese cities. At the same time, this paper innovatively applies regression discontinuity and the Spatial Durbin Model for empirical testing. Considering the endogeneity, we choose the air flow index as an instrumental variable and the generalized space two-stage least squares method for the endogenous test. Additionally, we use dynamic regression and different spatial weight matrix to conduct robustness tests and reselect data from 2008 to 2012 and 2013 to 2016 as samples. Moreover, we test corporate heterogeneity from three perspectives: pollutant type, firm equity, and an industry's technological level. The results show that the deterioration of local air quality significantly inhibits firm productivity, while the spatial spillover effects of pollution from surrounding cities also have a significant dampening effect on firm productivity. This negative effect is transmitted through research and development innovation capacity, human capital, and government subsidies. This empirical evidence from listed companies can be used for evaluating air quality management to enhance enterprise productivity, as well as to provide policy recommendations for boosting firm productivity through improved air quality.

KEYWORDS

air quality, enterprise productivity, regression discontinuity, spatial Durbin model, GS2SLS

1 Introduction

Due to modernization, China's economy has shifted from a stage of high-speed growth to high-quality development. High-quality development has become the primary task for China to move towards Chinese-style modernization. The key to promoting high-quality development lies in the transformation of economic momentum, which means that China must transform from "extensive growth" to "intensive growth." Moreover, "intensive growth" can be achieved by increasing total factor productivity is regarded as the source of power for high-quality development. At the same time, any development must be based on the premise of protecting the ecological environment. Accelerating green and low-carbon development is the key link to promoting a comprehensive green transformation of economic and social development. As one of the main causes of environmental pollution, air pollution emission has become a matter of concern in academia and government. Therefore, this paper analyzes the impact of air quality on enterprise productivity, which has important theoretical value and practical significance for China to speed up green development to achieve high-quality economic development.

Particulate matter (PM) has become increasingly prominent as regional and composite air pollution and is one of the most significant air pollution sources threatening the health of people worldwide. With the intensification of air pollution, PM2.5, the primary pollutant hazardous to human health, has been receiving increasing attention from the public and governments[1] In terms of public health, PM2.5 seriously harms immunity and triggers respiratory and cardiovascular diseases (Kioumourtzoglou et al., 2016). In the urbanization process, for every 10% increase in PM2.5, there are 2.7 outflows per 100 residents (Chen et al., 2017), which exacerbates regional health inequalities and shifts the focus of labor mobility decisions from urban-rural binary choices to multiple choices of healthier zones. Moreover, it has an irreversible impact on the inflow of regional labor and triggers the phenomenon of escaping from "Beijing, Shanghai, and Guangzhou," which affects the urbanization process (Hanlon, 2016). Additionally, air pollution seriously impacts the stock prices and financial decisions of micro-enterprises (Lepori 2016), the cost of debt financing (Tan et al., 2022), the accrual earnings management (Jiang et al., 2022a; Jiang et al., 2022b), and investment efficiency (He and Lin 2022). Thus, air pollution with PM2.5 as the primary pollutant not only seriously affects regular life but also has a huge negative impact on microeconomic agents in China.

With China's comprehensive promotion of green and high-quality development, enterprises are not only micro-entities for economic development but also important forces of environmental protection and the main landing point for implementing environmental regulation policies (Lin et al., 2020; Zhang and Liu 2021). For a long time, there have been many highly polluting, inefficient, and energy-consuming enterprises in the urbanization process in China (He et al., 2012) that seek benefits at the expense of air quality. However, López (2017) pointed out that there is a non-linear inverted U-shaped relationship between environmental pollution and income. Aznar and Ruiz (2016) also mentioned that when environmental pollution reaches a certain level, the economy will be difficult to sustain growth. Thus, air quality is closely related to macroeconomic growth; however, there is scant literature that goes deep into the micro-enterprise level, especially the listed company level. Therefore, the impact of air quality with PM2.5 as the primary pollutant on enterprise productivity deserves in-depth exploration to achieve high-quality economic growth from an ecological perspective.

Based on the above, this study empirically tests the impact of local air quality and spillover from surrounding cities on enterprise productivity using regression discontinuity and the spatial Durbin model (SDM) by selecting the PM2.5 as a proxy variable for air quality, with enterprises as micro subjects. Considering the endogeneity, we choose the air flow index as an instrumental variable and the generalized space two-stage least squares (GS2SLS) method for the endogenous test. Then, a series of robustness tests are conducted using the dynamic Gaussian mixture model (GMM) regression, using different spatial weight matrix and reselecting data from 2008 to 2012 and 2013 to 2016 as subsamples. The impact of air quality on firm productivity is explored from three perspectives: research and development (R&D) innovation capacity, human capital, and government subsidies. Furthermore, we test corporate heterogeneity from three perspectives: pollutant type, firm equity, and the technology industry.

This paper makes valuable contributions to the existing literature in four aspects. First, most of the previous studies examined the impact of air pollution from macroscopic aspects such as economic development and human health, and few of them involved enterprise productivity in the microscopic field. Therefore, this research provides important perspectives and ideas for China to promote high-quality economic development through green development. Second, this study not only analyzes how air quality affects enterprise productivity using regression discontinuity but also examines the impact of spatial spillover effects brought about by air pollution on listed enterprise productivity using the SDM and GS2SLS, to fully understand the relationship from the spatial perspective. Third, in terms of using data and selecting variables, most of the existing literature has used industrial enterprise databases; this study, however, uses micro-sample data of listed companies to measure the response variables and the PM2.5 obtained from ArcGIS software to measure the core explanatory variable of air quality, to avoid data manipulation and human measurement bias. Finally, this paper thoroughly analyzes the impact mechanism, clarifies the transmission pathway between air quality and enterprise productivity from the three intermediary mechanisms of R&D innovation capability, human capital effect, and government subsidy, and provides a useful supplement to the existing literature.

2 Literature review and mechanism analysis

Since Grossman and Krueger (1995) proposed the theory of the environmental Kuznets curve, many scholars have examined the relationship between air pollution with economic development and human health or behavior. For instance, about air pollution and economic development, Ibukun and Omisore (2022) proved that there is a bidirectional causal relationship between air pollution and economic development through the data of four MINT countries. Hu Q. et al. (2021) attributed it to the huge medical expenditure caused by air pollution. Shang et al. (2022) found that air pollution will also seriously restrict the development of a circular economy, lead to the outflow of foreign direct investment (Huang and Hsu 2022), reduce the upgrading of regional industrial structure (Zhang et al., 2022), and exacerbate the income gap (Liu et al., 2020).

On the other hand, air pollution seriously damages human physical health (Hassan et al., 2021) and mental health (Hu X. et al., 2021). For example, Hu and Guo (2021) systematically investigated the negative impact of air pollution on human health from the respiratory, urinary, circulatory, digestive, and nervous systems, as well as the probability of conception and life expectancy. Liu et al. (2021) considered human health as the transmission mechanism through which air pollution affects human wellbeing. Shen et al. (2021) found that air pollution greatly increased the possibility of depression; sad emotions, poor self-control, and comprehension are all seriously affected by air pollution (Balakrishnan and Tsaneva 2022). At the same time, air pollution can also have a serious impact on human behavior. Lin et al. (2022) found that air pollution makes people get jobs nearby, and it also makes people move away from heavily polluted residential areas (Yang et al., 2022), and even increases people's crime rate (Kuo and Putra 2021).

1 PM2.5 refers to particulate matter in ambient air with an aerodynamic equivalent diameter of less than or equal to 2.5 μm.

However, Chang et al. (2016) showed in a study of a pear-packing plant that PM 2.5 with high penetration capacity in outdoor air significantly reduced the productivity of indoor workers, while pollutants with low penetration capacity (e.g., ozone) had almost no significant effect. Therefore, after a deep investigation, it was found that the impact of PM2.5 seems to have more importance.

In recent years, with deeper mining of firm-level data, many articles have delved into the micro domain to assess the impact of air pollution on enterprise development. For example, Xue et al. (2021) studied the relationship between air pollution and corporate human capital and they found that people are more inclined to seek jobs in less polluted locations. Liu et al. (2022) used human capital as the influencing mechanism to verify the negative effect between air pollution and corporate social responsibility. Tan et al. (2021) proved that air pollution reduces the liquidity of corporate property and the decision-making efficiency of operators, thus making companies need to hold more cash to resist unknown risks. Li et al. (2022) also found that air pollution increases the number of zombie firms and decreases corporate investment efficiency. Cui et al. (2021) investigated the location of enterprises' foreign investment and found that foreign-invested enterprises are more willing to choose countries with good air quality to invest.

According to the literature, we can note that previous studies on the impact of air pollution focused more on macro aspects such as economic development and human health. Although some articles have gone into the microscopic field to assess the impact of air pollution on enterprise development, few have dealt with enterprise productivity. Cao et al. (2022) only studied the impact of air pollution on enterprises in the Yangtze River Delta region of China, while this paper expands the research perspective to listed companies in China, and examines the impact of spatial spillover effects brought about by air pollution on the productivity of listed companies. Thus, using a case study from China, we empirically investigate the impact of air quality (PM2.5) on listed firm productivity through the intermediate mechanisms of R&D innovation capacity, human capital, and government subsidies as follows.

1) PM2.5 can reduce enterprise productivity through R&D innovation capabilities. Akpalu and Normanyo (2017) found that mining areas will provide some environmental subsidies or increase the amount of medical insurance to compensate people affected by air pollution, Wang L. et al. (2021) and Lin et al. (2021) also found that to prevent brain drain caused by air pollution, companies will improve employee treatment, which increases the additional cost of enterprises, resulting in the reduction of investment funds for enterprise innovation. Wei and Liu (2022) attributed the negative effects of air pollution and innovation ability to labor costs, while Ai et al. (2022) subdivided this cost into internal pollution control costs and external pollution prevention costs. You (2022) proved by examining the structure of the three major industries that air pollution mainly affects the structure of the tertiary industry, thereby inhibiting the level of urban innovation. On the other hand, Tuncel and Oktay (2022) demonstrated that Turkish manufacturing firms improved their productivity through increased spending on innovation. Zhu et al. (2021) divided innovation into possibility innovation brought by R&D and process innovation brought by information and communication technology and proved that both innovations can improve enterprise productivity. However, Mishra et al. (2021) believe that product innovation and process innovation can improve enterprise productivity, while organizational innovation only brings negative effects. Fazlıoğlu et al. (2019) divide innovation into innovation input and innovation output. Since innovation input needs certain conditions and time to transform into innovation output, the latter can promote productivity more than the former.
2) PM2.5 reduces enterprise productivity through the human capital effect. Balakrishnan and Tsaneva (2021) described the level of human capital from the three aspects of basic learning skills, academic performance, and school grades, and found that air pollution has an adverse impact on it; Liu and Yu (2020) found that air pollution affects the physical health, mental health, and job satisfaction of workers, thereby reducing the willingness of migrants to settle in cities, and causing the loss of corporate talent, especially high-performance employees (Tan and Yan 2021). Similarly, Lai et al. (2021) found that air pollution greatly increases the probability of college graduates going to other cities for employment from the selection of employment locations of college graduates, leading to the loss of higher education talents. Chen et al. (2022) proved that air pollution has caused a sharp increase in the number of net immigrants in China, and people with higher education are also the main group of population loss. Air pollution mainly affects the level of human capital through the loss of population, especially the loss of high-quality and higher education talents. High-quality talents have richer management experience (Timothy 2022), and can better exert the corporate brand value (He et al., 2020). Therefore, when there is a shortage of high-quality talent, it will have a serious impact on the innovation ability of enterprises and the upgrading of industrial structure (Wang M. et al., 2021), thereby reducing productivity (Ramirez et al., 2020).

3) PM2.5 can reduce enterprise productivity through increasing government subsidies. Li et al. (2019) found that air pollution will stimulate the government to actively participate in the control of air pollution and increase government subsidies for environmental pollution. Similarly; Zhang and Zhang (2022) from the perspective of the iron and steel industry believe that the iron and steel industry will cause serious air pollution, so the government should implement active subsidy policies. It can be seen that in order to improve air pollution, the government often invests a lot of money (Xie and Wang 2019). However, government subsidies may lead to information asymmetry and adverse selection problems, leading to market failure, since enterprises receiving government subsidies are not entirely determined by the market but are also influenced by the relationship between the government and the enterprise (Fox and Heller 2000). To obtain more compensation, enterprises may overstate the degree of air pollution, resulting in rent-seeking behavior by some enterprises (Mao and Xu 2018). When enterprises engage in rent-seeking activities, they will incur corresponding costs. These non-productive expenditures will not only reduce the compensatory effect of government subsidies (Tassey 2004), but also not conducive to the formation of competitive advantages for enterprises, and will also reduce the profitability of enterprises (Ren and Zhang 2013), thus hindering the improvement of enterprise productivity.

Based on the above discussions, air quality has an impact on firm productivity. Therefore, we propose the following hypotheses:

Hypothesis 1: PM2.5 (as measured by the air quality) reduces firm productivity.

Hypothesis 2: The main channels by which PM2.5 reduces firm productivity are (1) reducing R&D innovation capacity, (2) reducing the number of employees, and (3) increasing government subsidies.

3 Methods and data

3.1 Regression discontinuity

This study refers to Chen et al. (2013) and uses a quasi-natural experiment on centralized heating policies in winter in northern China (north of the Qinling-Huaihe River boundary) to address the possible endogeneity problem between air pollution and firm productivity using regression discontinuity and Stata software. The reason for choosing the Qinling-Huaihe River is that there is a significant difference in the average January temperature between the south and north areas of the boundary; therefore, the centralized heating policy in winter in the north is an exogenous policy in a quasi-natural experiment. This study sets the following estimating equation.

$$D_{it} = \begin{cases} 1, & L_c \geq 0 \\ 0, & L_c < 0 \end{cases} \tag{1}$$

$$TFP_{it} = \delta_0 + \delta_1 D_{ict} + \delta_2 f(L_c) + \sum_{n=2}^{k} \delta_n {}^*Con_{it} + \tau_i + \gamma_t + \varepsilon_{it} \tag{2}$$

$$PM2.5_{it} = \gamma_0 + \gamma_1 D_{ict} + \gamma_2 f(L_c) + \sum_{n=2}^{k} \gamma_n {}^*Con_{it} + \tau_i + \gamma_t + \varepsilon_{it} \tag{3}$$

$$TFP_{it} = \alpha_0 + \alpha_1 PM2.5_{it} + \alpha_2 f(L_c) + \sum_{n=2}^{k} \alpha_n {}^*Con_{it} + \tau_i + \gamma_t + \varepsilon_{it} \tag{4}$$

where c denotes the city; the explanatory variable TFP_{it} represents the productivity of firm i in year t; $PM2.5_{it}$ is the air quality of the city where the firm is located; Con_{it} represents a set of control variables; τ_i, γ_t, and ε_{it} are the individual and time dummy variables and random disturbance terms, respectively; L_c is the driving variable, which denotes the difference between the latitude of the city and the Qinling-Huai River boundary[2] D denotes the indicator variable, which takes the Qinling-Huai River boundary under the background of China's centralized heating policy as a discontinuity. When city c is located north of the boundary, that is, the city is located north of the Qinling-Huai River, L_c >0 and D takes 1. Otherwise, when city c is located south of the boundary, that is, the city is located south of the Qinling-Huai River, L_c <0 and D takes 0. $f(L_c)$ is the higher-order polynomial adjustment function of the driving variable L_c.

3.2 Spatial effects regression

Referring to Tang et al. (2017), there is a spatial autocorrelation effect of environmental pollution in cities. Therefore, considering that firm productivity is affected by local urban air pollution and also by the spatial spillover effects of air pollution from other cities, we use local pollution and pollution from surrounding areas as the core variables to explore the total impact of local firm productivity by local pollution and pollution spillover from surrounding areas. Through the Moran index, it can be shown that there is a spatial autocorrelation effect of air pollution PM2.5 in the city where the enterprise is located, and this is consistent with the conclusions obtained by Fan et al. (2019) through the spatial correlation of haze pollution measurement[3] Next, we add a spatial econometric model, as shown in Equations 5, 6.

$$TFP_{it} = \beta WPM_{it} + \beta_0 + \beta_1 PM2.5_{it} + \sum_{n=2}^{k} \beta_n {}^*Con_{it} + \tau_i + \gamma_t + \varepsilon_{it} \tag{5}$$

$$WPM_{it} = \sum_{j=1}^{c=214} W_{ij} {}^*pm_{jt} \tag{6}$$

where WPM_{it} represents the total impact of air pollution in the city of other enterprise j on the city of local enterprise i, that is, $\sum_{j=1}^{c=214} W_{ij}{}^*pm_{jt}$. W is the 214*214 spatial weight matrix, and this study uses MATLAB software to calculate the distance between cities and form the inverse geographic distance weight matrix W_{ij} by using the latitude and longitude data of 214 major cities. W_{ij} denotes the inverse geographic distance weight matrix of the city where firm i is located and the city where other firm j is located; pm_{jt} denotes the air quality of the city where other firm j is located in year t, and the rest of the variables are consistent with the previous section.

3.3 Variables

The subject of this study is firm productivity, traditionally measured using ordinary least squares and fixed effects; however, these two methods may cause serious bias and endogeneity problems. There are two semi-parametric methods of OP and LP proposed by Olley and Pakes (1996) and Levinsohn and Petrin (2003) to estimate firm productivity. In the OP method, it is assumed that a manufacturer's investment is a strictly increasing function of its own productivity, so the corresponding productivity can be determined by deriving the inverse function of the investment demand function. The OP method introduces survival probability and investment amount as proxy variables to solve the problems of selectivity and simultaneity bias, but the firm's real investment value must be greater than zero. Thus, samples with zero investment are not estimated. However, as not every firm invests every year, many firm samples are discarded in the estimation process. Meanwhile, the LP method has lower data requirements. It does not use the amount of investment as a proxy variable and can instead use the input indicators of intermediate goods, which allows the researcher the flexibility to choose data. Therefore, we measure firm productivity using the LP method to determine the response variables in the benchmark regression.

The core explanatory variable in this study is air quality, as measured by the PM2.5. Air pollutants currently emitted in China are mainly sulfur dioxide, carbon dioxide, soot, and PM. Since the

2 The Qinling-Huai River boundary covers the latitude range of 33.03°–34.25°. Hence, referring to Chen et al. (2013), this study selects the value of 33.64 as the latitude of the breakpoint boundary.

3 For details of the spatial autocorrelation analysis of pollution in the cities where the enterprises are located, please refer to Supplementary Appendix S1.

PM2.5 can synthetically include the above pollutants emitted from the combustion of fuels and further chemical reactions in the air, it is useful for the analysis of gaseous pollutants emitted from production enterprises and suitable for measuring air quality. Owing to the short time span and difficulty in obtaining pollution data in China, there may be problems such as data manipulation and falsification. Therefore, we used the world PM2.5 density map from 1998 to 2016, publicly available at the Data Center of the Astronaut Earth Observing System Data and Information System hosted by Columbia University[4] Then, we positioned each raster to municipal administrative units by ArcGIS software, and then averaged the raster data falling in the municipal administrative units as the value of PM2.5 emission concentration of cities. Unlike ground-observed air pollution data, satellite-extracted data are better able to match mobile population data in time and space while avoiding problems such as data manipulation and human measurement bias (Ghanem and Zhang 2014).

Based on the mechanism analysis, we select the number of patent applications, number of enterprise employees, and government subsidies as mediating variables to represent the enterprise R&D innovation effect, human capital effect, and policy spillover effect, respectively, to test the mechanism of the effect of air quality on enterprise productivity. Among them, enterprise patents include three types of invention patents, utility model patents, and design patents. We choose the sum of three types of patent applications plus one to take the logarithm to measure the number of enterprise patent applications (Hall and Harhoff 2012); to narrow the data differences and obtain smoother data, the number of enterprise employees and government subsidies are logarithmically processed in this study.

In addition to the required variables to estimate air pollution and firm productivity, we include the following control variables. (1) Firm size. As the size of the firm increases, the firm will have a higher scale effect, stronger finances, a more standardized management system, and usually higher firm productivity (Lucas 1978; Majumdar 1997). (2) Return on total assets. We choose the ratio of the firm's net profit for the year and total assets at the end of the period to measure the return on total assets. The more profitable a firm is, the more likely it is that sufficient funds will be available for R&D innovation and high-quality production activities (Bogliacino and Pianta 2013). (3) Fixed assets ratio and capital expenditure ratio. Fixed assets are a category of assets formed when capital expenditure is capitalized. When the fixed assets ratio or capital expenditure ratio is lower, the liquidity of the enterprise's assets is faster and the capital operating capacity is stronger (Wang 2002). (4) Current gearing ratio and gearing ratio. Both reflect a firm's financing constraint ability to a large extent. When the current gearing ratio is lower, the firm may face higher financial risk, which reduces productivity (Ayyagari et al., 2010). (5) Cash flow. In general, cash flow has a positive effect on firm productivity, and firms maintain a certain amount of cash flow to avoid the shortage of funds (Chen and Guariglia 2013). (6) Firm age: There may be two effects of firm age on firm productivity. On the one hand, as firms age, they accumulate more technical information, beneficial to firm productivity (Farinas and Moreno 2000). On the other hand, new market entrants may be more dynamic; in this case, firm productivity decreases as firms age (Brandt et al., 2012). Therefore, we add firm age and the squared terms of firm age as control variables. The specific expressions are shown in Table 1.

4 Sourced from http://beta.sedac.ciesin.columbia.edu. These data cover earth pollution information from 70° N to 60° S, with an observation accuracy of.5 ° × 0.5 °.

3.4 Data

Considering that the data on listed companies in China before 2007 are missing and/or inadequate, the sample period selected for this study is 2008–2016. Our sample includes A-share companies listed on the Shanghai and Shenzhen stock markets by securities code and year identifier. We processed the data by removing the following: (1) missing control variables, (2) enterprises established after the listing time, and (3) and financial and insurance services and enterprises containing ST, ST*, and PT categories[5] Then, the filtered data were matched with the PM2.5 level for 214 major cities. Next, most of the variables were logarithmically processed, resulting in a final sample of 8,594 observations from the 1,829 enterprises listed. Table 2 reports the descriptive statistics of all variables. To determine the viability of the variables, we performed multicollinearity and heteroscedasticity tests; the results showed that we did not need to worry about multicollinearity and homoscedasticity among the variables[6]

4 Empirical results

4.1 Regression discontinuity results

Before conducting regression discontinuity estimation, it is first observed whether air pollution and firm productivity show discontinuity change and the results are shown in Figure 1. Figure 1 shows that regardless of whether the fit is linear or quadratic, both the productivity and PM2.5 of enterprises jump significantly at the discontinuity, that is, the PM2.5 emissions in the northern region are significantly higher than those in the southern region, this conclusion agrees with the findings of Chen et al. (2013). While the enterprises in the southern region have significantly higher productivity, indicating that relatively good air quality is beneficial to enterprise productivity. In addition, to accurately identify the causal relationship between variables, we also perform an endogeneity test in the 5.3 section.

The results of this estimation are reported in Table 3; column (1) shows that the central heating policy has a significant impact on enterprise productivity, that is, the central heating policy makes the enterprise productivity in the southern region significantly higher than

5 If a listed company experiences losses for two consecutive years, loss for 1 year and its net assets fall below par, or if there is a major violation of the law in the course of the company's business, the exchange will give special treatment to the company's stock, also known as the ST system. For ST companies, if further problems arise, such as continued losses in the following year, thus reaching the limit of three consecutive years of losses as stipulated in the Company Law, the company will be subject to PT treatment. The asterisk (*) after ST is the delisting risk warning, and ST* stocks will be suspended if they continue to lose money the following year.

6 For the results of the multicollinearity and homoscedasticity tests, please refer to Supplementary Appendix S2.

TABLE 1 Expression of variables.

Variables	Definition	Expression
Response variables	Enterprise productivity (TFP)	Business productivity estimated by the LP method
Intermediate variables	R&D Innovation (Patent)	Natural logarithm of the number of patent applications
	Human Capital (Num)	Natural logarithm of the number of employees in the company
	Government Subsidies (Gov)	Natural logarithm of the number of government subsidies
Explanatory variables	Air Quality (PM2.5 Indicator)	PM2.5 emission concentration values obtained by ArcGIS software
Control variables	Company size (Size)	Natural logarithm of total corporate assets
	Return on total assets (RoA)	Ratio of the enterprise's net profit to its total assets at the end of the year
	Percentage of fixed assets (PPE)	Ratio of enterprise fixed assets to total assets
	Current gearing ratio (Liq)	Ratio of current assets to current liabilities of an enterprise
	Gearing ratio (Lev)	Ratio of total liabilities to total assets of the enterprise for the year
	Cash flow (CF)	Ratio of enterprise monetary capital to total assets
	Capital expenditure ratio (Cap)	Ratio of enterprise capital expenditure to total assets
	Company age (Age)	Current year minus year of incorporation

Source: Compiled from regression results.

TABLE 2 Descriptive statistics.

Variables	Obs	Mean	Std. Dev	Min	Max
TFP_LP	8,594	16.600	1.045	12.255	21.874
PM2.5	8,594	12.634	1.018	9.178	15.170
Num	8,594	7.651	1.225	3.664	13.165
Gov	8,594	7.039	1.564	−1.595	15.432
R&D	8,594	17.528	1.472	5.094	25.025
Size	8,594	12.647	1.264	9.871	19.294
RoA	8,594	.051	.061	−.762	1.202
PPE	8,594	.212	.148	.001	.920
Liq	8,594	3.456	5.757	.075	190.872
Lev	8,594	.380	.209	.008	2.024
CF	8,594	.224	.168	.001	.960
Cap	8,594	.056	.050	.001	.412
Age	8,594	3.024	.229	2.197	4.159
Age2	8,594	9.198	1.395	4.828	17.296

Source: Compiled from regression results.

that in the northern region at the level of 1%. When control variables and fixed effects are added in columns (2) and (3), the regression results do not change significantly. Similarly, the results in column (4) show that the central heating policy has a significant impact on air pollution. After introducing control variables and controlling for fixed effects in columns (5) and (6), the central heating policy makes the average PM2.5 concentration in the southern region about 0.23 μg/m^3 lower than that in the northern region. The estimation results in column (7) show that air pollution significantly reduces the productivity of enterprises. Columns (8) and (9) gradually add the corresponding control variables and fixed effects, and the regression results are all significant at the 1% level, that is, with every 1% increase in PM2.5 concentration, firm productivity decreases by 0.32%.

In addition, we consider the air quality index (AQI) as a surrogate indicator of air pollution PM2.5 for robustness testing, which monitors six pollutants: sulfur dioxide, nitrogen dioxide, PM10, PM2.5, carbon monoxide, and ozone. We take the natural logarithm of AQI, and the regression results are reported in column (10) of Table 3. The results show that after adding a series of control variables and fixed effects, AQI still significantly reduces enterprise productivity, which is consistent with the explanatory variable PM2.5, showing the robustness and reliability of the conclusions.

4.2 Dynamic regression

Considering that firm productivity may be affected by its own lags, the model is constructed to examine its dynamic effects, as expressed in Equation 7.

$$TFP_{it} = \beta_0 + \beta_1 TFP_{i,t-1} + \beta_2 PM2.5_{it} + \sum\nolimits_{n=3}^{k} \beta_n {}^* Con_{it} + \tau_i + \gamma_t + \varepsilon_{it}. \tag{7}$$

Eq. 7 indicates that the productivity of firm *i* in year *t-1* will affect that in year *t*. As indicated in column (1) in Table 4, the coefficient of PM2.5 is −0.01, which is highly significant. In addition, the coefficient of $TFP_{i,t-1}$ is significantly positive. This result implies that the higher a company's productivity in the previous year, the higher its productivity in the second year; that is, it has a certain "inertia."

Considering unobservable individual effects, this may lead to inconsistent estimation results and endogeneity problems. In dynamic regression, GMM tests are generally used to solve the endogeneity problem, but compared to the systematic GMM, the instrumental variables of differential GMM are often weak.

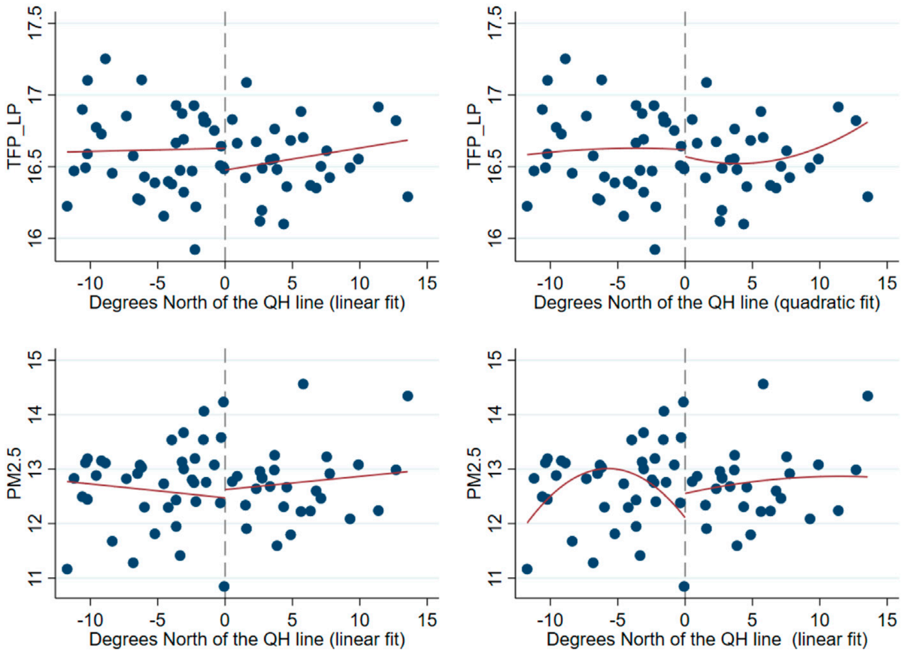

FIGURE 1
Discontinuity diagram of enterprise productivity and PM2.5 at the Qinling-Huai River boundary. Source: Compiled from regression results.

TABLE 3 Regression Discontinuity test.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	TFP_LP			PM2.5			TFP_LP			TFP_LP
North	−.49***	−.16***	−.16***	.187***	.181***	.216***				
	(.098)	(.052)	(.052)	(.023)	(.023)	(.023)				
PM2.5							−.31**	−.47***	−.32***	−.40**
							(.137)	(.122)	(.094)	(.173)
LR chi2							−8.52	−16.88	−13488.8	−8,586.4
(*p*-value)							.000	.000	.000	.000
F							65.074	61.075	90.117	296.23
(*p*-value)							.000	.000	.000	.000
Observations	8,594	8,594	8,594	8,594	8,594	8,594	8,594	8,594	8,594	6,054
FE	No	No	Yes	No	No	Yes	No	No	Yes	Yes
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes

Source: Compiled from regression results.
Note: Values in parentheses are standard errors, and ***, **, and * indicate variables at the 1%, 5%, and 10% significance levels, respectively.

Therefore, we use the systematic GMM method to re-estimate this model to solve the endogenous problem of fixed effects (Blundell and Bond 1998), as presented in column (2) of Table 4. The regression results of the systematic GMM show that the first-order lagged terms of the explanatory variables pass the significance test, and this result is consistent with the fixed effects regression results, which indicate that an increase in PM2.5 effectively reduces firm productivity, further strengthening the reliability of our results.

In addition, at the theoretical level, the systematic GMM test needs to satisfy two hypotheses. First, the validity of the instrumental variables used is tested by the Sargan or Hansen overidentification constraint test, based on the original assumption that the instrumental variables are uncorrelated with the error term. The *p*-value of the Hansen test is greater than 0.1 in column (2) of Table 4, indicating that the null hypothesis is accepted; that is, the instrumental variables of the systematic GMM model are valid. Second, the second-order serial correlation of the random error terms of the difference equation is

TABLE 4 Robustness test.

Variables	(1) TFP_LP	(2) GMM TFP_LP	(3) 2008–2012 TFP_LP	(4) 2013–2016 TFP_LP
L.TFP_LP	.808***	.724***		
	(.006)	(.064)		
PM2.5	−.010***	−.029***	−.019***	−.020***
	(.003)	(.009)	(.009)	(.007)
Constant	1.567***	2.145***	8.572***	7.598***
	(.333)	(.648)	(1.138)	(.645)
AR (1)		.000		
AR (2)		.744		
Hansen test		78.15		
Control variables	Yes	Yes	Yes	Yes
Enterprise	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes
Obs	6,308	6,308	2,726	5,868
R^2	.944		.789	.755

Source: Compiled from regression results.
Note: Values in parentheses are standard errors, and ***, **, and * indicate variables at the 1%, 5%, and 10% significance levels, respectively.

tested by the Arellano-Bond autocorrelation test, where the original hypothesis is that there is no second-order serial correlation in the random error terms of the first-order difference equation. If the original hypothesis is not rejected, it implies that the instrumental variables are valid and the model is set up correctly. Therefore, we need to focus on the *p*-value of the second order autoregressive model (AR (2)). The *p*-value of the AR (2) test in column (2) of Table 4 is greater than 0.1, indicating that the null hypothesis is accepted; that is, there is no second-order autocorrelation problem in the residual term of the systematic GMM model difference, and the model setting is reasonable.

4.3 Adjusting the sample period

Owing to the global financial crisis in 2008, China's economic growth rate has dropped significantly since 2013 and has entered a new normal mode. Therefore, we reselect the data from 2008 to 2012 and from 2013 to 2016 as samples to eliminate exogenous effects and shocks caused by the financial crisis and new economic normal. Table 4 presents the regression results, with air pollution still having a significant inhibitory effect on corporate productivity, consistent with previous empirical findings.

5 Spatial econometric regression results

5.1 SDM regression results

Table 5 shows the selection process of the spatial effects model and the corresponding regression results. First, from the log-likelihood function values, the SDM has greater values than the spatial lagged model (SLM) and the spatial error model (SEM), which indicates that the SDM model is the best fit. Second, we test whether the SDM model degrades to the SLM or SEM model, and the likelihood ratio (LR) and Wald statistics both reject the original hypothesis at the 1% level, indicating that the SDM model cannot degenerate into an SLM or SEM model. Therefore, the SDM is determined to be most suitable for this study.

Based on the existence of spatial autocorrelation of pollution in the city where the firm is located, column (3) of Table 5 reports the regression results of PM2.5 in the city where the firm is located and pollution spillover from surrounding cities on firm productivity under the SDM. The results show that both PM2.5 in the firm's city and pollution spillover from surrounding cities significantly reduce firm productivity, indicating that firm productivity is not only negatively affected by local air pollution but also by PM2.5 spillover from surrounding cities.

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TABLE 5 Spatial Durbin Model Regression test.

	(1) SLM	(2) SEM	(3) SDM
PM2.5	−.037***	−.032**	−.038**
	(−2.63)	(−2.24)	(−2.27)
WPM2.5			−.070***
			(−4.963)
Observations	8,594	8,594	8,594
FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Log-likelihood	−470.417	−469.893	−391.255
R^2	.778	.779	.778
LR test			158.325***
(H0: SLM nested in SDM)			(.000)
LR test			157.275***
(H0: SEM nested in SDM)			(.000)
Wald test for SLM			4,521.263***
(*p*-value)			(.000)
Wald test for SEM			3,344.845***
(*p*-value)			(.000)

Source: Compiled from regression results.
Note: Values in parentheses are standard errors, and ***, **, and * indicate variables at the 1%, 5%, and 10% significance levels, respectively.

5.2 Considering different regions and spatial weight matrix

China's regional development is unbalanced and the terrain system is extremely complex; we should not ignore the differences in different regions. Therefore, this paper divides enterprises into 11 eastern enterprises such as Beijing, eight central enterprises such as Shanxi Province, and 12 western enterprises such as Sichuan Province according to the provinces where the enterprises are located[7] and investigates the impact of PM2.5 on enterprise productivity in different regions. Meanwhile, purely distance-based spatial weights cannot effectively capture spatial relationships, especially if the phenomenon is environmental in nature. Therefore, in addition to the inverse distance spatial weight matrix W1 calculated by latitude and longitude, we also select the economic distance type spatial weight matrix W2 constructed by urban *per capita* GDP and the economic-geographic distance type spatial weight matrix W3, constructed by multiplying the two and normalizing the result.

According to the regression results in Table 6, under the three spatial weight matrix settings, the productivity of enterprises in the eastern, central, and western regions will be negatively affected by PM2.5. Poor air pollution will have a greater negative effect on the productivity of eastern enterprises, indicating that enterprises in eastern provinces are more sensitive to air pollution. In addition, the WPM2.5 coefficient is significantly negative at the levels of 1%, 5%, and 10%, indicating a significant spatial correlation between air pollution at similar geographical locations or similar levels of economic development. Pollution spillover from surrounding areas has a negative spillover effect on the productivity of enterprises in the central area, and enterprises in the central and western regions are more affected by PM2.5 in surrounding cities.

5.3 Endogeneity test with GS2SLS

Although regression discontinuity can effectively solve the endogeneity problem, it can only be locally random (near the discontinuity), resulting in weak external validity. We have to further consider the endogeneity of the air pollution question. Specifically, on the one hand, air pollution may drag down enterprise productivity by affecting the human capital, government subsidies, and R&D innovation capabilities; on the other hand, enterprise productivity itself may also affect air pollution levels through factors such as economic activities and population aggregation. Therefore, in order to solve the endogeneity problem,

7 According to the statistical method of the National Bureau of Statistics, the eastern region is divided into Beijing City, Tianjin City, Hebei Province, Liaoning Province, Shanghai City, Jiangsu Province, Zhejiang Province, Fujian Province, Shandong Province, Guangdong Province, and Hainan Province; the central region is divided into Shanxi Province, Anhui Province, Jilin Province, Heilongjiang Province, Jiangxi Province, Henan Province, Hubei Province, and Hunan Province; the western region is divided into Inner Mongolia Autonomous Region, Guangxi Zhuang Autonomous Region, Chongqing City, Sichuan Province, Guizhou Province, Yunnan Province, Tibet Autonomous Region, Shaanxi Province, Gansu Province, Qinghai Province, Ningxia Hui Autonomous Region, and Xinjiang Uygur Autonomous Region.

TABLE 6 SDM Regression test: Considering different region and spatial weight matrix.

	Eastern areas			Middle areas			Western areas		
	(1) W_1	(2) W_2	(3) W_3	(4) W_1	(5) W_2	(6) W_3	(7) W_1	(8) W_2	(9) W_3
PM2.5	−.058***	−.062***	−.060***	−.032***	−.041***	−.039***	−.028**	−.034***	−.035**
	(−3.47)	(−4.05)	(−3.81)	(−4.58)	(−4.27)	(−3.36)	(−2.17)	(−3.58)	(−2.24)
WPM2.5	−.024*	−.037**	−.031**	−.045**	−.058***	−.049***	−.078***	−.065***	−.071***
	(−1.88)	(−2.16)	(−1.97)	(−2.15)	(−4.57)	(−3.82)	(−5.57)	(−4.19)	(−5.33)
ρ	.247***	.318**	.283***	.284**	.275***	.344**	.318***	.359***	.335***
	(13.28)	(2.21)	(5.05)	(2.17)	(12.05)	(1.98)	(10.81)	(5.49)	(6.14)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,170	6,170	6,170	1,245	1,245	1,245	1,179	1,179	1,179
Log-likelihood	−304.586	−486.512	−289.647	−499.057	−415.218	−384.274	−352.108	−328.511	−305.749
R^2	.845	.816	.858	.749	.758	.762	.827	.836	.844

Source: Compiled from regression results.
Note: Values in parentheses are standard errors, and ***, **, and * indicate variables at the 1%, 5%, and 10% significance levels, respectively.

referring to Broner et al. (2012); Hering and Poncet (2014), we use the air flow coefficient (Airflow) as an instrumental variable of air pollution. The reason for this is that air mobility is correlated with air pollution, and the air mobility coefficient depends on wind speed and atmospheric boundary layer height, which is not directly related to enterprise productivity, thus satisfying the validity and exogenous assumptions of instrumental variables (Broner et al., 2012; Hering and Poncet 2014). Meanwhile, we use GS2SLS to effectively control for endogeneity and spatial spillover effects.

The regression results are shown in Table 7. We still conduct inspections from the east, middle, and west, and report the GS2SLS two-stage estimation results based on the economic-geographical weight matrix (W3)[8]. All the regressions control for the control variables presented above and the fixed effects of year and city. According to the first-stage regression results, air flow is significantly negatively correlated with PM2.5 concentration, indicating that stronger air flow is more conducive to alleviating air pollution. The LM statistic and p-value at the 1% significance level rejected the null hypothesis of "no endogeneity in explanatory variables," indicating that air pollution is an endogenous variable and that the endogeneity issue must be addressed in this paper. Furthermore, the F statistic is much greater than 10, indicating that air flow and PM2.5 are highly correlated, and thus rejecting the null hypothesis of "instrumental variables are weak instrumental variables."

In the regression results of the second stage, PM2.5 significantly inhibited enterprise productivity. In terms of spatial latitude, the coefficient estimation result of the spatial lag variable WPM2.5 based on the nested weight matrix W3 of economic-economic-geographical distance is significantly negative at the levels of 1%, 5%, and 10%, indicating that air pollution in surrounding cities has a significant negative spatial spillover effect on the productivity of firms located in central cities. It is consistent with the basic regression results, indicating that the conclusions are still reliable after dealing with the endogeneity issue.

8 Table 6 shows that both the likelihood and R2 values are higher than W1 and W2, indicating that the goodness of fit of the economic-geographic spatial weight matrix is better. Hence, we report only the regression results of W3 in 5.3 section.

6 Analysis of heterogeneity

6.1 Distinguishing investigation based on pollutant type

Different air pollutants may have different impacts on firm productivity. In this study, we match existing data with the newly released environmental research data of listed companies in the CSMAR database to obtain information such as emissions of listed companies by subdivision. However, after distinguishing the subsamples of two air pollutants, sulfur dioxide and soot emissions, only a small amount of data remains, as shown in columns (1) and (2) of Table 8. The regression results show that the coefficients of both air pollutants are negative, but neither is significant. To compensate for the above lack of sample size, this study collects sulfur dioxide and soot emissions from each city to match the existing data, as shown in columns (3) and (4) of Table 8. From the regression results, it can be seen that the data collected from each city and the data from the CSMAR database of environmental studies of listed companies are consistent, that is, the coefficients of sulfur dioxide and soot emissions are both negative, but neither is significant. This indicates that these two air pollutants bring much less inhibitory effect on firm productivity compared to PM2.5, which reflects the importance of choosing PM2.5 as the core variable in this study.

TABLE 7 Endogeneity test with GS2SLS.

	(1) Eastern areas	(2) Middle areas	(3) Western areas
GS2SLS	TFP_LP		
PM2.5	−.145***	−.116***	−.381***
	(−4.15)	(−4.33)	(−4.73)
WPM2.5	−.082*	−.175***	−.164**
	(−1.86)	(−5.17)	(−2.08)
ρ	.176**	.286***	.367***
	(2.18)	(4.52)	(4.83)
Controls	Yes	Yes	Yes
FE	Yes	Yes	Yes
Observations	6,170	1,245	1,179
R^2	.857	.806	.834
Second−stage	TFP_LP		
PM2.5	−.417***	−.395***	−.373***
	(−2.94)	(−4.27)	(−5.19)
R^2	.480	.307	.339
First-stage	PM2.5		
Airflow	−.032***	−.099***	−.020***
	(−4.49)	(−5.37)	(−3.19)
Kleibergen-Paap	24.994***	34.746***	32.827***
rk LM statistic	[.000]	[.000]	[.000]
Kleibergen-Paap rk Wald F statistic	20.154***	28.859***	21.421***
R^2	.561	.349	.458

Source: Compiled from regression results.
Notes: ***, **, and * denote 1%, 5%, 10% significance levels, respectively; t-values in parentheses; *p*-values or Stock-Yogo critical value at the 10% level in or brackets.

6.2 Distinguishing investigation based on equity and technical level

By the end of 2020, the total assets and operating income of state-owned enterprises (SOEs) in China reached 218.3 and 59.5 trillion yuan, respectively, and their average annual growth rate during the "13th Five-Year Plan" period was 12.7% and 7.4%, respectively. After years of reform and development, SOEs have laid a solid foundation for China's new stage of development. Simultaneously, the rapid development of the non-public sector has played a pivotal role in labor employment, technological innovation, national taxation, and economic development. Compared with SOEs, the vitality of non-SOEs is more affected by external policies and the environment. Meanwhile, compared with non-SOEs, the factor market price distortion of SOEs is more serious. Therefore, what is the difference in the impact of air quality on the productivity of SOEs and non-SOEs? For a better comparative analysis, columns (1) and (2) of Table 9 report the results of these two types of samples. The results show that the coefficient of PM2.5 is significantly negative at the 1% level, indicating that air pollution reduces productivity in SOEs and non-SOEs, with a greater impact on SOEs. Possibly, in China, the central and local governments control or invest in SOEs, which are not as sensitive as non-SOEs with respect to the cost pressure caused by air pollution control and the green innovations required to improve air quality. In addition, compared with non-SOEs, SOEs have insufficient information on the improvement of air quality, since the free flow of production factors is not flexible enough and the efficiency of resource reallocation is not high enough, which causes air pollution to have a greater impact on the productivity of SOEs.

Further, innovation is the first driving force for development. Generally, high-tech enterprises have a strong sense of innovation and carry out R&D activities continuously to enhance their core independent intellectual property rights. Columns (3) and (4) of Table 9 report the regression results of dividing the total sample into high-tech and non-high-tech companies, according to their industry category. The results indicate that the coefficients of PM2.5 are all significantly negative. Specifically, the former coefficient is −0.014, and the absolute value is smaller than the latter's coefficient of −0.031. This shows that air pollution reduces the productivity of enterprises in all industries. Compared with enterprises in high-tech industries, air pollution has a higher negative impact on enterprises in non-high-tech industries, which is contrary to the research of Cao et al. (2022). One possible reason is

TABLE 8 Heterogeneity: Pollutant type.

Variables	(1) TFP_LP	(2) TFP_LP	(3) TFP_LP	(4) TFP_LP
SO2	−.019		−.018	
	(.031)		(.058)	
dust		−.021		−.032
		(.023)		(.048)
Constant	14.626***	14.692**	7.859***	7.366***
	(3.570)	(6.403)	(.575)	(.569)
Control variables	Yes	Yes	Yes	Yes
Enterprise	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes
Observations	142	74	8,459	8,463
R-squared	.849	.880	.769	.766

Source: Compiled from regression results.
Note: Values in parentheses are standard errors, and ***, **, and * indicate variables at the 1%, 5%, and 10% significance levels, respectively.

TABLE 9 Heterogeneity: Equity and technical level.

Variables	(1) State-owned enterprise TFP_LP	(2)Non-state-owned enterprise TFP_LP	(3) High-tech TFP_LP	(4) Non-high-tech TFP_LP
PM2.5	−.048***	−.017***	−.014**	−.031**
	(.012)	(.006)	(.006)	(.013)
Constant	5.067***	9.098***	8.400***	6.428***
	(1.092)	(.648)	(.578)	(1.389)
Control variables	Yes	Yes	Yes	Yes
Enterprise	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes
Obs	2,820	5,774	6,437	2,157
R^2	.769	.716	.769	.736

Source: Compiled from regression results.
Note: Values in parentheses are standard errors, and ***, **, and * indicate variables at the 1%, 5%, and 10% significance levels, respectively.

that human capital capabilities and contribution to corporate productivity of high-tech companies are greater. Therefore, in the face of air pollution, companies will try to make up for the environmental requirements of high-quality labor, and the productivity of high-tech enterprises will not be hit as badly as that of non-high-tech enterprises.

7 Analysis of influence mechanism

Based on the influence of air quality on enterprise productivity, this study analyzes how air quality affects enterprise productivity. According to a previous analysis, a mediation effect model was constructed. As expressed in Equations 8, 9,

TABLE 10 Mechanism test.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	R&D	TFP_LP	Num	TFP_LP	Gov	TFP_LP
PM2.5	−.067***	−.014***	−.058***	−.013**	.057***	−.018***
	(.013)	(.005)	(.007)	(.005)	(.013)	(.006)
R&D		.072**				
		(.004)				
Num				.097***		
				(.008)		
Gov						−.009**
						(.005)
Constant	11.737***	7.461***	−1.941**	8.173***	−6.280***	8.002***
	(.298)	(.551)	(.168)	(.554)	(.332)	(.559)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes
Obs	8,594	8,594	8,594	8,594	8,560	8,594
R^2	.314	.776	.674	.773	.440	.769

Source: Compiled from regression results.
Note: Values in parentheses are standard errors, and ***, **, and * indicate variables at the 1%, 5%, and 10% significance levels, respectively.

$$Med\_var_{it} = \beta_0 + \beta_1 PM2.5_{it} + \sum\nolimits_{n=2}^{k} \beta_n {}^*Con_{it} + \tau_i + \gamma_t + \varepsilon_{it}, \quad (8)$$

$$TFP_{it} = \beta_0 + \beta_1 Med\_var_{i,t} + \beta_2 PM2.5_{it} + \sum\nolimits_{n=3}^{k} \beta_n {}^*Con_{it} + \tau_i + \gamma_t + \varepsilon_{it}, \quad (9)$$

where Med_var represents the mechanism test variable, including the human capital (Num), number of patent applications (R&D), and government subsidies (Gov). Table 10 reports the results of the mechanism tests. Columns (1), (3), and (5) report the regression results of formula (8); columns (2), (4), and (6) report the regression results of formula (9). In the test with R&D as the mediating variable, in column (1), R&D is negatively significant with respect to PM2.5 at the 1% level, indicating that R&D investment is negatively correlated with air pollution; in column (2), R&D and TFP_LP are positively significant at the 5% level, indicating that R&D investment is positively correlated with enterprise productivity; PM2.5 is negatively significant with respect to TFP_LP at the 1% level, indicating that air pollution will reduce TFP_LP by reducing R&D. R&D investment partially mediates air pollution and firm productivity. Similarly, in the tests in columns (3) and (4) with the Num as the mediating variable, Num is significantly negative with respect to PM2.5 and TFP_LP at the 1% level, and PM2.5 is significantly negative for TFP_LP at the 5% level; in columns (5) and (6) in the test with Gov as the mediating variable, Gov is significantly positive with respect to PM2.5 at the 1% level and significantly negative with respect to TFP_LP at the 5% level. Further, PM2.5 is significantly negative with respect to TFP_LP at the 1% level. The above results also show that air pollution can hamper productivity by reducing the number of employees and increasing government subsidies.

To test the possibility that highly skilled people are reluctant to work in highly polluted areas, this study uses the ratio of people employed in the three types of highly skilled industries to the city population from the China Urban Statistical Yearbook as an explanatory variable. We use the regression discontinuity model to test the effect of air quality on highly skilled people[9] The results show that air pollution leads to loss of highly skilled people[10].

8 Conclusion and policy implications

We selected 8,594 samples from 1,829 A-share companies listed on the Shanghai and Shenzhen stock markets from 2008 to 2016 to analyze the impact of air quality on firm productivity. We used

9 In the China Urban Statistics Yearbook, three categories of industries can be considered high technology industries: information transmission and computer services and software; financial intermediation; and scientific research and technical service.

10 We validate the impact of air quality on highly skilled people with regression discontinuity; please refer to the specific empirical results in Supplementary Appendix S3.

regression discontinuity to address the possible endogeneity of air pollution and firm productivity and a quasi-natural experiment on centralized heating policies in winter in northern China (north of the Qinling-Huai River boundary). As per the results, PM2.5 emissions in the northern region are significantly higher than those in the southern region, while enterprise productivity in the southern region is higher than that in the northern region, and air pollution significantly reduces firm productivity. Then, considering the possible spatial autocorrelation effect of environmental pollution in cities, we used local pollution and pollution from surrounding areas as the core variables in our analysis. The results showed that firm productivity is not only negatively affected by local air pollution but also by PM2.5 spillover from surrounding cities. Further, considering that China's terrain system is extremely complex, purely distance-based spatial weights cannot effectively capture spatial relationships. Therefore, we divide the eastern, central, and western regions into three regions and changed the spatial weight matrix for SDM test. Meanwhile, we use the air flow coefficient as an instrumental variable along with the GS2SLS method for endogeneity tests. The results show that poor air pollution has a significant negative effect on the productivity of enterprises, and pollution spillovers from surrounding areas dampen local firm productivity in the eastern, central, and western regions. The conclusions of this paper are still reliable after addressing the endogeneity problem. Furthermore, we used dynamic GMM regression, and reselected data from 2008 to 2012 and 2013 to 2016 as samples for robustness tests. The results showed that regardless of the model, method, or sample employed in the estimations, deterioration of air quality significantly inhibits firm productivity. This conclusion is caused by reducing firms' R&D innovation capacity and labor force, while eliciting them to receive more government subsidies. Using heterogeneity analysis, we also found that pollution emissions of sulfur dioxide and soot emissions have much weaker inhibitory effects on firm productivity than PM2.5. Meanwhile, deterioration in air quality leads to lower firm productivity in all equity properties and technology industries. In particular, the effect of air quality on SOEs and non-high tech industries is greater compared to non-SOEs and high tech industries.

While making policy recommendations, we must recognize that environmental protection and economic growth are not mutually exclusive, which provides important guidance for China to achieve high-quality economic development by accelerating green transformation in the future. The basic research in this paper concludes that severe air pollution has greatly reduced enterprise productivity. Therefore, the government should accelerate the improvement of the air quality regulatory system and develop environmental regulations of appropriate intensity. It is also necessary to increase investment in environmental protection, actively guide enterprises to cleaner production, and provide funding or financing channels for measures necessary to reduce environmental pollution. For enterprises, it is necessary to abandon overly polluting enterprises, regulate the factor endowment structure of enterprises, and promote the transformation and upgradation of enterprises.

This paper also finds that air pollution reduces firm productivity by affecting firm innovation levels and human capital effects. To this end, we can actively enhance the innovation capacity of enterprises, increase the investment in science and technology innovation, accelerate the transformation and upgradation of enterprises and green development; focus on the working environment of the workforce, and create a good working environment for the labor force, and increase investment in talent training and health insurance to prevent loss of highly skilled personnel. In addition, in the spatial measurement test, it is found that air pollution has a greater negative impact on the productivity of enterprises in the east. It can be because high energy-consuming and high-emission industries in the east coastal areas may be transferred to some central cities, inhibiting the productivity of local enterprises. Therefore, central cities need to combine their characteristics and competitive advantages and implement active talent introduction policies, avoid undertaking overly polluting enterprises, and implement clean and efficient production. Finally, in the heterogeneity test, it is found that the impact of air quality on non-high-tech industries is greater than that on high-tech industries. Thus, it is more relevant for enterprises in non-high-tech industries to consider possible environmental pollution problems, which fundamentally lie in regulating the factor endowment structure of enterprises and accelerating the transformation of the leading industrial structure from labor-intensive to capital- and technology-intensive.

It should be noted that owing to limited availability of data, our sample only contains A-share companies listed on the Shanghai and Shenzhen stock markets from 2008 to 2016; the data for 2017–2021 and a large number of unlisted companies are not included, resulting in a substantial reduction in the sample size. The findings can be empirically tested in future studies using more comprehensive data. In addition, air quality may affect corporate productivity through other areas of corporate finance, such as corporate investment and capital attraction, as well as corporate executive behavior, which can be investigated in future research.

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

Introduction and Literature review, SL and YY; Method and data, SL and YY; Empirical results and discussion, SL; Heterogeneity analysis, SL and YY; Conclusions and discussions, SL and LC; Writing–Original Draft Preparation, SL and YY; Writing–Review and Editing, LC, SL, and YY. All authors have read and agreed to the published version of the manuscript.

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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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2022.1095393/full#supplementary-material

References

Ai, H., Wang, M., Zhang, Y. J., and Zhu, T. T. (2022). How does air pollution affect urban innovation capability? Evidence from 281 cities in China. *Struct. Change Econ. Dyn.* 61, 166–178. doi:10.1016/j.strueco.2022.02.012

Akpalu, W., and Normanyo, A. K. (2017). Gold mining pollution and the cost of private healthcare: The case of Ghana. *Ecol. Econ.* 142, 104–112. doi:10.1016/j.ecolecon.2017.06.025

Ayyagari, M., Demirgü-Kunt, A., and Maksimovic, V. (2010). Formal versus informal finance: Evidence from China. *Rev. Financial Stud.* 23 (8), 3048–3097. doi:10.1093/rfs/hhq030

Aznar-Marquez, J., and Ruiz-Tamarit, J. R. (2016). Environmental pollution, sustained growth, and sufficient conditions for sustainable development. *Econ. Model.* 54, 439–449. doi:10.1016/j.econmod.2016.01.017

Balakrishnan, U., and Tsaneva, M. (2021). Air pollution and academic performance: Evidence from India. *World Dev.* 146, 105553. doi:10.1016/j.worlddev.2021.105553

Balakrishnan, U., and Tsaneva, M. (2022). Impact of air pollution on mental health in India. *J. Dev. Stud.* 2022, 1–15. doi:10.1080/00220388.2022.2120804

Blundell, R., and Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *J. Econ.* 87 (1), 115–143. doi:10.1016/S0304-4076(98)00009-8

Bogliacino, F., and Pianta, M. (2013). Profits, R&D, and innovation: A model and a test. *Industrial Corp. Change* 22 (3), 649–678. doi:10.1093/icc/dts028

Brandt, L., Van, J. B., and Zhang, Y. (2012). Creative accounting or creative destruction? Firm-level productivity growth in Chinese manufacturing. *J. Dev. Econ.* 97 (2), 339–351. doi:10.1016/j.jdeveco.2011.02.002

Broner, F., Bustos, P., and Carvalho, V. M. (2012). Sources of comparative advantage in polluting industries. *Natl. Bureau Econ. Res.* 2012, 18337. doi:10.3386/w18337

Cameron, T. A., and McConnaha, I. T. (2006). Evidence of environmental migration. *Land Econ.* 82 (2), 273–290. doi:10.3368/le.82.2.273

Cao, Y., Wang, Q., and Zhou, D. (2022). Does air pollution inhibit manufacturing productivity in Yangtze River Delta, China? Moderating effects of temperature. *J. Environ. Manag.* 306, 114492. doi:10.1016/j.jenvman.2022.114492

Chang, T., Graff Zivin, J., Gross, T., and Neidell, M. (2016). Particulate pollution and the productivity of pear packers. *Am. Econ. J. Econ. Policy* 8 (3), 141–169. doi:10.1257/pol.20150085

Chen, M., and Guariglia, A. (2013). Internal financial constraints and firm productivity in China: Do liquidity and export behavior make a difference? *J. Comp. Econ.* 41 (4), 1123–1140. doi:10.1016/j.jce.2013.05.003

Chen, S., Oliva, P., and Zhang, P. (2022). The effect of air pollution on migration: Evidence from China. *J. Dev. Econ.* 156, 102833. doi:10.1016/j.jdeveco.2022.102833

Chen, Y., Ebenstein, A., Greenstone, M., and Li, H. (2013). Evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River policy. *Proc. Natl. Acad. Sci.* 110 (32), 12936–12941. doi:10.1073/pnas.1300018110

Chen, Y., Ge, R., Pittman, J. A., Veeraraghavan, M., and Zolotoy, L. (2017). *Obscured by clouds: The impact of weather-induced managerial mood on corporate tax avoidance*. SSRN Working Paper. doi:10.2139/ssrn.3067343

Cui, Q., Yuan, B., Zhou, Y., Chen, H., and Hu, Y. (2021). Will bad air quality affect the siting of foreign-invested manufacturing enterprises? The evidence from China. *Appl. Econ.* 53 (45), 5221–5241. doi:10.1080/00036846.2021.1922588

Fan, Q., Yang, S., and Liu, S. (2019). Asymmetrically spatial effects of urban scale and agglomeration on haze pollution in China. *Int. J. Environ. Res. Public Health* 16 (24), 4936. doi:10.3390/ijerph16244936

Farinas, J. C., and Moreno, L. (2000). Firms' growth, size, and age: A nonparametric approach. *Rev. Industrial Organ.* 17 (3), 249–265. doi:10.1023/A:1007834210622

Fazlıoğlu, B., Dalgıç, B., and Yereli, A. B. (2019). The effect of innovation on productivity: Evidence from Turkish manufacturing firms. *Industry Innovation* 26 (4), 439–460. doi:10.1080/13662716.2018.1440196

Fox, M. B., and Heller, M. (2000). *Lessons from fiascos in Russian corporate governance*. SSRN Working Paper. doi:10.2139/ssrn.203368

Ghanem, D., and Zhang, J. (2014). Effortless perfection: Do Chinese cities manipulate air pollution data? *J. Environ. Econ. Manag.* 68 (2), 203–225. doi:10.1016/j.jeem.2014.05.003

Grossman, G. M., and Krueger, A. B. (1995). Economic growth and the environment. *Q. J. Econ.* 110 (2), 353–377. doi:10.2307/2118443

Hall, B. H., and Harhoff, D. (2012). Recent research on the economics of patents. *Annu. Rev. Econ.* 4 (1), 541–565. doi:10.1146/annurev-economics-080511-111008

Hanlon, W. W. (2016). *Coal smoke and the costs of the industrial revolution*. NBER Working Paper 22921. doi:10.3386/w22921

Hassan Bhat, T., Jiawen, G., and Farzaneh, H. (2021). Air pollution health risk assessment (AP-HRA), principles and applications. *Int. J. Environ. Res. Public Health* 18 (4), 1935. doi:10.3390/ijerph18041935

He, C., Pan, F., and Yan, Y. (2012). Is economic transition harmful to China's urban environment? Evidence from industrial air pollution in Chinese cities. *Urban Stud.* 49 (8), 1767–1790. doi:10.1177/0042098011415719

He, G., and Lin, T. (2022). Does air pollution impair investment efficiency? *Econ. Lett.* 215, 110490. doi:10.1016/j.econlet.2022.110490

He, Q., Guaita-Martinez, J. M., and Botella-Carrubi, D. (2020). How brand equity affects firm productivity: The role of R&D and human capital. *Econ. Research-Ekonomska Istraživanja* 33 (1), 2976–2992. doi:10.1080/1331677X.2019.1686045

Hering, L., and Poncet, S. (2014). Environmental policy and exports: Evidence from Chinese cities. *J. Environ. Econ. Manag.* 68 (2), 296–318. doi:10.1016/j.jeem.2014.06.005

Hu, F., and Guo, Y. (2021). Health impacts of air pollution in China. *Front. Environ. Sci. Eng.* 15 (4), 74–18. doi:10.1007/s11783-020-1367-1

Hu, Q., Feng, Y., and Xu, M. (2021). Are there heterogeneous impacts of air pollution on mental health? *Front. Public Health* 9, 780022. doi:10.3389/fpubh.2021.780022

Hu, X., Sun, H., Luo, X., Ni, S., and Yan, Y. (2021). Health and economic impacts from PM2. 5 pollution transfer attributed to domestic trade in China: A provincial-level analysis. *Environ. Sci. Pollut. Res.* 28 (36), 49559–49573. doi:10.1007/s11356-021-13954-y

Huang, J. T., and Hsu, H. S. (2022). Air pollution and outward foreign direct investment—a cross-country empirical study. *Singap. Econ. Rev.* 2022, 1–16. doi:10.1142/S0217590822500382

Ibukun, C. O., and Omisore, W. M. (2022). Air pollution, health expenditure and economic growth in MINT countries: A trivariate causality test. *J. Econ. Adm. Sci.* (ahead-of-print). doi:10.1108/JEAS-03-2022-0074

Jiang, D., Li, W., Shen, Y., and Yu, S. (2022b). Does air pollution affect earnings management? Evidence from China. *Pacific-Basin Finance J.* 72, 101737. doi:10.1016/j.pacfin.2022.101737

Jiang, D., Li, W., Shen, Y., and Zhang, Y. (2022a). Does air quality affect firms' investment efficiency? Evidence from China. *Int. Rev. Econ. Finance* 79, 1–17. doi:10.1016/j.iref.2022.01.001

Kioumourtzoglou, M. A., Schwartz, J. D., Weisskopf, M. G., Melly, S. J., Wang, Y., Dominici, F., et al. (2016). Long-term PM2. 5 exposure and neurological hospital admissions in the northeastern United States. *Environ. Health Perspect.* 124 (1), 23–29. doi:10.1289/ehp.1408973

Kuo, P. F., and Putra, I. G. B. (2021). Analyzing the relationship between air pollution and various types of crime. *PLoS One* 16 (8), e0255653. doi:10.1371/journal.pone.0255653

Lai, W., Song, H., Wang, C., and Wang., H. (2021). Air pollution and brain drain: Evidence from college graduates in China. *China Econ. Rev.* 68, 101624. doi:10.1016/j.chieco.2021.101624

Lepori, G. M. (2016). Air pollution and stock returns: Evidence from a natural experiment. *J. Empir. Finance* 35, 25–42. doi:10.1016/j.jempfin.2015.10.008

Levinsohn, J., and Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. *Rev. Econ. Stud.* 70 (2), 317–341. doi:10.1111/1467-937X.00246

Li, B., Liu, Y., Yang, Y., and Wang, Y. J. (2022). Impact of air pollution on the formation of zombie firms: Evidence from China. *J. Environ. Prot. Ecol.* 23 (3), 1290–1298.

Li, B., Zhang, X., and Zeng, Y. (2019). The impact of air pollution on government subsidies obtained by Chinese listed companies. *Ekoloji* 28 (107), 1947–1954.

Lin, S., Xiao, L., and Wang, X. (2021). Does air pollution hinder technological innovation in China? A perspective of innovation value chain. *J. Clean. Prod.* 278, 123326. doi:10.1016/j.jclepro.2020.123326

Lin, T., Qian, W., Wang, H., and Feng, Y. (2022). Air pollution and workplace choice: Evidence from China. *Int. J. Environ. Res. Public Health* 19 (14), 8732. doi:10.3390/ijerph19148732

Lin, Y. C., Chen, C. L., Chao, C. F., Chen, W. H., and Pandia, H. (2020). The study of evaluation index of growth evaluation of science and technological innovation micro-enterprises. *Sustainability* 12 (15), 6233. doi:10.3390/su12156233

Liu, F., Zheng, M., and Wang, M. (2020). Does air pollution aggravate income inequality in China? An empirical analysis based on the view of health. *J. Clean. Prod.* 271, 122469. doi:10.1016/j.jclepro.2020.122469

Liu, J., Pan, X., Qu, Y., Wang, C., and Wu, W. (2022). Air pollution, human capital and corporate social responsibility performance: Evidence from China. *Appl. Econ.* 54 (4), 467–483. doi:10.1080/00036846.2021.1963413

Liu, Y., Zhu, K., Li, R. L., Song, Y., and Zhang, Z. J. (2021). Air pollution impairs subjective happiness by damaging their health. *Int. J. Environ. Res. Public Health* 18 (19), 10319. doi:10.3390/ijerph181910319

Liu, Z., and Yu, L. (2020). Stay or leave? The role of air pollution in urban migration choices. *Ecol. Econ.* 177, 106780. doi:10.1016/j.ecolecon.2020.106780

López, R. (2017). "The environment as a factor of production: The effects of economic growth and trade liberalization 1," in *International trade and the environment* (London, UK: Routledge), 239–260.

Lucas, R. E., Jr (1978). Asset prices in an exchange economy. *Econ. J. Econ. Soc.* 46 (6), 1429–1445. doi:10.2307/1913837

Majumdar, S. K. (1997). The impact of size and age on firm-level performance: Some evidence from India. *Rev. Industrial Organ.* 12 (2), 231–241. doi:10.1023/A:1007766324749

Mao, Q., and Xu, J. (2018). The more subsidies, the longer survival? Evidence from Chinese manufacturing firms. *Rev. Dev. Econ.* 22 (2), 685–705. doi:10.1111/rode.12361

Mishra, A. K., Sinha, A. K., Khasnis, A., and Vadlamani, S. T. (2021). Exploring firm-level innovation and productivity in India. *Int. J. Innovation Sci.* 13, 583–609. doi:10.1108/IJIS-10-2020-0179

Olley, G. S., and Pakes, A. (1996). The dynamics of productivity in the telecommunications equipment industry. *Econometrica* 64 (6), 1263–1297. doi:10.2307/2171831

Ramirez, S., Gallego, J., and Tamayo, M. (2020). Human capital, innovation and productivity in Colombian enterprises: A structural approach using instrumental variables. *Econ. Innovation New Technol.* 29 (6), 625–642. doi:10.1080/10438599.2019.1664700

Ren, S. M., and Zhang, J. (2013). The subsidy, the rent-seeking cost and the rate of the markup: A case study on the equipment-manufacturing enterprises in China. *Manag. World* 2013 (10), 118–129.

Shang, Y., Song, M., and Zhao, X. (2022). The development of China's circular economy: From the perspective of environmental regulation. *Waste Manag.* 149, 186–198. doi:10.1016/j.wasman.2022.05.027

Shen, W. T., Yu, X., Zhong, S. B., and Ge, H. R. (2021). Population health effects of air pollution: Fresh evidence from China health and retirement longitudinal survey. *Front. Public Health* 9, 779552. doi:10.3389/fpubh.2021.779552

Tan, J., Chan, K. C., and Chen, Y. (2022). The impact of air pollution on the cost of debt financing: Evidence from the Bond market. *Bus. Strategy Environ.* 31 (1), 464–482. doi:10.1002/bse.2904

Tan, J., Tan, Z., and Chan, K. C. (2021). Does air pollution affect A firm's cash holdings? *Pacific-Basin Finance J.* 67, 101549. doi:10.1016/j.pacfin.2021.101549

Tan, Z., and Yan, L. (2021). Does air pollution impede corporate innovation? *Int. Rev. Econ. Finance* 76, 937–951. doi:10.1016/j.iref.2021.07.015

Tang, X., Chen, X., and Tian, Y. (2017). Chemical composition and source apportionment of PM2.5: A case study from one year continuous sampling in the chang-zhu-tan urban agglomeration. *Atmos. Pollut. Res.* 8 (5), 885–899. doi:10.1016/j.apr.2017.02.004

Tassey, G. (2004). Underinvestment in public good technologies. *J. Technol. Transf.* 30 (1), 89–113. doi:10.1007/s10961-004-4360-0

Timothy, V. L. (2022). The effect of top managers' human capital on SME productivity: The mediating role of innovation. *Heliyon* 8 (4), e09330. doi:10.1016/j.heliyon.2022.e09330

Tuncel, C. O., and Oktay, D. (2022). Innovation and productivity in Turkish manufacturing firms. *Appl. Econ. Lett.* 29 (17), 1610–1614. doi:10.1080/13504851.2021.1950904

Wang, L., Da, Y., and Kong, D. (2021). Air pollution and employee treatment. *J. Corp. Finance* 70, 102067. doi:10.1016/j.jcorpfin.2021.102067

Wang, M., Xu, M., and Ma, S. (2021). The effect of the spatial heterogeneity of human capital structure on regional green total factor productivity. *Struct. Change Econ. Dyn.* 59, 427–441. doi:10.1016/j.strueco.2021.09.018

Wang, Y. J. (2002). Liquidity management, operating performance, and corporate value: Evidence from Japan and taiwan. *J. Multinatl. Financial Manag.* 12 (2), 159–169. doi:10.1016/S1042-444X(01)00047-0

Wei, L. Y., and Liu, Z. (2022). Air pollution and innovation performance of Chinese cities: Human capital and labour cost perspective. *Environ. Sci. Pollut. Res.* 1, 67997–68015. doi:10.1007/s11356-022-20628-w

Xie, X., and Wang, Y. (2019). Evaluating the efficacy of government spending on air pollution control: A case study from beijing. *Int. J. Environ. Res. Public Health* 16 (1), 45. doi:10.3390/ijerph16010045

Xue, S., Zhang, B., and Zhao, X. (2021). Brain drain: The impact of air pollution on firm performance. *J. Environ. Econ. Manag.* 110, 102546. doi:10.1016/j.jeem.2021.102546

Yang, Y., Zhang, X., and Fu, Y. (2022). Foreign tourists' experiences under air pollution: Evidence from big data. *Tour. Manag.* 88, 104423. doi:10.1016/j.tourman.2021.104423

You, Y. (2022). Air pollution, service development and innovation: Evidence from China. *PloS One* 17 (5), e0263883. doi:10.1371/journal.pone.0263883

Zhang, C., and Zhang, X. (2022). Evolutionary game analysis of air pollution Co-investment in emission reductions by steel enterprises under carbon quota trading mechanism. *J. Environ. Manag.* 317, 115376. doi:10.1016/j.jenvman.2022.115376

Zhang, F., Li, Y., Li, Y., Xu, Y., and Chen, J. (2022). Nexus among air pollution, enterprise development and regional industrial structure upgrading: A China's country panel analysis based on satellite retrieved data. *J. Clean. Prod.* 335, 130328. doi:10.1016/j.jclepro.2021.130328

Zhang, R. L., and Liu, X. H. (2021). Evaluating ecological efficiency of Chinese industrial enterprise. *Renew. Energy* 178, 679–691. doi:10.1016/j.renene.2021.06.119

Zhu, F., Li, Q., Yang, S., and Balezentis, T. (2021). How ICT and R&D affect productivity? Firm level evidence for China. *Econ. Research-Ekonomska Istraživanja* 34, 1–19. doi:10.1080/1331677X.2021.1875861

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Has the development of the digital economy improved green total factor productivity in China?—A study based on data at the provincial level in China

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China's economic development has entered a new historical stage, and it is crucial to coordinate the linkage between economic development, resource allocation and environmental protection in this new stage. In view of this, this paper selects the panel data of 30 provinces (municipalities and autonomous regions) in China from 2011 to 2020, and firstly measures the Green Total Factor Productivity (GTFP) by using Slack Based Measure -Malmquist Luenberger method (SBM-ML); Then, the relationship between the development of digital economy and regional GTFP is analyzed by using the two-way fixed effect model and threshold effect; Finally, relevant policy suggestions are put forward. This paper found that: firstly, the development of digital economy significantly improves China's GTFP, and the conclusion still valid after considering a series of robustness tests; Secondly, there are obvious disparities in the development level of digital economy among provinces, and the development level of coastal areas is generally higher than that of inland areas, and according to the sub-regional regression results, the positive effect of digital economy on GTFP has regional heterogeneity, and the development of digital economy in coastal areas has a more significant effect on the enhancement of GTFP, while this effect in inland areas does not pass the significance test; Thirdly, according to the threshold effect test results, there is also a single threshold effect with institutional environment and technological innovation as the threshold variables for the impact of digital economy on GTFP in China.

KEYWORDS

digital economy, green total factor productivity, fixed effects, differential GMM, threshold effect

1 Introduction

In recent years, with the rapid development of the Internet, big data and other modern information and communication technologies, the digital economy is an emerging economic development model that uses data as a key factor of production and digital technology as an important carrier, which is regarded as a "new engine" for economic development (Carlsson, 2004). According to the data from the "White Paper on China's Digital Economy" published by China Academy of Information and Communication Technology (CAICT), from 2012 to 2021, the scale of China's digital economy increased from 11 trillion yuan to 45.5 trillion yuan, and the proportion of GDP increased from 21.6% to 39.8%, indicating that the digital economy is increasingly becoming one of the important engines of China's national economic development (Lyu et al., 2023). However, while the digital economy is developing rapidly, China's economic development is now facing multiple sustainable development pressures such as declining labor force and increasing labor costs due to the aging population, waste of resources, mismatch between supply and demand, and environmental pollution. Meanwhile, according to the Global Environmental Performance Index 2022 report released by Yale University and Columbia University, China's environmental performance score in 2022 is 28.4, ranking 160th out of 180 economies (Denmark scores 77.9, ranking first; the United States scores 51.1, ranking 43rd). This shows that the idea of relying on inherent labor, capital, and resource inputs to promote development is no longer sustainable, and there is an urgent need to crack the double problem of economic and environmental synergy, transform the economic development mode, accelerate the green transformation of the development mode, and find new economic development momentum has become an important issue for China's economy to achieve sustainable development.

Faced with the dual tasks of sustainable economic growth and coordinated development of resources and environment, the 14th Five-Year Plan clearly proposes to enhance the quality and quantity of economic development and promote green economic development. The emphasis on the development of green economy is an inevitable requirement from the emphasis on the "quantity" of economic development to the "quality" of economic development, and GTFP is an important indicator of high-quality economic development, and its overall improvement is the key to green economy (Young, 1996; Feng and Serletis, 2014). Liu et al. (2021) mention that the digital economy has become a major trend in global economic development, and its vigorous development will have an important impact on accelerating the transformation of old and new dynamics and improving GTFP. Many scholars have studied the impact of ICT technologies[6], digital finance[7] and other important components of the digital economy on GTFP. Specifically on how the digital economy enhances GTFP, Zhou et al. (2021) finds that the development of the digital economy enhances GTFP in our cities by optimizing the allocation of capital factors (Zhu et al., 2022); studies the development of the digital economy to enhance GTFP in our textile industry by optimizing the industrial structure. In terms of its spatial spillover effects, the digital economy not only has a positive effect on local GTFP, but also has a significant enhancement effect on other regions (Deng et al., 2022).

The marginal contribution of this paper is mainly reflected in the following three aspects: firstly, considering that the indicators for measuring digital economy and GTFP have not yet been unified, a system of measurement indicators is constructed to scientifically measure the level of development of digital economy and GTFP in each province; Secondly, from the perspective of regional heterogeneity, we divide coastal and inland regions for in-depth theoretical analysis and empirical research; Third, from the perspectives of market environment and technological innovation, a panel threshold model is used to verify whether there is a "threshold effect" of digital economy on GTFP.

The rest of the paper is framed as follows: The second chapter is literature review, compares the literature on the digital economy and GTFP. The third chapter analyses the transmission mechanism of digital economy to GTFP. The fourth chapter presents the variable setting and data selection. The fifth chapter is empirical analysis. The sixth chapter draws conclusions, policy recommendations and limitations.

2 Literature review

2.1 Digital economy

A great deal of research has been conducted in academia on the digital economy. Early foreign studies focused on the specific connotation of the digital economy from a theoretical level, considering it as a production activity directly related to digital technology (Kling and Lamb, 1999), while with the development and increasingly widespread application of modern communication technology, Quah (2003) extends the concept of digital economy to the sum of all economic activities transacted using the Internet. In contrast, domestic research on the digital economy started late and gradually enriched in recent years. Zhang and Ma, (2022) define the digital economy as an emerging way of economic development that uses data as a key production factor, ICT technology as a means of information transfer, and the Internet as a platform for information exchange. In addition, although research on the digital economy has been increasing in popularity, most studies have focused on exploring the economic effects of the digital economy, including the impact of digital economy development on optimizing and upgrading the industrial structure (Qin et al., 2022; Zhao et al., 2022), on improving the efficiency of regional green innovation (Dai et al., 2022), and thus on promoting high-quality economic development (Ding et al., 2022). Some scholars pay attention to the application of information technology in environmental governance (Ren et al., 2022a), and the impact of green investment on environmental pollution (Ren et al., 2022b). While few scholars pay attention to the environmental effects brought by digital economy. Some scholars have found that the digital economy can significantly reduce regional carbon emissions based on China's "3,060" vision (i.e., achieving carbon peaking by around 2030 and carbon neutrality by around 2060) (Xie, 2022). And some scholars have analyzed the impact of China's Internet development on environmental quality based on the spatial Durbin model, found that environmental pollution can be reduced through technological innovation, industrial upgrading, human capital and financial development (Ren et al., 2022c). From city-level data, the digital economy can optimize industrial structure, reduce emissions, thus improving urban environmental quality (Sun and Hu, 2021).

2.2 Green total factor productivity

Green Total Factor Productivity (GTFP) is a comprehensive indicator that builds on the traditional Total Factor Productivity (TFP) and organically combines economic efficiency, resource efficiency and environmental efficiency. Many useful discussions have been conducted by academics on GTFP. On the one hand, some scholars have measured GTFP in different industries and regions based on the super-efficient SBM model (Cheng and Jin, 2020; Chen et al., 2021; Li et al., 2021). On the other hand, some scholars have explored the factors influencing GTFP, which can be divided into two main categories of factors: policy and market. At the policy level, Liu Q. et al. (2022) examines the impact of China's innovative city pilot policies on green development, and finds that innovative city pilot policies can significantly improve GTFP through green innovation, energy saving and consumption reduction, and environmental rules. At the market level, Hou and Wang (2022) shows that the business environment effect has become a new driver of GTFP improvement.

2.3 The effect of digital economy on GTFP

Based on the existing literature, on the one hand, more scholars focus on TFP considering only the desired output. For example, Tian and Liu (2021) found that the digital economy has a significant positive impact on TFP based on the micro perspective of enterprises. Hu et al. (2022) found that the development of digital economy has a significant positive direct effect and spatial spillover effect on TFP growth. On the other hand, the mechanism of the impact of China's digital economy development on GTFP is more complex and may be influenced by a variety of factors. Cheng and Qian (2021) shows that there is a single threshold effect of China's digital economy development on GTFP in the industrial sector with regional industry size and institutional environment as thresholds, and shows a non-linear characteristic of marginal increment and U-shaped relationship respectively; Liu S. et al. (2022) finds that under the constraints of industrial structure, technological innovation and marketization degree, the impact of digital economy on GTFP exhibits a non-linear relationship.

In summary, the existing literature has conducted richer studies and discussions on the digital economy and GTFP. Distinguishing the existing literature, this paper 1) combines the existing literature and methods to construct a framework for measuring the digital economy and GTFP. 2) Explore whether the impact of the digital economy on GTFP is heterogeneous based on the variability of regional development. 3) To investigate whether there is a "non-linear" relationship between the impact of the digital economy and GTFP using threshold effects. This study is of great importance in bringing into play the value of the digital economy in enhancing economic efficiency and improving resource allocation efficiency, and in achieving green and high-quality development in China's economy.

3 The transmission mechanism of digital economy to GTFP

3.1 Direct transmission mechanism of digital economy affects GTFP

With the popularity and development of information and communication technologies such as the Internet, big data and artificial intelligence, the digital economy not only affects the production and operation activities of enterprises, but also has a profound impact on the lives of Chinese residents. An and Liu (2022) points out that the development of the digital economy is not only manifested in the increase in the proportion of the digital economy to GDP, but also in the role of the digital economy in "improving quality and efficiency" of the economy. The GTFP is a combination of economic efficiency, resource utilization efficiency and environmental efficiency, taking into account both the "quality" and "quantity" of economic development (Li and Liao, 2022). Therefore, this paper will analyse the direct transmission mechanism of the digital economy on GTFP based on above, and propose a research hypothesis.

On the one hand, the development of the digital economy, led by digital technologies such as the Internet and big data, can facilitate easier information transfer, effectively reduce the cost of information search, break down "information silos," promote the rational distribution of resources and energy, improve the efficiency of resource and energy use (Li et al., 2021). When digital technology is combined with government administration, it can reduce government corruption (Sadik-Zada et al., 2022) and improve the efficiency of government administration (Niftiyev, 2022a). Yang (2020) mentions that the digital economy is growing at a faster rate, accounting for an increasing share of China's GDP and has a significant effect on economic efficiency. In summary, the digital economy promotes the improvement of China's GTFP by unblocking information transmission channels and improving the efficiency of resource utilization.

On the other hand, from the perspective of digitalization and digital industrialization, digital industrialization, as an important part of the digital economy, is usually dominated by information technology service industries such as Internet enterprises and information service industries, which tend to pay more attention to the environment benefits of the enterprises due to their strong economic power (Jardim-Goncalves et al., 2012). However, Lin and Zhang (2011) found that the location choice of such IT service companies tends to be in areas with better accessibility, while the eastern coastal region of China is a gathering place for various digital industries due to its historical conditions and geographical location, and therefore has a good foundation for the development of the digital economy. The digitalization of industries, as the focus of the development of the digital economy, is the integration of digital technology with traditional industries, and the use of digital technology for real-time monitoring of various types of production links in traditional manufacturing industries, which not only improves their production efficiency (Niftiyev, 2022b), but also reduces the emission of pollutants in various links and promotes the improvement of GTFP.

Based on the above analysis, this paper proposes the relevant Hypothesis 1, Hypothesis 2:

Hypothesis 1: The development of the digital economy can improve the GTFP.

Hypothesis 2: There is regional heterogeneity in the role of the digital economy on GTFP.

3.2 Non-linear relationship of the digital economy affecting GTFP

3.2.1 Market environment

The development of the digital economy is constantly changing our market environment, blurring the boundaries between market players in space and time, breaking the disadvantages of poor factor mobility in traditional markets, and reducing transaction costs (Goldfarb and Tucker, 2019). When the market environment is poor, the barriers to factor mobility are high and the high efficiency of the digital economy is not fully exploited, which is not conducive to enterprises using the digital economy to integrate traditional supply chains and has a negative impact on enterprises using the digital economy to reshape production processes (Iqbal et al., 2018). In recent years, the word "digital" has appeared more and more frequently in the Communist Party of China (CPC) and state policy documents. In 2017, the digital China was written into the programmatic document of the CPC and the state for the first time, and the report of the 19th National Congress clearly pointed out the construction of "a strong network country, a digital China and a smart society;" In 2020, the "14th Five-Year Plan" explicitly mentioned the need to speed up digital development and build a digital China; in 2022, the State Council issued the Digital Economy Development Plan for the 14th Five-Year Plan, which proposed to promote the deep integration of the real economy and digital technology, develop the digital economy comprehensively, and strive for the core industries of the digital economy to account for 10% of GDP by 2025. To sum up, Chinese government has issued various documents to stimulate market subject to use digital technology for innovation, which provides a good business environment for the smooth operation of the digital economy, thus realizing the improvement of GTFP.

3.2.2 Technological innovation

The digital economy itself has certain technological attributes, and with the continuous development of the digital economy in the region will promote the continuous improvement of the innovation capacity in the region, while the learning effect and scale effect brought by the agglomeration of digital industries also drive the improvement of the scientific and technological innovation capacity, promote the innovation of green technology and improve GTFP (Li, 2019). Boer and During (2001) mentions that innovation is essentially a process of information collection and processing, and the digital economy represented by the Internet acts as a medium in the process of information exchange, which makes information transfer more convenient. To sum up, the application of digital technology shortens the time of information collection, improves economic efficiency, thus increasing the overall GTFP of China.

Based on the above analysis, this paper proposes the relevant Hypothesis 3, Hypothesis 4:

Hypothesis 3: There is a threshold effect of the impact of digital economy development on GTFP with the market environment as the threshold.

Hypothesis 4: There is a threshold effect of the impact of digital economy development on GTFP with technological innovation as the threshold.

4 Variable setting and typical facts

4.1 Model construction

To test Hypothesis 1 above, the following model is constructed the following model:

$$GTFP_{it} = a_0 + a_1 DIG_{it} + a_j \sum X_{jit} + \mu_i + \delta_t + \varepsilon_{it}$$

Where, $GTFP_{it}$ denotes the explanatory variable green total factor productivity, DIG_{it} denotes the core explanatory variable the development level of digital economy, and X_{jit} denotes a series of control variables of the model, mainly containing: regional economic development level, foreign direct investment, industrial structure, etc. μ_i are individual fixed effects, δ_t is the year fixed effect, and ε_{it} is the random disturbance term.

In addition, in order to verify Hypothesis 3 and Hypothesis 4, and examine whether there is a threshold effect of the development of digital economy on GTFP in terms of market environment and technological innovation, the panel threshold model is set as follows:

$$GTFP_{it} = \omega_1 DIG_{it} {}^* I(Tv_{it} \le r) + \omega_2 DIG_{it} {}^* I(Tv_{it} > r) + \omega X_{it} + \varepsilon_{it}$$

Where, $I(\cdot)$ is the demonstrative function, Tv_{it} represents the threshold variable, and r is the threshold value. If the inequality inside the parentheses holds, $I(\cdot) = 1$; and *vice versa*, $I(\cdot) = 0$.

4.2 Variable selection

4.2.1 Explanatory variable: Green total factor productivity (*GTFP*)

Green total factor productivity (GTFP) is developed on the basis of TFP, which is a comprehensive indicator considering economic efficiency, resource utilization efficiency and environmental efficiency. In the calculation of GTFP, the measurement methods adopted by domestic and foreign scholars mainly include parametric and non-parametric methods. The SBM model based on non-expected output incorporates slack variables into the objective function and uses a non-radial and non-angular measure to effectively solve the problem of slackness of input-output variables and the problem of efficiency measurement when considering non-expected output. Drawing on Chung et al. (1997) research, this paper uses the super-efficient SBM model with the Malmquist-Luenberger index to measure the GTFP of each province in China, in order to enhance the comparability between effective decision-making units. The specific measurement formula is as follows.

$$GTFP = \frac{\frac{1}{m}\sum_{i=1}^{m} \frac{S_i^-}{x_{io}}}{\frac{1}{s_1+s_2}\left[\sum_{q=1}^{s_1} \frac{S_q^g}{y_{q0}^g} + \sum_{q=1}^{S_2} \frac{S_q^b}{u_{q0}^b}\right]}$$

Satisfy $x_{io} = \sum_{i=1, j\neq k}^{n} x_{ij}\lambda_j + S_i^-$, $y_{io}^g = \sum_{i=1, j\neq k}^{n} y_{ij}^g \lambda_j - S_i^g$, $u_{io}^b = \sum_{i=1, j\neq k}^{n} u_{ij}^b \lambda_j + S_i^b$ at the same time.

Where, $GTFP$ are the values of GTFP for each province, the $S-$, S^g, S^b are input slack, desired output slack and non-desired output slack, respectively; and are all greater than or equal to zero.

Further the ML productivity index from period t to period t+1 can be expressed as

$$ML_t^{t+1} = \left| \frac{1 + D_0^t(x^{t+1}, y^{t+1}, c^{t+1}, g^{t+1})}{1 + D_0^t(x^t, y^t, c^t, g^t)} * \frac{1 + D_0^{t+1}(x^{t+1}, y^{t+1}, c^{t+1}, g^{t+1})}{1 + D_0^{t+1}(x^t, y^t, c^t, g^t)} \right|^{\frac{1}{2}}$$

In addition, the corresponding input and output indicators were selected by drawing on the method of selecting relevant indicators from Qifeng et al. (2022), specifically from three aspects: input variables, desired output variables and non-desired output variables, which mainly include labor input, measured by the number of employees at the end of the year in each province; capital input, as the capital stock is difficult to measure, this paper uses the method of replacing capital stock with fixed assets, which is expressed as total investment in fixed assets of the whole society; energy input, which is measured by the electricity consumption of each province. Expected output is measured by the real GDP of each province, which is based on the GDP index to eliminate the effect of inflation. Non-desired output indicators are measured by the "three wastes" of industry, mainly including sulfur dioxide emissions, smoke (powder) dust emissions and wastewater emissions. The specific evaluation indicators are shown in the Table 1.

4.2.2 The core explanatory variables: Digital economy (*DIG*)

At present, there is no unified index for measure the development level of digital economy. In this paper, according to the definition of digital economy in "China Digital Economy White Paper" published by China Institute of Information and Communication Technology, the digital economy development index is constructed at the provincial level from two dimensions: digital industrialization and industrial digitalization. Referring to the research of Liu Y. et al. (2022), digital industrialization is measured from three aspects: Internet and telecommunication industry, electronic information manufacturing industry and software and information technology service industries, etc., and industrial digitalization is measured from three aspects: Digital talents, digital infrastructure and digital transactions. The specific evaluation indicators are shown in the Table 2.

On the basis of the above digital economy development level evaluation index system, the comprehensive index of digital economy development level is measured. The commonly adopted methods are subjective assignment method and objective assignment method. The subjective assignment method includes principal component analysis, AHP, etc., and the objective assignment method includes cluster analysis, entropy value method, etc. In order to avoid artificial subjective influence, this paper uses the entropy method to assign the weights of each index by referring to the research of Wang and Zhu, (2021).

Since there are significant differences in both the magnitude and order of magnitude of the above index values, they are first standardized and the specific formula is as follows: $x_{ij} = \frac{x_{ij} - min\left\{x_j\right\}}{max\left\{x_j\right\} - min\left\{x_j\right\}}$

Where, $max\left\{x_j\right\}$ is the maximum value of the indicator in all years, and $min\left\{x_j\right\}$ is the minimum value of the indicator for all years, and x_{ij} is the normalized value.

Calculate the proportion of the j index in the year i, using w_{ij} indicates that $w_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}$.

Calculate the information entropy and redundancy of the metrics. The information entropy is $e_j = -\frac{1}{ln\, m}\sum_{i=1}^{m}(w_{ij}{}^{*}\, ln\, w_{ij})$ and the redundancy degree is $d_j = 1 - e_j$.

Where, m is the evaluation year, and the index weights are calculated based on the information entropy redundancy $\varphi_j = \frac{d_j}{\sum_{j=1}^{m} d_j}$.

Based on standardized indicators x_{ij} and measured indicator weights φ_j, the index level of digital economy development level is derived using the weighting of multiple linear functions: $DIG_i = \sum_{j=1}^{m}(\varphi_j{}^{*} x_{ij})$.

Finally, the combined value can be calculated DIG_i between 0 and 1, indicating the level of digital economy development in each province. The development of digital economy in each province in 2020 is shown in Figure 1.

4.2.3 Control variables

Referring to the research of Wu et al. (2021) and Cao et al. (2021), the following three variables are selected as the main control variables in this paper: 1) the level of economic development (*PERGDP*), the gross regional product *per capita* was selected to measure. On the one hand, the improvement of economic development level requires not only the expansion of the overall scale of economic development, but also the improvement of energy utilization efficiency and environmental efficiency, which may have a positive impact on GTFP. On the other hand, the GDP-only growth theory, which sacrifices the environment for GDP growth, may have a negative effect on GTFP; 2) Industrial structure (*IS*), the secondary industry is the main source of all kinds of pollutants and the development of tertiary industry promotes the transformation and upgrading of industrial structure, so this paper selects the ratio of the added value of tertiary industry to GDP to indicate the industrial structure; 3) Foreign direct investment (*FDI*). According to the pollution halo hypothesis, the learning effect, scale effect and technology spillover effect brought by the entry FDI may have a positive effect on the improvement of GTFP in the host country (Hao et al., 2020). This paper selects the actual amount of FDI utilized in the current year as a proportion of the regional GDP in the current year after being converted by annual average exchange rate to measure.

4.2.4 Threshold variables

The market environment (ME) can be regarded as a new type of production factor, and a good market environment can have an important impact on both supply and demand. Therefore, this paper uses the inverse of the marketability index as a threshold variable to explore the possible impact on GTFP when the regional marketability index exceeds the threshold value. Technological innovation (TEC) can affect both the development of the digital economy and China's GTFP. This paper uses the number of domestic patents granted as measure of regional technological innovation and explores the possible impact on GTFP when regional innovation capacity exceeds the threshold.

4.3 Data sources and descriptive statistical results

This paper selects panel data of 30 provinces (autonomous regions and municipalities) in China except Tibet Autonomous Region, Hong Kong, Macao and Taiwan from 2011 to 2020 for empirical analysis. The data used in this paper are mainly come from China Statistical Yearbook, EPS database, CSMAR database and statistical yearbooks of various provinces (autonomous regions and municipalities), among which some missing data are filled by interpolation method, and the non-ratio data in this paper are logarithmically processed to reduce the heteroscedasticity. The descriptive statistics of the data are shown in Table 3, and the correlation analysis of the core variables is shown in Figure 2.

5 Empirical analysis

5.1 Regression results of benchmark model

In order to examine the influence of digital economy development on GTFP in China, a model with time and region double fixation was selected for the benchmark regression. Table 4 reports the regression results of the benchmark model. Model (1) analyzes the impact of the digital economy on GTFP without considering control variables, and it can be found that the influence coefficient of the digital economy is 3.8723, which is significantly positive at the 1% confidence level, indicating that the development of the digital economy can significantly increase GTFP. Model (2) is shown the results of adding control

TABLE 1 Evaluation index system of provincial green total factor productivity in China.

	Level 1 indicators	Secondary indicators	Variable selection
Green total factor productivity	Input Indicators	Labor input	Number of employees at the end of the year/10,000 people
		Capital input	Total social fixed asset investment/billion yuan
		Energy input	Electricity consumption/billion kWh
	Expected output	Economic output	Real GDP/billion yuan
	Non-expected outputs	Industrial waste	sulfur dioxide emissions/million tons
			smoke (powder) dust emissions/million tons
			wastewater emissions/million tons

TABLE 2 Index system of digital economy development level among provinces in China.

	Level 1 indicators	Secondary indicators	Variable selection
Digital economy development level	Digital Industrialization	Internet and Telecommunications	Internet broadband access ports/million
			Cell phone penetration rate/units per 100 people
			Total telecom business/added value of tertiary industry/%
		Electronic Information Manufacturing	Computer, communication and other electronic equipment manufacturing employment/10,000 people
		Software and Information Technology Services	Software business income/tertiary industry added value/%
			Information transmission, software and information technology services employment/10,000 people
			Number of software and information technology services enterprises/ea
	Industry Digitization	Digital Talent	Number of degrees awarded by higher education institutions/person
			Full-time teachers in higher education institutions/person
		Digital Infrastructure	Number of pages/billion
			Long distance fiber optic cable line length/km
		Digital Trading	Above-standard industrial enterprises new product sales revenue/above-standard industrial enterprises main business income/%
			Courier volume/million pieces
			Original insurance premium income/added value of tertiary industry/%
			Technology market turnover/billion yuan

variables, the influence coefficient of the digital economy is 3.5589, which is still significantly positive at least at 1% confidence level. It can be seen that the digital economy can significantly improve GTFP whether adding control variables or not, that is, assuming H1 holds. The reason for this can be mainly analyzed from the input side and the output side to analyze the positive effect of the digital economy on GTFP. From the input side, the digital economy relies on information technology and the Internet as a platform to improve the efficiency of information transmission and reduce the waste of resource caused by information asymmetry; it also promotes the optimization of production factor inputs through digital technology innovation and promotes the improvement of GTFP (Ishida, 2015). From the output side, the integration of digital technology with the traditional manufacturing industry not only enables real-time monitoring of its production process, but also unifies the supervision of pollutant emissions from relevant enterprises and reduces the difficulty of government environmental supervision, thus achieving the purpose of reducing pollutant emissions.

In terms of control variables, all the selected control variables in this paper are significant positive at 1%, 5% and 10% level of significance respectively. The positive relationship between the level of economic development and GTFP indicates that the more developed the regional economy is, the higher the requirements for environmental protection in the region, and the coordinated positive development of economic development and environmental protection

TABLE 3 Descriptive statistics of data.

Variables		Sample size	Average value	Standard deviation	Minimum	Maximum
Explained variables	Green Total Factor Productivity (*GTFP*)	270	1.5034	0.4412	0.8920	2.6135
Core explanatory variables	Digital Economy (*DIG*)	270	0.2302	0.1122	0.0573	0.6750
Threshold variables	Market Environment (*ME*)	270	0.1585	0.0547	0.8333	0.3953
	Technological innovation (*TEC*)	270	10.1962	1.4023	6.2186	13.4726
Control variables	Level of economic development (*PERGDP*)	270	10.8779	0.4215	9.8889	12.0130
	Industrial structure (*IS*)	270	0.4793	0.0951	0.3094	0.8387
	Foreign direct investment (*FDI*)	270	0.5303	2.0932	0.0477	34.2064

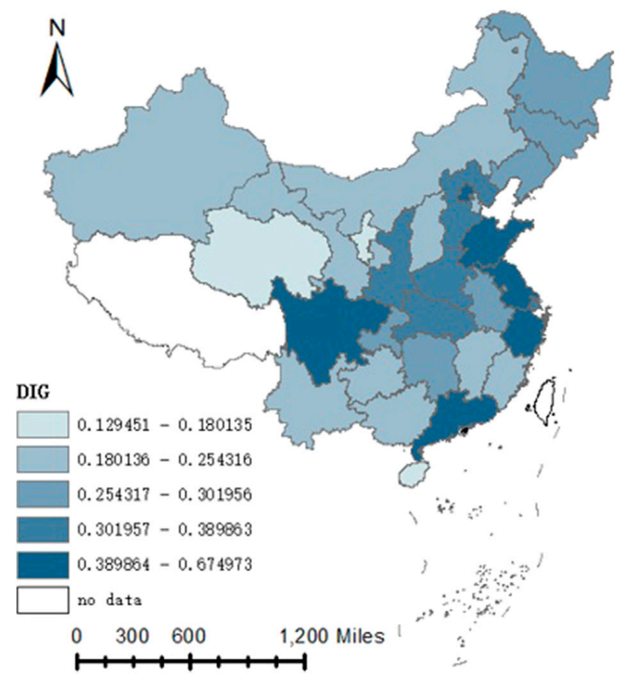

FIGURE 1
Development level of digital economy in China provinces in 2020.

leads to the higher GTFP. Foreign direct investment promotes the improvement of GTFP in China through the technology spillover effect and learning effect (Yoon and Nadvi, 2018); the secondary industry is one of the main sources of pollutants. The measurement index of industrial structure selected in this paper is the ratio of tertiary industry to GDP. There is an obvious positive correlation between industrial structure and GTFP, indicating that the more advanced the industrial structure is, the higher its GTFP.

5.2 Robustness analysis

In order to verify the reliability of the above regression results, the following two approaches are used to perform robustness tests in this paper.

5.2.1 Adding control variables

To examine the possible omitted variables in the model, three control variables, education support (GOV), human capital (HC) and fiscal decentralization (FDE), are added by drawing on the method of Wei Junying et al. (2022), which were respectively expressed by the ratio of education to general budget expenditure, the number of graduates to undergraduate students and the ratio of general budget revenue to general budget expenditure. The results are shown in Table 5 (1). It can be found that the regression results after adding the control variables are consistent with the baseline regression, indicating that the baseline regression results are somewhat robust.

5.2.2 Dynamic panel regression

To ensure the robustness of the above findings, this paper uses a dynamic panel model that lags the variables by one order, and chooses

TABLE 4 Baseline regression results.

Variables	Explained variable:GTFP	
	(1)	(2)
DIG	3.8723***	3.5589***
	(2.8305)	(2.9283)
PERGDP		1.0728***
		(5.7931)
IS		2.3187**
		(2.7184)
FDI		0.0053*
		(1.9744)
Constant	0.3992*	−11.8793***
	(1.7403)	(−6.6570)
Observations	270	270
R-squared	0.6774	0.7413
Regional fixed effects	Yes	Yes
Time fixed effects	Yes	Yes

Note: 1) *, **, *** represent significant at the 10%, 5% and 1% levels respectively; The *t*-value are in parentheses. 2) The following table is the same as.

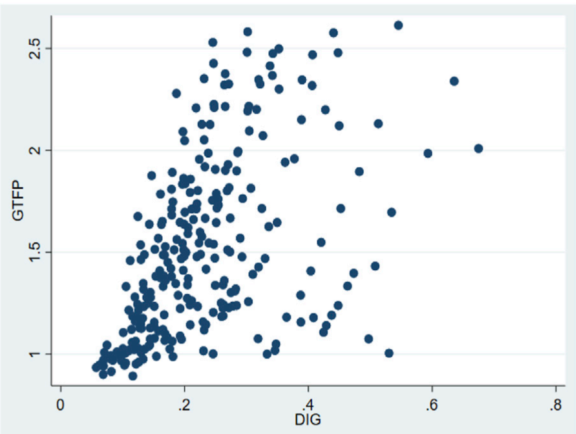

FIGURE 2
Correlation analysis of core variables.

a differential GMM approach for regression. The results are shown in Table 5 (2) and (3). It can be found that the *p*-values of AR(1) test are all less than 0.1, and the *p*-values of AR(2) test are all greater than 0.1, which indicates that there is no second-order autocorrelation. Meanwhile, the *p*-values of Hansen test are 0.2579 and 0.2598 are greater than 0.1, indicating that the instrumental variables are valid, and the regression results of differential GMM again confirm the robustness of the benchmark regression results.

5.2.3 Endogenous treatment and instrumental variables

In order to avoid the problem of endogeneity caused by factors such as two-way causality and possible omitted variables, this paper will adopt the instrumental variable method for endogeneity testing. Referring to the study by Huang et al. (2019), the number of landline telephones by region in 1984 is selected as the instrumental variable for the digital economy. The reason for this is that the development of Internet technology should have started with the popularization of landline telephones, so that regions with historically high landline penetration are also most likely to be regions with high Internet penetration. In addition, as the research sample in this paper is panel data and the original data for the instrumental variables selected are cross-sectional, the interaction term between the number of landline telephones per 10,000 people in 1984 and national IT service revenues in the previous year was constructed for each region as an instrumental variable for the 2SLS regression, drawing on the setup of Nunn and Qian (2014). The results are shown in Table 5 (4) and (5). It can be seen that after accounting for endogeneity, the coefficient on the impact of the digital economy on GTFP is still significantly positive and the benchmark regression results remain robust. Meanwhile, the Kleibergen-Paap rk LM statistic is 40.013, corresponding to a *p*-value of 0, indicating that there is no under-identification problem; the value of the Cragg-Donald Wald F is 46.626, which is greater than the critical value of the Stock-Yogo test of 16.38, indicating that there is no weak instrumental variable problem.

TABLE 5 Results of robustness analysis.

Variables	Explained variable: GTFP				
	(1)	(2)	(3)	(4)	(5)
L.TFPCRS		0.7916***	0.6690***		
		(7.0650)	(4.2873)		
DIG	3.4896***			29.5328*	27.9986*
	(2.9098)			(1.7361)	(1.9553)
L.DIG		0.5547*	0.7423*		
		(1.6591)	(1.8696)		
PERGDP	1.1397***			0.5342	0.4982
	(6.0663)			(1.0072)	(0.9119)
L.PERGDP		0.2722	0.3638**		
		(1.0346)	(2.0582)		
IS	2.3943**			4.6229**	4.6327**
	(2.7011)			(1.9755)	(2.1473)
L.IS		0.0491	0.0910		
		(0.0837)	(0.1550)		
FDI	0.0061**			0.0420	0.0406
	(2.4164)			(1.4159)	(1.5547)
L.FDI		−0.4678	−0.1497		
		(−1.1565)	(−0.4421)		
GOV	2.6960				3.7674
	(1.5982)				(0.9617)
L.GOV			3.6639		
			(1.5467)		
HC	0.1176				1.6464
	(0.0739)				(0.4843)
L.HC			−0.7026		
			(−0.3779)		
FDE	−1.2213*				−0.0923
	(−1.7846)				(−0.0618)
L.FDE			−0.7179		
			(−1.0724)		
Constant	−12.4849***	−2.5072	−3.5927*	−19.5528***	−19.5265***
	(−7.2438)	(−0.9273)	(−1.8266)	(−3.2057)	(−3.4484)
Observations	270	270	270	270	270
R-squared	0.7498			0.3270	0.3470
Regional fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
AR(1) test p-value		0.0218	0.0226		
AR(2) test p-value		0.5600	0.5642		
Hansen		0.2579	0.2598		

TABLE 6 Results of heterogeneity analysis.

Variables	Coastal region			Inland region		
	(1)	(2)	(3)	(4)	(5)	(6)
DIG	4.0540**	3.7724*	3.3553*	3.4262	2.9267	2.7412
	(2.3113)	(1.9606)	(1.9585)	(1.0597)	(1.6913)	(1.4385)
PERGDP		0.5072	0.8934		1.3392***	1.3915***
		(0.9791)	(1.8081)		(6.8669)	(6.6392)
IS		−0.5478	0.8418		2.2483**	2.1307**
		(−0.1579)	(0.3337)		(2.8383)	(2.5239)
FDI		0.0029	0.0041		−0.4522**	−0.4943*
		(0.5103)	(0.9134)		(−2.1501)	(−2.0966)
GOV			6.7291**			−1.3062
			(3.1035)			(−0.5781)
HC			−1.4521			−0.4097
			(−0.4226)			(−0.2471)
FDE			−2.0956**			−0.3189
			(−2.4685)			(−0.3390)
Constant	0.2449	−4.9811	−9.2368	0.5319	−14.2080***	−14.2191***
	(0.7217)	(−0.7631)	(−1.5869)	(1.0846)	(−6.3813)	(−6.2318)
Observations	99	99	99	171	171	171
R-squared	0.7547	0.7747	0.8074	0.6401	0.7684	0.7700
Regional fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

TABLE 7 Threshold effect test.

Threshold variables	Number of thresholds	*p*-value	F-value	Number of BS	Threshold value		
					1%	5%	10%
Market Environment	Single Threshold	0.0300	23.78	300	29.3054	21.6791	17.8236
	Double Threshold	0.5833	6.87	300	24.6924	16.8118	14.4540
Technology Innovation	Single Threshold	0.0567	24.60	300	33.4531	25.7120	20.3840
	Double Threshold	0.2500	11.30	300	32.3484	22.4991	17.3227

5.3 Heterogeneity analysis

Influenced by historical conditions, geographical location and other factors, there are large disparities in the level of economic development among different regions in China, and there are also large disparities in the level of development of digital economy and GTFP in different regions, which generally show that the development of digital economy in coastal areas is better than that in inland areas. Therefore, in order to study whether there is regional heterogeneity in the influence of digital economy on GTFP, this paper divides the 30 provinces into two sub-samples of coastal areas and inland areas according to their geographical location, and the regression results are shown in Table 6 again. It can be seen that there is significant regional heterogeneity in the influence of digital economy development on GTFP, that is, Hypothesis 2 holds. The development of digital economy in the eastern coastal region has a obviously promoted the regional GTFP. The reason is that the coastal region is more conveniently located, and generally speaking, the level of regional economic development is higher, the digital infrastructure is relatively complete, and the overall development of the digital economy is better. By promoting regional innovation, the digital economy in the region can improve the utilization efficiency of capital and resources, improve the economic development efficiency, and at the same time achieve the goal of reducing pollutant emissions. In contrast, in China's inland areas, the digital economy foundation is weaker, and the role of digital economy in promoting regional GTFP is not significant.

TABLE 8 Threshold estimates.

Threshold variables	Number of thresholds	Estimated value	Confidence interval
Market Environment	Single Threshold	0.1054	[0.1030 0.1062]
Technology Innovation	Single Threshold	7.2612	[7.0504 7.5310]

TABLE 9 Threshold model estimation results.

Threshold variables	Market environment	Technology innovation
DIG_1	1.5148*	7.6433***
	(1.9205)	(6.6285)
DIG_2	2.2271***	1.9805**
	(3.4682)	(2.6241)
PERGDP	0.9294***	0.9142***
	(5.6458)	(4.7558)
IS	0.9724	1.6063***
	(1.2970)	(2.7865)
FDI	0.0025	0.0037**
	(1.3386)	(2.3035)
GOV	1.9411	2.1769*
	(1.3200)	(1.7759)
HC	−0.3338	0.6312
	(−0.2921)	(0.5192)
FDE	−0.4396	0.0849
	(−0.7539)	(0.1630)
Constant	−9.5837***	−10.2207***
	(−5.3662)	(−5.5155)

5.4 Threshold effect of digital economy on GTFP

The empirical analysis conducted above implicitly assumes the prerequisite that the factor endowment characteristics of all regions in China are non-differentiated. However, in fact, the influence of the digital economy on GTFP will also be constrained and influenced by various objective factors. To study whether there is a non-linear relationship between the digital economy and GTFP, this paper will introduce threshold variables, market environment and technological innovation, to analyze the threshold effect.

5.4.1 Threshold test

Firstly, the threshold variables market environment and technological innovation are verified to determine whether there is a threshold effect, and the test results are shown in the following Tables 7, 8. It can be seen from Table 7 that the threshold variables market environment and technological innovation both passed the single threshold effect test, and from Table 8, the threshold values of market environment and technological innovation are 0.1054 and 7.2612 respectively.

5.4.2 Threshold regression results

As shown from the results of the threshold effect in Table 9, when the market environment is lower than the threshold value of 0.1054, the impact of digital economy on GTFP is significant at the 10% confidence level with a coefficient of 1.5148; When the market environment is higher than the threshold value of 0.1054, the impact of digital economy on GTFP is significant at the confidence level of 1%, with a coefficient of 2.2271. It indicates that in regions with better market environment, the influence of digital economy on GTFP is more significant. In regions with good external market environment, these regions tend to have a higher level of economic development and a better development of digital economy. In these areas, digital economy has a great direct impact on GTFP, that is, H3 is assumed to be true. However, when the technological innovation is lower than the threshold value of 7.2612, the impact of digital economy on GTFP is significant at the 1% confidence level, and the impact coefficient is 7.6433; When the technological innovation is higher than the threshold value of 7.2612, the influence coefficient of digital economy on GTFP is 1.9805, which passes the significant level test of 5%. It indicates that the effect of digital economy on GTFP is more significant where the level of technological innovation is lower, that is, Hypothesis 3 holds.

6 Conclusion, policy recommendations and limitations

6.1 Conclusion

In the context of digital economy becoming an important driving force for green and high-quality economic development, this paper focuses on the dynamic interaction among economic efficiency, resource utilization efficiency and environmental efficiency. Based on provincial panel data from 2011 to 2020, using the super-efficient SBM-ML model measure the GTFP of each province. And a digital economy measurement system is constructed to measure the development level of digital economy in each province from two dimensions: digital industrialization and industrial digitalization. On this basis, we empirically tested whether the development of digital economy can improve GTFP in China. The results of the study show that: firstly, from an overall perspective, the development of digital economy can significantly improve GTFP in China; Secondly, the analysis of regional heterogeneity shows that the positive impact of digital economy development on regional GTFP is more significant in coastal areas than inland areas with a lower level of digital economy development; Thirdly, the results of threshold effect analysis show that in regions with better market environments and poor technological innovation level, the promotion of digital economy to GTFP is more significantly influenced by external market environment and a lower level of regional technological innovation.

6.2 Policy recommendations

Based on the above analysis and conclusions, this paper puts forward the following policy recommendations:

First, the findings of this paper find that the development of the digital economy can significantly enhance China's GTFP, therefore strengthening the development of the digital industry should accelerate the integration of digital technology with traditional industries when developing the economy, improve the efficiency of energy and resource conversion, and bring into play the role of the digital economy in enhancing GTFP.

Second, in terms of regional heterogeneity, the eastern coastal regions of China should continue to actively and steadily promote the development of the digital economy and foster new competitive advantages, while the central and western inland regions should actively undertake the technological spillover from the eastern coastal regions, strengthen the application of modern digital technology to traditional industries, encourage enterprises to carry out digital technology innovation and digital reform, and continuously explore new dynamics of economic growth while trying to avoid the loss of factors.

Third, at the market environment level, the impact of the digital economy on GTFP is more significant in regions with a better market environment, so the government should formulate corresponding policies, laws and regulations to create a good market environment and development space for the development of the digital economy (Gao et al., 2022). In terms of technological innovation, the impact of the digital economy on GTFP is more significant in regions with less technological innovation, so the government should play the role of a "guide," and such regions should invest more in digital technology, accelerate the construction of digital infrastructure, and provide the foundation for the development of the digital economy. Actively promote the development of the digital economy (Jia et al., 2022).

6.3 Limitations

First of all, affected by the objective factors of different statistical indicators and incomplete statistical data, this paper only collected the relevant data of 30 provinces (municipalities and autonomous regions) in China from 2011 to 2020, and the data collection year span was short. Secondly, the digital economy is in a high-speed development stage, with the development of economy, it may show new development characteristics, which need to be included in the index system of digital economy development for measurement.

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

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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.

Publisher's note

References

An, Q., and Liu, J. (2022). The development of digital economy and the improvement of regional total factor productivity-an empirical test based on provincial panel data in China [J]. *J. Chang 'an Univ. Soc. Sci. Ed.* Available at: https://kns.cnki.net/kcms/detail/61.1391.c.20220420.1607.002.html 24 (02), 32–44.

Boer, H., and During, W. E. (2001). Innovation, what innovation? A comparison between product, process and organizational innovation[J]. *Int. J. Technol. Manag.* 22 (1-3), 83–107. doi:10.1504/ijtm.2001.002956

Cao, X., Deng, M., and Li, H. (2021). How does e-commerce city pilot improve green total factor productivity? Evidence from 230 cities in China. *J. Environ. Manag.* 289, 112520. doi:10.1016/j.jenvman.2021.112520

Carlsson, B. (2004). The digital economy: What is new and what is not? *Struct. Change Econ. Dyn.* 15 (3), 245–264. doi:10.1016/j.strueco.2004.02.001

Chen, Y., Miao, J., and Zhu, Z. (2021). Measuring green total factor productivity of China's agricultural sector: A three-stage SBM-DEA model with non-point source pollution and CO2 emissions. *J. Clean. Prod.* 318, 128543. doi:10.1016/j.jclepro.2021.128543

Cheng, W., and Qian, X. (2021). Digital economy and China's industrial green total factor productivity growth [J]. *Explor. Econ. issues* (08), 124–140.

Cheng, Z., and Jin, W. (2020). Agglomeration economy and the growth of green total-factor productivity in Chinese Industry. *Socio-Economic Plan. Sci.* 83, 101003. doi:10.1016/j.seps.2020.101003

Chung, Y. H., Färe, R., and Grosskopf, S. (1997). Productivity and undesirable outputs: A directional distance function approach. *J. Environ. Manag.* 51 (3), 229–240. doi:10.1006/jema.1997.0146

Dai, D., Fan, Y., Wang, G., and Xie, J. (2022). Digital economy, R&D investment, and regional green innovation—analysis based on provincial panel data in China. *Sustainability* 14 (11), 6508. doi:10.3390/su14116508

Deng, H., Ge, B., Shen, Z., and Xia, L. (2022). Digital economy and its spatial effect on green productivity gains in manufacturing: Evidence from China. *J. Clean. Prod.* 378, 134539. doi:10.1016/j.jclepro.2022.134539

Ding, C., Liu, C., Zheng, C., and Li, F. (2022). Digital economy, technological innovation and high-quality economic development: Based on spatial effect and mediation effect. *Sustainability* 14 (1), 216. doi:10.3390/su14010216

Feng, G., and Serletis, A. (2014). Undesirable outputs and a primal Divisia productivity index based on the directional output distance function. *J. Econ.* 183 (1), 135–146. doi:10.1016/j.jeconom.2014.06.014

Gao, D., Ge, L., and Yu, J. (2022). Does digitization improve green total factor energy efficiency? Evidence from Chinese 213 cities. *Energy* 247, 123395. doi:10.1016/j.energy.2022.123395

Goldfarb, A., and Tucker, C. (2019). Digital economics. *J. Econ. Literature* 57 (1), 3–43. doi:10.1257/jel.20171452

Hao, Y., Wu, Y., Wu, H., and Ren, S. (2020). How do FDI and technical innovation affect environmental quality? Evidence from China [J]. *Environ. Sci. Pollut. Res.* 27 (8), 7835–7850. doi:10.1007/s11356-019-07411-0

Hou, B., and Wang, B. (2022). Business environment and green total factor productivity-an empirical study based on the global level [J]. *world Econ. Pap.* (05), 104–120.

Hu, X., Yang, J., and Guo, P. (2022). Measurement of digital economy and total factor productivity and its spatial correlation test [J]. *statistics Decis.* 38 (04), 10–14.

Huang, Q., Yu, Y., and Zhang, S. (2019). Internet development and manufacturing productivity improvement: Internal mechanism and China experience [J]. *China Ind. Econ.* (08), 5–23.

Iqbal, J., Khan, M., Talha, M., Farman, H., Jan, B., Muhammad, A., et al. (2018). A generic internet of things architecture for controlling electrical energy consumption in smart homes. *Sustain. Cities Soc.* 43, 443–450. doi:10.1016/j.scs.2018.09.020

Ishida, H. (2015). The effect of ICT development on economic growth and energy consumption in Japan. *Telematics Inf.* 32 (1), 79–88. doi:10.1016/j.tele.2014.04.003

Jardim-Goncalves, R., Popplewell, K., and Grilo, A. (2012). Sustainable interoperability: The future of Internet based industrial enterprises. *Comput. Industry* 63 (8), 731–738. doi:10.1016/j.compind.2012.08.016

Jia, L., Hu, X., Zhao, Z., He, B., and Liu, W. (2022). How environmental regulation, digital development and technological innovation affect China's green economy performance: Evidence from dynamic thresholds and system GMM panel data approaches. *Energies* 15 (3), 884. doi:10.3390/en15030884

Junying, W., Hu, R., and Chen, Y. (2022). How does the development of digital economy affect the consumption gap between urban and rural areas: Widening or narrowing? [J]. *Consum. Econ.* 38 (03), 40–51.

Kling, R., and Lamb, R. (1999). IT and organizational change in digital economies. *ACM SIGCAS Comput. Soc.* 29 (3), 17–25. doi:10.1145/572183.572189

Li, G., and Liao, F. (2022). Input digitalization and green total factor productivity under the constraint of carbon emissions. *J. Clean. Prod.* 377, 134403–136526. doi:10.1016/j.jclepro.2022.134403

Li, J., Chen, L., Chen, Y., and He, J. (2021). Digital economy, technological innovation, and green economic efficiency—empirical evidence from 277 cities in China. *Manag. Decis. Econ.* 43, 616–629. doi:10.1002/mde.3406

Li, T., Han, D., Ding, Y., and Shi, Z. (2020). How does the development of the internet affect green total factor productivity? Evidence from China. *IEEE Access* 8, 216477–216490. doi:10.1109/access.2020.3041511

Li, X. (2019). New features of digital economy and formation mechanism of new kinetic energy of digital economy [J]. *Reform.* Available at: https://kns.cnki.net/kcms/detail/50.1012.F.20191106.1540.002.html (11), 40–51.

Li, Y., and Chen, Y. (2021). Development of an SBM-ML model for the measurement of green total factor productivity: The case of pearl river delta urban agglomeration. *Renew. Sustain. Energy Rev.* 145, 111131. doi:10.1016/j.rser.2021.111131

Lin, S., and Zhang, H. (2011). Accessibility, location choice and information service industry agglomeration-A case study of Shanghai [J]. *Finance Trade Econ.* (05), 106–114+137.

Liu, Q., Ma, Y., and Xu, S. (2022). Has the development of digital economy improved the efficiency of green economy in China? [j]. *china Popul. Resour. Environ.* 32 (03), 72–85.

Liu, S., Yang, B., and Song, L. (2022). Research on the influence mechanism of China's innovative city pilot policy on green development [J/OL]. *Soft Sci.*, 1–12.

Liu, Y., Lei, J., and Zhang, Y. (2021). A study on the sustainable relationship among the green finance, environment regulation and green-total-factor productivity in China. *Sustainability* 13 (21), 11926. doi:10.3390/su132111926

Liu, Y., Yang, Y., Li, H., and Zhong, K. (2022). Digital economy development, industrial structure upgrading and green total factor productivity: Empirical evidence from China's cities. *Int. J. Environ. Res. Public Health* 19 (4), 2414. doi:10.3390/ijerph19042414

Lyu, Y., Wang, W., Wu, Y., and Zhang, J. (2023). How does digital economy affect green total factor productivity? Evidence from China[J]. *Sci. Total Environ.* 857, 159428. doi:10.1016/j.scitotenv.2022.159428

Niftiyev, I. (2022b). China's interests in the industrialization of the South Caucasus: Comparative analysis of labor productivity in the manufacturing sector. *Econ. Soc. Changes Facts, Trends, Forecast* 15 (2), 205–222. doi:10.15838/esc.2022.2.80.13

Niftiyev, I. (2022a). "The role of public spending and the quality of public services in E-government development," in *Materials II international conference "digital economy: Modern challenges and real opportunities*. https://www.econstor.eu/handle/10419/256899 (Baki: Publishing House UNEC-Azerbaijan State Economic University), 28–29.

Nunn, N., and Qian, N. (2014). US food aid and civil conflict. *Am. Econ. Rev.* 104 (6), 1630–1666. doi:10.1257/aer.104.6.1630

Qifeng, W., Tan, J., and Shi, L. (2022). Measurement and spatial differentiation of industrial green total factor productivity in Chengdu-Chongqing economic circle [J/OL]. *Soft Sci.* Available at: https://kns.cnki.net/kcms/detail/51.1268.G3.20220613.1823.002.html, 1–13.

Qin, J., Zhao, J., and Wang, W. (2022). Intermediary effect and empirical evidence of the impact of digital economy on industrial structure upgrading [J]. *statistics Decis.* 38 (11), 99–103. doi:10.13546/j.cnki.tjyjc.2022.11.020

Quah, D. (2003). Digital goods and the new economy[J]. *LSE Res. Online Documents Econ.* (4), 2–44.

Ren, S., Hao, Y., and Wu, H. (2022c). Digitalization and environment governance: Does internet development reduce environmental pollution?[J]. *J. Environ. Plan. Manag.* 2022, 2033959. doi:10.1080/09640568.2022.2033959

Ren, S., Hao, Y., and Wu, H. (2022b). How does green investment affect environmental pollution? Evidence from China. *Environ. Resour. Econ.* 81, 25–51. doi:10.1007/s10640-021-00615-4

Ren, S., Liu, Z., Zhanbayev, R., and Du, M. (2022a). Does the internet development put pressure on energy-saving potential for environmental sustainability? Evidence from China. *J. Econ. Analysis* 1, 50–65. doi:10.58567/jea01010004

Sadik-Zada, E. R., Gatto, A., and Niftiyev, I. (2022). E-government and petty corruption in public sector service delivery. *Technol. Analysis Strategic Manag.*, 1–17. doi:10.1080/09537325.2022.2067037

Sun, Y., and Hu, Z. (2021). Digital economy, industrial upgrading and improvement of urban environmental quality [J]. *statistics Decis.* 37 (23), 91–95. doi:10.13546/j.cnki.tjyjc.2021.23.020

Tian, J., and Liu, Y. (2021). Research on total factor productivity measurement and influencing factors of digital economy enterprises. *Procedia Comput. Sci.* 187, 390–395. doi:10.1016/j.procs.2021.04.077

Wang, J., and Zhu, J. (2021). Measurement of the development level and evolution of digital economy in China [J]. *Tech. Econ. Res. Quantitative Econ.* 38 (07), 26–42. doi:10.13653/j.cnki.jqte.2021.07.002

Wu, H., Hao, Y., Ren, S., Yang, X., and Xie, G. (2021). Does internet development improve green total factor energy efficiency? Evidence from China. *Energy Policy* 153, 112247. doi:10.1016/j.enpol.2021.112247

Xie, Y. (2022). Effect of digital economy on regional carbon emission intensity and its mechanism [J]. *Contemp. Econ. Manag.* 44 (02), 68–78. doi:10.13253/j.cnki.ddjjgl.2022.02.008

Yang, P. (2020). The value, development focus and policy supply of digital economy [J]. *J. Xi 'an Jiaot. Univ. Soc. Sci. Ed.* 40 (02), 57–65+144. doi:10.15896/j.xjtuskxb.202002007

Yoon, S., and Nadvi, K. (2018). Industrial clusters and industrial ecology: Building "eco-collective efficiency" in a South Korean cluster. *Geoforum* 90, 159–173. doi:10.1016/j.geoforum.2018.01.013

Young, N. D. (1996). An analysis of the causes of genetic isolation in two Pacific Coast iris hybrid zones. *Can. J. Bot.* 74 (12), 2006–2013. doi:10.1139/b96-241

Zhang, L., and Ma, L. (2022). Digital economy, industrial structure upgrading and total factor productivity [J]. *statistics Decis.* 17 (11), e0277259. doi:10.13546/j.cnki.tjyjc.2022.03.001

Zhao, S., Peng, D., Wen, H., and Song, H. (2022). Does the digital economy promote upgrading the industrial structure of Chinese cities? *Sustainability* 14 (16), 10235. doi:10.3390/su141610235

Zhou, X., Liu, Y., and Peng, L. (2021). Digital economy development and green total factor productivity improvement [J]. *Shanghai Econ. Res.* (12), 51–63. doi:10.19626/j.cnki.cn31-1163/f.2021.12.006

Zhu, X., Zhang, B., and Yuan, H. (2022). Digital economy, industrial structure upgrading and green total factor productivity—evidence in textile and apparel industry from China. *PLoS ONE* 17 (11), e0277259. doi:10.1371/journal.pone.0277259

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The impact of the CEO's green ecological experience on corporate green innovation—The moderating effect of corporate tax credit rating and tax burden

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Using the data of listed companies in the Chinese capital market from 2014 to 2020, this paper studies the impact of the CEO's green ecological experience on corporate green innovation and further analyzes the moderating effects of tax credit rating and tax burden. The results show that 1) the CEO's green ecological experience can enhance corporate green innovation, 2) China's tax credit rating positively moderates the impact of the CEO's green ecological experience on corporate green innovation, and 3) corporate tax burden will negatively moderate the impact of the CEO's green ecological experience on corporate green innovation.

KEYWORDS

capital market, green innovation, CEO's green ecology experience, tax credit rating, tax burden

1 Introduction

The acceleration of industrialization and urbanization in the world has caused numerous environmental issues. For instance, global warming has been one of the severe consequences, which challenges the global environment and threatens the coastal dweller. So far, many countries have taken actions to decelerate the trend of environmental disruption by reducing carbon emissions. For instance, by developing information and communication technology (ICT), both high-income and middle-income countries have decreased carbon emissions (Sun et al., 2023). However, the climate policy uncertainty will block R&D input, decreasing cash flows (Ren et al., 2023a). Most people are also transferring their attentions from less effective development to protecting the environment. Yousaf et al. (2022) claim that various laws and policies are focused on protecting the environment. These policies may regulate corporate operation and force them to allocate more resources to green innovation in a more sustainable way. Furthermore, as the COVID-19 pandemic has huge economic impacts globally, many countries are trying to promote economic recovery through economic policies, and these economic policy uncertainties are positive for the overall market (Wang et al., 2023b). From the productivity perspective, Bucea-Manea-Tonis et al. (2021) state that green innovation has a positive impact on people's health and thus increases their productivity. Additionally, in the fast-paced world, knowledge, innovation, and technology are becoming more crucial (Tullani et al., 2018). It is required for the corporations to increase their competence by focusing on R&D and launching more eco-friendly products to attract consumers. Furthermore, many stakeholders like to search for CEOs' and executives' backgrounds to determine their educational level, habits, and abilities since these may be related to corporate operation. For instance, the CEO's green ecological experience influences the positive environmental deviance and the CEO's foreign experience enhances the green innovation (Walls and Hoffman, 2013; Quan et al., 2023). Moreover, a "U" shape relationship is shown between the company executive political connections and the corporate pollution (Wang et al., 2022). In addition to these, taxes may also be one of the influencing factors since the tax payment directly relates to the cash-holding level. A higher tax burden may force enterprises to ignore the R&D, creating financial constraints for corporations and thus influencing green innovation (Wang et al., 2023a). However, these negative impacts can be controlled by some actions from governments, for instance, adjusting environmental tax rates to the optimal level and controlling the uncertainty of oil price to enhance resource integration and increase the green technology (Wang and Yu, 2021; Ren et al., 2023b). Additionally, governments can put forward dynamic climate policies to overcome energy price fluctuations (Ren et al., 2023c). Also, the digital finance will foster urban innovation (Ren et al., 2023a). These may be helpful for green innovation development. In conclusion, corporate green innovation may be restricted by many factors and it protects the environment and motivates corporations to obtain advantages in competition for sustained development.

Corporate green innovation has been studied by many scholars. To the best of our knowledge, the existing literature mainly focuses on the study of the external influence and internal mechanism of green innovation, including the input, expenditure, and efficiency of green innovation. Research studies on green innovation have ignored the role of the CEO's experience in the business operation activities of enterprises and they rarely involve the mechanism of factors directly related to the corporate cash flow and corporate management, such as tax credit rating and tax burden.

This paper will study the impact of the CEO's green ecological experience on corporate green innovation and further explore the moderating role of corporate tax credit rating and tax burden. The innovations and contributions of this study may include the following: 1) It studies the impact of the CEO's green ecological experience on corporate green innovation, which enriches the research literature on corporate green innovation. 2) It explores the moderating effects of tax credit rating and tax burden on the impact of the CEO's green experience on corporate green innovation. 3) This study also inspires CEOs to strengthen the study of green knowledge, guiding enterprises to control their tax level reasonably, which results in a Chinese example for other countries to develop corporate green innovation.

2 Literature review and research frameworks

2.1 Green innovation

Scholars propose different definition of green innovation from different perspectives. Lai and Zhan (2021) define green innovation as green and technological innovation, which reflects the environmental responsibility of technological innovation. Additionally, Zhu et al. (2018) define green innovation as innovative and valuable innovation that can protect the environment and save resources, which includes three characteristics, namely, resource conservation, environment protection, and sustainable development. In addition to technology, process, and product innovation, Dai and Liu (2009) also propose system innovation, which refers to organizational innovation and management innovation of enterprises. Li (2015) and Sun et al. (2022) propose that green innovation would bring spillover externalities from which competitors and stakeholders would benefit. However, Rennings and Rammer (2011) believe that external policies are beneficial to promote corporate green innovation, which is beneficial to improve corporate performance, create a good atmosphere, and improve corporate competitiveness.

The existing research on systematic innovations about the connotation of green innovation mainly focuses on external factors and internal mechanisms. From the perspective of external factors, these include policies and market factors, for example, fintech can improve the green innovation performance of enterprises, and resource mismatching plays the role of a mediator in this process (Liu et al., 2022b); government subsidies, policy pressures, and external incentives can also encourage enterprises to conduct green innovation-related R&D (Tian and Pan, 2015; Chen et al., 2022). From the perspective of the internal mechanism of enterprises, the organizational strategies and green organizational identities will positively affect green innovation and thus enhance the green development (Wang et al., 2014; Yousaf et al., 2022). In terms of corporate strategy, Hart and Dowell (2011) point out five factors affecting corporate green innovation strategy. These are conventional green capabilities based on investments in products and production processes, employee participation and training for environmental issues, green organization capability across internal functions, formal environmental management systems and procedures, and strategic planning considering environmental issues, and these prove to have a positive impact on corporate green innovation. Scarpellini et al. (2020) state that green innovation may enhance environmental management capabilities and form an innovation circle.

In addition, scholars also conduct research studies from three perspectives: input, output, and efficiency of green innovation. In terms of green innovation input, Ghisetti and Rennings (2014) point out that green innovation can improve environmental performance, build a good image of enterprises, enhance the competitiveness of enterprises, and as an internal driving factor, influence enterprises to invest in the green innovation practice. Bucea-Manea-Tonis et al. (2021) claim that green innovation increases employee productivity and enhances corporate performance. The output of corporate green innovation can be measured by the green patent output, and venture capital has a positive impact on the green patent output of new energy enterprises (Qi et al., 2017). Furthermore, Tullani et al. (2018) state that green innovation increases consumer intention. In terms of the influencing factors of green innovation efficiency, Chen (2016) points out that the optimization of the technology level and property rights structure can improve the green total factor productivity. Liu et al. (2022a) and Zeng et al. (2022) point out that the heterogeneity of the intelligent background of an enterprise's management team has positively influenced the green innovation practice of an enterprise. Self-regulation and green marketing will also impact the green capacity of the corporation (Demirel and Kesidou, 2019).

2.2 CEO's green ecological experience and tax

The CEO's experience has been a hot topic for corporation research studies. Hambrick and Mason (1984) believe that CEOs can form different traits through their past education and work experiences, which to some extent affect their psychological structures such as attention tendency, cognitive ability, and values, and ultimately affect the corporate behavior, decision-making, and performance. For these reasons, CEO traits may be considered when mentioning innovation decisions as innovation is full of risks, is unpredictable, and requires continuous improvement (Holmstrom, 1989; Wang and Yu 2021). For the process of shaping a green experience, growing up with a mother and increasing outdoor time will help children to shape their environmental attitude as they will focus more on the nature value (Evans et al., 2018; DeVille et al., 2021). However, education matters, not the child's attitude (Evans et al., 2018). After shaping their green attitude, CEOs who have environmentally conscious values would be more concerned about the nature and pay more attention to the demands of stakeholders on environmental issues (Wolf, 2014). Environmental protection values and green ecological experience will prompt CEOs to choose the decision plan consistent with their ecological values after weighing the feasibility of alternative plans (Zeng et al., 2022).

Scholars commonly research tax for macro and micro perspectives. From the macro perspective, taxation is believed to influence the national economic growth and has profoundly effective influence on the economy (Lee and Gordon, 2005; Baker et al., 2021). Higher tax rates may increase tax evasion, but they are effective in guaranteeing social insurance (Affes, 2020; Kindermann and Krueger, 2022) while decreasing tax rate is beneficial to enhance the macroeconomy, attracting more enterprises and gaining increasing outputs (Conefrey and Fitz Gerald, 2011; Shevlin et al., 2019). Furthermore, tax rates can be measured by tax administration; Basri et al. (2021) claim that improving tax administration is equal to raising the tax rate to eight percent. From the micro perspective, Guo et al. (2021) find that the percentage of decreasing sales resulting in tax deductions are less than the percentage of increasing sales resulting in tax enhancements, which proves that the tax expenditures are sticky. Furthermore, different from general cognition, low corporate tax rates have no relationship with foreign direct investments (Jensen, 2012). For individual characteristics, it is mentioned that tax morale declines when the incomes are higher (Grundmann and Graf Lambsdorff, 2017).

2.3 Research framework

To sum up, when studying green innovation, it is found that scholars mainly focus on the factors affecting green innovation in the external aspects of external resource input, future development, environmental performance, scientific and technological progress, and employee productivity. For the internal perspective, the previous literature mainly focuses on the environmental management and corporate strategy, which refer to the macro level. However, when testing the green innovation of enterprises from the perspectives of input, output, and efficiency, the research from the perspective of investment in green innovation ignores the external financing factors and the capital of enterprises. The influence on managerial characteristics should not be ignored (Zhang and Shi, 2022) when studying green innovation. In addition to that, scholars rarely refer to the moderating effect of taxation on the impact of green innovation. This study uses the CEO's green ecological experience, tax credit rating, and tax burden as variables to study the impact of the CEO's green ecological experience on corporate green innovation and further analyzes the moderating effect of tax credit rating and tax burden.

CEOs with green ecological experiences are more accustomed to being close to nature. They sincerely care about nature and try to reduce the impact on the environment. From the perspective of the enterprise, the natural affinity of the CEO is conducive to improving the overall awareness of the enterprise to protect the environment. Moreover, it is conducive for the enterprise to respond to the global green policy and mainly focus on the green innovation R&D to improve the overall technical performance and ability of the enterprise, which will establish a superior social image and implement stakeholder interests.

Reducing tax rate provides working capital to guarantee that enterprises carry out green innovation as enterprises have high incentives to use tax savings for green innovation (He and Xiao, 2022). In addition, tax credit rating saves taxes and fees, improves corporate reputation, and creates a better financing environment for enterprises. It creates conditions for the increase in corporate working capital and encourages enterprises to carry out green innovation.

Based on the aforementioned discussion, this study argues that the green ecological experience of CEOs will affect the overall concern of the enterprises for the nature. Enterprises will be more motivated to invest more green innovation capital and reduce environmental pollution caused by the operation. In addition, since the tax credit rating reflects the standardization of the companies and the corporate tax burden reflects the costs of the enterprises, all these may directly or indirectly affect the impact of the CEOs on the green innovation of the enterprise. So, this study proposes the research framework shown in Figure 1.

3 Theoretical analysis and research hypothesis

3.1 Impacts of the CEO's green ecological experience on green innovation

Zhang and Shi (2022) define the academic experience as the experiences of working in relevant academic positions. Taking this methodology, green experience can be measured by participating in green and environment-related education. The relevant education is judged based on whether the education majors belong to the majors of pulp and paper making, environment, environmental engineering, and environmental science. According to the natural connection theory, CEOs with high-quality ecological environment experiences will establish a complete and strong nature connection by themselves and thus generate a strong sense of belonging to ecological nature and form values centered on the ecological environment (Evans et al., 2018). Therefore, they have a potential consciousness of environmental protection, stronger willingness and emotion for environmental protection, and a stronger motivation to preserve nature (Deville et al., 2021). According to Hambrick and Mason (1984), the characteristics of CEOs play a significant role in making corporate decisions and influencing corporate performance.

It is seen that the green ecological experience of the CEO is conducive for the enterprise to pay attention to the demands of its stakeholders, improving its sensitivity to policies related to sustainable development. In addition, it is significant for enterprises to pay

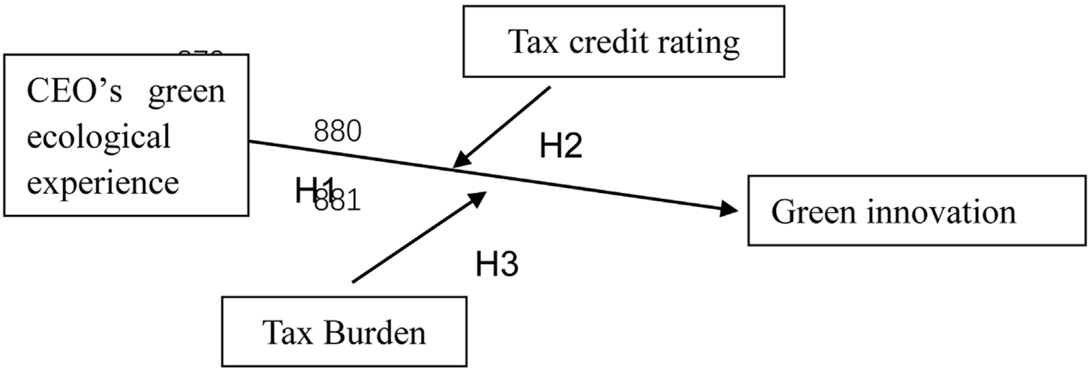

FIGURE 1
Research framework.

attention to sustainable development issues and formulate corresponding corporate policies. The green ecological experience of the CEO will also impact the decision of the enterprise on green innovation and thus affect the management process. Furthermore, CEOs having green ecological experience will own the sense of natural belonging and tend to invest more green innovation R&D to protect the environment when making corporate decisions. Therefore, H1 is proposed in this paper.

H1: The CEO's green ecological experience will positively affect the corporate green innovation.

3.2 The moderating effect of tax credit rating and tax burden

3.2.1 The moderating effect of tax credit rating on corporate green innovation

Since 2014, the Chinese taxation department has been evaluating enterprises as "A, B, C, D" levels (with the addition of "M" in 2018), which is significant for the standardized tax collection process to improve the integrity of taxpayers. Tax credit rating is "flexible tax collection and administration" with "universality" and "softness" (Sun and Lei, 2019). The taxation department implements incentive rewards for "A-level" taxpayers, which is conducive to improving the credit of enterprises, thus easing the financing constraints of enterprises (Sun and Lei, 2019). From the perspective of tax compliance, "A-level" tax credit ratings are conducive to offset the tax burden raised by the tax compliance of enterprises, reducing the tax burden of enterprises (Guo, 2022). In addition, "A-level" taxpayers can significantly increase their R&D input by improving their financing capacity through tax incentives (Zhang, 2021). From the internal perspective of enterprises, tax credit ratings can effectively reduce the level of excessive cash holdings of enterprises, which are beneficial for corporate governance (Sun, 2022). Tax credit ratings may also promote enterprise innovation through marketing and management (Sun and Lei, 2019).

It is seen that tax credit ratings start from the standardization of the tax payment process, guarantee that enterprises benefit from the legal tax payment, and impact on improving the fluent capital. The specific impacts are as follows: from the perspective of enterprises, "A-level" enterprises have better social reputation, enjoy various channels, higher financing amount, and improve the fluent cash flow compared with "non-A-level" enterprises. Meanwhile, due to the "tax shield" effect, "A-level" enterprises can reduce their own tax burden (Sun et al., 2019; Zhang, 2021; Guo, 2022; Sun, 2022).

To conclude, tax credit ratings can improve the smooth cash flow by improving the standardization of the tax payment process and external financing to enable enterprises to invest funds in R&D. Then, CEOs with the green ecological experience may pay more attention to the overall impact of green innovation on enterprises and invest more funds in green innovation to meet the demands of environment-friendly enterprises. In view of these statements, this study proposes H2.

H2: Compared with "non-A-level" enterprises, "A-level" enterprises can positively moderate the effect of the CEO's green ecological experience on the enterprise's green innovation.

3.2.2 The moderating effect of tax burden on corporate green innovation

Tax burden is a factor considered in the production and operation of enterprises which will affect the green innovation input through the cash flow. For the national level, tax burden plays an "inverted U-shaped" role in Chinese economic growth (Lu and Li, 2019). For enterprises, Liu and Huang (2018) state that the increasing tax burden led to the marginal deviation of production factors from the optimal level of society. When ignoring the government transfer, the tax burden will have a "crowding-out effect" and inhibit the economic growth of enterprises (Xiao et al., 2021). Therefore, tax burden is crucial to measure the proportion of the working capital in the process of business operations.

Due to the adverse impact of high tax burden on enterprises, enterprises will take tax burden into consideration when making decisions related to green innovation. With the increase in tax burden, the relevant cash flow held by enterprises will decrease, and the capital pressure of enterprises will increase. As a consequence, the overall capital will not be guaranteed. Although CEOs with green ecological experience may focus primarily on the environment when making decisions related to environmental protection, they may transfer the focus to the development of main business and ignore R&D activities. Given these considerations, CEOs with green ecological experience may not spend excessive capital on R&D activities. In view of these, this study proposes H3:

H3: If ceteris paribus, the tax burden will reversely moderate the positive impact of the CEO's green ecological experience on corporate green innovation.

4 Research design

4.1 Data sources

The data in this study are mainly from the following three sources: 1) the information about tax credit ratings is from the official website of the Chinese taxation department (www.chinatax.gov.cn); 2) the relevant data about enterprise green innovation are from Chinese Research Data Service Platform (CNRDS); and 3) the financial data about enterprises are from the China Stock Market and Accounting Research database (CSMAR).

The tax credit rating policy was published in 2014 and listed "A-level" taxpayers in 2015. This study takes A-stock market enterprises from 2014 to 2020 as the research sample, referring to the methodology of Guo (2022) and Sun et al. (2019) and removes statistics according to the following steps to ensure the representativeness of the samples: 1) financial industry samples, 2) ST and ST* samples, 3) data missing samples, and 4) samples with the ratio of liability to asset greater than one and negative net assets. At the same time, all samples are processed with 1% and 99% winsorization to prevent the interference of the abnormal data. After processing, 20,585 data were obtained.

4.2 Description of variables

4.2.1 Dependent variable: Green innovation

The commonly used indicators to measure the performance of green innovation are green total factor productivity ratio, the number of green patents granted, and the number of green patent applications (Chen et al., 2022; Zhang et al., 2022). This study adopts the methodology of Chen et al. (2022) and Zhang et al. (2022) and uses the number of green patent applications to measure green innovation. The specific reasons are as follows: first, the authorization of green patents needs to be reviewed by relevant departments and can only be identified as enterprise patents when meeting the conditions. Therefore, the number of authorized green patents to measure the innovation level of enterprises is delayed (Chen et al., 2022). Second, it is difficult to extract the green environmental protection data of enterprises, and there is a lack of data between consistent years (Zhang et al., 2022), so it is not suitable to adopt the green total factor productivity ratio. In addition, green patent application cannot be imitated and the application conditions are strict, so it can reflect the green innovation ability of enterprises. This study adopts the methodology of Zhang et al. (2022), using the number of green innovation patents applied by the companies in the current year in the database as the proxy variable of the green innovation capacity of the enterprise. Specifically, the number of green innovation patents applied = the number of green patents applied by the enterprise independently + the number of green patents applied by the enterprise jointly. After calculating that, one is added to the number, and the statistics are processed with the natural logarithm to the regression model.

4.2.2 Independent variable: CEO's green ecological experience

Referring to Zhang and Shi (2022), this study focuses on a CEO who has studied a relevant green major to determine whether he/she has a green ecological environment experience. If a CEO has a green ecological environment experience, the value is 1; otherwise, it is 0.

4.2.3 Moderating variables

4.2.3.1 Tax credit rating (Treat)

Since the Chinese taxation department only discloses the "A-level tax" taxpayers, this study adopts the methodology of Guo (2022), which takes the tax credit rating as the explanatory variable and divides enterprises into two categories: "A-level" and "non-A-level." If the tax credit rating is "A-level," the value is 1; otherwise, it is 0.

4.2.3.2 Tax burden

This study adopts the methodology of Xiao et al. (2021) and Guo (2022) and uses the percentage of "tax paid by the enterprise/ enterprise business income" to represent enterprise tax burden. In the equation, tax paid by the enterprise = business and additional tax + income tax expense.

4.2.4 Control variables

The previous literature has proved that the characteristics of an enterprise can affect the choice of green innovation. Considering the timeliness of research studies, this study selects the control variables from the characteristic and nature of enterprises by referring to Chen et al. (2022), Zhang et al. (2022), Sun et al. (2022), and Guo (2022). For characteristics, this study selects the indicators of the company size (Size), ratio of liability to asset (LEV), and return on assets (ROA). As for the nature of the enterprise, this study selects the indicators of equity concentration (Cncon), proportion of independent directors (IDR), board size (Boardsize), and includes the property rights (ROE). The definitions are listed in Table 1.

4.3 Empirical models

Based on the aforementioned theoretical analysis and hypotheses, this study constructs the following three empirical models to test hypotheses H1, H2, and H3, respectively:

$$Greeninnovation_{it} = \alpha_0 + \alpha_1 Greenexperience_{it} + \sum \alpha_j Controls_{it} + \varepsilon_{it}, \tag{1}$$

$$\begin{aligned} Greeninnovation_{it} = \beta_0 &+ \beta_1 Greenexperience_{it} \\ &+ \beta_2 Treat_{it} {}^* Greenexperience_{it} \\ &+ \beta_3 Treat_{it} \\ &+ \sum \beta_j Controls_{it} + \varepsilon_{it}, \end{aligned} \tag{2}$$

$$\begin{aligned} Greeninnovation_{it} = \gamma_0 &+ \gamma_1 Greenexperience_{it} \\ &+ \gamma_2 Burden_{it} {}^* Greenexperience_{it} \\ &+ \gamma_3 Burden_{it} \\ &+ \sum \gamma_j Controls_{it} + \varepsilon_{it}. \end{aligned} \tag{3}$$

Greeninnovation represents the green innovation of the enterprise, *Greenexperience* represents the CEO's green ecological experience,

TABLE 1 Definition of variables.

Type	Variable	Definition
Dependent variables	*Greeninnovation*	Enterprise green innovation capability = ln (number of green inventions applied independently in the current year + number of green utility models applied independently in the current year + number of green inventions applied jointly in the current year + number of green utility models applied jointly in the current year +1)
Independent variables	*Greenexperience*	Value = 1, if the CEO has green ecological experience, 0 if not
Moderating variables	*Treat*	Value = 1, if the enterprise is "A-level," 0 if not
	Burden	Actual taxes paid/business income
Control variables	*Size*	Company size = ln (total company assets at end of period)
	LEV	Ratio of liability to asset = total liabilities/total assets
	ROA	Return on assets = net profit/total assets
	Cncon	Equity concentration = the proportion of the largest shareholder
	IDR	Proportion of independent directors = number of independent directors/numbers of board members
	Boardsize	Board size = ln (total number of directors)
	ROE	Property rights, value = 1 if the enterprise is nation-owned, otherwise 0

TABLE 2 Descriptive statistics.

	(1)	(2)	(3)	(4)	(5)
Variable	N	Mean	Sd	Min	Max
Greeninnovation	20,585	0.487	0.890	0	3.951
Greenexperience	20,585	0.214	0.410	0	1
Treat	20,585	0.650	0.477	0	1
Burden	20,585	0.0338	0.0384	−0.0194	0.228
Cncon	20,585	0.342	0.147	0.0877	0.740
EOS	20,585	0.334	0.472	0	1
Size	20,585	22.23	1.299	19.98	26.27
Boardsize	20,585	2.115	0.196	1.609	2.639
IDR	20,585	0.377	0.0534	0.333	0.571
Grade	20,585	0.650	0.477	0	1
LEV	20,585	0.411	0.201	0.0580	0.876

$Treat$ represents the tax credit rating, *Burden* represents the tax burden of the enterprise, $Treat$*$Greenexperience$ represents the interaction items between the CEO's green ecological experience and the tax credit rating of the enterprise, *Burden**Greeninnovation* represents the interaction items between the CEO's green ecological experience and the tax burden of the enterprise, and *Controls* represents the control variable. α, β, γ are the regression coefficients, respectively, and ε is the random disturbance term.

5 Empirical analysis

5.1 Descriptive statistics

Table 2 shows the descriptive statistical results. It can be seen that the mean value of *Greeninnovation* of enterprises is 0.487 and the standard deviation is 0.890, indicating that there is little difference in the overall level of green innovation among companies. The mean credit rating (*Treat*) is 0.65, indicating that more than half of the sample is "A-level." In addition, the minimum value of Burden is −0.0194, the maximum value is 0.228, and the average value is 0.0338, which means that the average tax burden of the company in the sample is about 3.4%, while the existence of negative tax burden indicates that there is tax retention or rebate. The average value of *Greenexperience* is 0.214, indicating that about 20% of the CEOs have a green ecological experience.

5.2 Correlation analysis

According to the Pearson correlation coefficient matrix, it can be found that green innovation is positively correlated with the CEO's green ecological experience at the significance level of 1%, which preliminarily indicates that the CEO's green ecological experience has a significant promoting effect on green innovation. However, green innovation is positively correlated with the tax credit rating and the CEO's green ecological experience at the significance level of 1%. This preliminarily indicates that tax credit ratings have a significant positive effect on green innovation and green ecological experience, while tax burden and green innovation are negatively correlated at the significance level of 1%, indicating that tax burden has an adverse effect on green innovation. In addition, Size, LEV, Boardsize, and ROE of property rights are significantly positively correlated with *Greeninnovation*. It is worth mentioning that IDR, Cncon, and *Greeninnovation* have no statistical correlation between the proportion of independent directors and *Greeninnovation*. The relevant results are shown in Table 3.

5.3 Regression results

5.3.1 CEO's green ecological experience and green innovation

As shown in Table 4, column (1) is the result without adding control variables, column (2) is the result after adding control variables

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TABLE 3 Pearson correlation coefficient matrix.

	|Burden	Cncon	ROE	Size	Boards~	IDR	Treat	|Greene~	LEV	Greenin~
Burden	1									
Cncon	0.129***	1								
EquityNatu~	0.072***	0.224***	1							
Size	0.150***	0.191***	0.384***	1						
Boardsize	0.030***	0.012*	0.257***	0.271***	1					
IDR	0.00500	0.045***	−0.055***	−0.014**	−0.577***	1				
Treat	−0.080***	−0.00300	−0.098***	−0.0110	0.015**	−0.014*	1			
Greenexperience~	−0.00500	0.037***	0.00300	0.101***	0.034***	−0.026***	0.059***	1		
LEV	−0.047***	0.060***	0.293***	0.544***	0.149***	−0.013*	−0.094***	0.067***	1	
Greeninnovation~	−0.125***	0.00800	0.021***	0.196***	0.054***	0.00900	0.114***	0.567***	0.110***	1

Note: *, **, *** represent the significance levels of 10%, 5%, and 1% respectively.

TABLE 4 Regression results of CEO's green ecological experience and green innovation.

	(1)	(2)	(3)
Variable	Greeninnovation	Greeninnovation	Greeninnovation
Greenexperience	1.230***	1.200***	1.196***
	(0.0125)	(0.0123)	(0.0123)
Size		0.107***	0.107***
		(0.00499)	(0.00503)
LEV		−0.0120	−0.0145
		(0.0300)	(0.0301)
Cncon		−0.215***	−0.218***
		(0.0356)	(0.0356)
IDR		0.673***	0.675***
		(0.117)	(0.117)
Boardsize		0.120***	0.120***
		(0.0338)	(0.0338)
ROE		−0.0675***	−0.0669***
		(0.0120)	(0.0120)
Constant	0.224***	−2.544***	−2.552***
	(0.00577)	(0.129)	(0.129)
Year	No	No	Yes
Observations	20,585	20,585	20,585
R-squared	0.321	0.344	0.347

Note: *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively, and standard errors are in parentheses.

without the fixed year effect, and column (3) is the result after adding control variables with the fixed year effect. It can be found that the regression coefficients of the CEO's green ecological experience are 1.230, 1.200, and 1.196 successively, all of which are significant at the 1% significance level and the coefficients are positive. This shows that the CEO's green ecological experience can positively impact the corporate green innovation. According to column (3), the regression coefficient of *Greenexperience* in the case of controlling years is 1.196, which indicates that CEOs with green ecological experience enhance 230.69% ($e^{1.196}$-1) % on green innovation. According to the comparison between column (1), (2), and (3), after adding control variables, the regression coefficient of the

TABLE 5 Moderating effects of tax credit ratings on CEO's green ecological experience and green innovation.

Variable	(4) Greeninnovation	(5) Greeninnovation	(6) Greeninnovation
Greenexperience	1.109***	1.094***	1.090***
	(0.0223)	(0.0220)	(0.0219)
Treat*Greenexperience	0.161***	0.139***	0.138***
	(0.0268)	(0.0264)	(0.0264)
Treat	0.119***	0.124***	0.133***
	(0.0119)	(0.0118)	(0.0119)
Size		0.102***	0.104***
		(0.00497)	(0.00501)
LEV		0.0282	0.0235
		(0.0300)	(0.0300)
Cncon		−0.220***	−0.227***
		(0.0354)	(0.0354)
IDR		0.660***	0.659***
		(0.117)	(0.117)
Boardsize		0.105***	0.101***
		(0.0336)	(0.0337)
ROE		−0.0537***	−0.0538***
		(0.0120)	(0.0120)
Constant	0.148***	−2.510***	−2.523***
	(0.00949)	(0.128)	(0.128)
Year	No	No	Yes
Observations	20,585	20,585	20,585
R-squared	0.329	0.352	0.355

Note: *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively, and standard errors are in parentheses.

CEO's green ecological experience is still relatively stable, which can verify the validity of H1.

5.3.2 Moderating effect

5.3.2.1 The moderating effect of tax credit rating on the CEO's green ecological experience and corporate green innovation

The regression results are shown in Table 5. Column (4) shows the moderating effect of the tax credit rating on the CEO's green ecological experience and corporate green innovation without adding control variables, column (5) shows the results after adding control variables without the fixed year effect, and column (6) shows results after adding control variables with the fixed year effect. Regardless of whether control variables are added or fixed for the year effect, the regression coefficients of the CEO's green ecological experience are positive and significant at the 1% significance level, and the coefficients of interaction terms are also positive and significant at the 1% significance level. It can be found that the coefficients of the interaction terms are 0.161, 0.139, and 0.138, respectively, indicating that when the tax credit rating of the enterprise is "A-level," the tax credit rating of the enterprise will positively moderate the relationship between CEO's green ecological experience and corporate green innovation. The reasons may be as follows: first, tax administration is emphasized by many developing countries (Baker et al., 2021), and tax credit rating is one of the evaluating criteria for enterprises to comply with the regulation. "A-level" enterprises show adaptability to restrictions and constraints, using their own tax self-inspection system to regulate the process and effectively respond for taxable preferential policies (Guo, 2022). For this reason, it can enjoy the tax return by the Chinese tax department. Second, based on the CEO's improvement of corporate green innovation, "A-level" enterprises have comprehensive management mechanisms. By paying taxes on time, they have more standardized management mechanisms for using funds. The tax incentive and financing funds to "A-level" enterprises reduce the financial constraints and are conducive to the enterprise to invest sufficient capital into green innovation to achieve sustainable development (Guo, 2022; Wang et al., 2023a).

TABLE 6 Moderating effects of tax burden on CEO's green ecological experience and green innovation.

Variable	(7) Greeninnovation	(8) Greeninnovation	(9). Greeninnovation
Greenexperience	1.445***	1.410***	1.407***
	(0.0161)	(0.0158)	(0.0158)
Burden*Greenexperience	−6.438***	−6.493***	−6.500***
	(0.312)	(0.309)	(0.308)
Burden	−1.388***	−1.953***	−1.985***
	(0.148)	(0.149)	(0.149)
Size		0.131***	0.133***
		(0.00494)	(0.00499)
LEV		−0.134***	−0.141***
		(0.0296)	(0.0297)
Cncon		−0.129***	−0.134***
		(0.0348)	(0.0348)
IDR		0.523***	0.520***
		(0.109)	(0.109)
Boardsize		0.128***	0.124***
		(0.0328)	(0.0328)
ROE		−0.0937***	−0.0943***
		(0.0118)	(0.0118)
Constant	0.271***	−2.957***	−2.968***
	(0.00756)	(0.125)	(0.125)
Year	No	No	Yes
Observations	20,585	20,585	20,585
R-squared	0.350	0.378	0.381

Note: *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively, and standard errors are in parentheses.

5.3.2.2 The moderating effect of tax burden on the CEO's green ecological experience and corporate green innovation

Regression results are shown in Table 6. Column (7) shows the moderating effect of tax burden on the CEO's green ecological experience and corporate green innovation without adding control variables, column (8) shows the result after adding control variables without the fixed year effect, and column (9) shows the result after adding control variables with the fixed year effect. It is found that the coefficients of the CEO's green ecological experience are 1.445, 1.410, and 1.407, respectively, and all are statistically significant at the 1% level. In addition, the coefficients of the interaction Burden**Greenexperience* are −6.348, −6.493, and −6.500, respectively, which are all negative coefficients and are significant at the 1% significance level, indicating that tax burden negatively moderates the impacts of the CEO's green ecological experience on the enterprise's green innovation, which also verifies H3. For this reason, this study argues that first, innovation requires enterprises to dedicate abundant funds to support R&D continuously (Zeng et al., 2022). Tax burden inflicts financing pressure on the enterprises, which forces enterprises to consider economic benefits while ignoring the environmental conflicts caused by enterprises and thus ignoring the development of green innovation. Therefore, high tax burden will reversely moderate the impact of the CEO's green ecological experience on green innovation. Furthermore, tax burden will influence the cash flow of the enterprises as the result revenue of green innovation cannot directly offset the dedication (Voegtlin and Scherer, 2017). Although the cash flow can be obtained through loaning, financing, and other means, it undoubtedly increases the burden of enterprises. Moreover, although CEOs with green ecological experience have closed natural connection and may have a long-term vision of protecting the environment, they may still insist on the development of the enterprise as it is related to their performances. Therefore, under high tax burden, they may neglect the future environmental benefits and thus neglect the green innovation due to the high uncertainty and complexity of green innovation (Wang and Yu, 2021).

TABLE 7 Subsampled regression.

Variable	(10) Greeninnovation	(11) Greeninnovation	(12) Greeninnovation	(13) Greeninnovation
Greenexperience	1.091***	1.087***	1.393***	1.389***
	(0.0232)	(0.0232)	(0.0171)	(0.0171)
Treat*Greenexperience	0.116***	0.115***		
	(0.0280)	(0.0280)		
Treat	0.122***	0.129***		
	(0.0124)	(0.0125)		
Burden*Greenexperience			−6.618***	−6.631***
			(0.345)	(0.344)
Burden			−1.874***	−1.895***
			(0.163)	(0.163)
Size	0.0868***	0.0875***	0.114***	0.115***
	(0.00523)	(0.00527)	(0.00521)	(0.00526)
LEV	−0.00757	−0.0104	−0.137***	−0.142***
	(0.0316)	(0.0316)	(0.0310)	(0.0311)
Cncon	−0.273***	−0.278***	−0.184***	−0.189***
	(0.0374)	(0.0374)	(0.0368)	(0.0368)
IDR	0.819***	0.815***	0.704***	0.702***
	(0.117)	(0.116)	(0.114)	(0.114)
Boardsize	0.204***	0.201***	0.223***	0.221***
	(0.0352)	(0.0352)	(0.0346)	(0.0346)
ROE	−0.0207	−0.0200	−0.0673***	−0.0671***
	(0.0127)	(0.0127)	(0.0125)	(0.0125)
Constant	−2.426***	−2.440***	−2.846***	−2.860***
	(0.134)	(0.134)	(0.132)	(0.132)
Year	No	Yes	No	Yes
Observations	17,473	17,473	17,473	17,473
R-squared	0.349	0.352	0.374	0.377

Note: *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively, and standard errors are in parentheses.

5.4 Robustness test

To verify the reliability of the aforementioned regression results, this study adopts the selection of subsamples and endogeneity tests to carry out the robustness test.

5.4.1 Selected subsamples

As the tax burden is one of the factors influencing enterprise green innovation, the macro tax burden of Chinese industries presents a distribution structure of "the middle stream stands the largest percentage, and the upstream and downstream industries take a relatively small proportion." Based on the value chain theory, this study adopts the definition of the middle downstream industries of the value chain by Yao et al. (2022) and selects the upstream and downstream industries, respectively, according to different tax burden rates of the industries. The regression results are shown in Table 7.

It can be found that the coefficients of the CEO's green ecological experience in columns (10), (11), (12), and (13) are 1.091, 1.087, 1.393, and 1.389, respectively, all of which are significant at the significance level of 1%. This indicates that H1 is robust. In addition, the interaction term Treat**Greenexperience* coefficient in the following results is also significant at the significance level of 1%, and the coefficient is positive regardless of the fixed year effect, which also proves H2. Similarly, the coefficient of Burden**Greenexperience* is negative, which is significant at the significance level of 1%. This indicates that H3 is a robust result.

TABLE 8 Fixed individual effects results.

Variable	(14) Greeninnovation	(15) Greeninnovation	(16) Greeninnovation	(17) Greeninnovation
Greenexperience	0.627***	0.618***	0.756***	0.746***
	(0.0251)	(0.0248)	(0.0222)	(0.0219)
Treat*Greenexperience	0.0517*	0.0499*		
	(0.0271)	(0.0268)		
Treat	−0.00704	0.000100		
	(0.00900)	(0.00910)		
Burden*Greenexperience			−2.862***	−2.861***
			(0.365)	(0.361)
Burden			0.0424	−0.0398
			(0.162)	(0.162)
Size	0.0301***	0.0146	0.0340***	0.0205*
	(0.0112)	(0.0127)	(0.0109)	(0.0123)
LEV	−0.0168	0.0144	−0.0450	−0.0163
	(0.0434)	(0.0440)	(0.0428)	(0.0433)
Cncon	−0.160**	−0.133	−0.149*	−0.127
	(0.0802)	(0.0832)	(0.0795)	(0.0827)
IDR	0.177	0.166	0.127	0.117
	(0.196)	(0.197)	(0.195)	(0.196)
Boardsize	−0.0285	−0.0192	−0.0229	−0.0149
	(0.0606)	(0.0601)	(0.0601)	(0.0596)
ROE	−0.0609	−0.0412	−0.0790**	−0.0590
	(0.0386)	(0.0386)	(0.0389)	(0.0390)
Constant	−0.244	0.0256	−0.314	−0.0758
	(0.306)	(0.333)	(0.303)	(0.326)
Year	No	Yes	No	Yes
Id	Yes	Yes	Yes	Yes
Observations	20,585	20,585	20,585	20,585
R-squared	0.211	0.226	0.217	0.232

Note: *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively, and standard errors are in parentheses.

5.4.2 Endogeneity test

To solve the endogeneity problem caused by missing variables, this study adopts the fixed individual control effect to test the endogeneity. The regression results are shown in Table 8. Columns (15) and (17) used the fixed individual and year effect, while columns (14) and (16) used the fixed individual effect. In the four scenarios, the positive impact of the CEO's green ecological experience on green innovation is significant at the significance level of 1%, the interaction coefficient between the tax credit rating and CEO's green ecological experience is positive, and it is significant at the 10% significance level, while the interaction term between tax burden and CEO's green ecological experience is negative and significant at the 1% significance level, which indicates that there is no endogeneity problem caused by missing variables, and the result is still robust.

5.4.3 SYS-GMM method

This study uses SYS-GMM method proposed by Blundell and Bond (1998) to verify the results. Table 9 shows the SYS-GMM regression results. It is seen that the p-value of AR (1) in columns (18) and (19) are both below 0.1. The p-value of AR (2) is above 0.1, which means the disturbance terms are not correlated. Additionally, the p-values of Hansen test columns (18) and (19) are all above 0.1 and below 0.25. For this analysis, the results are valid. In column (19), Burden**Greenexperience* is significant at the significance level of 1%. In column (18), Treat is significant at the level of 5%. Treat**Greenexperience* and Burden are significant at the significance level of 10%. According to the regression results, it is seen as robust.

TABLE 9 SYS-GMM regression results.

	(18)	(19)
	Greeninnovation	Greeninnnovation
L.Greeninnovation	−0.202***	−0.150***
	(0.042)	(0.045)
Greenexperience	3.041***	3.491***
	(0.408)	(0.213)
Treat*Greenexperience	0.992*	
	(0.591)	
Treat	0.329**	
	(0.140)	
Burden*Greenexperience		−38.252***
		(3.692)
Burden		4.838*
		(2.693)
Size	−0.045	0.063
	(0.038)	(0.047)
LEV	0.056	−0.322
	(0.288)	(0.478)
Cncon	0.141	0.699
	(0.503)	(0.577)
IDR	−0.583	5.848*
	(3.993)	(3.427)
Boardsize	−0.470	2.136
	(0.973)	(1.306)
ROE	−0.038	−0.591***
	(0.104)	(0.219)
Constant	2.025	−8.107**
	(3.265)	(3.405)
Obs.	16623	16623
AR 1) (*p*-value)	0.000	0.000
AR 2) (*p*-value)	0.237	0.713
Hansen test (*p*-value)	0.182	0.130

Note: *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively, and standard errors are in parentheses.

6 Conclusion, implications, and limitations

6.1 Conclusion

This study takes the A-stock market enterprise from 2014 to 2020 as the research sample. From the perspective of green innovation, it explores whether the CEO's green ecological experience can positively affect green innovation and explores the moderating effect of tax credit rating and tax burden. The results show that the CEO's green ecological experience can improve corporate green innovation. The reason may be that the leadership characteristics of the CEO and the stronger affinity for nature lead enterprises to be more inclined to take measures to protect the environment (Hambrick and Mason, 1984; Evans et al., 2018; Deville et al., 2021). In addition, the "A-level" enterprises have high allowance and enjoy tax incentives to invest more in scientific research funds for corporate green innovation through effective financing means and reducing the cost of the corporate working capital (Sun and Lei, 2019; Guo, 2022; Sun, 2022). Because of that, tax credit ratings can positively moderate the relationship between the CEO's green ecological experience and green innovation. This result is put forward based on the fact that the tax credit rating is beneficial to corporate social reputation, enterprises' financing level, and cash-holding level (Sun and Lei, 2019; Guo, 2022). Furthermore, tax burden may reversely moderate the relationship between CEO's green ecological experience and green innovation. The reason is that tax burden causes financial restraints for enterprises as the revenue may be received in the long-term and cannot be directly return (Voegtlin and Scherer, 2017; Wang et al., 2023a). Due to the high complexity of green innovation, enterprises may take the green innovation decision into account seriously (Wang and Yu, 2021).

6.2 Implications

The implications of this study for the government and enterprises are as follows.

First of all, when the enterprises need to innovate the corresponding national green policies and global guidelines, CEOs with green ecological experience will create the affinity for the environment through the influence of CEOs on employees and implement long-term strategies to achieve sustainable development and improve the corporate image. Furthermore, enterprises should strengthen the awareness of green development, create a culture of environmental protection, and enhance the sense of closeness between employees and nature to achieve long-term and sustainable development of enterprises. Furthermore, enterprises should be fully aware of the role of taxes during the corporate operation. In the process of tax payment, enterprises should pay corporate tax in accordance with the formal procedures on time and in sufficient quantity to get an "A-level" tax credit rating so that they can improve their reputation and gain more external financing. By taking these actions, enterprises can invest more funds in green innovation to correspond to the national green policies, strengthen the corporate image globally, meet the global requirement, and achieve green and high-efficiency development. Additionally, CEOs with the ecological experience should effectively manage the process of tax payment. This is to increase the tax credit rating level and control a moderate tax burden for the enterprise. As the tax credit rating level rises and the tax burden is controlled, the enterprise enjoys more tax incentive and is willing to devote more funds for future R&D voluntarily. This will improve the corporate image and corporate social responsibility. Finally, the government needs to maintain a reasonable tax rate. On one hand, a reasonable tax burden rate is a sufficient condition for enterprises to maintain a high working capital. On the other hand, a reasonable tax burden rate is conducive to the long-term development of enterprises and conducive for enterprises to voluntarily undertake tax obligations. In addition, the government can increase the reward for green innovation patents and vigorously support enterprises to carry out green innovation while maintaining a reasonable tax burden rate, which provides incentives for enterprises and helps them use surplus funds for green innovation. Moreover, the government should carry out education and publicity on environmental protection so that enterprises can realize the benefits of green innovation and actively carry out R&D.

6.3 Limitations and further study

The limitations of this study are as follows: 1) corporate green innovation is composed of many aspects. This study uses the applied green patents as indicators, but it does not include all dimensions of green innovation, so it may need to be measured comprehensively. In the future, more comprehensive indicators can be used to measure green innovation. 2) This study only focuses on Chinese samples and fails to explore the developed countries and emerging entities; further research studies may be taken to test if the conclusions are suitable for those areas.

Data availability statement

The data analyzed in this study are subject to the following licenses/restrictions: Data will be availability on requirement. Requests to access these datasets should be directed to philipw3178@163.com.

Author contributions

All authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by YL, LW, and SL. The first draft of the manuscript was written by YL, and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript. More specific contribution details are as follows: YL: validation, resources, software, data curation, writing—original draft, formal analysis, review and editing, and visualization. LW: conceptualization, methodology, supervision, project administration, and writing—review and editing. SL: writing—review and editing, investigation, and visualization. VB: critical review, conceptualization, manuscript revisions, and language improvement.

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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References

Affes, W. (2020). The impact of tax rates on tax evasion: A macroeconomic study. *Account. Manag. Inf. Syst.* 19 (2), 252–282. doi:10.24818/jamis.2020.02003

Baker, S. R., Johnson, S. R., and Kueng, L. (2021). Shopping for lower sales tax rates. *Am. Econ. J. Macroecon.* 13 (3), 209–250. doi:10.1257/mac.20190026

Basri, M. C., Felix, M., Hanna, R., and Olken, B. A. (2021). Tax administration versus tax rates: Evidence from corporate taxation in Indonesia. *Am. Econ. Rev.* 111 (12), 3827–3871. doi:10.1257/aer.20201237

Blundell, R., and Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *J. Econ.* 87 (1), 115–143. doi:10.1016/S0304-4076(98)00009-8

Bucea-Manea-Tonis, R., Prokop, V., Ilic, D., Gurgu, E., Bucea-Manea-Tonis, R., Braicu, C., et al. (2021). The relationship between eco-innovation and smart working as support for sustainable management. *Sustain. (Basel, Switz.)* 13 (3), 1437. doi:10.3390/su13031437

Chen, C. (2016). China's industrial green total factor productivity and its determinants-an empirical study based on ML index and dynamic panel data model. *Stat. Res.* 33 (03), 53–62. doi:10.19343/j.cnki.11-1302/c.2016.03.007

Chen, L., Zhang, L., and Wang, H. (2022). Research on the influence of government subsidies on green innovation of new energy enterprises. *Friends Account.* 11, 150–157. doi:10.3969/j.issn.1004-5937.2022.11.022

Conefrey, T., and Fitz Gerald, J. D. (2011). The macro-economic impact of changing the rate of corporation tax. *Econ. Model.* 28 (3), 991–999. doi:10.1016/j.econmod.2010.11.009

Dai, H., and Liu, X. (2009). Some comments on research of environmental innovation. *Stud. Sci. Sci.* 27 (11), 1601–1610. doi:10.16192/j.cnki.1003-2053.2009.11.020

Demirel, P., and Kesidou, E. (2019). Sustainability-oriented capabilities for eco-innovation: Meeting the regulatory, technology, and market demands. *Bus. Strategy Environ.* 28 (5), 847–857. doi:10.1002/bse.2286

DeVille, N. V., Tomasso, L. P., Stoddard, O. P., Wilt, G. E., Horton, T. H., Wolf, K. L., et al. (2021). Time spent in nature is associated with increased pro-environmental attitudes and behaviors. *Int. J. Environ. Res. Public Health* 18 (14), 7498. doi:10.3390/ijerph18147498

Evans, G. W., Otto, S., and Kaiser, F. G. (2018). Childhood origins of young adult environmental behavior. *Psychol. Sci.* 29 (5), 679–687. doi:10.1177/0956797617741894

Ghisetti, C., and Rennings, K. (2014). Environmental innovations and profitability: How does it pay to be green? An empirical analysis on the German innovation survey. *J. Clean. Prod.* 75, 106–117. doi:10.1016/j.jclepro.2014.03.097

Grundmann, S., and Graf Lambsdorff, J. (2017). How income and tax rates provoke cheating – an experimental investigation of tax morale. *J. Econ. Psychol.* 63, 27–42. doi:10.1016/j.joep.2017.10.003

Guo, F., Gan, S., Yang, W., and Kuang, P. (2021). Are sales and taxes "sticky"? Empirical evidence of the impact of tax enforcement on tax revenue growth in China. *Appl. Econ. Lett.* 28 (8), 663–667. doi:10.1080/13504851.2020.1770675

Guo, L. (2022). The impact of tax credit rating on corporate tax burden. *J. Zhongnan Univ. Econ. Law* 01, 86–97. doi:10.19639/j.cnki.issn1003-5230.2022.0011

Hambrick, D. C., and Mason, P. A. (1984). Upper echelons: The organization as a reflection of its top managers. *Acad. Manag. Rev.* 9 (2), 193–206. doi:10.5465/amr.1984.4277628

Hart, S. L., and Dowell, G. (2011). Invited editorial: A natural-resource-based view of the firm. *J. Manag.* 37 (5), 1464–1479. doi:10.1177/0149206310390219

He, H., and Xiao, L. M. (2022). Tax reduction and fee reduction, green innovation and high-quality development -- based on the research of Chinese manufacturing enterprises. *Fujian Trib.* 02, 86–98.

Holmstrom, B. (1989). Agency costs and innovation. *J. Econ. Behav. Organ.* 12, 305–327. doi:10.1016/0167-2681(89)90025-5

Jensen, N. M. (2012). Fiscal policy and the firm: Do low corporate tax rates attract multinational corporations? *Comp. Polit. Stud.* 45 (8), 1004–1026. doi:10.1177/0010414011428594

Kindermann, F., and Krueger, D. (2022). High marginal tax rates on the top 1 percent? Lessons from a life-cycle model with idiosyncratic income risk. *Am. Econ. J. Macroecon.* 14 (2), 319–366. doi:10.1257/mac.20150170

Lai, X., and Zhan, W. (2021). The connotation and influencing factors of green technology innovation. *Sci. Technol. Industry* 21 (10), 320–327. doi:10.3969/j.issn.1671-1807.2021.10.054

Lee, Y., and Gordon, R. H. (2005). Tax structure and economic growth. *J. Public Econ.* 89 (5–6), 1027–1043. doi:10.1016/j.jpubeco.2004.07.002

Li, X. (2015). Analysis and outlook of the related researches on green innovation. *R&D Manag.* 27 (02), 1–11. doi:10.13581/j.cnki.rdm.2015.02.001

Liu, J., Liu, Y., and Liu, S. (2022a). The impact of functional background heterogeneity of senior management team on green innovation. *J. Nat. Sci. Hunan Normal Univ.* 12, 164. doi:10.3390/bs12060164

Liu, J., Zhang, C., and Tian, W. (2022b). Fintech, resource mismatch and urban green innovation. *J. Finance Econ.* 06, 68–78. doi:10.19622/j.cnki.cn36-1005/f.2022.06.008

Liu, Q., and Huang, J. (2018). How does firm taxation influence the resource allocation efficiency? *World Econ.* 41 (01), 78–100. doi:10.19985/j.cnki.cassjwe.2018.01.005

Lu, Q., and Li, Z. (2019). The "inverted U-shaped" curve relationship between the macro tax burden rate and economic growth: Based on the theoretical analysis and empirical research of the supply-side structural reform. *J. Guangxi Univ. Finance Econ.* 32 (01), 13–35.

Qi, S., Zhang, Q., and Wang, B. (2017). Market-oriented incentives to the innovation of new energy companies-evidence from venture capital and companies' patents. *China Ind. Econ.* 12, 95–112. doi:10.19581/j.cnki.ciejournal.20171214.009

Quan, X., Ke, Y., Qian, Y., and Zhang, Y. (2023). CEO foreign experience and green innovation: Evidence from China. *J. Bus. Ethics* 182 (2), 535–557. doi:10.1007/s10551-021-04977-z

Ren, X., Li, J., He, F., and Lucey, B. (2023a). Impact of climate policy uncertainty on traditional energy and green markets: Evidence from time-varying granger tests. *Renew. Sustain. Energy Rev.* 173, 113058. doi:10.1016/j.rser.2022.113058

Ren, X., Liu, Z., Jin, C., and Lin, R. (2023c). Oil price uncertainty and enterprise total factor productivity: Evidence from China. *Int. Rev. Econ. Finance* 83, 201–218. doi:10.1016/j.iref.2022.08.024

Ren, X., Zeng, G., and Gozgor, G. (2023b). How does digital finance affect industrial structure upgrading? Evidence from Chinese prefecture-level cities. *J. Environ. Manag.* 330, 117125. doi:10.1016/j.jenvman.2022.117125

Rennings, K., and Rammer, C. (2011). The impact of regulation-driven environmental innovation on innovation success and firm performance. *Industry Innovation* 18 (3), 255–283. doi:10.1080/13662716.2011.561027

Scarpellini, S., Valero-Gil, J., Moneva, J. M., and Andreaus, M. (2020). Environmental management capabilities for a "circular eco-innovation. *Bus. Strategy Environ.* 29 (5), 1850–1864. doi:10.1002/bse.2472

Shevlin, T., Shivakumar, L., and Urcan, O. (2019). Macroeconomic effects of corporate tax policy. *J. Account. Econ.* 68 (1), 101233. doi:10.1016/j.jacceco.2019.03.004

Sun, H., and Lei, G. (2019). The impact of tax-paying credit rating system on of enterprises technological innovation. *Public Finance Res.* 12, 87–101. doi:10.19477/j.cnki.11-1077/f.2019.12.008

Sun, R. (2022). Tax credit rating mechanism and level of excess cash holdings. *Mark. Manag. Rev.* 01, 151–153. doi:10.19932/j.cnki.22-1256/F.2022.01.151

Sun, X., Xiao, S., Ren, X., and Xu, B. (2023). Time-varying impact of information and communication technology on carbon emissions. *Energy Econ.* 118, 106492. doi:10.1016/j.eneco.2022.106492

Sun, X., Zhai, S., and Yu, S. (2019). Can flexible tax enforcement ease corporate financing constraints-evidence from a natural experiment on tax-paying credit rating disclosure. *China Ind. Econ.* 03, 81–99. doi:10.19581/j.cnki.ciejournal.2019.03.015

Sun, Y., Yu, H., and Sun, L. (2022). External financing and enterprise green technology innovation: Based on signaling effect of government subsidies. *J. Shandong Univ. Finance Econ.* (04), 101–110. doi:10.3969/j.issn.1008-2670.2022.04.010

Tian, H., and Pan, C. (2015). Study on the impact of corporate environmental ethics on green innovation performance. *J. Xi 'an Jiaot. Univ. Soc. Sci.* 35 (03), 32–39. doi:10.15896/j.xjtuskxb.201503005

Tullani, H., Saha, R., and Dahiya, R. (2018). Green innovation and ethical responsibility: Do they improve customer's green purchase intentions? *Int. J. Sustain. Entrepreneursh. Corp. Soc. Responsib.* 3 (1), 35–52. doi:10.4018/IJSECSR.2018010103

Voegtlin, C., and Scherer, A. G. (2017). Responsible innovation and the innovation of responsibility: Governing sustainable development in a globalized world. *IDEAS Work. Pap. Ser. RePEc* 143 (2), 227–243. doi:10.1007/s10551-015-2769-z

Walls, J. L., and Hoffman, A. J. (2013). Exceptional boards: Environmental experience and positive deviance from institutional norms. *J. Organ. Behav.* 34 (2), 253–271. doi:10.1002/job.1813

Wang, C., Chen, P., Hao, Y., and Dagestani, A. A. (2023a). Tax incentives and green innovation—the mediating role of financing constraints and the moderating role of subsidies. *Front. Environ. Sci.* 10. doi:10.3389/fenvs.2022.1067534

Wang, X., Li, J., Ren, X., Bu, R., and Jawadi, F. (2023b). Economic policy uncertainty and dynamic correlations in energy markets: Assessment and solutions. *Energy Econ.* 117, 106475. doi:10.1016/j.eneco.2022.106475

Wang, X., Qin, S., and Wang, K. (2014). The exploration of corporate green technology innovation drive green development. *J. Tech. Econ. Manag.* (08), 26–29. doi:10.3969/j.issn.1004-292X.2014.08.006

Wang, Y., and Yu, L. (2021). Can the current environmental tax rate promote green technology innovation? evidence from China's resource-based industries. *J. Clean. Prod.* 278, 123443. doi:10.1016/j.jclepro.2020.123443

Wang, Z., Fu, H., and Ren, X. (2022). The impact of political connections on firm pollution: New evidence based on heterogeneous environmental regulation. *Petroleum Sci.* In press. doi:10.1016/j.petsci.2022.10.019

Wolf, J. (2014). The relationship between sustainable supply chain management, stakeholder pressure and corporate sustainability performance. *J. Bus. Ethics* 119 (3), 317–328. doi:10.1007/s10551-012-1603-0

Xiao, Z., Zheng, G., and Cai, G. (2021). Tax burden of enterprise, investment squeezing and economic growth. *Account. Res.* 06, 19–29. doi:10.3969/j.issn.1003-2886.2021.06.002

Yousaf, Z., Radulescu, M., Sinisi, C., Nassani, A. A., and Haffar, M. (2022). How do firms achieve green innovation? Investigating the influential factors among the energy sector. *Energies (Basel)* 15 (7), 2549. doi:10.3390/en15072549

Zeng, C., Luo, M., and He, X. (2022). On executives' high-quality ecological environment experience and corporate green innovation. *J. Guangdong Univ. Finance Econ.* 37 (03), 82–97.

Zhang, N., Sun, J., and Wu, C. (2022). The impact of internal control on green innovation of environmental protection enterprises. *Commer. Account.* 01, 55–58. doi:10.3969/j.issn.1002-5812.2022.01.014

Zhang, S., and Shi, H. (2022). CEO's academic experience and firms' green technological innovation. *Sci. Technol. Manag. Res.* 42 (03), 135–144. doi:10.3969/j.issn.1000-7695.2022.3.017

Zhang, Y. (2021). Can ratepaying integrity promote firms' R&D investment Evidence from the disclosure of China's listed companies' rate paying credit rating. *J. Shanxi Univ. Finance Econ.* 43 (09), 70–85. doi:10.13781/j.cnki.1007-9556.2021.09.006

Zhu, C., Liu, R., and Wang, H. (2018). Green innovation performance evaluation and promotion path of patent intensive industries. *J. Quantitative Technol. Econ.* 35 (04), 61–79. doi:10.13653/j.cnki.jqte.2018.04.004

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Spatio-temporal evolution and influencing factors of coupling coordination between urban resilience and high-quality development in Yangtze River Delta Area, China

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The coordination relationship between urban resilience and high-quality development is of paramount importance for improving disaster-alleviated resilient governance and sustainable development in response to the globalized crisis. However, few studies have investigated the coupling between urban resilience and high-quality development. Therefore, based on the analysis of the coupling and coordination mechanism between urban resilience and high-quality development, this paper innovatively calculates the indicators of urban resilience and high-quality development of 41 cities in the Yangtze River Delta Area (YRDA) from 2005 to 2020. Moreover, we explore the spatiotemporal patterns, evolution characteristics of the coupling coordination degree (CCD) between urban resilience and high-quality development using the entropy method, coupling coordination model, kernel density estimation curve, and further analyze the influence factors with the spatial econometric models. The results revealed that urban resilience maintained a steady growth, while high-quality development displayed a trend of an initial increase and a subsequent decline. The coupling coordination degree continued to rise and the regional difference decreased conspicuously, manifesting a robust developing trend. From the perspective of spatial patterns, the coupling coordination degree, which was characterized by "being high in the east and low in the west, tended to be balanced in the north and south and was prominent in the middle of the distribution." Furthermore, economic strength, industrial structure, transportation facilities, and government intervention exerted a dominant influence on the development of coupling coordination degree, resulting in the spatial spillover effects as well. This study can reveal the interactive relationship between urban resilience and high-quality development can as well as help Yangtze River Delta Area provide a benchmark for promoting economic and social development while focusing on prevention and control of risk.

KEYWORDS

urban resilience, high-quality development, coupling coordination, spatio-temporal evolution, Yangtze River Delta Area

1 Introduction

The city, as is known to all, is not only a reflection of the progress of mankind civilization, but also significantly symbolizes the mankind existence. People reside in cities for an improved living standard, and they inhabit cities for refined life conditions. In other words, people build cities with a view to accomplishing the ideal of a better place to live in. China's urbanization, which is notable for a remarkable spurt of the economic growth and the urban population growth, has been accelerated tremendously since the Opening-up Policy carried out in 1978 (Fan et al., 2019). The recent years, however, witnesses that the deplorable consequences caused by the frenzied urbanization expansion has gradually mushroomed. The problems triggered by urbanization, such as overloading infrastructure (Fritz and Vollmer, 2006), severe energy waste (Li et al., 2023; Wang et al., 2023), water pollution (Zhang et al., 2021), greenhouse gas emission (Sun et al., 2023), soil contamination (Cui et al., 2022), and decline of public space (Dong et al., 2022), all of which have become increasingly prominent, results in frequently-occurring natural calamities and catastrophes oriented by mankind, both of which severely affect the personal safety and the quality of urban residents' living standards. According to relevant statistics, China is one of the countries which are the most severely-stricken by disasters (Liu et al., 2021). Over 112 million people in China were influenced tremendously by natural disasters and public safety emergencies, with 12,071.6 thousand hectares of crops being harshly affected and a devastating economic loss of 238.65 billion RMB last year (Xinhua News, 2023). "Being enormously vulnerable" has become a prominent problem which is not only against China's urban development, but also impedes the progress of the livelihood of urban residents. It is in this context that the Chinese government, for the first time at the Fifth Plenary Session of the 19th Central Committee, incorporates a systemic approach and the integration of development and safety into the national vital guiding principles which can be a guiding beacon for the national economic and social development during the stint of the 14th Five-Year Plan, evincing the relationship between the urban economic fantastic spurt and safety in the new era. Urban resilience and high-quality development, both of which are the paramount indicators for evaluating the urban safety governance capabilities and the comprehensive development levels, can provide effective support of decision-making information for the unceasing upgrading of urban residents' quality of life. It is, therefore, exceedingly urgent to develop the methods of keeping speedy growth both sustainably and accessibly, which could maintain the exuberant vitality, strength and glamour of the city through the coordinated development between urban resilience and high-quality development.

The term "resilience" was initially applied to the study of ecosystems by Holling (1973), who is renowned for putting forward the theory of "hierarchical structure and adaptive cycle" has further enriched the implication of sustainable development. Resilience theory is gradually being applied to the urban studies as the research proceeds. The original conception of urban resilience (Godschalk, 2003; Campanella, 2006), promotion pathway (Desouza and Flanery, 2013) and practical significance (Bahadur and Thornton, 2015) have been under discussion by a multitude of prestigious scholars. By combining and coordinating countless viewpoints, Meerow et al. (2016) originally put forward a revised concept, namely, urban resilience which is widely acclaimed, the concept being defined that "Urban resilience refers to the ability of an urban system, and that all its constituent socio-ecological and socio-technical networks across the temporal and spatial scales, and that it maintains or rapidly returns to the desired functions in the face of a tremendous disturbance so as to adapt to the remarkable changes and to quickly transform the systems which confine the current or future adaptive capacity." This definition renders us aware of the fact that urban resilience, which is dynamic and is filled with vitality and tension, is deeply embedded in humanistic care. It coincides with fundamental humanistic values and dynamic balancing of the spatio-temporal diversity pursued by high-quality development. The high-quality development proposed by the 19th National Congress of the Communist Party of China is a subject both ground-breaking and controversial, which gets many aspects involved, such as economic health, efficient and intensive resource utilization, and optimization of the environmental space. The theory emphasizes that people's sensation of gaining, satisfaction, and mirth can be enhanced with the rational allocation of the social wealth, via capturing the correlation between the supply and demand and via ameliorating the habitable environment (Wang and Feng, 2020; Gao, 2021). It accomplishes a shift from a focus on form to substance, liberating itself from blind trust and dogmatic dependence on irrational urbanization-orientation. More importantly, it is based on a self-conscious awareness of the contradiction of urban development, constantly adjusting the pace of urban development and constantly shaping the dynamic equilibrium. There is no doubt that this idea of dynamic properties of the systems is also indispensable for the construction of resilient cities. All in all, as an important proposition for promoting sustainable development and enhancing urban livability, urban resilience and high-quality development in the future will be the mainstream direction of urban planning.

Recent years witnesses that innumerable scholars have adopted numerous methods such as composite index method (Xun and Yuan, 2020; Jiang et al., 2021; Du et al., 2022; Li and Wang, 2023), gray correlation analysis (Yang et al., 2021) and fuzzy comprehensive evaluation (Sun et al., 2020) to assess the level of urban resilience and high-quality development, based on all of which, the measured levels are used as the target variables, and the panel regression models are constructed to analyse the strength of the influence of various factors upon them. These methods, which objectively broaden the multidimensional perspective of high-quality development and urban resilience analysis, cannot provide an accurate reflection of the interplay between the two systems. Indeed, urban resilience and high-quality development, being two similar but discrepant systems on the whole, not only have static similarities, but also have dynamic interactions. From a local perspective, the harmony and coherence between the various subsystems and elements within both systems is conducive to the quantitative and spatial optimization of urban resource allocation among diverse functions, thereby effectively addressing the diverse developing needs of urban subjects. Consequently, in the context of a comparatively slower domestic urbanization and the gradual emergence of hazardous disasters, examining the interplay between urban resilience and high-quality development can better assist us in accomplishing the goal of a more mirthful and a more harmonious life while stably striving for progress. Moreover, for the sake of China's large territory and imbalanced regional development (Zhang et al., 2022), there will also be some regional characteristics in the interaction between two systems. Thus, there is a need to compare the coupling and the coordination characteristics of regional urban resilience and high-quality development

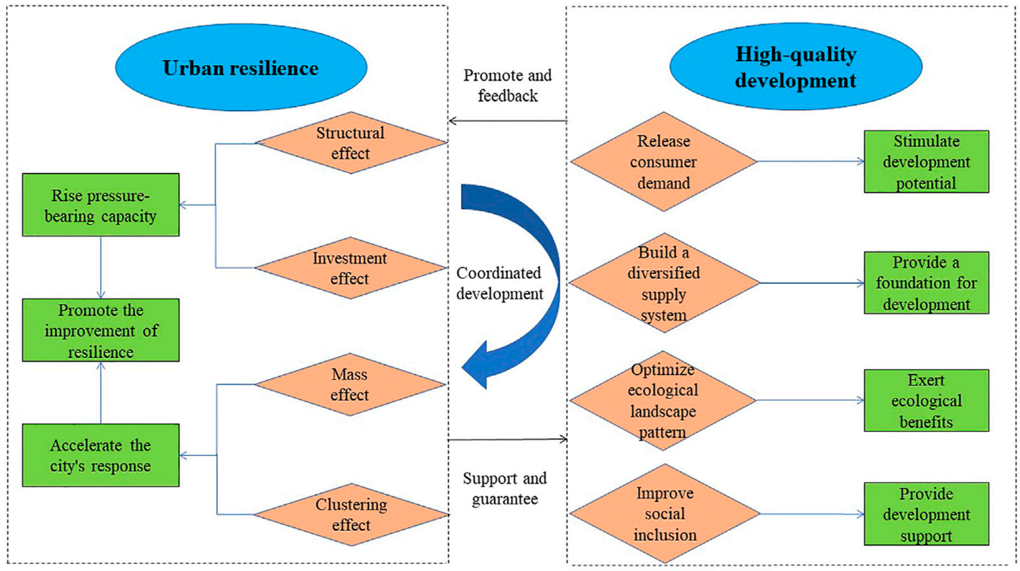

FIGURE 1
Mechanism analysis diagram.

from the multiple spatial and temporal scales. We choose YRDA as a case. On the one hand, the YRDA contributes almost one-quarter of China's total economic output with less than 4% of the country's land area, which is highly representative of the high-quality development process in China. On the other hand, as an area with the highest land-use intensity and the highest average rate of urbanization in China, the YRDA has made great sacrifices for China's development. It has become a high risk area for natural disasters in China and has been listed as the key object for public safety management as well as the prevention and control of ecological risks by the Chinese government. All in all, evaluating the overall synergistic effect between urban resilience and high-quality development in the YRDA and clarifying the driving factors which exert tremendous influence upon their coordinated development are urgent issues to be addressed now.

The rest of this paper is organized as follows, in the second section of which, the mechanism analysis, research methods and data sources are introduced and a comprehensive evaluation index system based on the connotation of urban resilience and high-quality development is constructed, and in the third section of which, we give a brief description of the empirical results, and in the fourth section of which, we discuss the empirical results in the context of the new era, finally summarizes the chief conclusions and discloses the demerits of the research.

2 Materials and methods

2.1 Mechanism analysis

Urban resilience and high-quality development are closely coupled and interactively coordinated (Figure 1). Here is the specific analysis:

Urban resilience, on the one hand, spans a number of dimensions horizontally, which include economic empowerment, social development, ecological governance, and infrastructure integration, and on the other hand, urban resilience vertically becomes the major axis linking regional integration and urban agglomeration development (Shamsuddin, 2020). It is an important guaranteeing factor for promoting high-quality development. First and foremost, improving economic resilience motivates high-quality development from the demand and supply levels. On the demand side, given that the macro economy is risky and uncertain (Wen et al., 2022), it is likely to increase the consumption concerns of the public. The improvement of economic resilience will help to eliminate the concerns of urban dwellers who dare to consume, and to further release consumers' demand to stimulate the high-quality development potential. When it comes to the aspect of supply, economic resilience advocates establishing a diversified supply chain to deal with the risks and capricious uncertainties of the economic development process, in the view of which, expanding the construction of a modern industrial system with the coordinated development of realistic economy, technological innovation, modern finance, and human resources can provide a solid foundation for high-quality development. Secondly, ecological resilience ensures the species diversity in the ecosystem and urban green space ratio by optimizing city's ecological landscape configuration, strengthens the self-purifying capacity of urban ecological environment, and then exerts ecological benefits in consolidating the green foundation for high-quality development. Finally, the increase in the level of social and engineering resilience is often accompanied by an increase in the level of the inclusion of transport, healthcare and communications. It facilitates the renewal and iteration of engineering and urban management systems, which in turn enhances the management of urban material stocks and enhances social welfare, so as to provide strong external support for the high-quality development.

High-quality development can enhance the city's overall capacity for fine-grained governance and create a more resilient and secure city. On the one hand, in order to bring off the goal of high-quality development, the government will set as the first

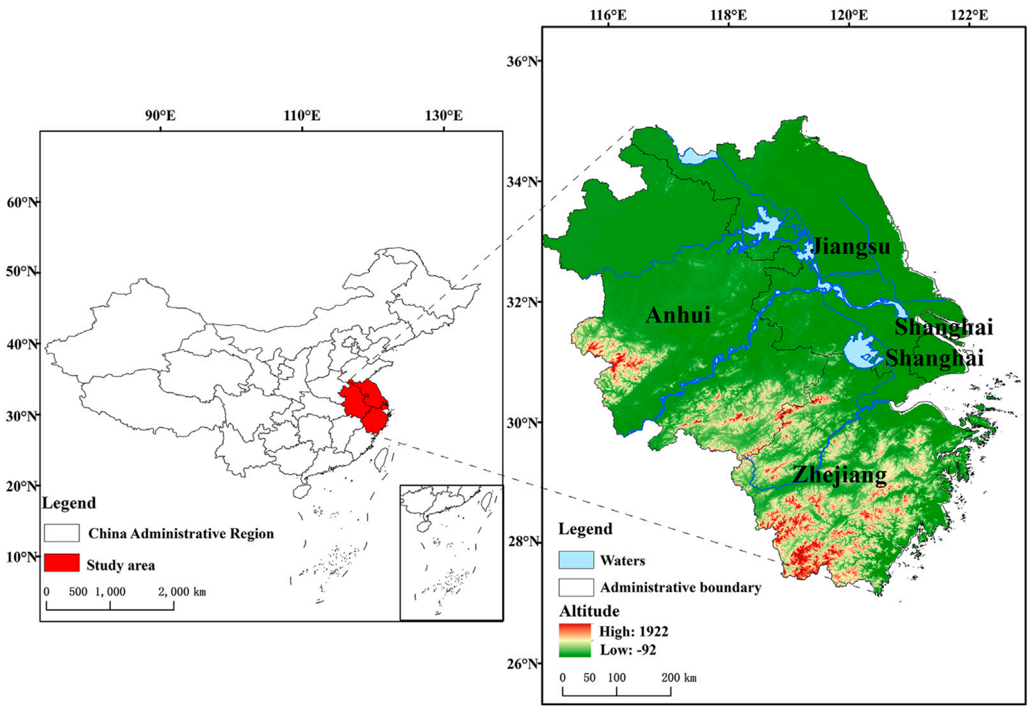

FIGURE 2
The study area.

priority meeting the relevant needs of industries with high productivity, low pollution, low energy consumption, and innovative industries, which constantly eliminates the backward industries with low unit output efficiency, so as to make room for the development of advantageous projects and high-quality enterprises. In the view of the condition above, the investment by high-quality firms and the upgrading of industrial structures will actively promote the improvement of infrastructure and increase public service supply, thus improving the city's pressure-bearing capacity and effectively promoting the improvement of resilience. On the other hand, under the requirement of high-quality development, the local governments will allocate more output revenue to the R&D and to the promotion of livelihood projects such as healthcare, social security and risk management, and guide the entire society to concentrate on good urban governance and planning through mass effect. Meanwhile, implementing policies such as "Low-carbon City Pilot," "Smart City Pilot" and "Innovation City Pilot," require strengthening the building of innovative talent and high-tech research (Gao and Yuan, 2022), which further promotes the concentration of talents and advanced technology, and ultimately accelerates the city's response to the crisis along with generating a positive feedback on the construction of urban resilience.

2.2 Selection of study area

The YRDA, which is nested in the alluvial plain in the lower reaches of the Yangtze River basin and borders upon the Yellow Sea and the East Sea with numerous ports, is a major intersection of the Belt and the Road Initiative as well as the Yangtze River Economic Belt. According to the "Outline of the Yangtze River Delta Regional Integrated Development Plan" officially issued by the State Council in December 2019, its scope was defined as the entire region of Jiangsu, Zhejiang, Anhui, and Shanghai (Figure 2), and it was clearly pointed out as a model area for high-quality development in China. Natural disasters such as inexpressibly devastating floods and formidably surging storms, however, frequently harasses the YRDA because of the influence of the natural geographic conditions and the properties of the underlying surfaces. Human activities and changes in land utilization will also further increase the risk of potential urban hazardous danger in the area, and therefore, it will be a remarkably significant strategic task for the YRDA to place the building of urban resilience on the agenda as an important part of new urban construction and the key urban regeneration project in order to strengthen the coordination of security and development, so that we can finally accomplish high-quality development from diverse perspectives, including natural environment, population society, and economic policy, *etc.*

2.3 Data sources

The relevant data, which were derived from the China Statistical Yearbook, the China Urban Statistical Yearbook, the provincial and municipal statistical yearbooks and their statistical bulletins, were adopted to estimate the composite value of urban resilience and high-quality development in the YRDA in the stint of 2005–2020, with the basis of the updated, continuous, reliable and accessible nature of the data.

TABLE 1 Classification standard of the CCD.

Coordination degree	Coordination level	Coordination degree	Coordination level
$D \le 0.25$	Serious imbalance	$0.55 < D \le 0.65$	Barely coordination
$0.25 < D \le 0.45$	Moderate imbalance	$0.65 < D \le 0.8$	Basic coordination
$0.45 < D \le 0.55$	Slight imbalance	$0.8 < D \le 1.0$	Good coordination

TABLE 2 Weight matrix description.

Spatial weight matrix	Meaning	Formula	Explanation
Geospatial weight matrix w_1	Geographical distance between cities	$w_1 = \frac{1}{d_{ij}}$	d_{ij} represents the longitude and latitude distance between city i and city j
Economic weight matrix w_2	Economic disparities between cities	$w_2 = \frac{1}{\lvert p_i - p_j \rvert}$	P_i and P_j represent the average of real
			GDP per capital between city i and city j over the sample
Weight matrix of economic geographic space w_3	Geographic distance and economic distance of each city	$w_3 = w_1 * w_2$	Product of geospatial matrix and economic matrix

2.4 Research methods

2.4.1 Entropy method

With a view to making the data comparable, this study adopted the extreme value method of standardizing each index, so that the value for each indicator is in the range from 0 to 1, based on which, the entropy value method was used to compute the weight of urban resilience and high-quality development indicators, so as to make one strife reasonable and scientific in the weighting results (Li et al., 2022). The formulae are as follows:

Standardization of positive indicators:

$$X'_{ij} = \frac{X_{ij} - \min X_{ij}}{\max X_{ij} - \min X_{ij}} \tag{1}$$

Standardization of negative indicators:

$$X'_{ij} = \frac{\max X_{ij} - X_{ij}}{\max X_{ij} - \min X_{ij}} \tag{2}$$

where X_{ij} refers to the original value of j th indicator in city i; $\max X_{ij}$ is the maximum value among all cities in all years; $\min X_{ij}$ is the minimum value among all cities in all years; X'_{ij} is the standardized value of j th indicator in city i and X'_{ij} is still denoted as X_{ij} in this study for convenience.

Calculation of the ratio:

$$p_{ij} = \frac{X_{ij}}{\sum_{i=1}^{n} X_{ij}} \tag{3}$$

Calculation of the entropy:

$$e_j = -\frac{1}{\ln(n)} \sum_{i=1}^{n} p_{ij} \ln(p_{ij}) \tag{4}$$

Calculation of the redundancy of the entropy value of each index:

$$g_j = 1 - e_j \tag{5}$$

Calculation of the weight:

$$w_j = \frac{g_j}{\sum_{i=1}^{m} g_j} \tag{6}$$

Calculation of the comprehensive score:

$$s_{ij} = \sum_{i=1}^{m} w_j * X_{ij} \tag{7}$$

2.4.2 Coupling coordination model

The coupling coordination model can not only be wielded to display the coherence of coordinated evolution between urban resilience and high-quality development, but also can reflect the overall efficiency and synergism of the interactive development of both systems. Correspondingly, this study built a model of coupling coordination to evaluate the relative level of development of the two systems and their coordination status. The equations are as follows (Yang et al., 2020):

$$C = 2\sqrt{\frac{U_1 U_2}{(U_1 + U_2)^2}} \tag{8}$$

$$T = \alpha U_1 + \beta U_2 \tag{9}$$

$$D = \sqrt{C * T} \tag{10}$$

where U_1 and U_2 are the composite values of urban resilience and high-quality development respectively; C refers to the coupling degree of urban resilience and high-quality development and ranges from 0 to 1. Larger values indicate better interaction of the two system elements; T denotes the coordination degree of urban resilience and high-quality development; α and β are the contribution rate of urban resilience and high-quality development, and in general, $\alpha + \beta = 1$, since the importance of urban resilience is equivalent to that of high-quality development, all values being taken as 0.5; D is the coupling coordination degree between urban resilience and high-quality development, with the value range being within $[0, 1]$.

In order to visually describe the coupling coordination between the two systems, the CCD was divided into the following grades according to the research results of Liu et al. (2018) (Table 1).

2.4.3 Non-parametric kernel density estimation curve

The non-parametric kernel density estimation is a method adopted to estimate probability density functions with continuous density curves in order to depict the distributional pattern of random variables, resulting in an improved continuity of the estimation results compared to histograms. Therefore, we adopted the kernel density estimation curve to display the distribution structure, locating and extending the CCD between urban resilience and high-quality development, so as to reveal its temporal evolution features. The formula is as follows (Deng et al., 2022):

$$f(x) = \frac{1}{nh}\sum_{i=1}^{n} k\left(\frac{x_{\mathrm{i}} - x}{h}\right) \tag{11}$$

in which h is the bandwidth; n is the total number of quantiles; k is a non-negative kernel function; and $f(x)$ is a probability density function estimation of the coupling degree between urban resilience and high-quality development.

2.4.4 Trend surface analysis

The purpose of this study is to use the trend surface method to analyze the overall diverging trends in CCD between urban resilience and high-quality development in the YRDA, which can map a mathematical surface across spatial data to illustrate spatial trends and patterns in the distribution of observed geographic factor values over a wide spatial range (Wang and Zuo, 2015). Suppose that $Z_i(x_i, y_i)$ is the real observation value of the i th geographic element, that $T_i(x_i, y_i)$ is the trend surface fitting value, that the X-axis represents the east-west direction, and that the Y-axis represents the north-south orientation. Then, there is the following calculation formula:

$$Z_i(x_i, y_i) = T_i(x_i, y_i) + \varepsilon_i \tag{12}$$

where (x_i, y_i) is the geographic coordinate; ε_i refers to the residual, which is the deviation between the true value and the fitted value.

2.4.5 Spatial autocorrelation

The spatial autocorrelation effect refers to the mutual influence of variables from different cities (Ren et al., 2023). This study used $Moran's\,I$ to measure the spatial agglomeration characteristics of the CCD between urban resilience and high-quality development in the YRDA, which is calculated as (Huo et al., 2022):

$$Moran's\,I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(X_i - \bar{x})(X_j - \bar{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(\mathrm{x}_i - \bar{x})^2} \tag{13}$$

where X_i and X_j represent the CCD in study unit i and study unit j respectively; w_{ij} is the spatial weight matrix.

The spatially dependent and heterogeneous characteristics of CCD can be further identified by I_i, which is calculated as:

$$I_i = z_i^{'}\sum w_{ij} z_j^{'} \tag{14}$$

where $z_i^{'}$ and $z_j^{'}$ are normalized observations and the other variables have the same meaning as in the equation above.

2.4.6 The spatial durbin model

Some of the cities in the YRDA, which boast resources and conditions of development which are quite similar to one another, tend to form "Convergence club" as a result. Moreover, affected by the shared culture of the area, the development patterns and pathways of adjacent areas have something in common, namely, policy-borrowing occuring from time to time. The co-evolution of urban resilience and high-quality development is thus likely to have spatial correlations, and on the basis of which, this paper considered the use of SDM incorporating spatial effects to relate geographical location to statistical parameters, in order to more efficiently estimate the spatial effects of each region on the surrounding areas, and simultaneously, this makes the estimation result more similar to the true situation (Baltagi and Li, 2006). The formula is as follows:

$$Y_{it} = C + \rho\sum w_{ij}Y_{it} + \beta X_{it} + \delta\sum w_{ij}X_{it} + \mu_i + \theta_t + \varepsilon_{it} \tag{15}$$

where Y_{it} is the explained variable, namely, the CCD of two systems; C refers to the constant term; X_{it} represents the explanatory variable; β is the coefficient of regression for explanatory variables; ρ and δ correspond to the spatial lag coefficients of the strain variables respectively; μ_i and θ_t represent spatial and temporal fixed effects respectively; w_{ij} is the spatial weight matrix, and on the basis of Li et al. (2022) study, the economic geographic weight matrix is constructed by considering the spatial effects of economy and geography, so that it can more accurately reflect the correlation and heterogeneity among different municipalities. The specific construction method is revealed in Table 2.

2.5 The construction of the indicator system

Urban resilience and high-quality development are multi-faceted, and therefore a single indicator cannot elaborately describe the relevant features of urban systems. A comprehensive assessment index system can reflect multidimensional features of them, making measurement outcomes more scientific. This paper thus constructed a comprehensive assessment index system from multiple levels to evaluate the level of resilience and high-quality development of the urban system.

2.5.1 Selection of urban resilience evaluation index

The index system is based on the existing research findings and is built from four dimensions, namely, the dimensions of being economic, social, ecological, and engineering of urban resilience (Chen et al., 2021; Shi et al., 2021). Firstly, economic resilience refers primarily to the stability, adjustment, and recovery capacity of the regional economic system following external shocks (Martin and Sunley, 2015), which can be reflected from the economic strength, economic diversity, and investment intensity, namely, the three aspects of the respective indicators. Secondly, social resilience is the ability to rely on the power of the social structure to accomplish the effective integration of diverse resources in the society when it encounters destructive shocks, so as to re-establish a balanced state

(Reuter and Spielhofer, 2017). It can be generally expressed in terms of three indicators: adaptability of the population, residents' income and social security. Thirdly, ecological resilience manifests itself primarily in the fact that urban ecosystems can still maintain their primary functions in the face of environmental pressures such as human activities and industrial pollution emission (Chen et al., 2020). They are an indispensable and remarkably important component of the urban system, which can be reflected in the pressure of the ecological environment, ecological environment service capacity and restoration capacity. Finally, engineering resilience is an important criterion by which we can judge whether the construction of urban infrastructure can effectively withstand various sudden risks and abrupt crises (Ranasinghe et al., 2020). The degree of perfection in the construction of transportation and communications can reflect the city's emergency coverage and external assistance capabilities in the crisis situations, both of which are important parameters of the resilience of engineers. At the same time, coupled with the frequent occurrence of flooding in the YRDA (Sun et al., 2020), we added indicators of urban drainage projects into the assessment system.

2.5.2 Selection of high-quality development evaluation index

The assessment of a city's level of high-quality development should not be assessed solely in terms of GDP growth rates. High-quality development is, in effect, a development that resolves the major contradictions in the current society and meets people's pursuit of quality. It takes innovation as its primary driving force, being environmentally-friendly as a universal form, sharing as a fundamental goal, and focuses on the development of opening up and intercommunication as well as social harmony (Liu et al., 2020). Therefore, this paper combined the connotation of high-quality development and referred to relevant literature (Sun et al., 2022) to construct a high-quality development evaluation index system from the five dimensions of "innovation driven—coordinated progress—environmentally-friendly development—opening up—sharing harmony," which is a complete reflection of the people's high quality needs for economic and social development.

Innovation driven refers to improving the output rate of production factors through technological change, relying on the creation of knowledge and scientific research and development to promote overall effectiveness, which is a vital driving force and engine for accomplishing high-quality development. Among the indicators selected, the sharing of science and technology expenditure in local fiscal expenditure is an important indicator for measuring innovation investment. The higher the proportion is, the greater the depth of local government's emphasis on innovation is and the greater the support is. By wielding a proportion of invention patents granted to the number of patent grants as a proxy for measuring regional innovation output, the overall development of regional innovation can be revealed. A key link in bringing science and technology together with economics is the transformation of scientific and technological achievements, which is typically characterized by the total industrial output value above scale in GDP.

Regional co-ordination is conducive to the narrowing of the policy unit, which thereby promotes the integration of science and technology with economic and social reforms and enhances policy relevance along with laying a solid foundation for high-quality development (Li and Yi, 2020). Coordinated progress, which involves the coordination between man and land, the supply and demand, as well as the gap between the rich and the poor, is an important reflection of the multidimensional and ordered development. Depending on the indicators chosen, per capital revenues may reflect government's regulation of the gap between rich and poor to some degree. The rate of urbanization can better reflect the coordinated development of population and building land, which is computed by the ratio of the permanent population to the total population. Streamlining the structure of consumption can fully boost the vitality of urban domestic demand, which is an important symbol of the coordination of supply and demand, characterized by the proportion of total retail sales of social consumer goods in GDP.

The environmentally-friendly development is an important precondition for high-quality development. Any development must comply with the law of nature, which is an integral premise, particularly by tracking ecological thresholds or ecological boundaries that objectively exists in nature (Martin et al., 2016). Since reducing pollution emission is one of the requirements for environmentally-friendly development, the choice of amount of the gas, SO_2 which is produced per unit of GDP, is regarded as an indicator for assessing the low-carbon cycle, and can reflect the environmental cost derived from local development. The electricity consumption per unit of GDP, which reflects the efficiency of resource utilization and the high consumption together with the product inefficiency of production, is an integral indicator for guiding the creation of a resource-conserving society. Moreover, in the practice of adhering to and refining the ecologically-civilized system, the capacity of ecological and environmental governance, which is expressed through the general industrial solid waste comprehensive utilization rate, needs to be continually improved.

The opening-up policy, a core national policy which China clings to in the phase of high-quality development, can contribute to the in-depth integration of national and global development. Among all the selected parameters, the ratio of tourism foreign exchange income to GDP, which reflects the extent of competitiveness of international trade in tourism service, can serve as an indispensable indicator of the degree of opening up to the outside world. The extent of foreign investment dependence reflects the degree of involvement in international trade and its impact on the regional economic growth, whereas the realistic amount of foreign investment per capital reflects the attractiveness of foreign regional capital.

High-quality development aims to elevate the level of social wellbeing, so as to entitle people to share the fruits of development and to improve their living standard. Consequently, we select the parameters from the perspective of three aspects, namely, fluctuation in employment, public transportation, and cultural sharing for evaluating the smooth effect of shared harmony. Table 3 displays all metrics and their measuring standards.

3 Result analysis

3.1 The level of urban resilience and high-quality development

Based on the evaluation index system, the comprehensive values of urban resilience and high-quality development during the stint of

TABLE 3 Evaluation index system of urban resilience and high-quality development.

Layer of target	Criterion level	Index level	Standard of measurements	Units	Attribute
Urban resilience	Economic resilience	Economic Strength	GDP per capital	yuan/person	+
		Economic diversity	Proportion of tertiary industry output in GDP	%	+
		Investment intensity	Investment in fixed assets per capital	yuan/person	+
	Social resilience	Population adaptability	Natural growth rate of population	%	+
		Residents' income	Average wage of active employees	yuan	+
		Social Security	Number of beds in medical and health institutions	sheet	+
	Ecological resilience	Environmental pressure	Industrial wastewater emissions	million ton	-
		Environmental Restoration Capability	Harmless disposal rate of domestic waste	%	+
		Environmental Service Capability	Green space per capital	m^2/person	+
	Engineering resilience	Transportation Construction	Urban road area per capital	m^2/person	+
		Construction of drainage projects	Density of drainage pipes in built-up areas	km/km^3	+
		Communication Construction	Number of Internet users	million door	+
High-quality development	Innovation driven	Innovation investment	Share of science and technology expenditure in local fiscal expenditure	%	+
		Innovation output	Proportion of the number of invention patents granted to the number of patent grants	%	+
		Innovation results	Total industrial output value above scale in GDP	%	+
	Coordinated progress	Level of financial coordination	Per capital revenue	yuan/person	+
		Level of human-land coordination	Urbanization rate	%	+
		Consumption structure	Proportion of total retail sales of social consumer goods in GDP	%	+
	Environmentally-friendly development	Environmental Costs	Amount of SO2 produced per unit of GDP	ton/10,000 yuan	-
		Resource Utilization	Electricity consumption per unit of GDP	kwh/yuan	-
		Environmental governance	General industrial solid waste comprehensive utilization rate	%	+
	Opening degree	Competitiveness of international trade in tourism services	Ratio of Tourism Foreign Exchange Income to GDP	%	+
		Foreign investment dependence	Proportion of total import and export to GDP	%	+
		Foreign regional capital	The realistic amount of foreign investment per capital	dollar/person	+
	Sharing harmony	Fluctuation in employment	Rate of unemployment	%	-
		Public Transportation	Number of buses per 10,000 people	vehicle/ 10,000 people	+
		Level of cultural sharing	Number of books in public libraries per 10,000 people	volume/ 10,000 people	+

2005–2020 are calculated by the entropy method (Table 4). At the same time, the mean values of urban resilience and high-quality development during the stint of 2005–2020 are also divided into low, middle and high levels by adopting the natural break point method in Arcgis to explore their spatial pattern of distribution, which is manifested in Figure 3.

TABLE 4 Comprehensive values of urban resilience and high-quality development.

Year	Urban resilience	High-quality development
2005	0.128	0.115
2006	0.118	0.125
2007	0.134	0.140
2008	0.147	0.150
2009	0.180	0.155
2010	0.192	0.158
2011	0.209	0.164
2012	0.229	0.178
2013	0.253	0.179
2014	0.268	0.183
2015	0.286	0.196
2016	0.310	0.212
2017	0.326	0.207
2018	0.340	0.202
2019	0.364	0.210
2020	0.390	0.198

3.1.1 Analysis of urban resilience

As is disclosed in Table 4, the composite resilience value of the YDAR increased over the studied period from the nadir of 0.128 in 2005 to the acme of 0.390 in 2020, which displayed a comparatively good pattern of development. In combination with Figure 3, there are five cities with a high degree of resilience in the YRDA, namely, Shanghai, Suzhou, Nanjing, Wuxi, and Hangzhou, with the mean values being 0.520, 0.413, 0.360, 0.383, and 0.377, respectively. On the contrary, cities with a low resilience level mainly display a continuous development trend in the west of the YRDA, such as Bozhou, Fuyang, Anqing, and Chizhou, all of which are nested in Anhui Province. Furthermore, the YRDA has the largest number of medium-level cities, which account for nearly 50% of the entire number and are mainly nested in the central region as well as the eastern coastal region, namely, the province of Jiangsu and Zhejiang. In a brief, the level of resilience of the cities in the YRDA exhibits a spatial pattern of "being highest in the east, comparatively lower in the middle, and the lowest in the west."

3.1.2 Analysis of high-quality development

The stint of 2005–2020 witnessed that the level of high-quality development in the YRDA presented a changing characteristics of a reversely-written "U" type, and in other words, it continued to rise from 0.115 to 0.212 during the period of 2005–2016, reaching its summit. After 2017, it displayed a rebound trend, slowly falling back to 0.198, which is mainly attributed to the fact that the intensification and the escalation of the Sino-US trade contradiction in August 2017 has exerted an enormous impact on the development of international trade and technological innovation between the two countries. In addition, the dissemination of the COVID-19 epidemic in 2020 has also inhibited the process of high-quality development.

As is conspicuously debunked in Figure 3, there are exceedingly significant regional differences in the level of high-quality development in the YRDA, which gradually form the spatial features of "being high in the south, and low in the north, with being prominent in the middle of the range." Specifically speaking, the high-level cities are primarily the provincial capitals and their surrounding cities, three cases of which are Shanghai, Nanjing, and Hangzhou. The elaborate analysis above indicates that the provincial capitals with their prominently advantageous positions as the corresponding centers which are paramount politically, economically, culturally, scientifically, and educationally, can provide an inexpressible impetus for high-quality development

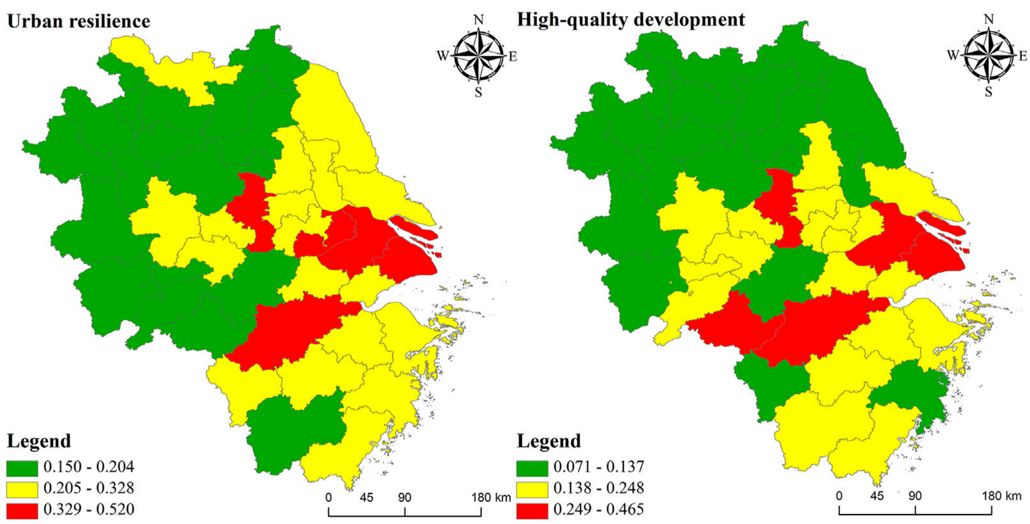

FIGURE 3
Spatial distribution of urban resilience and high-quality development.

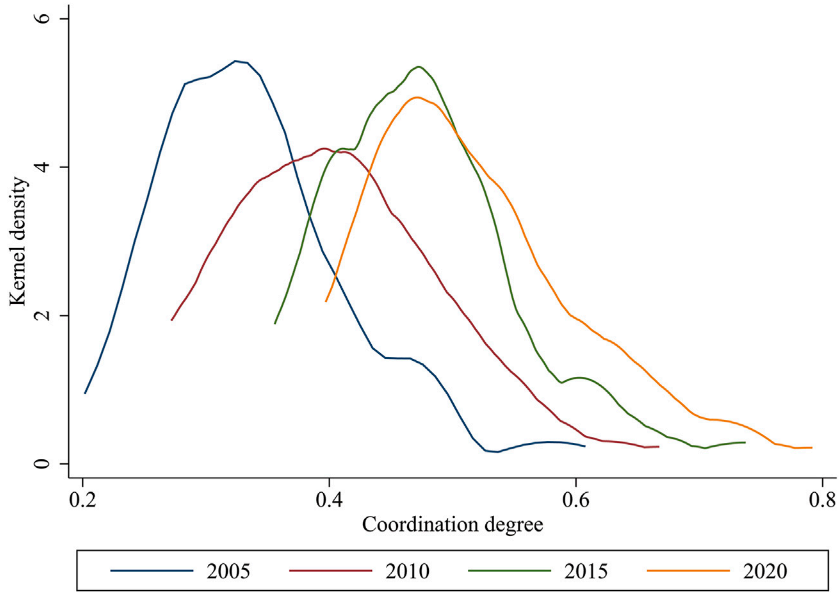

FIGURE 4
Kernel density curve of CCD.

and are capable of, to some degree, propelling the development of surrounding cities. The medium-level cities are mainly located in the southern and central parts of the YRDA, and are clustered around the high-level metropolises, displaying a clear proximity. By contrast, the northern region has a conspicuous gap with the southern and central regions in terms of resource abundance, locating conditions and national policy support, resulting in the fact that the high-quality development level of the northern region will be comparatively low and the low-level cities mostly gathered here.

3.2 The coupling and coordination relationship between urban resilience and high-quality development

3.2.1 Temporal characteristics of the CCD

Figure 4 vividly expatiates the characteristics of the temporal dynamic evolution of the CCD between urban resilience and high-quality development in the YRDA. It can be conspicuously disclosed that the kernel density function of the CCD is a single-peak distribution shape and the height of the peak decreases significantly in the time periods excluding the stint of 2010–2015 during which there is a slight increase. Furthermore, the stint of 2005–2020 witnesses that the centre of gravity of the core density curve continues to shift to the right, and the right tail is larger than the left tail, which displays a tendency to become longer and thicker year by year, which reflects that the CCD between urban resilience and high-quality development in the YRDA has a single polarization phenomenon, with the CCD exhibiting an overall rising evolution feature and a gradually-balanced trend.

3.2.2 Spatial differentiation characteristics of CCD

The spatial distribution map of the CCD between urban resilience and high-quality development, which is based on the relevant data pertaining to four stints, is drawn with adopting the Arcgis.

Figure 5 vividly illustrates that the CCD between urban resilience and high-quality development in 41 cities nested in the YRDA is on the rise. Coordination types are mostly moderate imbalanc, slight imbalanc and barely coordination, whereas a good coordination does not appear. Specifically speaking, the year of 2005 witnesses that there were mainly numerous moderately-imbalanced cities and a scattered distribution of seriously-imbalanced and slightly-imbalanced cities, with the exception that exclusively one city, Shanghai, was barely coordinated. By 2010, cities with serious imbalance perished, and the proportion of cities with a slight imbalance increased to 22%, with the development of clusters in the central-eastern part of the YRDA and the emergence of basic coordination city. In 2015, the number of moderately-imbalanced cities continued to decline to exclusively 18, while the number of the slightly-imbalanced cities spurt to 17, both of whose numbers gradually converge with an increase in the number of basic coordination cities. The year of 2020 was regaled with the phenomenon that there was an obvious increase in the number of slightly-imbalanced cities, which covered most of the eastern and southern parts of the YRDA, whereas the range of moderately-imbalanced cities regressed to the northwestern part of the YRDA. In addition, the number of the barely-coordinated and basically-coordinated cities also continued to grow, forming a “Z"-shaped pattern from Hefei to Zhoushan. Among these cities, Shanghai, Nanjing, Suzhou, and Hangzhou had the highest degree of coupling coordination. All in all, the low-level coordinated cities are predominantly distributed in the northwest, while the high-level

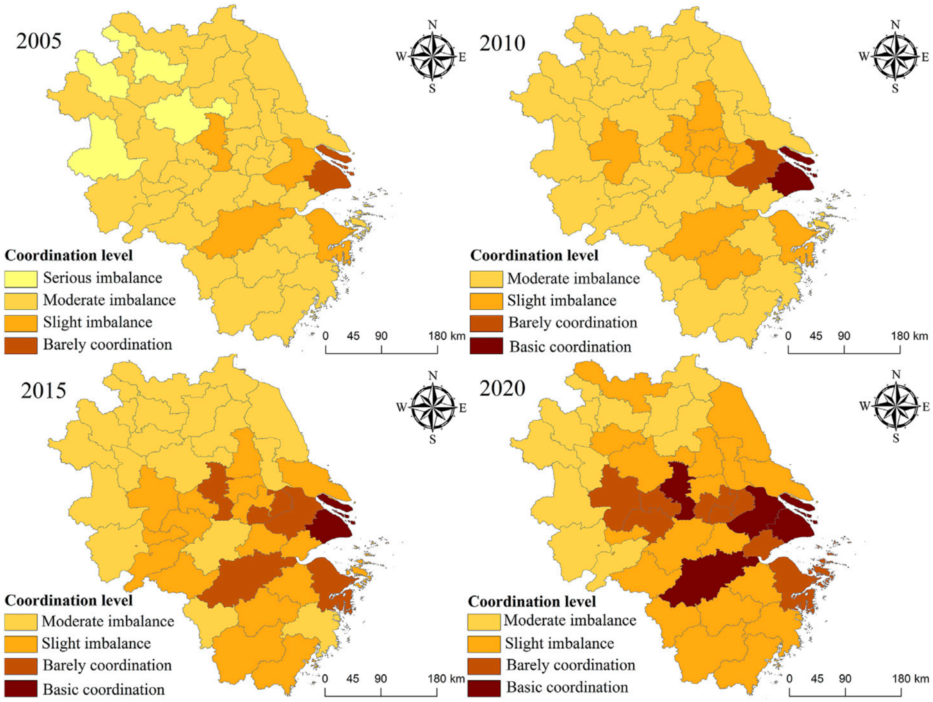

FIGURE 5
Spatial distribution of CCD between urban and high-quality development.

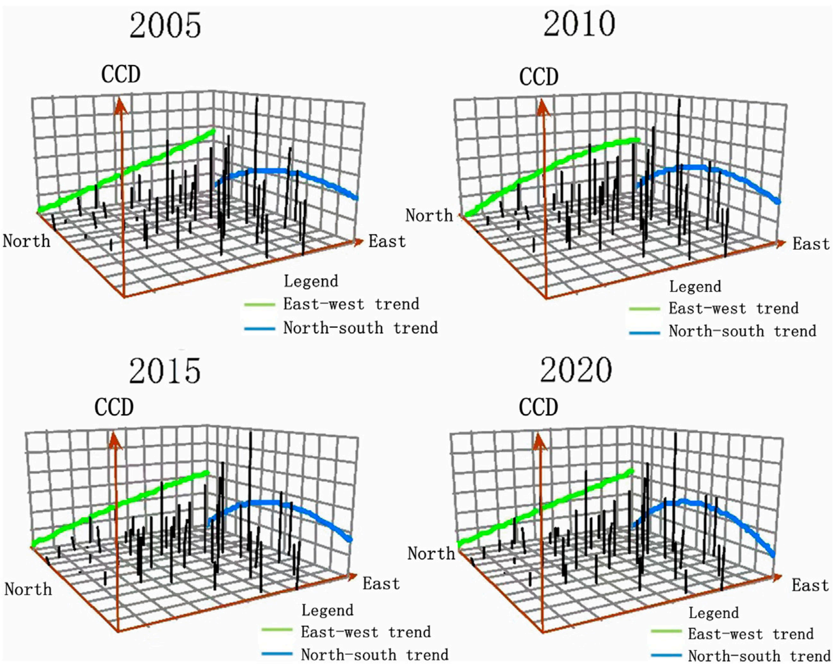

FIGURE 6
The variation trend of CCD.

TABLE 5 The global Moran's I of CCD in the YRDA from 2005 to 2020.

Year	Moran's I	Z value	Year	Moran's I	Z value
2005	0.557***	8.463	2013	0.557***	8.456
2006	0.522***	8.026	2014	0.529***	8.067
2007	0.550***	8.339	2015	0.501***	7.691
2008	0.551***	8.374	2016	0.495***	7.584
2009	0.559***	8.434	2017	0.497***	7.555
2010	0.555***	8.374	2018	0.479***	7.317
2011	0.584***	8.840	2019	0.470***	7.192
2012	0.577***	8.736	2020	0.500***	7.628

Note: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

coordinated cities are prominently concentrated on the central part of the YRDA.

The trend surface analysis is adopted to further verify the spatial distribution pattern and changing trend of the CCD. As is symbolically illustrated in Figure 6, the trend lines in the east-west direction of the YRDA are entirely diagonal during the studied period, which indicates that the CCD between urban resilience and high-quality development has been divergent both historically and spatially in the YRDA, with "being high to the east and low to the west." Moreover, in the north-to-south direction, the 2020 trend surface, in comparison with that of 2005, becomes steeper, and the spatial trend between the central and southern areas, which is close to a straight line, continues to sink with the passing of time as the overall trend gradually changes from an "L" to an inverted "U" shape. This means that with the fantastic spurt of economic development of the central areas, the discrepancies between the north and the south are narrowing, and in general, the CCD is evolving from "being high in the centre and south, but steeply plummeting in the north" to "being balanced in the north and south, but being prominent in the centre."

3.3 Spatial correlation pattern of CCD

In order to explore the characteristics of spatial correlation of the CCD between urban resilience and high-quality development in the YRDA, the global Moran's I of the CCD among municipal units in the YRDA is calculated with adopting the Stata software (Table 5). Moran's I of the CCD in the YRDA from 2005 to 2019 is invariably greater than zero, and both the p-value and the Z-value pass the test for significance. In summary, the results display that there is a significant positive spatial correlation among the municipal units of the YRDA.

The global Moran's I has verified the enhancement of the spatial distribution agglomeration of the CCD in the YRDA. Then, the local auto-correlation model is introduced again for testing, and the Moran scattered plots of 2005, 2010, 2015 and 2020 respectively are drawn to reflect the spatial correlation between a certain area and its surrounding areas. It can be conspicuously revealed from Figure 7 that most of the observation in all the 4 years fall within the first and the third quadrants, indicating that the spatial distribution of the CCD between urban resilience and high-quality development in the YRDA displays a positive correlation between the high values and between the low values. In a brief, the local spatial auto-correlation is mainly manifested in H-H and L-L regions, and spatial homogeneity is more prominent than heterogeneity.

3.4 Analysis of influencing factors

3.4.1 Selection of influencing factors

The results of the analysis above render us aware of the fact that the CCD between urban resilience and high-quality development in the YRDA is, to some degree, spatially correlated with each other. Thus, spatial factors must be taken into account when the impact of various factors upon it is under consideration. With the basis of previous studies (Martin and Sunley, 2015; Shi et al., 2021; Ma et al., 2022), we combine the spatial econometric model to analyse the driving factors exerting an influence on the CCD between urban resilience and high-quality development in the YRDA from the diverse perspectives of regional economic strength, industrial structure, transportation facilities, environment regulation, government intervention, science and technology, the factors relevant to labour force, and people's living standards. The relevant variables were selected as below: GDP per capital (X1) represents the regional economic strength; industrial structure is expressed in terms of the proportion of the value added by secondary and tertiary industries relative to GDP (X2); the size of the cargo volume (X3) reflects the perfection of the transportation facilities; replacing the environment regulation by the proportion of "environmental protection" words in the regional annual government work report (X4); the ratio of the local budget expenditure to GDP (X5) represents the strength of government intervention; the chosen proportion of expenditure in science and technology in fiscal spending (X6) represents the level of science and technology development; the sum of employment in the secondary and tertiary industries (X7) is the labour factor; urban per capital income (X8), expenditure (X9) and Engels Coefficient (X10) are adopted to reflect people's living standards.

To prevent pseudo-regression from taking place, this paper refers to the study of Miao et al. (2022) and tests for multicollinearity by variance inflation factors (VIFs), and the results show that the VIFs are below 10. There is no serious multicollinearity problem in the regression. Furthermore, the stationarity test is performed for all variables, of which X9 and X10 fail the ADF test and are therefore eliminated. To simultaneously remove the influence of heteroskedasticity, we also take the logarithm of all variables.

3.4.2 Selection of spatial econometric model

We carry out the test ideas of Yang and Liu (2022) to identify the spatial econometric model. Firstly, the statistical values of LM and Robust LM are adopted to determine whether the spatial error model (SEM) or the spatial lag model (SLM) is wielded depends on whether they are significant or not. From the test results of Table 6, the statistics of LM-spatial lag, LM-spatial error, Robust LM-spatial error and Robust LM-spatial lag all pass the significance level test of at least 5%, manifesting that the model of the influence of each factor on the CCD is both in the form of spatial error and spatial lag.

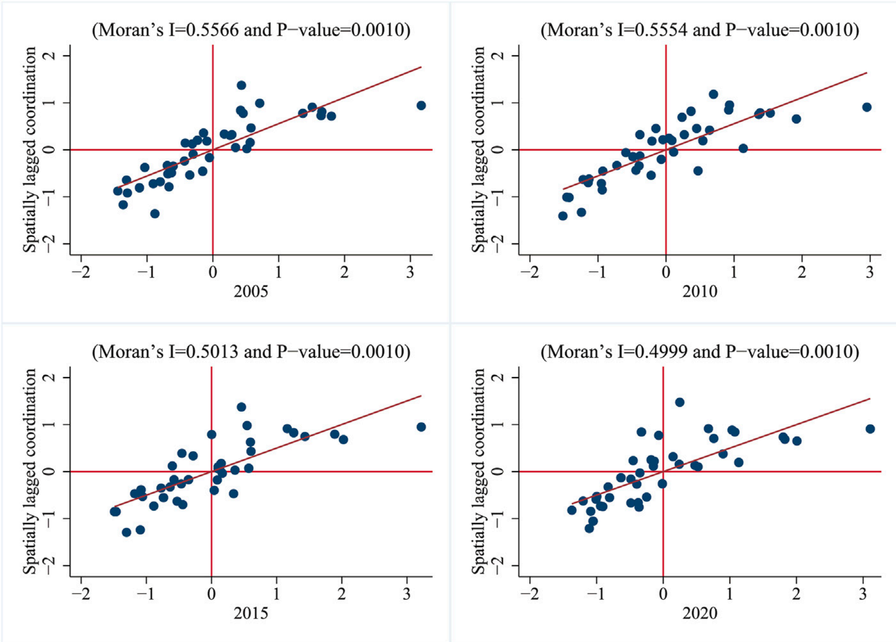

FIGURE 7
Moran Scattered plot of CCD between urban resilience and high-quality development in YRDA in 2005, 2010, 2015, and 2020 respectively.

TABLE 6 Spatial econometric model test results.

Test of spatial econometric model		Statistics
LM test	LM_Spatial error	51.10***
	Robust LM_Spatial error	65.017***
	LM_Spatial lag	4.209**
	Robust LM_Spatial lag	18.126***
Hausman Test		41.60***
LR Test	LR Test for SLM	30.74***
	LR Test for SEM	38.70***
	LR Test for spatial fixed effects	44.88***
	LR Test for time fixed effects	810.20***
Wald Test	Wald Test for SLM	30.23***
	Wald Test for SEM	37.13***

Note: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Secondly, we further test whether the SDM can be degraded into SEM or SLM, and the statistics of Wald-spatial lag, Wald-spatial error, LR-spatial lag, and LR-spatial error all pass the significance level of 0.01, which rejects the original hypothesis that the SDM cannot be degraded to a spatially measured model in its simplified form, with SDM being the most suitable model. Thirdly, the Hausman test is again adopted to determine whether fixed effects or random effects are chosen. The test result displays that the Hausman index is 41.60, which passes the 0.01 level of significance test, manifesting that the selection of fixed effects is more appropriate. Finally, the SDM fixed effects come in different forms, such as time fixed effects, spatial fixed effects, and dual space-time fixed effects. The LR test results for the joint significance of time and spatial fixed effects indicate that the dual space-time fixed effects are better than any others, for which, the dual space-time fixed effects SDM is selected to evaluate the impact of each factor on the CCD between urban resilience and high-quality development.

3.4.3 Analysis of model results

Table 7 provides the SDM estimation results. The regression coefficients of economic strength (X1) and industrial structure (X2) are significantly positive, but their spatial lag coefficients are not significant, indicating that both of these factors can effectively synergize the resilience and high-quality development in this area, but have a poor radioactive effect on the neighboring cities. The regression coefficient and lagged coefficient of transportation facilities (X3) are both significantly positive, displaying that the transportation accessibility not only has a significant positive impact on the synergistic evolution of urban resilience and high-quality development, but also has a rippling effect on the development of adjacent municipalities and neighboring area. Meanwhile, neither the regression coefficient for environmental regulation (X4) nor the lagged coefficient is significant, which implies that the impact of environment regulation upon urban resilience and high-quality development is not large in the current period and that its effect can be achieved only after a lag of one or more years. For government intervention (X5) and science and technology (X6), the regression coefficients are significantly positive in magnitude, and the cross-lagged coefficients are significantly negative, suggesting that both of these factors have a role in promoting urban resilience and high-quality development but have a strong

TABLE 7 The regression results of spatial durbin model.

Explanatory variable	SDM		The lagged item result		
	Coefficient	Standard error	Variable	Coefficient	Standard error
X1	0.0466***	0.0127	W*X1	0.0387	0.0252
X2	0.0526**	0.0222	W*X2	0.0721	0.0446
X3	0.0208***	0.0052	W*X3	0.0228*	0.0120
X4	0.0036	0.0044	W*X4	−0.0049	0.0107
X5	0.0470***	0.0160	W*X5	−0.1646***	0.0345
X6	0.0366***	0.0048	W*X6	−0.0215*	0.0124
X7	−0.0222***	0.0076	W*X7	0.0161	0.0181
X8	0.0533	0.0414	W*X8	−0.1767**	0.0887
ρ	0.3761***				
N	656				
R^2	0.7754				

Note: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

TABLE 8 The regression results of the robustness test.

Explanatory variable	SDM		The lagged item result		
	Coefficient	Standard error	Variable	Coefficient	Standard error
X1	0.1071***	0.0117	W*X1	−0.1867***	0.0329
X2	0.0463**	0.0210	W*X2	0.0567	0.0699
X3	0.0231***	0.0054	W*X3	0.0379**	0.0155
X4	0.0029	0.0043	W*X4	−0.0121	0.0153
X5	0.0826***	0.0153	W*X5	−0.2879***	0.0470
X6	0.0354***	0.0046	W*X6	−0.0262*	0.0151
X7	−0.0312***	0.0073	W*X7	−0.0234	0.0283
X8	0.0248	0.0420	W*X8	−0.4198***	0.1391
ρ	0.4516***				
N	656				
R^2	0.8544				

Note: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

competitive relationship with neighboring municipalities. For the labor factor (X7), the regression coefficient is significantly negative, indicating that excessive population densities places pressure on the city development and increases resource consumption, which is not conducive to the continued promotion of urban resilience and high-quality development. The coefficient on people's living standard (X8) is significantly negative, displaying that increasing this factor will, to some degree, inhibit the synergy of urban resilience and high-quality development in the surrounding regions.

3.4.4 Robustness test

In this paper, the robustness test is carried out with replacing the distance attenuation space matrix used by Zhou and Tang (2022). The results are displayed in Table 8. After the influence of economic distance upon the model is excluded, it can be vividly disclosed that the spatial lag coefficient of economic strength (X1) changes from being positive to negative, and that the estimation results of other variables have not changed fundamentally, so that it can be concluded that the estimation results of this paper are reliable.

4 Discussion

Last century has witnessed a remarkable process of global urbanization, with multitudinous cities throughout the globe accomplishing the great feat of moving from nothing to a tiny village or town to a major metropolis (Mcneill and Engelke, 2016). It is worth noting, however, that the inexpressibly rapid growth of urbanization has also triggered a range of disasters and public crises, causing unpredictable damage to people of all countries (Moore et al., 2003). At this critical moment, the Chinese government has proposed accelerating the construction of an urban spatial planning system with resilience as the core, and has proposed high-quality development being an element, in order to work towards a better and more prosperous world as is described by the United Nations in the 2030 Agenda for Sustainable Development. So, what can we learn from this research?

4.1 It is necessary to rely on mega-cities with strong radiation capacity to promote common development of small and medium-sized cities

There is a close relationship between the size of a city and the functions it undertakes, and the functions undertaken by diverse classes of cities within the urban system vary as well (Clark, 1945). As the mega-cities in the YRDA, Shanghai, Nanjing and Hangzhou are all the core and major areas of high-quality development, as well as the sensitive and severely affected areas where innumerable risks and countless crises are concentrated, and therefore, these metropolises, which are in a unique position to propel the synergistic evolution of urban resilience and high-quality development, assume especially duty-bound functions which cannot be assumed by other cities. This view is also supported by our study, as the results of the spatio-temporal pattern analysis in Part 3 of this paper vividly display that Shanghai, Nanjing and Hangzhou are not only the regions with high levels of urban resilience and high-quality development, but also the first-tier cities to achieve basic coordination between the two systems. In this case, they form the three major growth poles in the spatial distribution of the YRDA, radiating and propelling the synergistic development of the surrounding cities.

Under the strategic deployment of efficient prevention and control of risks as well as the economic and social development, both of which are regarded as a paramount node hub for collaboratively promoting urban resilience and high-quality development, the mega-cities in the YRDA have the potential to cement the modernization of urban service management capabilities, the modernization of urban co-construction and co-governance capabilities, and the modernization of urban risk prevention and control capabilities. Thus, there is an urgent need to scientifically or rationally plan and promote the construction of metropolitan areas, by the close inter-personal and economic ties between cities and in keeping with the trend of industrial upgrading and spatial development. On the one hand, we can take Shanghai, Nanjing and Hangzhou as the axis, through the establishment of a robust coordination mechanism for the metropolitan area, accelerate the outward extension of infrastructure, the mutual flow of factor resources, the dispersal of functional industries from the local to the outside, and the coverage of public services to the periphery, better promote the all-round development of the surrounding cities, so as to gradually narrow the discrepancies in the development between cities varying from being large, medium and small, and to promote regional coordination. On the other hand, in response to a multitude of emergent conditions, mega-cities should actively call for governments at all levels within the metropolitan area to form a unified caliber and a prescriptive system for the prevention, reporting and management of public crises, and implement a standardized, effective and timely information notifying system. Based on this very solid foundation, temporary emergency headquarters in the metropolitan area will be established to actively coordinate the advantageous resources of the cities, in order to effectively organize pre-crisis prevention, exercises and reserves, joint defense in the crisis, and post-crisis reconstruction and recovery.

As far as we know, a series of similar guiding rules were introduced in the “Nanjing Metropolitan Area Development Plan”, which was fully disseminated to the entire society in 2021. For example, it actively guides the transfer of Nanjing’s higher education and healthcare resources to other cities within the metropolitan area in an appropriate and orderly manner, explores the establishment of a tax-sharing mechanism for the metropolitan area, and collaborates to create a unified standard for supervision and management, all of which are planning rules that, to some extent, support the feasibility of the policy proposals presented in this paper. While the plan covers the period extending to 2025, with a long-term outlook extending to 2035, which is also a reflection of the applicability of our policy recommendations in the future.

4.2 Government services provide important support for urban resilience and high-quality development

Since the inception of the 21st century, the Chinese government has actively explored the path of a transformation from administrative functions to service functions (Zhang and Lv, 2021). The service-oriented government is dedicated to establishing a relatively comprehensive public service system, with increased public funding in education, culture, health, ecological environment, infrastructure, and social security as well as investment derived from other aspects, aiming to promote the equalization of basic public services (Xia et al., 2019). The over-two-decade stint of time witnesses that with a view to building a service-oriented government, China has achieved splendid accomplishments such as a comprehensively free and compulsory education, a basic medical security system covering over 90% of residents inhabiting both the urban and the rural area, and a complete victory in the fight against poverty.

These achievements have laid a solid foundation for the synergistic promotion of urban resilience and high-quality development. Our study also displays that the governmental factors such as the perfection of the transportation facilities, the ratio of the local budget expenditure to GDP and the proportion of spending on science and technology in fiscal spending, play a significant role in contributing to the improvement of the CCD between urban resilience and high-quality development. This also reflects, to a certain extent, the vital importance of building a service-oriented government. As a result, the government should adhere to the goal of promoting sustainable development of the region with high-level government services, and abide by the principle of giving full play to its positive spatial spillover effect of "harmonizing with neighbors". Through comprehensive investigation and careful planning, the factor resources of all kinds are reasonably and appropriately allocated throughout the economic, social, ecological, and engineering development process, so that the coordinated coupling of urban resilience and high-quality development can be maximized and that the transition from basic coordination to good coordination can be realized.

4.3 The synergy between urban resilience and high-quality development also requires consideration of ethical implications

The introduction of the conception of "high-quality development" has gradually transformed China's urban development from a wildly disorientated expansion in the past to a new phase of all-encompassing revitalization, and the criteria for evaluating urban development in the community also changed simultaneously (Falco, 2015). The city, regarded as an organic life form, has not been able to evaluate its level of development simply from the alteration in mechanical data. Gradually, the quality of people's lives and the degree of social equity are emerging as new criteria to measure urban development and social construction (Yang and Fu, 2019). The synergy between urban resilience and high-quality development should therefore be based on a humanist tone, which is adopted to pursue the ultimate goal of profound social 'equality' and common prosperity for all people. So, are policies and practices which promote urban resilience and high-quality development fully equitable and inclusive in reality ? In our perspective, the answer is 'never'. Considering the current situation, the local governments, in the process of promoting urban resilience and high-quality development, often assist highly-educated, capable and high-income people in obtaining urban identity-certifying registry, which is well called Hu Kou in the Chinese language, through diversified talent-enrolling policies. In contrast, migrant workers, who are deplorably educated, less thoroughly skilled and financially challenged, are more eager to work in the cities and but their identity-certifying registry is in rural areas (Wang et al., 2023). For this group of people, receiving equitable distribution of benefits and effective assistance derived from the government policy is often a challenge, which in turn confines the further development of the city and the urban habitat enhancement to some degree. It may also be a paramount factor in the inability of labor factors and in people's living standards in the YRDA which play a facilitating role in the synergistic evolution of urban resilience and high-quality development. Furthermore, China's control over the identity-certifying registry which is equivalent to Hu Kou in Chinese, and the manner in which the benefits it carries are distributed also renders it easier for residents with local urban identity-certifying registry to receive the corresponding rights and benefits well compared to both rural and foreign population (Pi and Zhang, 2016). This is especially evident in major cities like Shanghai and Nanjing. A growing number of youth are choosing to move from rural areas to urban areas in pursuit of a life of a higher quality, rendering a series of social problems, such as tiny empty villages which only senile citizens inhabit and young people leave for cities, left-behind children and talent shortage in rural areas, all of which are increasingly prominent. This leads us to making another hypothesis: improving urban resilience and high quality development in a region (country) will sacrifice the interests of some rural areas. This claim needs to be verified in future research.

5 Conclusion and deficiencies

In the new era of building resilient cities and promoting high-quality development in China, strengthening the theoretical perceiving and empirical research on the synergistic evolution of urban resilience and high-quality development is not only the central task and inevitable trend of future urban planning and governance, but also an active exploration of a new model of human social development in the post-epidemic era, in the view of which, we have constructed an evaluation index system for urban resilience and high-quality development, and then measured the coupled and coordinated development of them, adopting kernel density curves and spatial statistical analysis to vividly reveal their spatio-temporal evolution characteristics, and analysed their influencing factors with the help of SDM. The findings of the research are that: 1) The stint of 2005–2020 witnessed that urban resilience maintained a steady growth, while high-quality development displayed a trend of an initial increase and a subsequent decline. In terms of spatial pattern, the former reveals a structural feature of "being highest in the east, comparatively lower in the central part and the lowest in the west," while the latter displays a pattern of "being high in the south, low in the north, and prominent in the middle." 2) The CCD between urban resilience and high-quality development continued to rise throughout the stint of 2005–2020, while the regional difference decreased conspicuously, manifesting a good developing trend. Overall, the spatial pattern was characterized by "being high in the east and low in the west, tending to be balanced in the north and south, and being prominent in the middle of the distribution." 3) In the YRDA, there is a significant positive spatial correlation in the CCD, which tends to exhibit the conspicuous clustering features and is more spatially homogeneous compared to being heterogeneous. 4) Driving factors that have a remarkably significant effect on ameliorating the CCD in the YRDA include the economic strength, the industrial structure, the transportation facilities, the science and technology, and the government intervention, although the labor factor plays an inhibiting role in improving the CCD in the region. The improvement of transportation facilities is the factor that promotes the improvement of the coupling coordination level of adjacent cities, while the government intervention, the science and technology and people's living standards are the factors that hinder the improvement of the coupling coordination level of adjacent cities.

Although this paper discusses the theoretical mechanism, spatio-temporal evolution and driving forces for the CCD between urban resilience and high-quality development in the YRDA from the perspective of being regionally systematical and comprehensive, there is still a large scope for improvement. The qualitative data provided by the field surveys and in-depth interviews can further support and enrich our research, as well as providing us with more profound insights and inspiration. Unfortunately, because of the long acquisition cycle of such data and the difficulty of retrieval, the research sample conducted by us has not contained it. As the technical equipment continues to be ceaselessly updated and as the research materials continue to be unceasingly enriched, further simulation and prediction of the developing trend of urban resilience and high-quality development can be made on the basis of combining qualitative and quantitative data to enrich relevant research findings.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Materials, further inquiries can be directed to the corresponding authors.

Author contributions

JZ: conceptualization, methodology, software, formal analysis, writing (original draft), and writing (review and editing). JY: writing (review and editing), supervision, visualization, and funding acquisition. YW: writing (review and editing), funding acquisition, and software. All authors contributed to the article 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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Supplementary material

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References

Bahadur, A. V., and Thornton, H. (2015). Analysing urban resilience: A reality check for a fledgling canon. *Int. J. Urban. Sustain.* 7 (2), 196–212. doi:10.1080/19463138.2015.1060595

Baltagi, B. H., and Li, D. (2006). Prediction in the panel data model with spatial correlation: The case of liquor. *Spat. Econ. Anal.* 1, 175–185. doi:10.1080/17421770601009817

Campanella, T. J. (2006). Urban resilience and the recovery of new orleans. *J. Am. Plann. Assoc.* 72 (2), 141–146. doi:10.1080/01944360608976734

Chen, Y., Su, X., and Zhou, Q. (2021). Study on the spatiotemporal evolution and influencing factors of urban resilience in the Yellow River basin. *Environ. Sci. Pollut. Res. Int.* 18, 10231. doi:10.3390/ijerph181910231

Chen, Y., Zhu, M., Lu, J., Zhou, Q., and Ma, W. (2020). Evaluation of ecological city and analysis of obstacle factors under the background of high-quality development: Taking cities in the Yellow River Basin as examples. *Ecol. Indic.* 118, 106771. doi:10.1016/j.ecolind.2020.106771

Clark, C. (1945). The economic functions of a city in relation to its size. *J. Econ. Soc.* 13, 97–113. doi:10.2307/1907009

Cui, Y., Khan, S. U., Deng, Y., and Zhao, M. (2022). Spatiotemporal heterogeneity, convergence and its impact factors: Perspective of carbon emission intensity and carbon emission per capita considering carbon sink effect. *Environ. Impact. Asses.* 92, 106699. doi:10.1016/j.eiar.2021.106699

Deng, Y., Cui, Y., Khan, S. U., Zhao, M., and Lu, Q. (2022). The spatiotemporal dynamic and spatial spillover effect of agricultural green technological progress in China. *Environ. Sci. Pollut. Res.* 29, 27909–27923. doi:10.1007/s11356-021-18424-z

Desouza, K. C., and Flanery, T. H. (2013). Designing, planning, and managing resilient cities: A conceptual framework. *Cities* 35, 89–99. doi:10.1016/j.cities.2013.06.003

Dong, Y., Ren, Z., Fu, Y., Hu, N., Guo, Y., Jia, G., et al. (2022). Decrease in the residents' accessibility of summer cooling services due to green space loss in Chinese cities. *Environ. Int.* 158, 107002. doi:10.1016/j.envint.2021.107002

Du, Y., Chen, X., Liu, Y., Wang, Y., Zhu, X., and Liu, S. (2022). Dynamic evolution and driving force of high-quality development in Harbin-Changchun urban agglomeration at the country level. *Econ. Geogr.* 42, 62–71. doi:10.15957/j.cnki.jjdl.2022.08.007

Falco, G. J. (2015). City resilience through data analytics: A human-centric approach. *Pro. Eng.* 118, 1008–1014. doi:10.1016/j.proeng.2015.08.542

Fan, Y., Fang, C., and Zhang, Q. (2019). Coupling coordinated development between social economy and ecological environment in Chinese provincial capital cities-assessment and policy implications. *J. Clean. Prod.* 229, 289–298. doi:10.1016/j.jclepro.2019.05.027

Fritz, J. J., and Vollmer, D. (2006). To what extent can technology compensate for institutional failure in an urban environmental management setting: The case of China. *Technol. Soc.* 28 (1-2), 95–104. doi:10.1016/j.techsoc.2005.10.006

Gao, F. (2021). A deeper understanding of the connotation of China's high-quality development based on the transformation of the principal contradiction facing Chinese society. *Shanghai. J. Econ.* 12, 14–21. doi:10.19626/j.cnki.cn31-1163/f.2021.12.002

Gao, K., and Yuan, Y. (2022). Is the sky of smart city bluer? Evidence from satellite monitoring data. *J. Environ. Manage.* 317, 115483. doi:10.1016/j.jenvman.2022.115483

Godschalk, D. R. (2003). Urban hazard mitigation: Creating resilient cities. *Nat. Hazards. Rev.* 4 (3), 136–143. doi:10.1061/(ASCE)1527-6988(2003)4:3(136)

Holling, C. S. (1973). Resilience and stability of ecological systems. *Annu. Rev. Ecol. S.* 4 (1), 1–23. doi:10.1146/annurev.es.04.110173.000245

Huo, K., Ruan, Y., Fan, H., and Guo, C. (2022). Spatial-temporal characteristics of cultivated land change and controlling factors in the Yangtze River Delta region of China. *Front. Environ. Sci.* 2140. doi:10.3389/fenvs.2022.871482

Jiang, L., Zuo, Q., Ma, J., and Zhang, Z. (2021). Evaluation and prediction of the level of high-quality development: A case study of the Yellow River basin, China. *Ecol. Indic.* 129, 107994. doi:10.1016/j.ecolind.2021.107994

Li, B., and Wang, H. (2023). Comprehensive evaluation of urban high-quality development: A case study of liaoning province. *Environ. Dev. Sustain.* 25 (2), 1809–1831. doi:10.1007/s10668-022-02129-5

Li, W., and Yi, P. (2020). Assessment of city sustainability—coupling coordinated development among economy, society and environment. *J. Clean. Pro.* 256, 120453. doi:10.1016/j.jclepro.2020.120453

Li, X., Lu, Y., Rafique, M. Z., and Asl, M. G. (2022). The effect of fiscal decentralization, environmental regulation, and economic development on haze pollution: Empirical evidence for 270 Chinese cities during 2007–2016. *Environ. Sci. Pollut. Res. Int.* 29, 20318. doi:10.1007/s11356-021-17175-1

Li, Y., Yan, C., and Ren, X. (2023). Do uncertainties affect clean energy markets? Comparisons from a multi-frequency and multi-quantile framework. *Energy Econ.* 121, 106679. doi:10.1016/j.eneco.2023.106679

Li, Z., Luo, Z., Wang, Y., Fan, G., and Zhang, J. (2022). Suitability evaluation system for the shallow geothermal energy implementation in region by Entropy Weight Method and TOPSIS method. *Renew. Energy* 184, 564–576. doi:10.1016/j.renene.2021.11.112

Liu, J., Zhang, L., and Zhang, N. (2022). Analyzing the south-north gap in the high-quality development of China's urbanization. *Sustainability* 14, 2178. doi:10.3390/su14042178

Liu, W., Jiao, F., Ren, L., Xu, X., Wang, J., and Wang, X. (2018). Coupling coordination relationship between urbanization and atmospheric environment security in Jinan City. *J. Clean. Pro.* 204, 1–11. doi:10.1016/j.jclepro.2018.08.244

Liu, X., Li, S., Xu, X., and Luo, J. (2021). Integrated natural disasters urban resilience evaluation: The case of China. *Nat. Hazards.* 107, 2105–2122. doi:10.1007/s11069-020-04478-8

Ma, D., Zhang, J., Wang, Z., and Sun, D. (2022). Spatio-temporal evolution and influencing factors of open economy development in the Yangtze River Delta area. *Land* 11, 1813. doi:10.3390/land11101813

Martin, J. L., Maris, V., and Simberloff, D. S. (2016). The need to respect nature and its limits challenges society and conservation science. *Proc. Nati. Acad. Sci.* 113, 6105–6112. doi:10.1073/pnas.1525003113

Martin, R., and Sunley, P. (2015). On the notion of regional economic resilience: Conceptualization and explanation. *J. Econ. Geogr.* 15, 1–42. doi:10.1093/jeg/lbu015

Mcneill, J. R., and Engelke, P. (2016). *The great acceleration: An environmental history of the Anthropocene since 1945*. Cambridge, USA: Harvard University Press.

Meerow, S., Newell, J. P., and Stults, M. (2016). Defining urban resilience: A review. *Landsc. Urban. Plan.* 147, 38–49. doi:10.1016/j.landurbplan.2015.11.011

Miao, S., Wen, F., and Zhang, Y. (2022). Industry tournament incentives and the speed of leverage adjustments: Evidence from China. *Int. Rev. Financ. Anal.* 83, 102332. doi:10.1016/j.irfa.2022.102332

Moore, M., Gould, P., and Keary, B. S. (2003). Global urbanization and impact on health. *Int. J. Hyg. Environ. Health.* 206, 269–278. doi:10.1078/1438-4639-00223

Pi, J., and Zhang, P. (2016). Hukou system reforms and skilled-unskilled wage inequality in China. China. *Econ. Rev.* 41, 90–103. doi:10.1016/j.chieco.2016.08.009

Ranasinghe, U., Jefferies, M., Davis, P., and Pillay, M. (2020). Resilience engineering indicators and safety management: A systematic review. *Saf. Health. Work.* 11, 127–135. doi:10.1016/j.shaw.2020.03.009

Ren, X., Zeng, G., and Gozgor, G. (2023). How does digital finance affect industrial structure upgrading? Evidence from Chinese prefecture-level cities. *J. Environ. Manage.* 330, 117125. doi:10.1016/j.jenvman.2022.117125

Reuter, C., and Spielhofer, T. (2017). Towards social resilience: A quantitative and qualitative survey on citizens' perception of social media in emergencies in europe. *Technol. Forecast. Soc. Change.* 121, 168–180. doi:10.1016/j.techfore.2016.07.038

Shamsuddin, S. (2020). Resilience resistance: The challenges and implications of urban resilience implementation. *Cities* 103, 102763. doi:10.1016/j.cities.2020.102763

Shi, T., Qian, Y., and Zhou, Q. (2021). Spatiotemporal evolution and spatial relevance of urban resilience: Evidence from cities of China. *Growth. Change.* 52, 2364–2390. doi:10.1111/grow.12554

Sun, J., Jiang, Z., and Hu, J. (2022). Spatio-temporal evolution pattern and driving factors of high-quality development of Chinese cities in the new era. *Geogr. Res.* 41, 1864–1882. doi:10.11821/dlyj020210719

Sun, J., Liu, S., Wang, L., and He, Z. (2020). Safety resilience evaluation of urban public bus based on comprehensive weighting method and fuzzy comprehensive evaluation method. *Icuems* 370–379. doi:10.1109/ICUEMS50872.2020.00086

Sun, R., Gong, Z., Gao, G., and Shah, A. A. (2020). Comparative analysis of multi-criteria decision-making methods for flood disaster risk in the Yangtze River Delta. *Int. J. Disast. Risk. Re.* 51, 101768. doi:10.1016/j.ijdrr.2020.101768

Sun, X., Xiao, S., Ren, X., and Xu, B. (2023). Time-varying impact of information and communication technology on carbon emissions. *Energy Econ.* 118, 106492. doi:10.1016/j.eneco.2022.106492

Wang, H., and Zuo, R. (2015). A comparative study of trend surface analysis and spectrum–area multifractal model to identify geochemical anomalies. *J. Geochem. Explor.* 155, 84–90. doi:10.1016/j.gexplo.2015.04.013

Wang, R., and Feng, Y. (2020). Research on China's ecological welfare performance evaluation and improvement path from the perspective of high-quality development. *Math. Probl. Eng.* 2020, 1–14. doi:10.1155/2020/5476089

Wang, Z., Fu, H., and Ren, X. (2023). Political connections and corporate carbon emission: New evidence from Chinese industrial firms. *Technol. Forecast. Soc.* 188, 122326. doi:10.1016/j.irfa.2021.101999

Wang, Z., Ma, D., Zhang, J., Wang, Y., and Sun, D. (2023). Does urbanization have spatial spillover effect on poverty reduction: Empirical evidence from rural China. *Econ. Res-Ekon. Istraz.* 36 (1), 2167730. doi:10.1080/1331677X.2023.2167730

Wen, F., Zhao, H., Zhao, L., and Yin, H. (2022). What drive carbon price dynamics in China? *Int. Rev. Financ. Anal.* 79, 101999. doi:10.1016/j.irfa.2021.101999

Xia, Z., Tian, S., and Yan, X. (2019). Mapping the knowledge domain: Research on service-oriented government in China. *J. Chin. Polit. Sci.* 24, 341–360. doi:10.1007/s11366-019-09604-3

Xinhua News. (2023). The Ministry of Emergency Management has released basic information on natural disasters in China in 2022. Available at: http://www.gov.cn/xinwen/2023-01/13/content_5736666.htm

Xun, X., and Yuan, Y. (2020). Research on the urban resilience evaluation with hybrid multiple attribute TOPSIS method: An example in China. *Nat. Hazards.* 103 (1), 557–577. doi:10.1007/s11069-020-04000-0

Yang, C., Zeng, W., and Yang, X. (2020). Coupling coordination evaluation and sustainable development pattern of geo-ecological environment and urbanization in Chongqing municipality, China. *Sustain. Cities. Soc.* 61, 102271. doi:10.1016/j.scs.2020.102271

Yang, F., and Liu, G. (2022). Research on spillover effect of urbanization on rural land transfer based on the SDM model of intelligent computing. *Mob. Inf. Syst.* 2022, 1–10. doi:10.1155/2022/9921309

Yang, J., and Fu, X. (2019). *The centre of city: Wind environment and spatial morphology*. Berlin: Berlin Book Springer.

Yang, Y., Fang, Y. P., Xu, Y., and Zhang, Y. (2021). Assessment of urban resilience based on the transformation of resource-based cities: A case study of panzhihua, China. *Ecol. Soc.* 26 (2), 20. doi:10.5751/ES-12280-260220

Zhang, A., and Lv, N. (2021). Research on the impact of big data capabilities on government's smart service performance: Empirical evidence from China. *Ieee. Access* 9, 50523–50537. doi:10.1109/ACCESS.2021.3056486

Zhang, Y., Khan, S. U., Swallow, B., Liu, W., and Zhao, M. (2022). Coupling coordination analysis of China's water resources utilization efficiency and economic development level. *J. Clean. Prod.* 373, 133874. doi:10.1016/j.jclepro.2022.133874

Zhang, Y., Liu, W., Cai, Y., Khan, S. U., and Zhao, M. (2021). Decoupling analysis of water use and economic development in arid region of China–based on quantity and quality of water use. *Sci. Total. Environ.* 761, 143275. doi:10.1016/j.scitotenv.2020.143275

Zhou, X., and Tang, X. (2022). Spatiotemporal consistency effect of green finance on pollution emissions and its geographic attenuation process. *J. Environ. Manage.* 318, 115537. doi:10.1016/j.jenvman.2022.115537

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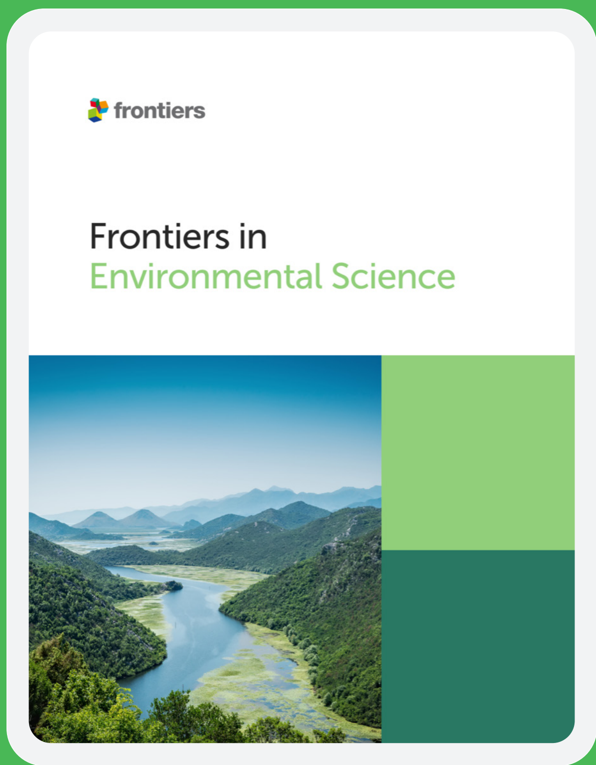

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