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Low-carbon transformation for sustainable development

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Low-carbon transformation for sustainable development

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Research on the impact of technical progress on the carbon productivity in China's service industry

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The energy consumption and carbon emission of the service industry should not be ignored. In order to achieve green and low-carbon development, improving the carbon productivity of the service industry is an extremely important method, and technical progress is a key path to improving the carbon productivity of the service industry. This paper decomposes the technical progress of China's service industry into technical progress of non-energy factors and technical progress of energy factor, and analyzes the impact and action mechanism of these two technical progress on the carbon productivity of China's service industry respectively from the theoretical and empirical perspectives. The main conclusions of this paper are as follows: From 2003 to 2019, technical progress had a significant positive impact on the carbon productivity of China's service industry. The influence coefficients of technical progress of non-energy factors and technical progress of energy factor are 0.285 and 0.306. In terms of the type of technical progress, the technical progress of energy factor has a greater impact. The technical progress of non-energy factors and energy factor have a significant promoting effect on the improvement of carbon productivity of service industry in all regions of China. In Eastern, central and Western China, the influence coefficients of the former are 0.318, 0.289 and 0.266, and the influence coefficients of the latter are 0.352, 0.296 and 0.273. The mechanism test finds that the technical progress of non-energy factors and energy factor directly affect the carbon productivity of China's service industry on the one hand, and indirectly affect the carbon productivity of China's service industry through the production efficiency and energy use efficiency of the service industry on the other hand.

KEYWORDS

service industry, technical progress, non-energy factors technical progress, energy factor technical progress, carbon productivity

1 Introduction

The global concentration of greenhouse gases in the atmosphere is breaking the highest value in the history of human meteorological observation, and the share of CO_2 in greenhouse gases is as high as 76.7%, according to the World Resources Institute. According to the BP World Energy Statistics Yearbook (2021), China's primary energy consumption in 2020 was 145.46 EJ, accounting for 26.1% of the global share. In the same year, China emitted 9.899 billion tons of CO_2, accounting for 30.7% of the global share. China has become the world's largest energy-consuming and carbon-emitting country. Saving energy and reducing carbon emissions have become a strategic requirement for

China's economic development, and improving carbon productivity is one of the important paths in balancing economic growth with low-carbon development. According to China's National Economic Classification of Industries (GB/T 4754-2017), the tertiary industry is the service industry, which refers to industries other than the primary and secondary industries. The service industry includes: wholesale and retail trade; transportation, storage and postal services; accommodation and catering; information transmission, software and information technology services; finance; real estate; leasing and business services; scientific research and technical services; water, environment and public facilities management; residential services, repair and other services; education; health and social work; culture, sports and entertainment; public management, social security and social organizations; international organizations; as well as agriculture, forestry, animal husbandry and fishery services in agriculture, forestry, animal husbandry and fishery; mining auxiliary activities in the mining industry; metal products, machinery and equipment repair in the manufacturing industry. Since 2015, the service industry has consistently contributed more than 50% to China's economic growth, according to the National Bureau of Statistics data. In the traditional concept of the Chinese, the service industry is subconsciously considered as a green and clean industry. In fact, the service industry, which occupies "half of China's national economy", has inevitably had much negative impact on the ecological environment while developing so rapidly. Department of Energy Statistics and National Bureau of Statistics, 2020 shows that China's total energy consumption in 2019 was 4.87 billion tons of standard coal, of which the service industry consumed 850 million tons of standard coal, accounting for 17.4%, an increase of 3.8% compared to 13.6% in 2009. Facing the problem of carbon emissions from the service industry, it is also necessary to improve the carbon productivity of the service industry for the healthy and sustainable development of China's national economy. Technical progress is an important factor that cannot be ignored to influence the carbon productivity of service industry (Li and Peng, 2018).

This paper takes the carbon productivity of China's service industry as the research object and makes great efforts to achieve the following main research purposes. Firstly, it calculates the service industry's carbon productivity and the technical progress level of non-energy factors and energy factor in various provinces and regions of China, and analyzes their temporal and spatial variation characteristics, this is the basis of follow-up research. Secondly, it discusses the impact of technical progress on the carbon productivity of China's service industry, and clarifies the mechanism of the impact of technical progress on the carbon productivity of China's service industry at both theoretical and empirical levels. Thirdly, proposes targeted countermeasures to improve the carbon productivity of China's service industry in terms of technical progress and so on.

In terms of theoretical research significance, at the industry level, most of the previous studies on carbon productivity have focused on the secondary industry, while studies on the service industry are quite rare, but in fact the issue of carbon productivity in the service industry also needs attention. This paper extends the impact of technical progress on carbon productivity to the field of China's service industry, constructs a scientific method to decompose the technical progress of China's service industry into non-energy factors and energy factor technical progress, and calculates it. As for practical research significance, improving carbon productivity in the service industry is an important way to reduce China's carbon emissions and achieve carbon neutrality. After clarifying the impact and mechanism of the technical progress of non-energy factors and energy factor in China's service industry on carbon productivity, this paper puts forward policy suggestions to improve the carbon productivity of China's service industry, which is of great practical significance to promote the green transformation and sustainable development of China's service industry and high-quality development of China's national economy.

The marginal contributions and innovations of this paper are as follows: Firstly, in terms of research objects, most of the existing literature on technical progress and carbon productivity starts from the macroscopic national or regional level. Even if it is specific to the industry level, the research objects are also concentrated on industry, agriculture, *etc.* This paper selects China's service industry as the research object, discusses the impact of technical progress on the carbon productivity in China's service industry and clarifies its action mechanism. It effectively complements the gap of research on the impact of technical progress on carbon productivity. Secondly, in terms of research methods, this paper expands the traditional two-factor model to a multi-factor model that includes energy factor, and constructs a decomposition method for technical progress in the service industry through the double-nested CES production function, that is, the decomposition method of decomposing technical progress in the service industry into technical progress of non-energy factors and energy factor, and uses this method to measure the level of these two types of technical progress in China's service industry. It also empirically tests the impact of these two types of technical progress on the carbon productivity of China's service industry. Finally, in terms of research conclusions, this paper finds that the technical progress of non-energy factors and energy factor directly affect the carbon productivity of China's service industry on the one hand, and indirectly affects the carbon productivity of China's service industry through the production efficiency and energy use efficiency of the service industry on the other hand. The results of theoretical analysis and empirical analysis are basically consistent. Based on the conclusions, some targeted policy suggestions are put forward to improve the carbon productivity of China's service industry.

The remainder of the paper unfolds as follows. The "Literature review" section reviews the relevant literature. The "Mechanism" section analyzes the mechanism of impact of technical progress on carbon productivity in the service industry. The "Methodology and Data" section describes methodology and data for calculation of carbon emissions, carbon productivity, and technical progress in China's service industry, empirical study on the impact of technical progress on carbon productivity in China's service industry. The "Results" section reports and analyzes the results of calculation of carbon productivity, technical progress, and baseline regression model. The "Further Analysis" includes regional regression analysis, robustness test, endogenous test, and mechanism test. The "Conclusion and suggestion" section summarizes the main conclusions and puts forward some policy suggestions for decision-making. The "Research limitations and future research directions" section summarizes the main limitations and future research directions of this study.

2 Literature review

Smith (1776) first provided a qualitative description of technical progress in "A Study of the Nature and Causes of National Wealth", where he argued that the increasing refinement of the division of labor in production activities could lead to technical progress and thus drive economic growth with increased production efficiency. In the quantitative study of technical progress, Solow (1956) and Swan (1956) both suggested that technical progress as an exogenous variable of economic growth could have a significant and positive impact on economic growth. At the same time, in order to quantify technical progress, Solow (1957) first proposed to measure the contribution of technical progress to economic growth by using the "Solow residual" method. Based on Solow's model, Massell (1961) used the component-weighted total factor productivity growth rate to reflect the overall technical progress and technical effects. Nishimizu and Page (1982) used a parametric frontier approach to decompose total factor productivity into technical progress and technical efficiency change. After that, according to the endogenous growth theory, Romer (1986), Lucas (1988) and others argued that the driving force for the economy to maintain growth must be endogenous, and technical progress is the central endogenous variable. Since technical progress has externalities, the marginal rewards of production factors can remain stable or even increase incrementally. This breaks through the limitations of the neoclassical growth model, and it is more conducive to explaining the long-term economic growth phenomenon. To study the multifactor technical progress including energy factor, the elasticity of substitution between factors needs to be measured first. Berndt and Christensen (1974) measured the elasticity of substitution among the three main factors of production (capital, labor, and energy) by constructing a translog cost function combined with a three-stage least squares estimation method under the assumption that technical progress is neutral. It was found that there is a weak substitution relationship between energy and labor, but energy and capital are complementary. Hassler et al. (2012) constructed a Cobb-Douglas production function and a nested CES production function, measured the level of technical progress under the two production function models, and described the advantages and disadvantages of these two function models in measuring the level of technical progress, and explored a reasonable range of values for the elasticity of factor substitution.

Productivity is divided into two categories: single-factor productivity and total factor productivity. Similarly, carbon productivity is divided into single-factor carbon productivity and total factor carbon productivity.

2.1 The measurement of carbon productivity

A part of scholars measured single-factor carbon productivity. Xiong et al. (2021) measured single-factor carbon productivity and found significant spatial differentiation of agricultural carbon productivity at the urban level in the Taihu Lake Basin, China. Sun et al. (2021) studied the carbon productivity of construction industry in Beijing-Tianjin-Hebei region using system dynamics model and predicted the value of carbon productivity under three scenarios.

Another part of scholars measured total factor carbon productivity. Gao and Zhu (2016) measured carbon productivity in the industrial sectors based on the DEA-DDF model. Xu et al. (2020) used SBM directional distance function and GML index method to measure the carbon productivity of manufacturing industry in Shanghai from 2001 to 2016, and found it improving constantly.

2.2 Factors of influencing carbon productivity

In terms of endogenous factors affecting carbon productivity, Meng and Niu (2012) conducted a systematic study. By decomposing the whole change of carbon productivity, they found that the two major endogenous factors affecting carbon productivity were technical progress and industrial structure adjustment. Through reviewing the literature, it is found that many scholars have verified this view. Hoffinann and Busch (2008) argued that technical innovation could affect the level of carbon performance of enterprises by improving the various carbon-containing materials used by enterprises in their production activities. Sun et al. (2020) used the DEA method to categorize the main influencing factors of total factor carbon productivity and CO_2 emissions as technical progress, scale efficiency and management efficiency, and found that technical progress is the largest driving factor, followed by scale efficiency and management efficiency. Ren et al. (2021) used the STIRPAT model and the spatial panel Durbin model to investigate the spatial spillover effects of environmental regulation and technical innovation on industrial carbon productivity in China, and found that technical innovation was beneficial to industrial carbon productivity, but there was no significant regional spillover of technical innovation. Zhang et al. (2014) decomposed the influencing factors of carbon productivity into technical progress and the substitution effect between capital and labor factors and energy factor, and through further empirical research proved that technical progress has a positive promoting effect on carbon productivity, while the substitution effect between labor factor and energy factor will not be conducive to the improvement of carbon productivity. Xu and Wang (2015) found through empirical research that technical progress is the core factor affecting the fishery carbon productivity in China's coastal areas, and industrial structure adjustment will also have a certain degree of impact.

In terms of exogenous factors affecting carbon productivity, there are energy price, energy structure, environmental regulation, research and development (R&D) input, economic spatial agglomeration, foreign direct investment (FDI), foreign trade, *etc.* Energy efficiency (Guo et al., 2021) and energy price (Tian and Yang, 2020) are important factors affecting carbon productivity. Jiang et al. (2022a) compared the carbon marginal abatement cost curves of China and India, they found that the cost of using fossil energy in China has increased more than that in India which made China reduce more energy consumption, so that the carbon emissions in China have fallen by a larger proportion than that in India. Tian and Yang (2020) found that energy price would have an impact on carbon emissions by affecting enterprises' choice of energy factor input. The higher the energy price is, the lower the carbon emissions of enterprises will be, but this impact would be weakened with the continuous rise of energy price. R&D input (Mo, 2021) and environmental policy (Li et al., 2020) also play an important role in promoting carbon productivity. Li et al. (2020) established a spatial Dubin model and found that the impact of green R&D input on carbon productivity improvement has a spatial spillover effect. Jiang et al. (2022b) adopted the CGE model to study the impact of demand-side policies related to electrification and decarbonization of private transportation in China on the environment and economy and found that the environmental policy of imposing carbon emission tax on fossil energy is the best way to reduce carbon emission and energy consumption. Although it will increase the production cost of enterprises in the early stage and lead to the decline of output and the loss of GDP, the loss of GDP will be reduced gradually in the long term. Liu and Hu (2016) and Long et al. (2020) both found that foreign direct investment has a significant impact on China's carbon productivity, and local FDI significantly improves local carbon productivity, while FDI from surrounding areas hinders local carbon productivity. Zhang et al. (2018) argued that there was a significant spatial spillover effect on China's carbon productivity, and foreign trade significantly increased China's carbon productivity.

2.3 The effect of technical progress on carbon productivity

There are abundant studies on the impact of technical progress on carbon productivity in the existing literature, and this issue is still deeply concerned by scholars in recent years. By reviewing the existing literature, many scholars have concluded that technical progress promotes the improvement of carbon productivity with the assistance of different decomposition methods. Zhang (2011) found that technical progress is the most important factor affecting carbon productivity through the Rasch decomposition method. Wang et al. (2016) decomposed the carbon productivity changes of 37 large global carbon emission countries based on the Luenberger productivity index. The results showed that the core factor of carbon productivity improvement was technical progress. Bai et al. (2019) measured the TFCP (total factor carbon productivity) of 88 economies worldwide using the Malmquist index method, and found that technical progress is the main reason for the growth of TFCP. Similarly, the studies of Han (2021), Cheng and Li (2021) and Du and Li (2019) all show that technical progress is the core influencing factor of the change of carbon productivity. In the further study of the impact of technical progress on carbon productivity, some scholars found that the impact of technical progress on carbon productivity is heterogeneous. Zhang and Xu (2016) found that the impact of environmental regulation and technical progress on the carbon productivity of China's second industry has sectoral heterogeneity. Environmental regulation has a more significant impact on the carbon productivity of capital and technology-intensive sectors and resource-intensive sectors, while technical innovation has a more significant impact on the carbon productivity of labor-intensive sectors. After further decomposing technical progress, some scholars found that different forms of technical progress have different degrees of impact on carbon productivity. For example, Fan et al. (2020) studied the impact of four forms of technical progress on carbon productivity in manufacturing industry based on DEA method, which are neutral technology, capital-embodied technology, energy technology and carbon emission reduction technology in the process of emission reduction. The results showed that capital-embodied technical progress is more important than neutral technical progress.

To sum up, it is not difficult for us to see, that the research results on carbon productivity are quite abundant among scholars from different countries. For the measurement of carbon productivity, scholars mainly use the methods of carbon average GDP, stochastic frontier analysis (SFA) and data envelopment analysis (DEA). For the study of the factors affecting carbon productivity, scholars found that the factors affecting carbon productivity are mainly technical progress, technical innovation, energy efficiency, R&D investment, environmental policy, foreign trade, and foreign direct investment. By decomposing the carbon productivity changes, scholars found that technical progress is the core influence factor of carbon productivity, and its influence on carbon productivity is heterogeneous, and after further decomposing technical progress, they found that different forms of technical progress have different degrees of influence on carbon productivity.

There is rich literature of research on the relationship between technical progress and carbon productivity by scholars in various countries. Specifically at the industry level, most previous studies by scholars on carbon productivity have focused on the secondary industry, and studies on the service industry are quite rare. Further, the literature that decomposes technical progress in service industry into non-energy factors and energy factor technical progress, and explores the impact of these two types of technical progress on carbon productivity of service industry is extremely rare. In this paper, we use the panel data of service industry in each province of China to study the impact of two types of factor technical progress on the carbon productivity of China's service industry, and propose corresponding policy suggestions to provide reference for China's government to promote the carbon productivity of the service industry from the perspective of technical progress, and promote China's service industry to develop towards the "carbon neutral" goal, it is of great significance to environmental protection and sustainable development in China and the world.

3 Mechanism

Since the carbon productivity of service industry is equal to the output of service industry divided by the carbon emission of service industry, the mechanism of the effect of technical progress on the carbon productivity of service industry may have two ways. On the one hand, it may increase output through the effect of technical progress on the output of the service industry; on the other hand, it may reduce carbon emissions because of technical progress on the carbon emissions of the service industry.

In order to discuss the above mechanism of technical progress more clearly, it is necessary to classify the technical progress of the service industry, and this paper divides the technical progress of the service industry into two categories: non-energy factors technical progress and energy factor technical progress. Technical progress in non-energy factors can be divided into two categories. One is technical progress that increases the output of the service industry when energy consumption is unchanged, or the same output of the service industry is obtained when less energy is consumed. The second is to use equipment that purifies emissions and thus reduces carbon emissions while output in the service industry remains unchanged. Technical progress of energy factor refers to the decline in the carbon content of the calorific value of the energy unit due to the technical progress of energy factor, so that more service output can be produced under the same carbon emissions.

Technical progress in the service industry leads to carbon productivity improvement, which can be summarized into two mechanisms as follows: one is that technical progress improves carbon productivity in the service industry by increasing the production efficiency of the service industry. The other is that technical progress in the service industry improves carbon productivity in the service industry by increasing the efficiency of energy use. The analysis of the influence mechanism of technical progress in the service industry on carbon productivity is shown in Figure 1.

The first mechanism: Because the improvement of service industry technology level can promote the increase of marginal output per unit input factor, which makes it possible to improve the production efficiency and produce more output with the same capital, labor, and energy input factors. Therefore, technical progress in the service industry can increase the carbon productivity of the service industry by directly driving the increase in the output of the service industry under constant carbon emissions. The technical progress of service industry corresponding to this mechanism refers to the first category of technical progress of non-energy factors. The second mechanism: specifically, it can be divided into the following three situations. First, the service industry can use the same energy input, reduce energy waste in the production process, and obtain more output, thus increasing the service industry carbon productivity. Second, the service industry adopts cleaner energy with a higher technology level, thus increasing the service industry's carbon productivity. Third, the service industry can use the same energy input and connect to emission purification equipment at the production terminal to reduce carbon emissions, thus increasing the carbon productivity of the service industry. The second and third situations of this mechanism correspond to the second category of technical progress in the service industry, which refers to technical progress in energy factor and technical progress in non-energy factors.

4 Methodology and data

4.1 Methodology and data for calculation of carbon emissions in China's service industry

Subject to the availability of data on China's service industry, this paper uses the energy fixed source combustion method

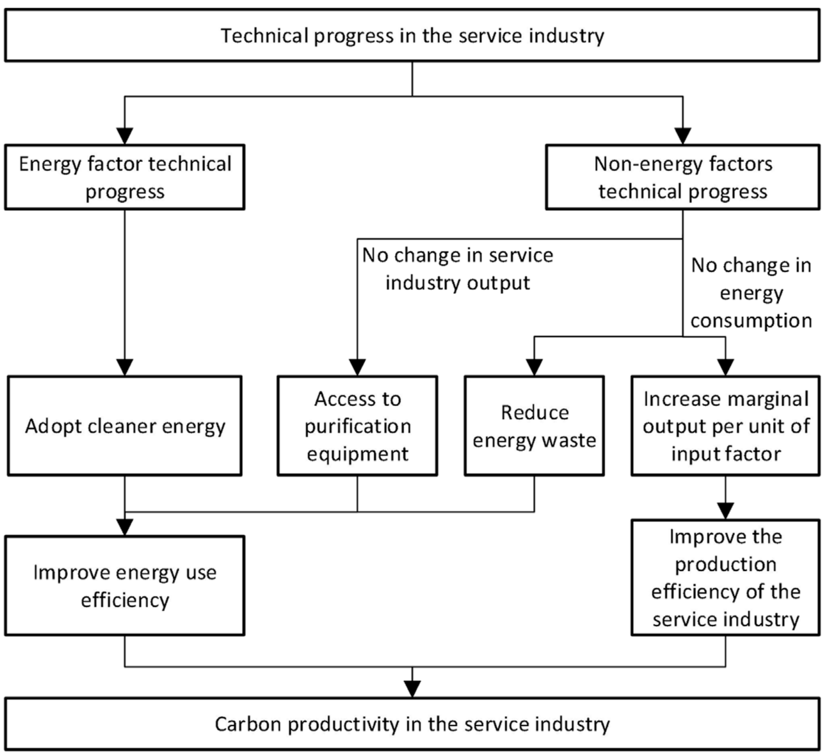

FIGURE 1
Mechanism analysis of impact of technical progress on carbon productivity in the service industry.

recommended by the IPCC in 2006 guidelines to calculate the CO_2 emissions of the service industry in various provinces in China, as shown in Eq. 1.

$$CO_2 = \sum_{i=1}^{8} E_i \times NCV_i \times CEF_i \times COF_i \times \frac{44}{12} \tag{1}$$

In Eq. 1, i denotes the type of energy, based on the 2006 version of IPCC guidelines, we choose eight major fossil energy sources, namely, raw coal, coke, crude oil, fuel oil, gasoline, kerosene, diesel, and natural gas, for carbon emission calculation. E_i denotes the consumption of energy of category i, the data are obtained from the regional energy balance sheets in *China Energy Statistics Yearbook (2004-2020)*. The energy consumption of the service industry in each province is obtained by summing up the end-use energy consumption of "transportation, storage and postal services", "wholesale, retail, accommodation and catering" and "other industries" from 2003 to 2019. NCV_i, CEF_i, COF_i are the average low-level heat generation, carbon content per unit calorific value and oxidation rate of energy category i, respectively, and the data are obtained from the *Guide to Chinese Provincial Greenhouse Gas List*.

4.2 Methodology and data for calculation of carbon productivity in China's service industry

In this paper, the level of GDP output per unit of CO_2 is chosen to measure the carbon productivity for the following reasons: ① The single-factor carbon productivity calculated through the carbon-averaged GDP treats carbon as a production factor input, which is a complement to capital productivity and labor productivity, and is more intuitive and effective for examining the role of carbon emissions in the economy. ② Compared with single-factor carbon productivity, the measurement of total factor carbon productivity takes into account the substitution between carbon emissions and factors such as capital, labor, and energy, but since the technical progress in this paper is measured using the CES production function, which also includes factors such as capital, labor, and energy. Therefore, if the total factor carbon productivity indicator is used, it may lead to unreliable regression results between technical progress and carbon productivity.

The carbon productivity of China's service industry is real added value of China's service industry at a given time divided by the CO_2 emissions of the service industry, as shown in Eq. 2.

$$CP_{i,t} = \frac{Y_{i,t}}{CO_{2i,t}} \tag{2}$$

In Eq. 2, $CP_{i,t}$ represents the carbon productivity of the service industry in province i in year t. $Y_{i,t}$ is the real added value of the service industry in province i in year t. The real added value of the service industry is calculated by using added value index of the service industry in each province in each year based on 2003, and the data are obtained from *China Statistical Yearbook (2004-2020)*. $CO_{2i,t}$ is the carbon emissions from the service industry in province i in year t. In view of the lack of energy and other related data in some provinces, this paper selects 30 provinces in China except Tibet, Taiwan, Hong Kong, and Macao as the research subjects.

4.3 Methodology and data for calculation of technical progress in China's service industry

4.3.1 Methodology for calculation of technical progress in China's service industry

Based on the research methods of Liao et al. (2018), Wu and Du (2018), this paper constructs a two-layer nested CES production function in the form of "(capital-labour) + energy", which divides the factors required in production activities into two types, energy factor and non-energy factors, on the basis of the manifestation of the production function. The CES production function has the advantage that the elasticity of substitution is not limited to 1. The specific form of the production function is given in Eq. 3.

$$Y_t = \left\{(1-\omega)\left[A_t K_t^{\alpha} L_t^{1-\alpha}\right]^{\frac{\sigma-1}{\sigma}} + \omega\left[A_t^E E_t\right]^{\frac{\sigma-1}{\sigma}}\right\}^{\frac{\sigma}{\sigma-1}} \tag{3}$$

In Eq. 3, Y_t represents output; K_t and L_t represent capital and labour inputs; A_t represents the level of capital-labour technical progress, that is the level of technical progress of non-energy factors, E_t represents energy inputs; A_t^E represents the level of technical progress of energy factor; σ represents the elasticity of substitution between energy factor and non-energy factors in the service industry and α represents the proportion of capital income share in the common share of labor and capital; ω ($\omega \in [0,1]$) is the energy intensity of the service industry.

Assuming that factor markets are perfect competition when marginal output and real prices of factors are equal, it can be deduced that:

$$L_t^{Share} = \frac{\partial Y_t}{\partial L_t}\frac{L_t}{Y_t} = (1-\alpha)(1-\omega)\left[\frac{A_t K_t^{\alpha} L_t^{1-\alpha}}{Y_t}\right]^{\frac{\sigma-1}{\sigma}} \tag{4}$$

$$K_t^{Share} = \frac{\partial Y_t}{\partial K_t}\frac{K_t}{Y_t} = \alpha(1-\omega)\left[\frac{A_t K_t^{\alpha} L_t^{1-\alpha}}{Y_t}\right]^{\frac{\sigma-1}{\sigma}} \tag{5}$$

$$E_t^{Share} = \frac{\partial Y_t}{\partial E_t}\frac{E_t}{Y_t} = \omega\left[\frac{A_t^E E_t}{Y_t}\right]^{\frac{\sigma-1}{\sigma}} \tag{6}$$

Modifying Eqs 4, 6, we can derive the level of technical progress for the non-energy factors and energy factor as:

$$A_t = \frac{Y_t}{K_t^{\alpha} L_t^{1-\alpha}}\left[\frac{L_t^{Share}}{(1-\alpha)(1-\omega)}\right]^{\frac{\sigma}{\sigma-1}} \tag{7}$$

$$A_t^E = \frac{Y_t}{E_t}\left[\frac{E_t^{Share}}{\omega}\right]^{\frac{\sigma}{\sigma-1}} \tag{8}$$

From Eqs 7, 8, to obtain the level of technical progress in two types, it is necessary to calculate the values of Y_t, K_t, L_t, E_t, L_t^{Share}, E_t^{Share}, α, σ and ω. Among them, for the value of ω, this paper takes $\omega = 0.05$ according to the setting of Hassler et al. (2012).

Regarding the value of the substitution elasticity σ between the non-energy factors and energy factor, this paper uses the estimation method in León-Ledesma et al. (2010), assuming technical progress satisfies the following process.

$$\begin{bmatrix}\rho_t \\ \rho_t^E\end{bmatrix} - \begin{bmatrix}\rho_{t-1} \\ \rho_{t-1}^E\end{bmatrix} = \begin{bmatrix}\theta^A \\ \theta^E\end{bmatrix} + \begin{bmatrix}\pi_t^A \\ \pi_t^E\end{bmatrix} \tag{9}$$

Among them, $\rho_t = \log\ (A_t)$, $\rho_t^E = \log(A_t^E)$, $\begin{bmatrix}\pi_t^A \\ \pi_t^E\end{bmatrix} \sim N(0,\Sigma)$.

From Eqs 7, 8 it can be deduced that:

$$\frac{A_t}{A_{t-1}} = \frac{Y_t}{K_t^{\alpha}L_t^{1-\alpha}}\frac{K_{t-1}^{\alpha}L_{t-1}^{1-\alpha}}{Y_{t-1}}\left[\frac{L_t^{Share}}{L_{t-1}^{Share}}\right]^{\frac{\sigma}{\sigma-1}} \tag{10}$$

$$\frac{A_t^E}{A_{t-1}^E} = \frac{Y_t}{E_t}\frac{E_{t-1}}{Y_{t-1}}\left[\frac{E_t^{Share}}{E_{t-1}^{Share}}\right]^{\frac{\sigma}{\sigma-1}} \tag{11}$$

Taking the logarithm of Eqs 10, 11, and substituting them into Eq. 9:

$$\begin{bmatrix} \log\left(\frac{Y_t}{K_t^{\alpha}L_t^{1-\alpha}}\right) - \log\left(\frac{Y_t}{K_{t-1}^{\alpha}L_{t-1}^{1-\alpha}}\right) \\ \log\left(\frac{Y_t}{E_t}\right) - \log\left(\frac{Y_{t-1}}{E_{t-1}}\right) \end{bmatrix} = \begin{bmatrix} \theta^A \\ \theta^E \end{bmatrix} - \frac{\sigma}{\sigma-1}\begin{bmatrix} \log\left(L_t^{Share}\right) - \log\left(L_{t-1}^{Share}\right) \\ \log\left(E_t^{Share}\right) - \log\left(E_{t-1}^{Share}\right) \end{bmatrix} + \begin{bmatrix} \pi_t^A \\ \pi_t^E \end{bmatrix} \tag{12}$$

Let $B_t^A = \log\left(\frac{Y_t}{K_t^{\alpha}L_t^{1-\alpha}}\right) - \log\left(\frac{Y_t}{K_{t-1}^{\alpha}L_{t-1}^{1-\alpha}}\right)$, $B_t^E = \log\left(\frac{Y_t}{E_t}\right) - \log\left(\frac{Y_{t-1}}{E_{t-1}}\right)$; $D_t^A = \log\left(L_t^{Share}\right) - \log\left(L_{t-1}^{Share}\right)$, $D_t^E = \log\left(E_t^{Share}\right) - \log\left(E_{t-1}^{Share}\right)$,

Simplify Eq. 12 as:

$$\begin{bmatrix} B_t^A \\ B_t^E \end{bmatrix} = \begin{bmatrix} \theta^A \\ \theta^E \end{bmatrix} - \frac{\sigma}{\sigma-1}\begin{bmatrix} D_t^A \\ D_t^E \end{bmatrix} + \begin{bmatrix} \pi_t^A \\ \pi_t^E \end{bmatrix} \tag{13}$$

By estimating a panel model for Eq. 13, the elasticity of substitution between energy factor and non-energy factors in the service industry for 30 provinces can be estimated. Summing up the data for the provinces, the value of the elasticity of substitution can be further estimated for China as well as for regions.

4.3.2 Data for calculation of technical progress in China's service industry

The data used in this paper is sourced from the China Statistical Yearbook, China Energy Statistical Yearbook, China Labour Statistical Yearbook, China's National Bureau of Statistics Database, CSMAR Database, and Wind Database.

① Output of the service industry (Y_t). The real added value of the service industry in each province of China from 2003 to 2019 was chosen to represent the output of the service industry. This paper uses the added value index to calculate the real added value of the service industry for 30 provinces in China using 2003 as the base period.

② Capital factor input (K_t). In this paper, the capital stock of China's service industry is used to represent the amount of capital input. The capital stock is measured using the perpetual inventory method, and the formula is: $K_t = I_t + (1-\delta)K_{t-1}$. K_t and K_{t-1} are the capital stock of the service industry in the current and previous periods respectively. I_t is the real fixed asset investment in the service industry in the current period, which is obtained by deflating using the fixed asset investment price index of each province, and δ represents the depreciation rate of the service industry, taking a value of 4%, which is more accepted in academia (Wu, 2009). As for the capital stock in the base period of 2003, this paper adopts the method recommended by Harberger (1978) for estimation, and the formula is: $K_{i,t-1} = I_{i,t}/(g_{i,t} + \delta_{i,t})$. Regarding the value of $g_{i,t}$, Harberger (1978) recommended using the average growth rate of output over a period, which can better reduce the effect of economic fluctuations. Therefore, this paper selects the average growth rate of real value added in the service industry in each province from 2003 to 2009 to represent $g_{i,t}$.

③ Labor factor input (L_t). This paper selects the number of employees in the service industry at the end of the year from 2003 to 2019 for each province in China to represent.

④ Energy factor input (E_t). This indicator is obtained by summing up the total coal, total oil, and natural gas consumption of the regional energy balance in the 2004 to 2020 China Energy Statistics Yearbook under "Transportation, storage and postal services", "Wholesale, retail trade and accommodation and catering" and "Other industries". As the quantitative unit of natural gas is "billions of cubic metres", it is necessary to convert its unit to ten-thousand tons. This paper takes the density of natural gas as 0.7174 kg/m^3 and converts it to get the total consumption of natural gas (ten-thousand tons).

⑤ The income shares of labour, capital, and energy (L_t^{Share}; K_t^{Share}; E_t^{Share}). Regarding labour income share, as China does not have direct data on labour remuneration in the service industry, this paper chooses to multiply the number of employees by labour prices to measure labour remuneration by year in each province in China. Regarding labour price, they are approximately represented by averaging the average wages of employees in urban units and urban private units in each sub-sector of the service industry from 2003 to 2019. Regarding capital remuneration, this paper refers to Lu and Liu (2016) and uses the sum of fixed asset depreciation and operating profit of service industry enterprises to represent. Regarding energy remuneration, it is calculated by multiplying the energy price by the energy input. Finally, the labour, capital and energy remuneration are deflated by the GDP deflator for each province in China to obtain the real values and then divided by the real added value of the service industry to obtain the labour income share, capital income share and energy income share, respectively.

⑥ The value of α. Based on Eqs 4, 5, the formula can be obtained as $\frac{L_t^{Share}}{K_t^{Share}} = \frac{1-\alpha}{\alpha}$, and the value of α can be calculated from this.

4.4 Methodology for empirical study

4.4.1 Model setting

Based on the existing literature research results (Xie et al., 2018; Yang et al., 2021), the following empirical model is constructed to study the impact of technical progress on carbon productivity in China's service industry:

$$CP_{i,t} = \beta_0 + \beta_1 A_{i,t} + \beta_2 A_{i,t}^E + \beta_3 X_{i,t} + \delta_i + \mu_t + \varepsilon_{i,t} \tag{14}$$

In Eq. 14, *i* represents 30 provinces, *t* represents time; $CP_{i,t}$ is the carbon productivity of the service industry; $A_{i,t}$ is the technical progress level of non-energy factors in the service industry, $A_{i,t}^E$ is the technical progress level of energy factor in the service industry; $X_{i,t}$ is the control variable, including environmental regulation level, energy structure, industrial structure, infrastructure level, urbanization level, foreign direct investment level, trade openness; δ_i and μ_t are regional fixed effects and time fixed effects, respectively; $\varepsilon_{i,t}$ is a random disturbance term.

4.4.2 Data for empirical study

4.4.2.1 Explained variable

The carbon productivity of the service industry ($CP_{i,t}$): It is calculated by the ratio of the real added value of the service industry to the carbon emission of the service industry. The specific calculation method and results can be found in the fourth part of this paper.

4.4.2.2 Core explanatory variables

The technical progress level of non-energy factors in the service industry ($A_{i,t}$) and the technical progress level of energy factor ($A^E_{i,t}$): The specific calculation method and results can be found in the fourth part of this paper.

4.4.2.3 Control variables

In addition to being affected by technical progress, carbon productivity is also affected by the level of infrastructure, the level of environmental regulation (Li et al., 2016), the level of foreign direct investment (Liu and Hu, 2016), the structure of energy consumption, industrial structure, the level of urbanization, and the degree of trade openness (Zhou and Nie, 2012). To avoid the influence of these factors on the regression results, this study controls these variables.

① Environmental regulation level ($Er_{i,t}$): Referring to Li and Tao (2012) and Yang (2015), the level of environmental regulation is measured by the actual investment in environmental pollution control in each province.
② Energy consumption structure ($Ec_{i,t}$): Considering that energy consumption has a direct impact on carbon emissions (Chen and Li, 2021), this paper measures the energy consumption structure of the service industry by the ratio of the energy consumption and CO_2 emissions of the service industry in each province, referring to the index construction method of Liu (2015).
③ Industrial structure ($Str_{i,t}$): The industrial structure is measured by the ratio of real added value of service industry to real GDP in each province.
④ Infrastructure level ($Inf_{i,t}$): Referring to the research of Wang and Han (2017), the infrastructure level is measured by the number of highway miles per 10,000 people in each province.
⑤ Urbanization level ($City_{i,t}$): The urbanization level is measured by the ratio of the resident urban population at the end of the year to the resident population at the end of the year in each province.
⑥ Foreign direct investment level ($FDI_{i,t}$): Referring to the research of Leng et al. (2015), the actual FDI after excluding the price factor is selected as the measurement indicator. During the calculation process, the US dollar needs to be converted into RMB according to the average exchange rate of RMB against the US dollar over the years.
⑦ Trade openness ($Tra_{i,t}$): It is measured by the ratio of the actual total import and export after excluding the price factor to the actual GDP of each province. During the calculation process, the US dollar needs to be converted into RMB according to the average exchange rate of RMB against the US dollar over the years.

5 Results

5.1 Results of calculation of carbon productivity

Considering the possible trend or periodicity of the variables over a long statistical time, in order to avoid non-stationarity of the sample data leading to pseudo-regressions and thus affecting the empirical results, we first perform a stationarity test on the data. In this paper, we use two panel unit root tests, LLC (Levin-Lin-Chu) test and Fisher-ADF(Augmented Dickey-Fuller) test, and the test results show that the variables all significantly reject the original hypothesis of the existence of unit root, and the subsequent regressions and tests can be performed.

Due to space limitations, this paper reports the carbon productivity of the service industry in 30 China's provinces, regions, and the whole country, as shown in Table 1.

From Table 1, we can get: the carbon productivity of service industry at the national level has been increasing from 1.49 in 2005 to 2.67 in 2019, with an increase of 72.3%. The growth rate shows a fluctuating upward trend, with an average annual growth rate of 6.31%. Thus, it can be seen, China has been working hard for the low carbon development of its service industry, and the green development strategy is steadily advancing with relatively remarkable results. In terms of all years from 2003 to 2019, except for the decline in individual years, the carbon productivity of China's service industry has increased in most years. For example, the decline in 2008 may be affected by the global financial crisis, which has led to a significant decline in the output growth rate of China's service industry, which is 5.6 percentage points lower than that of the previous year.

At the regional level, from 2003 to 2019, the carbon productivity of the service industry was in a state of continuous improvement in most years. In terms of regional horizontal comparison, the average values for each region are 2.47 in the Eastern region, 1.59 in the central region, and 1.28 in the Western region, decreasing from East to West. But in terms of annual average growth rates, in contrast to the trend reflected in the average values, the figures for each region are 7.41% in the eastern region, 4.59% in the central region, and 5.15% in the Western region, the western region is 0.56% points higher than the central region. This shows that there is a large difference in the carbon productivity of the service industry across regions, which is closely related to the development of the service industry and carbon energy consumption in each region.

At the provincial level, the mean value of carbon productivity in the service industry of the 30 provinces selected for this paper has a maximum value of 4.0 in Jiangsu and a minimum value of 0.53 in Guizhou, indicating a wide gap between the provinces. As the average annual growth rate is positive, the carbon productivity of the service industry in China shows a continuous improvement, with the highest annual average growth rate being 17.36% in Ningxia and the lowest being 2.15% in Hunan.

TABLE 1 The carbon productivity of the service industry in 30 China's provinces, regions, and the whole country.

Region	Year							Mean	Annual average growth rate (%)
	2005	2010	2015	2016	2017	2018	2019		
Eastern Region									
Beijing	2.10	2.82	3.67	3.89	4.17	4.30	4.64	3.07	8.20
Tianjin	0.97	1.49	2.42	2.49	2.69	3.00	3.14	1.83	14.16
Hebei	1.41	1.55	2.56	2.52	2.90	3.53	3.82	2.16	7.62
Liaoning	1.12	1.27	1.47	1.53	1.62	1.75	1.85	1.43	2.48
Shanghai	1.34	1.53	2.26	2.27	2.27	2.61	2.75	1.83	6.37
Jiangsu	2.95	3.91	4.49	4.88	5.13	5.25	5.28	4.00	7.46
Zhejiang	2.83	3.42	4.07	4.41	4.80	5.50	6.35	3.77	10.75
Fujian	2.10	2.33	3.26	3.43	3.57	3.67	3.78	2.71	7.01
Shandong	1.05	0.98	2.68	2.86	2.82	3.13	3.33	1.85	13.60
Guangdong	2.09	2.62	3.52	3.44	3.65	3.87	4.26	2.96	6.07
Hainan	1.11	1.06	1.65	1.86	1.92	2.13	2.27	1.37	11.10
Central Region									
Shanxi	1.20	0.82	1.15	1.18	1.24	1.42	1.58	1.09	6.42
Jilin	0.60	0.90	1.21	1.35	1.59	2.09	2.17	1.11	14.22
Heilongjiang	0.86	1.34	0.54	0.57	0.69	0.98	1.13	0.85	5.34
Anhui	2.87	3.32	2.72	2.93	3.04	3.17	3.44	2.95	2.52
Jiangxi	1.74	2.20	1.97	2.14	2.20	2.14	2.19	2.02	7.73
Henan	2.46	2.86	2.70	2.96	3.38	3.03	3.24	2.76	5.11
Hubei	1.02	1.10	1.69	1.62	1.73	1.86	1.87	1.32	7.40
Hunan	1.25	1.85	1.86	1.91	2.01	2.03	2.13	1.78	2.15
Western Region									
Inner Mongolia	0.71	0.73	0.92	1.45	1.93	2.04	2.13	1.09	6.31
Guangxi	1.20	1.30	2.13	2.28	2.39	2.60	2.93	1.72	10.16
Chongqing	1.86	1.72	2.08	2.16	2.26	2.78	2.82	1.97	8.75
Sichuan	1.70	2.03	2.53	2.32	2.38	2.38	2.45	2.00	4.78
Guizhou	0.57	0.48	0.44	0.48	0.52	0.63	0.69	0.53	5.86
Yunnan	1.07	1.12	1.41	1.54	1.67	1.62	1.63	1.30	3.78
Shanxi	0.83	0.99	1.95	2.44	2.71	2.84	3.14	1.57	12.18
Gansu	1.22	1.58	1.55	1.60	1.69	1.92	2.02	1.53	9.18
Qinghai	0.89	0.90	1.24	1.22	1.18	1.14	1.18	1.04	2.55
Ningxia	0.74	0.81	1.28	1.39	1.52	1.84	1.83	1.11	17.36
Xinjiang	0.80	1.13	1.07	1.08	1.16	1.38	1.56	1.09	7.60
Eastern Region	1.71	2.01	3.01	3.12	3.28	3.59	3.84	2.47	7.41
Central Region	1.33	1.55	1.60	1.68	1.86	2.05	2.19	1.59	4.59
Western Region	1.04	1.10	1.34	1.51	1.65	1.81	1.93	1.28	5.15
Whole Country	1.49	1.79	1.96	2.10	2.24	2.44	2.67	1.86	6.31

5.2 Results of calculation of technical progress

According to the results of Eqs 7, 8, when compared vertically, the trend of the technical progress level of the two types of factor in the service industry in China as a whole and in three regions from 2003 to 2019, is shown in Figure 2.

According to Figure 2, at the national level, the level of technical progress for non-energy factors and energy factor in the service industry generally showed an upward trend from 2003 to 2019, indicating that technical progress can continuously increase the marginal output of non-energy factors and energy factor. By comparing the levels of technical progress of the two types of factor, it can be concluded that the level of technical progress of the non-energy factors is higher, and the gap between the levels of technical progress of the two types of factor is larger during 2004–2012, and the gap between the levels of technical progress of the two types gradually decreases after 2012, indicating that the growth rates of the two types of technical progress have gradually converged. The gap between the two types of technical progress in the service industry in the eastern region is larger, while the gap in the central and Western regions is smaller, but all regions have shown a trend of gradually narrowing the gap in the past three years. In recent years, China has paid particular attention to energy saving

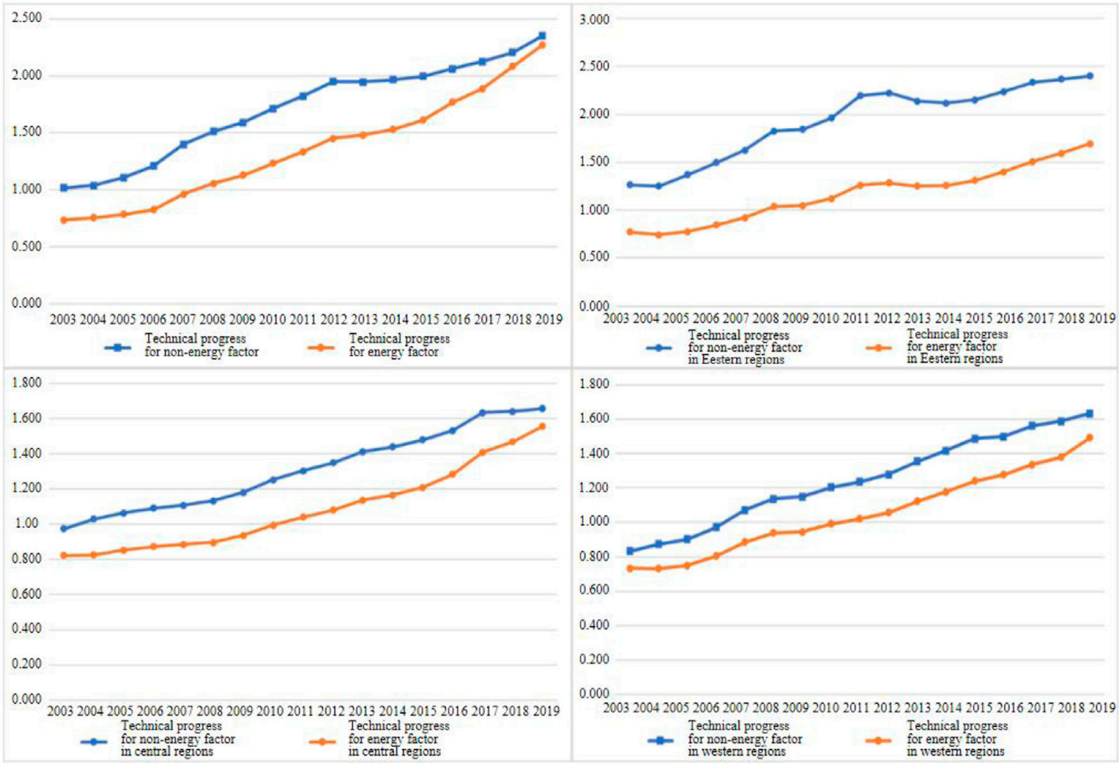

FIGURE 2
Trends in the level of technical progress in the service industry in China and in the Eastern, central, and Western regions.

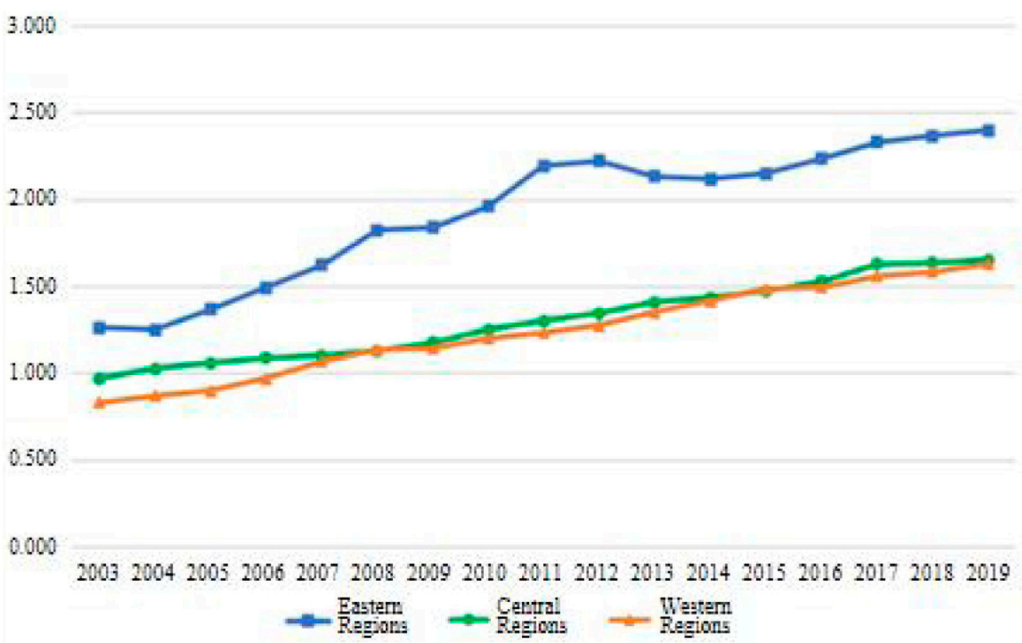

FIGURE 3
Comparison of the level of technical progress of non-energy factors in the service industry in the Eastern, central, and Western regions of China.

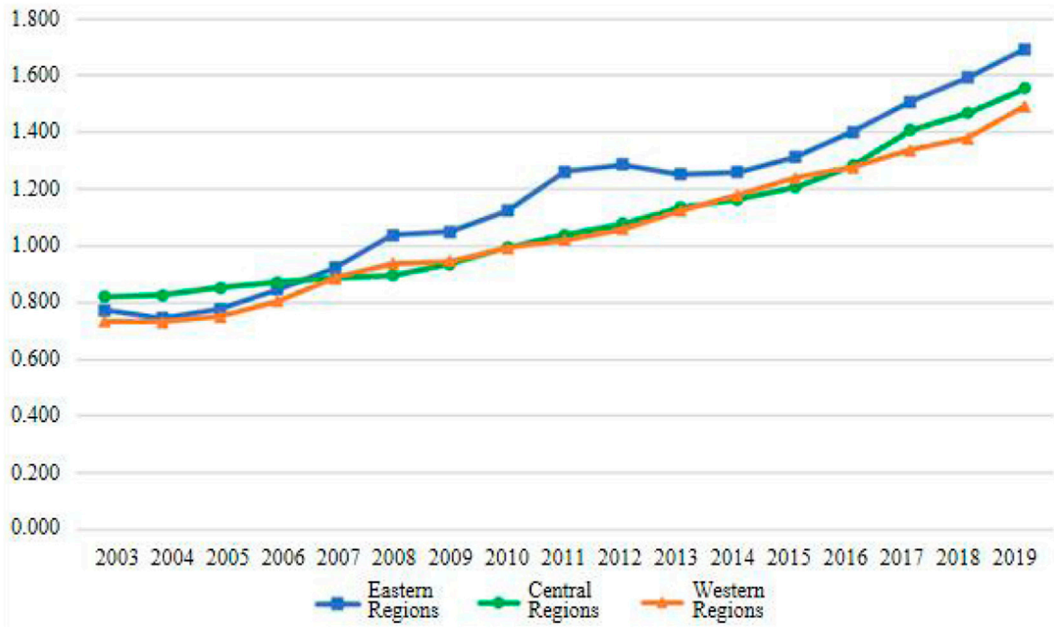

FIGURE 4
Comparison of the technical progress of energy factor in service industry in the Eastern, central and Western regions of China.

and emission reduction, requiring governments at all levels to strictly implement energy saving and emission reduction policies. After the implementation of the carbon emission trading pilot in 2013, it has become an urgent matter to reduce carbon emissions and improve the efficiency of energy use, which requires enterprises in the service industry to pay more attention to technical development in energy, so the growth rate of technical progress in energy factor has been increasing.

In a side-by-side comparison, the comparison of the two types of technical progress level in the service industry in the eastern, central, and western regions of China is shown in Figures 3, 4.

Figure 3 shows a line graph comparing the level of technical progress of non-energy factors in the service industry in the Eastern, central and Western regions of China. The analysis of Figure 3 shows that the level of technical progress of non-energy factors in the Eastern region is higher than that in the central and Western regions. The eastern region has always been the region where China's capital and labour force are concentrated and fast-moving, and the overall level of the service industry development has always been ahead of the central and Western regions, and the concentration of service industry enterprises is also higher. In general, the Eastern region has a higher level of technology and greater innovation capacity in terms of capital and labour. The level of technical progress in non-energy factors in the central and Western regions is relatively similar, but overall the level of technical progress in non-energy factors is slightly higher in the central region. In terms of specific values, the average values of technical progress level of non-energy factors in the service industry in the Eastern, central, and Western regions from 2003 to 2019 are 1.931, 1.309, and 1.247, respectively, decreasing in descending order from East to West.

Figure 4 shows a line graph comparing the technical progress level of energy factor in the service industry in the Eastern, central, and Western regions of China horizontally. From the situation reflected in the line graph, the level of technical progress of energy factor in the service industry in the Eastern region is higher than that in the central and Western regions, but the difference with the central and Western regions is smaller than the level of technical progress of non-energy factors. The level of technical progress in energy factor in the eastern region was lower than that in the central region until 2007. The central region is richer in energy resources, for example, Shanxi, as China's major coal mining province, has a higher level of technology in the extraction and use of coal mines, and the transportation industry is more developed in the central region, so before 2007, the central region probably had higher technical innovation in improving the efficiency of energy use than the eastern region because of its resource endowments. The level of technical progress in the energy factor of the service industry in the central and Western regions is relatively close, showing a multi-point intersection. In terms of specific values, the average values of the level of technical progress of energy factor in the service industry in the Eastern, central, and Western regions from 2003 to 2019 are 1.167, 1.084, and 1.052, respectively, decreasing in order from East to West.

5.3 Results of all variables of baseline regression model

All the empirical analyses in this paper are done using Stata15.1 software, and the descriptive statistics of each variable are shown in Table 2.

TABLE 2 Summary statistics of variables.

Variable	Observations	Mean	Std	Max	Min
$CP_{i,t}$	510	1.780	0.984	5.275	0.429
$A_{i,t}$	510	1.503	0.624	3.132	0.697
$A^E_{i,t}$	510	1.114	0.531	2.193	0.508
$Er_{i,t}$	510	5.442	1.032	6.613	2.245
$Ec_{i,t}$	510	0.453	0.105	0.769	0.272
$Str_{i,t}$	510	0.464	0.082	0.683	0.264
$Inf_{i,t}$	510	3.146	0.312	3.762	2.215
$City_{i,t}$	510	0.523	0.124	0.796	0.257
$FDI_{i,t}$	510	4.752	1.310	7.855	2.467
$Tra_{i,t}$	510	0.428	0.473	1.437	0.062

5.4 Results of baseline regression model

We firstly analyze the relationship between technical progress and carbon productivity in the service industry by baseline regression. According to the results of the Hausman test, the null hypothesis of the random effect model was rejected ($p = 0.000$), so models 1 to 3 in the baseline regression analysis all use fixed-effects models. In Model 1, only two core explanatory variables are regressed with the carbon productivity of the service industry. On the basis of Model 1, Model 2 added three control variables, including environmental regulation level, energy consumption structure, and industrial structure. Model 3 added all the control variables. The baseline regression results of the impact of technical progress on carbon productivity in China's service industry are shown in Table 3.

Baseline regression results from Table 3 show that both non-energy factors technical progress and energy factor technical progress are positively correlated with carbon productivity of service industry in China, and both are significant at the 1% significance level. Specifically, in terms of regression coefficient, for every unit of technical progress in non-energy factors, the carbon productivity of service industry will increase by 0.285 unit, for every unit of technical progress in energy factor, the carbon productivity of service industry will increase by 0.306 unit. The regression coefficient shows that technical progress can significantly promote the improvement of carbon productivity in the service industry, and technical progress in energy factor has greater impact than technical progress in non-energy factors. The reason may be that in the case of stable output of service enterprises, the key to improving the carbon productivity of service industry is to achieve the same output with less carbon emissions, and the technical progress of energy factor has a more direct impact on carbon emissions. Among the control variables, the influence of control variables is significantly positive except urbanization level and trade openness which have insignificant effects on carbon productivity of service industry.

6 Further analysis

6.1 Regional regression analysis

This section examines the impact of regional technical progress on carbon productivity of service industry in China. The regression results of the impact of regional technical progress on the carbon productivity of service industry in China are shown in Table 4.

From the regional regression results in Table 4, it can be seen that the technical progress of non-energy factors and the technical

TABLE 3 Baseline regression results of the impact of technical progress on carbon productivity in China's service industry.

Variable	Model 1	Model 2	Model 3
$A_{i,t}$	0.572*** (7.752)	0.328*** (4.134)	0.285*** (2.831)
$A^E_{i,t}$	0.623*** (8.203)	0.359*** (4.812)	0.306*** (2.821)
$Er_{i,t}$		0.032*** (2.858)	0.006*** (2.749)
$Ec_{i,t}$		2.327** (2.213)	2.124** (2.143)
$Str_{i,t}$		1.241** (2.467)	1.078** (2.347)
$Inf_{i,t}$			0.003* (1.890)
$City_{i,t}$			0.612 (1.122)
$FDI_{i,t}$			0.001* (1.767)
$Tra_{i,t}$			−0.748 (−1.191)
Time FE	YES	YES	YES
Region FE	YES	YES	YES
Constant	0.467*** (12.288)	−0.814*** (−4.564)	−1.315*** (−3.779)
Observations	510	510	510
R-squared	0.757	0.731	0.712

Note: *, **, *** represent the significant at the level of 10%, 5% and 1%, and the value t in parentheses. The following similar symbols have the same meaning as this table.

TABLE 4 Regression results of the impact of regional technical progress on carbon productivity of service industry in China.

Variable	Eastern region	Central region	Western region
$A_{i,t}$	0.318*** (2.674)	0.289** (2.317)	0.266** (2.359)
$A^E_{i,t}$	0.352*** (2.722)	0.296** (2.273)	0.273** (2.418)
Constant	−1.746*** (−4.124)	−1.326** (−2.451)	−1.281*** (−3.531)
Controls	YES	YES	YES
Time FE	YES	YES	YES
Region FE	YES	YES	YES
Observations	187	136	187
R-squared	0.842	0.762	0.823

progress of energy factor have a positive impact on the carbon productivity of the service industry in eastern China at a significance level of 1%, and the influence coefficients are 0.318 and 0.352, respectively, that is, technical progress has significantly promoted the carbon productivity of service industry in Eastern China. Similarly, the two types of technical progress in the central and western regions of China have a positive and significant impact on the improvement of carbon productivity in the service industry in the region.

Specifically, in the central and western regions of China, the influence coefficients of technical progress of non-energy factors are 0.289 and 0.266, respectively, and the influence coefficients of technical progress of energy factor are 0.296 and 0.273, respectively. It can also be seen from the regression results in Table 4 that in the case of constant control variables, the impact of non-energy factors technical progress and energy factor technical progress on carbon productivity of service industry is positive in all regions of China, which is in line with the law of economic development. However, the influence degree is different, and the influence of the Eastern region is greater and more significant. Since the economic development of Eastern China has always been in a leading position, compared with the central and Western regions, its innovation infrastructure is better, the development level of the service industry is higher, and the whole innovation capability of service industry enterprises is stronger. Furthermore, some provinces in the Eastern region take the lead in carbon emissions trading pilot in the country, which makes the regional service industry enterprises have stronger awareness of carbon emission reduction.

6.2 Robustness test

6.2.1 Retest of tail shrinkage treatment

In order to eliminate the possible influence of extreme values, all the relevant variables are processed with a 1% Winsorize tail up and down, and then repeats the baseline regression steps. The regression results are shown in Table 5. It can be seen from the regression results that the technical progress of energy factor and non-energy factors in China and the Eastern, central, and western regions has significant and positive impact on the carbon productivity of the service industry. From this perspective, the baseline regression results are robust.

6.2.2 Retest of replacing the measured indicators of explained variable

In order to test the sensitivity of the indicators, we replace the method of measuring carbon emission indicator in carbon productivity of China's service industry with the method of Zhang and Zhang (2015), and re-measure the carbon productivity of service industry in each province, the measurement method of carbon emissions is replaced by Eq. 15:

$$CO_2 = \sum_{i=1}^{8} E_i \times SCC_i \times CEC_i \tag{15}$$

In Eq. 15, SCC_i is the converted standard coal coefficient of eight fossil energy; CEC_i is the carbon emission coefficient of each energy listed in IPCC Guidelines for National Greenhouse Gas Inventories (2006). The specific indicators and coefficients are shown in Table 6.

The model (14) is re-regressed using the carbon productivity data of China's service industry after changing the measurement method, and the regression results are shown in Table 7. It can be found that the technical progress of non-energy factors and the technical progress of energy factor still have a significant positive impact on the carbon productivity of China's service industry. From this perspective, the results of the baseline regression are robust.

TABLE 5 Regression results of the impact of technical progress on carbon productivity of service industry in China after tail shrinkage treatment.

Variable	Nationwide	Eastern region	Central region	Western region
$A_{i,t}$	0.294*** (2.741)	0.321*** (2.683)	0.292*** (2.653)	0.272** (2.338)
$A^E_{i,t}$	0.319*** (2.759)	0.346*** (2.626)	0.304*** (2.766)	0.281** (2.409)
Constant	−1.372*** (−3.292)	−1.821*** (−2.982)	−1.402** (−2.264)	−1.343** (−2.367)
Controls	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Region FE	YES	YES	YES	YES
Observations	510	187	136	187
R-squared	0.748	0.825	0.863	0.804

TABLE 6 Various indicators and coefficients after replacement of measurement method.

Energy type	SCC	CEC	Energy type	SCC	CEC
coal	0.714	0.756	diesel fuel	1.457	0.619
coke	0.971	0.862	kerosene	1.471	0.571
crude	1.429	0.554	fuel oil	1.429	0.586
gasoline	1.471	0.592	natural gas	1.330	0.448

6.2.3 Retest for reselection of sample interval

Since the global financial crisis that broke out in 2008 had a great impact on the world economy and had a very serious impact on China's national economy, we shortened the time period to 2009-2019, reprocessed the data of each variable with 2009 as the base year, and then regressed. Table 8 shows the regression results after re-selecting the time period, it can be seen from the regression results that the baseline regression results in this paper are still robust.

Synthesis of the above three robustness test results, the baseline regression results in this paper are robust, that is, the technical progress of non-energy factors and the technical progress of energy factor have a significant and positive impact on the carbon productivity of China's service industry. But in terms of the degree of impact, the Eastern region is larger than the central and Western regions, and the technical progress of energy factor has a greater impact on the carbon productivity of China's service industry.

6.3 Endogenous test

6.3.1 The problem of reverse causation

Considering that there is a reverse causal relationship between the explained variable carbon productivity and the explanatory variable non-energy factors technical progress and energy factor technical progress, in order to test the impact of reverse causality on the regression results, we refer to the practice of most literature and choose the one-period lag of non-energy factors technical progress and energy factor technical progress as instrumental variables to estimate the model by two-stage least squares (2SLS). Table 9 shows the regression results of the instrumental variable method, in which the LM statistic and the F statistic reflect the validity of the instrumental variable, indicating that they have passed the "unidentifiable" and "weak instrumental variable" tests. The regression results in Table 9 are basically consistent with the baseline regression results, indicating the conclusion that technical progress of non-energy factors and technical progress of energy factor can significantly improve the carbon productivity of the service industry is still valid.

TABLE 7 Regression results of the impact of technological progress on carbon productivity in China's service industry after replacement of explained variable.

Variable	Nationwide	Eastern region	Central region	Western region
$A_{i,t}$	0.142** (2.231)	0.186** (2.316)	0.137* (1.816)	0.125* (1.802)
$A_{i,t}^{E}$	0.156** (2.463)	0.204** (2.207)	0.134* (1.904)	0.130* (1.834)
Constant	−0.743*** (−3.745)	−0.816*** (−3.262)	−0.613* (−1.854)	−0.489* (−1.757)
Controls	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Region FE	YES	YES	YES	YES
Observations	510	187	136	187
R-squared	0.612	0.543	0.508	0.537

TABLE 8 Regression results of the impact of technical progress on carbon productivity in China's service industry from 2009 to 2019.

Variable	Nationwide	Eastern region	Central region	Western region
$A_{i,t}$	0.314*** (2.910)	0.342*** (2.788)	0.307*** (2.838)	0.282** (2.121)
$A_{i,t}^{E}$	0.349*** (2.852)	0.376*** (2.714)	0.335*** (2.727)	0.309** (2.378)
Constant	−1.615*** (−3.967)	−2.026*** (−3.862)	−1.547*** (−3.314)	−1.428*** (−3.071)
Controls	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Region FE	YES	YES	YES	YES
Observations	330	121	88	121
R-squared	0.738	0.826	0.765	0.814

TABLE 9 Regression results of instrumental variable method.

Variable	Nationwide	Eastern region	Central region	Western region
$A_{i,t}$	0.215*** (2.694)	0.244*** (2.812)	0.208** (2.285)	0.175* (1.878)
$A_{i,t}^{E}$	0.247*** (2.782)	0.283*** (2.704)	0.226** (2.431)	0.199* (1.729)
Constant	−1.046*** (−3.257)	−1.413*** (−3.118)	−1.015** (−2.332)	−0.825*** (−3.701)
Controls	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Region FE	YES	YES	YES	YES
Observations	480	176	128	176
R-squared	0.564	0.574	0.527	0.553
Kleibergen-Paap rk LM statistic	86.175	48.614	75.653	37.627
Kleibergen-Paap Wald rk F statistic	124.616	72.023	113.432	56.246

TABLE 10 Regression results after adding omitted variables.

Variable	Nationwide	Eastern region	Central region	Western region
$A_{i,t}$	0.263*** (2.802)	0.312*** (2.659)	0.271** (2.306)	0.239** (2.067)
$A_{i,t}^{E}$	0.287*** (2.788)	0.347*** (2.745)	0.288** (2.282)	0.253** (2.178)
Constant	−2.168*** (−3.526)	−2.874*** (−3.143)	−2.134*** (−3.372)	−1.675** (−2.089)
Controls	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Region FE	YES	YES	YES	YES
Observations	510	187	136	187
R-squared	0.791	0.804	0.772	0.828

6.3.2 Missing variables problem

In order to test whether there is an endogenous problem caused by omitted variables, we add more control variables to the model by referring to Liu et al. (2020), and then examine the regression coefficient and significant changes of core explanatory variables. We incorporate the level of innovation drive and labor education into the control variables of the model, and then conduct the baseline regression. In terms of indicator construction, firstly, the indicator of innovation-driven level of the whole region is based on patent grants per 10,000 people in each province; secondly, the indicator of the educational level of the regional labor force is based on the average education years of the population over 6 years old in each region. The regression results are shown in Table 10, the results show that the baseline regression results in this paper are still robust.

6.4 Mechanism test of the impact of technical progress on carbon productivity of China's service industry

This part empirically tests the mechanism of technical progress on carbon productivity of China's service industry.

6.4.1 Test of the first mechanism: The production efficiency of service industry

In order to test whether technical progress has an impact on China's service industry carbon productivity through production efficiency of service industry, the following model is set:

$$CP_{i,t} = \beta_0 + \beta_1 A_{i,t} + \beta_2 A_{i,t}^{E} + \beta_3 A_{i,t} \times Pe_{i,t} + \beta_4 A_{i,t}^{E} \times Pe_{i,t} + \beta_5 X_{i,t} + \delta_i + \mu_t + \varepsilon_{i,t} \quad (16)$$

In Eq. 16, the production efficiency of service industry ($Pe_{i,t}$): we select the labor productivity of China's service industry as a proxy variable to measure the production efficiency of China's service industry. Production efficiency of service industry in provinces of China = real added value of service industry in provinces/number of service industry employed in provinces. The other variables in Eq. 16 are the same as the description in Eq. 14. The regression results of the first mechanism test are shown in Table 11 model 4.

From the regression results in Table 11 model 4, it can be seen that after adding service industry $A_{i,t} \times Pe_{i,t}$ and $A_{i,t}^{E} \times Pe_{i,t}$ to Eq. 16, the coefficient of technical progress of non-energy factors and technical progress of energy factor decreases, that is, the

TABLE 11 Results of the first mechanism test in China's service industry.

Variable	Model 4	Model 5
$A_{i,t}$	0.221*** (2.642)	0.198** (2.253)
$A^E_{i,t}$	0.258*** (2.667)	0.236** (2.432)
$A_{i,t}\times Pe_{i,t}$	0.107** (2.564)	0.093* (1.778)
$A^E_{i,t}\times Pe_{i,t}$	0.089 (1.571)	0.074 (1.434)
Constant	0.312*** (3.674)	0.456*** (3.578)
Controls	YES	YES
Time FE	YES	YES
Region FE	YES	YES
Observations	510	480
R- Squared	0.694	0.736
Kleibergen-Paap rk LM statistic		87.273
S- Kleibergen-Paap Wald rk F statistic		139.162

TABLE 12 Results of the second mechanism test in China's service industry.

Variable	Model 6	Model 7
$A_{i,t}$	0.207*** (2.052)	0.174** (2.167)
$A^E_{i,t}$	0.233*** (2.145)	0.243** (2.366)
$A_{i,t}\times Ee_{i,t}$	0.158** (2.070)	0.087* (1.674)
$A^E_{i,t}\times Ee_{i,t}$	0.134** (2.211)	0.068* (1.888)
Constant	−1.253*** (−3.621)	0.356** (2.010)
Controls	YES	YES
Time FE	YES	YES
Region FE	YES	YES
Observations	510	480
R-squared	0.673	0.687
Kleibergen-Paap rk LM statistic		86.789
Kleibergen-Paap Wald rk F statistic		132.374

coefficient of technical progress of non-energy factors decreases from 0.285 to 0.221, and the coefficient of technical progress of energy factors decreases from 0.306 to 0.258, but they remain significant at the 1% significance level, the coefficients of $A_{i,t}\times Pe_{i,t}$ and $A^E_{i,t}\times Pe_{i,t}$ are 0.107 and 0.089, and the former remain significant at the 5% significance level, indicating that the production efficiency of China's service industry, has played a partial mediator role, that is, technical progress of non-energy factors and technical progress of energy factor directly affect the carbon productivity of China's service industry on the one hand, and indirectly affect the carbon productivity of China's service industry through the service industry production efficiency on the other hand.

Considering that there is a reverse causal relationship between the explained variable carbon productivity and the explanatory variable non-energy factors technical progress, energy factor technical progress and production efficiency, in order to test the impact of reverse causality on the regression results, we refer to the practice of most literature and choose the one-period lag of non-energy factors technical progress, energy factor technical progress and production efficiency as instrumental variables to estimate the model by two-stage least squares (2SLS). Table 11 model 5 shows the regression results of the instrumental variable method, in which the LM statistic and the F statistic reflect the validity of the instrumental variable, indicating that they have passed the "unidentifiable" and "weak instrumental variable" tests. The regression results in model 5 are basically consistent with the regression results in model 4, indicating the regression results in model 4 is still valid.

6.4.2 Test of the second mechanism: The energy use efficiency of service industry

To test whether technical progress has an impact on carbon productivity of China's service industry through energy use efficiency of service industry, the following model is set:

$$CP_{i,t} = \beta_0 + \beta_1 A_{i,t} + \beta_2 A^E_{i,t} + \beta_3 A_{i,t}\times Ee_{i,t} + \beta_4 A^E_{i,t}\times Ee_{i,t} + \beta_5 X_{i,t} + \delta_i + \mu_t + \varepsilon_{i,t} \tag{17}$$

In Eq. 17, the energy use efficiency of service industry ($Ee_{i,t}$): We refer to the research method of Liu (2015), and select the ratio of real added value of service industry to energy consumption of service industry to measure the energy use efficiency of service industry in China. The regression results of the second mechanism test are shown in Table 12 model 6.

The regression results in Table 12 model 6 show that after adding $A_{i,t}\times Ee_{i,t}$ and $A^E_{i,t}\times Ee_{i,t}$ of service industry, to Eq. 17, the coefficient of technical progress of non-energy factors and technical progress of energy factor decreases, that is, the coefficient of technical progress of non-energy factors decreases from 0.285 to 0.207, the coefficient of technical progress of energy factor decreases from 0.306 to 0.233, but it remains significant at the 5% significance level, the coefficients of $A_{i,t}\times Ee_{i,t}$ and $A^E_{i,t}\times Ee_{i,t}$ are 0.158 and 0.134, and they remain significant at the 5% significance level, indicating that energy use efficiency of service industry, has played a partial mediating effect, that is, technical progress of non-energy factors and technical progress of energy factor directly affect the carbon productivity of China's service industry on the one hand, and indirectly affect the carbon productivity of China's service industry through energy use efficiency of service industry on the other hand.

Considering that there is a reverse causal relationship between the explained variable carbon productivity and the explanatory variable non-energy factors technical progress, energy factor technical progress and energy use efficiency, in order to test the impact of reverse causality on the regression results, we refer to the practice of most literature and choose the one-period lag of non-energy factors technical progress, energy factor technical progress and energy use efficiency as instrumental variables to estimate the model by two-stage least squares (2SLS). Model 7 shows the regression results of the instrumental variable method, in which the LM statistic and the F statistic reflect the validity of the instrumental variable, indicating that they have passed the "unidentifiable" and "weak instrumental variable" tests. The regression results in model 7 are basically consistent with the regression results in model 6, indicating the regression results in model 6 is still valid.

7 Conclusion and suggestion

We firstly explain the mechanism of technical progress on carbon productivity of service industry in theory. Secondly, we measure and analyze the technical progress of non-energy factors and energy factor in China's service industry. Then we empirically study the impact of technical progress non-energy factors and technical progress of energy factor on carbon productivity in China's service industry. And finally, we conduct an empirical test on the mechanism of technical progress of non-energy factors and energy factor on carbon productivity in China's service industry, and draw the following main conclusion.

First, in terms of carbon productivity, the carbon productivity of China's service industry increased continuously from 2003 to 2019, and the overall growth rate showed a fluctuating upward trend with an average annual growth of 6.31%. Second, the technical progress level of non-energy factors and energy factor in the whole country and the eastern, central, and western regions of China has shown an upward trend on the whole, and the technical progress level of non-energy factors is relatively high. The gap between the technical progress of non-energy factors and the technical progress of energy factor was large during 2004–2012 but gradually narrowed after 2012. The technical progress of non-energy factors and energy factor in service industry was the highest in the eastern region, and relatively close in the central and western regions. Third, technical progress had a significant and positive impact on the carbon productivity of China's service industry from 2003 to 2019. In terms of types of technical progress, technical progress of energy factor had a greater impact. In terms of regions, technical progress had significant promoting effect on the improvement of carbon productivity of service industry in various regions, and the order is the eastern, central, and western according to the size of the regression coefficient. Besides, through the test of the mechanism, it is found that the technical progress of non-energy factors and technical progress of energy factor directly affect the carbon productivity of China's service industry, and indirectly affect the carbon productivity of China's service industry through the production efficiency of service industry and energy use efficiency of service industry.

According to the research conclusions of this paper, we put forwards the following policy suggestion for the improvement of carbon productivity in China's service industry:

Firstly, faced with the increasing carbon emissions in China's service industry, we can optimize the energy structure by improving the energy policy system to alleviate this problem. On the demand side, first of all, relevant policies should be formulated based on the development characteristics of China's service industry and combined with the industrial characteristics of China's service industry to improve the energy policy system focusing on improving carbon productivity. Secondly, policy guidance, energy subsidies, strengthening the supervision of energy conservation and emission reduction and other methods can be used in the short term to promote the popularization of clean energy and guide the energy demand of service enterprises to lean towards clean energy. Finally, it is necessary to reduce the various costs of clean energy used by service enterprises and promote the greening of the whole service industry. On the supply side, we should vigorously develop clean energy, encourage investment in clean energy, broaden access to using clean energy, increase the proportion of clean energy in China's energy supply structure, provide sufficient clean energy supply for the energy market, gradually increase service enterprises' preference for clean energy in the long term and promote the wide application of clean energy in China's service industry, so as to reduce carbon emissions in China's service industry.

Secondly, focusing on technical innovation, we should give full play to the role of technical progress in promoting carbon productivity in China's service industry. First of all, we should support non-energy technology innovation activities of service enterprises using industrial orientation policy. Besides, special support should be given to technical innovation of China's service enterprises in clean energy to reduce carbon emissions. Finally, we should pay more attention to the cultivation of outstanding talents in the service industry and the input in scientific innovation to promote the industrial upgrading of China's service industry and improve the carbon productivity of the service industry.

Finally, according to the level of regional development, the carbon productivity of China's service industry should be improved according to local conditions. For the eastern of China where the development of the service industry is relatively mature, the output level of the service industry has always been in a leading position and tends to be stable, the focus of improving carbon productivity can be placed on reducing CO_2 emissions through technical innovation of energy factor. We need to increase subsidies for research and development of clean energy technology and encourage the development of the clean energy industry to provide technical support for service enterprises to develop cleaner production models. For the central and western of China where the service industry is still in the development stage, the output of the service industry still has a large space for improvement. We should actively implement relevant policies and plans for the development of the service industry in the central and western of China, narrow the development gap with the eastern of China. Meanwhile, both the improvement of production efficiency and energy use efficiency should be taken into account to achieve win-win development of output growth and low-carbon emission reduction in service industry, so as to improve the carbon productivity of service industry.

8 Research limitations and future research directions

There are some limitations in this paper. Firstly, when discussing the factor input of production activities, energy factor is introduced into the production function composed of traditional two factors (labor factor and capital factor) and becomes the third input factor, but the factors are only divided into non-energy factors and energy factor when setting the production function, which means non-energy factors only include labor factor and capital factor without considering other factor input. In fact, other factors such as institutions will also have an important impact on production. Secondly, in terms of data, due to the limitations of various data acquisition of the service industry, the heterogeneity analysis only analyzes the regional heterogeneity and there is a lack of analysis in the heterogeneity of segmented industries of the service industry. Finally, in terms of the estimation of elasticity of substitution, the research method in this paper can only estimate the fixed elasticity of substitution in each region, and cannot analyze its dynamic changes. Further studies are needed in the future.

The future directions of improvement are as follows: Firstly, the selection of input factors will be more diversified. By constructing a multi-factor production function model to analyze the relationship between the multiple factors and explore the impact of these factors on the carbon productivity of China's service industry. Secondly, the research objects will be more detailed. With the continuous development of the service industry, all kinds of data of the service industry in the world will be gradually enriched, and the analysis of the service industry segments will be realized. Finally, static analysis will be transformed into dynamic analysis. Current studies rarely analyze the dynamic changes of elasticity of substitution between factors. Future studies will gradually focus on the dynamic changes of elasticity of substitution between factors, so as to make the research conclusions closer to reality.

Data availability statement

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

Author contributions

All authors contributed to the study conception and design. Conceptualization, formal analysis, funding acquisition, resources, supervision and visualization were performed by ZW. Conceptualization, data curation, formal analysis, investigation, methodology, project administration, resources, software, validation, visualization, roles/writing—original draft and writing—review and editing were performed by WH. Writing—review and editing and visualization were performed by YG, YD, and FZ. All authors read and approved the final manuscript.

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Conflict of interest

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

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Analysis of spatial-temporal evolution and influencing factors of carbon emission efficiency in Chinese cities

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Improving carbon emission efficiency and reducing carbon emissions is crucial to achieving the goal of carbon neutrality and carbon peak. This paper focuses on 278 cities in China from 2000 to 2017, and uses the undesired output SBM model to measure the carbon emission efficiency of each city. The results showed that during the research period the average carbon emission efficiency of China gradually dropped from 0.6 to 0.5. After classifying the carbon emission efficiency of each city. The number of cities in 2005 belonging to high-efficiency areas decreased by 11.76% compared with 2000. From 2005 to 2010, the number of cities in the medium-low-efficiency areas and low-efficiency areas increased from 122 to 143. It is found that the spatial-temporal evolution of carbon emission efficiency, on the whole follows a certain evolution law and has spatial auto-correlation. In addition, the spatial Durbin model model is selected to explore the influencing factors of urban carbon emission efficiency. The findings demonstrate that optimizing the quality of urban development, improving the ability of scientific, and technological innovation, grasping government intervention, and encouraging the introduction of high-quality foreign capital will play a positive role in improving the low efficiency of carbon emissions in cities.

KEYWORDS

carbon emission efficiency, super-efficient SBM model, spatial autocorrelation, spatial durbin model, environment

1 Introduction

Climate problems and ecological imbalance have become the problems that endanger the human living environment and health security. In the Fourth Assessment Report on Global Climate Change, the United Nations Intergovernmental Panel on Climate Change (IPCC) stated that greenhouse gas emissions from human activities mainly cause the warming of the Earth from the mid-20th century to the present. In 2015, 178 parties to the United Nations Framework Convention on Climate Change signed the Paris Agreement to combat climate change, ensuring that the global average temperature rise does not exceed 2°C compared to the pre-industrial revolution and striving to keep it within 1.5°C. Therefore, governments accelerate the pace of low-carbon economic transformation and promote the sustainable improvement of the natural ecological environment. As one of the largest exporters of carbon emissions, General Secretary Xi (2021) proposed to build a 'community of life between humans and nature', reflecting China's great concern about solving the contradiction between ecological and economic development caused by industrial civilization. The key to resolving this contradiction is to achieve carbon peak, and carbon neutrality and to promote the green transformation of production and lifestyle. Researching the improvement of carbon emission efficiency is an important path to achieving China's carbon emission reduction goals. Promoting the implementation of carbon emission reduction policies and measures in prefecture-level cities is an important measure to promote low-carbon, circular development and achieve sustainable development in China.

In recent years, scholars have investigated carbon emission efficiency from different dimensions mainly including carbon emission intensity and carbon productivity. Carbon emission intensity is measured by carbon emission and physical production (Zhang, 2009; Zhang, 2010; Su et al., 2013; Yu et al., 2018). The research on carbon productivity is divided into two stages. The preliminary research primarily focuses on measuring the single factor carbon emission efficiency, which is equivalent to using the ratio between carbon emissions and a single factor to respond to the characteristics of carbon emission efficiency (Otavio and José, 1999; Sun, 2005). A single factor cannot fully reflect the influencing factors of carbon emission efficiency scholars began to study carbon emission efficiency from a total factor perspective in the later period by taking into account the influence of political, economic, ecological, technological, and other factors on carbon emission efficiency (Hu and Kao, 2007; Wang et al., 2020). In terms of measuring carbon emission efficiency, domestic and foreign scholars mainly use two methods, DEA (Zofio and Prieto, 2001; Zhou et al., 2010; Wang, 2022; Zhang, 2023) and SFA (Du and Zou, 2011). Since the SFA method cannot eliminate the problem of subjective factors on weight setting and the traditional DEA model requires all input factors to be cut by the same proportion. Which is inconsistent with the actual economic production activities and makes its efficiency measurement biased. Therefore, an increasing number of scholars have improved based on previous studies. Some scholars combined RAM model with SFA method (Cai, 2017) and some scholars combined RAM model with DEA model (Meng et al., 2017). But at present, most scholars tend to combine the three-stage DEA model with the super-efficiency SBM model to measure the efficiency problem (Wang, 2019; Wang et al., 2021a; Zhang, 2022; Li, 2022; Zhu et al., 2022). Due to different time scales, sources of carbon emissions and analysis methods current studies on carbon emission efficiency are different even if the research objects are the same among different references. From the perspective of spatial econometrics, the rise of spatial econometrics some scholars focus on the spatial effects of carbon emission efficiency. Most studies on the influencing factors of carbon emission are carried out based on IPAT model and KAYA identity. However, due to the different research objects and research periods, the influencing factors of carbon emission efficiency of different research objects will have certain characteristics in different research periods. But scholars have not reached a consensus on defining the influencing factors of carbon emission efficiency. Most scholars' influencing factors of carbon emission efficiency are carried out from science and technology and industrial structure (Ma, 2015; Song et al., 2018; Zhao, 2019; Guo and Zou, 2020; Li et al., 2020; Yin, 2021; Shang et al., 2022). It is confirmed that the impact of these two factors on carbon emissions has been widely recognized by the academic community. However, due to the differences in the study area, research period, and calculation error the significance of these factors is also different.

Due to the difficulty in gathering data, most extant studies estimate carbon emission efficiency at the national, provincial, or regional level, with only a few studies conducted at the national city level and in a period before 2015. Secondly, most scholars mainly use stochastic Frontier analysis (SFA) or data envelopment analysis (DEA) and use the division of three major regions and four major economic regions to measure carbon emission efficiency. Some new measurement models that have overcome the shortcomings of SFA and traditional DEA methods can better meet the actual production measurement needs. Considering the three major regions and the four major economic regions can no longer accurately reveal the differences and regularities of China's regional economic development. Therefore, according to the report of the Development Research Center of the State Council. This paper adopts the division standard of eight comprehensive economic zones, and each regional division has epochal characteristics. This is a new perspective to study issues related to carbon emission efficiency and provides new ideas for the subsequent research of other scholars. In addition, for cities in different provinces, their carbon emission efficiency will affect each other due to geographical proximity and other reasons. Therefore, from the perspective of spatial effect the discussion on the spatial-temporal evolution of carbon emission efficiency at the national urban scale cannot be ignored. China has a large number of prefecture-level cities with a complex socio-economic backgrounds. To carry out research on carbon emissions of prefecture-level cities and explore the spatial-temporal evolution of carbon emissions and its influencing factors at the prefecture-level scale is conducive to the national and governments at all levels to formulate feasible carbon emission reduction plans according to local conditions based on improving the quality of economic development and steadily promoting the process of urbanization. Improving energy conservation and emission reduction policies have important reference value. It is also helpful for readers to understand the carbon emission situation of different cities. This study can provide a theoretical basis and guide readers to think deeply about carbon emissions.

So this paper takes the data of 278 cities in China from 2000 to 2017 as a sample, and adopts the super-efficient SBM model with non-expected output to measure the carbon emission efficiency. This paper dividing China into eight comprehensive economic zones combines spatial econometric models to explore the spatial and temporal evolution patterns of carbon emission efficiency. Its influencing factors provide theoretical support and practical reference for improving carbon emission efficiency.

2 Research methodology and data sources

2.1 Research methodology

2.1.1 Measurement of carbon emission efficiency using a super-efficiency SBM model with undesirable outputs

In this paper, Super-efficiency SBM model that considers environmental factors based on undesirable outputs is selected to solve the slack problem of input-output and the problem of efficiency analysis in the presence of undesirable output. Tone

(Kaoru, 2001) proposed the SBM (Slack-based Measure, SBM) model based on considering the slack variable, defining the production possibility set as $P = \{(x, y)|x \geq X\lambda, y \leq y\lambda, \lambda \geq 0\}$, for which the input variable x_0 of the 0th decision-making unit can be expressed as $X\lambda + S^-$ and the output variable y_0 can be expressed as $Y\lambda - S^+$.

The specific calculation formula is:

$$\rho^* = min\frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}}{1 + \frac{1}{s}\sum_{r=1}^{s}\frac{s_r^+}{y_{r0}}}$$

$$S.T.\begin{cases} x_0 = X\lambda + S^- \\ y_0 = Y\lambda - S^+ \\ \lambda \geq 0, S^- \geq 0, S^+ \geq 0 \end{cases} \tag{1}$$

In this formula: ρ^* is the efficiency value; X_{ij} and Y_{rj} are the "ith" input variable and the "rth" output variable of the "jth" decision-making units, respectively.

The super-efficiency SBM model supposes to solve when the efficiency value of multiple decision units is 1. The removal point (x_0, y_0) redefines the production possibility set. The super-efficiency SBM model makes the efficiency calculation more accurate and efficient. However, the impact of environmental factors on the efficiency of the production system is increasing and cannot be ignored. Tone (Kaoru, 2002) stated the super-efficient SBM model with non-desired output considering environmental factors. There are still n decision units DMUs, m input variables x, s1 desired output variables y_r, adding s2 non-desired outputs y_k, and $s = (s_i^-, s_r^+, s_t^{b-})$ its corresponding slack variable.

The formula for measuring the DMU of the evaluated unit is:.1

$$\rho = \min\frac{1 + \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}}{1 - \frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{s_r^g}{y_{r0}^g} + \sum_{k=1}^{s_2}\frac{s_k^b}{y_{k0}^b}\right)}$$

$$S.T.\begin{cases} x_{i0} \geq \sum_{j=1}^{n}x_{ij}\lambda_j - s_i^-, i = 1, \ldots, m \\ y_{r0}^g \leq \sum_{j=1}^{n}y_{rj}\lambda_j + s_r^+, r = 1, \ldots, s_1 \\ y_{k0}^b \geq \sum_{j=1}^{n}y_{kj}\lambda_j + s_i^b, k = 1, \ldots, s_2 \\ 1 - \dfrac{1}{s_1 + s_2}\left(\sum_{r=1}^{s_1}\dfrac{s_r^g}{y_{r0}^g} + \sum_{k=1}^{s_2}\dfrac{s_k^b}{y_{k0}^b}\right) > 0 \\ \lambda, s^b, s^g \geq 0 \\ j = 1, 2, \ldots, n \end{cases} \tag{2}$$

In this formula: ρ is the leading surface distance of DMU; x is the input variable, y_r is the expected output variable, y_k is the unexpected output; $s = (s_i^-, s_r^+, s_t^{b-})$ is the corresponding relaxation variable.

2.1.2 Estimating the effect of influencing factors by spatial durbin model

James and Kelly (2009) extend the SLM model and propose the spatial Durbin model (SDM), which contains the lag term of the explained variable and in turn includes the lag term of the explained variable. In this paper, the spatial Durbin model (SDM) is selected to analyze the influence of each indicator factor on carbon emission efficiency, which can reflect the spatial correlation of both the explained variable and explanatory variables as a formula (3):

$$y = \rho Wy + X\beta + WX\theta + \varepsilon \tag{3}$$

In this formula: W is the spatial weight matrix, ρWy denotes the spatial autocorrelation between y and adjacent area y, X is the independent variable, and WXθ represents the spatial autocorrelation between y and adjacent region X, ρ, β, θ are the corresponding coefficient vectors; ε is the random error term.

2.2 Index selection and data sources

2.2.1 The basis for selecting indicators and data sources for the carbon emission efficiency model

The super-efficient SBM model contains input variables, non-expected output variables, and expected output variables. This paper draws on the perpetual inventory method of Xiang (2011), Liu et al. (2017), and others using social aggregate investment in fixed assets as investment indicators. Refers to the literature of Guo and Lin (2017) and other scholars on carbon emission efficiency accounting and Wu et al. (2014), Zou et al. (2014) and others using provincial nighttime lighting data to extrapolate urban scale data. The stock of fixed assets, labor input, and energy input are selected as input variables. Carbon emissions are undesired output indicators the level of economic development is the desired output indicator. Data required for calculating fixed asset stocks and economic development levels are obtained from the China City Statistical Yearbook. And the data on labor input are obtained from the China Statistical Yearbook for Regional Economy. The final labor input is expressed by averaging the number of employees at the end of the previous year with the number of employees at the end of the current year. Some missing data are obtained by linear interpolation. Data on energy input came from the China Energy Statistical Yearbook.

The process of obtaining carbon emission data of prefecture-level cities is as follows: provincial night light data to invert city-scale data by Wu et al. (2014) and Zou et al. (2014) night light data to invert county carbon emission data by Wang et al. (2021a) and the data had advantages of consistent statistical caliber and strong continuity. First process DMSP/OLS night light data and NPP/VIIRS night light data to obtain night light data for each year from 2000 to 2017. The data includes provincial night light data and municipal night light data. Secondly, many scholars have demonstrated the correlation between carbon emissions and the total value of night light. Therefore, referring to the research of relevant scholars fitted the correlation between carbon emissions and the total value of annual night light in 30 provinces or cities in China (excluding Taiwan, Tibet, Hong Kong, and Macao). Then selected the quadratic polynomial with the best goodness of fit is the fitting model. The total carbon emissions of each province can be calculated through the consumption of fossil energy provided in the China Energy Statistical Yearbook. Finally, the relevant fitting coefficient of each province can be obtained, and its reliability can be determined by a precision test. Finally, using DMSP/OLS and NPP/VIIRS night light data of prefecture-level cities and relevant fitting coefficients of their provinces and cities, carbon emissions of prefecture-level cities can be derived.

2.2.2 Influential factors model index selection basis and data sources

The carbon emission efficiency is affected by various factors. By analyzing the existing research results, the main academic views are that the industrial structure dominated by the secondary industry is the

FIGURE 1
Map of China's eight comprehensive economic zones.

main reason for the increase in carbon emissions, and scientific and technological progress has a significant effect on reducing carbon emissions. The influence of these two factors on carbon emission has been widely recognized by the academic circle. Fan et al. (2019) proposed that the rapid development of urbanization would lead to a rapid increase in population density, which would significantly promote carbon emissions. In addition, factors such as ecological environment, government intervention and foreign investment were also proved by Ma (2015) and Li et al. (2020) to be important factors in inhibiting or promoting carbon emission efficiency.

Based on the existing research results, this paper selects the carbon emission efficiency of cities throughout the country as the dependent variable. Selects the industrial structure, urbanization level, technological progress, population density, ecological environment, government intervention and foreign investment of cities as explanatory variables to conduct a spatial econometric analysis of influencing factors. The relevant data are from the China City Statistical Yearbook, missing data using the linear interpolation method.

3 Analysis and discussion of the spatial and temporal evolution of carbon emission efficiency

3.1 Spatial-temporal evolution characteristics of carbon emission efficiency

Based on the eight comprehensive economic zones, the spatial and temporal evolution of carbon emission efficiency of 278 cities in China is studied and explored (Figure 1). Due to the shortage of energy and carbon emission statistics in Tibet, Hong Kong, Macao, and Taiwan Province, the four regions in this study were not included in the calculation.

From the overall perspective (Figure 2), overall carbon emission efficiency decreased continually from around 0.6 to 0.5, with a significant increase in 2009. Zhao (2013) and Wang et al. (2021b) both believe that the economy is an important factor affecting carbon emissions in both the long and short term. It was disturbed by the international financial crisis in 2008, which seriously affected the economic development of various regions and led to the overall economic recession. The carbon emission efficiency also fluctuated significantly. In 2009, due to the impact of the United Nations Climate Change Conference, the issue of carbon emissions was pushed to the forefront of public opinion. The government strengthened the control of carbon emissions, and the efficiency of carbon emissions was improved. After that China's carbon emission efficiency has shown a continuous decrease. Zhao (2019) stated that the average national carbon emission efficiency from 2000 to 2016 shows an overall decreasing trend. Indicating that the country still puts economic construction in first place, which has caused some negative impacts on the environment.

From the perspective of the eight comprehensive economic zones, the average carbon emission efficiency of each region is quite different (Figure 2). (Excluding Tibet, Taiwan, Hong Kong, and Macao) The middle Yellow River region has the highest mean carbon emission efficiency with a total mean value of 0.6184 from 2000 to 2017, which makes a major contribution to China's carbon emission efficiency. This was followed by the southwest region at

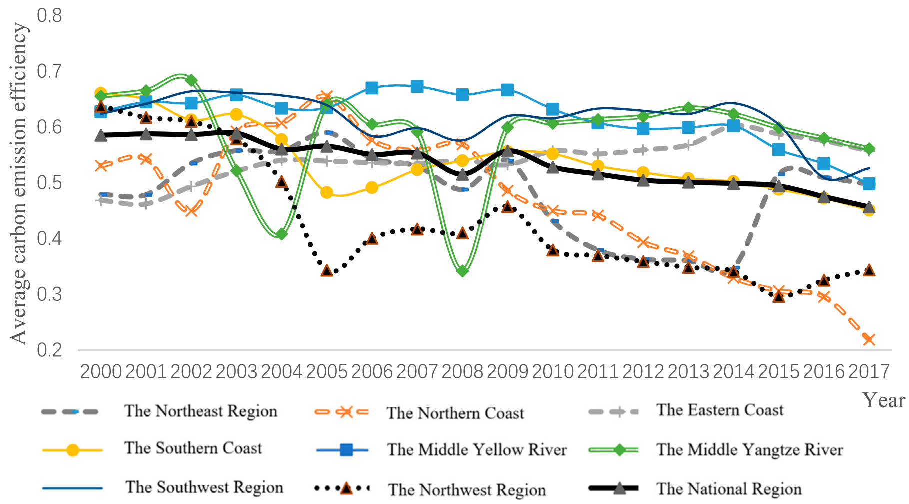

FIGURE 2
2000–2017 China's eight regions and the national carbon emission efficiency mean change chart.

0.6135. The middle Yellow River and the southwest region use advanced carbon emission technology to take the path of low-carbon industrial structure, adjust and upgrade the industrial structure, and continuously improve energy efficiency. The impact of the financial crisis in 2008 eliminated some industries with low output and high energy consumption, so the average carbon emission efficiency of the two regions is always at a higher level in the country. In addition, these two regions have vast territories, and the environment has a greater ability to purify pollutants. Coupled with abundant energy resources led to the continuous transfer of high-energy-consuming industries in other regions to these two regions. However, the technical capabilities of these two regions are not as good as the eastern coastal areas and the middle Yangtze River. The carbon emission efficiency of the middle Yellow River and the southwest region has lagged behind that of the eastern coastal areas and the middle Yangtze River especially after 2015. The region with the lowest mean value of carbon emission efficiency is the Northwest Region. The mean value of carbon emission efficiency has been decreasing since 2000 and rebounded a small amount after 2005. Its maintenance is low but has improved significantly in 2015. Although the northwest region is remote, it is rich in energy resources. Therefore, after 2000 the development strategy of the western region led to the rapid development of energy-intensive industries it increased development opportunities and economic investment, and the proportion of the secondary industry increased. However, the technical level is limited and the management experience is insufficient, resulting in energy waste so that the carbon emission efficiency is decreasing. After 2015, possibly affected by the Paris Climate Conference the Northwest region continues to optimize the quality of industrial development, resulting in improved carbon emission efficiency. The average carbon emission efficiency of the northern coast and the northeast region is lower than the national average of 0.5345. The average carbon emission efficiency of the northern coast began to rise in 2002 reached a peak point in 2005 and decreased significantly since 2005. Due to the closure of many energy-intensive and polluting enterprises during the '10th Five-Year Plan' the control of carbon emissions before 2005 was effective. In order to maintain a stable economic development rate the task of reducing carbon emissions still facing difficulty. The average carbon emission efficiency in the Northeast region showed a downward trend after 2009, which is related to the excessive dependence on heavy industry and the lack of technological innovation in Northeast China. High energy consumption, high emission and high pollution are serious, and the carbon emission efficiency is still low. After 2015 influenced by the Paris Climate Conference, the government issued a series of policies to help enterprises in the northeast region to transform and upgrade by adjusting industrial structure, continuously reduceing carbon emissions and enhanceing environmental awareness. Coupled with the decline of heavy industry and ecological environment restoration, the average carbon emission in the northeast region was higher than the national average level. The average carbon emission efficiency of the eastern coast overall situation is relatively stable with slow increase but still retention at a higher level in the country. This is due to the high degree of opening up of the eastern coastal areas, advanced technology and management experience. In addition, enterprises with high energy consumption and high emissions continue to move out, and the tertiary industry with low carbon emission intensity grows faster so that the carbon emission efficiency continues to increase. The average carbon emission efficiency of the southern coast continued to decrease between 2000 and 2005 and increased since 2005, generally staying with the national average level. This is because the region's economic development and technology are relatively developed. In the early stage of development, a series of environmental problems such as strengthening construction, environmental protection, promoting emission, *etc.*, Led to a decrease in the average emission efficiency. After that, as the recovery of the national economy once again promoted the development of the region, the average carbon emission efficiency of the southern coast did not lower the national average in the later period. Although the eastern coast

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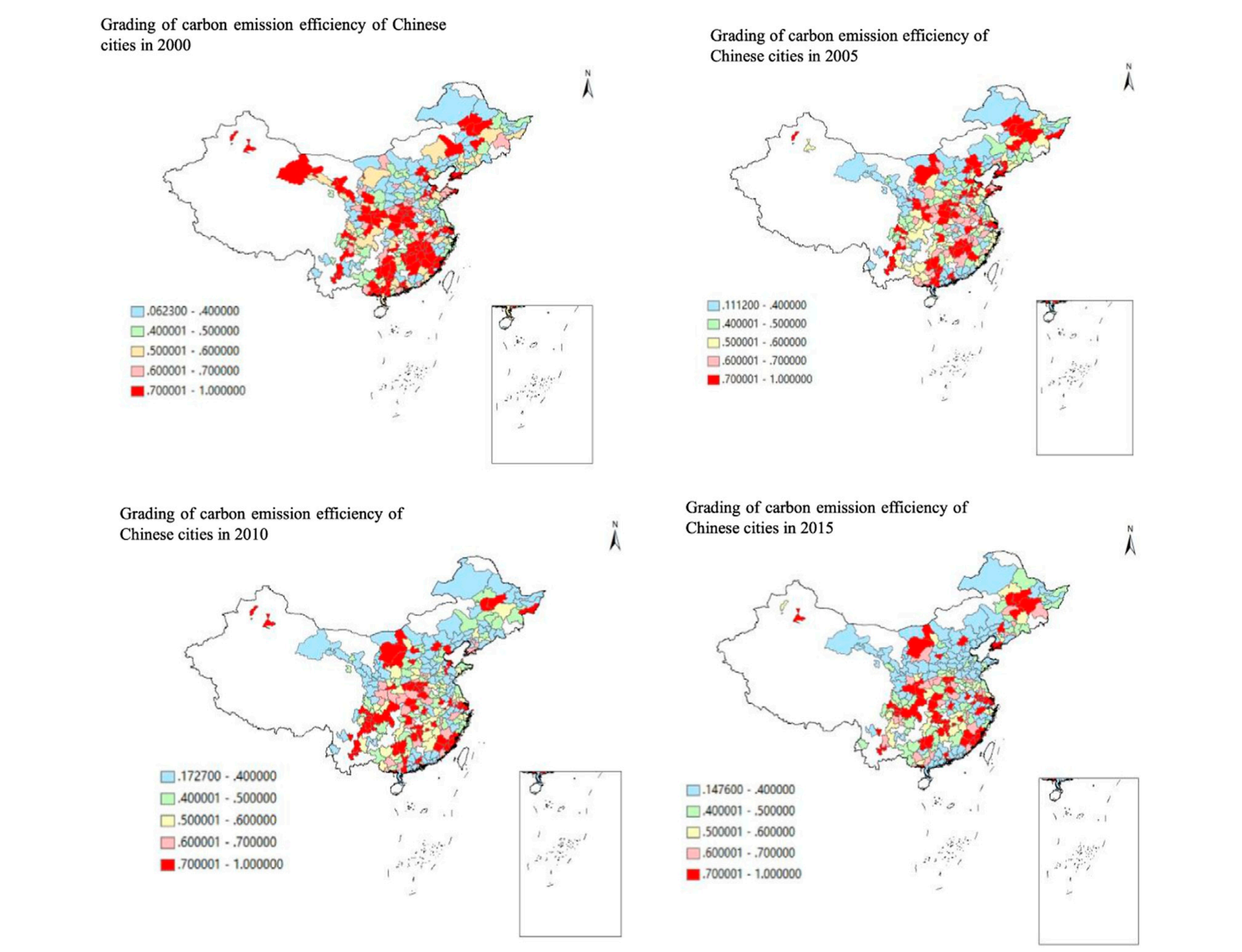

FIGURE 3
Grading of carbon emission efficiency in Chinese cities.

and the southern coast have a high degree of openness to the outside world, they invested heavily in infrastructure construction in 2008 in response to the financial crisis, resulting in an increase in demand for steel and cement, resulting in a large number of carbon emissions. However, due to the advanced level of technology application, rich management experience, and a series of measures taken by the government, the carbon emission efficiency of the eastern coast and the southern coast in 2008 fluctuated less. The average carbon emission efficiency in the middle Yangtze River reached a trough in 2004 and 2008 respectively and finally stabilized after 2009. It is speculated that economic development is emphasized while environmental pollution is neglected, so the average carbon emission efficiency is reduced in 2004. Due to its high degree of opening to the outside world, so affected by the 2008 international financial crisis, in response to the financial crisis, the government investment stimulus, resulted in a large number of carbon emissions, resulting in low overall carbon emissions efficiency. After 2009, affected by the United Nations Climate Change Conference, coupled with a series of government measures, the region's carbon emissions efficiency has improved. Although the fluctuation in the middle Yangtze River is large, the overall carbon emission efficiency in the region is high, which also benefits from the local advanced technology and rich management experience. From 2000 to 2017, the mean carbon emission efficiency of each region has a large difference, showing a downward trend.

To deeply analyze the changes in carbon emission efficiency this paper selects the carbon emission efficiency values of Chinese cities in 2000, 2005, 2010 and 2015 and uses ARCGIS to classify and visualize the carbon emission efficiency (Figure 3). Among them, [0.7, 1] is the high-efficiency area, [0.6, 0.7] is the more efficient area, [0.5, 0.6] is the mid-high efficient area, [0.4, 0.5] is the medium-low-efficiency area, below 0.4 is the low-efficiency area, and the white area indicates no data.

In 2005, the number of cities belonging to high-efficiency areas decreased by 11.76% compared with 2000. From 2005 to 2010, the number of cities in the medium-low-efficiency areas and low-efficiency areas increased from 122 to 143, and the increase was more obvious. By 2015, it can be seen that some cities adjacent to high-efficiency areas gradually changed from high-efficiency areas to medium-low-efficiency areas or low-efficiency areas. It shows that the carbon emission efficiency of China's cities are in a downward trend, fewer cities in the high-efficiency areas, and more cities in the medium-low-efficiency areas and low-efficiency areas. In the selected 4 years, it can be seen that the carbon emission efficiency of Beijing, Shanghai, Daqing, Wuxi, Shenzhen, Zhengzhou, Liuzhou and other cities has always remained at 1, most of which are located east of the 'Hu Huanyong Line'. The carbon emission efficiency of Fuxin, Tieling, Chaoyang, Huludao, Xingtai, Langfang, Heze, Lianyungang, Huzhou, Quzhou, Lishui, Meizhou, Shanwei, Heyuan, Qingyuan, Sanya, Xinzhou, Hulun Buir, Bayannur, Ulanchap, Anshun, Lijiang, Yinchuan and Guyuan is always lower than 0.4, of which 37.5% are distributed in the eastern coast and southern coast, 33.33% are distributed in the middle Yellow River, Southwest China and Northwest China, 29.17% are distributed in the northeast and northern coastal areas, while the middle reaches of the Yangtze River are not distributed. This study finds that carbon emission efficiency is bounded by the 'Hu Huanyong Line', and there are more high-efficiency cities to the east of the line than those to the west of the line, but the significance gradually decreases, indicating that the distribution of high-efficiency cities is gradually dispersed. It shows that although the cities to the east of the 'Hu Huanyong Line' are more effective in carbon emission efficiency, carbon emission efficiency still shows a general downward trend. After all, although advanced technology has improved carbon emission efficiency, it will also bring more capital investment and carbon emission demand, which will lead to a decrease in carbon emission efficiency. Two reasons can be inferred for cities with carbon emission efficiency always higher than 1. First, due to the more developed regions, high energy-consuming and high-polluting enterprises continue to migrate outward, making carbon emission intensity effectively reduced, thus improving carbon emission efficiencies, such as Beijing, Shanghai and Shenzhen. Second is that capital investment makes some high-energy-consuming industries continue to develop and carbon emissions increase, but at the same time, it pays attention to environmental protection. With the support of relevant policies, advanced production technology and rich management experience have effectively improved carbon emission efficiency, such as Daqing, Wuxi, Zhengzhou and Liuzhou. For cities whose carbon emission efficiency is always lower than 0.4, all regions are distributed except the middle Yangtze River, indicating that the middle Yangtze River has achieved relatively significant results in energy conservation and emission reduction, while cities in other regions should become key areas for improving carbon emission efficiency.

3.2 Spatial correlation test of carbon emission efficiency

To explore whether the spatial distribution characteristics of carbon emission efficiency in China's cities are affected by spatial auto-correlation during the sample period. It is necessary to test the spatial correlation of carbon emission efficiency in China's cities, including the global spatial correlation test and local spatial correlation test.

This paper uses the Global Moran's I to test whether there is a spatial correlation in the overall carbon emission efficiency of cities in China. The calculation formula is shown in (4). The value domain is [-1, 1]. If the result is greater than zero, it indicates that there is a spatial positive correlation between the carbon emission efficiency of each city. The larger the value, the more obvious the spatial correlation. The positive correlation of space indicates that the correlation is more significant with the aggregation of spatial distribution. There is a spatial negative correlation when it is less than zero, and the spatial negative correlation indicates that the correlation becomes significant with the dispersion of the spatial distribution. Equivalent to zero indicates no correlation, using ARCGIS to get results.

$$\text{Moran's I} = \frac{\sum_{i,j=1}^{n} W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{s^2 \sum_{i,j=1}^{n} W_{ij}} \tag{4}$$

Where $s^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2$ is the sample variance; x is the city's carbon emission efficiency value; n is the sample size; $\sum_{i,j=1}^{n} W_{ij}$ is the sum of spatial weights, and W_{ij} refers to the spatial weight matrix, indicating the adjacent relationship between the two cities. If the adjacent is 1, the non-adjacent is 0.

This paper uses the local Moran index to further test whether there is a significant local spatial agglomeration or differentiation in the carbon emission efficiency of cities during the sample period. Local spatial autocorrelation analysis is a clustering and outlier analysis of the given elements and fields, if the cities with high carbon emission efficiency are clustered together, they are "HH" (High-High) clustering, and if cities with low carbon emission efficiency are clustered together, they are "LL" (Low-Low) clustering. Both "HH" and "LL" are "positive spatial autocorrelation"; if cities with high carbon emission efficiency and cities with low carbon emission efficiency are clustered together, they are "HL" (High-Low) outliers or "LH" (Low-High) outliers, both of which represent spatial outliers. If the cities with high carbon emission efficiency and the cities with low carbon emission efficiency are randomly distributed, the local Moran index p is not less than 0.05, indicating that the correlation is not significant.

3.2.1 Global spatial correlation analysis

By observing the global Moran index of Chinese cities from 2000 to 2017 (Table 1), the values were greater than zero, and all Moran values passed the significance test. From 2000 to 2007, the Moran index decreased in volatility, indicating that the spatial correlation between carbon emission efficiency in China's cities weakened in volatility. The Moran index showed a rising trend in 2008–2017, from 0.15567 from 2008 to 0.225,294 in 2017. It shows that during the study period, the carbon emission efficiency of 278 cities in China as a whole shows a positive spatial correlation of 'first fluctuation and then rise', and the spatial distribution of carbon emission efficiency of cities in China is not random. Cities with similar carbon emission levels show a state of agglomeration. That is the number of cities with 'high-high agglomeration' and 'low-low agglomeration' first fluctuates and then increases.

3.2.2 Analysis of local spatial agglomeration

To further explore which cities have spatial agglomeration, 2000, 2005, 2010 and 2017 were selected for the local Moran index test, and the spatial clustering distribution map of carbon emission efficiency in Chinese cities was obtained (Figure 4), and specific cities were listed in Supplementary Appendix S1–S4.

From 2000 to 2017, the spatial distribution of carbon emission efficiency in Chinese cities gradually tended to be stable, with

TABLE 1 China's urban global moran index 2000–2017.

year	Moran	*p*-value	Z value	Significance test
2000	0.159,905	0.0000	7.66282	significant
2001	0.141,788	0.0000	6.813,256	significant
2002	0.180,743	0.0000	8.639,139	significant
2003	0.099378	0.00001	4.827,407	significant
2004	0.138,098	0.0000	6.643,657	significant
2005	0.082151	0.000058	4.020071	significant
2006	0.11029	0.0000	5.34207	significant
2007	0.075632	0.000203	3.71582	significant
2008	0.15567	0.0000	7.472,492	significant
2009	0.116,993	0.0000	5.65395	significant
2010	0.15806	0.0000	7.58034	significant
2011	0.182,281	0.0000	8.716,996	significant
2012	0.219,277	0.0000	10.453,189	significant
2013	0.230,632	0.0000	10.984,433	significant
2014	0.259,218	0.0000	12.322,869	significant
2015	0.214,649	0.0000	10.235,706	significant
2016	0.207,547	0.0000	9.909,321	significant
2017	0.225,294	0.0000	10.745,582	significant

significant north-south differentiation and spatial agglomeration characteristics. It can be seen from Figure 4 that compared with 2000, the total number of cities with 'high-high' agglomeration and 'low-low' agglomeration decreased in 2005. Compared with 2005, the number of cities with 'high-high agglomeration' and 'low-low agglomeration' increased in 2010 and 2017, and gradually connected into pieces, which was basically consistent with the results of the global spatial correlation test.

Compared with 2000, the total number of cities with 'HH' aggregation and 'LL' aggregation increased from 76 in 2000 to 78 in 2017. The total number of cities with 'HL' and 'LH' characteristics decreased from 22 in 2000 to 19 in 2017. This shows that the spatial positive auto-correlation characteristics of urban carbon emission efficiency are gradually increasing and showing a trend of polarization. The distribution of cities with high carbon emission efficiency and cities with low carbon emission efficiency is gradually dispersed. Cities with high carbon emission efficiency are gradually adjacent to cities with high carbon emission efficiency, and cities with low carbon emission efficiency are gradually adjacent to cities with low carbon emission efficiency.

The cities that have always maintained the characteristics of 'HH' in the 4 years are Ji 'an, Yichun, Xinyu, Pingxiang, and Zhuzhou. These cities are distributed in the middle Yangtze River. In addition, the number of cities with 'HH' characteristics in the middle Yangtze River and the eastern coast is increasing. The number of cities in the middle Yangtze River has increased from 13 to 19, and the number of cities on the eastern coast has increased from 0 to 10. These areas have advanced technical levels, rich management experience and high energy utilization rates, so the overall carbon emission efficiency is constantly improving. In these 4 years, cities in the northwest region have not shown 'HH' characteristics. Due to the remoteness of the region and the limited technical level, the overall carbon emission efficiency is low. And the cities with 'HH' characteristics in the middle Yellow River, southwest region, southern coast and northern coast are decreasing. Therefore, these areas should improve carbon emission efficiency for their own development problems.

It can be seen from the table that no city has always maintained the 'LL' characteristics, but the number of cities with 'LL' characteristics in the northern coast and northwest region is significantly higher than that in other regions, and the number of cities with 'LL' characteristics in the northern coast is increasing. From five in 2000 to 28 in 2017 indicating that the cities in this region ignore the importance of carbon emission reduction while pursuing economic development. The number of cities with 'LL' characteristics in the northwest region has decreased, indicating that the region has continuously optimized the quality of industrial development. Thus improving carbon emission efficiency but there is still a long way to go. There have been no cities with 'LL' characteristics in the middle Yangtze River. And the number of cities with 'LL' characteristics in the middle Yellow River, southwest region, the southern coast, northeast region and eastern coast is decreasing, indicating that cities in these areas have achieved considerable results in controlling carbon emissions.

In these 4 years, none of the cities has always maintained the 'HL' and 'LH' characteristics. However, compared with other regions the number of cities with 'HL' characteristics in the middle Yellow River and the northern coast is relatively large, and the number of cities with 'LH' characteristics in the middle Yellow River and the middle Yangtze River is quite large. Because the geographical location of these cities connects the developed eastern regions and the western regions with low carbon emission efficiency, the concentration of LH or HL is more obvious. The above results and reason analysis are also largely consistent with the findings of Liu et al. (2015), Wang et al. (2016). and Shi (2017).

To sum up, the spatial distribution of carbon emission efficiency in China at this stage shows an increasing positive auto-correlation. Low-carbon emission efficiency cities should focus on their own problems and rely on the experience of neighboring high-efficiency cities to drive their own economic and industrial restructuring, actively tap their carbon emission reduction potential, and improve carbon emission efficiency.

3.3 Spatial econometric analysis of carbon emission influencing factors

When combined with studies on the carbon emission efficiency of Chinese cities over the last 20 years. It is clear that there is a spatial auto-correlation between carbon emission efficiency and distance between cities, with distance having varying degrees of influence on carbon emission efficiency. Further estimation of the spatial Durbin model yields R^2 = 0.7769, a preliminary judgment that the explanatory variables can explain 77.69% of the explained variables, and the fit is good. Using the estimated coefficients of the variables, the direct effect, indirect effect, and total effect of each

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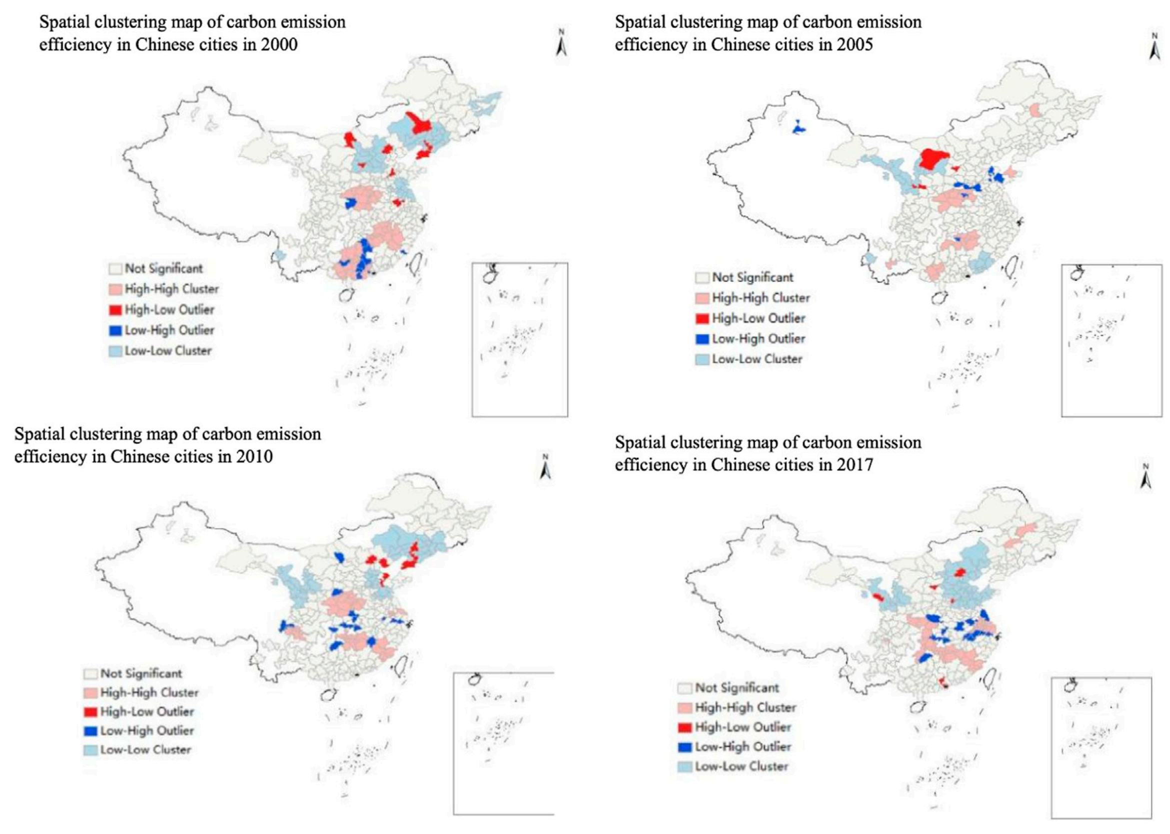

FIGURE 4
Spatial clustering map of carbon emission efficiency in Chinese cities.

TABLE 2 Direct and indirect effects of the spatial durbin model.

Variable	Direct effect	Indirect effect	Total effect
Industrial Structure (CY)	0.0008	0.009464	0.010339
Urbanization (CZ)	0.022641**	−0.047179	−0.024538
Technological advances (JS)	0.097435*	0.113,938	0.211,373**
Population density (RK)	−0.002026	−0.01102	−0.013046
Ecological Environment (ST)	0.022938	0.14361	0.166,549
Government intervention (ZF)	−0.443,914*	0.458,532*	0.014619
Foreign Investment (WS)	−0.084809	0.705,825**	0.621,016**

explanatory variable on carbon emission efficiency can be deduced (Table 2).

From the estimation results, it can be seen that the direct effect coefficient of urbanization on urban carbon emission efficiency is 0.22641. That passes the significance level test of 5%, and the indirect effect coefficient is −0.047179, which does not pass the significance test. It indicates that increasing the urbanization rate of a city is beneficial to improving the carbon emission efficiency of this city but not to the improvement of the carbon emission efficiency of urban clusters. Xu et al. (2022) also concluded that the level of urbanization was significantly and negatively correlated with the carbon emission efficiency of the research cities. In recent years, the urbanization development mode of China's cities has been changing from extensible development to connotative development, i.e., from the model of capital investment, the pursuit of speed and scale in the past to the development model of improving efficiency and pursuing efficiency. The development of new urbanization has a significant role in promoting carbon emission efficiency.

Both the direct and indirect effects of technological progress on carbon emission efficiency show a positive effect, and the coefficient of the direct effect is 0.097435 and passes the 1% significance level test. This shows that technological progress significantly promotes the improvement of urban carbon emission efficiency. Ning et al. (2021) concluded that the level of science and technology has a significant contribution to the improvement of carbon emission efficiency. Wei (2019) suggested that technological innovation promotes industrial upgrading. Thus improving carbon emission efficiency can reduce carbon emissions while ensuring economic growth. Therefore, Technology is the first productive force, and technological progress can serve urban economic development and urban environmental protection. Since China put forward the strategy of "developing the country through science and education," it has taken scientific and technological progress as the "ballast stone" to coordinate the economy and the environment. Technological progress in adjusting the industrial structure, promoting the competitiveness of low-carbon industries, cultivating new energy and energy-saving industrial clusters, and promoting carbon emission reduction plays an important role in eliminating high energy-consuming industries and further improving carbon emission efficiency in this city and adjacent cities.

The coefficient of the direct effect of government intervention on the carbon emission efficiency of cities is −0.443,914. The indirect effect coefficient is 0.458,532, both pass the 1% significance test. It indicates that government intervention has a significant effect on the carbon emission efficiency of this city and neighboring cities. The development of the financial business of cities needs the government to provide the necessary financial guarantee and policy support. The smooth development of the city's environmental protection business also needs the government's policy leadership and regulations. Cai (2017) also suggested that the degree of government intervention is negatively correlated with the efficiency of carbon emissions in the region. One reason could be that the proportion of fiscal expenditure related to the control of CO2 emissions is not enough. The other reason may be that the effectiveness of emission reduction cannot be effectively stimulated for the time being due to pathway technology and so on. As the contradiction between the ecological environment and economic development is becoming more prominent. The state wrote the construction of ecological civilization into the working document in the 17th Party Congress, raised it to the national development layout in the 18th Party Congress, and reaffirmed the critical status of ecological civilization construction in the 19th Party Congress. It is evident that the state is paying more attention to the synergistic benefits of ecology and economy, and the effect of government intervention on carbon emission efficiency is becoming more and more significant.

The coefficients of direct and indirect effects of foreign investment on the carbon emission efficiency of cities are −0.084809 and 0.705,825, but the overall effect is positive. Zhao (2019) also suggested that changes in foreign direct investment showed a non-significant negative effect on carbon emission efficiency in the region. It suggests that China is not all green when introducing foreign investment, and to some extent takes on the bad products of polluting enterprises in developed countries, all of which have a negative effect on carbon emission efficiency in China. And increasing foreign investment has a significant effect on enhancing the carbon emission efficiency of neighboring cities. From the development trajectory of the past decades, most of the high-consumption and high-pollution industries invested by foreign investors will hurt the region's environment. Simultaneously, it will bring the labor force of adjacent cities into this metropolis, propelling its continued expansion. As a result, most high-consumption and high-pollution businesses will migrate into this city, reducing the industries in neighboring cities. However, the degree of influence of foreign investors from different sources on the region is different. The hypothesis of 'Pollution Paradise' is too absolute for China, which has more and more discourse power in the world. China will inevitably introduce high-quality and high-efficiency foreign investment in the future and transform the city's negative effect into a positive one.

It can be seen from the table that the previous industrial structure has not played a significant role in improving the carbon emission efficiency of cities and adjacent cities. Zhao (2019) also argued that the impact of industrial structure changes on adjacent areas showed a non-significant positive effect. China has continuously adjusted its industrial structure in recent years, shifting from a high-speed development model to a high-quality development model. Also pay more attention to the protection of the ecological environment in its development, the ecological benefits have also been continuously improved, but the economic benefits have decreased. So the overall benefits have not been significantly affected. The coefficient of the direct effect of population density on carbon emission efficiency is-0.002026, and the coefficient of the indirect effect is-0.01102. Both direct and indirect effects show negative effects, but the impact on carbon emission efficiency is not significant. In recent years, the population structure of various cities has been constantly adjusted and changed. The improvement of living standards has promoted the increase of energy consumption for basic living needs, which has increased carbon emissions and is not conducive to the improvement of carbon emission efficiency. The above results are also largely consistent with the findings of Zhao (2019), which are attributed to China's long-standing family planning policy and low population growth rate, thus having less impact on carbon emission efficiency. The direct and indirect effects of the ecological environment on carbon emission efficiency are both positive, but the same effect is not significant. Although the state is paying more and more attention to environmental management and focusing on carbon emission efficiency at this stage, ecological and environmental development is a thousand-year plan. The economic benefits are difficult to quantify significantly in a short period. Hence, the state needs to be able to continuously develop policies related to environmental protection to guide the benign development of the local urban environment.

4 Conclusions and recommendations

4.1 Research findings and analysis of causes

Based on the data from 278 Chinese cities year 2000–2017, this paper uses the super-efficiency SBM model of undesirable output to calculate the carbon emission efficiency of 278 Chinese prefecture-level cities with complete data available. Prefecture-level cities are an important part of the realization of new-type urbanization and agricultural modernization. Revealing the spatial-temporal pattern evolution of carbon emission in prefecture-level cities and its influencing factors play a significant role in improving China's new-type urbanization strategy. Through promoting ecological civilization construction and green transformation development. Also has important policy significance for China's construction of low-carbon cities. The study of carbon emission efficiency in prefecture-level cities in this paper improves the understanding of the differences in the spatial and temporal distribution patterns of carbon emission at different scales.

1) In exploring the changing trend of carbon emission efficiency in the whole country and the eight comprehensive economic zones. It is found that the carbon emission efficiency of China as a whole and the eight comprehensive economic zones generally shows a gradually decreasing trend, indicating that the whole country still puts economic construction in the first place, which has caused some negative effects on the environment. So the carbon emission efficiency has not improved significantly. Specifically, there are differences among the mean carbon emission efficiency of each region. The middle Yellow River region has the highest total mean carbon emission efficiency from 2000 to 2017, which makes a major contribution to China's carbon emission efficiency, while the northwest region has the lowest mean carbon emission efficiency. In exploring the changing trend of carbon emission efficiency in 278 cities found that the carbon emission efficiency of all cities in China is in a downward trend. Fewer cities in the high-efficiency areas, more cities in the medium-low-efficiency areas and low-efficiency areas. The boundary of carbon emission efficiency is 'Hu Huanyong Line'. In the four selected years, it can be seen that the cities with carbon emission efficiency always maintain one are Beijing, Shanghai, Daqing, Wuxi, Shenzhen, Zhengzhou and Liuzhou, most of which are located to the east of the "Hu Huanyong Line". In addition, it can be seen from the figure that there are more high-efficiency zone cities east of the line than west of the line, but the significance gradually decreases, and the number of high-efficiency zone cities decreases and their distribution gradually disperses. Although the cities to the east of the 'Hu Huanyong Line' have achieved more significant results in carbon emission efficiency, carbon emission efficiency still shows a general downward trend. Although advanced technology has improved carbon emission efficiency. It will also bring more capital investment and carbon emission demand, resulting in a decrease in carbon emission efficiency. Of the cities whose carbon emission efficiency is always lower than 0.4, 37.5% are distributed in the eastern and southern coastal areas, 33.33% are distributed in the middle Yellow River, Southwest China and Great Northwest China, and 29.17% are distributed in the northeast and northern coastal areas. However, there is no distribution in the middle Yangtze River, indicating that the middle Yangtze River region has a relatively significant effect on energy conservation and emission reduction. Cities in other regions still have a lot of room for improvement in carbon emission efficiency.
2) In the spatial correlation test of urban carbon emission efficiency, the carbon emission efficiency of 278 cities in China as a whole shows a positive spatial correlation of 'first fluctuation reduction and then rise'. Cities with similar carbon emission levels in China gradually gather, showing a trend of polarization. That is the distribution of cities with high carbon emission efficiency and low carbon emission efficiency is gradually dispersed. Cities with high carbon emission efficiency are gradually adjacent to cities with high carbon emission efficiency, and cities with low carbon emission efficiency are gradually adjacent to cities with low carbon emission efficiency. In 2000, 2005, 2010 and 2017, the cities that always maintain the 'HH' characteristics are distributed in the middle Yangtze River. The cities with 'HH' characteristics in the middle Yellow River, the southwest region, the southern coast and the northern coast are decreasing. No city can maintain the 'LL' feature, but the number of cities with 'LL' feature in the northern coast and the northwest regions is significantly higher than other regions. The number of cities with 'HH' characteristics in the middle Yangtze River has not appeared. The number of cities with 'LL' characteristics in the middle Yellow River, the southwest region, the southern coast, the northeast region and the eastern coast is decreasing, indicating that cities in these areas have achieved considerable results in controlling carbon emissions. No city always maintains 'HL' and 'LH' characteristics, but compared with other regions, the number of cities with 'HL' characteristics in the middle Yellow River and the northern coast is relatively large, and the number of cities with 'LH' characteristics in the middle Yellow River and the middle Yangtze River is relatively large. Because the geographical location of these cities connects the developed eastern regions and the western regions with low carbon emission efficiency. The concentration of LH or HL is more obvious. Therefore, each city should formulate policies according to its own situation and deeply tap its own carbon emission reduction potential to improve carbon emission efficiency.
3) In exploring the influencing factors of carbon emission efficiency, it is found that urbanization, technology, government intervention and foreign investment have an important impact on the improvement of carbon emission efficiency.

Specifically, the urbanization rate is conducive to improving the carbon emission efficiency of this city, but not conducive to improving the carbon emission efficiency of urban clusters. Because China has changed from the past mode of capital investment, speed and scale to the development mode of improving efficiency and pursuing efficiency. Technological progress significantly promotes the improvement of the carbon emission efficiency in cities. It adjusts the industrial structure using technological progress, promotes the competitiveness of low-carbon industries, cultivates new energy and energy-saving industrial clusters, and promotes carbon reduction and emission reduction. All of them play an important role in eliminating energy-intensive industries and further improving carbon emission efficiency in the city and neighboring cities. The degree of government intervention is negatively related to the carbon emission efficiency of the region. One reason may be that the proportion of fiscal expenditure related to the treatment of carbon dioxide emissions is not enough, and another reason may be that the emission reduction effect cannot be effectively stimulated for the time being due to the pathway technology,*etc.* Foreign investors directly show a non-significant negative impact on the carbon emission efficiency of the region, indicating that China has taken over the bad products of polluting enterprises in developed countries to a certain extent when introducing foreign investment.

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At the same time, it will make the labor force of neighboring cities flow into this city and drive this city to develop continuously, which eventually makes most of the high-consumption and high-pollution industries flow into this city and reduce the gathering of high-consumption industries in neighboring cities to a certain extent.

4.2 Recommendations

The 14th Five-Year Plan and the Long-Range Objectives Through the Year 2035 put forward the 14th Five-Year Plan period must follow the new development concept. To effectively transform the development mode, promote quality change, efficiency change, and power change to achieve higher quality, more efficient, more equitable, more sustainable and safer development (The People's Daily, 2020). Improving the carbon emission efficiency of cities in each region of China is an important part of the 14th Five-Year Plan and achieving the 2035 vision. Therefore, based on the findings of the study, the following suggestions are put forward:

1) Optimize the quality of town development.

Cities with high carbon emission efficiency should focus on optimizing the quality of urban development, pay attention to the characteristics and development trend of population factors, make good use of resource factors, and match them with the layout of the industrial economy. Reduce the uncoordinated development between urban and rural areas. Improve the quality of urban development. In contrast, cities with low carbon emission efficiency like Chifeng City and Tianshui City should speed up the upgrading of urban development mode, increase the optimization of urban patterns and break through the bottleneck of new urbanization and high-quality development.

2) Improve science and technology innovation capacity.

Cities with high carbon emission efficiency pay more attention to scientific research investment and technological innovation. So they can play a significant role in improving carbon emission efficiency. However, cities with low carbon emission efficiency ignore the importance of science and technology innovation capacity. This requires that the person in charge of the cities with low carbon emission efficiency should raise the awareness of science and technology innovation and incorporate science and technology innovation into the strategic planning of urban development. And rely on the "double assistance" mechanism of national technology, funds, actively introduce talents and technology. In contrast, the cities with high carbon emission efficiency should strengthen the investment in R&D, make efforts to adjust the energy structure, fully explore the potential of carbon emission reduction on green productivity and improve the ecological compensation mechanism. Take the northern coastal region as an example, Beijing's science and technology resources can be poured into cities such as Tianjin and Tangshan to shorten the "rich-poor gap" in technology development between cities and achieve coordinated improvement of regional carbon emission efficiency.

3) Grasp the strength of government intervention.

Cities with high carbon emission efficiency can increase fiscal expenditure, support emerging industries and promote regional urban transformation and upgrading, or intervene in urban development by strengthening governance and promoting environmentally friendly development of regional cities. Cities with low carbon emission efficiency like Yinchuan and Guyuan in northwest China, and Siping and Chaoyang in northeast China can adopt the former for government intervention, increase capital and scientific resources, and use high-tech or new industries to achieve low-carbon green development. In contrast, cities like Shijiazhuang, Hengshui, and Jinan on the northern coast can adopt the latter for government intervention, increase the investment in environmental pollution control, improve the quality of the urban environment, and increase the efficiency of carbon emission to achieve sustainable regional development. However, government intervention needs to grasp the scale. If the intervention is excessive it will affect the free flow of various resources in the city. It cannot realize the effective allocation of resources, which cannot improve the efficiency of carbon emissions and may hinder the green development of the city.

4) Encourage the introduction of high-quality foreign investment.

China's early development focused on economic development more than environmental harmony, and economic development focused on quantity rather than quality. Hence, the introduction of foreign investment is mostly a highly polluting industy. Although China has gone through the developed countries hundreds of years of industrial development in just a few decades. The resulting environmental problems are difficult to reverse. Since the Third Plenary Session of the 18th Party Central Committee proposed to deepen reform in all aspects, and the 19th Party Congress proposed to establish a sound economic system of green, low-carbon, and cyclic development, "high-quality" development has become the consensus. Therefore, cities with high carbon emission efficiency should take advantage of their own development advantages to attract high-quality foreign investment with high-level opening up. While accelerating the process of high-level opening up, they should form an institutional environment to attract high-quality foreign investment and give full play to the role of foreign investment to achieve mutual benefit and win-win results. Cities with low carbon emission efficiency should clarify their strategic goals, examine their advantages, evaluate external opportunities, and selectively and purposefully choose high-tech, low-pollution projects or industries to complement their strengths and weaknesses. In addition, take active measures to share resources or risks with neighboring regions, realize "mutual benefit" between cities instead of "beggar-my-neighbour," enhance the autonomy and enthusiasm of cities to develop green, low-carbon economy, and improve regional carbon emission efficiency.

4.3 Deficiencies and future prospects

This paper calculates the carbon emission efficiency of 278 prefecture-level cities in China with complete data available and explores the spatial autocorrelation and influencing factors of carbon emission efficiency of each city on the basis of dividing China into eight comprehensive economic zones. Due to the limitations of data and methods the research level of this paper needs to be further deepened, and in future research. There are still some issues that need to be explored further:

First, all countries in the world have not established unified carbon emission efficiency measurement indicators, so the domestic prefecture-level city carbon emission efficiency measurement indicators can be further studied.

Second, this paper only refers to relevant literature to extract some indexes as influencing factors of carbon emission, so it will be important direction to use quantitative methods to extract more scientific and reasonable influencing factor indexes.

Third, due to the difficulty and limitation of data collection, this paper does not cover all prefecture-level cities in China. There are some errors in data analysis and comparative studies between cities. In addition, the current research on carbon emission efficiency is usually limited to domestic perspectives and a few countries. There are still few comparative studies on most countries in the world, and transnational and trans-continental studies are relatively scarce. Therefore, international carbon emission is also one of the future research directions.

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 authors.

Author contributions

HH and ZW each wrote the section of the manuscript. All authors contributed to data curation, analysis. ZW and QG contributed to manuscript revision. All authors approved the submitted version.

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Conflict of interest

Author QG was employed by the company China Huaxing Group Co., Ltd.

The remaining 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

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2023.1119914/full#supplementary-material

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The impact of internet finance on green technology innovation in manufacturing companies --mediating role based on financing constraints

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To empirically analyze the relationship between internet finance and green technology innovation of manufacturing firms, this paper selects listed manufacturing firms from 2011 to 2020 as the sample. A panel regression model is then constructed and a causal stepwise regression test is used to examine the mediating effect of financing constraints on the role of internet finance in green technology innovation. The results show that the growth of Internet finance can significantly alleviate the financing problems of industrial enterprises and promote their adoption of green technologies. Further research found that enterprises in less developed areas in central and western China, in regions with weaker environmental regulations and smaller size, play a greater role in promoting green technology innovation. Consequently, improving the incentive system for Internet finance to promote green technology innovation in enterprises can effectively link the development of Internet finance and green innovation in enterprises, promote the development of ecological civilization, and serve as an important decision-making tool to help China achieve its "double carbon" goal.

KEYWORDS

internet finance, green technology innovation, manufacturing enterprises, financing constraints, mediating effect

1 Introduction

China's manufacturing industry has made incredible progress since the reform and opening up, both in terms of overall size and technological depth. High-quality manufacturing development is hindered by traditional extensive development, which causes China's economic growth and pollution to remain in the front part of the environmental Kuznets curve for a long period of time. Green transformation and manufacturing development have been elevated to a national strategic level by the "Made in China 2025" program, which explicitly calls for "accelerating green transformation and upgrading of the manufacturing industry" The report of the 20th National Congress of the Communist Party of China further emphasized the need to jointly promote carbon reduction, pollution reduction, green expansion and economic growth, and promote intelligent and green development of the manufacturing industry.

Innovation in science and technology is increasingly becoming the basis of economic and even national competitiveness (Yu et al., 2022a). In 2019, the National Development and

Reform Commission and other ministries also issued the "Guidance on Building a Market-Oriented Green Technology Innovation System." An important step in implementing the new development concept of "Innovation, Coordination, Green, Share" is the development of "green technology innovation," which refers to technology innovation activities aimed at saving resources and energy and preventing, eliminating or reducing environmental pollution and damage. Green technology innovations are a crucial strategic tool to achieve sustainable development of enterprises. They can increase the market value of a company's goods, reduce the cost of environmental investment, and increase the utilization rate of a company's resources, giving the company a competitive advantage (Jaffe, 1995). According to some researchers, proactive green technology innovation also has a significant positive impact on the financial performance of enterprises (Qing et al., 2022). In today's dynamic global climate, environmental management is becoming increasingly important, and more and more enterprises are willing to invest more in green technology development (Jiang and Tian, 2014). However, according to Wanhong et al. (2013), green technology innovation is characterized by strong externalities, long cycles, expensive investment, and high risks. The question of how to consistently and effectively support green technology innovation in manufacturing enterprises has become a practical challenge to be addressed in today's highly unstable market and technology environment.

In the short term, R&D investment in green technology innovation will reduce the productive investment of enterprises, but it will also increase the capital requirements of the product and make it more difficult for enterprises to access finance (Liang and Liu, 2022). Therefore, financial resources are crucial in promoting entrepreneurial innovation in green technologies and achieving environmental policy goals. The advantages of financial instruments such as capital, credit, and the market can be used to support enterprises' efforts to protect the environment. According to Jun (2016), the main function of the incentive mechanism in resource allocation should be capital allocation. The financial environment can also have a significant positive impact on the efficiency of green financing (Yu et al., 2022b).

Internet finance is the result of the increasing use of Internet technologies in financial activities due to the development of technologies such as the Internet, cloud computing and Big Data. According to Huang and Zhuo (2018), the term "Internet finance" broadly refers to the use of digital technologies by both traditional financial institutions and Internet companies to facilitate financing, payment, investment, and other innovative financial business models. Internet finance integrates digital technologies such as the Internet, cloud computing, Big Data, and blockchain into the financial sector to provide long-term access to a variety of financial services offered by different financial institutions and effectively promote the enterprise-wide adoption of green technological innovations (Zhang, 2023). On the one hand, with the advantages of networking and information technology, Internet finance can enhance financing convenience while increasing financing efficiency and reducing costs. On the other hand, digital information technology transforms the credit system, enables Big Data to make scientific and thorough assessments of all market participants, lowers the cost of identifying green innovation projects, strengthens the risk control of green innovation projects, and provides efficient allocation of financial market resources (Li, 2022). Therefore, it is not yet known whether Internet finance can promote green technology innovation in industrial enterprises. Greening and digitalization have emerged as two key concepts in enterprise development. Many companies face the challenge of putting digitalization and greening into practice. Can Internet finance, a byproduct of the digital economy, help companies become greener and give them a competitive edge? Discussing this question in light of the inevitable trends of digitalization and greening is extremely practical.

In this study, listed A-share manufacturing companies from 2011 to 2020 are used as the sample. A panel regression model is constructed to empirically analyze the relationship between Internet finance and green technology innovation of manufacturing firms, a causal stepwise regression test is used to examine the mediating role of financing constraints on the role of Internet finance on green technology innovation, and whether the impact of Internet finance on green technology innovation is positive or negative.

The main contributions of this study are: First, from the perspective of Internet finance, this study extends existing research on the financial market and corporate green technology innovation. The study concludes that the growth of Internet finance contributes to the realization of the incentive mechanism for the allocation of financial resources, and emphasizes the contribution of financial market growth to the promotion of innovation in green production enterprises from the perspective of Internet finance. The relationship between macrofinancial markets and microenterprise behavior is further promoted by this discovery. Second, using a mediation effects test model, this study investigates and evaluates the impact paths and effects of Internet finance on green technology innovation of manufacturing enterprises from the perspective of financial constraints. Moreover, through the empirical investigation of the transmission mechanism of the impact of green technology innovation of enterprises, it becomes clear that financing constraints play a mediating role in the impact of Internet finance on green technology innovation of manufacturing enterprises, which provides a theoretical basis and guidance for the in-depth discussion on the healthy development of Internet finance and the formulation of related policies in China.

The remaining parts of this paper are organized as follows: The second part is devoted to the theoretical analysis and research hypothesis, the third to the research methodology and index selection, the fourth to the main regression results and analysis of Internet finance and green technology innovation of manufacturing enterprises, the fifth to a heterogeneity analysis of Internet finance for green technology innovation of manufacturing enterprises, and the sixth to the conclusion.

2 Literature

Green technology innovation is defined as adhering to ecological principles and ecological economic laws, conserving resources and energy, preventing, eliminating or minimizing pollution and damage to the environment, and minimizing the negative ecological impact of "environmentally friendly" or "less harmful" technologies, processes and products (Yu et al., 2022a). Green technology innovations include various technological advances as well as product design, environmentally friendly materials, environmentally friendly processes, environmentally friendly equipment, recycling, and packaging (Aguilera-Caracuel and Ortiz-de-Mandojana, 2013). Most of the research on green technology innovation focuses on two main areas: One is measuring the efficiency and performance of green technology innovation, for example, Yu et al. (2022a) measured the efficiency of green innovations in 64 resource-based cities in China using the super-efficient SBM model with non-expected output, Moran's I index and a spatial econometric model (Yu et al., 2022a; Wang et al., 2016) used the DEA method to measure regional green growth performance and green technology innovation efficiency in China from 2007 to 2011. On the other hand, studies have been conducted on the drivers of green technology innovation. Research on the drivers of green technology innovation has been analyzed by scholars mainly from the perspectives of institutional theory, market theory and NRA (Yang and Chai, 2015). From the institutional perspective, the existing literature mainly analyzes industrial policy (Lai and Cheng, 2016), finance and technology investment (Miao et al., 2019) and institutional environment (Shi and Yuanyuan, 2022); from the market perspective, the existing studies analyze customer demand, equity and investor demand; in terms of the NRA viewpoint, the literature mainly analyzes a cultural and green viewpoint. It can be simply concluded that a systemic project, primarily consisting of policy, institutions, and factor supply, which serves as the foundation for the growth of green technological innovation activities in enterprises, is necessary to effectively drive green technological innovation in microenterprises. Without the necessary financial, policy, and market support, firms will not be able to fully leverage their own factors, and their technological innovation efforts will likely remain stuck in a low-level equilibrium deficit.

There are many studies on enterprise green technology innovation in the digital economy, and the main literature has examined the impact of enterprise digital transformation on enterprise green technology innovation and the combination of enterprise digital transformation and innovation activities. For example, Shi and Yuanyuan (2022) used hierarchical regression and fsQCA methods to empirically validate the effects of the adoption process of digital green innovation activities and digital green knowledge creation on digital green innovation performance, and investigated the moderating role of digital green risk perception and digital green complexity perception in the integration of digital technologies with green innovation and production processes. The application of Big Data by companies affects their green innovation activities (El-Kassar and Singh, 2019). Manufacturing enterprises are actively using the new generation of information and communication technologies such as Internet Big Data and artificial intelligence to solve the practical problems of green innovation by moving from internal transformation to external coordination and from single-point application to global optimization (Shi et al., 2020a; Yin et al., 2020b). The digital transformation of enterprises helps to achieve green production, i.e., saving energy and reducing consumption through digital technology, smart production, improving production efficiency, and achieving the same or even higher production value with less consumption and emissions (Acquah et al., 2021; Mandal et al., 2021). All these studies in the literature show that digital transformation in enterprises can improve green innovation performance. However, the rapid development of digital technology has not only changed the internal operations of enterprises, but also the external environment on which they depend, especially the financial environment. Internet finance is a product of the integration of digital technology and traditional finance. The development of Internet finance can promote resource allocation and mitigate the financing constraints of green technology innovation. The development of Internet finance can effectively improve the problem of insufficient resource liquidity and resource mismatch that exists in the traditional financial system, improving the efficiency of the flow of unused resources between market participants (Demertzis et al., 2018) and making innovation resources flow in a timely manner to enterprises that need to carry out green technology innovation. Internet finance can also mitigate firms' financing constraints while optimizing resource allocation. Therefore, this paper explores how the application of digital technology in financial services affects firms' green technology innovation activities from the perspective of their external finance supply.

Finance plays an important role in economic growth (Long and Lin, 2018). However, China's bank-dominated financial supply structure has not adapted to the requirements of industrial structure modernization (Wu and Liu, 2017), and instead has a detrimental effect on the modernization of the manufacturing sector. The insufficient effective financing demand of manufacturing enterprises, the structural imbalance on the supply side of financing, the information asymmetry, and the challenges SMEs face in accessing credit services make it difficult to provide financial support for high-quality manufacturing development in the current environment (Ren and Jia, 2019). At present, studies on the impact of Internet finance on green technology innovation have mainly been examined at three levels: Macro, meso and micro levels. At the macro level, internet banking alleviates regional financial constraints and directs social capital flows to support the modernization of industrial structures, thereby promoting regional technological innovation (Nie et al., 2021). At the meso level, Internet finance promotes the innovation ability and willingness of innovation subjects, which leads to the upgrading of industrial structure (Du and Wang, 2022). It also directs the innovation direction of the industry. The "incremental supplement" and "inventory optimization" functions of Internet finance are used at the micro level to solve financing problems for enterprises and successfully resolve traditional financial inconsistencies, which supports the technological innovationof enterprises (Tang et al., 2020).

In summary, this study has benefited from the concise findings of the current literature. However, very few of them have addressed financial growth as a motivator for green technological innovation in firms. In terms of research methods, scholars have mainly developed regression models at the provincial, municipal, and industry levels, lacking firm-level microdata and very few thorough and in-depth discussions of heterogeneity. The aim of this study is to fill this knowledge gap by identifying linkages between Internet finance and green technology innovation in manufacturing firms and exploring the impacts and intermediary transformation processes between them.

3 Theoretical analysis and hypothesis derivation

3.1 The role of internet finance on green technology innovation in manufacturing companies

The real economy and even technical innovation activities are significantly affected by finance, and the efficient provision of finance can directly affect these activities (Jia et al., 2017). The structural transformation and high-quality development of China's economy, which are necessary for the rapid progress of Internet finance, have been greatly hindered by the underdeveloped financial system in China and the lack of traditional financial services (Huang and Zhuo, 2018). With the support of information technologies such as the Internet, cloud computing, and Big Data, Internet finance has ameliorated the problems of high risk premium and high operating cost in traditional financial services caused by information asymmetry (Hao, 2018), and thanks to its own networking and informatization advantages, it has provided technical support to expand the scale and scope of financial services (Guo et al., 2017). Internet finance can thus reduce the cost of financing green technology innovations in manufacturing companies, while opening up new options for these companies' green technology innovation efforts.

Theoretically, financial growth has a significant stimulating effect on the development of green technologies. To achieve high-quality development, a variety of new technologies, industries, and other innovative projects require financial support. On the other hand, market-oriented financial solutions, especially green financial solutions, can also be used to eliminate backward production capacity with high pollution and high emissions, thus supporting green technological innovation. By virtue of its own network and information technology, with the support of information technologies such as the Internet, cloud computing, and Big Data, Internet finance can greatly improve the problems of high risk premium and high operating cost in traditional financial services due to information asymmetry (Hao, 2018) and provides technical support for expanding the reach and scope of financial services (Guo et al., 2017). Internet finance can thus reduce the cost of financing green technology innovation in manufacturing enterprises, while opening up new options for these enterprises' green technology innovation efforts. The beneficial effect of the development of Internet finance on the adoption of green technologies by manufacturing firms is evident in two ways: First, Internet finance provides enterprises with a wider range of financing options, lowers the barrier to enterprise financing, and effectively fills the gap created by a lack of traditional financing, as Internet finance channels are more advantageous than traditional ones in terms of cost and volume (Fengqi, 2015). Second, Internet finance uses digital information technology to improve the information verification and risk assessment capabilities of both enterprises and individuals. This greatly improves the service efficiency of financial institutions while reducing transaction costs, including information processing and risk assessment (Hao, 2018), lowering the financing costs of enterprises and providing sufficient financial support for their green technology. In addition, thanks to information technologies such as Big Data, cloud computing, Internet, and blockchain, Internet finance helps process enormous amounts of data at lower costs and risks (GomberKauffman et al., 2018). The expansion of Internet finance has accelerated the integration of financial services with the green industry, and the use of information technology to mine and analyze huge amounts of data makes it possible to match financial resources with the risk characteristics of enterprises' green innovation projects, greatly improving the effectiveness of financial resource allocation and risk management capacity (Song et al., 2019) and promoting the growth of green technology innovation.

In conclusion, this paper puts forth the claim:

Hypothesis 1. The growth of online finance has encouraged manufacturing companies to adopt green technology.

3.2 The role of financing constraints in the impact of internet finance on green technology innovation in manufacturing companies

Green technology innovation initiatives in manufacturing companies are not just about one aspect of the business. The company's green technology innovation efforts encompass everything from research and development of green technologies to the introduction of green product manufacturing or processes (Miao et al., 2019). The problem of high financing and adjustment costs affects green technology innovation activities as much as other types of innovation. Due to the information asymmetry between the company and the investor, the investor is likely to impose many constraints on the company when investing capital, which has a negative impact on the company's green technology innovation (Wu et al., 2022). Alternatively, the investor may forego the investment directly, increasing the company's financing costs. Innovations in green technology require significant ongoing investment in human and material resources. Innovations in green technology require significant ongoing investment in human and material resources. The research and development stage of green technology requires significant capital investment, and due to the information asymmetry between enterprises and investors, it is very likely that investors will impose many restrictions on enterprises when investing funds, which will affect the innovation of green technology of enterprises, or investors will directly abandon their investment, which will correspondingly increase the financing cost of enterprises. Once the enterprises start their green technology innovation activities, they will invest many resources and the input will exceed the output for a short period of time, which will make it impossible for the enterprises to use cash for other purposes, resulting in high adjustment costs (Tang and Tang, 2010).

Due to a significant information asymmetry between providers of financial resources and companies, the existing underdeveloped financial system is unable to keep pace with the rapidly growing and increasing volume of economic activity. This leads to an imbalance between supply and demand. Viewed from different angles and orientations, the features of internet finance can increase the quality and effectiveness of services for financial services companies (Temelkov and Gogova, 2018). Through technologies such as Big Data retrieval and information sharing, Internet finance can increase the speed of information flow while expanding the number of financial products. This can also speed up credit appraisal and screening to reduce financing costs and remove financing constraints for SMEs (Tsai and Kuan Jung, 2017), further increasing financing options so that companies have sufficient funds and resources to support green technology innovation activities rather than being prevented from doing so.

In conclusion, this paper puts forth the claim:

Hypothesis 2. By easing their financial limitations, the growth of internet finance is supporting the use of green technology by manufacturing companies, i.e., the financial restrictions have a mediating effect on the impact of the growth of internet finance on green technology adoption.

3.3 Heterogeneity analysis of internet finance for green technology innovation in manufacturing companies

1. There are significant differences in the level of economic development, human capital, and scientific and technological innovation between the eastern coastal regions and the central and western inland regions when examining the impact of Internet finance on the green technological innovation capability of manufacturing enterprises from the perspective of the region where the production urn is located. This may also complicate the relationship between the impact of Internet finance and manufacturing innovation ability in these areas (Zheng and Zhao, 2021). The impact of Internet finance on green technological innovation of manufacturing enterprises may be inhibited by the higher level of economic development, better financial system, and overall higher awareness of environmental protection in eastern coastal regions (Qian et al., 2015).
2. When the promotion effect of Internet finance on green technological innovation of enterprises is studied from the perspective of environmental regulation, it may also vary depending on the location of enterprises and the degree of environmental control. According to Shichun et al. (2012), there are differences in the incentive effect of different environmental regulation policies on enterprises' technology innovation, and the government can improve the incentive effect of enterprises' green technology innovation by prescribing the stringency of environmental regulation.

In regions with a higher degree of environmental regulation, the government has stricter control over pollution, and enterprises need to implement green technology innovation to reduce pollution fines and environmental management costs and improve their own environmental management capabilities. Compared with the higher degree of environmental regulation, the promotion of green technology innovation by enterprises is inhibited by Internet finance. In areas with a higher degree of environmental regulation, the government has stricter control over pollution, and enterprises are required to engage in green technology innovation activities to reduce the price of pollution penalties and environmental management costs, as well as improve their own environmental management capabilities. The promotion of green technology innovation by enterprises through Internet finance is hindered compared to the more stringent environmental regulations.

3. In terms of company size, SMEs benefit more from the ability of Internet finance to overcome financial bottlenecks. SMEs are more reliant on external financing for their technological innovation activities because, compared to large firms, they are smaller and have fewer internal resources, most of which are needed to sustain their operations. Second, there is a larger knowledge gap between SMEs and external investors: first, small and medium-sized enterprises (SMEs) cannot afford to hire external organizations to audit and disclose information, so their information transparency is low. As a result, it is difficult for outside investors to evaluate SMEs' investment analysis, which increases borrowing costs and raises financing costs for SMEs. Internet finance supported by information technologies such as Big Data, the Internet and blockchain can accurately evaluate SMEs, improve the transparency of SMEs' information, reduce information asymmetry to a greater extent, and provide accurate financial services to SMEs, which promotes the development of green technology in SMEs.

The Hypothesis 3a, Hypothesis 3b, and Hypothesis 3c in this work is based on the analysis above.

Hypothesis 3a. Inland manufacturing businesses in the central and western regions are more significantly impacted by Internet finance than their counterparts in the more developed eastern regions.

Hypothesis 3b. Internet finance plays a bigger role in encouraging green technology innovation in manufacturing companies in regions with a lower level of environmental regulation than it does in areas with a greater level of environmental regulation.

Hypothesis 3c. Compared to large companies, SMEs see a greater reduction in financial constraints thanks to Internet finance, which has an impact on the development of green technology innovation in SMEs.

In conclusion, Figure 1 depicts the conceptual model of this paper.

4 Empirical study design

4.1 Sample selection and data sources

Taking into account data availability, this paper selects A-share manufacturing listed companies from 2011 to 2020 as the research sample. The eligible conditions for sample selection are: excluding companies with ST in any year during the study period; excluding companies with net profit loss in any year during the study period.

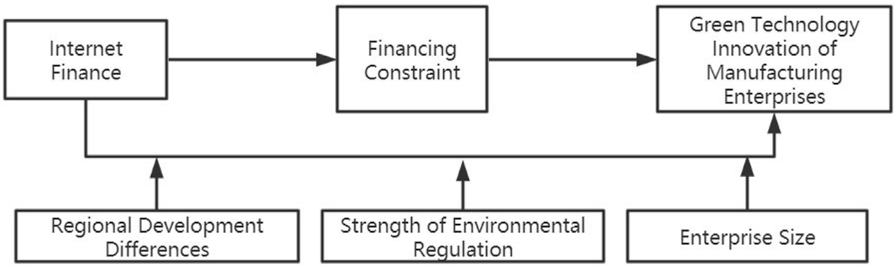

FIGURE 1
Conceptual model.

After the screening of the above conditions, 2,409 listed companies with a total of 15,416 sample observations were finally selected. To avoid the effect of outliers, all continuous variables are Winsorized at the upper and lower 1% level. The financial data of listed companies were obtained from the Cathay Capital (CSMAR) database, and all the empirical analysis processes were completed by statistical software such as Excel and Stata 16.0.

4.2 Model setting and variable definition

4.2.1 Explained variables

Company green technology innovation (GTI): This paper refers to the research methods of Qi et al. (2018) and Li and Xiao (2020), and matches the IPC classification numbers of patents retrieved from the "International Patent Green Classification List" launched by the World Intellectual Property Organization in 2010 and the listed patents retrieved from the State Intellectual Property Office of China (SIPO). The number of green patent applications per year was obtained by matching the patent types of listed companies retrieved from the "International Patent Green Classification List" launched by the World Intellectual Property Organization in 2010 and the patent types of listed companies retrieved from the State Intellectual Property Office of China (SIPO).

4.2.2 Explanatory variables

Since Internet finance is a new thing, the representative data currently available are not abundant. A review of the relevant literature reveals that most of the existing literature uses a single indicator to measure the level of Internet development, which is limited to only one aspect of the development level. Zou et al. (2017) used the third-party payment amount as an index of Internet finance to study the impact of Internet finance on the systemic risk of Chinese commercial banks. Yang et al. (2018) measures the level of development of Internet finance in China through four aspects: payment methods, resource allocation, risk control, and information processing. Among the self-constructed indices, the China Digital Inclusive Finance Index is more authoritative and comprehensive, and is widely used in the analysis and research of Internet finance.

To comprehensively reflect the development level of Internet finance, this paper selects the China Digital Inclusive Finance Index as the Internet finance index, which measures the three dimensions of the breadth of coverage, depth of use and digitalization, taking into account the breadth and depth of Internet finance development, as well as the comparability of the index horizontally and vertically. Therefore, this paper adopts the data of 31 provinces in mainland China from 2011 to 2020 of this index as the Internet finance index.

4.2.3 Mediating variables

There are three main approaches to the measurement of financing constraints in the literature: the first approach is to use a single indicator as a constraint index, with indicators such as interest coverage multiple, dividend payout ratio, and asset size; the second is to construct an index with multiple variables, such as the WW index and ZFC index; the third is to build quantitative models, such as the investment-cash flow model and the cash -cash flow models. Since a single index cannot comprehensively measure the degree of financing constraints of companies and is easily disturbed by other factors, its robustness is difficult to guarantee, while there are strict assumptions for constructing indices with multiple indicators, and the applicability to Chinese companies is yet to be tested, the quantitative model cannot truly reflect the limitations of industry characteristics and financing constraints faced by companies. Therefore, this paper refers to the KZ index measurement method and selects four indicators: cash stock (cash), current ratio (cr), total assets growth rate (tag), and return on net assets (roe) to construct the financing constraint index (FCI) to measure the degree of financing constraint from four aspects: cash flow, solvency, development ability, and profitability, respectively. The indicators for constructing the financing index and their calculation methods are shown in Table 1.

This paper uses a binary logistic model regression analysis to construct indicators of financing constraints.

$$\boldsymbol{FCI_{i,t} = \alpha\beta_1 cash_{i,t} + \beta_2 cr_{i,t} + \beta_3 tag_{i,t} + \beta_4 roe_{i,t}}$$

The higher the financing constraint index, the higher the degree of financing constraint received by the company. This paper constructs financing constraint dummy variables based on interest coverage multiples, categorizing those greater than the median as the low financing constraint group and those less than the median as the high financing constraint group. The four variables are first grouped together to test for differences in means, and the results are shown in Table 2. The differences in means of each indicator are significant at the 1% level, indicating that the four variables are well differentiated under different

TABLE 1 Table of variables for the construction of the financing constraint index FCI.

Variable name	Variables conform to	Calculation method
Cash Inventory	cash	Cash and other cash equivalents/total assets at end of period
Current Ratio	cr	Current assets at end of period/Current liabilities at end of period
Total assets growth rate	tag	(Total assets at the end of the period—Total assets at the end of the previous period)/Total assets at the end of the previous period
Return on Net Assets	roe	Net income/average net assets

TABLE 2 Variable mean difference test for the financing constraint index FCI.

Variables	Grouping	Average value	Standard deviation	Mean difference	Significance of difference
cash	Low financing constraints	0.1670	0.1251	0.0407	19.8901***
	High financing constraints	0.2077	0.1288		
cr	Low financing constraints	2.0801	2.3478	0.9686	24.1861***
	High financing constraints	3.0488	2.6174		
tag	Low financing constraints	0.1938	2.0982	0.0647	2.2865**
	High financing constraints	0.2911	3.0900		
roe	Low financing constraints	0.0106	0.1661	0.0977	46.8767***
	High financing constraints	0.1082	0.0765		

TABLE 3 Logit regression results for the financing constraint index FCI.

Variables	Coefficient	Z-statistic	Clustering robust standard error	Significance
cash	0.0479	0.25	0.1922	0.803
cr	−0.1612	−12.22	0.0132	0.00
tag	−0.0038	−0.74	0.0052	0.00
roe	−11.7828	−29.83	0.3950	0.00
Cons	1.2291	28.48	0.0432	0.00

TABLE 4 Variable definitions.

Variable type	Variable name	Variable symbols	Calculation method
Explanatory variables	Digital Inclusive Finance Development Index	difi	BYU Digital Inclusive Finance Index/100
Explained variables	Green Technology Innovation	GTI	Number of green patent applications, the natural logarithm of the number of applications plus 1 for the year
Intermediate variables	Financing Constraints Index	FCI	Logit regression construction
Control variables	Company size	size	Natural logarithm of total assets at the end of the period
	Business Growth	growth	Operating income growth rate
	Company Age	age	(Sample year—IPO year) + 1
	Annual	year	Dummy Variables

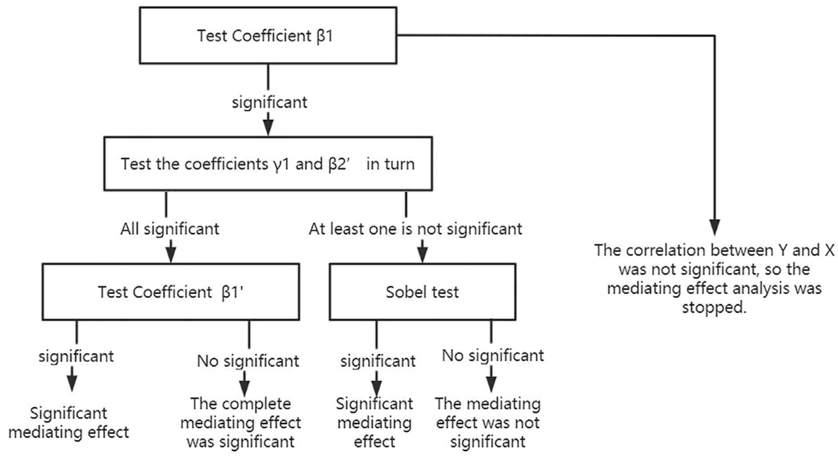

FIGURE 2
Steps of intermediate effect test.

groupings. Logit regression was performed on the model and the results are shown in Table 3. Based on the regression coefficients, the final financing constraint index is obtained as:

$$\boldsymbol{FCI_{i,t}} = \mathbf{1.2290} + \mathbf{0.0479}\boldsymbol{cash_{i,t}} - \mathbf{0.1612}\boldsymbol{cr_{i,t}} - \mathbf{0.0038}\boldsymbol{tag_{i,t}} - \mathbf{11.7828}\boldsymbol{roe_{i,t}}$$

4.2.4 Control variables

Many factors affect corporate innovation, and combined with the production and operation characteristics of listed companies, company size (size), total assets growth rate (tag), operating income growth rate (growth), and time to market (age) are selected as control variables in this paper, and annual dummy variables are also controlled in this paper.

The specific meanings and metrics of the variables involved in the model in this paper are shown in Table 4.

4.3 Model construction

This research first builds the benchmark regression model below to examine the association between Internet finance and green technology innovation of manufacturing companies.

$$\boldsymbol{GTI_{i,t}} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1 difi_{i,t}} + \boldsymbol{\beta_2 controls_{i,t}} + \boldsymbol{u_{i,t}} + \boldsymbol{\vartheta_{i,t}} + \boldsymbol{\varepsilon_{i,t}} \quad (1)$$

Where $\boldsymbol{GTI_{i,t}}$ represents the output of green technology innovation results of company i in year t, $\boldsymbol{\beta_0}$ is a constant term, $\boldsymbol{difi_{i,t}}$ represents the level of internet finance development in company i's region in year t, $\boldsymbol{controls_{i,t}}$ represents each control variables, $\boldsymbol{u_{i,t}}$ represents the effect of each individual company, $\boldsymbol{\vartheta_{i,t}}$ is the annual time effect, $\boldsymbol{\varepsilon_{i,t}}$ is residual term, $\boldsymbol{\beta_1}$ and $\boldsymbol{\beta_2}$ represent the parameters that need to be estimated for the explanatory and control variables, respectively.

This paper adopts a mediation effect test procedure suggested by Zhonglin et al. (2004) to test the mediating role of financial constraints in the impact of Internet finance development on green technology innovation of listed manufacturing companies. The procedure's sum of the first and second type of error rates is typically lower than that of a single test, and it can perform both partial and full mediation tests. Figure 2 depicts the steps of this mediation effect test. Therefore, the following two models are built on the basis of the above model:

$$\boldsymbol{FCI_{i,t}} = \boldsymbol{\gamma_0} + \boldsymbol{\gamma_1 difi_{i,t}} + \boldsymbol{\gamma_2 controls_{i,t}} + \boldsymbol{u_{i,t}} + \boldsymbol{\vartheta_{i,t}} + \boldsymbol{\varepsilon_{i,t}} \quad (2)$$

$$\boldsymbol{GTI_{i,t}} = \boldsymbol{\beta_0}' + \boldsymbol{\beta_1}'\boldsymbol{difi_{i,t}} + \boldsymbol{\beta_2' FCI_{i,t}} + \boldsymbol{\beta_3' controls_{i,t}} + \boldsymbol{u_{i,t}} + \boldsymbol{\vartheta_{i,t}} + \boldsymbol{\varepsilon_{i,t}} \quad (3)$$

The specific test steps are as follows, and they are based on the stepwise regression analysis of mediating effects.

In the first step, it is concompanyed that Internet finance has an impact on manufacturing companies' adoption of green technologies. If model (1)'s coefficient $\boldsymbol{\beta_1}$ of $\boldsymbol{difi_{i,t}}$ is significant, it indicates that there is a direct relationship between Internet finance and green technology innovation in manufacturing companies, i.e., that the direct transmission mechanism is there. If so, move on to step two. The test is over if the coefficient $\boldsymbol{\beta_1}$ of $\boldsymbol{difi_{i,t}}$ is not significant.

The second phase is verifying how Internet finance affects financial restrictions. If the coefficient $\boldsymbol{\gamma_1}$ of $\boldsymbol{difi_{i,t}}$ in model (2) is significant, it means that funding restrictions are impacted by Internet finance.

The third step is to concompany the financing restrictions' mediating role in the relationship between corporate green technology innovation and Internet finance development. If coefficients $\boldsymbol{\beta_1}'$ of $\boldsymbol{difi_{i,t}}$ and $\boldsymbol{\beta_2'}$ of $\boldsymbol{FCI_{i,t}}$ in model (3) are significant, then the mediation effect is substantial as well. Sobel test is required if there is only one significant coefficient between coefficient $\boldsymbol{\gamma_1}$ of $\boldsymbol{difi_{i,t}}$ in model (2) and coefficient $\boldsymbol{\beta_2'}$ of $\boldsymbol{FCI_{i,t}}$ in model (3).

This paper also applies the following treatments to the regression: First, this paper treats the Internet finance index with a lag, which can help mitigate the reverse causality problem, considering the fact that it takes some time for Internet finance

TABLE 5 Descriptive statistics of main variables.

Variables	Average value	Standard deviation	Minimum value	Maximum value	Number of samples
GTI	0.756	1.114	0.000	7.083	15,416
difi	2.711	0.849	0.615	4.319	15,416
FCI	0.124	1.719	−4.965	12.217	15,416
lev	0.397	0.196	0.014	0.999	15,416
size	22.040	1.184	19.092	27.062	15,416
growth	3.460	386.320	−0.991	4.8e+04	15,416
age	9.624	6.991	1.000	30.000	15,416
tag	0.242	2.641	−0.972	254.455	15,416

TABLE 6 Correlation analysis of main variables.

Variables	GTI	FCI	difi	Size	Growth	Age	tag
GTI	1.0000						
FCI	−0.0251*	1.0000					
difi	0.1044*	−0.0357*	1.0000				
size	0.4962*	−0.0201	0.0832*	1.0000			
growth	−0.0000	−0.0051	−0.0129	0.0048	1.0000		
age	0.1603*	0.1483*	0.0261*	0.4128*	0.0125	1.0000	
tag	0.0290*	−0.0402*	−0.0141	0.0695*	0.1162*	0.0177	1.0000

to influence the green technology innovation actions of companies. Second, this paper controls for individual effects and time effects for testing.

5 Analysis and discussion of the main regression results of internet finance and green technology innovation in manufacturing companies

5.1 Descriptive statistics

Table 5 presents the descriptive statistics of the Internet Finance Index, the number of green patents of companies, and other company-level variables. From the results in Table 5, it can be seen that the valid sample is 15,416. The maximum value of the green technology innovation level index (GTI) of listed companies is 7.083, the minimum value is 0, and the mean value is 0.756, indicating that the green technology innovation level varies widely among different manufacturing companies. The maximum value of the internet finance index (difi) is 4.319, the minimum value is 0.615, and the mean value is 2.711, which indicates that there are differences in the development of internet finance among different regions. The financing constraint (FCI) has a maximum value of 12.217, a minimum value of −4.965, and a mean value of 0.124, which indicates that there are also large differences in the financing constraints faced by different companies.

TABLE 7 Multicollinearity results.

Variable	VIF	1/VIF
age	1.24	0.804875
size	1.23	0.814397
fci	1.03	0.967568
tag	1.02	0.979850
growth	1.01	0.986194
difi	1.01	0.991328
Mean VIF	1.09	

5.2 Correlation analysis

The Pearson test was employed in this study to examine the relationships between the variables, and the findings are displayed in Table 6. The expansion of Internet finance has, to some extent, encouraged the green technology innovation of companies, as evidenced by the considerable positive connection between green technology innovation variables and the Internet finance index, supporting Hypothesis 1. The rise of Internet finance has, to some extent, eased the funding constraint, which is in line with the expectation of this article, as indicated by the significant negative

TABLE 8 Regression results of Internet finance and green technology innovation of manufacturing companies.

Variables	(1)	(2)	(3)
	GTI	GTI	GTI
difi	0.209***		
	(3.456)		
Lagging Phase I difi		0.221***	
		(3.271)	
Two-phase lagged difi			0.241***
			(3.138)
size	0.467***	0.484***	0.501***
	(21.164)	(21.223)	(21.270)
growth	−0.000**	−0.000**	0.007
	(−2.134)	(−2.505)	(1.336)
age	−0.003	−0.003	−0.003
	(−1.001)	(−0.887)	(−1.046)
tag	−0.003	−0.009***	−0.010***
	(−0.744)	(−3.747)	(−3.763)
_cons	−10.319***	−10.721***	−11.114***
	(−21.555)	(−21.539)	(−21.539)
adj. R2	0.310	0.317	0.323
F	64.737	76.033	65.525
N	15,416	12,969	10,723

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

TABLE 9 Tests of mediating effects of financing constraints.

Variables	(1)	(2)	(3)
	GTI	FCI	GTI
difi	0.209***	−0.287***	0.205***
	(3.456)	(−3.677)	(3.391)
FCI			−0.014**
			(−2.108)
size	0.467***	−0.148***	0.465***
	(21.164)	(−6.525)	(21.179)
growth	−0.000**	−0.000	−0.000**
	(−2.134)	(−1.155)	(−2.200)
age	−0.003	0.046***	−0.002
	(−1.001)	(12.780)	(−0.735)
tag	−0.003	−0.024*	−0.004
	(−0.744)	(−1.900)	(−0.825)
_cons	−10.319***	3.024***	−10.277***
	(−21.555)	(6.229)	(−21.580)
adj. R2	0.310	0.044	0.310
F	64.737	35.907	61.224
N	15,416	15,416	15,416

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

correlation coefficient between the Internet finance index and the financing constraint index. Regression is used in this study to further concompany the relationship between the pertinent variables.

5.3 Multicollinearity results

The variance inflation factor of each variable is calculated in this paper to avoid the potential for serious multicollinearity among the variables, which could affect the model results. The results are shown in Table 7, and the mean value of VIF is 1.09, indicating that there is no significant collinearity among the variables chosen in this paper.

5.4 Analysis and discussion of regression results of internet finance and green technology innovation in manufacturing companies

Given that there may be a lag in the impact of Internet finance on companies' green technology innovation, this paper also verifies the impact of Internet finance index on green technology innovation with one period lag and two periods lag, and the results are in columns (2) and (3), respectively. Column (1) in Table 8 displays the regression results of Internet finance and green technology innovation. The regression results show that Internet finance has a coefficient of 0.209, which is significantly positive at the 1% level, indicating that it can encourage green technology innovation in businesses and has an incentivizing effect on the adoption of green technologies by manufacturing companies. Accordingly, Hypothesis 1 is true. This result is consistent with the findings of Tang et al. (2020) and Demertzis et al. (2018). This indicates that the better the degree of Internet finance development, then the higher the level of green technology innovation output of companies. The results in columns (2) and (3) demonstrate that the coefficients of the Internet finance index with one lag and two lags, with coefficients of 0.221 and 0.241, respectively, are significantly positive at the 1% level. The coefficients of Internet finance with two lags are also marginally higher than those of Internet finance with one lag and no lag, which further suggests that there is some lag. This indicates that the development of Internet finance has helped to enhance the green technology innovation capability of companies, strengthen their core competitiveness in innovation, and demonstrate significant innovation momentum.

5.5 Analysis and discussion of the results of the test of mediating effects of financing constraints

The impact of Internet finance on green technology innovation in manufacturing companies is examined in this paper using a causal

TABLE 10 Analysis of heterogeneity between Eastern and Midwestern regions.

Variables	East					Midwest				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	GTI	FCI	GTI	GTI	GTI	GTI	FCI	GTI	GTI	GTI
difi	0.051	−0.220*	0.048			0.965***	−0.377	0.962***		
	(0.526)	(−1.871)	(0.491)			(4.456)	(−1.094)	(4.444)		
FCI			−0.015*					−0.007		
			(−1.697)					(−0.792)		
difi1				0.047					1.063***	
				(0.439)					(4.540)	
difi					0.027					1.150***
					(0.222)					(4.254)
size	0.510***	−0.171***	0.507***	0.525***	0.544***	0.395***		0.395***	0.413***	0.427***
	(17.668)	(−6.229)	(17.667)	(17.638)	(17.866)	(13.516)		(13.517)	(13.473)	(13.179)
growth	0.005*	−0.007	0.005*	0.003	0.003	−0.000*	0.000	−0.000*	−0.000***	−0.002
	(1.816)	(−1.295)	(1.745)	(0.541)	(0.241)	(−1.883)	(0.396)	(−1.890)	(−2.899)	(−0.277)
age	0.001	0.049***	0.001	0.002	0.002	−0.009**	0.035***	−0.008**	−0.009**	−0.011**
	(0.164)	(10.537)	(0.370)	(0.459)	(0.417)	(−2.131)	(6.137)	(−2.016)	(−2.168)	(−2.298)
tag	−0.010***	−0.013	−0.010***	−0.012***	−0.013***	0.005	−0.055*	0.005	0.021	0.019
	(−3.817)	(−1.553)	(−3.794)	(−3.435)	(−3.470)	(0.829)	(−1.842)	(0.769)	(1.510)	(0.984)
_cons	−11.078***	3.534***	−11.024***	−11.445***	−11.848***	−9.363***	−0.205	−9.347***	−9.792***	−10.152***
	(−17.701)	(5.721)	(−17.701)	(−17.651)	(−17.751)	(−14.186)	(−0.560)	(−14.197)	(−14.139)	(−13.818)
adj. R^2	0.337	0.044	0.338	0.345	0.353	0.275	0.040	0.275	0.281	0.282
F	47.639	12.756	45.435	50.033	50.487	34.179	28.233	32.386	30.873	23.120
N	10,383	10,383	10,383	8,677	7,107	5,033	5,033	5,033	4,292	3,616

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

stepwise regression test, and columns (1), (2), and (3) of Table 9 present the regression results for the three models of the stepwise regression of mediating effects, respectively. The results in column (1) demonstrate that Internet finance and green technology innovation are significant at the 1% level, allowing the next part of the mediating effect test, i.e., testing the impact of Internet finance on financing limitations, to be conducted, and the results in column (2) demonstrate that the relationship between Internet finance and financial constraints is statistically significant at the 1% level, suggesting that Internet finance can free manufacturing companies from financial constraints. The regression results are in line with Hypothesis 2. The findings in column (3) demonstrate that the correlations between Internet finance and financial constraints are significant at the 1% and 5% levels, respectively, indicating that the mediating effect of financial constraints is significant and partial, i.e., Internet finance can encourage green technology innovation of manufacturing companies by easing financial constraints. This result is consistent with the findings of Wu et al. (2022) and Qi et al. (2018). A large number of empirical studies have verified that financing constraints inhibit technological innovation. Internet finance largely complements the shortcomings that exist in traditional finance by providing richer and more diverse financing tools, which in turn better serve the financial resource needs of microcompany subjects. With the help of the Internet financial platform, companies can obtain funds in a short period of time and at low cost, which to a certain extent reduces the financing constraint of companies.

6 Heterogeneous analysis and discussion of internet finance for green technology innovation in manufacturing companies

6.1 Analysis and discussion of the heterogeneity of the eastern and midwestern regions

The level of economic development and technological innovation in the eastern coastal region is much higher than that

TABLE 11 Regional environmental regulation heterogeneity analysis.

Variables	Weak environmental regulation					Strong environmental regulation				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	GTI	FCI	GTI	GTI	GTI	GTI	FCI	GTI	GTI	GTI
difi	0.305***	−0.528***	0.289***			0.134**	−0.083	0.134**		
	(3.736)	(−5.010)	(3.532)			(2.262)	(−0.824)	(2.266)		
FCI			−0.030***					0.002		
			(−2.961)					(0.251)		
difi1				0.316***					0.149**	
				(3.538)					(2.238)	
difi2					0.357***					0.146*
					(3.660)					(1.858)
size	0.434***	−0.122***	0.430***	0.456***	0.477***	0.502***		0.502***	0.508***	0.518***
	(15.352)	(−3.835)	(15.281)	(15.208)	(14.914)	(22.546)		(22.635)	(22.094)	(21.711)
growth	−0.000*	−0.000	−0.000*	−0.000	0.006	0.004	−0.074***	0.004	0.013	0.012
	(−1.757)	(−0.629)	(−1.759)	(−0.459)	(1.031)	(0.467)	(−3.817)	(0.478)	(1.104)	(1.020)
age	−0.007**	0.051***	−0.005	−0.008**	−0.010**	−0.000	0.032***	−0.000	0.001	0.000
	(−1.993)	(9.717)	(−1.506)	(−1.989)	(−2.245)	(−0.011)	(7.823)	(−0.039)	(0.205)	(0.071)
tag	0.007	−0.031**	0.006	−0.007	−0.014	−0.010***	−0.019*	−0.009***	−0.010***	−0.010***
	(0.850)	(−2.186)	(0.724)	(−0.539)	(−0.905)	(−5.267)	(−1.660)	(−5.278)	(−5.089)	(−4.829)
_cons	−9.632***	2.764***	−9.550***	−10.126***	−10.585***	−11.350***	−0.065	−11.357***	−11.437***	−11.573***
	(−15.517)	(4.149)	(−15.447)	(−15.350)	(−15.065)	(−23.802)	(−0.194)	(−23.920)	(−22.952)	(−22.421)
adj. R^2	0.304	0.058	0.306	0.313	0.323	0.320	0.034	0.320	0.325	0.327
F	38.799	42.587	36.335	40.575	31.292	57.434	9.837	54.746	57.747	57.490
N	7,701	7,701	7,701	5,978	4,414	7,715	7,715	7,715	6,991	6,309

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

in the central and western regions; therefore, the development of Internet information technology is faster and better in the eastern region, while the level of Internet technology development in the central and western regions is more backward. From this aspect of analysis, the level of development of Internet finance in the eastern region is higher, so the incentive effect on green technology innovation of manufacturing companies may also be stronger. However, from another aspect, the eastern region is more developed and has closer communication with foreign companies, and its environmental awareness is also better than that of the central and western regions, so the level of green technological innovation of companies in the eastern region itself is higher than that of the central and western regions, then, this may also weaken the incentive effect of Internet finance on green technological innovation. In order to study the regional heterogeneity of Internet finance on green technology innovation of manufacturing companies, this paper will divide the companies into two groups according to the regions they are located in, the eastern region includes Heilongjiang, Jilin, Liaoning, Hebei, Beijing, Tianjin, Shandong, Jiangsu, Zhejiang, Fujian, Guangdong and Hainan, and the regression results are obtained as Table 10.

The regression results show that according to column (1) (6), in the eastern region, the coefficient under Internet finance on green technology innovation is positive but not significant, while in the central and western regions, the coefficient of Internet finance is significantly higher than that of the eastern region and significant at the 1% level, which indicates that compared to the developed eastern region, the impact of Internet finance on the green technology innovation capability of manufacturing companies located in the central and western inland regions The effect is more significant, and the regression results of Internet finance with one and two lags show consistent [shown in column (4) (5) (9) (10)], and Hypothesis 3a is verified. In the eastern region, the Internet finance and financing constraints are significantly negative at the 10% level, indicating that Internet finance alleviates the financing constraints of manufacturing companies located in the eastern region to some extent, but the effect of Internet finance on financing constraints is not significant in the central and western regions.

TABLE 12 Company size grouping test.

Variables	Smaller group size					Larger groups				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	GTI	FCI	GTI	GTI	GTI	GTI	FCI	GTI	GTI	GTI
difi	0.310***	−0.405***	0.291**			0.080	−0.131	0.080		
	(2.672)	(−3.788)	(2.504)			(1.516)	(−1.307)	(1.512)		
FCI			−0.048***					−0.003		
			(−3.534)					(−0.448)		
difi1				0.309**					0.097	
				(2.473)					(1.595)	
difi2					0.328**					0.115
					(2.402)					(13)
growth	−0.000**	−0.000*	−0.000**	−0.000***	0.008	−0.002***	−0.010***	−0.002***	−0.006**	−0.006**
	(−2.438)	(−1.732)	(−2.510)	(−2.701)	(0.937)	(−2.728)	(−2.868)	(−2.734)	(−2.552)	(−2.378)
age	0.020***	0.017***	0.021***	0.022***	0.022***	0.001	0.066***	0.001	−0.000	−0.002
	(4.236)	(3.897)	(4.383)	(4.341)	(4.253)	(0.312)	(13.169)	(0.367)	(−0.017)	(−0.840)
tag	0.004	−0.017**	0.003	0.002	−0.000	0.074***	−0.972***	0.072***	0.084**	0.115***
	(0.902)	(−2.297)	(0.740)	(0.529)	(−0.022)	(2.965)	(−9.076)	(2.856)	(2.520)	(2.650)
_cons	−0.448***	0.221	−0.438***	−0.410**	−0.434**	−0.039	−0.412***	−0.040	−0.065	−0.003
	(−2.852)	(1.147)	(−2.787)	(−2.411)	(−2.360)	(−0.513)	(−2.613)	(−0.524)	(−0.741)	(−0.027)
adj. $R2$	0.132	0.022	0.136	0.132	0.133	0.042	0.112	0.042	0.043	0.043
F	31.836	50.846	29.905	32.443	32.717	13.566	21.716	12.710	12.814	10.923
N	7,708	7,708	7,708	6,986	6,219	7,708	7,708	7,708	5,983	4,504

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

6.2 Analysis and discussion of regional environmental regulation heterogeneity

The intensity of environmental regulation varies in different regions, so the impact of Internet finance on companies' green technological innovation may differ under different environmental regulation intensity. To examine whether there is regional environmental regulation heterogeneity of Internet finance on manufacturing companies' green technological innovation, this paper refers to Zhang et al. (2020) and selects the ratio of pollutant emissions to industrial value added in each province to measure each province's environmental The lower the pollutant emissions per unit of industrial value added, the greater the intensity of environmental regulation in that region. In this paper, two groups of strong environmental regulation and weak environmental regulation were divided according to the median of environmental regulation, and the influence of Internet finance on companies' green technology innovation was examined separately, and the results were obtained as shown in Table 11.

The results of the subgroup regressions show that the results in column (1) (6) find that the coefficient of Internet finance and green technology innovation in the subgroup with weaker environmental regulation is 0.305 and significant at the 1% level, while the coefficient of Internet finance and green technology innovation in the subgroup with stronger environmental regulation is 0.134, with a slightly lower coefficient than that of the region with weaker environmental regulation, and the significance is also weaker, only significant at the 5% level, and the regression results for Internet finance with one and two lags are also consistent. [Column (4) (5) (9) (10) results] This indicates that the incentive effect of Internet finance on green technological innovation of manufacturing companies is greater in regions with weaker environmental regulations, while in regions with stronger environmental regulations, local policies and more stringent controls on the environment require local companies to reduce pollution emissions, and in order to reduce environmental management costs, companies have to carry out green technological innovation, which will weaken the impact of Internet finance on companies' green technology innovation.

The results of the mediation effect test are in column (2) (3) (7) (8), and the results show that Internet finance is more likely to promote the financing constraints of companies in regions with weaker environmental regulations compared to companies in regions with stronger environmental regulations, and the mediation effect of financing constraints is significant in the grouping of regions with weaker environmental regulations, while the mediation effect in the grouping of regions with stronger environmental regulations remains to be verified. The study concludes that Internet finance has a more significant role in promoting green technology innovation among companies in regions with lower environmental regulations than in regions with higher environmental regulations, and Hypothesis 3b is verified.

6.3 Analysis and discussion of company size heterogeneity

To examine whether there is company size heterogeneity in the green technology innovation of manufacturing companies by Internet finance, the full sample is divided into two groups of samples analyzed by the median of company size for larger companies and smaller companies, and the regression results are shown in Table 12.

The results of the company size grouping test show that the results in columns (1) and (6) show that the coefficient of Internet finance and green technology innovation is significantly positive at the 1% level in the smaller company size grouping, while the coefficient of Internet finance and green technology innovation is positive but not significant in the larger companies, and the regression results of Internet finance with one and two lags [columns (4) (5) (9) (10) columns] are also consistent with this result, which indicates that the incentive effect of Internet finance on green technology innovation is more significant for smaller manufacturing companies compared to larger manufacturing companies. This finding supports the hypothesis that small and medium-sized manufacturing companies have lower internal capital than large manufacturing companies, are more reliant on outside funding, and are more likely to experience "difficult financing" issues when investing in green technology innovation initiatives.

In the intermediary effect test, since the coefficient of Internet finance and green technology innovation is not significant in the grouping of larger companies, there is no need to conduct the next round of intermediary effect test, and the intermediary effect does not exist. As for the test results of the smaller-scale company subgroup, column (2) shows that the coefficient of Internet finance and financing constraints is significantly negative at the 1% level, and Internet finance can alleviate the financing constraints of smaller-scale manufacturing companies to some extent. In column (3), the coefficients of Internet finance and financing constraints are significant at the 5% and 1% levels, respectively, indicating that the mediating effect of financing constraints is significant and partially mediated in the smaller group of companies. Therefore, it is concluded that the mitigating effect of Internet finance on financing constraints is more significant in SMEs compared to larger companies, which in turn affects the promotion of green technology innovation in SMEs, and Hypothesis 3c is tested. This illustrates the reality that small manufacturing companies have more financial restraints and issues than large manufacturing companies. These funding issues are resolved by traditional financial services, and Internet finance, as an addition to traditional finance, brings up new financing options for these SMEs with "financing difficulties" attributable to its technical advantages, thus resolving their issues.

7 Conclusion

7.1 Research findings

This study examines listed A-share manufacturing firms from 2011 to 2020, empirically tests the relationship between Internet finance and green technology innovation in manufacturing firms, and uses a causal stepwise regression test to examine the mediating role of financing constraints on the role of Internet finance on green technology innovation. It also examines whether the impact of Internet finance on green technology innovation in manufacturing firms is positive or negative.

First, Internet finance can encourage manufacturing firms to innovate in green technology. Internet finance effectively compensates for the lack of traditional finance, expands the range of financial services, provides more flexible financing options, lowers the cost of financing for firms, and increases the effectiveness of resource allocation and risk management, creating a financial environment that supports the development of green manufacturing technologies.

Second, Internet finance can reduce the financial constraints of manufacturing enterprises and, to some extent, solve the problem of difficult financing of green projects, which in turn promotes the ability of manufacturing enterprises to innovate in green technologies. The financial constraints contribute to the intermediate effect of Internet finance on the adoption of green technologies by enterprises. Green innovation projects in manufacturing enterprises can get the funds they need through the many financing channels and diverse financing services offered by the Internet finance system. On the other hand, Internet finance innovates the method of matching the financing needs and financial data of manufacturing enterprises through the use of information technology. Internet finance encourages enterprises to increase their investment, which in turn has a direct positive impact on their green technology innovation by easing the financial constraints faced by manufacturing enterprises.

Third, the impact of Internet finance on green technology innovation among manufacturing firms differs between the more developed eastern regions and the central and western regions. Compared with the developed eastern regions, the impact of Internet finance on the innovation capability of manufacturing enterprises is more significant in the landlocked regions of central and western China. The eastern region of China is more economically developed and has advantages in various factors such as capital and information, and the resources brought by Internet finance can be fully utilized by the manufacturing industry in the transformation process. In addition, the development of Internet finance in the central and western regions is at an early stage of development, and the corresponding facilities and penetration rate in the central and western regions are still very different from those in the eastern regions, which is somewhat disadvantageous in the short term, but with the promotion of Internet finance, the central and western regions will gain more benefits.

Fourth, the degree of regional environmental regulation will affect the contribution of Internet finance to the adoption of green technologies by manufacturing enterprises. The promotion effect of Internet finance on the green technological innovation of enterprises in the regions with a lower degree of environmental regulation is more significant compared with the regions with a higher degree of environmental regulation, because the strong regional environmental regulation weakens the effect of Internet finance on the green technological innovation of manufacturing enterprises.

Fifth, firm size heterogeneity is a determinant of the effect of Internet finance on manufacturing firms' green technological innovation. The promotion of green technological innovation in SMEs is influenced by the fact that Internet finance on financing constraints more in SMEs compared to large enterprises. Small and medium-sized enterprises (SMEs) have less internal capital and lower levels of information transparency than large enterprises, and it is difficult for external investors to effectively evaluate SME investment analysis. As a result, SME green innovation projects face significant financing challenges.

7.2 Policy recommendations

In response to the research findings, this study makes numerous legislative proposals to promote Internet finance as well as green technology innovation in manufacturing companies.

First, promote the growth of online finance. The empirical results show that Internet finance can support the adoption of green technologies in manufacturing firms. Because Internet finance is still at an early stage of growth and offers few goods, it can play only a limited role in encouraging firms to adopt green technologies. To effectively link financial capital and green development, it is critical to advance the development of Internet finance, strengthen policies for financial institutions to support low-carbon development, and innovate and develop financial products such as green finance, green loans, and green bonds.

Second, we should strengthen policy support for green technology innovation. The government should introduce various policies to support green technologies and provide government subsidies for green innovation projects of manufacturing enterprises, especially for small and medium-sized private manufacturing enterprises facing major financing constraints. Second, the Patent Examination Department should introduce the list of green patents as soon as possible, which will also help financial institutions to effectively evaluate green projects.

Third, appropriate Internet finance models should be introduced according to the differences in regional economic development to support the green transformation and upgrading of the manufacturing sector. From the results of the sub-regional estimation, there are some differences in the impact of digital financing on the green technology innovation of manufacturing enterprises in different regions, which is due to the unbalanced development in the eastern and western regions of China. Implementing the same development strategy across the country would lead to a waste of resources, and Internet finance should be developed selectively, and appropriate Internet finance models should be adopted for manufacturing development in different regions to achieve the maximum effect of Internet finance.

7.3 Limitations and future research

First, the company data used in this paper are mainly micro data of listed manufacturing companies with a small sample size, and the impact of Internet companies on green technology innovation of unlisted SMEs is not considered. The number of SMEs in China is huge, and compared with listed companies, the innovative R&D activities of SMEs are more restricted by the shortage of capital. However, due to the undisclosed information of unlisted SMEs, is the data acquisition larger. Therefore, it is not considered in the study.

Second, this study employs a panel model to test the relationship between Internet finance and businesses' adoption of green technology. Future studies may modify this approach by employing threshold models, non-linear smoothed transformation models, etc. to conduct more in-depth analyses of this relationship.

Third, there may be a non-linear relationship between Internet finance and green technology innovation of manufacturing companies, and the promotion effect of Internet finance development on green technology innovation of manufacturing companies is not necessarily steady and durable. Future research should examine the existence of a non-linear relationship between Internet finance and green technology innovation of manufacturing businesses.

Fourth, digitalization has enabled the national economy and microenterprises to change and improve their dynamics. At the policy and practical levels, digital transformation has become an important lever to drive industry optimization and upgrading, and achieve green and high-value development. The contribution of digital technology to green innovation is reflected in the following aspects: first, the effect of knowledge sharing. Enterprise digitalization can realize internal information sharing and knowledge integration to optimize green innovation resources. Second, transaction cost reduction. The development of digital technology can not only reduce the external search, negotiation, negotiation and monitoring costs caused by information asymmetry, but also enable organizational management through information technology to improve the transparency and effectiveness of information, thereby reducing the internal and external transaction costs of enterprises and motivating them to carry out green innovation activities. Third, demand incentive effect. The development of digital technology has stimulated demand for a variety of consumer products and changed the nature of communication between product supply and demand, making it easier to align consumer demand with corporate research and development of green processes. On this basis, the topic of "enterprise digitalization—green innovation performance" needs to be analyzed in depth to clarify the potential mechanism of the influence of digital technology on green innovation and to show the compatible path between enterprise digitalization and green sustainable development.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: (CSMAR) (https://www.gtarsc.com/); (STATISTICAL YEARBOOK OF CHINA) (http://www.stats.gov.cn/).

Author contributions

YY and YL contributed to conception and design of the study. TN organized the database. CG performed the statistical analysis. YL wrote the first draft of the manuscript. YY, YL, TN, and CG wrote sections of the manuscript. All authors contributed to manuscript revision, read, and approved the submitted version.

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Conflict of interest

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

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Investigating the N-shaped EKC in China: An imperious role of energy use and health expenditures

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Since the industrial revolution, the concentration of greenhouse gases (GHGs)has been increasing steadily. It is to be noted that China emitted 27% of the world's GHGs in 2019, making it the world's most significant contributor to climate degradation. The key objectives of this investigation are to ascertain the N-shaped association between CO_2 emissions and economic growth in the presence of energy use and domestic government health expenditures. In addition, the research inspected the role of Belt and Road Initiative through economic globalization in China. This study utilized the autoregressive distributed lag model and found that an N-shaped environmental Kuznets curve exists in China. Furthermore, the study discovered that economic globalization improves ecological excellence in the short run. Nonetheless, energy consumption and health expenditures considerably amplify the intensity of CO_2 emanation in China in the long run. The research suggested that installing green industries through economic globalization can imperatively lessen environmental degradation. Moreover, installing technological firms will be more beneficial in the long run to overcome environmental degradation rather than importing from other countries. The study elaborated momentous causation effects among the study variables through the Granger causality test.

KEYWORDS

N-shaped EKC, economic growth, energy use, economic globalization, CO_2, health expenditures, BRI, ARDL

1 Introduction

Climate change engenders an increasing threat to survival and human growth, including food scarcity, loss of species, and extreme weather conditions (Wang et al., 2020). Since the industrial revolution, the concentration of greenhouse gases (GHGs) has continued to rise, and the average global temperature has increased by 0.85°C from 1980 to 2012 (Pathak, 2021). Mainly, China emitted 27% of the globe's GHGs in 2019, ranking first in the world (BBC, 2021). Therefore, ecological dilapidation and climate change are among the main debatable and discussed topics in the 21st century. In light of the 2015 Paris Climate Agreement (PCA), countries worldwide are designing their policies to limit global warming below 1.5°C above the pre-industrial level, which requires rapid, far-reaching, and unprecedented changes in all aspects of society. It is to be noted that immediate changes in lifestyles, technology, consumption patterns, and production methods have elevated environmental problems (Yilanci and Gorus, 2020; Ahmad et al., 2021a; Ahmad et al., 2022; Ekeocha, 2021; Shehzad et al., 2021; Arif et al., 2022). Moreover, it is commonly believed that many countries have prioritized economic development regardless of the consequences, leading to the problems of high fossil fuel energy consumption and environmental pollution (Bertinelli et al., 2012).

In recent decades, China has accredited sudden economic development to the enormous utilization of its resources. This nations have faced structural transformation from agricultural to industrial and service-based economies. Hence, this development is not without cost, and environmental quality is the price. This region is in the initial phase of industrialization, which has incalculably increased the demand of energy. Indeed, electricity consumption in China has almost doubled from 2010 to 2021, i.e., from 4199.9 to 8310 TW h. Moreover, burning up of total energy has been augmented by 2.2% recently in comparison with 2019 (Wong, 2021). The studies of various authors such as Belke et al. (2011) and Tang et al. (2016) reported that energy plays a vital role in boosting economic growth. In addition, Zeraibi et al. (2020) declared that the use of energy directly impacts the economic growth, while indirectly effecting the environmental excellence. Thus, there is an urgent need to develop the most promising economic and energy strategies to accomplish the sustainable development goals (SDGs). Furthermore, Arouri et al. (2012) and Arif et al. (2022) revealed the direct impact of economic growth on environmental degradation. Consequently, the environmental nexus of energy consumption and economic development raise questions about sustainable economic growth, and it becomes indispensable to maintain a balance between economic development, energy use, and ecological sustainability. Numerous studies examined the relationship between economic growth and environmental degradation through the environmental Kuznets curve (EKC) theory introduced by Kuznets (1955), which documented that economic expansion and environmental degradation have a non-linear relationship that can be characterized by an inverted U-shaped curve. As per the EKC theory, an economic boost increases environmental degradation at the initial level but improves environmental excellence after attaining a specific point. Hence, despite significant changes, society will maintain environmental protection, and people will enjoy healthy lives (Stern, 2004; Ahmad et al., 2021b).

The EKC concept is attributed to three approaches, i.e., scale, component, and the technique effect through which economic growth can affect the environmental excellence in a country (Grossman and Krueger, 1995). In the first stage, a scale effect occurs where natural resources are extracted and valuable resources are put into the manufacturing cycle. When a manufacturing cycle begins, various toxic chemicals are produced, and the by-products of this manufacturing process drastically increase environmental degradation. In order to enhance the economic conditions, the government neglects the destructive aspects of this expansion which, as a result, affects environmental sustainability. At this stage, the use of energy and wages are increasing, and the country's economic system is experiencing constant change; thus, the market framework begins to transform (Stern, 2004). This is the level where compositional impact occurs on environmental management, and the impact of socioeconomic development on environmental sustainability becomes positive. During this progression, additional markets develop , and the industry moves toward using sustainable technologies (Bagliani et al., 2008). Moreover, this variation upgrades the lifestyle and urges the desire for a healthier society. At this stage, industries adopt clean technologies that augment efficiency without harming environmental sustainability, and the economic system becomes information intensive instead of wealth intensive. At this moment, the government expenditure on innovations and pollutant technology is replaced (Tunç et al., 2009). This whole process is known as the EKC theory. However, some studies have shown that this relationship can sometimes be N shaped (Shehzad et al., 2022) documenting that environmental dilapidation will increase again shortly after the income levels rise above the appropriate level (Figure 1).

Torras and Boyce (1998) proclaimed that the N-shaped EKC occurs when technological transition transpires. The effectiveness of linkage depends on the small scale and extent of the enhanced classification of industries.

Additionally, China has stoutly built the economic relationship to the world through its Belt and Road Initiative (BRI). The BRI aims to improve China's underdeveloped regions, particularly its western regions, and to broaden China's opportunities for cooperation and collaboration with other nations in order to improve connectivity and integration. An integrated logistics layout, a new trade route and fresh trade possibilities, cross-border trade by eliminating cross-border uncertainty, entrepreneurship in developing nations, and this global initiative ultimately increased China's GDP (Akbar et al., 2020; Lee and Shen, 2020; Han et al., 2022). In addition, by increasing cooperation and mutual benefits, deepening relations and connecting diverse nations, and promoting global economic infrastructure, this initiative promotes global economic infrastructure. Likewise, partner nations and Europe's global presence could grow as a result of the BRI, and China and Europe could work together more in markets such as those in West Africa, the Indian Ocean, and Central Asia (Haggai, 2016). It is anticipated that trade between One Belt One Road (OBOR) nations will rise from \$5 billion to \$135 billion (Enderwick, 2018). Accordingly, it is essential to ascertain the environmental concerns of economic globalization. Moreover, recent studies reported that environmental pollution was the major cause of the spread of novel coronavirus (COVID-19) (Bashir et al., 2020; Fattorini and Regoli, 2020; Travaglio et al., 2021). Furthermore, Wu et al. (2020) acknowledged that carbon emissions and COVID-19 cases had a bidirectional impact on each other. Thus, it becomes significant to include domestic government health expenditures in the nexus of economic growth, energy use, economic globalization, and environmental degradation so that constructive strategies can be constructed.

After taking into account the impact of energy use, the primary objectives of this study are to determine the N-shaped association between economic growth and environmental degradation in China. In addition, the investigation examined the connection between environmental degradation in China and BRI (through economic globalization) and domestic government health expenditures. The subsequent reservations of policymakers, academics, researchers, and government officials are dispelled by the study. First, what is the nature of the economic growth, energy use, and ecological dilapidation nexus for the long term era, and does the N-shaped EKC hypothesis exist? Second, can domestic government health

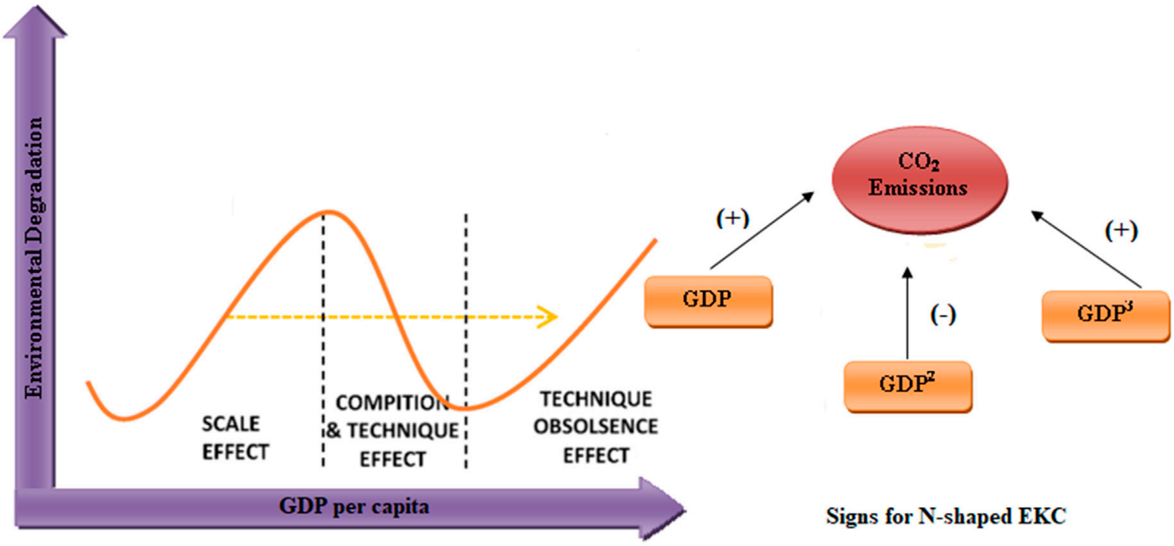

FIGURE 1
Stages of the N-shaped EKC

expenditures reduce the level of CO_2 emissions? Third, does economic globalization benefit environmental sustainability? The reason to choose these variables is highly based on the study objectives. This study significantly analyzed the impact of economic growth on the environmental pollution in China through the N-shaped EKC. The sudden economic growth in China has raised many questions relevant to environmental excellence and health level. Hence, exploring the linkage between environmental pollution, health expenditures, and economic growth becomes essential. This study contributes to the literature in three ways. First, this investigation explored the nexus of economic growth, energy use, and environmental degradation through the N-shaped EKC theory. Second, this study evaluated how spending budget in health facilities effects environmental pollution. Third, this study reported the imperious role of the Belt and Road Initiative in terms of environmental excellence in China. As per the author's best knowledge, this is the first examination that evaluates the energy–growth–environmental degradation nexus in a single model. Moreover, it is the first study that measured the impact of the BRI through economic globalization.

The rest of this study is organized as follows. The second section exhibits the recent literature published in environmental economics. The third section discusses the methods applied in this study. The fourth section specifies the results and discussion. Last, the fifth section nominates the conclusion derived from the study's findings.

2 Literature review

2.1 An N-shaped EKC

The EKC explains the involvement of a state's economic expansion and its related environmental degradation level. It portrays how a country's environmental excellence will progress if the development level of a nation goes up (Chenghu et al., 2021). Grossman and Krueger (1991) argued that the connection between environmental quality and economic growth was not linear and varied along the development level of an individual nation. In other words, every nation has its own specific EKC based on the use of resources, economic activities, and social background of that country. Various researchers (Ozcan, 2013; Narayan et al., 2016; Arif et al., 2022) reported an inverted U-shaped relationship between economic growth and environmental degradation. However, some researchers reported that an inverted U-shaped relationship does not always exist. Brajer et al. (2008) analyzed the city-wise EKC in China using panel data models. The study stated that an inverted U-shaped and N-shaped EKC exists in China after controlling the health benefits given to the public. The study used SO_2 to nominate the environmental degradation in China. Moreover, Zeraibi et al. (2022) scrutinized the role of broad money supply and government expenditures on environmental degradation in China. The study reported that an inverted U-shaped EKC does not exist in China, though the N-shaped relationship between economic growth and CO_2 emissions was significant. However, Etokakpan et al. (2021) examined the N-shaped EKC in China in the presence of urbanization and natural gas consumption from 1971 to 2018. The study documented that the N-shaped EKC does not exist in China, while confirming that a reversed N-shaped EKC was present. The research reported that natural gas consumption and urbanization directly impact CO_2 emissions. Barış-Tüzemen et al. (2020) investigated the EKC in turkey after indicating the impact of ICT on CO_2 emissions. The study utilized the data from 1980 to 2017 and employed the autoregressive distributed lag (ARDL) model. The findings revealed that ICT has a positive impact on CO_2 emissions and an inverted significant N-shaped EKC exists in Turkey. However, the study verified these findings through the Quantile regression method and reported that an insignificant inverted N-shaped EKC was evident. Additionally, Park and Lee, (2011) scrutinized the EKC hypothesis in 16 regions of Korea. The study utilized the panel data of 16 years and employed SO_2, NO_2, and CO_2 to nominate the air pollution. The study revealed that each region in Korea has its own specific shape of EKC by using SO_2 and NO_2. However, the study noted a possible subsistence of the U-shaped and N-shaped EKC. Moreover, using CO_2 emissions, the study found evidence of the U-shaped EKC in most regions across Korea. Moreover, the study mentioned that energy consumption was the highest factor determining the level of environmental degradation in Korea. Rashdan et al. (2021) inspected the EKC hypothesis by using the capture fisheries production (CFP). The research utilized data from 14 nations and employed panel data modeling. The examination discovered the N-shaped affiliation between economic growth and capture fisheries product. Moreover, the study argued that financial development and imports negatively impact the capture fisheries production, while exports positively impact the CFP. Furthermore, Bisset (2022) used the panel data of 41 SSA nations classified into three income classes from 1996 to 2018. The study used the panel data model of SSA states and found that an EKC of the N-shaped exists merely in upper-middle-income groups. The study achieved these findings in the presence of three key governance indicators, i.e., government effectiveness, political and institutional governance, and economic governance.

2.2 Nexus between health expenditures and environmental degradation

Khan et al. (2020) examined the ramifications of renewable energy use and health expenditures on CO_2 emissions in BRI countries. The study employed the data from 1995 to 2016 and panel data models, i.e., fully modified ordinary least square (FMOLS) and generalized method of moments (GMM). The study found that renewable energy imperatively reduces CO_2 emanation. However, the study noted that health expenditures and economic expansion significantly diminish the environmental excellence in BRI states. In addition, Gövdeli (2019) examined the nexus among economic growth, health expenditures, and CO_2 emissions in Organization for Economic Co-operation and Development (OECD) nations. The study used secondary data from 1992 to 2014 and applied the panel data models. The study's results exposed that economic growth imperatively surges environmental degradation. The outcomes of the Granger causality model tested by the vector error correction model (VECM) showed momentous causality in a row from CO_2 emissions to health expenditures. Likewise, Ullah et al. (2020) examined the correlations among health expenditures, renewable energy use, trade, and CO_2 emissions for the nation of Pakistan by using annual data from 1998 to 2017. The study made known that trade increases environmental degradation, resulting in a major upsurge in health expenditures. However, the study discovered that renewable energy improves environmental quality, which, as a result, significantly diminishes health expenditures. Also, Chaabouni et al. (2016) analyzed the data from 51 nations from 1995 to 2013. The study used panel data techniques and discovered that health expenditures and CO_2 emissions have a unidirectional causality relationship, whereas economic growth and health expenditures divulged bidirectional causation.

2.3 Environmental degradation and economic globalization nexus

The Belt and Road Initiative of China has strong potential to increase its *per capita* income. Moreover, other developing nations can also benefit its economy through the BRI project of China. You and Lv (2018) investigated the spatial impact of economic globalization on environmental degradation. The study used data from 83 nations through 1985 to 2013 and depicted that CO_2 emissions and economic globalization have a negative relationship. Hence, the study suggested that highly globalized nations have better environmental quality. Additionally, Shahbaz et al. (2017) applied the ARDL model to ascertain the impact of globalization on environmental degradation in China. The study verified that globalization significantly decreases environmental degradation in China; nevertheless, the use of coal significantly upsurges CO_2 emissions. The Granger causality upshots showed that CO_2 emissions appreciably cause globalization. Liu et al. (2020) explored the sway of G7 state's globalization by employing panel data techniques. For this reason, the KOF globalization indicator was utilized. The study documented that globalization and CO_2 emissions have an upturned U-shaped association, which proves the existence of the EKC hypothesis. Moreover, the study stated that economic growth increases environmental pollution while renewable energy helps to reduce it.

2.4 Energy use and environmental degradation

Energy use imperatively boosts the economic growth of a nation (Zeraibi et al., 2020). However, it has also environmental consequences, which cannot be ignored to achieve sustainable development. The investigation by Zhang and Lin (2012) used data from 1995 to 2010 and analyzed the impact of energy consumption on CO_2 emissions at the provincial level of China. The investigation applied the STIRPAT technique and discovered that energy use has a significant nexus with CO_2 emissions and urbanization. Similarly, Wang et al. (2016) explored the nexus among energy consumption, CO_2 emissions, and economic growth. The study made known that a unidirectional causality was moving from energy use to CO_2 emissions; however, the examination also accounted that CO_2 emissions had a momentous effect on energy use. Shafiei and Salim (2014) exposed the role of energy use when utilizing the STIRPAT model for OECD territories. The study compared the impact of renewable and non-renewable energy use on CO_2 emissions and stated that non-renewable energy has a direct impact while renewable energy has an indirect impact on CO_2 emissions. Also, Khan et al. (2019) utilized the time series technique by employing the secondary data from 1971 to 2016. The consequences inspected that energy consumption significantly heightens the level of greenhouse gas emissions in Pakistan. The study also argued that economic globalization, urbanization, and economic growth have

TABLE 1 Description of the study variables.

Variables	Abbreviation	Proxy	Data source
Carbon dioxide	CO_2	CO_2 emissions (metric tons *per capita*)	World Bank
Domestic health expenditures	DHE	Domestic general government health expenditure	World Bank
Per-capita energy consumption	PCEU	Per-capita energy use	Our word in data
Foreign direct investment	FDI	Foreign direct investment, net (BoP, current US$)	World Bank
Economic growth	GDP	GDP *per capita* (constant 2015 US$)	World Bank

TABLE 2 Unit root testing results.

	Augmented Dickey–Fuller				Phillips–Perron			
	Level		1st difference		Level		1st difference	
Variable	T-statistic	Probability	T-statistic	Probability	T-statistic	Probability	T-statistic	Probability
CO_2	−2.207886	0.2053	−8.485288	0	−2.103739	0.2439	−9.155442	0
DHE	−2.328715	0.1658	−8.491923	0	−2.153812	0.2248	−8.537211	0
ECG	−2.944677	0.0456	−1.715629	0.4189	−2.127644	0.2346	−3.374587	0.015
PCEU	−0.808193	0.8106	−6.47566	0	4.511428	1	−5.695158	0
GDP	1.00793	0.9964	−2.833326	0.0593	5.532951	1	−2.601576	0.0972
GDP^2	1.475328	0.9991	−3.435027	0.0544	16.84114	1	−3.408625	0.0579
GDP^3	3.610094	1	−10.09979	0.0001	29.70435	1	−9.996632	0

Source: The author's calculation.

TABLE 3 Results of the bound test.

	Value	Significance (%)	I (0)	I (1)
F-statistic	4.68	10	3.02	3.51
K	6	5	3.62	4.16
		2.5	4.18	4.79
		1	4.94	5.58
Null hypothesis: No level relationship				
Equation: CO2 = f (DHE, ECG, PECU, GDP, GDP2, GDP3)				

Source: The author's calculation.

direct association with CO_2 emissions in china. In addition, the study by Zhang et al. (2023) verified that environmental policies imperatively reduced the air pollution. Moreover, Hou et al. (2023) stated that environmental sustainability is highly connected to renewable energy use. However, the study of Jun et al. (2020) argued that trade openness significantly increases the environmental pollution due to more usage of energy in industry. Hence, the abovepresented literature review shows the significance of testing the N-shaped EKC in China. Moreover, it can also be seen that no research has already investigated the N-shaped relationship between CO_2 emissions and economic growth in China after considering the energy use and domestic government health expenditures. Moreover, no study has evaluated the impact of the BRI through economic globalization in China.

3 Data and methodology

3.1 Data

The fundamental purpose of this investigation is to analyze the N-shaped association of economic growth with environmental degradation in China. Second, the study revealed the importance of the OBOR project in China measured through economic globalization for environmental excellence in China. Moreover, the study examined the role of energy use on CO_2 emissions in the presence of the EKC. For the defined aim, the on-hand research used the quarter data from 2000 to 2019. This selected duration is based on the availability of the data. The study converted the annual data into the quarter form using the methodology of Shehzad et al. (2019). To ascertain the N-shaped EKC in China, the study employed GDP, a square form of GDP, and a cubic form of GDP. Particularly, the proxies used in the study are mentioned in Table 1.

3.2 Methodology

Our model defines the functional equation as follows:

TABLE 4 Long-run and short-run dynamics of the study variables.

Variable	Coefficient	Std. error	t-statistic	Probability
Long run				
DHE	0.8665***	0.0602	14.3831	0.0000
ECG	−0.0116	0.0128	−0.9063	0.3681
PECU	0.3504***	0.0614	5.7008	0.0000
GDP	0.8937***	0.0636	14.0401	0.0000
GDP2	−0.0524***	0.0154	−3.3999	0.0012
GDP3	0.9099***	0.0357	25.4252	0.0000
C	−0.0521*	0.0279	−1.8670	0.0664
Short run				
D (CO_2(-1))	0.6095***	0.0579	10.5153	0.0000
D (DHE)	−0.0032**	0.0014	−2.6231	0.0108
ECG	0.0057***	0.0014	3.9469	0.0002
D (GDP)	0.0047***	0.0005	9.0409	0.0000
D (GDP2)	−0.0115	0.0077	−1.4896	0.1411
D (GDP3)	0.8741***	0.0607	14.3960	0.0000
ECTt-1	−0.0408**	0.0167	−2.447891	0.0171
R-squared	0.9635	Adjusted R-squared		0.9529
		Durbin–Watson		2.1936

Source: The author's calculation. Here, *, **, and *** represent the 10%, 5%, and 1% level of significance, respectively.

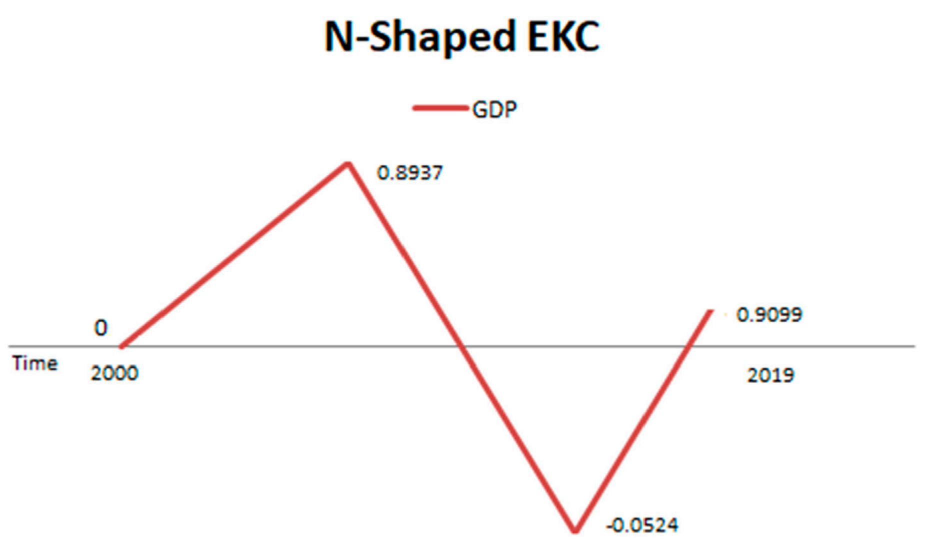

FIGURE 2
N-shaped EKC based on the coefficients calculated through the ARDL model.

$$CO2 = f\left(DHE, ECG, PCEU, GDP, GDP^2, GDP^3\right) \quad (1)$$

Here, CO_2 nominates the CO_2 emissions used to evaluate the environmental degradation in China. Moreover, DHE, ECG, and PCEU indicate the domestic general government health expenditures, economic globalization, and *per capita* energy use, respectively. In addition, GDP, GDP^2, and GDP^3 symbolize the economic growth, square of economic growth,

TABLE 5 Robustness testing through the CCR model.

Variable	Coefficient	Std. error	t-statistic	Probability
DHE	4.040814***	0.60913	6.633749	0
PCEU	1.083647	0.748235	1.448271	0.152
ECG	0.014536***	0.004943	2.940355	0.0045
GDP	1.173376***	0.049949	23.49172	0
GDP2	−1.49831*	0.78535	−1.90783	0.06080
GDP3	1.686764***	0.580404	2.906190	0.004900
C	−0.25970**	0.12716	−2.04239	0.04510

Source: The author's calculation. Here, *, **, and *** represent the 10%, 5%, and 1% level of significance, respectively.

TABLE 6 Outcomes of the stability testing.

Breusch–Godfrey serial correlation LM test			
F-statistic	0.165181	Probability	0.8481
Obs*R-squared	0.3586	Prob. chi-square (1)	0.8359
Breusch–Godfrey heteroskedasticity test			
F-statistic	0.792877	Probability	0.5021
Obs*R-squared	2.43343	Prob. chi-square (2)	0.4874

Source: The author's calculation.

and cubic form of economic growth, respectively, to evaluate the N-shaped EKC in China. We utilized the autoregressive distributed lag model to estimate the study factors' long- and short-run dynamics (Pesaran et al., 2001). We employed the ARDL model for the following reasons: ARDL is the best fit for a small dataset. Additionally, this approach does not bound the data to be stationary at the same level of integration, i.e., I (0) or I (1), and can be applied to mixed co-integrated data. Furthermore, the ARDL model diagnoses the behavior of the dependent variable in terms of its own and prior values of the independent factor (Cherni and Essaber Jouini, 2017; Shehzad et al., 2020). The ARDL co-integration model based on a bound testing approach can be written as follows:

$$\begin{aligned}\Delta CO_{2t} = {} & \omega_0 + \omega_1 (CO_2)_{t-1} + \omega_2 (DHE)_{t-1} + \omega_3 (ECG)_{t-1} \\ & + \omega_4 (PCEU)_{t-1} + \omega_5 (GDP)_{t-1} + \omega_6 (GDP^2)_{t-1} \\ & + \omega_7 (GDP^3)_{t-1} + \sum_{j=0}^{p} \varphi_1 (CO_2)_{t-i} + \sum_{j=0}^{p} \varphi_2 (DHE)_{t-j} \\ & + \sum_{j=0}^{p} \varphi_3 (ECG)_{t-k} + \sum_{j=0}^{p} \varphi_4 (PCEU)_{t-l} + \sum_{j=0}^{p} \varphi_5 (GDP)_{t-m} \\ & + \sum_{j=0}^{p} \varphi_6 (GDP^2)_{t-n} + \sum_{j=0}^{p} \varphi_7 (GDP^3)_{t-o} + \mu_t\end{aligned}.$$

Here, $\omega_1, \omega_2, \omega_3, \omega_4, \omega_5, \omega_6, and\ \omega_7$ signify the short-term coefficients, while ω_0 measures the constant term. Likewise, $\varphi_1 - \varphi_7$ symbolize the long-term parameters. Furthermore, Δ and μ_t define the first difference and the error terms, respectively. The ARDL model utilized the F-bound test approach to observe the long-term co-integration in the study variables. Consequently, this approach is based on two limits. First, we define the upper-bound limit, and second, we describe the lower-bound limit. Thus, if the calculated F-bound analysis coefficient is less than the lower limit, then it means there is no long-run co-integration. Moreover, an F-bound value greater than the upper limits indicates significant long-run co-integration in the data. Nonetheless, if the F-bound weights lie between the upper and lower bounds, the results are inconsequential (Pesaran et al., 2001). The ARDL-based error correction term can be specified as follows:

$$\begin{aligned}\Delta CO_{2t} = {} & \omega_0 + \omega_1 (CO_2)_{t-1} + \omega_2 (DHE)_{t-1} + \omega_3 (ECG)_{t-1} \\ & + \omega_4 (PCEU)_{t-1} + \omega_5 (GDP)_{t-1} + \omega_6 (GDP^2)_{t-1} \\ & + \omega_7 (GDP^3)_{t-1} + \gamma_1 ECT_{t-1} + \mu_t\end{aligned}.$$

Here, ECT_{t-1} nominates the error correction term, which measures the adjustment speed of the dependent variable to gain an equilibrium level. The study engaged the Bruesch–Godfrey serial correlation heteroskedasticity in the model. Furthermore, the cumulative sum of recursive residuals (CUSUM) and its square (CUSUMSQ) techniques are utilized to measure the stability of the ARDL model. At last, the study applied the canonical integration regression technique for robustness testing of the long-run results of the ARDL model.

4 Results and discussion

4.1 Unit root evaluation and co-integration analysis

This investigation has employed the Phillips–Perron (PP) and Augmented Dickey–Fuller (ADF) test (Dickey, D. and Fuller, W., 1979) to ascertain the stationary level of the study factors. The findings of these tests are given in Table 2, which state that complete elements are stationary at the 1st difference level. However, ECG is also stationary at the level, which specified that the stationary order of the study elements is mixed, and the ARDL approach is best to deal with this kind of data. This study used the bound test approach based on the F-test to evaluate the long-run co-integration in the data. The upshots of the bound test are exhibited in Table 3, which shows that the null hypothesis of no co-integration has been rejected

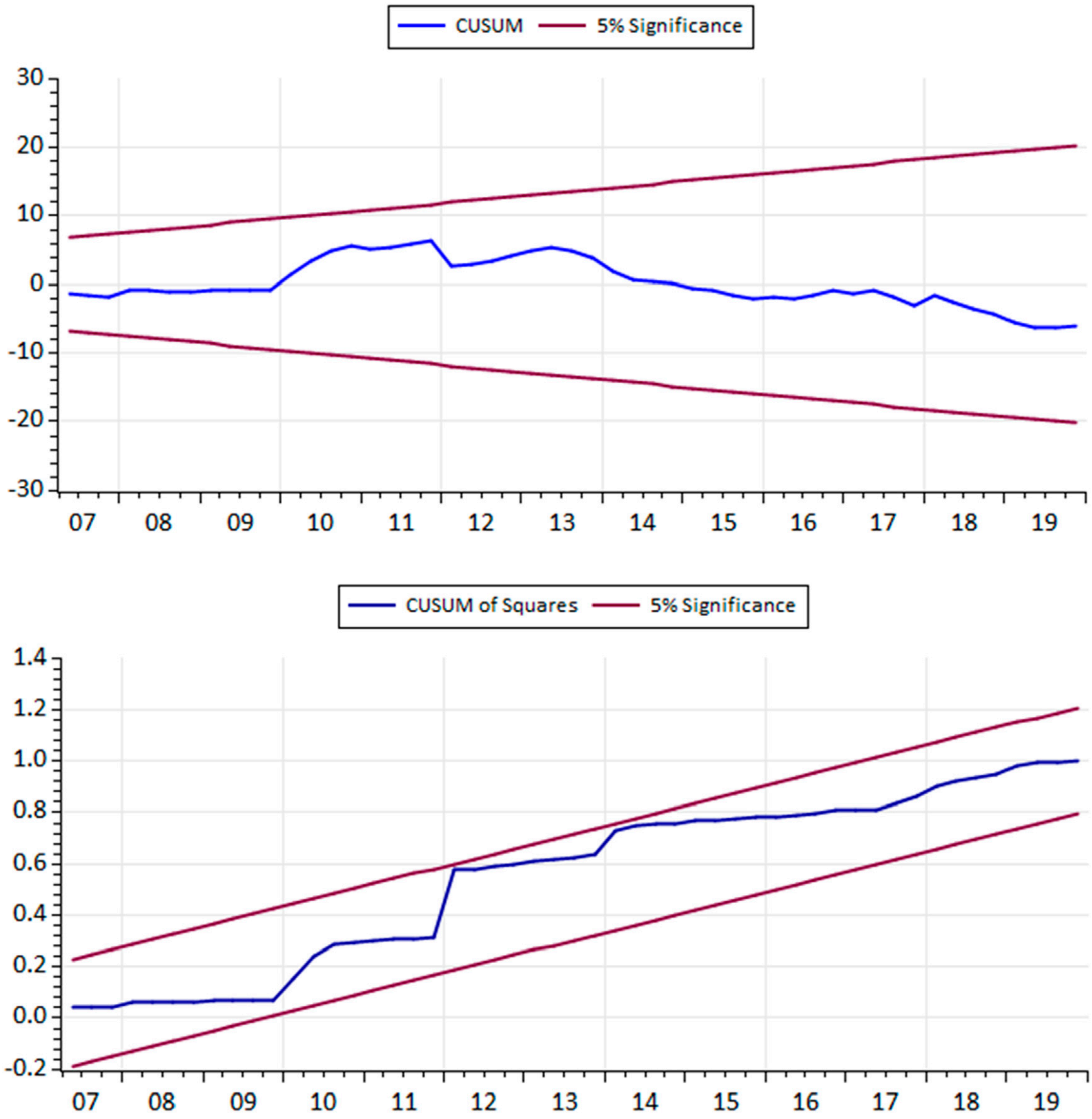

FIGURE 3
CUSUM and CUSUMSQ graph with a 5% level of significance.

at a 5% significance level. Hence, the ARDL model can be utilized to examine the long- and short-run dynamics.

4.2 Long- and short-run dynamics

Table 4 displays the long-run and short-run dynamics among the study variables. The study demonstrated that one unit increase in GDP significantly increases the CO_2 emissions by 0.89 units implying that GDP positively effects the environmental degradation in China. However, after achieving the threshold level, the square of GDP (GDP^2) revealed that one unit increase in GDP^2 lessens the CO_2 emission. Moreover, again, when GDP exceeds the threshold level, it increases environmental degradation as one unit increase in GDP^3 upsurges the CO_2 emissions by 0.909 units. Thus, as per the concept of Narayan and Narayan (2010), these findings demonstrated that there is a long-term N-shaped relationship between economic growth and environmental degradation in China (see Figure 2). Additionally, in the short run, economic growth variables (GDP, GDP^2, and GDP^3) do not reveal a significant N-shape association with CO_2 emissions. Brajer et al. (2008) analyzed the city-wise data of China and documented that both an inverted U-shaped and N-shaped relationship exist between GHGs and economic growth in China. The study used SO_2 as a proxy for GHGs. Moreover, the study by Liu et al. (2021) also verified the existence of the EKC hypothesis in China in the presence of agricultural development. However, these findings do not match those of Etokakpan et al. (2021). In addition, the findings expressed that one unit increase in domestic general government health expenditures considerably improves the CO_2 emanation for the long period. Nevertheless, for the short-term era, DHE indicated a harmful and noteworthy influence on China's CO_2 emissions. These findings documented that action

TABLE 7 A causality analysis.

Null hypothesis	F-statistic	Probability
DHE does not Granger cause CO_2	2.9496*	0.0592
CO_2 does not Granger cause DHE	4.51366**	0.0145
ECG does not Granger cause CO_2	0.24309	0.7849
CO_2 does not Granger cause ECG	1.17734	0.3144
PCEU does not Granger cause CO_2	5.02178***	0.0093
CO_2 does not Granger cause PCEU	1.60887	0.2077
GDP does not Granger cause CO_2	0.14892	0.8619
CO_2 does not Granger cause GDP	0.51094	0.6023
GDP^2 does not Granger cause CO_2	0.0513	0.9575
CO_2 does not Granger cause GDP^2	2.91867*	0.0609
GDP^3 does not Granger cause CO_2	0.04276	0.9582
CO_2 does not Granger cause GDP^3	9.37838***	0.0003

Source: The author's calculation. Here, *, **, and *** represent the 10%, 5%, and 1% level of significance, respectively.

taken by the general government to improve health conditions also improves the environmental quality and discourages carbon dioxide emissions in China. These findings matched with the study of Chaabouni et al. (2016), Zeeshan (2021), and Bilgili et al. (2021).

This analysis inspected the effects of economic globalization on CO_2 emissions, which showed a negative but insignificant liaison with CO_2 emissions in the long run. Nonetheless, in the short run, it confirmed the positive association with CO_2 emissions. These findings imply that increasing the economic affiliation of China with other countries needs strict policies and strategies that can immensely control the import of polluted goods and services. These results are harmonized with the study of Ahmad M. et al. (2021). The results of PCEU stated that enlarging the energy consumption puts a significant burden on the environmental quality in China. Zhang and Lin (2012) and Wang et al. (2016) also explored the impact of energy consumption on CO_2 emissions in the presence of urbanization and economic growth and documented its imperious role for environmental degradation. The error correction term (ECT_{t-1}) specified a negative indication with a value of −0.040 at a significance of a 1% level, implying that divergence occurred in the equilibrium of CO_2 emissions because of the independent elements engaged in the study will be accurate with the velocity of 4% in a quarter. Furthermore, the model signified that 96.3% of changes in CO_2 emissions are due to the study variables and 95.2% are because of significant factors among them. The Durbin–Watson value is 2.193, entailing that model is free from serial correlation.

The study also applied the canonical co-integrating regression (CCR) model for the robustness of the ARDL upshots. Table 5 illustrates the findings of the CCR model, which also confirms the existence of the N-shaped EKC in China. Hence, it discloses that the results generated through the ARDL model are correct and reliable. However, CCR showed an insignificant impact of PCEU.

4.3 Discussion and suggestions

In the analysis, we found that GDP has an encouraging effect on environmental degradation. However, GDP^2 designated a negative effect on environmental degradation, which documented that achieving a specific level of economic growth helps improve environmental quality. However, the excess of economic growth again degrades the environmental quality in China as GDP^3 represents a positive connection with CO_2 emissions. Consequently, it verifies the existence of an N-shaped EKC in China (see Figure 2). In addition, this investigation demonstrated that an increase in energy consumption adversely affects environmental quality and human health. Various studies such as those by Belke et al. (2011); Tang et al. (2016); and Ren et al. (2022) also confirmed that the increase in energy consumption boosts the economic activities and *per capita* income. In this situation, the study suggested that the government should focus on sustainable development through the installation of the green industry with the help of economic globalization. Moreover, the government should import the green technologies, improving the production process and discouraging pollutant technology use. Moreover, domestic investment in advanced technologies can also boost the final products' energy efficiency and effectiveness, enhancing environmental excellence. Short-term CO_2 emissions were also negatively impacted by domestic general government health expenditures. As a result, the government ought to spend more money on activities that boost health and directly discourage rising CO_2 emissions. In order to build institutes that improve health facilities and can advance environmental excellence, the government ought to make it easier for foreign companies to construct such facilities by providing tax breaks and duties.

4.4 Constancy assessment of the ARDL approach

Table 6 explains the findings of heteroskedasticity and serial correlation evaluation. The outcomes showed that the ARDL approach implemented in this investigation is unoccupied from heteroskedasticity and serial correlation. Moreover, CUSUM and CUSUMSQ lines are also under the limit of a 5% level of significance, meaning that the model is stable and consistent (Figure 3).

4.5 Causality evaluation

Table 7 shows the causality test results, which declare that DHE and CO_2 emissions have a bidirectional causation relationship with each other. It entails that a policy focusing the domestic general health expenditures will also impact the environmental excellence in China and *vice versa*. Moreover, the causality findings of economic growth made known that a remarkable causality effect is moving from CO_2 emissions to GDP^2 and GDP^3, confirming that environmental excellence has a strong bond with economic growth and strategies regarding to control CO_2 emissions can improve economic activities. The examination carried out by Esso and Keho (2016) used the panel causality model and showed that a reverse causality was running from GDP to CO_2 emissions in several countries of Africa, although the study reported that GDP Granger caused the level of carbon emission in Nigeria. The outcomes of our causality test for economic growth are also in line with the study of Gorus and Aydin (2019). Furthermore, a unidirectional causality attachment of PCEU was documented in the examination, which corroborates that the use of energy causes the CO_2 emission augmentation. Mirza and Kanwal (2017) also employed the Granger causality model and highlighted that energy use and CO_2 emissions have a bi-variate causality affiliation. On the other hand, Nain et al. (2017) argued that the nature of causality affiliation between energy use and CO_2 emissions varies for different sectors.

5 Conclusion and policy implications

5.1 Summary

This study's critical objective is to analyze the N-shaped EKC in China in the presence of domestic general government health expenditures. Moreover, the investigators evaluated the role of OBOR by using the proxy variable of economic globalization on environmental degradation in China. Moreover, the investigation ascertained the impact of energy use on CO_2 emissions. The study utilized the quarter data from 2000 to 2019 and employed the autoregressive distributed lag model. Moreover, for the robustness of the findings, the study engaged the CCR model.

5.2 Key findings

The findings of the ARDL model discovered that an N-shaped relationship exists between economic growth and CO_2 emissions in China. Moreover, domestic general government health expenditures illustrated a negative impact on CO_2 emissions in the short run. However, in the long run, it showed a constructive bonding with CO_2 emissions. Also, energy usage illustrated a direct impact on CO_2 emissions. The results of the CCR model also confirm the N-shaped EKC in China. Hence, these results successfully answered the queries mentioned in Introduction.

5.3 Policy implications

The investigation revealed that amplification in the energy usage heightens the environmental degradation in China. In addition, the study established that China's economic intensification and CO_2 discharge have an N-shaped association, implying that excess economic growth considerably discourages environmental excellence. Therefore, the study suggested that the Chinese government should promote the green industry through economic globalization in order to achieve sustainable development. In a similar vein, the Chinese government must encourage nations along the One Belt One Road to invest in and set up technological businesses that can clean the manufacturing process and improve environmental excellence. Green energy use, which directly reduces environmental degradation, should also be encouraged. The study found that health-promoting activities reduce carbon dioxide emissions. Hence, the Chinese government should increase the health budget and collaborate internationally to improve health-related activities in the country. This study also defines some limitations to achieving these outcomes; i.e., first, the data used in the study are from 2000 to 2019. Second, CO_2 emission is utilized to nominate the environmental deprivation. Furthermore, future studies can be conducted by including carbon and ecological footprints to represent the environmental deprivation. Furthermore, urbanization, financial development, environmental innovations, financial globalization, overall globalization, and ICT can be included in the model to verify these findings.

Data availability statement

The data used in the study is online available at https://data.worldbank.org/.

Author contributions

MN, MS, and KS: Conceptualization, methodology, software, formal analysis, investigation, resources, writing—original draft, and writing—review and editing. SZ: Supervision and funding.

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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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Toward carbon neutrality: The impact of manufacturing agglomeration on total factor energy efficiency

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Improving energy efficiency is an effective way to achieve carbon neutrality in the context of growing advocacy for a green economy in both academia and government. In this study, we analyzed the impact mechanism of the manufacturing agglomeration on total factor energy efficiency. Based on this work, we identified 30 provinces (autonomous regions and municipalities) in China using 2002 to 2017 panel data. We used the data envelopment analysis game cross-efficiency model to calculate the interprovincial current state of energy efficiency. We constructed a spatial Durbin model and used an adjacent space weight matrix, geographic distance weight matrix, and economic distance weight matrix to study the impact of manufacturing agglomeration on total factor energy efficiency. The results showed that under different spatial weights, the interprovincial total factor energy efficiency had a significant spatial dependence; under the three spatial weights, we identified a U-shaped relationship between manufacturing agglomeration and total factor energy efficiency. Industrial agglomeration had obvious spatial spillover effects on total factor energy efficiency, and the spillover effects under the weight of geographic distance were higher than other spatial weights. During the sample period, the direct, indirect, and total effects of the manufacturing industry had an impact on energy efficiency. It all had a negative number indicating that there was a crowding effect in manufacturing agglomeration, and it had an inhibitory effect on energy efficiency.

KEYWORDS

energy efficiency, DEA game cross-efficiency model, manufacturing agglomeration, spatial overflow, spatial Durbin mode

1 Introduction

Achieving carbon neutrality is an important goal for governments to pursue economic development and environmental protection. Since the reform and opening up, China's economy has continued to grow rapidly and has received world attention. Looking back on the history of China's economic development, this rapid economic growth has been accompanied by an increase in the industrial agglomeration level, especially the manufacturing industry. The long-term growth pattern characterized by high energy dependence, however, has made China the world's largest carbon emitter. A 20th National Congress of the Chinese government report emphasized that promoting economic and social green and low-carbon development is the key link to achieving high-quality development. The massive consumption of traditional fossil energy (coal, oil) is the primary source of carbon emissions. Improving energy efficiency has become an efficient way to alleviate the contradiction between economic growth and environmental constraints, and it is an inevitable choice for achieving sustainable economic development and carbon neutrality in China (Pu et al., 2022; Wang and Liang, 2022; Yu and Shi, 2022). The academic community, however, has not reached a consensus on how to improve energy efficiency. Many studies have shown that industrial agglomeration can have a profound external impact on economic growth through agglomeration effects. Krugman (1991) and Fujita et al. (2001) noted that industrial agglomeration has produced positive externalities to enterprises in the same areas through technology spillover and knowledge diffusion effects. Understanding whether the positive externalities of industrial agglomeration have a positive or negative impact on energy efficiency is an important issue in the current process of China's economic development. From the perspective of industrial economic theory, and under the guidance of a market mechanism, industrial agglomeration with the goal of maximizing profits is conducive to promoting the optimal allocation of resources and economic growth. Under China's fiscal decentralization system, however, local governments tend to provide high-quality policy support and services to enterprises within their jurisdictions to improve growth performance, thus forming policy rents. To obtain more policy rents, enterprises unite and form a superficial industrial agglomeration. This kind of industrial agglomeration formed in the pursuit of policy rent cannot produce technology spillover and sharing effects. On the contrary, this superficial industrial agglomeration easily leads to market segmentation, industry convergence, and distortion of resource allocation. Against this backdrop, in this study, we selected manufacturing industrial agglomeration as the starting point to explore whether the positive externalities of manufacturing industrial agglomeration have a positive or negative impact on energy efficiency. This is an important issue in the current process of China's economic development.

By combining many previous studies, most scholars have attributed the key influencing factors of energy efficiency changes to technological progress. Technological progress promotes the improvement of energy efficiency in direct and indirect ways. An example of a direct effect is that, with the advancement of technology, the efficiency of equipment in the production department can be improved, thereby reducing the intensity of energy consumption. An example of an indirect effect is that, with the advancement of technology, the quality of the labor force and the level of science and technology in the whole society can be improved. As a result, the phenomenon of energy waste in the production process is effectively suppressed, and energy efficiency is improved (Einhorn, 1982; Anderson, 1995). Some scholars, however, believe that although technological progress can improve energy efficiency and promote economic growth in the short term, in the long term, rapid economic growth will bring about more energy consumption, which will offset the delayed savings brought by efficiency improvements. This results in a rebound effect of technological progress (Hu, 2014). Some scholars later studied the impact of industrial structure changes on energy efficiency. Denison (1967) and Maddison (1987) found that in accordance with the productivity level, energy factors transferred from low-level industries to high-level industries, and their utilization efficiency in the entire national economy was improved. This is also called a "structural dividend." According to the basic idea of a "hypothesis," the industrial structure acts on energy efficiency through externalities. A phenomenon closely related to industrial externalities is industrial agglomeration. Research on industrial agglomeration began in the 1990s (Kim, 1995), and externalities are considered to be an important cause of industrial agglomeration (Henderson, 1974). Marshall (1920) noted that the formation of industrial geographic agglomeration (agglomeration) is largely due to the external economy generated by agglomeration, that is, the creation of a skilled labor market, professional service-oriented intermediate industries, and technology spillovers. By analogy, energy is an input element, and its utilization efficiency is likely to be affected by the spillover of other companies' energy use technology. Wang and Chen (2010) used empirical methods to verify the hypothesis that industrial agglomeration and the resulting externalities effectively improved total-factor energy efficiency and single-factor energy efficiency. Pan et al. (2017) found that industrial agglomeration significantly promoted the improvement of total factor energy efficiency and identified a stable inverted U-shaped relationship between the two. Liu et al. (2017) used a dynamic spatial panel model to analyze the impact of industrial agglomeration on energy efficiency and found that the agglomeration of producer services and the coaggregation of manufacturing and producer services were beneficial to the improvement of energy efficiency. Guo and sun. (2019) explored the impact of different types of industrial agglomeration on energy efficiency. The study found significant differences in the effects of different types of industrial agglomeration on energy efficiency. Shao et al. (2019) proved that economic agglomeration directly affected carbon emissions through its various positive externalities, and at the same time, it also has an indirect impact on carbon emissions through energy intensity. Carbon emissions and energy intensity had a significant "snowball" effect in the time dimension and also had a clear strategic competitive effect in the space dimension.

In addition, some recent studies also focused on the impact of industrial agglomeration on energy efficiency. Hou et al. (2022) took China's provincial-level energy-intensive industries from 2004 to 2017 as the research object and used a multidimensional panel fixed-effect model to study the impact of industrial agglomeration on energy efficiency and its mechanism. According to the study, industrial agglomeration had a significant inverted U-shaped relationship with energy efficiency, and industrial agglomeration improved energy efficiency by increasing human capital and promoting investment in fixed assets. Utilizing data for China from 2006 to 2018, Sun and Guo (2022) used a variety of spatial Dubin models with near-neighbor weights to test the spillover effects of environmental regulation, industrial agglomeration, and integrated development on energy efficiency. They found that industrial agglomeration (specialization and diversification) effectively boosted the energy efficiency of China and its neighboring regions (geographical proximity and economic interaction). The spatial spillover effect of environmental regulation and industrial agglomeration on energy efficiency was not only caused by geographical proximity but was also the result of coordination between geographical proximity and economic interaction between regions. The integrated development of environmental regulation and specialized agglomeration inhibited the positive effect of specialization, whereas the integrated development of environmental regulation and diversified agglomeration had a stronger effect on promoting the improvement of energy efficiency. Liu et al. (2022) empirically studied the non-linear impact of spatial agglomeration on energy efficiency of enterprises and further tested its heterogeneity and mechanism based on panel data from the China Industrial Enterprise Database and the China Industrial Enterprise Pollutant Emission Database from 2003 to 2012. They found a significant U-shaped relationship between spatial agglomeration and enterprise energy efficiency, which suggested that enterprises made full use of the benefits introduced by spatial agglomeration.

In summary, domestic and foreign scholars have carried out a significant amount of research on the impact of industrial agglomeration on energy efficiency and have obtained valuable research results, which have established a solid theoretical foundation for this study. Some aspects, however, require further research. First, from the existing research, most of the total factor energy efficiency evaluation methods have been based on the data envelopment analysis (DEA) model. The DEA model, however, has a non-unique solution, and when the efficiency values of multiple decision-making units are less than 1, they can no longer be sorted. Additionally, in the process of calculating the efficiency value of the decision-making unit, the weight coefficient is often artificially enlarged, resulting in the false validity of a disadvantaged decision-making unit DEA in the mutual evaluation process. Second, in the process of quantitative analysis of energy efficiency influencing factors in the existing literature, the spatial spillover effect is often ignored. To account for the deficiencies of previous studies, in this study, we investigated breakthroughs in the following aspects: First, in the process of model construction, we considered the competitive relationship between decision-making units and adopted the DEA game cross-efficiency model to improve the scientific basis of the energy efficiency calculation and the results. Second, considering that the energy consumption demand of manufacturing is significantly higher than that in other industries, we constructed a spatial measurement model of energy-efficiency influencing factors and used the adjacent space weight matrix, geographic distance weight matrix, and economic distance weight matrix to spatially correlate an energy efficiency analysis. We constructed a spatial Durbin model to analyze the impact of manufacturing agglomeration on energy efficiency, and we identified direct effects and spillover effects. Third, although many studies have discussed the spatial spillover effects of industrial agglomeration on energy efficiency, we analyzed this issue from a non-linear perspective rather than from the linear perspective commonly used in previous studies to provide a more accurate basis for policymakers to formulate economic policies.

2 Theoretical model and mechanism analysis

Under the long-term extensive economic growth mode, local governments often pay too much attention to gross domestic product (GDP) growth during their tenure, and ignore the long-term growth factors of sustainable economic development, resulting in rapid economic development in the short term with excessive resource consumption and serious environmental load. For the price, given the study of the impact of manufacturing agglomeration on energy efficiency, we referred to the Gowri et al. (2015) model and included first industrial agglomeration in the short-term production function of manufacturers, as follows:

$$Q = Gf(K, E) = GK^{\alpha}E^{-\alpha}, \tag{1}$$

where G represents the level of industrial agglomeration; K also represents capital input, and capital input is positively correlated with output, that is $\partial Q/\partial K > 0$; E represents the energy efficiency investment of a manufacturer; and α represents the elastic coefficient of factor output (note that these definitions apply to the other formulas given in this paper). The more energy efficiency investment the manufacturer has, the higher the energy utilization efficiency is. Assuming that the total amount of investment by manufacturers in the short term is constant, the investment of capital by manufacturers to improve energy efficiency will inevitably lead to a reduction in capital investment for production. Considering the lag effect of energy saving and emission reduction on an output increase, in the short term, energy efficiency investment and output are negatively correlated, $\partial Q/\partial E < 0$.

Manufacturers need to pay interest to obtain capital to purchase machinery and equipment. Considering the sharing effect of infrastructure brought about by industrial agglomeration, in this study, we assumed that the remuneration $(R = G^{-\gamma}Kr)$ paid by manufacturers to equipment is shared by all manufacturers. At the same time, capital investment is transformed into machinery and equipment, and manufacturers need to consume energy to provide power for machinery and equipment-making power costs $(C = E^{-\beta}K)$. After considering the capital interest and power cost, the manufacturer's production profit function is as follows:

$$\pi = GK^{\alpha}E^{-\alpha} - G^{-\gamma}Kr - E^{-\beta}K, \tag{2}$$

where r represents the interest rate; γ represents the elasticity of the sharing effect of industrial agglomeration infrastructure $\gamma > 0$; and β represents the elasticity of the power cost of energy efficiency investment. Because this indicator has irreversible constraints, $\beta > 1$.

We calculated the first-order condition for maximizing the manufacturer's profit according to formula (2):

$$\partial\pi/\partial K = \alpha GK^{\alpha-1}E^{-\alpha} - G^{-\gamma}r - E^{-\beta} = 0, \tag{3}$$

$$\partial\pi/\partial E = GK^{\alpha}E^{-\alpha-1} + \beta E^{-\beta-1}K = 0. \tag{4}$$

Then, the optimal capital stock in equilibrium is as follows:

$$K^{*} = \beta\left[(\beta - 1)G^{\gamma}/r\right]^{(\alpha-\beta)}/\alpha G. \tag{5}$$

The optimal energy efficiency investment is as follows:

$$E^{*} = \left[(\beta - 1)G^{\gamma}/r\right]^{1/\beta}. \tag{6}$$

Further analysis of the relationship between energy efficiency and industrial agglomeration and interest rates shows the following:

$$\partial E^* \big/ \partial G = (\gamma/\beta)\left[(\beta-1)/r\right]^{1/\beta} G^{(\gamma-\beta)/\beta} > 0, \tag{7}$$

$$\partial E^* \big/ \partial r = (-1/\beta)\left[(\beta-1)G^{\gamma}\right]^{1/\beta} r^{(-1-\beta)/\beta} < 0. \tag{8}$$

According to an analysis of Eq. 6, when $\beta < 1$, the optimal energy efficiency of the enterprise was negative, which violated the constraint of irreversible investment, so a = 1. Eqs 7, 8 are the first-order conditions of Eq. 2 on industrial agglomeration and interest rate under the condition of energy efficiency maximization. Eqs 7, 8, respectively, represent the influence of industrial agglomeration and interest rate on the optimal behavior of enterprises—that is, the optimal energy efficiency investment was positively correlated with industrial agglomeration and negatively correlated with interest rate. Under the market mechanism, improvements in the level of industrial agglomeration encourage enterprises to make additional investments in energy efficiency. Thus, the higher the industrial agglomeration level was, the more beneficial it was to the improvement of industrial energy efficiency. Eqs 7, 8 show a positive correlation between industrial agglomeration and optimal energy efficiency investment. Because optimal energy efficiency investment and energy efficiency also are positively correlated, it can be obtained at a higher level of industrial agglomeration, thus improving energy efficiency.

As stated, industrial agglomeration with the goal of maximizing profits can achieve optimal allocation under the regulation of a pure market mechanism, promote economic growth, and improve energy efficiency. Under the system of fiscal decentralization, the alienation of local government goals has led to the emergence of differentiated policy rents (credits, subsidies, tax reductions), which are aimed at protecting local interests and intervening in corporate investment behavior, in turn inducing the pursuit of policy rents. An "industrial cluster" indicates areas where enterprises connect. Qian et al. (2019) found that the phenomenon of enterprise clustering driven by policy rents not only failed to produce technology spillovers and sharing effects but also caused repeated construction, convergence of industrial structure, and distortion of resource allocation because of market segmentation.

Although industrial agglomeration affects the energy efficiency of the region, it can also produce positive or negative externalities as well as spillover effects on neighboring and other regions. In this study, we analyzed these effects from the perspectives of external economies of scale and external economies of scope. First, external economies of scale may improve energy efficiency and also may increase environmental load and inhibit energy efficiency. Conversely, high-industry agglomeration and high-quality development areas can play a demonstrative role in promoting the spread of advanced energy-saving technologies among regions, thereby driving the improvement of energy-saving technologies in neighboring areas and improving overall energy efficiency. Additionally, the positive industrial agglomeration externalities can attract more foreign investors, intensify market competition in the region, and force companies to accelerate innovation in energy utilization technologies to maintain their competitive advantage, thereby bringing about improvements in energy efficiency. The wealth demonstration effect caused by industrial agglomeration, however, also may lead to the occurrence of enterprise clustering and industrial homogeneity, leading to the crowding effect (Wang and Qiu, 2017). This crowding, in turn, can trigger vicious competition and inhibit the improvement of energy efficiency. Second, external economies of scope may improve energy efficiency and also may inhibit energy efficiency in neighboring or other regions. Industrial agglomeration has brought about an increase in the number of enterprises. To realize the positive externalities of agglomeration, enterprises have established a "forward association" and "backward association" among enterprises. This vertical association has improved the division of labor and specialization among enterprises within the region and also has improved the quality and energy efficiency of the value chain in the region. At the same time, to obtain external economies of scope, companies have established a collaboration and division of labor relations with surrounding areas, forming close forward and backward relationships, improving the quality and efficiency of the value chain between different regions, and ultimately achieving energy efficiency. Of course, industrial agglomeration also may trigger a "race to the bottom" (Esty and Dua, 1997), inhibiting the improvement of energy efficiency. Areas with a higher level of economic development will inevitably eliminate low-efficiency and high-emission enterprises in the initial stage of agglomeration as the industrial agglomeration becomes more mature, whereas neighboring or other areas with a lower level of economic development will promote the spillover effect of industrial agglomeration. Economic development will lower the threshold of environmental regulation and absorb low-end industries eliminated from areas with higher economic development levels, resulting in increased environmental pollution and reduced energy efficiency, as shown in Figure 1.

3 Econometric model and data description

3.1 Model setting

To investigate manufacturing agglomeration spatial spillover effects of all factors of energy efficiency, we built a spatial panel data model to test the relationship between the two. Given that the spatial Durbin model contains spatial lag terms of both independent and dependent variables, it can reflect the influence of spatial autocorrelation on regression results more comprehensively. Therefore, we selected this model to test the relationship between industrial agglomeration and total factor energy efficiency. The model is set as follows:

$$\begin{gathered} lnEE_{it} = \rho WEE_{it} + \beta_1 IA_{it} + \theta_1 WIA_{it} + \beta_2 IA_{it}^2 + \theta_2 WIA_{it}^2 + \beta_3 X_{it} + \theta_3 WX_{it} + \delta_i + \eta_t + \mu_{it}, \\ \mu_{it} = \lambda W \mu_{it} + \varepsilon_{it} \end{gathered} \tag{9}$$

where EE_{it} represents total factor energy efficiency; IA_{it} is the explained variable; X_{it} is a series of control variables; ρ, θ is the spatial autoregression coefficient; W is the spatial weight matrix; δ_i represents the province fixed effect; and η_t represents the time fixed effect. In this study, we used adjacency spatial weight matrix, geographical distance spatial weight matrix, and economic distance spatial weight matrix for comparison, where i represents province, t represents time, and ε

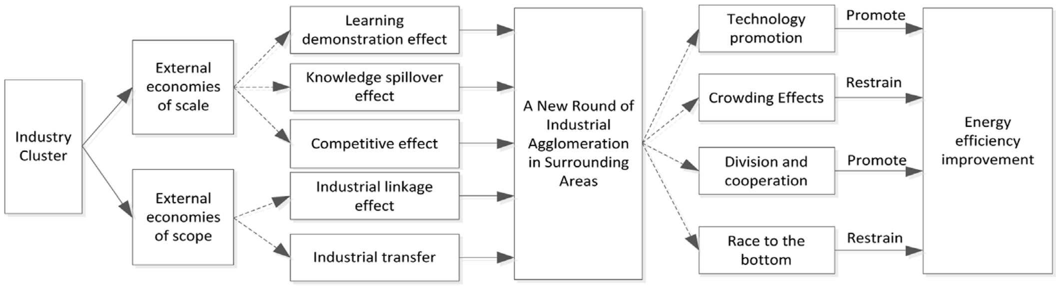

FIGURE 1
The path map of the impact of industrial agglomeration on energy efficiency.

represents random disturbance term. When $\rho \neq 0, \theta = 0$, Eq. 9 was the spatial lag model (SLM). When $\lambda \neq 0, \rho = 0$, Eq. 9 was the spatial error model (SEM); When $\lambda \neq 0, \theta \neq 0$, Eq. 9 was the spatial Dubin model (SDM).

3.2 Decomposition of spatial spillover effects

If there is a spatial lag term, the regression coefficient cannot reflect the true influence between the variables, resulting in deviation. To overcome the impact of space lag, in this study, we referred to the research results of Lesage and Pace (2009) and decomposed the impact of energy efficiency into overall effects, direct effects, and indirect effects. The overall effect reflected the average influence of the independent variable on the dependent variables in all regions; the direct effect reflected the average influence of the independent variable on the dependent variable in the region; the indirect effect reflected the average influence of the independent variable in the region on the dependent variable in other regions. To this end, we transformed the spatial Doberman model into the following:

$$y = \sum_{r=1}^{k} \left[S_r(W)_{i1} x_{1r} + S_r(W)_{i2} x_{2r} + \dots + S_r(W)_{in} x_{nr} \right] + V(W)\tau_n \alpha + V(W)\varepsilon. \tag{10}$$

The overall effect is the mean value of all elements in the matrix, which is expressed as follows:

$$\bar{M}(r)_{total} = n^{-1} \tau_n S_r(W) \tag{11}$$

The direct effect is the mean value of the diagonal elements in the matrix, which is expressed as follows:

$$\bar{M}(r)_{direct} = n^{-1} tr(S_r(W)). \tag{12}$$

The indirect effect is the mean value of the off-diagonal elements in the matrix, that is, the difference between the overall effect and the direct effect, which is expressed as follows:

$$\bar{M}(r)_{indirect} = \bar{M}(r)_{total} - \bar{M}(r)_{direct}. \tag{13}$$

3.3 Figure data source and variable descriptions

3.3.1 Explained variable: Total factor energy efficiency

The DEA method is a non-parametric method often used in efficiency estimation, which can solve the problem of relative efficiency evaluation of multiple inputs and outputs. Traditional DEA methods, however, fail to consider the unexpected outputs—that is, when the output index values are all positive (Chen et al., 2021). In this study, based on the DEA game crossover efficiency model proposed by Liang et al. (2008), we incorporated carbon emission into the energy efficiency evaluation model as a non-desirable output. If the energy efficiency value of the decision-making unit $\boldsymbol{DMU_d}$ (different provinces and cities) is $\boldsymbol{ee_d}$, other decision-making units $\boldsymbol{DMU_j}$ can maximize their own efficiency $\boldsymbol{DMU_d}$ on the premise that the energy efficiency value is not reduced, and the game cross energy efficiency value of the decision-making unit (relative to) is defined as follows:

$$ee_{dj} = \frac{\sum_{r=1}^{s} \mu_{rj}^{d} y_{rj}}{\sum_{i=1}^{m} \omega_{ij}^{d} x_{ij}}, d = 1, 2, \dots, n, \tag{14}$$

where $\boldsymbol{ee_{dj}}$ is the game cross-efficiency value relative to the decision-making unit; and $\boldsymbol{\mu_{rj}^{d}}$ and $\boldsymbol{\omega_{ij}^{d}}$ is the feasible weight of the model, which can be solved by the following linear programming model:

$$\begin{gathered} \max \sum_{r=1}^{s} \mu_{rj}^{d} y_{rj} \\ \text{s.t.} \sum_{i=1}^{m} \omega_{ij}^{d} x_{il} - \sum_{r=1}^{s} \mu_{rj}^{d} y_{rl} > 0, l = 1, 2, \dots, n, \\ \sum_{i=1}^{m} \boldsymbol{\omega_{ij}^{d} x_{ij}} = \mathbf{1} \\ ee_d \times \sum_{i=1}^{m} \omega_{ij}^{d} x_{ij} - \sum_{r=1}^{s} \mu_{rj}^{d} y_{rd} \leq 0 \\ \omega_{ij}^{d} \geq 0, i = 1, 2, \dots, m, \text{and } \mu_{rj}^{d} \geq 0, r = 1, 2, \dots, s \end{gathered} \tag{15}$$

where $ee_d \leq 1$ is an initial parameter value, which represents the DMU_d average cross-efficiency value of the decision-making unit. If the optimal solution of this model is $\mu_{rj}^{d}(ee_d)$, the average game

TABLE 1 Chinese interprovincial energy efficiency Moran's *I* inspection, 2002–2017.

Years	Adjacency space weight matrix (w_1)			Geographic distance weight matrix (w_2)			Economic distance weight matrix (w_3)		
	I	*Z*	*P*	*I*	*Z*	*P*	*I*	*Z*	*P*
2002	0.395	3.468	0.000	0.092	3.735	0.000	0.185	2.531	0.006
2003	0.332	2.979	0.001	0.095	3.820	0.000	0.250	3.266	0.001
2004	0.252	2.341	0.010	0.060	2.828	0.002	0.181	2.224	0.010
2005	0.277	2.533	0.006	0.074	3.229	0.001	0.149	1.945	0.021
2006	0.195	1.870	0.031	0.051	2.534	0.006	0.137	1.877	0.032
2007	0.209	1.977	0.024	0.057	2.725	0.003	0.106	1.486	0.065
2008	0.163	1.606	0.054	0.032	1.974	0.024	0.098	1.352	0.081
2009	0.120	1.254	0.105	0.022	1.682	0.046	0.082	1.232	0.109
2010	0.155	1.535	0.062	0.037	2.124	0.017	0.105	1.473	0.070
2011	0.166	1.627	0.052	0.039	2.159	0.015	0.126	1.688	0.046
2012	0.221	2.067	0.019	0.049	2.447	0.007	0.150	1.943	0.026
2013	0.253	2.322	0.010	0.058	2.734	0.003	0.147	1.904	0.028
2014	0.254	2.330	0.010	0.059	2.739	0.003	0.146	1.891	0.029
2015	0.229	2.128	0.017	0.049	2.454	0.007	0.140	1.829	0.034
2016	0.251	2.314	0.012	0.056	2.729	0.004	0.145	1.875	0.027
2017	0.301	2.702	0.003	0.074	3.201	0.001	0.174	2.185	0.014

DMU_j crossover efficiency of the decision-making unit can be defined as follows:

$$ee_j = \frac{1}{n}\sum_{d=1}^{n}\sum_{r=1}^{s}\mu_{rj}^{d} \times (ee_d) y_{rj}. \tag{16}$$

Based on this analysis, we used the following steps to solve the regional energy efficiency value based on game intersection under the carbon emission constraint.

Step 1: Let t = 1, $ee_d = ee_d{}^1 = \bar{E}_d$ to solve Eq. 15, and determine a set of average cross efficiency values.

Step 2: Calculate Eq. 16 to solve the optimal weight. Let $ee_j{}^2 = \frac{1}{n}\sum_{d=1}^{n}\sum_{r=1}^{s}\mu_{rj}^{d} \times (ee_d{}^1) y_{rj}$ to get the general expression, where $\mu_{rj}^{d} \times (ee_d{}^1)$ represents $ee_d = ee_d{}^t$, which is the optimal solution μ_{rj}^{d} in Eq. 15.

Step 3: If there is a decision-making unit DMU_j, make $|ee_j{}^{t+1} - ee_j{}^t| \geq \varepsilon$ true, where ε represents a sufficiently small positive number, and if $ee_j = ee_j{}^{t+1}$, return to the second step; if it is true for all decision-making units DMU_j, then stop and obtain the final average game cross-efficiency value $ee_j{}^{t+1}$.

3.3.2 Core explanatory variable: Manufacturing agglomeration

At present, research on industrial agglomeration has been abundant, and the selection of indicators for industrial agglomeration also is different. Given the degree of the manufacturing industry's impact on energy efficiency, this study draws on the practice of Tang et al. (2018) and uses the location entropy method to calculate the following:

$$\boldsymbol{AI_{ij}} = \frac{\boldsymbol{q_{ij}/q_i}}{\boldsymbol{q_j/q}}, \tag{17}$$

where i represents the province; j represents the manufacturing industry; the AI_{ij} represents the location entropy index of the i province's j industry in the country; q_j represents the number of employees in the province's industry j; q_i represents the number of employees in the national industry; the number of employees in the province i; and q represents the number of employees in all provinces in the country.

3.3.3 Other explanatory variables

The level of technological progress (TP_{it}), which represents improvements in the technological level, will bring about an increase in the efficiency of production equipment, save energy consumption in the production process, and directly affect energy efficiency. At the same time, improvements in the technical level are conducive to improving the quality and energy-saving awareness of producers, which indirectly affect energy efficiency. In this study, we selected the number of invention patent applications in each province as the proxy indicator for the level of technological progress (ER_{it}). This environmental regulation draws on the research of Li (2016), which used the percentage of the sewage

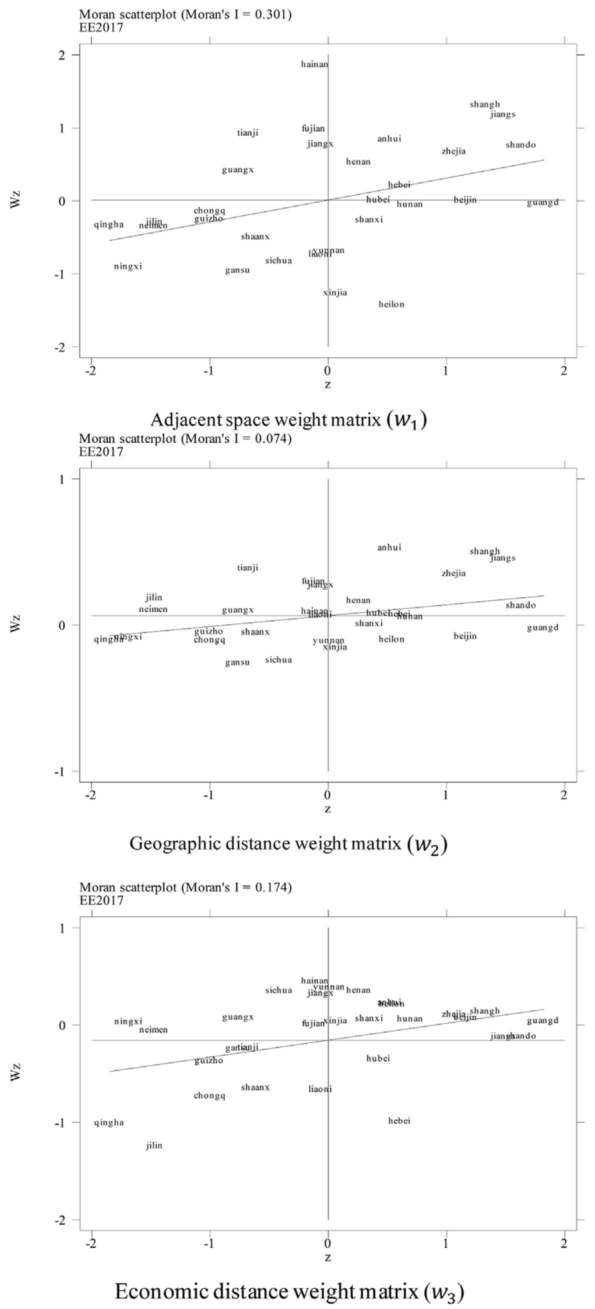

FIGURE 2
Interprovincial Moran's *I* energy efficiency scatter plot, 2017.

TABLE 2 Hausman test results.

Test	Fixed effect	Random effect
Hausman test-statistic	798.812	680.282
p-value	0.000	0.000

charges levied in each region in the local GDP as a proxy indicator. The industrial structure (IS_{it}) was based on the research of Qian et al. (2011), which adopted the industrial advancement index as the

TABLE 3 LR test results.

Inspection type	Statistics value	*p*-value
SAR	496.15	0.000
SEM	496.08	0.000
SDM	501.19	0.000

TABLE 4 Model selection test result.

Inspection type	Statistics	*p*-value
Spatial fixed-effect SDM model	698.497	0.000
Time fixed-effect SDM model	697.893	0.000
Two-way fixed-effect SDM model in time and space	712.477	0.000

proxy indicator of the industrial structure. Energy consumption structure (ES_{it}), which was the structural adjustment, mainly included the adjustment of the industrial structure and energy consumption structure. Regional energy consumption structure directly affected energy efficiency, which was caused by the differences in and characteristics of various energy sources. In this study, we selected the proportion of regional coal consumption in total energy consumption as a proxy indicator of the energy consumption structure. In terms of the level of urbanization (UL_{it}), which is the impact of the level of urbanization on energy efficiency, different scholars have arrived at differentiated conclusions. An increase in the level of urbanization will intensify the demand and consumption of energy for the socioeconomic system, thereby inhibiting the improvement of energy efficiency; however, urbanization will inevitably increase the level of economic development and residents' awareness of energy conservation, thereby promoting energy to improve efficiency. Therefore, we selected the proportion of urban population in the total population as a proxy indicator for the level of urbanization. The level of economic development ($PGDP_{it}$), using the province's *per capita* GDP (2002 as the base period), was the proxy indicator.

The data used for these variables are all from the "China Statistical Yearbook" (2003–2018), "Statistical Yearbook of Provinces and Municipalities" (2003–2018), "China Environmental Statistical Yearbook" (2003–2018), "China Population and Employment Statistical Yearbook" (2003–2018), and "China Energy Statistical Yearbook" (2003–2018).

4 Empirical analysis

4.1 Spatial correlation test

In this study, we used Moran's *I* index to test the spatial correlation of total factor energy efficiency from the global spatial level. Moran's *I* index is used to estimate the similarity of total factor energy efficiency observations in spatially adjacent area units, which can reveal whether there is a spatial agglomeration trend in total factor energy efficiency (Chen et al., 2021). The results are given in Table 1.

TABLE 5 Spatial SDM model estimation results based on different weight matrices.

Variable name	Adjacent space weight (w_1)	Geographic distance weight matrix (w_2)	Economic distance weight matrix (w_3)
ln*IA*	−0.101*** (0.001)	−0.168*** (0.000)	−0.142*** (0.000)
ln*IA* × ln*IA*	0.094*** (0.002)	0.113*** (0.000)	0.099*** (0.006)
ln*ER*	0.011** (0.028)	0.014*** (0.005)	0.012** (0.018)
ln*IS*	0.439*** (0.000)	0.205** (0.015)	0.470*** (0.000)
ln*ES*	−0.035* (0.061)	−0.102* (0.076)	−0.059** (0.013)
ln*TP*	0.149*** (0.002)	0.137** (0.011)	0.145*** (0.008)
ln*Pgdp*	0.014*** (0.000)	0.018*** (0.000)	0.015*** (0.003)
ln*UL*	0.082*** (0.000)	0.094*** (0.000)	0.012** (0.033)
W × ln *IA*	−0.146*** (0.007)	−0.103** (0.038)	−0.128*** (0.006)
W × ln *IA* × ln*IA*	0.083 (0.253)	0.104* (0.084)	0.097** (0.023)
W × ln*ER*	0.077*** (0.003)	0.115** (0.026)	0.094*** (0.001)
W × *lnIS*	0.104** (0.019)	0.131*** (0.000)	0.122*** (0.007)
W × *lnES*	−0.044*** (0.007)	−0.036*** (0.009)	−0.041*** (0.002)
W × *lnTP*	0.131*** (0.000)	0.142* (0.085)	0.138** (0.046)
W × *lnPgdp*	0.021*** (0.002)	0.032*** (0.000)	0.027*** (0.000)
W × *lnUL*	0.043** (0.021)	0.058** (0.027)	0.035** (0.033)
R^2	0.93	0.88	0.96

Note: The *p*-value in parentheses. *, ** and *** represent the significance at the 10%, 5% and 1% levels, respectively.

From the results in Table 1, we calculated the *p*-values of the Moran index test based on the three spatial weight matrices, except for the critical value of 0.5 in 2009, which significantly rejected the null hypothesis of "no spatial autocorrelation" in other years. China had a significant spatial autocorrelation in interprovincial energy efficiency. At the same time, it was apparent that the index of the spatial weight matrix of economic distance Moran's *I* was greater than the spatial weight matrix of geographic distance. This result indicated that geographic distance reduced the positive spatial dependence of energy efficiency in various regions to a certain extent, whereas economic factors increased this positive direction. We drew the scatter plot in Figure 2 according to the indices calculated by the three weight matrices Moran's *I*.

Adjacent space weight matrix (w_1)

Geographic distance weight matrix (w_2)

The results, as shown in Figure 2, demonstrate that based on the scatter plot of the three weight matrices, most provinces fall in the first and third quadrants. The spatial weight matrix of economic distance was particularly significant, with 12 provinces and cities falling in the first quadrant; seven provinces and cities falling in the second quadrant; eight provinces and cities falling in the third quadrant; and two provinces and cities falling in the second quadrant. The first and third quadrants included most provinces and cities, indicating that low-energy-efficiency provinces and cities were surrounded by high-energy-efficiency provinces and cities; low-energy-efficiency provinces and cities were surrounded by low-energy-efficiency provinces and cities; and energy efficiency spatial autocorrelation characteristics were significant. The six provinces and cities of Shanghai, Jiangsu, Zhejiang, Guangdong, Shandong, and Beijing were located far away from the origin in the first quadrant, further showing that these six provinces and cities were in a leading position of energy efficiency in the country and promoted the improvement of energy efficiency of neighboring provinces and cities. Jilin and Qinghai Provinces were in the third quadrant far from the origin, which indicated that they were at a lower level of national energy efficiency, and neighboring provinces and cities had a weaker driving effect on their energy efficiency.

4.2 Model selection test

We used the Hausman test to verify the results of this study and used the LR test and model selection test to determine the model type. The specific test results are given in Tables 2, 3, 4.

The results in Table 2 show that the Hausman test result value was 0.000, indicating that it passed the hypothesis test at a significance level of 1%, and the statistic of the fixed-effects model was 798.812, which was significantly larger than the statistic of the random-effects model of 680.282. Therefore, we constructed a fixed-effect panel model. To determine whether or not the SDM model degenerated into the SAR model or the SEM model, we performed a degradation test. The results are given in Table 3.

TABLE 6 Decomposition of direct effects and spillover effects of spatial SDM model.

Effect	Variable name	Adjacent space weight (w_1)	Geographic distance weight matrix (w_2)	Economic distance weight matrix (w_3)
Direct effect	ln*IA*	−0.099*** (0.003)	−0.157*** (0.000)	−0.141*** (0.000)
	ln*IA* × ln*IA*	0.043** (0.032)	0.052** (0.028)	0.049** (0.019)
	ln*ER*	0.018** (0.020)	0.021*** (0.006)	0.013** (0.016)
	ln*IS*	0.432*** (0.000)	0.302*** (0.001)	0.483*** (0.000)
	ln*ES*	−0.713** (0.044)	−0.028* (0.067)	−0.059** (0.011)
	ln*TP*	0.055*** (0.006)	0.074*** (0.004)	0.068*** (0.003)
	ln*Pgdp*	0.017*** (0.000)	0.018*** (0.004)	0.025*** (0.001)
	ln*UL*	(0.000) −0.014*	0.221* (0.057)	−0.028* (0.088)
Indirect effect	ln*IA*	−0.093** (0.023)	−0.140*** (0.001)	−0.125*** (0.000)
	ln*IA* × ln*IA*	0.009** (0.046)	0.017** (0.041)	0.024** (0.025)
	ln*ER*	0.011** (0.029)	0.013** (0.018)	0.012** (0.024)
	ln*IS*	0.408*** (0.003)	0.253*** (0.002)	0.469** (0.014)
	ln*ES*	−0.041 (0.601)	−0.027* (0.087)	0.039*** (0.003)
	ln*TP*	0.042** (0.034)	0.044** (0.046)	0.038*** (0.004)
	ln*Pgdp*	0.011*** (0.002)	0.014*** (0.007)	0.022*** (0.005)
	ln*UL*	0.131* (0.061)	0.104* (0.071)	0.117** (0.021)
Total effect	ln*IA*	−0.192*** (0.000)	−0.297*** (0.007)	−0.267*** (0.002)
	ln*IA* × ln*IA*	0.052** (0.033)	0.069** (0.048)	0.073** (0.037)
	ln*ER*	0.029** (0.042)	0.034** (0.036)	0.025** (0.019)
	ln*IS*	0.840*** (0.000)	0.555*** (0.003)	0.982*** (0.001)
	ln*ES*	−0.754* (0.065)	−0.055** (0.043)	−0.020** (0.047)
	ln*TP*	0.096*** (0.008)	0.118*** (0.005)	0.104*** (0.000)
	ln*Pgdp*	0.028*** (0.008)	0.032*** (0.003)	0.047*** (0.000)
	ln*UL*	0.117* (0.078)	0.325* (0.077)	0.089* (0.069)

Note: The p-value in parentheses. *, ** and *** represent the significance at the 10%, 5% and 1% levels, respectively.

The results in Table 3 show that the test results of the SAR model and the SEM model were both 0.000, which indicated that they passed the hypothesis test at a significance level of 1%, and the statistics were 496.15 and 496.08, respectively, which were significantly less than the test result of the SDM model 501.19. This result indicated that the SDM model should be used. We then tested which type of SDM model should be used for model selection. The results are given in Table 4.

4.3 Spatial Durbin model estimation

According to the previous test results, and based on the adjacent space weight matrix, geographic distance weight matrix, and economic distance weight matrix, we used the space-time two-way fixed-effect spatial Durbin model to estimate the spatial spillover effects of energy efficiency. The results are given in Table 5.

According to the estimated results in Table 5, under the three spatial weight matrices, the regression coefficients of the spatial lags of the explanatory variables of total factor energy efficiency were all positive, and all passed the test at the 1% significance level. At the same time, the explanatory variables' spatial lag terms W×lnIA, W×lnER, and W×lnIS all passed the test at the 5% significance level, indicating that the total factor energy efficiency had a strong spatial dependence and was not independent. Because the regression coefficient of the variable spatial lag term was not zero, the regression coefficient of the explanatory variable and its spatial lag term could not be used to explain the change of the explained variable, and the regression coefficient of the explanatory variable indicated the degree of its direct influence on the explained variable. In the spatial econometric model, the regression coefficients of explanatory variables included not only direct effects but also feedback effects. Therefore, it was necessary to eliminate the feedback effect and further decompose the spillover effect into direct and indirect effects. The results are given in Table 6.

Table 6 shows the total effect, direct effect, and indirect effect of manufacturing agglomeration on total factor energy efficiency under the weight of neighboring space, geographical distance, and economic distance. Under the adjacent space weight matrix, the spillover effect of manufacturing agglomeration was −0.099, and the direct effect was −0.093, and they passed the test at 5% and 1% significance levels, respectively. The regression coefficient of the quadratic spillover effect of manufacturing agglomeration was 0.009, the direct effect was 0.043, and all passed the test at the 5% significance level. Under the spatial weight matrix of geographic distance, the spillover effect of manufacturing agglomeration was −0.57, and the direct effect was −0.140, and both passed the test at a significant level of 1%. The regression coefficient of the quadratic spillover effect of manufacturing agglomeration was 0.017, the direct effect was 0.052, and all passed the test at the 5% significance level. Under the economic distance spatial weight matrix, the spillover effect of manufacturing agglomeration was −0.125, and the direct effect was −0.141, and both passed the test at a significant level of 1%. The regression coefficient of the quadratic spillover effect of manufacturing agglomeration was 0.024, the direct effect was 0.049, and all passed the test at the 5% significance level. These results showed that under the three spatial weight matrices, a U-shaped relationship existed between manufacturing agglomeration and total factor energy efficiency. Before manufacturing agglomeration reached a critical point, the degree of agglomeration had a negative spatial spillover to total factor energy efficiency. In other words, the agglomeration of manufacturing industries in the region would have an inhibitory effect on the total factor energy efficiency of other neighboring regions. When the agglomeration degree of manufacturing in the region crossed the critical point, the increase in the degree of agglomeration would have an impact on the overall factor energy efficiency and thus have a promoting effect. Manufacturing agglomeration had a significant spatial spillover effect on total factor energy efficiency. This conclusion verified the results of the previous theoretical analysis that a non-linear relationship existed between manufacturing agglomeration and total factor energy efficiency. Thus, proper manufacturing agglomeration was conducive to the improvement of total factor energy efficiency and had a spatial spillover effect.

Among other explanatory variables, under the three spatial weight matrices, the direct effects of environmental regulation, technological progress, economic development level, and industrial structure on total factor energy efficiency were all positive, which indicated that these factors had a positive impact on energy efficiency in the region. The regression coefficients of energy consumption structure and urbanization level were negative, however, which indicated that these factors had an inhibitory effect on energy efficiency in the region. This conclusion was related to the proxy indicators selected in this study. We selected the proportion of coal consumption in total energy consumption as a proxy indicator for the energy structure. Coal had low calorific value and high carbon and oxidation factors, and the increase in its consumption inevitably led to a decrease in energy efficiency. In this study, we selected urbanized population, and the proportion of the total population was used as a proxy indicator for the level of urbanization. This indicator reflected only the quantity of urbanization and not its quality. The suppression of energy efficiency caused by the rapid increase in the level and speed of urbanization in the western region offset the promotion of energy efficiency cause by the improvement of urbanization quality in the eastern region, and finally showed a suppression effect of urbanization level on energy efficiency. Previous scholars have called this the "rebound effect." In terms of spillover effects, the regression coefficients of most explanatory variables had no change in the direction and were smaller than the direct effects, which indicated that the spillover effects of these factors between regions were smaller than those within regions. Note that the spillover effect of the level of urbanization was positive, contrary to the direct effect, which indicated that areas with high levels of urbanization had a positive spillover effect on the energy efficiency of neighboring areas. At the initial stage when low-level urbanization areas absorb the spillover effects of high-level urbanization areas, the number and speed of urbanization have not yet reached the turning point that affects energy efficiency, and thus it has a positive effect on energy efficiency. From the perspective of overall effects, industrial structure optimization had the largest overall effect on energy efficiency, followed by the level of urbanization. This result was also in line with the current status of China's economic development. The current central supply-side structural reform and the promotion of urbanization will promote the steady improvement of regional energy efficiency.

5 Conclusion and policy recommendations

In this study, we used China's interprovincial panel data from 2002 to 2017, selected the spatial Durbin model, and considered the influence of adjacent spatial distance weights, geographic distance weights, and economic distance weights on spatial effects. We decomposed the impact of manufacturing agglomeration on total factor energy efficiency as well as its direct effect, indirect effect, and total effect. The study results showed the following: 1) Under different spatial weights, the agglomeration of interprovincial manufacturing had a significant spatial dependence on total factor energy efficiency. 2) Under the three spatial weights, there was both agglomeration of manufacturing and total factor energy efficiency. A U-shaped relationship with manufacturing agglomeration had clear spatial spillover effects on total factor energy efficiency, and the spillover effect under the weight of geographic distance was higher than other spatial weights. The spillover effect under the geographical distance weight was higher than that of other spatial weights, which indicated that the spatial spillover effect of industrial agglomeration on energy efficiency in China's provinces was generated mainly by geographical proximity during the sample period. This further indicated that the direct effect of industrial agglomeration drove the improvement of energy efficiency in regions close to it through the form of demonstration imitation, and interprovincial economic interaction should be further strengthened to jointly promote the improvement of energy efficiency. 3) Both the direct effect of manufacturing on energy efficiency during the sample period and the indirect effect were negative, which indicated that the agglomeration of the manufacturing industry had an inhibitory effect on energy efficiency, which was the crowding effect noted in the previous analysis.

Based on these research conclusions, we propose the following policy implications: First, the Chinese government should formulate differentiated regional industrial development policies. China has a vast territory, and regional economic development, technological innovation, and resource endowments are quite different. Each regional government should combine its own development stage and regional characteristics, cultivate competitive industries, and actively promote the coordinated development of manufacturing and producer services to stimulate the positive externalities of industrial agglomeration. Second, the government should formulate a reasonable industrial transfer policy. Given the imbalance of economic development and industrial structure in the eastern, central, and western regions of China, and to overcome the crowding effect in the eastern region where the manufacturing concentration level is relatively high, part of the marginal manufacturing industry should be transferred to the central and western regions. The development of the producer service industry in the region would provide more space to promote industrial upgrading and improve energy efficiency. Third, the government should formulate a reasonable ecological environment monitoring policy, establish a cross-regional and cross-industry cooperation mechanism, implement division of labor and coordination within and between regions, monitor each other, identify the threshold of industrial access, implement strict environmental regulations, restrict the entry of high-energy consumption and high pollution enterprises, and ensure the promotion of industrial agglomeration. In addition to economic development, the efficiency of energy utilization should be improved to minimize the environmental load. Fourth, the government should promote local industries to actively embed global value chains. Technological progress is an effective way to improve energy efficiency. Through high-frequency external contacts, we can obtain external advanced knowledge and technology, improve the technical content, add value of products, and strive to overcome low technology levels and low-end value chain lock-in, as the global value chain continues to climb toward higher value-added links.

The results in Table 4 show that the three fixed-effects models all passed the test at the 1% significance level, and the statistics of the spatial fixed-effects model and the temporal fixed-effects model were both smaller than the statistics of the two-way spatiotemporal fixed-effects model. Therefore, in this study, we selected a two-way fixed-effect model of time and space.

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, HJ and ZHC; methodology, HJ, ZHC, and WZ; software, HJ, ZHC, and WZ; validation, FW and JX; formal analysis, FW and JX; investigation, ZHC, WZ, FW, and JX; resources, HJ; data curation, HJ, ZHC, WZ, FW, and JX; writing–original draft preparation, HJ and ZHC; writing–review and editing, WZ, FW, ZYC, and JX; visualization, FW and ZHC; supervision, HJ and WZ; project administration, HJ; funding acquisition, HJ. All authors have read and agreed to the published version of the manuscript.

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Conflict of interest

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

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The influencing factors and pathways of China's green finance development towards the Carbon Peaking and Carbon Neutrality —evidence from fuzzy-set qualitative comparative analysis based on 30 provinces of China

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In the context of the Carbon Peaking and Carbon Neutrality, the significance of green development, including the development of green finance, has gained increasing attention. It is important to explore the factors and pathways that have impacts on the progress of green finance; however, these are not clearly defined. In this paper, using data from 30 provinces (autonomous regions and municipalities directly under the central government) in China, we investigate the factors that drives the advancement of green finance in China. We utilize the fuzzy set qualitative comparative analysis (fsQCA) technique to scrutinize the effects of economic development, industrial structure, government investment in environmental protection and green innovation capability on the progress of green finance development. The results show that the development of green finance is not solely dependent on the four aforementioned conditions alone. However, according to the group analysis, we find three pathways towards achieving the development of green finance, among which the conditions show relationships of complementarity and substitutability. In order to promote the growth of green finance in China, the local government should leverage the distinctive characteristics of the regions by the method of encouraging green patents, developing clean and green projects and strengthening the regional innovation capacity. Furthermore, the government should play a leading role in enhancing the promotion of green patent applications. Finally, it is essential for each region to conduct a comprehensive analysis of their local resources and devise differentiated strategies for the development of green finance.

KEYWORDS

carbon peaking, carbon neutrality, green finance, fuzzy-set qualitative comparative analysis, sustainable development

1 Introduction

Green finance aims to promote environmental protection and governance, and guide resources from industries with high pollution and energy consumption to sectors with advanced concepts and technologies. The economic development has exacerbated CO2 emissions to some extent (Ali and Oliveira, 2022b). The discharge of various pollutants in the process of social production is constantly increasing, causing damage to the natural environment including water and air, and provoking drastic climate changes (Gao et al., 2020). In recent years, issues about reducing environmental pollution and promoting the sustainable development of human society have become the key concerns of the international community (Ali and Oliveira, 2022a). In order to mitigate global climate change and achieve Sustainable Development Goals (SDGs), many countries are actively taking measures to reduce carbon emissions and developing green economy (Lee & Lee, 2022). At the 75th session of the UN General Assembly, China promised that carbon emissions would peak around 2030–2040 and achieve carbon-neutral before 2060, which is not only the embodiment of great nation responsibility, but also the requirement of promoting sustainable development through green and low-carbon transformation.

The carbon peaking and carbon neutrality goals mean that China will go through economic growth decoupled with emissions. However, compared with other developed countries, China's carbon peaking and carbon neutrality goals are tight in time and heavy in task. Green finance is an important source of funds to support the energy structure optimization and the acceleration of the construction of carbon emission trading system. To promote economic sustainable development with the growth of green industries and green projects, it is necessary to rationally allocate financial resources and guide social capital flow to green industries. Existing studies have shown that green finance which can reduce carbon emissions and provide for environmental sustainability is crucial in financing renewable energy and green energy projects. Thus, green finance plays a critical role in facilitating the achievement of the carbon peaking and carbon neutrality targets. It is thus of great pragmatic importance of determining the factors that influence the development of green finance and investigating the trajectory of its development.

In this paper, We use case-oriented qualitative comparative analysis (QCA), which was put forward by Charles Larkin in 1980s, to explore the driving factors and design pathways of the high-quality development of green finance. This QCA technique can collect available information from intensive case studies and is suitable for solving the common "multiple coincidence points" causality problem in comparative theory.

Compared with the existing literature, this paper reflects its marginal contribution from the following aspects. First, it focuses on the development level of green finance, explores the development mode and path of green finance, and enriches the existing literature on the qualitative and quantitative research of green finance development. Second, regarding the measure of the level of green finance development, compared with the methods of single evaluation index. The multidimensional evaluation system can cover green finance more comprehensively. Finally, Finally, a creative use of fuzzy set qualitative comparative analysis is employed to explore the path to improve the level of green finance development.

This paper is structured as follows: Section 2 presents literature review. Section 3 describes methodology and research design, the results of which are presented in Section 4. Section 5 discusses the main findings, followed by the conclusion in Section 6.

2 Literature review

2.1 Green financial development

The goal of transition to green economy greatly contribute to the development of green finance. Existing literature suggests that green finance is the best financial strategy to reduce CO2 emissions (Meo & Abd Karim, 2022), while the development level of green finance directly affects the allocation efficiency of funds in the field of green economy. Many studies have focused on investigating the driving factors of the development of green finance. (Coulson, 2003). found that the development of green finance is influenced by multidimensional factors. According to the OECD report in 2007, financial support and foreign environmental factors are important for the development of green finance ("Trends in Environmental Finance in Eastern Europe, Caucasus, and Central Asia (EECCA)", OECD, 2007). By combining the development features of China's green finance, (Zeng et al., 2014), as well as (Fu & Peng, 2020), studied the influencing factors of green finance's development from the perspective of index system construction. They showed that the development of green finance was directly affected by five factors: green credit, green insurance, green investment, green securities and carbon finance (Zhang et al., 2018) used DEA and entropy method to measure the development level of green finance of enterprises in China. It is worth noting that although the existing literature on evaluating the development level of green finance is abundant, most of them use entropy method to calculate the content of green credit, green fund, *etc.* However, the development of green finance is also influenced by market popularization and policy promotion. Evaluating these factors can gain deep insight into the correlation between local green finance and local financial capacity, macro-economic development level and ecological environment quality, and may make the development blueprint of green finance more reasonable.

2.2 Influencing factors of the green finance development

2.2.1 The level of economic development and green finance

There is positive relationship between the level of economic development and green finance development, i.e., the higher the level of economic development, the stronger the awareness and ability of propelling green finance development. An important indicator to measure the development level of green finance is to test the change of social expenditure (Lyeonov et al., 2019). (Yin & Xu, 2022) found that the development of green finance had obvious synergy with economic growth through the coupling coordination scheduling model (Ren, 2020) suggested that the level of economic development will have an impact on the efficiency of green finance, that is, the higher the level of economic development, the higher the level of green finance in the region. Similarly, based on 30 Chinese provinces, (Zhang, et al., 2022), showed that industrial structure and level of economic development positively affect the coordination of green finance and environmental performance.

2.2.2 Industrial structure and green finance

Industrial upgrading and optimization can effectively promote green development (Zhu et al., 2019) found that upgrading industrial structure in China had a positive impact on the efficiency of green development by using the measurement of industrial structure adjustment, the measurement of super-efficient bad output and the panel regression model. By employing system GMM model, (Wang & Wang, 2021), found that the tertiary industry had the strongest correlation with the development of green finance, followed by the primary industry and the secondary industry. (Zhao, 2022). used DEA method to measure regional green innovation efficiency from input and output aspects. Their results provided evidence hat industrial structure had a significant impact on green innovation efficiency in three regions of China.

2.2.3 Government support and green finance

After the government contributes to guide the market capital, it can leverage social capital to participate in the development of green finance. Renewable energy spending can have a clear policy-driven impact on the development of green finance (Mngumi et al., 2022). (Ikram et al., 2019) did literature review and showed that few scholars studied the relationship between government expenditure and green development. In this part of the research, (Feng et al., 2022), found that government support had a positive and significant impact on the performance of green economy from the perspective of the state. Environmental investments by local governments not only mitigate the negative effects of green credit policies on radical innovation, but also promote the positive effects of green development (Zhang et al., 2022a).

2.2.4 Green innovation and green finance

Green technology innovation is the preferred instrument to achieve green economic growth, and green financial development can positively regulate the sensitivity between the two (Dong et al., 2022). Through the analysis of Asian countries, (Tolliver et al., 2021), found that the adaptability of each country in green patent registration, green bond issuance and green investment will affect the process of the country's transition to sustainable development mode (Du et al., 2021) stated that the financing constraints faced by enterprises in green innovation are an important driving force to improve the green financial policy when taking the listed companies in China as the research object. Later, (Ali et al., 2022a) deepen their research on Chinese companies and conclude that green innovation has a positive mediating effect on the relationship between TI environmental performance and clarify the transmission mechanism between green innovation and green development. It is thus clear that green finance has become the main propellant of green development, and scholars such as (Yang et al., 2022) considered that green innovation has become the key method.

Green finance is of irreplaceable importance to the country. According to existant literature, we can form a clear understanding of the research framework of green finance. However, most studies focusing on the influencing factors and development paths of green finance are mainly based on quantitative research, and use the degree of influence as a proxy for the development level of green finance. Few scholars combine qualitative and quantitative research on how various factors work jointly to promote green finance. Although there are some studies on the development of green finance in North America and East Asia, research on the development model of green finance in China remains limited. Therefore, this paper employs fuzzy-set qualitative comparative analysis method and use development level of green finance as the outcome variable, and taking the level of economic development, industrial structure, government investment in environmental protection, and green innovation capability as the explanatory variables for configuration analysis, with the aim of exploring how each of these factors affects the development level of green finance (Zhou, 2022). Figure 1 illustrates the framework of this research.

3 Methodology

3.1 Fuzzy-set qualitative comparative analysis

We used a combination of qualitative and quantitative methods, focusing on the analysis of the degree of correlation among various factors. Namely, which factors will significantly improve the level of green finance and which factors will adversely affect the level of green finance in the process of regional economic development. The development of green finance is often the result of multiple factors, not caused by a single factor, therefore, it is reasonable to adopt the fuzzy set qualitative comparative analysis method when studying the drivers of green finance development. This method integrates the advantages of traditional qualitative analysis and quantitative analysis, and is a research method beyond qualitative analysis and quantitative analysis (Ragin & Ragin, 2014).

The qualitative comparative analysis method imposes some constraints on the sample size. The sample size is preferably in the range of 10–60 (X.-m. Zeng & Dai, 2020). In addition, there are three variants of QCA method, separately for csQCA (crisp set QCA), mvQCA (multi-value QCA) and fsQCA (fuzzy-set QCA) (Pappas & Woodside, 2021). The fsQCA method jumps out of the limitation of mvQCA and csQCA, the variable is no longer binary, but an arbitrary value in the range of 0–1. fsQCA has attracted more and more attention because of this feature (Xiong & Sun, 2022) used the panel data of 34 provinces in China to explore the mixed effects of green finance on carbon dioxide emissions through fuzzy-set qualitative comparative analysis (Peng & Hou, 2020) take the panel data of 29 provinces, regions and municipalities as the research samples, and use the fuzzy-set qualitative comparative analysis method to investigate the condition configuration and path that affect the improvement of regional innovation capability. These studies all make good use of fuzzy-set qualitative comparative analysis method to study the mechanism and path of the interaction of multiple factors on the results.

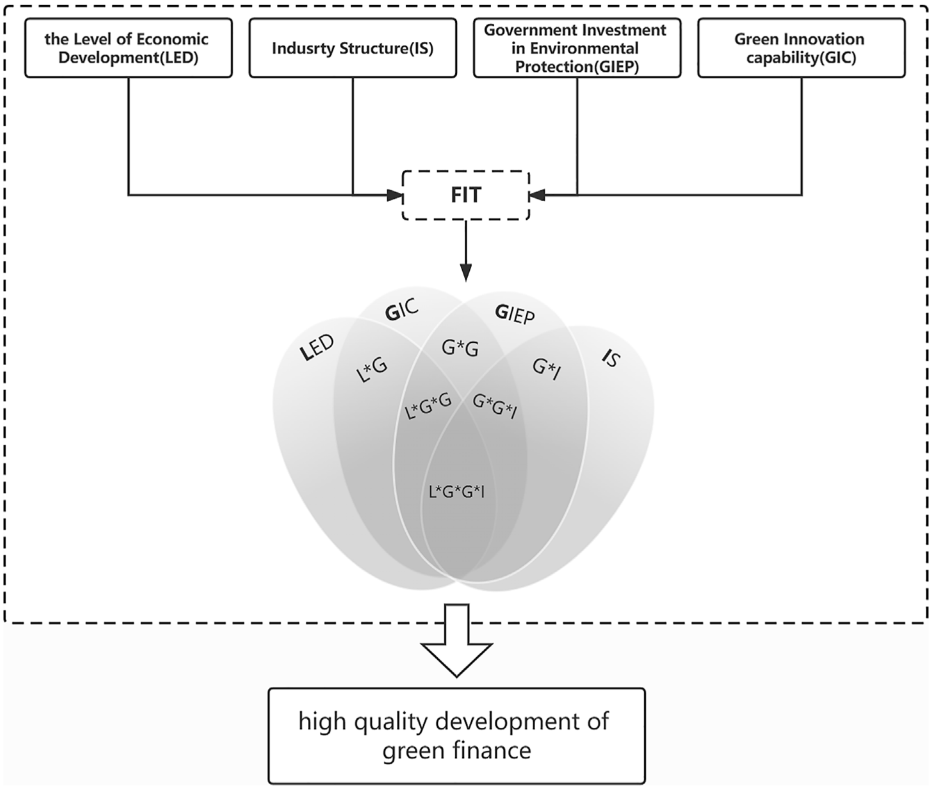

FIGURE 1
Conceptual framework.

The reasons for adopting fuzzy-set qualitative comparative analysis method in this paper are as follows: Firstly, this method is suitable for small samples' data analysis. We use the data of development level of green finance from 30 provinces in China in 2020, the number of samples thus meets the requirements of fuzzy-set qualitative comparative analysis method. Secondly, the improvement of the development level of green finance is the consequence of the multifaceted interaction enhancement, and the influencing mechanism is complicated. Using fuzzy-set qualitative comparative analysis, we can determine the configuration by comparing different cases, sort out the configuration and core conditions for realizing the high-level development of green finance, and provide reference for the development of green finance in each area.

3.2 Data and descriptive analysis

3.2.1 Data

Green financial development level: The International Research Institute of Green Finance in Central University of Finance and Economics released the Local Green Financial Development Index and Evaluation Report (2020) in 2021, in which the Green Financial Development Index objectively evaluated the developing status of green finance in provincial administrative regions, and it has strong authority and representation in China. Therefore, this paper takes the 2020 China Local Green Finance Index published by this institution as the outcome variable.

Based on the existing research, this paper uses economic development level, industrial structure, financial support and regional innovation capability as explanatory variables. On the level of economic development, most of existing studies use *per capita* GDP to measure economic growth. As the studies of (Surugiu & Surugiu, 2012; Lyeonov et al., 2019), this paper uses the *per capita* GDP of each region to represent the local economic development level; In terms of industrial structure, this paper drawing on the research of (Ren & Zhu, 2017), and constructs $industry = O + 2T + 3R$ as the industrial upgrading index system to measure it, where O is the proportion of the added value of the primary industry to the regional GDP, T is the proportion of the added value of the secondary industry to the regional GDP, and R is the proportion of the added value of the tertiary industry to the regional GDP; In the aspect of government investment in environmental protection, we borrowed from (Zhou, 2022), and measures government investment in environmental protection by the provincial fiscal expenditure on energy conservation and environmental protection.; In terms of green innovation capability, we take a cue from (Scarpellini et al., 2019) and (Yu et al., 2021), and take the number of green patents in each province as the green innovation index. Table 1 explains the variable names as well as the definitions.

This paper takes 30 provinces, autonomous regions and municipalities as the research objects (Tibet was excluded due to serious data deficiency). The data of the green financial development level score of the outcome variable comes from the Evaluation Report of China Local Green Financial Development Level

TABLE 1 Description of variables.

Variable	Index description
Level of economic development	Per capita gross domestic product (GDP/population)
Industrial structure Government investment in environmental protection Green innovation capability	$industry = O + 2T + 3R$ Fiscal expenditure on energy conservation and environmental protection Number of green patents each province

TABLE 2 Descriptive statistics.

	Number of observations	Mean	Standard deviation	Min	Max
Green finance level	30	32.804	11.661	17.38	57.1
Level of economic development	30	65982.04	29330.68	31336.1	140211
Government investment in environmental protection	30	230.968	140.345	54.32	746.19
Industrial structure	30	2.429	0.108	2.307	2.806
Green innovation capability	30	28.086	10.838	18.14	59.49

(2020), considering the time lag of the impact of each explanatory variable on the development of green finance, we use the data of the *per capita* GDP data, industrial structure data, financial expenditure on energy conservation and environmental protection, and green patent data in 2018 for observation, and the above information is obtained from the statistical yearbook of each province, autonomous region and municipality directly under the central government.

3.2.2 Descriptive analysis

Next, the specific situation of each region in green financial development will be analyzed, and the descriptive statistics of each variable data are shown in Table 2.

From the table, we can see that the green financial development scores of each province are comparatively low, and the values of green innovation capability and government investment in environmental protection are low, but level of economic development and the industrial structure are high, which indicates that the green financial development in China is still in the initial stage, and at this stage, although the economic development level is high in all parts of China, the economy is mainly dominated by the secondary industry, and the development of the secondary industry has not stimulated the vitality of green innovation. Government investment in environmental protection has not played a good role in escorting the green development process.

3.2.3 Calibration

This paper use the direct calibration method to calibrate the data, and set the fully subordinate degree, intersection point and fully non-subordinate point respectively to 0.75, 0.5 and 0.25 (Garcia-Castro & Francoeur, 2016). All data are calibrated to fuzzy subordinate values between 0 and 1. After calibration, a sample data occurs 0.5. If the retained value is 0.5, the data may be ignored in the subsequent operation. Therefore, this paper adopts the correction measure of adding 0.001 to the data (Fiss, 2011). Subordinate degree of each variable is shown in Table 3.

4 Results

In the process of configuration analysis, firstly, it is necessary to explore the relationship between the necessity and sufficiency of explanatory variable to the outcome variable. The judgment of necessity relationship is measured by consistency, if the consistency is greater than 0.9, it is considered that this variable is a necessary condition for the occurrence of the outcome variable (Morgan, 2010). If the variables pass the consistency test, the coverage test is conducted to measure the degree of explanation of a single variable to the outcome variable. The higher the interpretation degree, the higher the coverage.

The explanatory variables of this paper are analyzed by necessity conditions, and the results are shown in Table 4. It can be found from the figure that the consistency of the four antecedents is less than 0.9. It can be seen that the four antecedents of economic development, industrial structure upgrading, government financial support for energy conservation and environmental protection and regional innovation capability are not necessary conditions for the development of green finance, so the development of green finance is the result of the interaction of many variables. Therefore, the explanatory variables of this paper are not absolutely necessary for the outcome variable, so further configuration analysis is needed to explore the influence degree of explanatory variables on the outcome variable.

In the configuration analysis, the truth table should be constructed first, and the fuzzy subordinate value between 0 and 1 should be converted into a clear value of 0 or 1. This paper uses fsQCA software to analyze the data. Since the number of cases in this paper is 30, the frequency is set to 1, and the consistency threshold is set to 0.7. The PRI consistency threshold is set to 0 by referring to (Patala et al., 2021). Three solutions can be obtained through conditional configuration analysis, namely, complex solution, median solution and simple solution. The median solution lies between the simple solution and the complex solution, and contains the logical remainder which accords with the theoretical direction and empirical evidence. Therefore, this paper adopts the median solution as the first choice for configuration

TABLE 3 Fuzzy-set membership calibrations.

	Fully subordinate degree	Intersection point	Fully non-subordinate point
Green finance level	35.928	31.265	28.848
Level of economic development	74275.975	53521.4	125586
Industrial structure	2.453	2.404	2.634
Government investment in environmental protection	278.985	208.11	258.92
Green innovation capability	29.115	24.335	20.98

TABLE 4 Set-theoretical necessity analysis.

Explanatory variable	Consistency	Coverage
Level of economic development	0.582311	0.625520
~ Level of economic development	0.510007	0.507060
Industrial structure	0.591349	0.619337
~ Industrial structure	0.477728	0.486522
Government investment in environmental protection	0.636540	0.649539
~ Government investment in environmental protection	0.446094	0.46262
Green innovation capability	0.679794	0.691853
~ Green innovation capability	0.382828	0.401218

Note: ~ sign refers to the absence of the condition.

TABLE 5 Configurations for achieving quality development of green finance.

	High performance path		
	H1	H2	H3
Level of economic development	⊗		●
Industrial structure		●	⊗
Government investment in environmental protection	●	●	⊗
Green innovation capability	●	●	●
Consistency	0.877	0.843	0.797
Original coverage	0.245	0.434	0.088
Unique coverage	0.125	0.312	0.041
Typical case of coverage	Anhui, Sichuan	Beijing, Guangdong	Fujian
Consistency degree of overall solution	0.820		
Coverage of overall solution	0.609		

Note: ● = core condition (present); ⊗ = core condition (absent); ● = peripheral condition (present); ⊗ = peripheral condition (absent); blank space = the conditions may be present or absent. The size of the expression symbol for the presence and absence of the core condition should be twice the size of the expression symbol for the presence and absence of the peripheral condition

analysis, and the simple solution is used as an auxiliary explanation. If a variable appears in the median solution and the simple solution at the same time, it is considered as the core condition. The configuration analysis results are shown in Table 5.

As can be seen from the table, under the interaction of economic development, industrial structure, government investment in environmental protection and green innovation capability, three pathways of high green financial development level are generated, with the consistency of 0.877, 0.843 and 0.797 respectively, and the consistency of the overall solution reaches 0.820. The consistency of two of three pathways is greater than 0.8, which satisfies the sufficiency analysis conditions, indicating that most pathways are sufficient conditions for the formation of high green finance development level.

Specifically, configuration 1 (~ economic development level * government investment in environmental protection * green innovation capability) means that with a large number of regional green patents and favorable technical support, the province may have a high level of green finance development, regardless of whether the local industrial structure is upgraded or not, even if the regional economic development level is not in the forefront of the national ranking. It is a "capital investment-innovation-driven" high green financial development path. This path covers 11.5% of the provinces, and the representative provinces are Anhui and Sichuan. Configuration 2 (industrial institution * government investment in environmental protection * green innovation capability) means that when government provides sufficient financial support for the region, well-matched industrial structure upgrading and regional innovation capability can lead to a high development level of green finance. Industrial structure transformation and upgrading play an important role in reducing greenhouse gas emissions, and is one of the key methods to achieve the carbon peaking and carbon neutrality goal. This pathway indicates that the development of green finance depends on the interaction of three factors: industrial structure upgrading, government financial support and regional innovation capability. This path covers 31.2% of the provinces, which is the main path to realize the development of green finance in all provinces of China. The representative provinces are Beijing and Guangdong. Configuration 3 (economic development level * ~ industrial structure upgrading * ~ government investment in environmental protection * green innovation capability) means that when a region forms a high level of regional innovation capability with the assistance of economic development, a high level of green financial development can be generated even if the industrial structure is not upgraded and the government's financial expenditure on energy conservation and environmental protection is lacking. It is an "economic development-innovation-driven" high green finance development path. The coverage rate of this path is 4.1%, and the typical province is Fujian.

In a word, through the research results, it can be found that no explanatory condition is sufficient in itself to achieve high performance in the process of green finance development. There are three different pathways in the analysis of green finance development in 30 provinces and cities of China. In order to better understand these pathways, the next part tries to give a deeper understanding through the combination of theory and practice.

5 Discussion

5.1 Empirical applications

Green finance development displays significant heterogeneity among the provinces and regions in China. While some provinces and cities, such as Jilin and Tibet, have struggled to keep up, others have made notable progress in policy promotion and market effectiveness evaluation. Although all regions are moving towards green finance development, they have achieved varying levels, of development, which reflect their distinct regional characteristics. Moreover, the analysis indicates that there are no certain conditions for improving the green finance development level. Based on the above findings, the following propositions are proposed.

Proposition 1: The deep integration of economic development and green innovation capability is conducive to promoting the development process of green finance and providing preferable technical support for the high-performance development of local green finance.

A comparative analysis of the three high development pathways of green finance shows that green innovation capability appears in all configurations and is the core condition which indicates that green patent application has a great influence on the development level of green finance. Under the condition that multidimensional factors work together to promote the development of green finance, increasing the number of green patent applications plays a more important role. In the past ten years, Fujian is the fastest economic growing province in China. In 2010, Fujian's economic development level ranked 12th among all provinces in China. After ten years of development, Fujian's economic development level has reached 7th place, providing a stable economic foundation for the development of green finance. During the "Thirteenth Five-Year Plan" period, Fujian gradually transformed into a supporting intellectual property province, and took the lead in exploring the related work of green patent development in the whole country. It was recognized by the State Intellectual Property Office as one of the ten provinces in the country to carry out green patent pilot work. Under the background of "carbon peaking and carbon neutrality goals", the application of green patent can promote the improvement and replacement of traditional technologies, promote the research and development of cleaner production processes, and create favorable conditions for the development of green finance as well as energy conservation and emission reduction.

Proposition 2: The deep integration of industrial structure upgrading and government investment in environmental protection will improve the environment of local green finance development and provide the capital elements needed for the high-performance development of local green finance.

It can be found that government investment in environmental protection exists in two configurations, which indicates that government financial support for energy conservation and environmental protection has a significant effect in promoting the high development of green finance, and the government plays a leading role in the process of achieving the "carbon peaking and carbon neutrality goals". Financial expenditure for energy conservation and environmental protection can reduce the production and operation costs of local enterprises, increase the enterprises' operating profits, and help improve the development level of green finance. It is "industrial upgrading-innovation-driven" path of high development of green finance. Take Guangdong province as an example. In 2019, Guangdong gave full play to the leading role of the government and issued the Decision on Promoting Industrial Structure and Labor Transfer, which reflected the importance attached to the upgrading of industrial structure. Guangdong Department of Finance helps the development of green finance through financial measures such as increasing clean energy credit support and reducing the cost of green bonds issuing. The overall layout of green patent technology in Guangdong is elaborate. The "green and low-carbon" industry includes three major fields: new energy automobile industry, new energy industry as well as energy conservation and environmental protection industry. Among the three major fields, Guangdong's patents account for more than 50% of the national patents, forming a dense green patent application atmosphere and promoting the development of green finance in Guangdong in many aspects.

Proposition 3: The explanatory configuration to realize the high-performance development of green finance is not unique, and there is a certain degree of substitutability among similar conditions.

The empirical results show that there are three pathways of high-performance development of regional green finance, hence, it shows that the path of high-performance development of green finance is not single. Each region should deeply analyze the local basic resources, choose different pathways of green finance development according to reality, and implement the differentiation strategy of green finance development.

We use fuzzy set qualitative comparative analysis to examine the drivers of green finance development in 30 provinces (autonomous regions and municipalities directly under the central government) in China, and we find that none of the four variables is necessary to constitute high-quality development of green finance, but in the group analysis, we obtain three paths of green finance development, and different regions can choose the green finance development path with the highest matching degree according to the actual local situation. Comparing and analyzing the three paths, we can know that the deep integration of economic development and green innovation capacity will provide good technical support for local green finance high performance development, and the deep integration of industrial structure upgrading and government investment in environmental protection will provide the capital elements needed for local green finance high performance development. This paper presents an in-depth analysis of the driving factors and development paths of green finance, and the results of the study will help all parties in society understand the current situation of green finance development and grasp the improvement direction of green finance development.

6 Conclusion

This study uses fsQCA to evaluate the influence of four variables. They are the level of economic development, industrial structure, government investment in environmental protection and green innovation capability. Using data from 30 provinces, autonomous regions and municipalities directly under the central government in China, we draw the following conclusions: (1) No variable alone in the four dimensions is a necessary condition to the development level of green finance, which is still valid after the robustness test. (2) Through configuration analysis of four variables, the three paths are the sufficient conditions for improving the development level of green finance. At the same time, various configurations also show that the factors driving the development of green finance have diversity and synergy.

Having concluded that, the government needs to emphasize the following points in the process of promoting the quality development of green finance. First, enhance regional innovation capability. The government should fully explore local characteristics and apply for green patents to develop clean and green projects. Second, give play to the leading role of the government. Provinces should strengthen the leading role of the government in promoting the development of green finance, and formulate reasonable fiscal expenditure plans according to local actual conditions. Third, implement a differentiated development strategy. All regions should deeply analyze the local basic resources, combine different realistic conditions to choose different green financial development paths and implement differentiated strategies for green financial development.

The main contribution of paper is that, different from the single qualitative and quantitative analysis in the existing literature, we apply a fuzzy-set qualitative comparative analysis method to explore the extent to which the level of economic development, industrial structure, government investment in environmental protection and green innovation capability on the development level of green finance, and design the development pathways of green finance according to different development levels.

Like many studies, this study inevitably has some shortcomings which need to be solved in future studies. On the one hand, this study can only discuss the limited antecedents so as to seek the balance between the number of conditions and cases due to the limitation of the number of cases. Future research can combine more theoretical perspectives to explore other antecedents, and further enrich the existing research framework with a large number of cases. On the other hand, although QCA method is used to study how to improve the development quality of green finance in various regions, the research angle is relatively macro, and it still remains unknown how micro-subjects such as enterprises and financial institutions help green finance development. In the future, we can combine other research methods to explore how each micro-subject participates in the development of green finance and further improve the research perspective.

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 author.

Author contributions

HW: validation, writing—review and editing, supervision, project administration, funding acquisition JL: Formal analysis, investigation, data curation, writing—original draft ZH: Conceptualization, methodology.

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.2023.1145671/full#supplementary-material

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Impact of COVID-19 and green finance on transportation energy carbon emissions in China: From the perspective of an automobile energy consumption structure

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Background: In China, the transportation sector is the main energy consumer and the main source of carbon emissions. Reducing carbon emissions in the transportation sector is an important goal for China, especially during the current period of economic development. Due to the impact of pandemic shocks, the rapid development of green finance is conducive to supporting the transportation sector in achieving a carbon peak. Thus, we examined whether the development of green finance is still effective under the impact of a pandemic and the actual effect of green finance on the reduction of carbon emissions.

Methods: In this study, we searched the internet for consumption structure data of vehicles and green finance indices of 30 Chinese provinces and cities from 2016 to 2021. A regression discontinuity model was constructed to test the effect of pandemic shock and green finance development on the reduction of transportation energy carbon emissions.

Results: The results show that the impact of the COVID-19 pandemic has helped people change their preference toward more energy-efficient vehicles and reduce carbon emissions in the transportation sector. Green finance can effectively contribute to the reduction of transportation energy carbon emissions; however, the overall mitigation effect is limited.

Conclusion: The empirical evidence is not only helpful in assessing the long-term impact of the COVID-19 pandemic but also conducive to the appropriate establishment of policy tools for supporting green finance development, which is further conducive to reducing carbon emissions in the transportation sector.

KEYWORDS

COVID-19 pandemic shock, green finance, transportation energy carbon emissions, RD model, China

1 Introduction

Global warming has contributed to the melting of Arctic ice and disease outbreaks in various countries. According to the report "Climate Change 2022: Mitigating Climate Change" released by the United Nations Intergovernmental Panel on Climate Change (IPCC), the average annual global greenhouse gas emissions in 2019 hit a record high of 59 billion tons. If the earth's temperature rises 1.5°C above pre-industrial levels, humans, natural systems, and biodiversity will face additional serious risks. The transportation sector is the main energy consumption and CO_2 emission sector in China; therefore, it is important to study the driving factors of low-carbon technological development and low-carbon fuel replacement to achieve carbon peak and carbon neutrality goals[1].

A sound and reliable transportation system is important for a province. The transportation sector is not only important to support the economic development of the province but is also the main source of citizen welfare improvement. However, the carbon emissions associated with transportation systems cannot be underestimated, and a sound green and low-carbon transportation system is important for China to achieve its carbon emission reduction goals. The reduction of carbon emissions depends on the development of different modes of transportation, the energy efficiency of vehicles, and the substitution level of low-carbon fuels. Transport vehicles are the main driver of carbon emissions in the transportation sector, and improvement in the energy efficiency of transport vehicles and the substitution of low-carbon fuels will contribute significantly to the reduction of carbon emissions (Wang and He, 2018). As private automobile consumption continues to grow, automobile energy consumption will become one of the biggest contributors to China's carbon emissions in the transportation sector and may even be a factor in the carbon peak. Therefore, the improvement of energy efficiency and increasing low-carbon fuel use are crucial factors for reducing transportation energy consumption and carbon emissions. For example, in the city of Xi'an, the carbon emissions from private cars of Chinese citizens are the highest in the urban transportation system (Li et al., 2017), while the carbon dioxide emissions of electric cars can be 10–26 times lower than those of fuel cars, even though carbon dioxide emissions in the process of energy production are very high. With the introduction of electric cars, annual carbon emissions have also significantly reduced (Teixeira and Sodré, 2018). Evidently, the consumption substitution of new energy vehicles is important for implementing the reduction of carbon emissions in the transportation sector.

It will not be easy to convert the potential demand for new energy vehicles into actual consumption; higher perceived risks and costs and lower perceived benefits are the main obstacles to consumer acceptance of new energy vehicles (Huijts et al., 2012; Wang and Wang, 2013). In particular, the COVID-19 pandemic possibly contributed to the uncertainty of the new-energy vehicle industry. Consequently, the National Development and Reform Commission and 10 other departments jointly issued the Smart Vehicle Innovation and Development Strategy (FGY [2020] No. 202), confirming that new-energy vehicles have become the strategic direction of China's automobile industry development. Simultaneously, the China Banking and Insurance Regulatory Commission (CBRC) issued a notice on further improving the financial services for epidemic prevention and control (CBRC Issue No. 15 [2020]), which requires financial institutions to improve the efficiency of online services and enhance their ability to serve the real economy. Furthermore, the relevant support policies for the development of the new-energy industry (hereafter, referred to as the new-energy industry support policy) occurred at the same time as the outbreak of COVID-19.

Has China achieved a reduction in carbon emissions in the transportation sector? Three years have passed since the outbreak of the pandemic, which provided us with an opportunity to study this issue. Logically, if the new-energy industry support policies dealing with the impact of the pandemic are effective, the pandemic will increase the dependence on new-energy vehicles for Chinese consumers and replace traditional-energy vehicles. Therefore, we can examine the impact of the pandemic on the automobile energy consumption structure to study the path of reducing China's transport energy carbon emissions.

Green finance (GF) refers to economic activities that support environmental improvement, climate change response, resource conservation, and efficient utilization. Green finance includes financial services provided for project investments, financing, project operations, and risk management in the fields of environmental protection, energy conservation, clean energy, green transportation, and green buildings. Most importantly, green finance promotes environmental protection and governance and direct resources from industries with high pollution and energy consumption to sectors with advanced concepts and technologies. China attaches great importance to the development of green finance, which has not only decreased the cost of green industry services, expanded service boundaries, and improved service quality (Demir et al., 2022), but also changed green financial service consumer behavior, increased financial availability, and promoted the popularization effect, such as poverty reduction (Siddik and Kabiraj, 2020).

Green finance has also reduced carbon emissions (Jiang et al., 2020). Specifically, from the perspective of consumption, green financial development can encourage consumers to buy clean energy or low-energy technological products, resulting in a decrease in energy consumption. From the perspective of production, green financial development reduces the risk of financial innovation, helps producers increase investment expenditure on advanced production technologies, and promotes technological progress. Thus, backward production with high energy consumption and high emissions is eventually replaced by clean technology.

In addition, financial development can also promote capital flow to low-carbon enterprises, with high energy and resource allocation efficiencies, thereby reducing energy consumption (Ge et al., 2018; Su and Lian, 2018). With the strengthening of policy support, green

1 Hereafter referred to as the "double carbon" target.

finance shows great potential in promoting the win–win results of "economy" and "environment" (Wang et al., 2019). One key to green finance is promoting transportation fuel substitution and low-carbon technology innovations to reduce the cost of project technology identification, supervision, and financing. Reducing carbon emissions in the transportation sector relies on low-carbon energy substitution and cannot be achieved without a balanced flow of financial resources between regions and industries. Financial services for green industries must be innovative, oriented, and liquidated, which is the core value of green finance (Li and Hu, 2014).

However, many questions remain to be answered, such as whether the development of green finance contributes to the reduction of carbon emissions in transportation energy. This study examined whether the development of green finance is still effective under the impact of a pandemic, and the actual effect of green finance on the reduction of carbon emissions. As the development of the new-energy vehicle industry plays an important role in solving the carbon emission problem of China's transportation sector, research on the aforementioned issues is conducive to objectively evaluating the effect of the pandemic and green finance on transportation energy carbon emissions. Our study also has important practical significance for formulating green financial support policies to help the transport sector actualize low-carbon transformation and achieve carbon emission reduction goals.

Our research has the following three main contributions. First, the carbon emission coefficient has been widely used in previous studies to calculate the carbon emission index of transportation energy, which cannot directly reflect the transformation of low-carbon consumption (Ma et al., 2019; Zeng et al., 2020). Therefore, this study used the Python crawler method to capture the transaction volume of automobile terminals from July 2017 to June 2022 and attempted to explore the impact of the pandemic on China's transportation carbon emissions innovatively from the proportion of traditional-energy vehicles to provide empirical data support for quantifying the economic impact of the pandemic. Second, the recognition assumption for the double-difference (DID) method is difficult to establish (Dong et al., 2021). Therefore, the regression discontinuity RD model was used to identify the causal relationship between the COVID-19 pandemic, green financial, and transportation energy carbon emissions. All of China's provinces suffered from the COVID-19 pandemic to different degrees, and the DID method renders it more difficult to identify the assumption, whereas the RD method of identity assumes that it is easier to obtain satisfaction. Third, it has been pointed out that the pandemic can help transform the energy structure and reduce carbon dioxide emissions in the construction and power sectors (Xian et al., 2019; Hepburn et al., 2020; Wang J. et al., 2020). However, quantitative analyses focusing on the transport sector are lacking. This study supplements the relevant research on the impact of major public health events on the low-carbon transformation of China's economy at the micro level. Moreover, it is novel to study the driving effect of the epidemic impact on carbon emission reduction based on the transportation sector.

2 Literature review

2.1 COVID-19 pandemic shock, household income, and carbon emissions from transportation energy

In terms of different levels and degrees of satisfaction with residents' lives, consumption can be divided into subsistence, developmental, and enjoyment consumption (Li and Pan, 2019). The main feature of subsistence consumption is that residents' consumption expenditure is mainly used for food, clothing, water, electricity, housing, *etc.*, and the purchase of necessary grain, oil, food, and clothing to meet the basic needs for survival. From the mid-1980s to the mid-1990s, the "four major items" of Chinese residents' consumption were upgraded to refrigerators, color television sets, washing machines, and recorders, indicating that Chinese residents' consumption was upgraded from subsistence consumption to developmental consumption. In the late 1990s, the "four major items" of Chinese residents' consumption were upgraded to durable consumer goods, such as air conditioners, computers, cars, and mobile phones, indicating that Chinese residents' consumption has increased from development consumption to enjoyment consumption.

As an enjoyable consumer good, the consumption of traditional cars reflects the level of economic growth, while the environmental deterioration caused by fossil energy consumption is significant and even counteracts economic growth (Mele and Magazzino, 2020; Udemba et al., 2020; Magazzino and Mele, 2021). Currently, the types of transportation energy consumption represented by vehicles can be divided into traditional energy (such as gasoline) and new energy (such as electricity). In terms of reducing carbon emissions from transportation energy, new-energy vehicles are alternatives to fuel vehicles. New-energy vehicles refer to the use of unconventional vehicle fuel as the power source (or the use of conventional vehicle fuel combined with the use of new on-board power devices), integrated vehicle power control, advanced technology, the formation of advanced technical principles, new technology, and the structure of the vehicle.

Classical economic theories of consumer spending are abundant. The "Absolute Income Hypothesis" points out that consumer psychology and current disposable income are important factors in determining consumption (Keynes, 1936). The "Life Cycle Hypothesis" states that rational consumers will make decisions on consumption and saving throughout their lives based on their expected income, according to the principle of utility maximization. Therefore, consumer consumption depends not only on their current income but also on their life-cycle income (Modigliani and Brumberg, 1954). The "Permanent Income Hypothesis" observes that permanent income is an important factor that affects consumption. Consumers respond to lasting and stable income, but do not respond equally to all income changes (Friedman, 1957). The pandemic not only had a huge impact on the income of people working in multiple industries in the first quarter of 2020 but also greatly reduced the ability and willingness of the society to consume. The continued spread of the pandemic overseas, aggressive public health policies, and uncertainty regarding the pace of economic recovery have also had a significant impact on consumers' future income expectations. Therefore, whether from an absolute income perspective, durable income perspective, or life-cycle perspective, the pandemic has had a dampening effect on current and future consumption.

According to “The Trend of Household Wealth Change in China Under the Pandemic—China Household Wealth Index Survey Report (Q1 2020),” the pandemic has hit low- and middle-income households harder. Specifically, according to the wage income index, the wage income of families with an annual income of more than 300,000 yuan has increased, whereas that of families with an annual income of less than 300,000 yuan has decreased. Compared with families with an annual income of 50,000–300,000 yuan, families with an annual income of 50,000 yuan or less have the largest reduction in wage income. The impact of the COVID-19 pandemic on China’s consumption is reflected in the fact that offline consumption for development and enjoyment suffered shock damage (Chen, 2020). In addition to daily necessities, the decline in medical care and communication equipment is relatively low. The expensive bulk-optional consumption, such as cars, home appliances, and furniture, declined significantly compared to the same period last year. Free-optional consumption, such as entertainment services, catering, tourism, and luxury goods, dropped significantly[2].

2.2 COVID-19 pandemic shock, consumer psychology, and carbon emissions from transportation energy

In addition to reducing carbon emissions from transportation energy from the income path, the pandemic also exhibits a restraining effect on the consumer psychological path. To control the spread of the pandemic, China has formulated a series of proactive public health policies, such as sealing off high-risk areas, banning large-scale gatherings, and tracing close contacts. However, proactive pandemic prevention and control measures have had a great impact on the resumption of business and production. Due to the existence of the pandemic prevention and control policy, the spread of positive cases can cause logistical stagnation, restrict the movement of people, make it difficult for employees to return to work on time, and restrict the flow of raw materials and products, which can seriously affect the normal operation of the economy (Dong et al., 2021). To reduce the probability of contact with positive cases and the risk of being controlled and isolated, the demand for car consumption by households should be significantly higher in the long-term. This means that there is a significant uncertainty in China’s future transportation energy carbon emissions.

New-energy vehicles are more advanced, which cannot be achieved without chips or electronic control. Most new-energy vehicles have over-the-air (OTA) technology, which endows vehicles with continuous upgrades and evolution; this is the key to determining the degree of intelligence of vehicles. Moreover, compared with traditional-fuel vehicles, linear control is also more conducive to the realization of the Internet of Things, and new-energy vehicles are undoubtedly the best carriers of automobile intelligence (Wang K. et al., 2020). Furthermore, internet companies are also willing to take the initiative to join the wave of changes in the automotive industry. They are not only competitive but also teammates in the development of smart electric cars. This is conducive to accelerating the transformation and promoting the development of the intelligent electric vehicle industry. These developments reduce consumers’ perceived risks and costs of new-energy vehicles and increase their perceived benefits. Compared with other major markets, such as the United States and Germany, Chinese consumers have a higher awareness of automobile intelligence and a higher adoption rate of in-vehicle software and human–computer interaction functions[3]. Residents who buy energy vehicles mainly focus on energy savings, modeling, and functions. The current mature intelligent driving system, electrical platform, and updatable software meet these requirements, and the electrical architecture at the technical level will further improve the driving experience of new-energy vehicles. It has been observed that 54.1% of Chinese consumers’ plan to purchase a new-energy vehicle in 2022, which can significantly help reduce the level of carbon emissions from transportation energy[4].

The reduction in an automobile consumption scale is temporary, and the transformation of the automobile energy consumption structure is the fundamental way to realize the reduction in carbon emissions in transportation energy. The formulation of a financial support policy for the new energy industry to cope with the impact of the pandemic will allow the society to have better online financial services to support its development of the new-energy industry. In particular, the existence of online consumption and supply chain finance makes consumers (or producers) more resistant to risks and weakens the external liquidity constraints formed by income shocks during epidemics (Li et al., 2022). If consumers can obtain loans in a timely and effective manner to smooth out their long-term consumption, their spending is not limited by the property they own and their current income (Zhao and Zhao, 2022). In particular, when online finance is linked with the consumption of new-energy vehicles, although it is necessary to take into account the possible large expenditures and income fluctuations in the future, online financial services make the cost of new-energy vehicle expenditures lower and reduce the perceived cost. However, online financial

2 The consumption data for the first quarter of 2020 are used as an example to observe the impact of the pandemic on consumption. Retail sales of consumer goods totaled to 7.86 trillion yuan in the first quarter of 2020, down 19 percent year-on-year, according to the National Bureau of Statistics. Clothing and textiles, gold and silver jewelry, household appliances and audio-video equipment, furniture, and automobiles were the most affected, with year-on-year declines of more than 30%. In particular, the consumption of gold and silver jewelry declined significantly, with a year-on-year decrease of 37.7%. The consumption of petroleum products, cosmetics, constructions, decoration materials, and tobacco and alcohol decreased by 10%–29%. Daily necessities and communication equipment were less affected, with a year-on-year decrease of less than 5%; only grain, oil, and food, which are daily necessities, went up 12.6% year-on-year.

3 Based on Roland Berger’s survey report on “The Exploration of Disruptive Data in the Automotive Industry.”

4 “Investigation on Chinese Consumers’ purchase of new energy vehicles in 2022” by iMedia Consulting.

services weaken the uncertainty of households' future incomes, making it difficult to form internal liquidity constraints and reducing the uncertainty of the expectations of the new-energy automobile industry by reducing the perceived risk of consumers. When making new-energy vehicle consumption decisions, households can reduce preventive savings and increase current consumption. Therefore, the link between online finance and consumption of new-energy vehicles is conducive to the purchase of energy vehicles by households, reducing the proportion of consumption of traditional-energy vehicles, thus curbing carbon emissions associated with transportation energy.

2.3 Mechanism of green finance promoting transportation energy carbon emission reduction

Green finance is an important support and guarantee force for the green economy and an important part of the digital economy (He and Song, 2020), and the online financing mentioned previously also belongs to this category. Theoretically, green financial services based on digital technology have brought about changes in payment methods; greatly reduced search costs, evaluation costs, and transaction costs; and have broken the spatial and temporal limitations of traditional financial services (Zeng and Reinartz, 2003; Li, 2015; Zhou and Liang, 2018), expanding the scope of traditional financial services (Campbell and Mankiw, 1991). From the consumer side, green finance reaches users online, making it easier for residents to obtain financial services (Yang et al., 2021). It can effectively supplement consumers' credit records and make use of the interrelated characteristics of payment and financing channels to alleviate the financial constraints of households and realize intertemporal consumption (Pi et al., 2018). For example, providing financial services, such as online consumption subsidies for new-energy vehicles for households, can stimulate residents' demand for consumption upgrades, thus releasing consumption potential. Therefore, the improvement of payment convenience and the easing of capital constraints by green finance will make a greater contribution to the enjoyment type of consumption expenditure, thus promoting the upgraded consumption of residents. Finally, the development of green finance based on digital platforms can help residents form wealth effects, diversify risks, reduce the uncertainty of households facing external shocks, and release the demand for upgraded consumption. The outbreak of the pandemic will further promote the development of digital technology and the implementation of digital financial services (Dong et al., 2021). For example, the scale of the financial platform Yu'ebao is about 1.2 trillion yuan, with individual investors accounting for 99.97% of the total, bringing 993.25 billion yuan of revenue to customers throughout the year in China. A high level of revenue lays the foundation for smooth consumption upgrading (up to 2020). Therefore, green finance can also reduce uncertainty and improve residents' income expectations by spreading risks and wealth effects to smooth the setback of new energy vehicle consumption caused by the impact of the pandemic.

3 Methodology and data

3.1 Sharp RD

To estimate the direction and degree of the pandemic impact on carbon emissions from transportation energy and whether the carbon emission reduction effect of green finance exists, we used the research studies of Salman et al. (2022) and Shi and Li (2022). We used the time nodes of COVID-19 and breakpoint regression settings to test the inhibitory effect of the pandemic impact and green finance on carbon emissions from transportation energy. The RD model uses discontinuous characteristics of external shocks as a measurement method to identify causal relationships. These external shocks consider economic individuals as treated when an observable characteristic variable (driving variable) is equal to or greater than a certain threshold. As long as an economic individual cannot fully manipulate the driving variable, discontinuous change in the dependent variable can be regarded as being caused by the processing state (Zhang and Chen, 2014). Consistent with the basic idea of this method, a pandemic has an unpredictable external impact. After the pandemic, the relevant policies formulated by the Chinese government to support the development of the new-energy vehicle industry included the notice on further improving the financial services for epidemic prevention and control and the intelligent vehicle innovation and development strategy. These policies will enable consumers to reach the new-energy vehicle industry directly through financial online services without leaving home, reducing the perceived risks and costs of the new-energy vehicle industry and improving the perceived benefits. Therefore, since the first quarter (Q1) of 2020, the Chinese society has been affected by the pandemic.

$$D_i = \begin{cases} 1, z_i \geq Q1, 2020 \\ 0, z_i < Q1, 2020 \end{cases}, \tag{1}$$

where D_i denotes the treatment state variable. This equation indicates whether a pandemic impact has been received. If the value is equal to one, the pandemic impact is received; otherwise, it is zero. Equation 1 shows that D_i is a discontinuous function of time z_i. Q1 of 2020 is a breakpoint, meaning that regardless of how close one gets to Q1 of 2020, there will be no change until that timepoint is reached. If Eq. 1 is valid, the causal influence of pandemic shock on variables Y_i[5] can be obtained by the regression of the following equation:

$$Y_i = \alpha_1 + \alpha_2 D_i + f(z_i) + \mu_i, \tag{2}$$

where $f(z_i)$ is the polynomial function of z_i. α_1 is a constant term. The coefficient α_2 of D_i indicates the difference in transportation energy carbon emissions by province and city before and after the "breakpoint." μ_i is the random error term. When Eq. 2 is established, we call the adopted RD "Sharp RD." In practice, the requirement of the functional form of Eq. 2 can be relaxed by limiting the sample to the vicinity of the breaking point during estimation. The distance between the selected samples and the breakpoint is called the

5 Considering the explanatory power of the regression results, we take the logarithm of Y_i in the actual regression.

bandwidth. The smaller the loan, the smaller the requirements for control variables and forms will be; however, more sample observations will be lost, and the error of parameter estimation will increase. In the subsequent estimation, we referred to control the piecewise linear function of age according to the calculation of the optimal bandwidth and reported the estimation results of multiple bandwidth settings near the optimal bandwidth to fully demonstrate the robustness of the results.

3.2 Data

This study used panel data from 30 provinces in China from 2016 to 2021 to assess the impact of the pandemic on carbon emissions from the transportation sector and the role of green finance in reducing emissions. Considering that the consumption of residents was seriously affected by the pandemic in January 2020, the initial operating rate was low, and the subsequent consumption response time was included, which has certain particularity. Therefore, this study chose quarter consumption data to more accurately assess the impact of the pandemic on the traffic energy of conventional incentives to reduce emissions and the timely and effective capture of the short-term finances for green transportation energy reduction of carbon emissions.

The original data of the green finance index were obtained from the quarterly data[6] of provinces and cities of the Baidu Search Index (BSI) from 2016 to 2021. The original data of transportation energy carbon emission measurements were from the quarterly data[7] of each province on the Autohome website. Data such as environmental regulation and urbanization level were mainly obtained from the China Fiscal Yearbook, China fixed-asset investment Statistical Yearbook, and statistical yearbooks or statistical bulletins of each province from 2016 to 2021. Among them, the individual missing data involved in the environmental regulation levels were replaced using linear interpolation and mean interpolation methods.

3.3 Variable definitions and descriptions

Explained variable: Carbon emissions from transportation energy (TRANC). In this study, the following formula was used as a proxy variable for transportation energy carbon emissions:

$$\frac{traditional\ automobile\ consumption\ (OIL)}{traditional\ automobile\ consumption + new\ energy\ automobile\ consumption\ (ELEC)}, \quad (3)$$

where *new energy automobile consumption* refers to the actual transaction volume of new cars as a statistical caliber. The use of new-energy vehicles will help China reduce carbon emissions from transportation energy. A lower proportion of traditional automobile consumption implies that the carbon emission level of transportation energy will be suppressed.

TABLE 1 Variable descriptions.

Variable	Obs	Mean	Std. dev	Min	Max
ELEC	660	3806.861	6071.212	0	56663
OIL	660	56917.894	46476.012	328	266815
TRANC	660	0.939	0.079	0.390	1
GF	660	0.183	0.148	0.005	0.967
URB	660	58.378	12.303	35.030	89.600
ENV	660	0.072	0.048	0.014	0.327

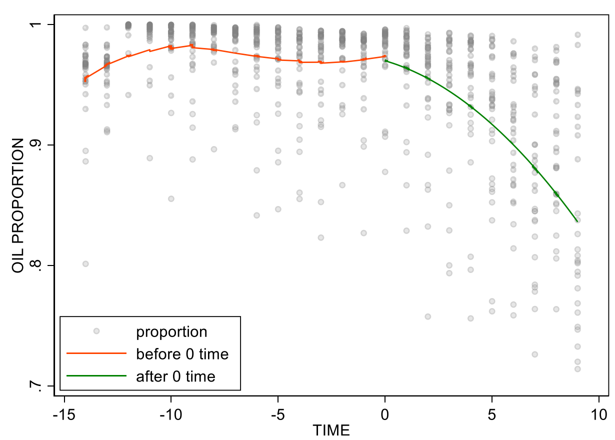

FIGURE 1
Relationship between COVID-19 pandemic shock and the share of traditional automobile consumption.

Explanatory variable: GF. To evaluate the green financial development level of provinces and cities, this study drew from studies by Sheng and Fan (2020) and Dong et al. (2021) to measure the level of regional financial technology from the demand side using the BSI of green finance-related keywords[8] and the coefficient of the variation method to construct a GF index for each province and city during the sample period. The network search data based on the demand level can better describe the development status of GF in various provinces and cities and meet the requirements of the provincial and municipal panel data in this study. We included the GF variable into the RD model to evaluate the promoting effect of GF on the reduction of carbon emissions in transportation energy under the pandemic shock.

Other **control variables** included urbanization level (URB). After urbanization reaches a certain stage, it leads to increased energy consumption, aggravated environmental pollution, traffic

6 For more information, please see: https://index.baidu.com/.

7 For more information, please see: https://www.autohome.com.cn/.

8 The keywords related to green finance mainly include conceptual-level, technical-level, payment-level, and policy-level terms. Specific terms include green finance, consumer finance, green consumption, big data, cloud computing, artificial intelligence, blockchain, biometric identification, online payment, mobile payment, third-party payment, new-energy policy, and auto finance. This article uses the "pc + mobile" search index.

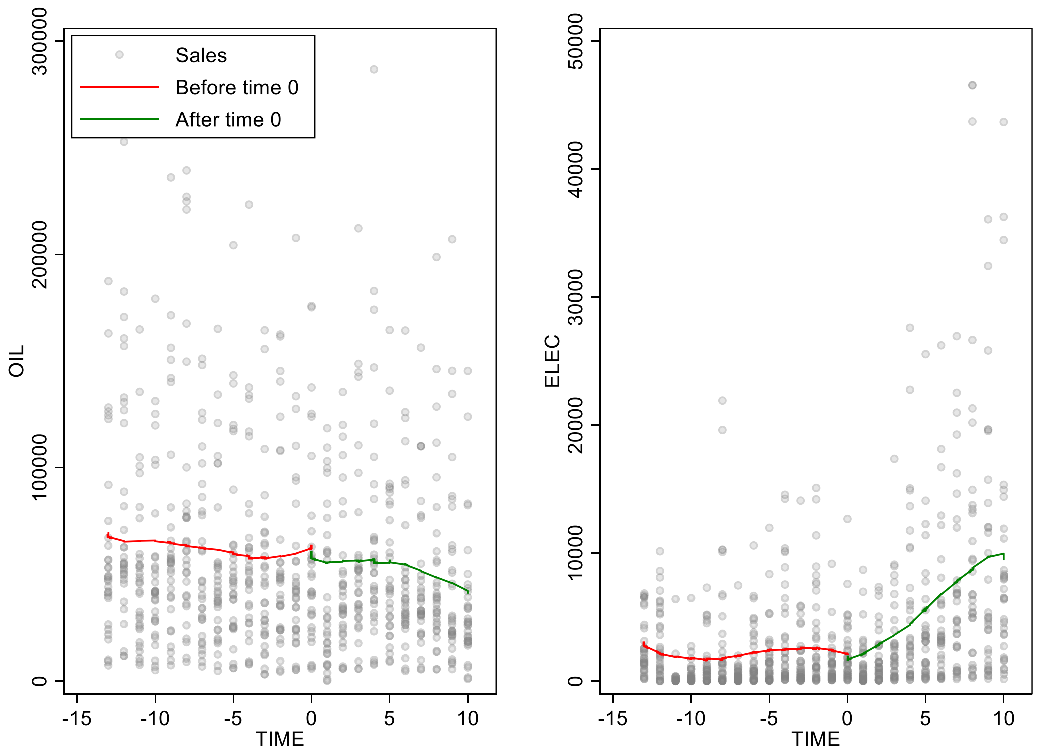

FIGURE 2
Relationship between COVID-19 pandemic shock and the consumption of traditional- and new-energy vehicles.

congestion, *etc.* Overall, China's urbanization has not reached the most conducive standard for carbon emission reduction (Wang, 2010; Zhang et al., 2016); therefore, this study used the ratio of urban population to rural population to represent the urbanization level (Lin and Liu, 2010). The "Porter hypothesis" states that the appropriate environmental regulation level (ENV) can stimulate enterprises' innovation activities, improve product competitiveness, and thus reduce carbon emissions (Lanoie et al., 2008). Therefore, this study considered the proportion of local fiscal environmental protection expenditure in the regional GDP as a representative value of the environmental supervision level (Zhang and Wang, 2020). Table 1 shows descriptions of the main variables.

4 Results

4.1 Graphic analysis

Figure 1 shows the relationship between the pandemic as a driving variable and traditional car consumption. A jump point near time 0 can be observed, which is consistent with the announcement of the COVID-19 outbreak on 20 December 2019. To smooth the short-term fluctuations in automobile consumption, the driving variable in this study was quarterly timed, the treatment state was the pandemic shock, and the treatment state was a discontinuous function of the driving variable. According to the results shown in Figure 1, at breakpoint time 0, the consumption of traditional vehicles and energy vehicles dropped significantly. We used the first quarter of 2020 as the breakpoint in the regression analysis.

Figure 2 shows the relationship between the pandemic shock and the consumption of traditional and new energy vehicles. Again, clear jumps can be observed, with a significant drop in car consumption at the breakpoint. This indicates that the impact of the pandemic significantly reduced the level of automobile consumption, changed the structure of automobile consumption, and affected the level of transportation energy carbon emissions. As automobile consumption can be divided into traditional- and new-energy vehicles, the relationship between driving variables, the consumption of traditional vehicles, and new-energy vehicles is highly similar. However, under the impact of the pandemic, the social demand for traditional energy and new-energy vehicles has undergone structural changes. Residents prefer new-energy vehicles, and the consumption of traditional-energy vehicles has decreased more than that of new-energy vehicles; thus, the proportion of traditional-energy vehicle consumption has decreased.

Figure 1 shows a significant decline in the share of sales of traditional- and new-energy vehicles at the breakpoint. Figure 2 shows that the sales volume of traditional-energy vehicles and new-energy vehicles exhibits a jump point under the impact of the pandemic, and the decline of traditional-energy vehicles is greater than that of new-energy vehicles. These graphs clearly show the discontinuous variation in the outcome variable (share of energy vehicle sales) caused by dealing with the treatment state variable (COVID-19 pandemic shock), and preliminary showed that the outbreak can effectively reduce the traffic impact on energy carbon

TABLE 2 Diagnostic tests.

	(1)	(2)	(3)
	Optimal bandwidth	+/−1.0	+/−3.0
GF	−0.0017 (−0.0600)	0.0326 (0.5900)	0.0203 (0.5000)
URB	1.86e-15 (0.0000)	0.1036 (0.0200)	0.2084 (0.0600)
ENV	−3.42e-18 (−0.0000)	−0.0055 (−0.2900)	−0.0112 (−0.7700)

Note: (1), (2), and (3) are the results of the RD model using the optimal bandwidth, doubled bandwidth, and tripled bandwidth computed by STATA, respectively.

TABLE 3 Benchmark regression results I.

	Triangle kernel			Rectangular kernel		
	(1)	(2)	(3)	(4)	(5)	(6)
	Optimal bandwidth	+/−1	+/−3.0	Optimal bandwidth	+/−1	+/−3.0
COVID-19	−0.0471** (−0.0216)	−0.0474** (−0.0216)	−0.0251* (−0.0150)	−0.0480** (−0.0216)	−0.0480** (−0.0216)	−0.0480** (−0.0216)
GF	No	No	No	No	No	No
Control variables	No	No	No	No	No	No
Province FE	No	No	No	No	No	No
Season FE	No	No	No	No	No	No
Observations	660	660	660	660	660	660

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. (1), (2), and (3) are the results of the RD model using the optimal bandwidth, doubled bandwidth, and tripled bandwidth computed using STATA, respectively. (4), (5), and (6) are the results of the RD model using the optimal bandwidth, doubled bandwidth, and tripled bandwidth computed using STATA, respectively.

emissions. The degree of how and whether new-energy vehicle consumption is still financially dependent on the green path to the parameter estimation results remains to be observed.

4.2 Diagnostic tests

We tested the second premise hypothesis of whether the control variables are continuous around the breakpoint. We used a non-parametric RD model for testing; the results are presented in Table 2. The regression coefficients of the control variables are insignificant in the RD model. This implies that before and after the first quarter of 2020, there is no significant difference in other characteristics that may affect transportation energy carbon emissions, except for the difference in the consumption proportion of new-energy vehicles caused by the development of provinces, cities, regions, and green finance.

4.3 Benchmark regression results

Table 3 shows the impact of the pandemic shock on the share of conventional energy vehicles consumed. Column (1) of the table is estimated using the optimal bandwidth calculated according to the study by Imbens and Kalyanaraman (2012), and the remaining columns were estimated using other similar bandwidth settings to fully test the robustness of the results. We obtained consistent results, and the F-value test for time breakpoints far exceeded the critical value of the instrumental variable test given by Stock and Yogo (2005). The results showed that the impact of the pandemic significantly reduced the sales share of traditional-energy vehicles. According to the estimation under the optimal bandwidth setting, in the case of uncontrolled area and time effect, the pandemic impact led to a 4.80% decrease in the sales share of traditional-energy vehicles. These results are consistent with the conclusions of Aghion et al. (2019) and Hepburn et al. (2020). In addition to the sharp slowdown in economic growth, the impact of the pandemic has significantly reduced the proportion of traditional-energy vehicle consumption. This is conducive to the transformation of China's transport energy consumption structure toward low carbon, thus reducing the carbon emissions in transport energy.

As the regression results of the rectangular kernel model are more stable, we added the green finance variable based on this model and controlled for time and province, investigated the change in the impact coefficient of the pandemic impact before and after adding the green finance variable, and then explored the role of green finance on the reduction of carbon emission in transportation energy under the pandemic impact. The results in Table 4 show that when regional and time effects are controlled and green finance variables are not added, the impact of the pandemic on the sales of traditional energy vehicles was −4.66%. After adding the green finance variable, the magnitude of the impact decreased by 0.42%, indicating that green finance had a positive effect on carbon emission reduction in transportation energy during the

TABLE 4 Benchmark regression results II.

	(1)	(2)	(3)	(4)	(5)	(6)
	Optimal bandwidth	+/−1.0	+/−3.0	Optimal bandwidth	+/−1.0	+/−3.0
COVID-19	−0.0466* (0.0220)	−0.0466* (0.0220)	−0.0466* (0.0220)	−0.0424* (0.0220)	−0.0424* (0.0220)	−0.0424* (0.0220)
GF	No	No	No	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Season FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	660	660	660	660	660	660

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. (1), (2), and (3) are the results of the RD model using the optimal bandwidth, doubled bandwidth, and tripled bandwidth computed using STATA, respectively. (4), (5), and (6) are the results of the RD model using the optimal bandwidth, doubled bandwidth, and tripled bandwidth computed using STATA, respectively.

TABLE 5 Robustness test I.

	(1)	(2)	(3)
	Optimal bandwidth	+/−1.0	+/−3.0
COVID-19	−0.0480*** (−4.5000)	−0.0490*** (−4.6700)	−0.0300* (−1.7200)
GF	−0.0680** (−2.1400)	−0.0950 (−0.4700)	−0.0630 (−1.0600)
URB	0.0100*** (4.9500)	0.0880*** (4.2300)	0.0420*** (3.1900)
ENV	−0.0900 (−1.2600)	−0.0290 (−0.1500)	0.0260 (0.2300)
Province FE	Yes	Yes	Yes
Season FE	Yes	Yes	Yes
Observations	660	660	660

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. (1), (2), and (3) are the results of the RD model using the optimal bandwidth, doubled bandwidth, and tripled bandwidth computed using STATA, respectively.

pandemic. This shows that under the impact of the pandemic, green finance is beneficial for Chinese residents for adopting green consumption behavior and achieving the carbon emission reduction target in the transportation sector. The aforementioned conclusions are consistent with those of Wang et al. (2019) and Jiang et al. (2020).

Some studies have indicated that global carbon emissions will be reduced by 5.7% on average in 2020, owing to the impact of COVID-19 (Le Quéré et al., 2020). From the perspective of the causes of carbon emissions reduction, in addition to the sharp slowdown of economic growth in various countries, the impact of COVID-19 on the transformation of industrial structures in various countries must not be ignored (Aghion et al., 2019; Wang Z. et al., 2020). Specifically, the impact of the pandemic can not only motivate countries' industrial sectors to improve energy efficiency and achieve emission reduction targets (Gao et al., 2019) but also encourage governments to develop green finance, "hydrogen economy," and "new infrastructure" investments. This helps transform the energy structure and reduce CO_2 emissions in the building and power sectors (Xian et al., 2019; Hepburn et al., 2020; Wang J. et al., 2020). Furthermore, green finance not only helps achieve carbon emission reduction in the transportation sector but also has the potential to fulfill a win–win situation of "low carbon" and "economy" (Wang et al., 2019; Jiang et al., 2020). Therefore, our empirical results are consistent with existing research results.

4.4 Robustness testing

For the following results, we used two methods: parametric model testing and a placebo test for testing robustness.

4.4.1 Parametric model testing

Following Lee and Lemieux, 2010, we use a parametric model for robustness testing to corroborate the results of the non-parametric test. The model is shown in Eq. 4, where STB is a dummy variable that takes the value of 1 when the sample time occurs after the first quarter of 2020 and 0 otherwise. β_1 is a constant term. The coefficient β_2 of STB indicates the difference in transportation energy carbon emissions by province and city before and after the "breakpoint." ε_i is the random error term. In addition, consistent with Eq. 2, we controlled for the fixed effects of green finance, environmental regulation, urbanization level, province, and time.

TABLE 6 Robustness test II.

	Q1, 2019			Q1, 2021		
	(1)	(2)	(3)	(4)	(5)	(6)
	Optimal bandwidth	+/−1.0	+/−3.0	Optimal bandwidth	+/−1.0	+/−3.0
COVID-19	−0.0186 (0.0145)	−0.0186 (0.0165)	−0.0186 (0.0175)	−0.0214 (0.0221)	−0.0163 (0.0260)	−0.0211 (0.0214)
GF	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Season FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	660	660	660	660	660	660

Note: (1), (2), and (3) are the results of the RD model using the optimal bandwidth, doubled bandwidth, and tripled bandwidth, respectively, with Q1 2019 as the breakpoint. (4), (5), and (6) are the results of the RD model using the optimal bandwidth, doubled bandwidth, and tripled bandwidth with Q1 2021 as the breakpoint.

$$Y_i = \beta_1 + \beta_2 \mathrm{STB}_i + f(z_i) + \varepsilon_i. \tag{4}$$

Table 5 shows the test results of the parametric model, and the parametric tests are consistent with the non-parametric tests for most bandwidths.

4.4.2 Placebo testing

Our regression results can show a mechanical correlation or because the price of new-energy vehicles has become cheaper over time. If this is the case, then we can observe a significant "jump" in the share of new-energy vehicles sold using any year as a breakpoint. To rule out this possibility, a placebo test was conducted. Specifically, we examined whether transportation energy carbon emissions were significantly different between 2019 and 2021, using the first quarter of 2019 and 2021 as hypothetical policy shocks. The results in Table 6 show that there were no significant differences in transportation energy carbon emissions within provinces and cities in the first quarters of 2019 and 2021.

5 Conclusion

The pandemic shock has opened a new phase of carbon emission reduction in the transportation sector in China and has effectively contributed to low-carbon transformation for transportation energy consumption. Based on the latest data, we estimated the possible emission reduction effect of the pandemic shock on transportation energy carbon emissions and the promotion of green finance using a breakpoint regression method. We observed that the pandemic shock led to a 4.24% decrease in the share of traditional-energy vehicle consumption. The mitigation of China's transportation energy carbon emissions by the pandemic shock is based on changing people's consumption preferences for traditional-energy vehicles and promoting people to buy new-energy vehicles. Green finance contributes to the impact of the pandemic shock on transportation energy carbon emission reduction, but the magnitude of the effect is limited. Although China exceeded the emission target of a 40%–45% reduction in carbon intensity by 2020, the impact of the pandemic has put some pressure on China to successfully achieve the CO_2 emission reduction target. In the long run, the impact of COVID-19 on China's climate goals mainly depends on the balance of "environmental" and "economic" policies. At the meeting of the Standing Committee of the Political Bureau of the CPC Central Committee in 2021, proposals were created to promote the development of green and low-carbon financial product services, establish monetary policy tools for carbon emission reduction, incorporate green credit into the macro-prudential evaluation framework, and guide banks and other financial institutions to provide long-term, low-cost funds for green and low-carbon projects. The construction and formulation of "Green finance" and related policy tools will contribute to the development and transformation of low-carbon technology. These will not only help boost the economy and strengthen new-energy automobile enterprises development and low-carbon technology enterprises but also help the low-carbon development of China's energy structure and promote the peak of China's CO_2 emissions at the earliest.

With the growing demand for household car consumption in China and the continuing process of urbanization, transportation energy carbon emissions are one of the key issues that need to be addressed for China to achieve the double-carbon target, and it is imperative to help residents' new-energy vehicle consumption behavior. This study shows that the pandemic shock is an opportunity to open up new-energy vehicle consumption among residents; green financial support policies dealing with the pandemic and superimposed green finance together reduced the share of traditional energy vehicle consumption, and further development of green finance can reduce residents' preference for traditional energy vehicles and mitigate the long-term threat posed by transportation energy carbon emissions. Therefore, the government must examine the time window of the pandemic impact to further promote and improve green finance consumption policies. First, it further accelerates the development of green finance to support the new-energy automobile industry; strengthen the research on the integration of green finance platforms based on 5G, the industrial Internet of Things, big data centers, artificial intelligence, and other technologies; and the low-carbon transformation and development of transportation energy. Second, it is necessary to improve the enthusiasm of residents to participate in green finance. This can be performed by establishing an incentive mechanism linking online financial consumption and the payment for energy vehicles by stages, encouraging residents' green financial behavior, and forming a long-term incentive for new-energy vehicles purchase. Third, it gradually reduces the financing cost of green finance so that consumers have a good expectation of green finance and new-energy vehicles, which is conducive to further encourages the residents to purchase new energy vehicles. Fourth, it is necessary to strengthen the coordination and connection between green finance and the new-energy automobile industry. This can be accomplished by allowing for the resource allocation function of green finance for low-carbon technology innovation, the transformation of automobile enterprises, and implementing the survival of the fittest in transportation energy low-carbon technology. Fifth, green financial services online will improve the efficiency of low-carbon technology innovation and transform the purchase of new-energy vehicles, which is particularly important for China's economy in the process of transformation.

This study has potential limitations that must be addressed in future research. First, in our empirical study, we considered China as a whole and did not consider the differences in carbon reduction effects among the eastern, middle, and western provinces. Second, we selected a sample of Chinese provinces for empirical testing in our study but did not conduct a comparative study with developed regions or underdeveloped countries or regions. Therefore, further research is needed when more abundant data are available. Additionally, this study only examined the economic effects of the pandemic shock from the perspective of carbon emissions from transportation energy, and further research is needed to fully assess the carbon reduction effects based on the pandemic shock and green finance. The pandemic shock may also affect the consumer's demand and the endogenous power of consumption, supply of industries, and economic growth and stability of the country. All these directions are worthy of further 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

Conceptualization, XZ; data curation, ZY; formal analysis, NG; funding acquisition, LL; investigation, YL; methodology, XZ; project administration, YL; resources, NG; software, LL; supervision, YL; validation, YC; visualization, YL; writing—original draft preparation, LL; writing—review and editing, LL; All authors have read and agreed to the published version of the manuscript.

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Conflict of interest

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

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How does education affect urban carbon emission efficiency under the strategy of scientific and technological innovation?

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Low-carbon economy is not only an important topic for the globe but also a serious challenge for China with its economy entering a new level. Based on the DEA-undesirable model and Malmquist index model, urban agglomeration of the Yangtze River Delta and the Guangdong–Hong Kong–Macao Greater Bay Area from 2010 to 2021 were selected as research samples. Based on that, a panel generalized method of moments model was constructed to analyze the effects of the education level, technological development, and their interaction on urban carbon emission efficiency. It found that 1) the carbon emission efficiency of the Yangtze River Delta and the Guangdong–Hong Kong–Macao Greater Bay Area urban agglomerations shows a steady growth trend, but the overall level is low and there are regional differences, among which pure technical efficiency mainly limits the improvement of comprehensive efficiency; 2) the education level and technological development have a high positive correlation on urban carbon emission, and their interaction is conducive to the improvement of carbon emission efficiency. The carbon emission efficiency has a significant advantage under the influence of control variables, such as the economic development level, industrial structure upgrading, opening-up degree, and Internet penetration rate. 3) According to the economic dimension and population dimension, the samples of the Yangtze River Delta and the Guangdong–Hong Kong–Macao Greater Bay Area were divided into large cities and small cities, and regression results showed no substantial changes. It shows that the research conclusion is scientific. According to the aforementioned conclusion, this paper puts forward corresponding countermeasures and suggestions.

KEYWORDS

science and technology innovation strategy, urban carbon emission efficiency, education level, Internet popularization, DEA-undesirable model

1 Introduction

Since the reform and opening up, China has made remarkable achievements with the transition dividend, investment dividend, and human capital dividend brought about by market-oriented reforms. Urbanization has increasingly amplified the contradiction between the economic development and ecological environment with deteriorating environment and soaring pollutant emission. Among the main pollutants, carbon dioxide is the main culprit causing the greenhouse effect, destroying the ecological environment and hindering sustainable development. Carbon emission efficiency, which can accurately estimate carbon dioxide emissions per unit of GDP, draws many academics' attention, who study the environment as a crucial component of evaluating environmental performance. Therefore, how to improve carbon emission efficiency has become a problem that people need to face. In order to identify the ways to achieve carbon sustainability, governments and academics are committed to researching the factors that affect carbon emission efficiency.

Theoretically, carbon emission is the result of many factors such as the development stage, economic structure, and consumption pattern. As the core driving force in promoting total factor production and economic transformation, technological innovation is considered as the main factor affecting carbon emission. The new endogenous growth theory holds that modern economic growth mainly comes from human capital, such as education, training, further learning, medical treatment, and migration, among which education is the main way of human capital accumulation. Therefore, it is imperative to explore the key roles of education and technology on carbon emission efficiency.

To create high-quality development of agglomeration economy, China has been devoted to optimizing the internal structure of urban agglomeration and enhancing the capacity of innovative policy to build an ecological security barrier (Guo et al., 2022). The Yangtze River Delta and the Guangdong–Hong Kong–Macao Greater Bay Area are not the only regions with the most prosperous economy, the highest level of development in education and science and technology, and the fastest speed of transformation and upgradation of the industrial structure in China but also low-carbon pilot cities with the theme of replacing old and new driving forces, which are highly representative. Thus, this paper chooses the two urban agglomerations to analyze the effect of technological innovation on the carbon emission.

At present, China is facing the dual challenge of balancing economic development and controlling carbon emissions. It is necessary to put forward this question: Can the "upgrading of education" promote the carbon emission efficiency of urban agglomeration? Can technology service industry be used as the future undertaker of economic growth to improve urban carbon emission efficiency? Based on these two problems, this paper adopted the DEA-undesirable model and the Malmquist index model, using the Yangtze River Delta and the Guangdong–Hong Kong–Macao Greater Bay Area urban agglomeration during 2010–2021, as research samples. Based on this, a panel tobit model was constructed to systematically investigate the impacts of the education level, technological development, and their interaction on the carbon emission efficiency of the Yangtze River Delta and the Guangdong–Hong Kong–Macao Greater Bay Area urban agglomeration.

This paper is structured as follows: Section 2 reviews the previous research studies. Section 3 puts forward the hypothesis of the influencing mechanisms of technological innovation and education on carbon emission efficiency. Section 4 illustrates the methods and data sources, followed by the research results in Section 5. Section 6 presents the conclusion, including the research limitations and prospects.

2 Literature review

The existing literature has fully demonstrated the important impact of carbon emission efficiency on economic growth and puts forward the concepts of carbon productivity (Wang et al., 2017), carbon emission intensity (Wang and Zheng, 2020), carbon emission performance (Wang et al., 2020), and carbon emission accounting (Hu et al., 2022). These studies are closely related to the coordinated realization of sustainable economic development and carbon reduction in the Report on The Work of The Government of 2021. Carbon emission efficiency fully expresses the supporting and leading role of carbon reduction in high-quality economic development, consistent with the relevant discussion of opening up the path of green and low-carbon transformation development with Chinese characteristics in the academic circle and police departments.

On the whole, the previous studies on the influencing factors of carbon emission efficiency are mostly conducted by generalized method of moments (GMM) estimation in academia, mainly including the urbanization rate (Zhou et al., 2022), innovation input (Gao et al., 2019), energy intensity (Lv et al., 2015), and environmental regulation (Long et al., 2013). Existing studies on higher education promoting the development of a low-carbon economy have been relatively mature. Educational level is an important factor to stimulate public awareness of environmental protection and to fulfill social responsibilities. Some scholars make use of CSS2013 data for research, reflecting that the more educated the workers are, the more likely they are to comply with environmental laws and regulations and fulfill legal obligations of environmental protection.

The new information technologies featuring big data, cloud computing, artificial intelligence, and the Internet of Things are the core factors driving the rising of the sixth Kondratyev long wave cycle, with the carbon emission efficiency of cities greatly improved. Empirical studies by using dynamic spatial econometric models show the influence of technological innovation on clean combustion and flexible use of fossil energy. Also, emission reduction can be achieved by combining carbon capture, usage, and storage (CCUS) technology and other means (Yang et al., 2021). Some scholars advocate the concept of low-carbon environmental protection "park city" and propose that the economic system of low-carbon development should embrace technological innovation. Carbon emissions can be reduced by strengthening key generic technologies of carbon neutrality and zero-carbon industrial process reengineering technologies through technology fusion and process optimization (Philip et al., 2022). In addition, other scholars' studies on the impact of technological development on industrial economic efficiency (Li, 2019), regional innovation performance (Hajek et al., 2019), environmental economy, and sustainable development (Yang et al., 2020) also provide an important reference for this paper.

It can be seen that there is a close correlation between the education level, technological development, and low-carbon economy. The academic research on low-carbon economy is mainly devoted to carbon emission efficiency, with the scope limited at several aspects: first, most existing research only involved the carbon emission management intensity or single-factor carbon emission efficiency, with little insight into the total factor carbon; second, the third-party effect of the education level on technological innovation and carbon emission efficiency remains to be examined; third, in terms of the research scale, most studies are extensively carried out from the international, national, and

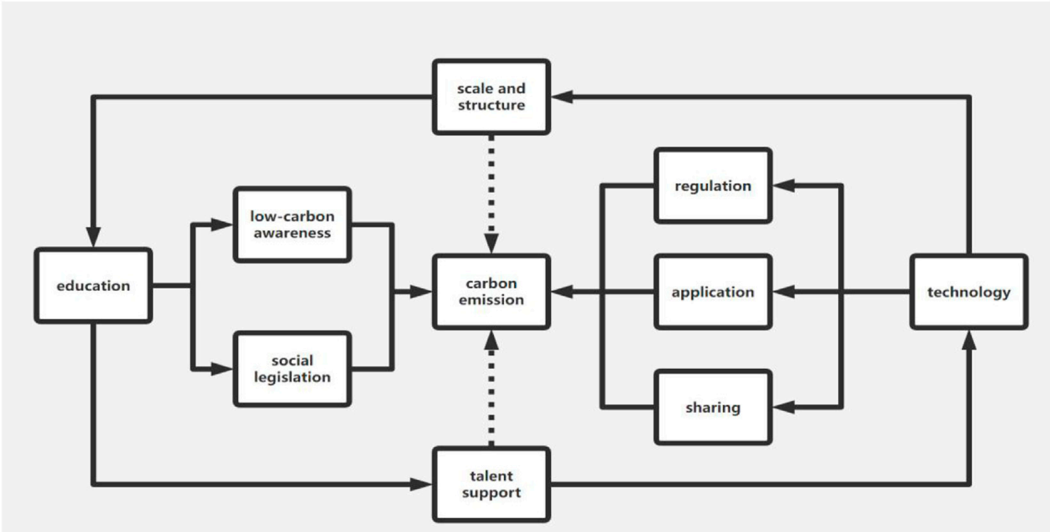

FIGURE 1
Influencing mechanism of education and technology on carbon emission.

provincial levels, cities, and enterprises, while there are few studies based on economic circle and urban agglomeration. Different from existing research studies, this paper specifies the scale of samples with urban agglomerations through the construction of GMM estimation to analyze the impacts of the education level, technological development, and their interaction on urban carbon emission efficiency.

3 Education and urban carbon efficiency

The influencing mechanism of education and technology on carbon emission efficiency is explained in Figure 1.

3.1 Education and urban carbon efficiency

First, education is conducive to the improvement of carbon emission efficiency. As the public education level and understanding of environmental protection laws have increased, the public now frequently uses legal ways to persuade polluters to cut carbon emissions when their operations endanger public health. Second, educated human capital can enhance public awareness of low-carbon alternatives. To some extent, higher education groups find it easier to live a low-carbon lifestyle. They can convert theoretical knowledge into practice and enhance public awareness of low-carbon living through professional human capital, thus contributing to carbon emission reduction.

Therefore, the first hypothesis of this paper can be concluded as follows: H1: Education is conducive to improving urban carbon emission efficiency.

3.2 Scientific technology development and urban carbon efficiency

First, the development of scientific technology has opened up new channels of network supervision. 5G and IPV6 technologies have dramatically changed the means, medium, and form of information dissemination. As the public increasingly calls for the right to know and supervise the environment, they can participate in the environmental governance through the environmental reporting hotline "12369," national government affairs service platforms, official Weibo and WeChat accounts, and other online channels. The pollution emission behaviors can be restricted to some extent when the reputation and stock price of polluters get affected by a large amount of pollutants produced, discharged, and the degree of environmental pollution. Second, the development and application of low-carbon technologies will reduce the carbon emission intensity. Technological innovation can produce profound changes in the future energy structure and utilization. For example, "electric vehicles," "semiconductor lighting," "clean coal utilization," and other new energy projects have improved the efficiency of urban carbon emission. Third, technological development improves urban carbon emission efficiency through sharing effects, obtaining innovation advantages, and realizing the improvement of carbon emission efficiency. The development of science and technology makes the connection between cities closer and makes use of formal and informal relationships to effectively share and integrate human, financial, material, and other resources, so as to gain innovative advantages and realize the improvement of carbon emission efficiency.

On this basis, the second hypothesis can be drawn as follows: H2: Technology is conducive to improving urban carbon emission efficiency.

3.3 "Science and technology innovation plus education" and urban carbon emission efficiency

As a revolution in the field of social production, "science and technology innovation plus education" plays an important role in the allocation of educational resources. On the one hand, higher education, acting as the incubator of talents and knowledge, meets the demands of society for innovative professionals in line with the times. In the process, a new educational ecosystem is often built where higher education becomes a gathering area and concentration of innovation, adhering to the educational concept of flexibility, openness, and diversity. On the other hand, the structure and scale of higher education can be adjusted through the employment substitution effect and compensation effect. In other words, the combination of science and technology innovation and education replaces the ordinary labor force with artificial intelligence robots to a great extent and energizes low-carbon economy through distance education and the integration of educational resources across time and space, which gives rise to the third hypothesis of this paper: H3: The deep integration of "technological innovation plus education" prompts urban carbon emission efficiency.

4 Measurement and analysis of carbon emission efficiency

4.1 Specification of the model

Data envelopment analysis (DEA) has the defect of scaling up or reducing in the same proportion based on radial and angle problems. Traditional non-parametric DEA methods often overestimate the efficiency of the decision-making unit due to radial selection and relaxation problems. To reflect the nature of urban carbon emission efficiency more objectively, Tone proposed that the relaxation variables of input and output should be directly placed into a non-angle and non-radial SBM-undesirable model of the objective function, avoiding input factor redundancy and undesired error generation in the traditional DEA model (Barros and Wanke, 2017). Based on this, this paper adopted the DEA–SBM-undesirable model to evaluate the carbon emission efficiency of the Yangtze River Delta and the Guangdong–Hong Kong–Macao Greater Bay Area urban agglomeration. Its model form is as follows.

Suppose there are n independent decision-making units (DMUs) in a production system with m inputs. Each DMU has three corresponding vectors: input factor X, expected output Y^g, and unexpected output Y^b, where the input matrix $X = \{X_1,X_2,.,X_n\}$, $X > 0$; the expected output matrix $Y^g = \{Y_1^g,Y_2^g,., Y_n^g\}$, $Y^g>0$; and the undesired output matrix $Y^b = \{Y_1^b,Y_2^b,., Y_n^b\}$, $Y^b>0$. Assuming that the unchanged reward scale is the production possibility, we set $p= \{(X, Y^g, Y^b)|X \geq X\lambda, Y^g \leq Y^g\lambda, Y^b \leq Y^b\lambda, \lambda \geq 0\}$, where λ is the density vector and represents the weight. According to Tone's method, the SBM model of non-expected output can be expressed as follows:

$$\rho^* = min \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{\lambda 0}}}{1 + \frac{1}{s_1+s_2}\left(\sum_{r\neq 1}^{s_1}\frac{s_r^g}{y_{r_0}^g} + \sum_{r\in 1}^{s_2}\frac{s_r^b}{y_{r_0}^b}\right)} \quad (1)$$

.

According to the formula, the objective function p^* expresses the efficiency value to be measured, and $p^* \in [0,1]$, where S^- represents the excess input, S^g represents the insufficient expected output, Sb represents the redundancy of the unexpected output, and λ is the weight vector. When $p^* = 1$, $S^- = S^g = S^b$ are all equal to 0, indicating that S^-, S^g, and Sb do not exist when the DMU is completely efficient. When $p^* \neq 1$, it means that the DMU is inefficient or has efficiency loss. In this case, the efficiency can be improved by adjusting the relaxation scale of the optimization factor of the input and output.

4.2 Data source and variable selection

Urban agglomeration refers to a relatively complete urban agglomeration functioning as a comprehensive center, which gathers considerable cities within a certain range through the modern transportation and information network. The development of urban agglomeration is an important way to optimize the urban function and layout. With the proposal of the new urbanization planning strategy, cities have become the center of the service industry. In order to specifically reflect the economic development process of the Yangtze River Delta and the Guangdong–Hong Kong–Macao Greater Bay Area urban agglomeration, relevant data are selected, published in China Urban Statistical Yearbook, Statistical Bulletin of National Economic and Social Development, and the official website of the National Bureau of Statistics from 2010 to 2021, with certain missing statistics supplemented based on interpolation.

The index system is constructed from the perspective of "resource input–economic output–pollution output," as shown in Table 1. The capital input is calculated through the sustainable inventory method, based on Humphrey's measure (Humphrey et al., 1984). The labor input selects employees from various cities over the years, on the basis of the work of Carvajal et al. (2012). Energy consumption refers to the work of Azadeh, which measures the whole society's electricity consumption (Azadeh et al., 2013). The expected output refers to the work of Groen (2010 as the base period); GDP is taken as the index of the desirable output, with the GDP deflator of each city made by the National Bureau of Statistics for deflating treatment (Groen et al., 2013). The non-desired output is calculated by using the calculation method given in the Second Volume (Energy) of the National Greenhouse Gas Inventory Guide of IPCC, based on the nine kinds of energy consumed in various regions and converted into heat and emission coefficients (Behera et al., 2015).

4.3 Analysis of carbon emission efficiency results

According to the production function, the weight of the expected output and the non-expected output is 50% by default in this paper, and the threshold varying from 0.2, 0.4, 0.6, 0.8, and 1 is set to divide the efficiency value into five levels: low efficiency, low efficiency, medium efficiency, high efficiency, and efficiency. As shown in Table 2, there are only 30 efficient cities, accounting for 9.091%; 15 high-efficiency cities (4.545%); and 39 medium-efficiency cities (11.818%). The number of less-efficient cities

TABLE 1 Carbon emission evaluation index system.

Index	Variable	Measure	Source of indicator
The input variable	Labor input	The total number of employees(ten thousand)	Barros, CP; Wanke, P
	Capital input	Capital stock (100 million Yuan)	Humphrey, C R; Gibson, J T; Cox, J F
	Energy input	Electricity consumption (100 million kW·h)	Carvajal, Manuel J; Deziel, Lisa; Armayor, Graciela M
The output variable	Desirable output	GDP (100 million Yuan)	Azadeh, A; Saberi, M; Asadzadeh, SM; Anvarian, N
	Undesirable output	CO2 emissions (tons)	Groen, JJJ; Paap, R; Ravazzolo, F

TABLE 2 Distribution of carbon emission efficiency levels in urban agglomeration from 2010 to 2021.

Efficiency class classification	Efficiency grade interval	Number of efficiency values	Proportion (%)
Inefficiency	(0.2,0.4]	85	25.758
Low efficiency	(0.4,0.6]	161	48.788
Medium efficiency	(0.6,0.8]	39	11.818
High efficiency	(0.8,1]	15	4.545
Effective rate	1	30	9.091

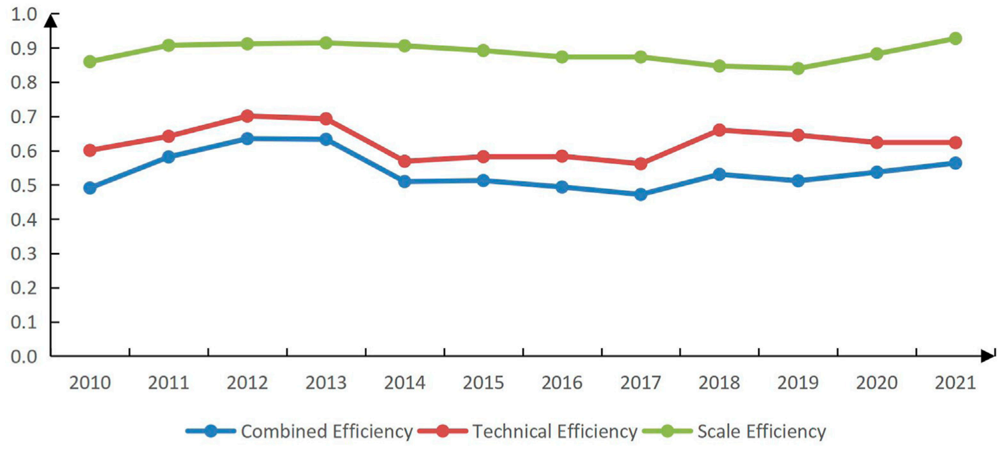

FIGURE 2
Global benchmark of carbon emission efficiency from 2010 to 2021.

reached 161 in total, accounting for approximately 48.788%, and 85 inefficient cities (25.758%). The DEA-Solver Pro 5.0 software is used to make an empirical analysis of the carbon emission efficiency of the Yangtze River Delta and the Guangdong–Hong Kong–Macao Greater Bay Area urban agglomeration during 2010–2021. The result shows that the carbon emission efficiency of the sample is in an unbalanced state, as demonstrated in the previous academic literature (Lu et al., 2022). Thus, considerable work has to be carried out to promote the green and low-carbon transformation of the energy and resource structure, and the Yangtze River Delta and the Guangdong–Hong Kong–Macao Greater Bay Area city clusters still have a lot of room for development to improve the carbon emission efficiency.

The annual mean variation of carbon emission efficiency in the Yangtze River Delta and the Guangdong–Hong Kong–Macao Greater Bay Area urban agglomeration from 2010 to 2021 is shown in Figure 2. The changes of technical efficiency and comprehensive efficiency show a trend of homogeneity, which indicates that technological progress is the main internal driving force for the improvement of urban carbon emission efficiency (Liu et al., 2018). The carbon emission efficiency shows a steady growth trend on the whole, most of which distributes the low-efficiency stage (0.4 and 0.6), proving that the Yangtze River Delta and the Guangdong–Hong Kong–Macao Greater Bay Area urban agglomeration bears the mission of balancing economic growth and low-carbon development, and science and technology would

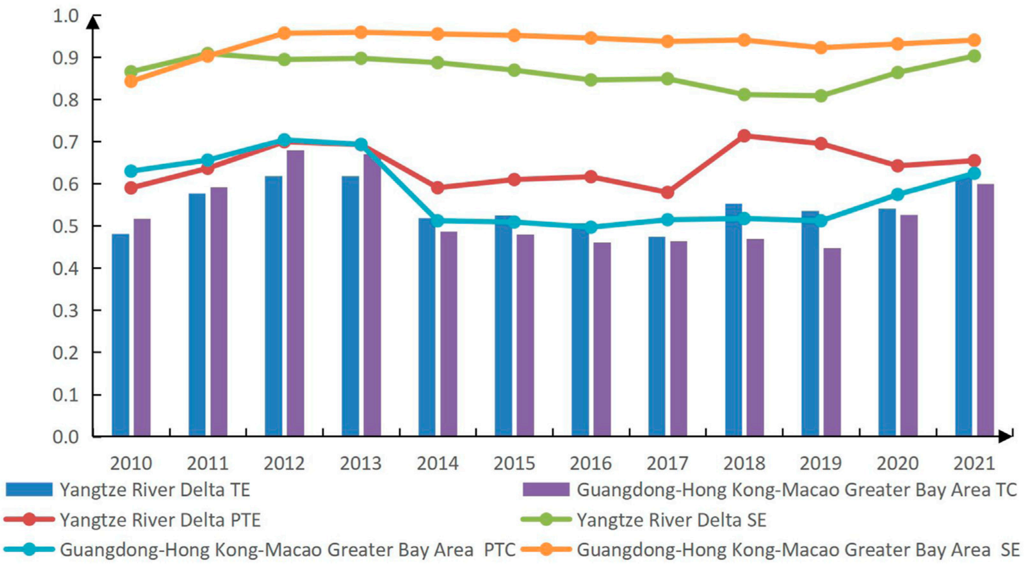

FIGURE 3
Carbon emission efficiency of urban agglomeration from 2010 to 2021.

TABLE 3 Carbon emission efficiency of urban agglomeration from 2010 to 2021.

	Global benchmark			Yangtze river delta			Guangdong–Hong Kong–Macao Greater Bay Area		
	TE	PTE	SE	TE	PTE	SE	TE	PTE	SE
2010	0.491	0.601	0.859	0.481	0.590	0.866	0.517	0.630	0.843
2011	0.581	0.642	0.907	0.577	0.636	0.909	0.592	0.656	0.903
2012	0.635	0.701	0.912	0.618	0.700	0.895	0.680	0.704	0.957
2013	0.633	0.693	0.914	0.619	0.693	0.898	0.671	0.693	0.959
2014	0.510	0.569	0.906	0.518	0.590	0.887	0.487	0.512	0.955
2015	0.513	0.582	0.892	0.525	0.610	0.869	0.480	0.509	0.952
2016	0.494	0.584	0.873	0.506	0.616	0.846	0.461	0.497	0.946
2017	0.472	0.562	0.873	0.475	0.579	0.849	0.464	0.514	0.938
2018	0.531	0.660	0.847	0.554	0.714	0.812	0.470	0.517	0.941
2019	0.512	0.645	0.840	0.536	0.695	0.808	0.448	0.512	0.923
2020	0.537	0.624	0.882	0.541	0.642	0.864	0.527	0.574	0.932
2021	0.564	0.603	0.927	0.616	0.655	0.903	0.592	0.624	0.941

become the core driving force for building the future urban carbon emission reduction system.

As shown in Figure 3, there was a similar state of oscillation in the trend of the annual Malmquist index of carbon emission efficiency in the Yangtze River Delta and the Guangdong–Hong Kong–Macao Greater Bay urban agglomeration from 2010 to 2021. The urban agglomeration of the Yangtze River Delta increased slowly from 2010 to 2013, began to decline after 2013, reached the lowest point in 2017, and then, showed an upward trend with an average value of 0.541. The Guangdong–Hong Kong–Macao Greater Bay city cluster was on the rise as a whole and fluctuated repeatedly from 2010 to 2021, with an average value of 0.527. Based on the analysis of the changes from 2010 to 2021, it was found that the growth range of the Yangtze River Delta urban agglomeration was higher than that of the Guangdong–Hong Kong–Macao Greater Bay urban agglomeration.

In order to clarify the reasons for the change of carbon emission efficiency in the Yangtze River Delta and the Guangdong–Hong Kong–Macao Greater Bay urban agglomerations, this paper also decomposed the annual Malmquist index of the two urban agglomerations, and the results are shown in Table 3. In general, the efficiency scale of the two urban agglomerations is higher than that of the technical efficiency of the decade, indicating that the improvement of carbon emission efficiency is mainly due to the progress of technology. More specifically, there are obvious gradient differences between the internal development stage of the Yangtze River Delta urban agglomeration and the regional economy. For example, different regions have their own advantages of resources and technology. Shanghai is the regional leader in terms of education, Jiangsu's advanced manufacturing industry is dense, and Zhejiang's private economy and Anhui's emerging industry are developing rapidly. These resource differentiation and synergic advantages bring high scientific research output to many emerging cities in the Yangtze River Delta. However, the Guangdong–Hong Kong–Macao Greater Bay Area city cluster is losing its original regional merit with the rise of increasingly prominent problems such as labor price, international trade friction, and serious environmental pollution in recent years, despite its superiority in the reform and opening up policies. Except for Shenzhen, Guangzhou, Hong Kong, and Macao, other cities show a lack of sustained momentum for a relatively low proportion of high-tech industries and knowledge-intensive and technology-intensive industries. They are dominated by labor-intensive enterprises and mid-end and low-end manufacturing industries. In general, there is a small gap in carbon emission efficiency between the Yangtze River Delta urban agglomeration and the Guangdong–Hong Kong–Macao Greater Bay urban agglomeration, and there is a trend of synchronous development for the future for a long time, as the two urban agglomerations are well matched.

5 Analysis of influencing factors of "science and technology innovation plus education" on carbon emission efficiency

5.1 Model construction and variable selection

Considering that urban carbon emission efficiency also affects the development of science and technology innovation and education, that is, there is a mutual influence between science and technology innovation, education, and the urban carbon emission efficiency, the system generalized method of moments (SYS-GMM) method is selected to estimate the equation model, and the mixed ordinary least squares (OLS) model is used for comparison. In addition, in the data pre-processing, in order to eliminate the influence of extreme values and heteroscedasticity, the control variables are taken from the natural logarithm, and the continuous variables are Winsorized at the upper and lower 1%.

We assume that there is a finite fourth-order moment for each period. However, the (2N*1) vectors, $f_t(\vartheta)$ and $g_r(\vartheta)$, are as follows:

$$f_t(\vartheta) = h_t \times \omega_t,$$

where $h_t = [1, z_{mt}], \omega_t = Z_t - \alpha - \beta Z_{mt}, \vartheta = [\alpha, \beta]$.

$$g_r(\vartheta) = \frac{1}{T}\sum_{t=1}^{T} f_t(\vartheta).$$

According to the model designed in this study, it is assumed that there are moment conditions, $E[f_t(\vartheta)] = 0$. Also, the GMM model is used to choose an estimator to make sure that the linear combination of moment conditions is zero, in particular, for a certain A matrix. Its rows have dimensions equal to the number of parameters, and columns have dimensions equal to $g_t(\alpha)$ and ϑ, which makes $A_{gT}(\vartheta) = 0$.

When A* satisfies,

$$A^* = D_0 S_0^{-1},$$

$$D0 = E\left[\frac{\partial_{gt}(\vartheta)}{\partial \vartheta}\right],$$

$$S_0 = \sum_{-\infty}^{+\infty} E\left[f_t(\vartheta) f_{t-l}(\vartheta)\right].$$

Then, the distribution of ϑ is asymptotically normal and satisfies $\partial N(\partial, \frac{1}{T}[D_0 S_0^{-1} D_0]^{-1})$.

Original hypothesis: $\alpha = 0$; using the consistent estimate Dr and Sr for D0 and SO, the following statistics are available:

$$J_2 = T\alpha\left[R\left[D_T S_T{}^{-1} D_T\right]R\right]^{-1} \alpha \chi_{2N},$$

where $R = 1_N \times (1, 0)$.

We assume for this reason

$$H_0: \beta = 0,$$

$$H_A: \beta \neq 0.$$

For this purpose, the validity of the instrumental variable selection and fitting effect was judged by AR(1), AR(2), and the Sargan test, and the following model test was established:

$$\ln CE_{it} = \beta_0 + \beta_1 \ln IT_{it} + \beta_2 \ln EDU_{it} \times \ln IT_{it} + \sum \beta_n \ln control_{it} + \varepsilon_{it}.$$

In the aforementioned formula, time is represented by i, region is represented by t, β0 represents the cross-sectional effect, β1-βn represents the estimation coefficient, ε represents the random error term, and "control" represents all control variables.

Explained variables: Considering the possible non-linear effects, combined with resource utilization and environmental costs, the natural logarithm of urban carbon emission efficiency (CEE) was taken for processing.

The instrumental variables used in the GMM model are the first and second lagged terms of the endogenous variables of education and technology. The reason for using these instrumental variables is mainly because the lagged terms of the endogenous variables are directly correlated with the endogenous variables instead of the dependent variable, which satisfies the conditions for the use of instrumental variables.

Core explanatory variable: Referring to Varela-Mato's research education level (lnEDU), the number of students in urban colleges and universities (10,000) was measured (Varela-Mato et al., 2012). According to Yang's research and technological development degree (limit), the number of urban researchers (10,000) was measured (Yang and Wei, 2019). In order to investigate the degree of substitution and complementarity between science and technology development and education more conveniently, their

TABLE 4 Descriptive statistical analysis.

Variable	Observation	Average	Median	Standard deviation	Minimum value	Maximum value
lnCE	330	0.803	0.869	0.956	−1.146	3.394
lnEDU	330	1.900	1.787	0.980	0.185	4.723
lnIT	330	−0.148	−0.460	1.218	−2.408	3.027
lnEDUxlnIT	330	0.672	−0.644	3.454	−2.665	13.24
lnED	330	3.875	3.809	0.746	2.112	5.952
lnID	330	3.856	3.885	0.188	2.787	4.325
EDU	330	64.84	45.12	59.65	8.269	384.4
lnINT	330	−0.736	−0.844	1.215	−3.219	3.544
lnFDI	330	3.875	3.809	0.746	2.112	5.952

interaction term, lnEDUxlnIT, was introduced into regression analysis to improve the reliability of the test.

Control variables: According to domestic and foreign research results and considering the internal relationship between the independence and comprehensiveness of index selection, the following measurement criteria are adopted: The economic development (ED) level is measured using the GDP growth rate of each city (Wang et al., 2014). There are obvious differences in the economic level between the Yangtze River Delta and the Guangdong–Hong Kong–Macao Greater Bay city clusters, and the level of economic development directly affects urban carbon emission efficiency. The industrial structure is measured using the ratio of the secondary industry to GDP (Chen and Li, 2011). Urban industrialization makes the rate of resource and environment loss exceed its carrying capacity, which is bound to interfere with urban carbon emission efficiency. Foreign direct investment (FDI) is expressed by the ratio of the total amount of actually utilized foreign capital to GDP (Ismail and Yuliyusman, 2013), and the export value is calculated by converting the average exchange rate of 12 months in the current year into RMB. Relying on the regions with high external orientation, the dependence of the foreign capital in the Yangtze River Delta and the Guangdong–Hong Kong–Macao Greater Bay city cluster must be taken into consideration. Internet popularity is represented by the number of Internet users, referring to the practices of the China Internet Network Information Center (CNNIC) and Nepomuceno et al. (2020). The descriptive statistical results of the main variables are shown in Table 4.

5.2 Correlation analysis

This study used the Pearson correlation coefficient to examine the correlation among the variables, and the results are shown in Table 5. According to the correlation analysis, the correlation coefficient between the educational level (lnEDU) and carbon emission efficiency (lnCE) is 0.136, which is significantly positive at 5%, preliminarily verifying hypothesis 1; the correlation coefficient between the technological development level (lnIT) and carbon emission efficiency (lnCE) is 0.098, which is significantly positive at 10%, preliminarily verifying hypothesis 2; and similarly, the correlation coefficient of the interaction between the technological development and educational level (lnEDUxlnIT) and carbon emission efficiency is 0.014, which is significantly positive, preliminarily verifying hypothesis 3.

In addition, the sample data of this study are an unbalanced panel data, and Stata commands are used to detect the variance inflation factor of the variables. The results show that the VIF coefficients of all explanatory variables are less than 3, indicating that there is no serious multicollinearity between the observed variables, and the sample data can be put into the regression model for further testing.

5.3 Full-sample test

Since this paper uses a model (4.1) system GMM regression model for analysis of the baseline regression test, robustness test, and heterogeneity test, the premise of the establishment of the system GMM regression model needs to pass two tests: first is the autocorrelation test of the perturbation term; that is, there is the first-order autocorrelation of the perturbation term, but the second order and higher order of the perturbation term will not be autocorrelated, which needs to be tested by using the Arellano–Bond method; the second is that since multiple instrumental variables are used, an over-identification test is required to ensure that the instrumental variables used are all valid, and the over-identification test requires the Sargan test after removing the robust standard errors of model I and regressing it again. Before conducting regression analysis, we also performed cross-sectional dependence tests on the panel data used using Pesaran’s test and Friedman’s test. The results, shown in Table 6, do not reject the null hypothesis that there is no cross-sectional correlation. This also indicates that there is no contemporaneous interference in the disturbance term of our regression, which leads to biased estimation results.

Table 7 reports the estimation results of the systematic GMM regression model, in which the explanatory variable is the urban carbon emission efficiency, and the results of the autocorrelation and over-identification test of the nuisance term of the systematic GMM regression model show that the p-value of AR(1) is 0.006,

TABLE 5 Correlation analysis results.

	lnCE	lnEDU	lnIT	lnEDUx ~ T	lnED	lnID	EDU	lnINT	lnFDI
lnCE	1								
lnEDU	0.136**	1							
lnIT	0.098	0.802***	1						
lnEDUxlnIT	0.014	0.815***	0.903***	1					
lnED	0.755***	0.166***	0.0800	0.009	1				
lnID	0.167***	0.416***	0.328***	0.477***	0.132**	1			
EDU	0.707***	0.231***	0.173***	0.046	0.889***	0.0930	1		
lnINT	0.004	0.457***	0.403***	0.487***	0.005	0.236***	−0.0420	1	
lnFDI	0.755***	0.166***	0.0800**	0.009*	0.089**	0.132**	0.889***	0.005*	1
VIF		1.23	1.17	1.29	1.15	1.28	1.36	1.45	1

TABLE 6 Cross-sectional dependence test.

	Statistic	*p*-value
Pesaran's test	0.909	0.363
Friedman's test	16.908	0.596

which is less than 0.1 over the significance test, while the *p*-value of AR(2) is 0.803, which is higher than 0.1. It shows that the perturbation term has the first-order autocorrelation at the 1% significance level, but no second-order autocorrelation. Also, it can be decided that the model difference equation avoids residual autocorrelation, so system GMM regression model I passes the autocorrelation test of the perturbation term. In addition, because system GMM model I uses instrumental variables, it also needs to be tested for over-identification of instrumental variables, and after removing the robust standard deviation and regression again, the Sargan test is performed, and the *p*-value of 0.692 is obtained, which is higher than 0.1; that is, the original hypothesis of "all instrumental variables are valid" is accepted, so the model I passed the over-identification test for instrumental variables, indicating the reasonableness of the selection of instrumental variables and the applicability of the data to the systematic GMM model for estimation.

The results of the systematic GMM and mixed OLS estimation are reported in model I in Table 7. It was found that the coefficient of education level positively affecting urban carbon emission efficiency is 0.126, which implies that the education level can promote urban carbon emission efficiency, and the results are consistent with the original hypothesis, and a similar finding was presented by Chao An (Liu et al., 2018). The public has the right to know, participate, express, and supervise carbon emissions, and the education level of workers is an important factor affecting environmental protection. Strengthening the education and publicity of carbon emission reduction will provide a good social atmosphere and a solid social foundation for improving the efficiency of urban carbon emissions and building a beautiful China. Accordingly, hypothesis 1 is confirmed. The regression coefficient of the level of science and technology development affecting urban carbon emission efficiency in model II is 0.214, which is significantly positive at the 1% level and both pass the 1% significance level test, and this study accepts the original hypothesis, which is similar to the results of Wang et al.'s (2022b) study. China's scientific and technological innovation is still in its infancy and has a wide space for development, and while broadening the breadth of energy sources, scientific and technological innovation can also promote energy efficiency, reduce total energy consumption, and use the spillover effect of technological efficiency to offset the expansion effect of carbon emissions in the production and living process and ultimately promote the efficiency of carbon emissions. Accordingly, hypothesis 2 is confirmed.

In addition, in order to make a comparison and to judge whether the regression results of GMM are robust or not, OLS (model II) with mixed regression is attached, and from the results, it can be seen that the text robustness test is a success.

According to the social survey report in the Statistical Bulletin of National Economic and Social Development of the People's Republic of China in 2021, the main causes of urban environmental pollution are the excessive use of high-carbon energy (42.7%) and the limited environmental awareness of the public (35.6%). This reveals that the carbon emission efficiency of the Yangtze River Delta and the Guangdong–Hong Kong–Macao Greater Bay Area urban agglomerations is closely related to levels of science and technology and education. In model 4, the interaction term (lnEDUxlnIT) between science and technology development and education level was verified, and the corresponding coefficient of the interaction term was significantly positive. It proves that higher education could maintain and even enhance the positive influence of science and technology development on carbon emission efficiency to a certain extent. With the improvement of the education level, people gradually increase their awareness of energy conservation and emission reduction and pay more attention to the improvement of the quality of life. Thus, the contradiction of the low utilization rate of science and technology caused by the low education level can be effectively resolved. This finding demonstrates hypothesis 3.

As we all know, in terms of the series of control variables, the results represented by model 4 indicate that the regression

TABLE 7 Estimation results of the effects of the education level and technology development level on the efficiency of urban carbon emissions.

	ModelI	ModelII
	System GMM	Hybrid OLS
EDU	0.126*** (2.784)	0.021*** (2.318)
IT	0.214*** (−4.761)	0.139*** (−3.392)
EDU x IT	0.349*** (1.834)	0.284*** (1.732)
lnEDUxlnIT	0.231*** (1.092)	0.210*** (2.371)
LnED	0.159*** (3.729)	0.326* (1.632)
LnID	0.080** (3.698)	0.115*** (3.519)
LnFDI	0.189*** (1.479)	0.154*** (1.021)
LnINT	0.362*** (−5.903)	0.479*** (−5.048)
Constant term	0.669** (3.821)	0.134*** (3.063)
AR(1) Pro b	0.018	
AR(2) Pro b	0.803	
Sargan Pro b	0.692	

*** indicates passing the 1% significance level test, ** indicates passing the 5% significance level test, * indicates passing the 10% significance level test, and data in parentheses are t-values. The statistics in the brackets represent "t"; ***, **, and * show significance at the 1% level, 5% level, and 10% level, respectively.

coefficient of the economic development level on urban carbon emission efficiency is 0.159 and significant at the 1% level, which is consistent with the study of Luo (Yang et al., 2019a). The improvement of the economic development level in the Yangtze River Delta and the Guangdong–Hong Kong–Macao Greater Bay Area urban agglomerations is conducive to the upgrading of the energy consumption structure, which stimulates the emergence of new technologies, thus greatly improving the utilization efficiency of clean energy and carbon emission reduction. The effect of the industrial structure on urban carbon emission efficiency is significantly positive, and the regression coefficient is 0.080, which passes the significance test of 1%, consistent with the study of Li (Li et al., 2017). With the continuous advancement of the industrial upgrading degree, the proportion of low-end industries with high energy consumption and high pollution decreases and gradually shifts or withdraws from the stage of economic development, while strategic emerging industries and high-end manufacturing industries become the pillar industries of industrial economy and even the whole economic system. In recent years, technology-intensive industries, such as new energy vehicles, industrial robots, integrated circuits, biomedicine, and aerospace equipment manufacturing, in the Yangtze River Delta and Guangdong–Hong Kong–Macao Bay area have become new engines of driving economic growth, while the growth of labor-intensive industries, such as metal manufacturing, garment and textile, food processing, and building construction, has slowed down, and the manufacturing industry has moved from the middle- and low-end levels to the middle- and high-end levels, which greatly improves the efficiency of urban carbon emissions. The regression coefficient of the degree of external development is positive and significant, which is consistent with the findings of Qu (Yang et al., 2019b). As enterprises in the Yangtze River Delta and the Guangdong–Hong Kong–Macao Greater Bay Area continue to become global, the overseas investment allows enterprises to break down trade and tariff barriers in the international market, alleviating the inhibitory effect of factor market distortions in improving urban carbon efficiency and, thus, improving resource mismatch. With a positive coefficient of 0.362 and passing the 1% significance level test, Internet development on carbon emission efficiency also provides information support for the improvement of carbon emission efficiency, which is in line with the findings of Yang (Yang et al., 2022). People who use the Internet platform can supervise and report the events that violate the environmental system, especially in the Yangtze River Delta and Guangdong–Hong Kong–Macao Greater Bay Area city clusters, where the Internet infrastructure is well built, and the Internet publicity is extremely popular than the traditional paper media, which is more conducive to significantly improving carbon emission efficiency.

5.4 Heterogeneity test

To ensure the reliability of the research results, the following heterogeneity test is conducted: the Yangtze River Delta urban agglomeration and the Guangdong–Hong Kong–Macao Greater Bay urban agglomeration are divided into large cities and small cities using the economic dimension and the population dimension. The regression results are detailed in Table 8. The particularity of urban agglomerations becomes more and more obvious when the differences become increasingly larger.

Considerable scientific reports and literature all believe that carbon dioxide emission is prone to the developing areas. Due to the lack of funds, transportation, science and technology, and education resources, less-developed cities produce urban carbon emissions (Jie et al., 2015). Considering that the carbon emission

TABLE 8 Heterogeneity test.

	Economic dimension heterogeneity		Population dimensional heterogeneity	
	Large-scale cities	Smaller cities	Large-scale cities	Smaller cities
Variable	Model 1	Model 2	Model 3	Model 4
EDU	0.167** (1.14)	0.389*** (1.79)	0.284*** (2.18)	0.176*** (3.17)
IT	1.158** (−5.00)	2.069** (−1.43)	0.209** (−1.17)	2.081*** (−5.55)
EDU x IT	0.146** (4.00)	0.127** (1.30)	0.351 (2.37)	0.046*** (4.72)
LnED	0.386** (3.57)	0.312** (1.39)	0.057 (1.53)	0.272** (2.84)
LnID	0.053 (0.317)	0.647** (1.17)	0.374** (1.31)	0.486* (1.73)
LnFDI	0.419** (1.203)	0.158** (1.43)	0.152** (1.25)	0.301** (2.47)
LnINT	0.167** (1.206)	−0.005 (−0.16)	0.234 (0.12)	0.104* (1.49)
Constant term	−5.094*** (−1.67)	−5.438*** (−2.50)	−4.482*** (−4.29)	−7.403*** (−5.18)

*** indicates passing the 1% significance level test, ** indicates passing the 5% significance level test, * indicates passing the 10% significance level test, and data in parentheses are the t-values.

efficiency is economically oriented, the sample urban agglomerations are divided as large-scale cities and small-scale cities based on GDP and the population size. As shown in Table 8, the regression coefficients of 0.167 for large-scale cities and 0.389 for small-scale cities significantly contribute to the carbon emission efficiency of the Yangtze River Delta city cluster and the Guangdong–Hong Kong–Macao Greater Bay city cluster at the 5% and 1% levels, respectively, in terms of the education level. In terms of science and technology development, the regression coefficient of 1.158 passed the 1% statistical significance test for large-scale cities and 2.069 passed the 5% statistical significance test for small-scale cities, and the heterogeneity is not significantly different in terms of science and technology development. In terms of the interaction term between science and technology innovation and education level, the coefficient of the interaction term 0.146 is significantly positive at the 1% level for large-scale cities and 0.127 is significantly positive at the 5% level for small-scale cities. The results show that the heterogeneity in the economic dimension between the Yangtze River Delta city cluster and the Guangdong–Hong Kong–Macao Greater Bay city cluster is mainly manifested in the gap of the education level, where the excellent education resources in large cities tend to be saturated, and too much investment is of little significance to improve urban carbon emission efficiency; small cities have fragile education ecology and are still in the period of rapid expansion of education scale, and strengthening education investment has a significant effect on the intensity, trend, and level of improvement of urban carbon emission efficiency.

It is well known that population, as one of the dynamic elements of the environment, have an impact on carbon emission efficiency through production, living and consumption behaviors (Liu et al., 2021). China is a vast and populous country, and while urban population expansion provides a favorable environment for capital accumulation in science and technology and education in the Yangtze River Delta city cluster and the Guangdong–Hong Kong–Macao Greater Bay city cluster, it also leads to an increase in CO2 emissions. Therefore, the same heterogeneity exists at the level of the urban population size. Here, cites with a permanent resident population over 1 million are set as large-scale cities, while others with 500,000 to 1 million are set as small-scale cities. As shown in Table 8, in terms of the education level, both large-scale and small-scale cities improving their education level significantly enhance urban carbon emission efficiency at the 1% confidence level, with regression coefficients of 0.284 and 0.176, respectively, which is not a significant difference. In terms of science and technology development, the regression coefficient for large-scale cities is 0.209 and passes the 5% statistical significance test, while the regression coefficient for small-scale cities is 0.281 and passes the 1% statistical significance test. In terms of interaction between science and technology innovation and education, the coefficient of the interaction term 0.046 is significantly positive at the 1% level for small-scale cities, while it is not significant for large-scale cities. The results indicate that the heterogeneity in the population dimension between the Yangtze River Delta urban agglomeration and the Guangdong–Hong Kong–Macao Greater Bay urban agglomeration is mainly manifested in the gap of science and technology level. Small cities are limited by the volume of education and the level of science and technology development, coupled with the lack of location advantages, such as capital, location, policies, and labor. Also, enterprises have vicious competition in limited resources, policies, and projects and insufficient capacity in low-carbon technology research and development. Large urban cities are able to meet the needs of urban low-carbon economic development in terms of market space, network infrastructure, capital, and talent, etc. With the support of science and technology, the development and application of low-carbon clean energy and energy-saving low-carbon technologies are more conducive to enhancing the efficiency of urban carbon emissions.

6 Conclusion and recommendation

6.1 Conclusion

To explore the effects of higher education level (lnEDU), technological development (lnIT), and their interaction terms (lnEDUxlnIT) on carbon emissions efficiency, the GMM model was used to construct a GMM model by analyzing macro and micro data of the carbon emission efficiency of the Yangtze River Delta city cluster and the Guangdong–Hong Kong–Macao Greater Bay Area city cluster from 2010 to 2021. The findings are as follows.

In terms of time trends, the overall carbon emission efficiency of the Yangtze River Delta and Guangdong–Hong Kong–Macao Greater Bay urban agglomerations is low and on the rise from 2010 to 2021, and the increasing emission efficiency of the urban agglomerations is mainly driven by technological progress; in terms of geography, the carbon emission efficiency of the Yangtze River Delta urban agglomeration grows faster than that of the Guangdong–Hong Kong–Macao Greater Bay urban agglomeration. The results of the full-sample regression show that the impact of higher education, technological development, and their interaction on urban carbon emissions has a high positive correlation. Carbon emission efficiency has a positive effect under the influence of control variables such as the level of economic development, industrial structure upgrading, the degree of foreign development, and the popularity of the Internet. The regression results of the heterogeneity test show that the carbon efficiency of the Yangtze River Delta urban agglomeration and the Guangdong–Hong Kong–Macao Greater Bay urban agglomeration show divergent characteristics in different levels of cities, but the significance and direction of the key variables do not change substantially.

6.2 Suggestions for countermeasures

In response to the research results, this study proposes four recommendations: first, establishing a long-term mechanism for securing capital investment, rewarding, and recommending in science and technology, higher education, and other fields to increase financial support for research and development fund projects, especially for technological innovation projects of high-tech enterprises; second, strengthening the protection of intellectual property rights, promoting the application of energy-saving and emission reduction technology achievements, and increasing technology market turnover (carbon capture and storage and other technologies) through multiple platforms online and offline; third, improving institutional accountability in the energy sector, establishing a compensation system for the ecological environment, an incentive system for low-carbon innovation, and a low-carbon GDP assessment system to curb the disorderly development of industries with high pollution and energy consumption, and vigorously developing high-output, low-energy consumption and low-emission service industries; and fourth, promoting the collaboration between enterprises, universities, and research institutions and implementing a number of incentives to cultivate skilled personnel in the cutting-edge field, so as to help China move to the middle and high end of the global carbon emission reduction value chain.

6.3 Research limitations and outlook

Based on the panel data of the Yangtze River Delta and Guangdong–Hong Kong–Macao Greater Bay Area cities from 2010 to 2021, this paper constructs a panel GMM model to analyze the effects of education level, technological development, and their interaction on the efficiency of urban carbon emissions and proposes relevant recommendations in the hope of contributing to the global environmental pollution control. One limitation of this study is about other models, such as the Tapio decoupling model and the semi-parametric space panel vector antiregression model. They can be used to further analyze the complex relationship between education level, technological development, and the interaction between them on urban carbon emissions in the future study. In addition, this study analyses data at a macro level and does not take into account the particular situation of the economic, educational, and technological development of urban agglomerations. There is a need to further study the population and other aspects of information to enrich and improve the conclusions.

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

MT: Conceptualization, writing—review and editing, methodology, and manuscript revision. DX: Acquisition of original data, software, formal analysis, methodology, and manuscript revision. QL: Reference management, funding acquisition, and manuscript revision critically. All authors contributed to the manuscript and approved the submitted version.

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

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2023.1137570/full#supplementary-material

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Does forestry public-private partnership promote the development of China's forestry economy?

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In 2016, China began to introduce the public-private partnership (PPP) model in forestry to explore the promotion and modern development of the nation's forestry industry. Based on the New Governance Theory, this study explores whether PPP, as an essential investment and financing model, can impact China's forestry economy. Based on provincial-level panel data from 2011 to 2020 in China, this study examines the effects of PPP on China's forestry economy using the difference-in-differences (DID) model. This study tests the robustness of the effects using a multi-stage propensity score matching-DID model and explores the mechanism of the effect. The relevant results are threefold. 1) PPP in forestry can significantly enhance China's forestry economy. 2) PPP in forestry can enhance the forestry economy through industrial structure and technological innovation effects. 3) Although forestry PPP has effectively promoted economic growth in forestry, the initial implementation process will have a negative ecological impact. This study provides a scientific basis for promoting forestry PPP and improving China's forestry economy's high-quality and sustainable development.

KEYWORDS

forestry economy, public-private partnership, social capital, DID, PSM-DID, China

1 Introduction

Forestry is a fundamental issue for sustainable national economic and social development, and only if forestry can develop sustainably can human survival and security, as well as economic and social development, be sustainable. Forests have multiple asset and service values. In February 2011, the United Nations Environment Programme (UNEP) released the first global study on the green economy, "Towards a Green Economy: Pathways to Sustainable Development and Poverty Eradication", which identifies forestry as one of the ten critical sectors for global green economic development. The forestry sector plays an irreplaceable role in promoting global sustainable development and global environmental governance, and forestry economic development has become a vital evaluation indicator of global sustainable development. Therefore, how to further realize the overall improvement of the forestry economy is a common problem facing humankind in the 21st century. Public-private partnership (PPP) in forestry is regarded as the key to enhancing the economic growth of forestry (Yu and Nilsson, 2021). PPP refers to the country's government and social capital cooperation. The government introduced a professional social capital party to form a benefit-sharing risk-sharing partnership, which can effectively alleviate the pressure of the government to bear all the risks, but also can play the advantages of social capital in an operational capacity, information capture, and other advantages. The implementation of PPP projects in the field of forestry is, on the one hand, conducive to transforming the functions of each country's government, improving the level of forestry project construction management, and accelerating the transformation of the forestry economy and industry. On the other hand, it can mobilize the enthusiasm for forestry development in each country and promote the employment and income of forestry workers.

In recent years, China has endeavored to enhance the nation's forestry economy using PPP to promote forestry progress. The issuance of a series of policy documents, including the National Reserve Forest System Program, Guidelines for Implementing Government and Social Capital Cooperation Projects in Traditional Infrastructure Areas, and Guidance on Using Government and Social Capital Cooperation Models to Promote Forestry Construction, has promoted the rapid development of PPP in forestry, which is considered to be an important means for enhancing the forestry economy.

The performance of PPP is affected by many factors; thus, some doubt remains regarding whether PPP in forestry can effectively promote China's forestry industry economy. The forestry economy concept refers to a development model that takes the carrying capacity of the forestry ecosystem as the basic constraint and uses forestry resources as the basic means of production to maximize its economic value without destroying the self-balancing and self-healing capacities of the forest system (Dong et al., 2017). Therefore, PPP in forestry considers economic concerns and the constraints of the natural environment and ecology. Forestry projects are affected by natural conditions, such as climatic factors of temperature and precipitation, in addition to the impact of water and soil nutrients in the forest on the economic benefits of forestry (Yi and Cao, 2016; Xue et al., 2017). Furthermore, planting, nurturing, managing and constructing forestry infrastructure requires considerable capital investment to maintain a sustainable operation. The cultivation and growth of forests require long cycles, making forestry a cyclical and risky endeavor. These circumstances have led to fewer forestry projects and a low project success rate. In this context, evaluating the effects of the PPP policy in forestry is crucial to improve its efficiency and quality, perfecting related policies, and promoting the modernization of China's forestry industry.

China formally introduced the concept of PPP in 2014, which has attracted extensive attention from both domestic and international scholars. The focus of PPP research has evolved from the initial analysis of its theoretical and practical implications (Shi, 2016) and analysis of the opportunities and risks that develop during PPP implementation (Cui et al., 2020) to performance evaluation research, which has increasingly become a significant aspect of PPP-related research. Existing analyzes examine PPP performance in healthcare, environment, energy efficiency, and other various fields (Kumar, 2019; Shahbaz et al., 2020; Tang et al., 2021), investigating the macro effects of PPP from a more comprehensive perspective; however, there are minimal studies on PPP in forestry, mainly including three categories. The first category analyzes how PPP applies in forestry projects and an in-depth investigation of the necessity and feasibility of PPP projects in forestry (Guo, 2017; Ngandwe et al., 2017; Wang et al., 2021a). The second category examines the effectiveness of existing forestry PPP projects, identifies the key challenges in the operation of forestry PPP projects, and proposes corresponding solutions for subsequent development (Tricia and Rickenbach, 2014; Tshidzumba et al., 2018; Guevara et al., 2020). The third category summarizes theoretical studies and practical case study experiences related to forestry PPP at domestic and international levels, proposes a framework for PPP governance in China, and provides corresponding policy suggestions (Jiang et al., 2019; Wang et al., 2021b).

In summary, the current research has three areas for improvement. 1) Research on forestry PPP is minimal and in its infancy, and more exploration is needed to practically evaluate the performance of forestry PPP on the forestry economy. 2) Most previous PPP studies in forestry apply qualitative or case study approaches based on practical summaries and need more scientific and reasonable empirical investigation based on macro data. 3) There is also a need for further mechanism testing on the internal channels of forestry PPP. The existing studies only portray the effect of PPP in specific implementation contexts but do not assess behavioral choices made under different channels.

Based on this research gap, this study systematically examines the impact of China's PPPs in forestry on the forestry economy using Chinese provincial panel data from 2011 to 2020, constructing a difference-in-differences (DID) model in a quasi-natural experimental approach and further employing mechanism analysis to explore the potential mechanisms of the effect of implementing PPP on the forestry economy. The contributions of this study are as follows: 1) This study is the first to empirically analyze the impact of PPPs on China's forestry economy based on provincial panel data, which enriches the research and broadens the research approaches for investigating the forestry economy and building a foundation for relevant studies on forestry economics based on a macro perspective. 2) This study combines micro-level data on forestry PPP with macro-level local economic and social data to build integrated micro and macro panel data, to analyze the impact of forestry PPPs on China's forestry economy, and provides innovative empirical evidence and realistic references for further expansion of the PPP model, and is of theoretical value and practical value in contributing to the growth of forestry economies worldwide. 3) To explore the impact of forestry PPP projects on forestry economic growth, this study is not simply limited to the relationship between the two. Further, it analyzes the mechanism of the role of forestry PPP on the forestry economy, providing a scientific basis for promoting strategic forestry PPP projects and improving the forestry economy.

The remainder of this study organizes as follows. Section 2 presents a review of the Frontier literature in the research field. Section 3 reviews the policy background and research hypotheses. Section 4 describes the research design and robustness tests. Section 5 presents the effect mechanism analysis. Sections 6–8 detail the discussion, conclusions, and proposed policy implications, respectively.

2 Literature review

Since Putnam and Leonardi (1994) proposed to develop social capital, this topic has gradually become hot in economics, political science, and sociological research (Robison and Flora, 2003). With the increasingly tricky environmental situation and the accumulation of environmental risks, searching for an effective public environmental governance model has become the key to developing a green economy. Social capital can influence the transaction costs of environmental governance behavior through three mechanisms: shared information, coordinated action, and collective decision-making (Tsai, 2008), determining the success or failure of collective action in environmental governance. Social capital as a non-market force can influence people's preferences and constraints, reduce transaction costs, and facilitate information exchange (Fukuyama, 1995). Existing theoretical studies have pointed out that social capital plays a significant role in enhancing environmental governance. Environmental actions such as community governance and civic governance is driven by social capital are beginning to prevail internationally and have yielded apparent results. There is growing evidence that social capital has an important impact on sustainable economic development.

The model of government-social capital cooperation has attracted widespread attention from academics and governments as a way to improve the efficiency of public provision and alleviate the pressure on government finances (Bjrstig and Sandstr, 2017). Academics generally believe that social capital parties should introduce to participate in environmental governance in addition to the government-led governance model. On the one hand, the PPP model can solve the problem of government funding shortage and inefficiency through the input of social capital, and on the other hand, it can guarantee the smooth implementation of the project through the government's supervision of the social capital party's behavior. Some scholars have studied the issues of applying the PPP model in green environmental protection. Manos et al. (2014) found that PPP has successfully improved agroecological management and solved inequality between urban and rural environmental services. Zhang et al. (2020) found that introducing social capital was important in rural domestic wastewater treatment. Karki et al. (2007) explored whether PPP projects could save water based on 29 projects and found that implementing PPP projects saved water costs compared to traditional schemes. Villani et al. (2017) argue that the PPP model allows for a gradual transfer of government functions to the project, significantly improving project efficiency and pollution control through a combination of payment and performance.

Theoretically, the PPP model has become an essential and popular tool for sustainable development because of its increased project efficiency. In economics, the New Governance Theory emphasizes the plurality of governance subjects, it requires the transformation of management from traditional control governance to regulatory governance, and it emphasizes meta-governance in multi-party participation in governance, as well as focusing on governance instruments. In governance, both the function of government and the active role of market subjects and civil society should be brought into effect, while the problem of alienation and dysfunction of multiple governance subjects should not ignore. Compared with the traditional governance model, the new one is more conducive to government functions, focuses on shared responsibility and balanced rights, and seeks to identify pragmatic and practical governance models through refined analysis. The PPP model brings social capital in project standard-setting, enabling the critical position played by nongovernmental subjects in the management of public affairs and redefining governance subjects in the process. Thus, the PPP model extends the plurality of governance subjects defined by the New Governance Theory. On the one hand, PPP provides a baseline for social capital to choose the regulation method, which is conducive to the realization of the pluralistic value of each subject and protecting the public interest. On the other hand, PPP is conducive to saving administrative resources and avoiding the risks brought by the shirking of government departments and the self-interest attribute of social capital, which promotes the standardized development of cooperative projects and the formation of a networked governance system in the New Governance Theory.

3 Policy background and research hypotheses

3.1 Policy background

The PPP model in China began in the 1980s, but the concept of PPP was only formally introduced in 2014. In 1984, with the *Shenzhen Shajiao B* power plant project as the starting point, China gradually explored applying the PPP model for infrastructure development. However, most of the social capital involved then was foreign capital. After 1994, the PPP model in China officially entered a trial stage, and various domestic experts and scholars in China also began to focus on investigating PPP models. In the spirit of "allowing social capital to participate in urban infrastructure investment and operation through franchising and other means," in the Third Plenary Session of the 18th Central Committee of the Communist Party of China, the Ministry of Finance fully deployed the promotion of PPP projects at the end of 2013. Since 2014, relevant policies have been intensively introduced to ensure the smooth implementation of PPP projects. China's six ministries jointly formulated the Measures for the Management of Infrastructure and Public Utilities Concessions, which established the institutional system under which social capital investors can participate in concessions. Following this, a series of policy documents, such as the Notice on Regulating the Management of Government and Social Capital Cooperation Contracts and the Notice on Regulating the Operation of the Comprehensive Information Platform for Government and Social Capital Cooperation, accelerated the development of PPP in China, and PPP investment opportunities have been expanding from the initial infrastructure approach to natural ecology and environmental protection.

PPPs for forestry in China started late. In 2016, the Opinions of the State Council on Deepening the Reform of the Investment and Financing System proposed to clarify the scope of government investment further, increase financial support for projects in the public service field, such as ecological and environmental protection and urban and rural infrastructure construction; continuously optimize the direction and structure of investment; and improve investment efficiency. On this basis, the government further issued the Guidance on the Promotion of Government and Social Capital Cooperation model in the Field of Public Services, clearly promoting the implementation of forestry PPP. Since then, the government has issued documents such as the Guidance on Using the Government and Social Capital Cooperation model to Promote Forestry Construction and the Guidance on Using the Government and Social Capital Cooperation model to Promote Forestry Ecological Construction and Protection and Utilization to accelerate the development of PPP in forestry. As of the end of 2020, the project management database of China's National PPP Comprehensive Information Platform indicates that the number of forestry PPP project transactions increased by as much as 93% annually, with the number of forestry projects in the database rising from only two prior to the above policy implementation to 156, with an investment amount of 234.4 billion yuan. Forestry PPP has rapidly developed, with an upward trend and the associated operating systems are maturing.

3.2 Research hypotheses

The PPP model can alleviate the current forestry development dilemma. The traditional forestry development model faces challenges such as backward industrial structure and insufficient technical management talent that have hindered China's forestry economy. Although the nation's forestry PPPs are still in the beginning stage, the PPP model is inherently applicable to the forestry economy, and adding social capital to forestry projects could be conducive to generating additional economic benefits while fully leveraging the ecological benefits of practical forestry.

This paper is based on the New Governance Theory to explain why PPPs promote economic growth in forestry. The critical feature of the governance model emphasized by the New Governance Theory is its collaborative nature. The government should encourage the development of diversified governance subjects and clarify the responsibilities of the government parties. The PPP model helps the government to develop the subject position of social capital in governance in the project and confirm the legitimacy identity of social capital in the field of governance. It enables the government and social capital to play their respective management advantages and support each other in the multiform cooperation mode of the main body and actively maximize the benefits based on pluralism. This study suggests that forestry PPP positively affects forestry economic growth, which is primarily reflected in the three aspects discussed below.

3.2.1 Alleviate the difficulties of forestry financing

The traditional financing mechanism has yet to meet the needs of the modern forestry economy. For many years, China's forestry economy has confronted the problem of a narrow capital chain (Beljan et al., 2022). Before the application of the PPP model, forestry projects were primarily led by state and local governments, and associated funding sources were government financial allocations, which were relatively limited and caused significant financial pressure on the government. The reason for this poor financing environment is that forestry investment involves natural risks, making its economic returns unstable, with high investment costs, long project cycles, and low return characteristics. Furthermore, the lack of a sound financing guarantee system and the tendency of forest resources assessment to overestimate the valuation of trees causes forestry production operators to be unable to repay loans on time, which leads to mortgaging forest ownership to address such difficulties. Therefore, it has long been not easy to obtain support for forestry projects via financial institutions or social capital.

From the perspective of existing PPP forestry projects, the approach effectively alleviates the investment risks of social capital entering forestry projects. PPP projects primarily adopt the return mechanism of government payment or the feasibility gap subsidy model. If project revenue does not meet the social capital investors' revenue expectations, government departments will support social capital parties through loan concessions and financial subsidies and leverage policy support to ensure reasonable economic returns. Furthermore, the operation rules of PPP enable social capital investors to participate in preparation activities such as feasibility studies. The government must provide inexpensive, quality public products and services to society, undertake administrative functions (i.e., planning, procurement, management, and supervision of PPP projects), and form legal relationships with social capital investors. The government must perform its obligations according to the PPP contract, which reduces investment risks, increasing private investors' enthusiasm to participate in PPP projects and alleviating the current financing difficulties in forestry.

3.2.2 Enhancing the professionalism of forestry projects

Traditional approaches to forestry profitability no longer apply to current circumstances, with three specific problems facing current forestry development. First, the overall forestry industry in China is still in a labor-intensive stage. China's forestry industry has taken advantage of cheap labor for a long time; however, the advantage of cheap labor has gradually disappeared with the rising cost of labor, the challenging environmental conditions of forestry production, relatively low income, and insufficient talent attraction. Second, the adequate supply capacity of China's forestry resources is insufficient. Overall, the *per capita* forest area and *per capita* forest accumulation are far below the world average. Furthermore, the quality of China's forests could be higher. The forest accumulation per unit area is 94.83 m^3/hm^2, notably lower than the world average, and the lack of forestry resources seriously limits the development of the nation's forestry economy. Third, the forestry industry is risky, with long cycles, a slow capital turnover time, the potential to be affected by climate disasters, and other unstable characteristics. The forestry economy faces both natural and market risks, and the benefits of forestry investment are conspicuously low compared to other industries.

The above indicates that China's forestry economy must transform the current development mode and can no longer rely on the increase of factor inputs, but also needs to continuously improve production efficiency and advance the technological upgrade in forestry projects. The PPP model can attract more professional social capital participation in forestry projects and absorb the strengths of private enterprises in management and technology, combining the advantages of social capital for advancing management and technology with the policy advantages of government departments. The government has a dominant position in the entire project construction process of forestry projects, which is prone to inefficiency and high transaction costs, minimizing the role of market mechanisms. Under the coordination of the government, PPP can enable social capital investors to participate in investment fields that were initially inaccessible and stimulate the increased mobilization of social capital. The primary purpose of social capital participation is to obtain profits. Given the reasonable return mechanism, social capital investors can be motivated to introduce more advanced management methods and technologies into PPP projects. By leveraging the financial, technical, and information advantages of PPP, a project's entire life cycle cost can be minimized. The professional skills of grassroots forestry workers can also be continuously driven to improve the productivity of forestry projects.

3.2.3 Improve profitability of forestry projects

The forestry industry is an essential industry representing a public welfare undertaking, and direct government investment is the primary source of funds for forestry projects in China. Under this management, most forestry projects are influenced by China's planning system, and the ability to mobilize market forces needs to be improved; thus, such projects generally face the challenge of poor profitability and low return on investment. A development model in which the government is the primary source of investment makes the government's financial burden significant. The government is often not inclined to upgrade technological innovation and management methods. The government has inherent limitations on resource integration and cannot maximize resource utilization, resulting in resource waste. In addition, because the government will prioritize ecological benefits, resulting in unclearly defined public welfare and economic attributes of forestry, such projects are prone to excessive public welfare characteristics, limiting economic revenue. Therefore, the current forestry economy must integrate market economic mechanisms using PPP for structural optimization, transformation, and upgrading.

Therefore, based on the New Governance Theory, the government's position as a meta-governance subject governance is not to have the government control everything but to promote the government's management style from command-based to monitoring-based, and to better play the leading role of the government. Social capital in the PPP model should be made to have the administrative governance subject status appropriate to its governance role as soon as possible. Government departments and social capital investors are collaboratively involved in the decision-making process of PPP forestry projects, and both parties influence decisions regarding projects' return mechanisms. In PPP projects, the government seeks to maximize social benefits, whereas social capital investors seek to maximize economic profits. The two sides form different divisions of responsibility, with government departments responsible for decision-making on macro issues, such as project planning schemes, primarily focusing on the public welfare aspects of a project. At the same time, social capital investors are responsible for decision-making on specific issues, such as technical schemes and economic benefits. For example, in a river management PPP project, the initiative's profit-seeking nature can optimize and integrate the project structure with the assistance of professional planning departments, integrating activities that enhance public welfare benefits with nonpublic welfare projects while also increasing the profitability of the project. Implementing forestry PPP projects can effectively promote the market operation mechanism in the forestry industry and feed into environmental protection and public welfare to achieve sustainable forestry development.

In summary, this study proposes research hypothesis H1: Forestry PPP improves China's forestry economy regarding financing, professionalism, and profitability.

Based on the above analysis, China's forestry industry currently needs help with problems such as backward infrastructure, low production efficiency, and return on investment. PPP projects can influence the forestry economy through three channels industrial structure, technological innovation, and ecological effects. First, PPP is a financing tool (Tan and Zhao, 2019). The government can use a small number of monetary funds in forestry PPP projects to provide a relatively stable and standardized forestry investment and financing channel for social capital, which will further rationalize the relationship between the government and the market, establish constraints on government behavior, and promote the forestry economy following the market economy, transforming the previous forestry financing mechanism. The current structure could be more stable and favorable to the sustainable development and use of forest resources, among other challenges (Nurrochmat et al., 2022). PPP offers a potentially effective approach to advancing the sustainable development of the forestry economy.

Second, PPP can attract substantial social capital into the forestry industry, effectively alleviate the problem of the low resource utilization rate under the dual pressure of the resource shortage and the demand gap in the forestry industry, and achieve superior output by improving technological innovation with the same combination of input factors. Social capital investors can provide more technical support and integrate innovative technology to plant, develop, and protect forestry resources more rationally by bringing funds and advanced skills into PPP projects. In addition, the infusion of social capital effectively alleviates the financial constraints that limit development and attract more professional and technical talent to address the technical talent limitations in China's forestry development process. Therefore, forestry PPP can promote the forestry economy by enhancing the technological innovation effect.

Finally, the development of forestry balances ecological and economic benefits. When social capital enters PPP projects, the profit-seeking behavior of social capital investors may reduce the ecological benefit standards previously regulated by the government based on forestry as a public good. In contrast, from another perspective, social capital can improve the trading market under the government's macro-regulation, encourage more social capital investors to enter the ecological and environmental protection field and maximize the motivation and creativity of the ecological market through price leverage and competition mechanisms, rearranging factors and resources to enhance ecological benefits more effectively.

In summary, this study proposes research hypothesis H2: Forestry PPP improves China's forestry economy through three channels, including industrial structure, technological innovation, and ecological effects.

4 Materials and methods

4.1 Sample processing and data sources

Currently, 21 provinces in China have begun implementing forestry PPPs, including Guangdong, Fujian, Zhejiang, Jiangsu, Shandong, Hebei, and Tianjin in the eastern region of China; Jiangxi, Anhui, Shanxi, Henan, Hubei, and Hunan in the central region of China; Guangxi, Sichuan, Inner Mongolia, Guizhou, Yunnan, Ningxia, and Xinjiang in the western region of China; and Liaoning in China's northeast region. Provinces that have not started implementing PPP projects in forestry, the eastern region includes Beijing, Shanghai, and Hainan; the western region includes Shaanxi, Chongqing, Gansu, and Qinghai; and Jilin and Heilongjiang in the northeast region.

The selection of the sample region" in 'his study and the basis for the selection are as follows: ① A region has provinces that have implemented forestry PPP projects and those that have not, making it easy to identify a control group. Every province in the central region of China has implemented forestry PPP projects; thus, the sample includes only the eastern, western, and northeastern regions of China. ② The sample size of the northeast region is too narrow to have empirical value, the economic development of the eastern region has begun to show significant polarizing differences in recent years, and the provinces in the western region differ less in various aspects and have relatively high homogeneity. The sample in this study must include provinces with similar development, following the hypothetical conditions of the DID model; therefore, provinces in China's western region that have implemented forestry PPP projects and those that have not been selected as the treatment and control groups. Because some of the data for Sichuan, Inner Mongolia, and Xinjiang in the central region are missing, these three provinces are not included in the study sample. In summary, the final sample areas selected are the eight provinces of Guangxi, Chongqing, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, and Ningxia. Furthermore, 30 provinces in China are used for a multi-period DID model robustness test. Data from Hong Kong, Macao, Taiwan, and Tibet are excluded because of incoherence. Considering the policy timing of China's emphasis on forestry PPP, this study takes 2011–2020 as the time dimension. The data are obtained from the China Forestry Statistical Yearbook, the China Energy Statistical Yearbook, the China Labor Statistical Yearbook, the China Environment Statistical Yearbook, and China's National PPP Comprehensive Information Platform.

4.2 Difference-in-differences model setting

Regarding the starting time of forestry PPP implementation, Guizhou began in 2013, and Ningxia, Yunnan, and Guangxi started in 2016. Accordingly, Guizhou, Ningxia, Yunnan, and Guangxi are the treatment group, as the provinces started forestry PPP implementation before 2017, and Chongqing, Shaanxi, Gansu, and Qinghai, which did not implement forestry PPP projects, are taken as the control group. The specific settings of the variables are as follows:

$$\boldsymbol{Treat_i} = \begin{cases} \boldsymbol{1, If\ the\ province_i implemented\ forestry\ PPP} \\ \boldsymbol{0, If\ the\ province_i has\ not\ implemented\ forestry\ PPP} \end{cases} \tag{1}$$

where $Treat_i = 1$ indicates that the province started forestry PPP and is taken as part of the treatment group, and $Treat_i = 0$ indicates that the province did not start forestry PPP and is taken as the control group.

$$\boldsymbol{Dummy_t} = \begin{cases} \boldsymbol{1, t > 2016, after\ forestry\ PPP\ implementation} \\ \boldsymbol{0, Else, before\ forestry\ PPP\ implementation} \end{cases} \tag{2}$$

where $Dummy_t = 1$ indicates after participation in forestry PPP and $Dummy_t = 0$ indicates before participation in forestry PPP. Thus, the DID model can be constructed as follows:

$$\boldsymbol{FGDP_{it} = \alpha_0 + \alpha_1 Dummy_t + \alpha_2 Treat_i + \alpha_3 Dummy_t \times Treat_i + \alpha_4 C_{it} + \delta_{it}} \tag{3}$$

where $FGDP_{it}$ is the ratio of value-added of the forestry industry to the total GDP of $province_i$ in year t. $Dummy_t$ is a Dummy variable denoting whether a province participated in forestry PPP, and $Treat_i$ is a Dummy variable for the treatment intervention. $Dummy_t \times Treat_i$ is the interaction term; C_{it} is a set of control variables; $\alpha_1, \alpha_2, \alpha_3$, and α_4 are all coefficients to be estimated; and δ_{it} represents the random disturbance term. Then we have the following:

$$\begin{aligned} \boldsymbol{DID} &= \boldsymbol{[E(FGDP_{i1}/Treat_i = 1) - E(FGDP_{i0}/Treat_i = 1)]} \\ &\quad \boldsymbol{- [E(FGDP_{i1}/Treat_i = 0) - E(FGDP_{i0}/Treat_i = 0)]} \\ &= \boldsymbol{[(\alpha_0 + \alpha_1 + \alpha_2 + \alpha_3) - (\alpha_0 + \alpha_2)] - [(\alpha_0 + \alpha_1) - \alpha_0] = \alpha_3} \end{aligned} \tag{4}$$

where α_3 is the result after applying the DID model, which indicates the pure effect of forestry PPP on the forestry economy. Considering that panel data are used in this study, the above model is transformed into a panel data DID model with two-way fixed effects as follows:

$$\boldsymbol{FGDP_{it} = \alpha_0 + \alpha_3 Dummy_t \times Treat_i + \alpha_4 C_{it} + \gamma_i + \varphi_t + \delta_{it}} \tag{5}$$

where γ_i is the individual fixed effect, φ_t is the time fixed effect, δ_{it} represents the random disturbance term, and the remaining variables and parameters have the same meaning as in Eq. 3. Two issues must be noted when using this model to assess the impact of forestry PPP on the forestry economy.

(1) The DID attributes the difference between the treatment and control groups to whether or not a forestry PPP was initiated, which requires the model to satisfy the common trend hypothesis, requiring that treatment and control groups have the same trend over time except for the policy intervention. In this study, we include control variables to reduce the influence of non-policy factors. The choice of control variables considers the economic and natural factors that can affect the forestry economy. Referencing previous studies (Valade et al., 2017; Guan et al., 2019), we include control variables (C_{it}) representing the forestry economy's industry

TABLE 1 Descriptive statistics of variables in the two-stage model.

Variable	Mean	Std.	Maximum	Minimum
FGDP	8.647	7.707	0.745	34.579
Dummy×Treat	0.250	0.436	0.000	1.000
Findustry	0.167	0.140	0.009	0.613
Fire	0.162	0.196	0.012	0.881
TE	0.617	0.356	0.115	1.268
ES	0.447	0.104	0.232	0.692
Forest	0.266	0.178	0.079	0.703
FS	0.198	0.128	0.029	0.788

structure, forest fire incidence, technological innovation efficiency, energy structure, *per capita* forest savings, and forestry scale.

(2) Different provinces do not initiate forestry PPPs at the same time; thus, the multi-period DID method is used to obtain more reliable conclusions. The establishment of this model and its robustness test will be discussed below.

4.3 Variable definitions

The explained variable, explanatory variable, and control variables of this study are as follows:

(1) Explained variable. The explained variable in this study is each province's forestry economy (FGDP) of each province. Due to the different stages of economic and forestry development patterns in each province, the ratio of forestry GDP to provincial GDP is chosen to mitigate the influence of the dimension and volatility on the estimation of regression results.

(2) Explanatory variable. In this study, we choose whether a province implemented PPP projects in forestry and agriculture to measure forestry PPP. If the province implemented forestry PPP, it is identified as part of the treatment group with Treat = 1; otherwise, it is considered part of the control group with Treat = 0. The explanatory variable is the interaction term (*Dummy×Treat*), which examines the circumstances before and the impact after the implementation of forestry PPP on the forestry economy.

(3) Control variables. Considering the influence of economic and natural factors on the forestry economy, the control variables include forestry industry structure (Findustry), which is measured by the proportion of the added value of the tertiary forestry to forestry GDP in each province. Forest fires incidence (Fire) is measured by the ratio of forest fires to the forest area in each province. Technological innovation efficiency (TE) is measured by referring to the efficiency of forestry green technology innovation in each province as measured using the slacks-based measure data envelopment analysis method used in previous studies (Shang and Yang, 2022). Energy structure (ES) measurement uses the ratio of coal consumption to total energy consumption in each province. Per capita forest savings (Forest) is measured using the ratio of forest area to resident population in each province. The forestry scale (FS) is measured using the ratio of individuals employed in forestry to the total employed population in each province.

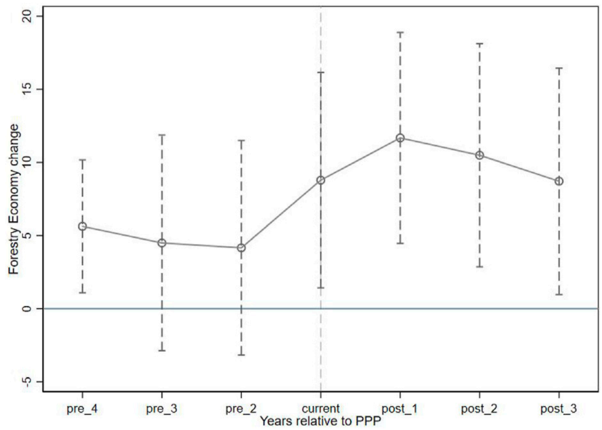

FIGURE 1
Results of parallel trend test.

TABLE 2 Regression results of the two-stage DID models.

Name	Model 1	Model 2
Dummy×Treat	4.070***	4.585***
	(3.56)	(3.92)
Constant	5.371***	23.934***
	(5.95)	(3.97)
Control variables	NO	YES
Province FE	YES	YES
Year FE	YES	YES
R^2	0.498	0.658
Group	8	8
N	80	80

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

The descriptive statistics of the variables of concern are presented in Table 1. Table 1 shows that the average value of the forestry economy (FGDP) is 8.647, which shows that the level of economic development of China's forestry industry is still in its initial stage. The minimum value of the forestry industry structure (Findustry) is 0.009, and the maximum value is 0.613, indicating a significant gap in the industrial structure among provinces and still needs national macro-control. The gap between the minimum and maximum values of *per capita* forest savings (Forest) and forestry scale (FS) are also significant, indicating that the current distribution of forest

TABLE 3 Regression results of counterfactual test.

Name	2012	2013	2014
Dummy×Treat	1.990	2.990	2.736
	(1.24)	(1.36)	(1.58)
Constant	15.107*	16.756*	12.190*
	(2.02)	(2.07)	(2.07)
Control variables	YES	YES	YES
Province FE	YES	YES	YES
Year FE	YES	YES	YES
R^2	0.577	0.636	0.624
Group	8	8	8
N	48	48	48

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

TABLE 4 Regression results of the placebo test.

Name	Model 1	Model 2
Dummy×Treat	2.937	0.947
	(1.21)	(0.36)
Constant	8.282***	16.39
	(6.04)	(0.56)
Control variables	YES	YES
Province FE	YES	YES
Year FE	YES	YES
R^2	0.296	0.530
Group	8	8
N	80	80

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

resources in China is not uniform, which is related to the resource endowment of each region.

4.4 Empirical results and analysis

4.4.1 Parallel trend test

The use of DID estimation presupposes a parallel trend, i.e., the trend of forestry economic change in the treatment and control groups before the implementation of the forestry PPP project is the same, and a parallel trend test is needed to exclude other factors interfering. This paper draws on Boler et al. (2015) to analyze the parallel trend of forestry PPP implementation using event analysis. The results of the parallel trend test are shown in Figure 1, the regression coefficients before the implementation of forestry PPP are not robustly significant, and both are significant after the implementation of the policy, which indicates that there is no significant difference in the trend of the forestry economic situation between the two groups before the implementation of the policy, and the parallel trend assumption is satisfied.

4.4.2 Regression results

The results of the DID model are presented in Table 2. First, for model 1, which represents only the *Dummy* × *Treat* explanatory variable of forestry PPP, the coefficient of *Dummy* × *Treat* is 4.070, which is significant at the 1% level, indicating that the implementation of PPP projects in forestry has a positive effect on forestry economic development. Second, considering that the DID model must satisfy the common trend hypothesis, to make the results more rigorous, we add control variables to obtain the estimation results of model 2, and *Dummy* × *Treat* remains significant at the 1% level, with a coefficient of 4.585, indicating that the implementation of PPP projects in forestry has a positive effect on the forestry economy. The estimation results of the above two models validate hypothesis H1 of this study, indicating that implementing forestry PPP has a significant promotional effect on China's forestry economy.

4.5 Robustness tests

We apply three robustness testing methods to test the credibility of our research results. First, a counterfactual test is conducted for the DID model. Second, considering the limitations of the DID model, a multi-period DID model is established for testing. Third, a propensity score matching (PSM)-DID model is established for testing, alleviating sample selection bias.

4.5.1 Counterfactual test

The counterfactual hypothesis assumes that if the time point of implementing forestry PPPs changes, then the results of the DID model will change accordingly. The assumption in the previous DID model uses 2017 as the start time of forestry PPPs. The counterfactual test supposes that forestry PPP occurred before 2017, selecting data from 2011 to 2016 as the study sample and repeating the estimation of the DID model with 2012, 2013, and 2014 as the start times of forestry PPPs, respectively. If the results are insignificant, this indicates that the trend of the treatment and control groups is relatively stable without the start of forestry PPP, and the common trend hypothesis is satisfied. The results of the counterfactual tests at different time points are presented in Table 3, demonstrating that the estimated coefficients of the *Dummy* × *Treat* explanatory variable are not significant when 2012, 2013, and 2014 are used as the start times, which indicates that the provinces had a common trend prior to the implementation of PPPs in forestry.

4.5.2 Placebo test

This study further conducts a placebo test on the two-stage model. The placebo test examines whether the impact of PPP implementation on the forestry economy was due to the event itself or whether other unobserved factors had an additional impact on the treatment group. DID methods typically include two types of placebo tests: One way is to change the timing of policy implementation, including the timing of policy implementation in the antecedent treatment group. In this case, the placebo test acts the same as the counterfactual test, testing the significance of the

TABLE 5 Descriptive statistics of variables in the multi-stage model.

Variable	Mean	Std.	Maximum	Minimum
FGDP	7.812	5.678	0.129	34.579
Dummy×Treat	0.300	0.459	0.000	1.000
Findustry	0.157	0.109	0.001	0.613
Fire	0.179	0.247	0.005	2.059
TE	0.646	0.382	0.115	1.720
ES	0.393	0.149	0.007	0.692
Forest	0.198	0.209	0.003	1.032
FS	0.202	0.295	0.007	1.666

coefficient on the time dummy variable in the base regression of the pre-policy implementation with the treatment group interaction term, and the test passes if it is not significant. This study refers to the second method. The second method is to randomly sample the control group of the two-stage model and then estimate it using the same DID model (Wang and Li, 2020). The results show that none of the estimated coefficients of the *Dummy* × *Treat* explanatory variable passed the significance test. The results after replacing the control group with Shanghai, Jilin, Heilongjiang, and Hainan are presented in Table 4. The results of replacing the control group also failed the significance test and are shown here agglomerated. The test results indicate that the provinces have a common trend before participating in forestry PPPs, indicating that the estimation results of the DID model are robust.

4.5.3 Multi-period DID model test

The multi-period DID model is developed based on data from 30 provinces in China (excluding Hong Kong, Macao, Taiwan, and Tibet) for two reasons. First, the starting times of provinces' participation in forestry PPPs differ, and the multi-period DID model can overcome this difference. Second, the multi-period DID model reduces the restriction on selecting treatment and control groups, and the sample can be expanded to all provinces in China.

The descriptive statistical analysis of the relevant variables for the 30 Chinese provinces is presented in Table 5.

The estimation results of the multi-period DID model are presented in Table 6. Model 1 is the regression result when only the *Dummy* × *Treat* variable is included. Its coefficient is 0.881, which is significant at the 5% level, indicating that the implementation of forestry PPPs has an improving effect on the

TABLE 6 Regression results of the multi-stage DID model.

Name	Model 1	Model 2	Model 3	Model 4	Model 5
Dummy×Treat	0.881**	0.807**	0.732*	0.772*	0.778*
	(2.16)	(2.00)	(1.72)	(1.82)	(1.83)
Findustry		1.707***	1.805***	1.752***	1.748***
		(5.47)	(5.35)	(5.19)	(5.16)
Fire			0.026	0.187	0.173
			(0.04)	(0.31)	(0.28)
TE			0.520	0.381	0.405
			(0.68)	(0.49)	(0.52)
ES				−6.670*	−6.808*
				(-1.94)	(-1.97)
Forest				14.20	14.74
				(1.43)	(1.48)
FS					−0.890
					(-0.50)
Constant	5.952***	8.300***	8.484***	8.546***	8.675***
	(17.73)	(9.92)	(8.37)	(3.27)	(3.29)
Province FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
R^2	0.218	0.308	0.318	0.333	0.334
Group	30	30	30	30	30
N	300	300	300	300	300

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

TABLE 7 Results of balance test.

Variable	Unmatched matched	Mean		%Bias	*t*-test	
		Treated	Control		*t*-Value	*p*-value
Findustry	Unmatched	0.169	0.139	30.6	2.19	0.03
	matched	0.161	0.155	5.9	0.65	0.52
Fire	Unmatched	0.212	0.092	56.6	3.75	0.00
	matched	0.167	0.158	4.3	0.50	0.62
TE	Unmatched	0.590	0.751	−42.6	−3.34	0.00
	matched	0.610	0.668	−15.4	−1.79	0.08
ES	Unmatched	0.434	0.319	81.9	6.41	0.00
	matched	0.426	0.433	−4.9	−0.62	0.54
Forest	Unmatched	0.180	0.278	−48.1	−3.60	0.00
	matched	0.188	0.181	3.4	0.35	0.73
FS	Unmatched	0.131	0.418	−85.5	−7.99	0.00
	matched	0.137	0.123	4.0	0.89	0.37

TABLE 8 Regression results of the PSM-DID model.

Outcome variable		Mean		*t*-test	
		Coef.	S. Err.	*t*-Value	*p*-value
Before	Control	16.389			
	Treated	15.953			
	Diff (T-C)	−0.437	0.629	−0.69	0.488
After	Control	15.651			
	Treated	18.945			
	Diff (T-C)	3.294	1.184	2.78	0.006***
Difference-in-differences		3.731	1.324	2.82	0.005***

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

forestry economy. Models (2)–(5) show the results after adding relevant control variables sequentially. The coefficients of *Dummy* × *Treat* are positively significant at 5% and 10% levels after adding some control variables. In summary, the findings show that the results obtained from the previous DID model are robust.

4.5.4 PSM-DID model test

To reduce the effects of data bias and confounding variables for a more reasonable comparison between treatment and control groups, the PSM model is applied to select treatment and control groups. The PSM requires testing whether the variables in the treatment and control groups become balanced after matching. We use the kernel matching PSM method using the six variables of Findustry, Fire, TE, ES, Forest, and FS. The group variable changes before and after matching are presented in Table 7. Significant biases are revealed for all variables among different provinces before matching, which is significant at the 1% level. The variables' bias decreased after PSM, and only the TE bias was insignificant at the 5% level. In comparison, all other variables were insignificant at the 10% significance level, indicating that using the PSM-DID method in this study is justified.

The balance test illustrates that the selection of treatment and control groups can eliminate the bias to the maximum extent through PSM under the kernel matching method. DID is then performed on the matched samples, and the results are presented in Table 8, where the regression coefficient of forestry PPP on the forestry economy is 3.731, which is positively significant at the 1% level, again confirming that the effect of implementing forestry PPP on the forestry economy is highly robust.

The above robustness tests demonstrate that the estimation results of the DID model are robust, indicating that the implementation of forestry PPP positively impacts the forestry economy, once again validating H1.

5 Mechanism analysis of forestry PPP on the forestry economy

This study further analyzes the impact mechanism of forestry PPPs on the forestry economy. Provinces primarily initiate forestry PPPs through industrial structure, technological innovation, and ecological effects. A DID model with two-way fixed effects is established as follows:

$$\boldsymbol{Y_{it} = \alpha_0 + \alpha_3 Dummy_t \times Treat_i + \alpha_4 C_{it} + \gamma_i + \varphi_t + \delta_{it}} \quad (6)$$

where Y_{it} is measured by $Findustry_{it}$, TE_{it}, and $Forest_{it}$, which represent forestry industry structure, green technology innovation efficiency, and *per capita* forest savings, respectively, to examine the industry structure, technology innovation, and ecological effects of implementing forestry PPPs. α_3 represents the estimated coefficient, γ_i is the entity fixed effect, φ_t is the time fixed effect, δ_{it} is the random

TABLE 9 Regression results of mechanism analysis.

Name	Industrial structure effect	Technological innovation effect	Ecological effect
Dummy×Treat	0.069***	0.102*	−0.014*
	(3.70)	(1.80)	(-1.90)
Constant	−0.148	0.604***	0.0220
	(-0.89)	(9.16)	(0.52)
Control variables	YES	YES	YES
Province FE	YES	YES	YES
Year FE	YES	YES	YES
R^2	0.695	0.462	0.383
Group	8	8	8
N	80	80	80

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

disturbance term, C_{it} is a set of control variables, and the meanings of other variables are the same as in Eq. 5. The control variables in the model testing the industrial structure effect include environmental regulation, social security, forestry investment, and forestry scale; the control variables for the technological innovation effect include forestry investment and FS; and the control variables for the ecological effect include the incidence of forest fires, the population employed in the forestry field, and the level of urbanization.

The regression results of the mechanism analysis are presented in Table 9. The regression coefficient of the effect of forestry PPP on industrial forestry structure is 0.069, which is positive and significant at the 1% level, indicating that forestry PPP implementation can promote the internal restructuring, transformation, and upgrading of the forestry industry, which is conducive to enhancing industrial vitality, enhancing the forestry economy. The regression coefficient of the effect of forestry PPP on forestry technological innovation is 0.102, which is positively significant at the 10% level, indicating that forestry PPP can provide a robust external incentive for environmental technology research and development. The mechanism of the technological innovation effect is primarily reflected in technological progress and increased human capital, which advances the high-quality development of the forestry economy driven by technological innovation. The regression coefficient of forestry PPP on the ecological effect is −0.014, which is negatively significant at the 10% level, indicating that forestry PPP has a negative effect on ecology, suggesting that forestry PPP may hinder ecological sustainability and special attention must be paid to environmental protection in future forestry PPP projects. The empirical results confirm hypothesis H2.

6 Discussion

The PPP model is not new and has long attracted widespread attention internationally, and there is relatively good experience in applying the PPP model in the field of environmental protection nationwide; for example, the PPP model has become a standard means of sustainable rural development in Europe (Bjrstig and Sandstr, 2017), as well as many countries have started implementing PPP earlier for projects with fixed benefits such as domestic waste and wastewater treatment (Zhang, 2015), however, whether these experiences apply to the development of forestry economy remains to be studied. An important reason for the controversy of the PPP model is that different areas of PPP implementation target different segments and use different approaches. Therefore, there needs to be more research on applying the PPP model to forestry in China and abroad. Unlike the existing studies that mostly take resource endowment as the starting point to study the drivers of forestry economic growth, this study is based on the perspective of New Governance Theory, takes China as the research object, and incorporates more influencing factors for research, providing a new way of thinking for forestry economic development and government governance, and deeply discusses the impact of public-private investment on forestry economic growth. In order to draw more reliable conclusions, in this study, the micro-level forestry PPP project data and macro-level local economic and social data from 2011 to 2020 are integrated to construct combined micro and macro panel data, and a quasi-natural experiment method is used to apply a DID model. A counterfactual test, a multi-period DID model, and a PSM-DID model are used for robustness testing, and further mechanism analysis is conducted to analyze the impact of forestry PPP on the forestry economy. To further investigate how the development of PPP plays a role in promoting forestry economic growth, the study further analyzes the mechanism of PPP in detail from three perspectives: industrial structure upgrading, technological progress and ecological effects, and it shows more clearly the path through which the PPP model affects economic growth. This study enriches the research in this field.

However, there are some limitations to this study. This paper is only a fundamental study of the relationship between PPP implementation and economic growth in China's forestry industry. The data for this study is limited by time and space, with the existing sample of studies being limited to Chinese provinces, whereas the study of PPP is a common long-term study worldwide. To extend our study, on the one hand, the government needs to collect relevant data to clarify the impact of different development situations and technology choices on PPP implementation and different categories of PPP projects cannot be generalized, so the collected data can support subsequent scientific studies. On the other hand, data should be obtained to monitor project implementation on time, paying particular attention to whether social capital enters the project during implementation rather than self-interested behavior to satisfy selfish desires. Only the projects jointly operated by the government and social capital sustainably are the focus of our research. Future research can be continued in the following aspects. First, it is to continue the multidimensional impact study of PPP on economic growth and obtain the data on a global scale so that more data can support the impact mechanism behind the PPP model. The corresponding optimization policies can be designated according to the different national conditions of each country. Second, it is based on the New Governance Theory perspective to explore the moderating role of the impact of PPP on economic growth is still to be explored. Forestry PPP implementation is a long-term development strategy, and the research is also worth exploring in depth with the accumulation and improvement of relevant data.

7 Conclusion

This paper takes China's forestry economy as the research object, puts forward two primary hypotheses on the relationship between forestry PPP on forestry economic growth and its mechanism of action, combines the current development dilemma of the forestry economy and conducts research on the current development model based on the perspective of New Governance Theory, and finds that forestry economic development not only requires the government to assume the responsibility of the most critical governance subject but also requires the government to lead social capital to participate in governance actively. This study complements the plurality of governance subjects emphasized by the New Governance Theory. It advocates the formation of a mutually constraining system of cooperative governance rules in the forestry field in the future. The study reaches three main conclusions. First, forestry PPP can significantly enhance the forestry economy, positively relieving the pressure of forestry financing and stimulating the market mechanism of forestry. In the process of studying forestry economic growth, we found that forestry industry structure, forest fire incidence, technological innovation efficiency, energy structure, *per capita* forest savings, and forestry scale all have an impact on the forestry economy, which indicates that in future governance, we should not only focus on model improvement, but also pay attention to resource endowment and science and technology improvement, and only the joint progress of "resource - technology - management" can improve forestry economy in all aspects. Second, the implementation of forestry PPP primarily enhances the economy through two mechanisms of industrial structure and technological innovation effects, indicating that the entry of social capital into forestry PPP projects will lead to industrial structure upgrading and technological progress, enhancing the forestry economy. Finally, a negative ecological effect is evident during the implementation of forestry PPP projects, indicating that the profit-seeking behavior of social capital investors does not focus on the public welfare nature of forestry economic development and further regulatory oversight is needed.

8 Policy implications

Based on the findings of the study, the following policy recommendations are proposed:

(1) Policymakers must develop a transparent return scheme and legal system, which is fundamental to forestry PPP. Profitability is the most severe concern of social capital participation in forestry projects, and the assurance of a reasonable return is essential for attracting social capital investors. Potential project problems should be regulated through laws, and penalties for violations should be established to avoid disputes during PPP project implementation. Social capital investors should be given maximum power outside the regulatory space so that inherent technical and management capabilities can be effectively exercised to maximize benefits. In the operation process, particular attention must be paid to the relevant policy documents, fully leveraging policy flexibility to obtain the maximum return on investment under the established legal framework.
(2) Policymakers should actively and strategically select professional social capital parties. The motives for social capital participation in forestry PPP projects are complex, and some social capital investors may seek personal profit under the guise of participating in PPP projects. Therefore, the government must examine prospective investors' professional capabilities to ensure they have the ability and motivation to achieve project objectives. Specifically, the government can effectively stimulate the market competition mechanism in selecting social capital links to establish an environment of equal competition among capital parties and ensure that they can compete under a common standard, which can accelerate the selection of eligible social capital investors to participate in forestry PPP projects. The government can establish a public information system for the operation of PPP projects, requiring investors to regularly publicize projects' progress and engage in formal assessment practices to remove unqualified investors on time to ensure that projects are efficiently conducted.
(3) Policymakers should strengthen environmental supervision in forestry PPP projects, which prevents environmental damage in forestry PPP projects. Developing a complete environmental supervision plan, setting strict and precise emission standards, and providing more comprehensive pollution control for projects are necessary. Ecological returns should also be

included in investors' performance assessments. Access standards could be relaxed for those with good environmental performance in project bidding to guide more social capital investors to prioritize ecological benefits and strive to simultaneously achieve economic and ecological benefits of forestry.

Data availability statement

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

Author contributions

For Conceptualization and funding acquisition, HS; methodology, data collection and analysis, CY; writing—review and editing, CY and HS. 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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Global drivers of timber carbon stock from income-based perspective

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Introduction: Timber and its products are key carriers of carbon stocks and can cause a hysteresis effect of carbon release in the carbon cycle of forest ecosystems. The literature regarding the cross-regional flow of timber carbon stock mainly pays attention to production- and consumption-based perspectives, which cannot reflect how the primary inputs drive timber carbon stock flow. The income-based perspective accounting can identify the influence of primary input suppliers and supplement research on timber carbon stock embodied in trade. The goal of this paper is to explore the cross-regional flow of global timber carbon stock and identify the critical countries from an income-based perspective.

Methods: We used the Ghosh-multi-regional input-output (MRIO) model to calculate the income-based timber carbon stock flow among 190 countries. Furthermore, combined with the Leontief-MRIO model, a comparative analysis is carried out to analyze the different results of the income-based, production-based, and consumption-based methods.

Results: The results showed that the income-based timber carbon stock of the United States and China were among the top countries in imports and exports simultaneously. However, their export volumes were significantly larger, meaning that these countries have invested more primary resources in timber products. The timber carbon stock of the United States mainly flows into Canada and Brazil. In China, the largest flow went to Canada. Furthermore, the flow to the United States increased significantly. Moreover, comparing the three perspectives shows that the United States' primary inputs have a greater impact on the global timber production chain than their production- and consumption-based roles. Brazil and Russia, as main primary resource suppliers of timber carbon stock, are more important than as final consumers.

Discussion: The research can contribute to clarify the flow of forest resources embodied in global trade activities. Furthermore, it also provides a scientific basis to fairly account for carbon offset shares to achieve better the goal of forest resource protection agreed upon in COP26.

KEYWORDS
timber carbon stock, income-based, MRIO, trade, consumption-based, production-based

1 Introduction

Global climate change has seriously endangered the living environments of human beings. As the largest ecosystem on land, forests play an important role in mitigating climate change by fixing carbon dioxide through photosynthesis (Abderrahmane et al., 2021). The ecological functions of forests are critical for maintaining biosphere stability (Winjum et al., 1992; Köhl et al., 2015; Zhang L. et al., 2020; Girona et al., 2023). According to the 15th Sustainable Development Goal proposed by the United Nations, deforestation and desertification caused by human activities and climate change have brought challenges to sustainable development. It also affects the livelihoods of millions of people and poverty alleviation goals. Furthermore, the twenty-sixth session of the Conference of the Parties (COP26) to the United Nations Framework Convention on Climate Change (UNFCCC) held in Glasgow, UK, in 2021 announced "Glasgow Leaders' Declaration on Forests and Land Use," committing to halt and reverse deforestation and land degradation by 2030. They also committed to providing $19 billion for protecting and restoring 13 million square miles of forest. All these international actions have shown the significance of forests in global sustainable development and climate change. Furthermore, they have determined how to manage forests and combat deforestation.

Timber and timber products, as key carriers of carbon stock (Beamesderfer et al., 2020), can cause a hysteresis effect of carbon release in the carbon cycle of forest ecosystems (Backéus et al., 2005; Lal, 2005; Jasinevičius et al., 2018; Johnston and Radeloff, 2019). Moreover, timber is one of the most critical production factors and raw materials in the processing industry, and the direct or indirect demand for timber in different sectors of various countries inevitably leads to the cross-regional flow of timber and timber carbon stock. We analyze global timber carbon stock from three perspectives: income-based perspective (enabled by the primary input, e.g., labor, land, and fixed assets) of a certain sector in a country), production-based perspective (directly produced by a certain sector in a country), consumption-based perspective (caused by the final demand of a certain sector in a country). These three perspectives are studied from different stages of the production chain. They can clarify the role of different countries in the production chain and provide a decision-making basis for promoting the timber production process. Studies have explored the cross-regional flow of timber carbon stock from production- and consumption-based perspectives. Zhang Q. et al. (2020) calculated the volume and flow of timber carbon stock in the main nations of the world from production and consumption perspectives, respectively. The results showed that developed nations consumed much carbon stock from undeveloped nations through international trade. Taking the countries of the Belt and Road as the research object; Li et al. (2022a) studied consumption-based timber carbon stock and pointed out the main factors having effects on the change of the timber carbon stock. They identified that final demand (products that have been finally processed or consumed in the region) has a positive effect. However, the production- and consumption-based perspectives cannot clearly bring out the supply-driven effect of upstream production chains, that is, the driving role of primary inputs (e.g., labor, land, and factory buildings) (Steininger et al., 2016; Li J. et al., 2021). The income-based perspective considers pollution emissions or resource consumption in subsequent production caused by production factor suppliers that obtain income by providing primary factors (Yan et al., 2016; Zhang et al., 2019; Zhang et al., 2022). For example, Liang et al. (2016) revealed the relative contribution of changes in primary supply-side inputs to greenhouse gases (GHG) in the United States. Changes in the primary input level (i.e., the amount of primary inputs *per capita*) were the largest contributor to GHG emissions from 1995 to 2009. Li et al. (2022b) investigated the global flows of trade-embodied polycyclic aromatic hydrocarbons (PAH) from consumption- and income-based perspectives. Our results showed that, in 2014, 16.8% and 10.1% of global PAH emissions were transferred through international trade by consumption and primary inputs, respectively. From an income-based perspective, India and the rest of Asia experienced a significant increase in net income-based outflows, indicating leakage of income-based emissions from emerging markets. These studies show that international trade not only separates the production and consumption sides in geographic space. Additionally, it also separates the primary input on the global supply chain. The analysis from primary suppliers perspective can complement production- and consumption-based studies to thoroughly understand the driving forces of the global transfer of pollution and resource consumption. However, research on the global flow of timber carbon stock has not been conducted from an income-based perspective. As a critical primary input, timber can influence downstream production; thus, income-based analysis can show the timber carbon stock embodied in trade driven by primary suppliers.

This study aims to identify the crucial primary suppliers that drive the transfer of timber carbon stock embodied in trade. Moreover, we analyze the various results by comparing income-based, production-based, and consumption-based analyses, emphasizing the significant role of primary input countries in the timber supply chain. The organization of this article is as follows. In Section 2, it presents the research methods and data sources. This study used the Ghosh-multi-regional input-output (MRIO) model to calculate the income-based timber carbon stock flow among 190 countries. Furthermore, combined with the Leontief-MRIO model, a comparative analysis is carried out to analyze the different results of the income-based, production-based, and consumption-based methods. Section 3 demonstrates the results of imports and exports as well as the net trade distribution of global timber carbon stock driven by primary inputs. It also demonstrates the patterns of the global flow of timber carbon stock from three perspectives. Finally, Section 4 concludes the study. The research results can help clarify the flow of forest resources embedded in global trade activities. Furthermore, it also provides a scientific basis to fairly account for carbon offset shares to achieve better the goal of forest resource protection agreed upon in COP26.

2 Methods and data collection

2.1 Income-based method of cross-regional pollution and resource consumption

The MRIO model reveals interdependent relationships between sectors across countries (Malik et al., 2018; Wiedmann and Lenzen, 2018; Xu et al., 2020). Production-based methods have been used to study resource consumption or environmental pollution caused by direct producers (Pan et al., 2008). However, they cannot reflect the pollution or resource consumption embodied in the cross-regional supply chain; thus, the consumption-based method is proposed to quantify the resource use and emissions caused by final demand (Rodrigues and Domingos, 2008). Numerous studies have been conducted to account for carbon emissions (Mi et al., 2017; Lenzen et al., 2018; Liang et al., 2020; Lu et al., 2020; Yang et al., 2020), energy consumption (Soulier et al., 2018; Ezici et al., 2020; Wang and Ge, 2020), particulate matter 2.5 emissions (Liang et al., 2017a), and water resource use (Lenzen et al., 2013; Yang et al., 2021). However, these two methods fail to capture the driving role of primary input at the beginning of the supply chain. Income-based methods can reflect resource consumption and pollution emissions driven by primary suppliers (Qi et al., 2019; Wang et al., 2020; Li R. et al., 2021; Yang et al., 2022). Income-based timber carbon stock accounting indicates timber carbon stock caused by income from wages, profits, and rents (payments for primary factors). The principle of income-based analysis is that the production factor suppliers provide primary factors to producers that use the factors to manufacture goods or provide services. Furthermore, the final products and services are supplied to downstream producers and consumers (Lenzen and Murray, 2010; Miller and Temurshoev, 2017). The income-based perspective states that although primary factor suppliers do not directly generate pollution emissions or resource degradation, they cause emissions by providing production factors for downstream producers. In this process, primary input suppliers obtain income from wages, profits, or rent from the production factors. Such economic benefits drive the generation of emissions in the production chain (Marques et al., 2012; 2013; Yuan et al., 2018). Liang et al. (2017b) found that the income-based accounting method can reveal new critical countries and sectors of GHG emissions by comparing production- and consumption-based analyses. Xie et al. (2017) estimated the amount of interprovincial carbon emissions transferred in China from a supply-side perspective. The results show that central and western regions mainly transferred their carbon emissions to eastern coastal regions. They put forward that the central and western regions should select downstream enterprises with low carbon emission intensity and high resource utilization to achieve low-carbon production goal. Chen et al. (2019) compared the CO2 emissions of 30 provinces in China from three perspectives based on production, consumption, and income. In previous studies, they found that the tertiary industry, generally considered a low-carbon industry, was the main contributor to China's income-based carbon emissions, accounting for 31% of China's total income-based carbon dioxide emissions. These studies show obvious differences between income-based, production-based, and consumption-based pollution and resource consumption transfer methods. Therefore, an income-based perspective can provide a new scientific reference for cross-regional pollution and resource transfer. We compare the differences between production-based, consumption-based and income-based in order to observe the role of different countries in the timber supply chain from the three perspectives, to better explore the income-based research findings and highlight the primary suppliers of timber carbon stock to provide a basis for the decision-making.

2.2 Calculation of timber carbon stock embodied in trade

We integrated the MRIO model and the accounting method for timber carbon stock to trace the global transfer of timber carbon stock embodied in trade. The Ghosh-MRIO model traces the global flow driven by primary suppliers. Furthermore, the Leontief-MRIO model reveals the characteristics from a consumption-based perspective. Previous studies have provided the basis for timber carbon stocks accounting methods (Zhang L. et al., 2020; Li et al., 2022a), the MRIO extended matrix of timber carbon stock was calculated using the carbon conversion factors released by the Intergovernmental Panel on Climate Change (IPCC) and timber harvest volume from the Food and Agriculture Organization of the United Nations (FAO) database[1]. We used the Global Trade Analysis Project (GTAP) database[2] for the MRIO analysis and selected 141 nations (regions) for data acquisition.

2.2.1 Ghosh-MRIO model to calculate income-based timber carbon stock

According to the Ghosh-MRIO model, X_{ij} represents the use of the intermediate input of the products of department i by department j and V_i denotes the primary input of department i (i.e., added value). The column balance of the input-output table can be expressed as

$$\sum_{i=1}^{n} x_{ij} + v_j = x_j \tag{1}$$

Introduce the direct sales factor: $b_{ij} = x_{ij}/x_i\,(i, j = 1, 2, \cdots, n)$, representing the share of direct sales from department i to department j. Thus, Eq. 1 is organized as follows:

$$\sum_{i=1}^{n} b_{ij} x_i + v_j = x_j \tag{2}$$

Eq. 2 is expressed as a matrix:

$$X^T \times B + V = X^T \tag{3}$$

$$X^T = V(1 - B)^{-1} \tag{4}$$

1 https://www.fao.org/faostat/en/#data/ FO

2 https://www.gtap.agecon.purdue.edu/databases/

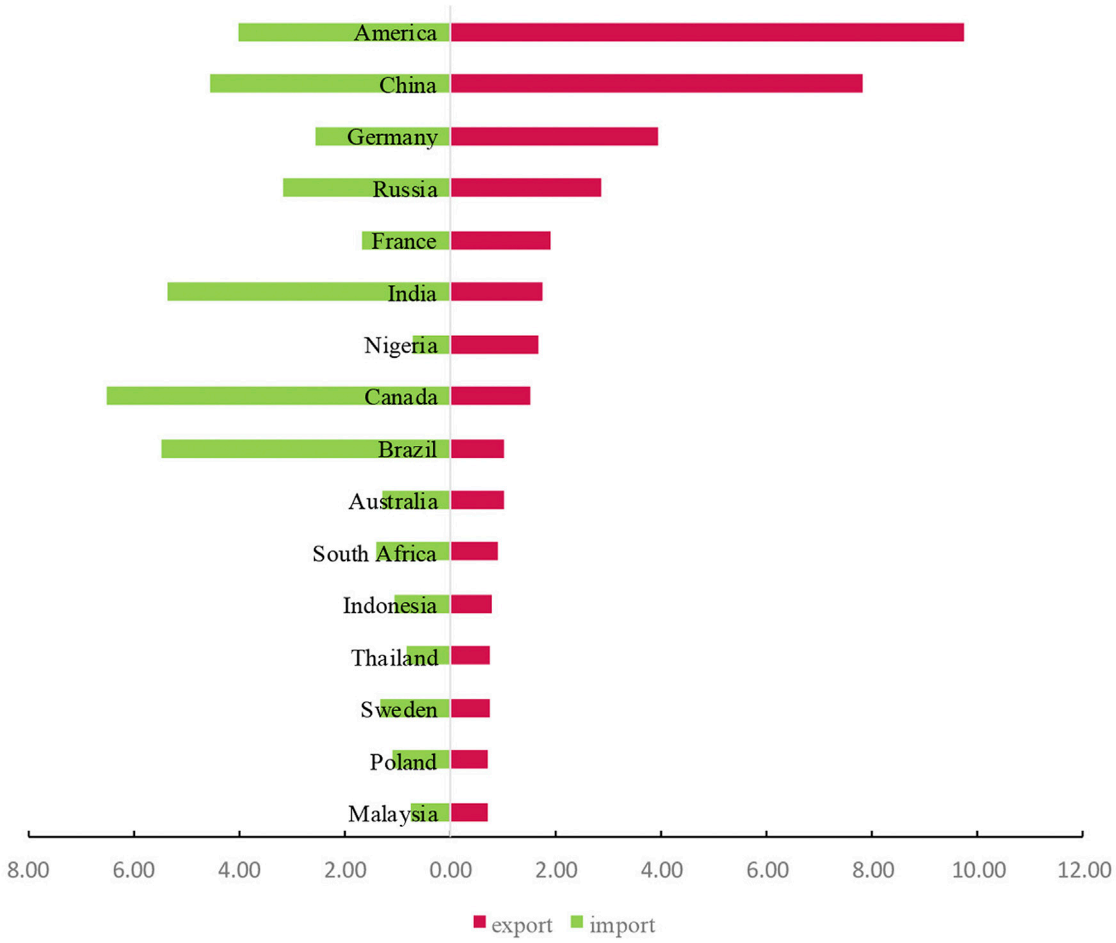

FIGURE 1
Income-based timber carbon stock in 16 main countries in the world in 2014 (unit: 10^4 tons).

X^T is the row vector of the total input, and V is the row vector of the sector-added value. I is identity matrix and B is supply coefficient matrix. Eq. 4 is the Ghosh model that reflects the relationship between the total input and intermediate input, where $(1-B)^{-1}$ is the Ghosh inverse matrix. Based on the above Ghosh model, we define income-based timber carbon stock (IBTCS) as the total amount of timber carbon stock caused by a nation's primary input (i.e., driven by the added value). Therefore, it is expressed as

$$\mathrm{IBTCS}^r = \mathrm{V}^r(\mathrm{I}-\mathrm{B})^{-1}E' \tag{5}$$

E is the coefficient matrix of the timber carbon stock, and E′ indicates the transpose of the matrix E.

2.2.2 Leontief-MRIO model to calculate production-based and consumption-based timber carbon stock

The total output X can be expressed based on the row balance of the input-output table and the Leontief-MRIO model principles as:

$$\mathrm{AX} + \mathrm{Y} = \mathrm{X} \tag{6}$$

Where A indicates consumption coefficient matrix and Y represents the final demand matrix. Eq. 6 can be transformed into:

$$\mathrm{X} = (1-A)^{-1}Y \tag{7}$$

Where $(1-A)^{-1}$ is the Leontief inverse matrix.

Our previous study (Zhang Q. et al., 2020) derived a calculation method for the carbon stock of timber on the production and consumption sides as follows:

$$\text{Production}-\text{based timber carbon stock: } PBTCS^r = EX^r \tag{8}$$

$$\text{Consumption}-\text{based timber carbon stock: } CBTCS^r = E(1-A)^{-1}Y^r \tag{9}$$

Where l_i^r denotes the proportion of production in sector i consumed by one unit of output in country r.

2.3 Data source

In this study, the MRIO data were obtained from the 10th edition of the GTAP database. The research objects included 141 countries

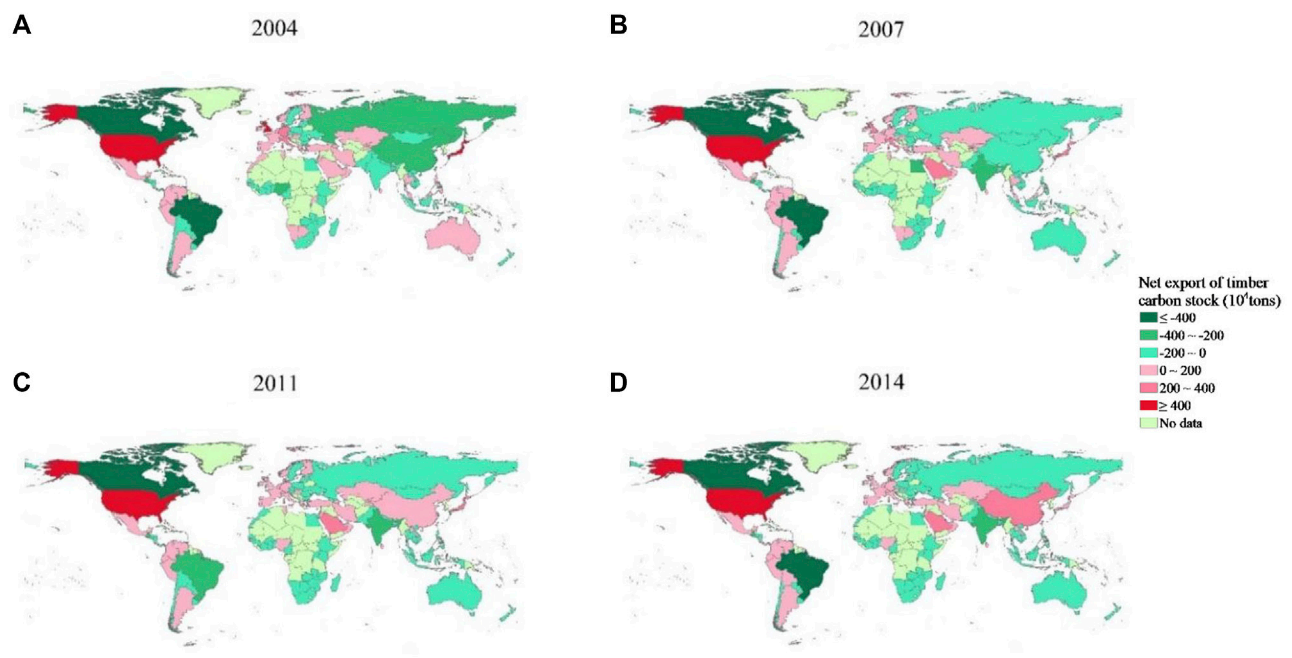

FIGURE 2
Global net exports of income-based timber carbon stock in 2004 **(A)**, 2007 **(B)**, 2011 **(C)**, and 2014 **(D)** (unit:10^4 tons). Note: The green represents net importers and the red represents net exporters.

and regions worldwide. Additionally, the time series data included 2004, 2007, 2011, and 2014. The timber harvesting data was obtained from the FAO, and we used the carbon conversion factor parameter from "the 2006 IPCC Guidelines for National Greenhouse Gas Inventories" to calculate timber carbon stock. Referring to our previous research method (Zhang L. et al., 2020; Li et al., 2022a), only the forestry logging sector has the primary input of timber carbon stock to calculate. Furthermore, other sectors do not conduct logging. Thus, the input coefficient of the timber carbon stock is zero in other sectors. Due to the differences in the carbon conversion factors of timber harvested in different climatic zones, we classified the countries according to the different climatic zones to improve the accuracy of the timber carbon stock (Zhang Q. et al., 2020)

3 Results and discussion

3.1 The main import and export countries of income-based timber carbon stock

Figure 1 reports the main importers and exporters of income-based timber carbon stock in 2014. It can be found that the top 5 countries in terms of export volume are the United States, China, Germany, Russia, and France. Among them, the United States, China, and Germany import and export timber carbon stock simultaneously. However, they export more, meaning that they are major suppliers of primary timber carbon stock products. China had a large population, and the cost of human resources was relatively low from 2004 to 2014. Therefore, more human capital is invested in timber production. With a rich forest resource endowment, the United States has a high *per capita* forest allocation. It has invested more primary resources (such as labor and land, among others) in timber products. Additionally, it has provided the world with more timber carbon stock (Zhang L. et al., 2020). Notably, Figure 1 shows that the import volume of Canada's income-based timber carbon stock is much higher than its export volume, indicating that Canada is a major country of importing income-based timber carbon stock. This result is the opposite of that of the United States (see Figure 2), although they are both developed forestry countries located in North America. A large part of Canada's domestic timber carbon stock comes from importing forest resources from other countries instead of its domestic primary input (Gilani et al., 2020). Thus, Canada obtained higher factor payments in the timber supply chain. Compared to the United States, Canada's population is one-tenth the size of the United States (according to the data from WorldBank[3]). This could be related to a relatively higher human resource cost, as previous studies have reported (Jones G. W., 1992). The wood-processing industry in the United States is more developed than in Canada (Das et al., 2005). The United States has produced approximately twice as many wood-processed products in the last decade (Hu et al., 2015). The climate in the United States is relatively better for tree growth (Peichl et al., 2006), especially in the South where trees grow much faster. In contrast, except for the west coast, the climate in other places in Canada is colder, where the timber grows more slowly (Tardif et al., 2006). Thus, the previous findings could be related to Canada's forests having a lower carbon stock capacity in Canadian forests in comparison with those

3 https://data.worldbank.org.cn

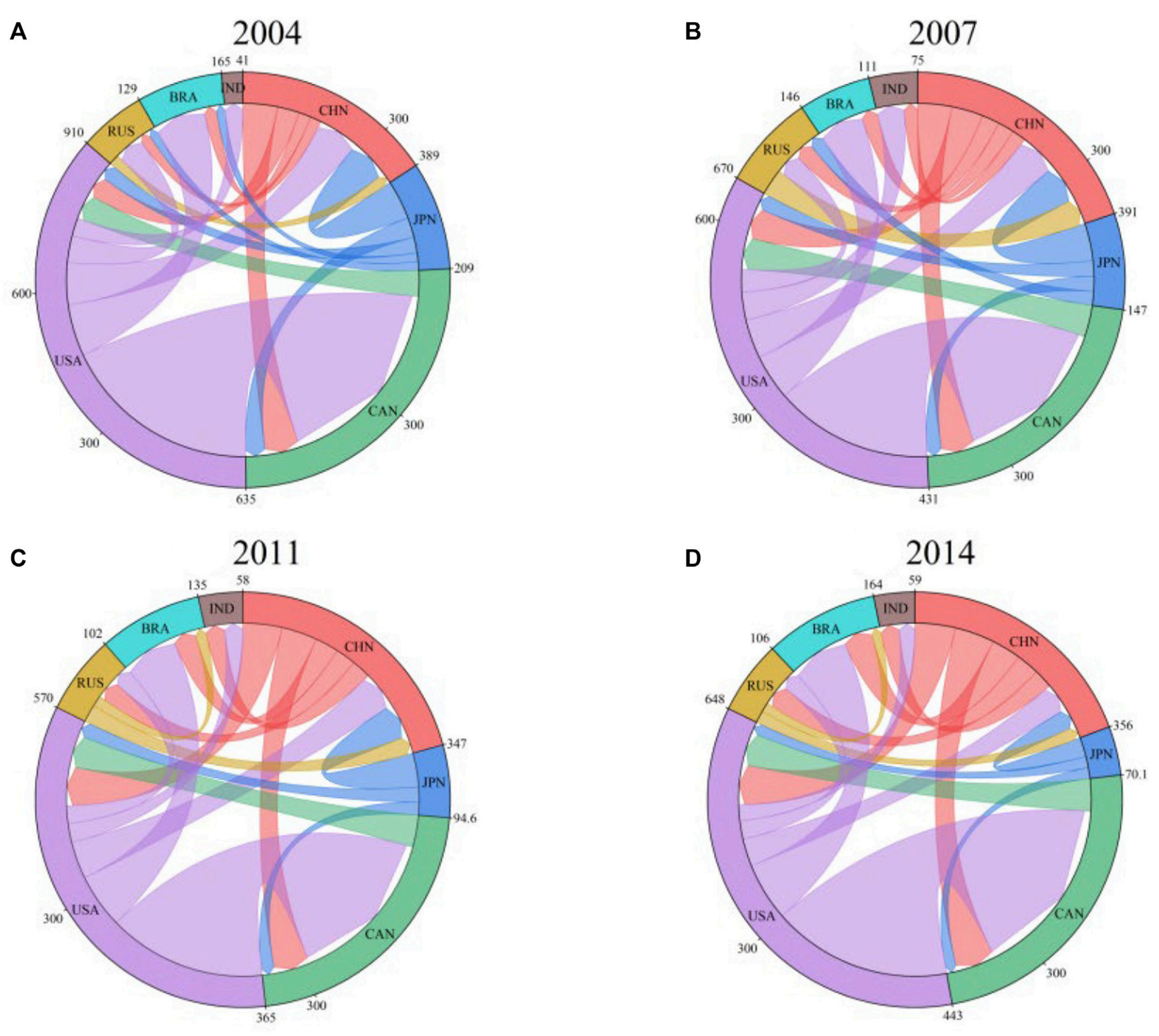

FIGURE 3
Income-based timber carbon stock flows among major countries in 2004 **(A)**, 2007 **(B)**, 2011 **(C)** and 2014 **(D)** (unit:10^4 tons).

from the United States. In addition, Canada's deforestation rate is low and the area of forest used for production only accounts 6% of the total forest area (Gilani and Innes, 2020). Thus, Canada's income-based timber carbon stock imports are affected by population, climate, and forests factors. In addition, they import more compared to the export volume of timber carbon stock in Brazil and India, indicating that they get more timber carbon stock processed products from abroad.

Global net exports and imports of timber carbon stock from the income-based perspective from 2004 to 2014 are shown in Figure 2. Bounded by 4 million tons, from the point of view of the net importing country, Canada and Brazil are large net importers of timber carbon stock. The other net importers mostly reveal a low volume of timber carbon stock. In the aspect of the net exporters, the nation with the large volume of timber carbon stock is the United States, and its net export value is much higher than that of China, which ranks second. From the perspective of the time change trend, compared with 2004, the regional distribution of the global net trade timber carbon stock in 2014 has changed greatly. Russia's imports of timber carbon storage have always been greater than exports from 2004 to 2014. However, the difference between imports and exports is narrowing. Notably, China's net trade in timber carbon stocks changed significantly between 2004 and 2014. China changed from a net importer to a net exporter after 2007. This change indicates that from 2004 to 2014, China provided an increasing primary input for processing timber products and gradually shifted from exporting simple processed timber to exporting high-value-added timber processing products.

In terms of outflows, as Figure 3 shows, the United States had the largest outflow of income-based timber carbon stock from 2004 to 2014. The largest volume of timber carbon stock of the United States flowed into Canada. Additionally, the flow from the United States to Brazil showed an evident upward trend. The outflow of China's income-based timber carbon stock increased significantly, with the

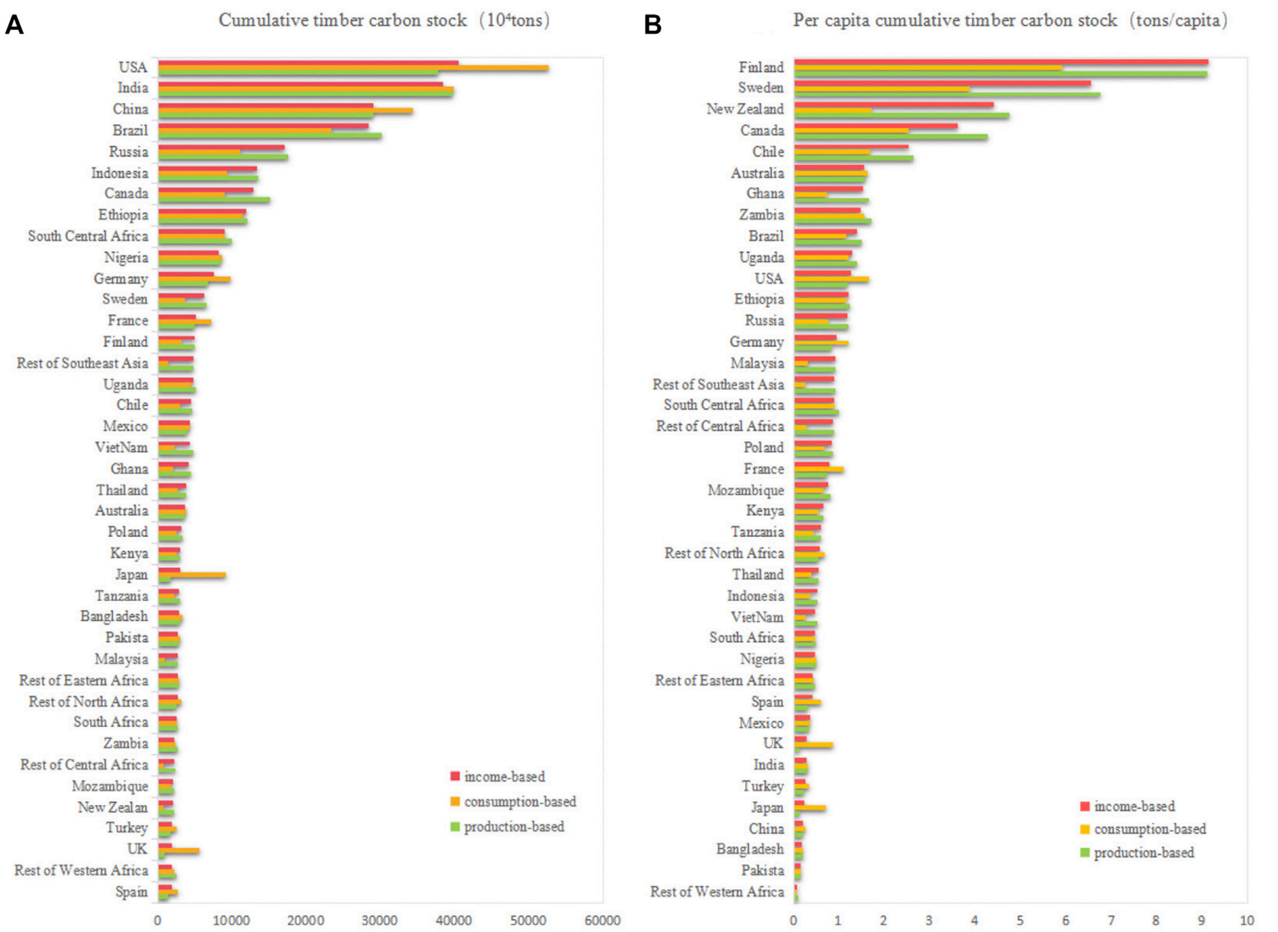

FIGURE 4
(A) Cumulative timber carbon stock. **(B)** Per capita cumulative timber carbon stock. Note: Cumulative timber carbon stock of nations is the sum of the results during 2004–2014. Per capita cumulative timber carbon stock of a nation is equal to its cumulative timber carbon stock during 2004–2014 divided by its population in 2014.

most volume flow going to Canada in 2004 and 2007. The flow from China to the United States increased by 38.7%, from 493,600 tons in 2004 to 684,700 tons in 2014. Japan's income-based timber carbon stock has mainly flowed to China, Canada, and the United States. However, the total outflow has been declining annually. In terms of inflows, Canada, Brazil, Russia, and India were net inflow countries from 2004 to 2014. Furthermore, most of their income-based timber carbon stocks were from the United States and China. However, the total timber carbon stock from the United States to these four countries have dropped by 31.68% in 2014 compared to 2004. In addition, China was a net importer before 2007. Furthermore, China was a net exporter in 2011 and 2014. The largest inflow source was the United States. However, from 2004 to 2014, the outflow of timber carbon stock from the United States to China decreased by 50.77%, from 951,200 tons to 468,300 tons, reflecting the US restrictions on the export of China's income-based timber carbon stock. To summarize the global trend of income-based timber carbon stock, it can be seen that from 2004 to 2014, the outflows of timber carbon stock enabled by the primary supply from the United States and Japan showed a downward trend, while that of China showed an upward trend.

3.2 The comparison of the income-based, consumption-based, and production-based timber carbon stock

Income-based accounting revealed a different profile of global timber carbon stocks compared to consumption- and production-based perspectives. This profile reflects the effect of primary input factors in the global timber production chain. This section compares these three perspectives. From the income-based perspective (Figure 4A), the top ten countries' timber carbon stocks, including the United States, India, China, Brazil, and Russia, account for 55.77% of the global total. From 2004 to 2014, the United States ranked first in income-based timber carbon stocks. Meanwhile, its income-based result is much larger than the consumption- and production-based results. These statistics imply that processed wood products containing primary resources from the U.S. have a significant implication for the global timber production chain. Brazil, Russia, and Indonesia, as the main suppliers of the primary input of timber carbon stock, are more important as primary resource suppliers of timber carbon stock than as final consumers. During 2004–2014, the cumulative income-based timber carbon stocks of Brazil, Russia, and Indonesia were 21%, 54%,

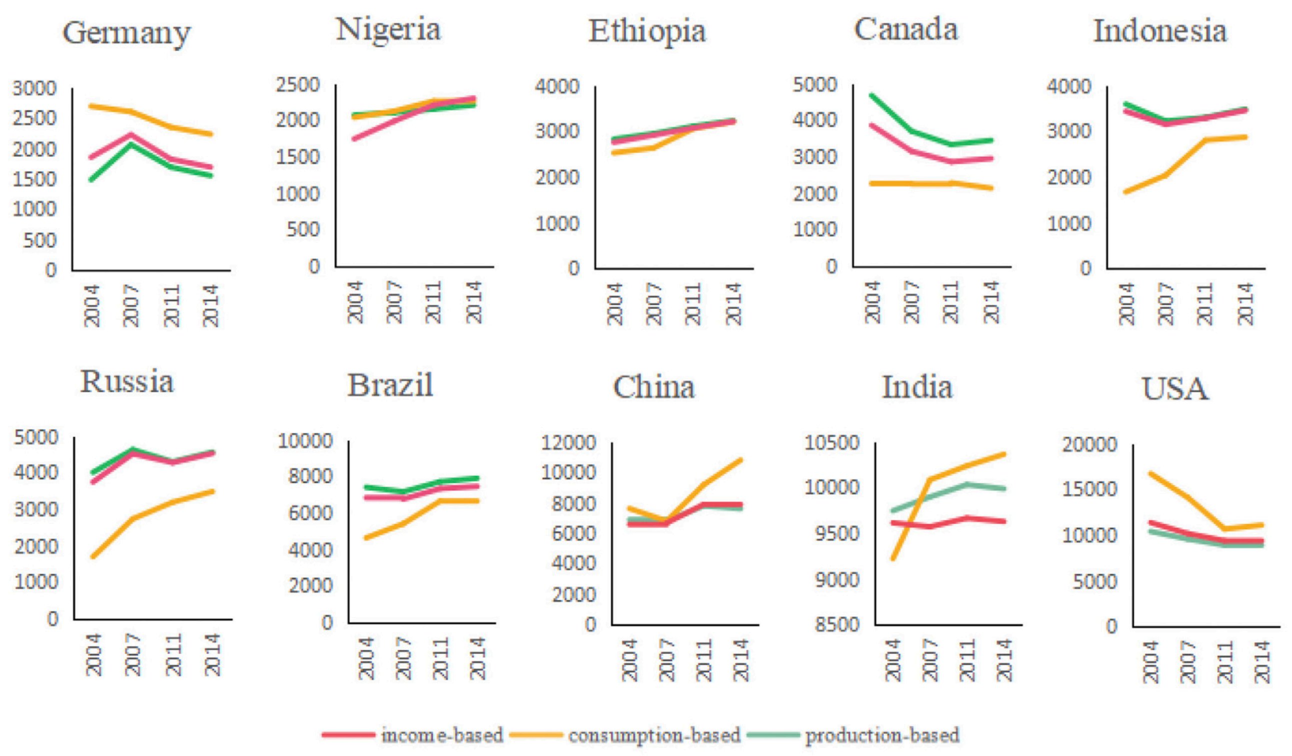

FIGURE 5
Temporal trend of income-based, consumption-based and production-based timber carbon stock of nations during 2004–2014 (unit:10^4 tons).

and 42% higher than their consumption-based cumulative carbon stocks, respectively (Figure 4A). China is a major importer of raw timber and a large exporter of processed wood products. Notably, the income-based results show that China's role as a primary input supplier is as important as that of a direct producer in the global timber supply chain. From 2004 to 2014, China was the third-largest contributor to income-based timber carbon stocks (Figure 4A). China ranks high because, in the midstream and downstream positions of the timber industry, China imports raw timber materials and exports intermediate products to other countries for subsequent processing. These actions have put in a great deal of workforce and land factors during manufacturing. Therefore, by comparing the three accounting methods, we find that the income-based perspective emphasizes the key role of primary resource inputs in the global timber carbon stock.

Regarding the *per capita* results of income-based, production-based, and consumption-based economies, the top-ranking countries from 2004 to 2014 mainly include Finland, Sweden, New Zealand, and Canada, which are developed economies with small populations. The *per capita* income-based timber carbon stock in developed nations is larger compared to developing nations, implying that developed nations own larger endowments of *per capita* natural resources (Figure 4B). In addition, China ranks 37th in *per capita* timber carbon stock, down 34 places compared to the cumulative result. A comparison of the three perspectives shows that the *per capita* income-based and production-based timber carbon stocks are remarkably larger than the consumption-based results because of the high resource *per capita* rate.

In Figure 5, income-based carbon stocks in developing countries (Nigeria, Ethiopia, Indonesia, Russia, Brazil, China and India) continued to grow during 2004–2014 because land and labor costs were relatively low. Furthermore, to promote the timber industry, developing countries put in a large amount of primary production factors resulting in a further increase in the income-based timber carbon stock. In 2014, income-based timber carbon stocks in China, Russia, and Brazil increased by 20.65%, 20.93%, and 9% (Figure 5), respectively, compared to their 2004 levels. The primary inputs they produce enable substantial downstream timber carbon stock flow. On the other hand, income-based timber carbon stocks in developed countries have remained relatively stable from 2004 to 2014 (e.g., the United States), while Germany and Canada have experienced obvious changes. Income-based timber carbon stock of Germany showed an upward trend from 2004 to 2007 and a sharp decline after 2007 due to the global economic crisis in 2008. With a relatively high export dependence, Germany was greatly influenced by the economic recession because of the sharp decrease in overseas orders due the economic recession. The decline in the German economy in 2009 exceeded the average level in other countries and further reduced the economic recovery. From 2004 to 2014, Canada's income-based timber carbon stocks showed a downward trend, consistent with the decline in production-based results. Most of Canada's exported timber consists of logs and primarily processed products. In 2014, Canada's income-based timber carbon stocks decreased by 23.6% compared with 2004 due to Canada's timber harvesting and export restrictions (Gilani and Innes, 2020).

Income-based perspective can reveal new changing trends of time in timber carbon stocks that consumption- and production-based perspective cannot present. Specifically, the rapid growth of labor and primary product exports in China, India, Indonesia, Brazil, and Russia has driven income-based timber carbon stock flows. In India and Brazil, income-based timber carbon stocks were lower than production-based ones from 2004 to 2014 (Figure 5). Germany's primary inputs had a greater impact on the flow of timber carbon stocks than direct harvesting activities. Moreover, production- and income-based timber carbon stocks present similar trends in China, Russia, and Indonesia, indicating that these countries not only process timber products but also invest a large amount of primary inputs such as labor and land production factors. In addition, income-based timber carbon stocks in Nigeria showed a sharp upward trend between 2004 and 2014 (Figure 5). In the early stages of industrialization, Nigeria's economy developed rapidly during the study period and became the largest economy in Africa. Nigeria's abundant resources and steady population growth have dramatically increased income-based timber carbon stocks. Overall, the above research results show that consumption- and production-based accounting cannot sufficiently reveal the drivers of the global flow of timber carbon stocks. Accounting from income-based perspective can be used to explore the effect of primary resource inputs in the global timber production chain.

4 Conclusion and management implications

This study uses an MRIO model to analyze the income-based timber carbon stock of 141 countries from 2004 to 2014. We also compare the differences from the production-, consumption-, and income-based perspectives to comprehensively clarify the cross-regional transfer of timber carbon stock and key driving countries. This research draws the following conclusions: 1) The top five countries in terms of export volume of income-based timber carbon stock were the United States, China, Germany, Russia, and France in 2014. The primary inputs to their production enable substantial downstream timber carbon stock flow. Among them, the United States and China were among the top in both imports and exports simultaneously. However, their export volumes were significantly larger, meaning that these countries have invested more primary resources in timber products and provided more timber carbon stock for the world. 2) The United States had the largest outflow of timber carbon stock from income-based perspective from 2004 to 2014, mainly flowed into Canada and Brazil. In China, the largest flow went to Canada. Furthermore, the flow to the United States increased significantly. Japan's income-based timber carbon stock has mainly moved to China, Canada, and the United States. However, the total outflow has been declining. 3) A comparison of the three perspectives shows that the United States' primary inputs have a greater impact on the global timber production chain than their consumption-and production-based roles. Brazil, Russia, and Indonesia, as main primary resource suppliers of timber carbon stock, are more important than as final consumers.

The strict policy of restricting deforestation has made Canada's forest area stable, which is conducive to Canada becoming an income-side timber carbon stock net-importer. Germany's income-based and consumption-based timber carbon stock was higher than directly produced timber carbon stock, which also shows the effectiveness of Germany's forest management policy. Forest management has become an effective way to achieve rational forest harvesting and cope with climate change. Therefore, countries should formulate corresponding management measures according to the different stages of timber production. Optimizing the allocation of primary factors from the source of the production chain is conducive to the rational utilization of forest resources, and promotes the achievement of carbon neutrality targets.

Our research reveals the pattern of income-based timber carbon stock, highlighting the important role of primary resource input in the global timber carbon stock. The research findings can contribute to identifying the driving countries of the cross-regional flow of timber carbon stock from the entire timber production chain. It also helps to understand better the role of timber carbon stock as an ecological resource in related countries, which can bring attention to forest quality and the ecological impact of forest product trade. Aguilar et al., 2022, Gauthier et al., 2023, Li Y. et al., 2022.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: https://www.gtap.agecon.purdue.edu/databases/v10/index.aspx https://www.fao.org/faostat/en/.

Author contributions

YW and CY contributed to conception and design of the research. YW wrote the manuscript. MY, YY and YY organized the data analysis and wrote the sections of the manuscript. WZ, RL and SW performed the data curation and visualization. CY and SW contributed funding acquisition. 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.

Publisher's note

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The direct and indirect spatial spillover effects of infrastructure on urban green and smart development

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Introduction: Economic development is not simply the accumulation of elements, but the improvement of efficiency, which is supported by infrastructure construction. In particular, the urban green and smart development (UGSD) in recent years has put forward higher requirements for infrastructure, and domestic trade as well as opening-up are of great significance during the process.

Methods: Based on the panel data of 221 prefecture-level cities in China from the year of 2005 to 2019, this paper adopts the undesirable SBM model and GML index to measure the level of UGSD. Then the spatial Durbin model is conducted to explore the direct spatial spillover effects and the spatial decomposition effects of energy, transportation, and information infrastructure on UGSD. Considering the context of dual cycle, the indirect effects of domestic trade and opening-up between infrastructures and UGSD are further analyzed.

Results: Results show that UGSD demonstrates strong spatial agglomeration and maintains a stable spatial positive correlation with different spatial matrices. In general, energy and transportation infrastructure show positive spatial spillover effects on UGSD. By contrast, information infrastructure presents positive spatial spillover effect on UGSD on the whole, while shows insignificant and negative spatial spillover effect with geographical distance matrix. Furthermore, the mediation effect indicates that both transportation and information infrastructure mainly promote local and adjacent cities' UGSD through domestic trade with economic distance matrix. By contrast, energy infrastructure exerts positive spatial spillover effect on UGSD through weakening the negative impact of opening-up.

Discussion: The conclusions of the research show that it is necessary to construct infrastructure in a reasonable way, strengthen the positive spillover effect of intercity factors, and promote the two-wheel driving effect of domestic trade and opening-up on the relationship between infrastructure and UGSD.

KEYWORDS

infrastructure, urban green and smart development, domestic trade, opening-up, spatial spillover effect

1 Introduction

China's current economic model is shifting to the stage of high-quality development (Xu et al., 2022); carbon peaking and carbon neutralization have put forward higher requirements for the green and low-carbon transformation of the economy. Green and smart development which includes resource conservation, ecological protection, and environmental governance (Du et al., 2020; Xu et al., 2021; Liao and Li, 2022) has become the crucial means to solve the contradiction between rapid economic growth and environmental problems (Li et al., 2019; Shamsuzzoha et al., 2021). Furthermore, as an important carrier, great importance has been attached to the role of infrastructures in achieving high-quality development. Under the dual background of the accelerated development of infrastructure and low-carbon economic transformation, it is urgent to explore the logical framework between infrastructures and urban green and smart development (UGSD), which responds to the realistic demand of China's high-quality economic development.

UGSD is a sustainable development mode, considering the constraint of resource and environmental capacity, which includes economic, energy, and other elements (Hao and Zhu, 2019; Moura and Silva, 2019; Jiang et al., 2021; Liao and Li, 2022). As such, many comprehensive evaluation indexes from multi-dimensional and multi-level perspectives were conducted to analyze the level and evolution characteristics of UGSD, and the data envelopment analysis (DEA) was primarily adopted to measure UGSD (Hao and Zhu, 2019; Du et al., 2020). Furthermore, the green total factor productivity (GTFP) containing energy consumption and undesirable output could estimate the efficiency of DMU (Decision-Making Unit) from the perspective of input-output, which is an objective and effective method (Liu et al., 2016; Jiang et al., 2021). Therefore, it has become an important criterion to measure UGSD due to its stronger inclusiveness (Yuan and Liu, 2019; Xu et al., 2022). As for the influencing factors of UGSD, existing literature mainly explored the impact of FDI (Gao et al., 2022; Xu et al., 2022), economic agglomeration (Hao et al., 2022), environmental regulation (Feng et al., 2021), and technological progress (Sun et al., 2022) on UGSD. Additionally, the technological innovation and information level would also effectively promote urban governance and service efficiency besides the energy element and release their supporting role for UGSD (Xu et al., 2021; Han et al., 2023).

UGSD also requires carriers to achieve corresponding goals, among which infrastructures are fundamental (Nondo, 2018). As the balanced growth theory points out, infrastructure is a prerequisite for economic growth (Chen et al., 2020), and it could promote urban transformation through the optimization of industrial structure and the structure upgrading of energy consumption (Xu et al., 2021). Studies have shown that infrastructure plays an important role in promoting urban development, especially in regional innovation, economic growth, and green development (Bronzini and Piselli, 2009; Bresson et al., 2016; Wang J et al., 2022; Zhang and Zhou, 2023), and the positive effect is more significant in lagging areas (Odongo and Kalu, 2016). As the representative scholar Aschauer (1989) pointed out, the stock of infrastructure such as highways and airports has a strong explanation for economic growth, which has been largely supported in later research. For instance, Bronzini and Piselli (2009) and Álvarez-Ayuso et al. (2011) found that infrastructure showed a positive impact on total factor productivity, and this conclusion worked well in both Italy and Mexico. Nondo (2018) focused on 26 African countries and found that infrastructure development is conducive to economic growth. With a large population and uncompleted urbanization, infrastructure construction is an inherent demand for economic and social development in China. As such, China's cities have actively deployed key infrastructure construction related to energy, transportation, and information, recently, to provide fundamental support for UGSD. Demurger et al. (2001) found that the stock of infrastructure, especially transportation infrastructure, is an important factor affecting the difference in economic growth performance among regions in China. Liu and Hu (2010) also affirmed the positive role of infrastructure on economic growth. Furthermore, infrastructure could release spatial spillover effects by promoting the flow of the production factor and extending the externality to the development of adjacent regions (McCartney, 2022). Additionally, infrastructure could also promote urban accessibility and facilitate technological innovation, which is conducive to evoking spatial preferences and agglomeration (Xie, 2018; Zeng et al., 2019). Konno et al. (2021) empirically analyzed the productivity effects of road infrastructure incorporating spatial spillover effects using a global database, and the statistical tests suggest that the direct impact of road infrastructure is significantly negative, the spatial spillover effect is significantly positive, and the overall effect is positive but insignificant. Marinos et al. (2022) applied a dynamic Durbin spatial model to estimate the spatial spillover effect of transportation infrastructures in the Greek economy, and results showed that the spillover effects of transport infrastructures are present and statistically significantly affect the regional product. Wang J et al. (2022) took the traffic infrastructure of 41 prefecture-level cities in the Yangtze River Delta as research objects and found that the transportation infrastructure of each city not only drives its own economic growth but also has a positive spatial spillover effect on the economic growth of adjacent areas. Previous research has given large evidence for the significance of infrastructure, which provided valuable experiences for our studies. However, the element input of infrastructure construction and the waste brought by reproduction may lead to more pollution, and the scale economy caused by factor agglomeration might also result in resource allocation distortion and inefficient utilization (Kong et al., 2018; Akbar et al., 2021; Yang et al., 2021), which would cause potential inhibition on UGSD. For example, Puga (2002) pointed out that the growth of infrastructure such as energy and transportation aggravated environmental pollution, which further threatened the health of residents. Furthermore, transportation infrastructure could reduce logistics costs and promote resource circulation, while also accelerating the resource flow to large cities. In consequence, the siphon effect and the differentiation degree of the regional economy would be deepened (Zhang et al., 2018).

Except for the direct effect, scholars have also explored the indirect effect from multiple perspectives. Li and Yao (2022) found that digital infrastructure investment mainly promotes the green growth of manufacturing by promoting technological progress and technological efficiency. Moreover, the mechanism of industrial and talent agglomeration (Cheng and Hu, 2019; Liu et al., 2022) and international trade (Peng et al., 2021) have also been explored between infrastructure and UGSD. As a result, infrastructure could enhance the intercity connections by factor flow, and the spatial spillover effect of infrastructure on UGSD would be further strengthened. The report of the 20th National Congress of the Communist Party of China further emphasized the construction of transportation and network infrastructure as an important direction for the "double cycle" development pattern. However, the roles of domestic trade and opening-up, especially under the dual circulation development mode of international and domestic markets, have not been given enough attention.

Accordingly, existing literature mainly explores the influencing factors of UGSD from the perspective of the economy, environmental regulation, and innovation, which ignores the important role that infrastructure may play. Furthermore, previous literature provides abundant evidence for understanding the direct impact of specific infrastructure on UGSD and provides a preliminary analysis of its spatial spillover effects. However, it is worth emphasizing that these studies have neglected the spatial spillover impacts of different infrastructures on UGSD from both direct and indirect perspectives. As for the influencing mechanism, previous literature mostly focused on innovation or international trade. Under the context of the double cycle, urban green development has ushered in a new opportunity; however, the roles of domestic trade and opening-up between infrastructure and UGSD have not been explored in depth. Therefore, a more comprehensive perspective considering both domestic and international lenses needs to be deeply explored. Finally, in existing related research, few works of literature consider the heterogeneous spatial correlation of variables, which may lead to bias in the conclusion.

Compared with existing studies, the possible marginal contributions of this study are as follows. First, we expand the research framework for the analysis of the influencing factors of UGSD from the perspective of different infrastructures. Figuring out the comprehensive roles of infrastructure construction and UGSD is the production basis for understanding the transformation of the economic development model. Second, we provide reliable empirical support for understanding the important role of domestic trade and opening-up in the process of transitioning to green and smart development. Furthermore, we expand the spatial empirical model, taking into account the geographical adjacency matrix, geographical distance matrix, and economic distance matrix to explore the heterogeneous relation between infrastructure and UGSD. The remaining parts of this study are organized as follows. Section 2 provides a theoretical analysis and research hypotheses. Section 3 introduces the research design and variable description of this research. Section 4 shows the empirical results and detailed analysis of the spatial spillover effects, decomposition effects, and mediation effects of domestic trade and opening-up. Furthermore, the discussion and robustness test are shown. Section 5 presents the conclusions, implications, limitations, and future work of this study.

2 Theoretical analysis and research hypotheses

2.1 The direct effect of infrastructure on UGSD

Due to the complex economic relations among cities, adjacent cities often interact with each other in the process of social and economic development. Meanwhile, adjacent cities are more likely to learn about others' successful governance experience, which is conducive to strengthening the circulation and integration of resources and elements among them. As the critical foundation of UGSD, infrastructure could affect UGSD through trade exchange, learning by imitation, and innovation spillover among regions. According to the functional standards, infrastructure can be divided into three types: economic infrastructure, social infrastructure, and administrative infrastructure. Considering the research characteristics of this paper, such as externality and network properties, and the availability of data, the economic infrastructure including energy, transportation, and information was selected.

2.1.1 Energy infrastructure and UGSD

Energy infrastructure provides important public products such as thermal power stations and hydroelectric stations for social production and operation. It is the foundation of social production and is of great significance to the sustainable development of cities (Xie, 2018). Energy supply and demand among cities are mostly constrained by resource endowment, geographical conditions, and other factors. As such, energy infrastructure, especially the construction of renewable energy, could optimize energy consumption structure and ease the imbalance of energy supply and demand among cities (Guo et al., 2021), which is beneficial to releasing the positive spatial spillover effect among cities. In addition, there is heterogeneity in industrial structure among cities, and the intensity impact of energy infrastructure on different industries is also heterogeneous (Gao and Yue, 2020). For example, energy infrastructure projects such as power transmission from the West to the East in China could deliver clean and high-quality power to the eastern region, driving the economic development of western cities while promoting industrial adjustment and easing the energy shortage in the eastern cities (Han et al., 2020). Therefore, energy infrastructure is beneficial in promoting the complementation of resources and realizing the mutual development of the economy and environment among regions.

2.1.2 Transportation infrastructure and UGSD

Transportation infrastructure is characterized by the network's external characteristics, which have a radiation effect on the development of adjacent areas. The construction of transportation logistics is constantly strengthened and the social division of labor is refined, which is conducive to regional economic growth, and transportation infrastructure directly promotes economic growth through the amplification of the investment multiplier (Wang L et al., 2022). On the one hand, transportation infrastructure could improve the accessibility and attraction of cities, and promote the flow of urban resources and elements (Xie, 2018; Wang L et al., 2022), which creates opportunities to learn advanced technology for urban green transformation. On the other hand, transportation infrastructure could also strengthen regional integration and optimize resource allocation among cities, thus promoting scale economics and improving urban productivity and living efficiency (Hao and Zhang, 2021). Therefore, transportation infrastructure would initiate a positive spatial spillover effect, which is conducive to achieving mutual development of local and adjacent cities.

2.1.3 Information infrastructure and UGSD

Information infrastructure could extend the width and breadth of information sharing and reduce the cost of information acquisition. The improvement of information infrastructure is conducive to breaking regional market restrictions and reducing coordination costs of enterprises, which is crucial to regional integrated market construction and beneficial to improving production efficiency through scale and intensive economy (Zhao et al., 2020). Furthermore, the upgrading and optimization of information infrastructure could break through temporal-spatial boundaries to promote resource matching degree and industrial agglomeration (Han et al., 2022). Also, information infrastructure provides a platform for joint technological innovation, which is conducive to achieving complementation of green technology and service among cities and improving the conversion rate of scientific and technological achievements (He and Ren, 2018; Yang and Liu, 2018). Therefore, information infrastructure creates favorable conditions for the flow of elements, enhancing the spatial spillover effect on adjacent cities.

Based on the above analysis, the following hypotheses are proposed:

H1: Energy infrastructure has a positive spatial spillover effect on UGSD.

H2: Transportation infrastructure has a positive spatial spillover effect on UGSD.

H3: Information infrastructure has a positive spatial spillover effect on UGSD.

2.2 The indirect effect of infrastructure on UGSD

In recent years, the Chinese government has built a new development pattern with the domestic great circulation as the main body and the domestic and international double circulation promoting each other. In domestic circulation, supply-side reform, industrial structure optimization, and scientific and technological innovations are the fulcrum to smoothen the internal circulation system and provide an inexhaustible driving force for economic development. At the same time, great importance has been attached to the support and guarantee function of the international circulation for the "double cycle," promoting a higher-level opening strategy by deeply integrating into the global value division of the labor system. However, the roles of domestic trade and opening-up between infrastructure and UGSD have not been explored in depth. As such, domestic trade and opening-up are selected to analyze the indirect effect of infrastructure on UGSD.

2.2.1 Mediation effect of domestic trade

2.2.1.1 The effect of infrastructure on domestic trade

Economic infrastructure provides the foundation for urban production and factor flow, which create favorable conditions for mutual development among cities (Xu et al., 2021). From the perspective of trade costs, infrastructure could lower transportation costs, reduce losses caused by information asymmetry, and improve resource allocation efficiency (Liu et al., 2020). As such, the domestic trade scale could be expanded and the trade structure could be optimized. Moreover, infrastructure also promotes product trade through the complementation of supply-demand among cities, enhancing the coordinated development of the regional economy and optimizing the spatial distribution of domestic industries.

2.2.1.2 The effect of domestic trade on UGSD

The impact of domestic trade on UGSD could be reflected in the following aspects. First, domestic trade could affect UGSD through the spatial spillover effect. Inter-city trade provides opportunities to gain advanced knowledge, technology, and governance experience, which might affect cities' industrial structure, economic growth, and competitive advantage. Furthermore, the element introduction from other cities could strengthen the positive effect of technological innovation on UGSD through the spillover effect (Zhang, 2021). Second, domestic trade could affect UGSD through the scale effect. That means domestic trade could affect UGSD by broadening the trade scale, enhancing intercity connection and economic integration, thus promoting urban productivity efficiency (Ma et al., 2019). Third, domestic trade could affect UGSD through the competitive effect. In a market-oriented economy, cities as supposed to improve productivity and reduce costs by encouraging product and technological innovation and reducing outdated manufacturing facilities, which is conducive to maintaining their competitiveness in domestic and overseas. Therefore, the level of UGSD could be improved.

2.2.1.3 The mediation effect of domestic trade between infrastructure and domestic trade

Infrastructure could promote domestic trade based on its carrier function, which further makes a difference to UGSD. For example, energy and transportation infrastructure could reduce logistic costs and enhance the complementation of supply-demand (Xie, 2018; Guo et al., 2021). As such, UGSD could be promoted through element conversion and industry upgrading. Furthermore, information infrastructure lays a solid foundation for information sharing, providing basic support for promoting the scope and speed of information exchange among cities (Ma et al., 2019). Thereby, green economic growth could be achieved through the spillover effect of knowledge as well as productive elements (Huang et al., 2019; Zhao et al., 2020).

Based on the above analysis, the following hypotheses are proposed:

H4: Infrastructure promotes UGSD through domestic trade.

H4a: Energy infrastructure promotes UGSD through domestic trade.

H4b: Transportation infrastructure promotes UGSD through domestic trade.

H4c: Information infrastructure promotes UGSD through domestic trade.

2.2.2 The mediation effect of opening-up

2.2.2.1 The effect of infrastructure on opening-up

Well-designed infrastructure could reduce the hidden cost and risk for foreign investors in transportation distance, informational island, and energy supply, thus improving the possibility of project operation profitability. The improvement of infrastructure is conducive to accelerating industrial agglomeration, promoting production convergence, reducing innovation costs, and attracting high-quality foreign investment (Tian and Li, 2019; Hao et al., 2022). For instance, information infrastructure could break market restrictions among cities, optimize the structure of opening-up, and enhance the attractiveness of international resources (Huang et al., 2019). Additionally, the development and application of information technology would reduce the revenue loss caused by time delay, which is beneficial to deepening the global division of labor and cooperation, promoting international trade interaction, and absorbing advanced experience (He and Ren, 2018).

2.2.2.2 The effect of opening-up on UGSD

Research has tested that expanding openness could exert bilateral impacts on China's environment and economy. Proponents of the "Pollution Paradise Hypothesis" argue that local governments are inclined to lower environmental standards to attract foreign investment (Zhang, 2016), which may lead to environmental pollution problems. However, the opening economy could also bring advanced technologies, promote local industrial structure, and unleash knowledge spillover effects (Gao et al., 2022), which help to facilitate urban green transformation through technological innovation as well as the upgrading of production elements (Yoon and Nadvi, 2018). These findings support the "Pollution Halo Hypothesis."

2.2.2.3 The mediation effect of opening-up between infrastructure and UGSD

Opening economies emphasize the utilization and interaction of foreign resources, and infrastructure provides a convenient condition and fundamental support for element flow (Mao, 2012). For instance, energy infrastructure is conducive to increasing the proportion of clean energy, adjusting the energy consumption structure, and improving the efficiency of asset operation. Transportation infrastructure could enhance inter-regional cooperation as well as innovation (Xie, 2018). Therefore, adjacent cities' UGSD would be promoted through clean raw materials usage and collaborative innovation. Furthermore, information infrastructure provides a platform for internationalization and improves the efficiency of transnational communication (Huang et al., 2019). Meanwhile, transnational investment could promote the technological progress and economic growth of the host country (Ma et al., 2019). As such, advanced technology and governance experience brought by opening-up could accelerate the spillover effect of production elements, which favors UGSD.

Based on the above analysis, the following hypotheses are proposed:

H5: Infrastructure promotes UGSD through opening-up.

H5a: Energy infrastructure promotes UGSD through opening-up.

H5b: Transportation infrastructure promotes UGSD through opening-up.

H5c: Information infrastructure promotes UGSD through opening-up.

The theoretical framework is constructed based on the above analysis, as shown in Figure 1.

3 Model construction and variable selection

3.1 Empirical model

3.1.1 Spatial regression model

The spatial model mainly consists of the spatial auto-regressive model (SAR), spatial error model (SEM), and spatial Durbin model (SDM). Among them, SAR is established as follows:

$$Y_{it} = \alpha + \beta X_{it} + \psi WY_{it-1} + \rho WY_{it} + \varepsilon_{it}, \varepsilon_{it} \in N\left(0, \sigma_{it}^2\right) \quad (1)$$

SEM is constructed as follows:

$$Y_{it} = \alpha + \beta X_{it} + \psi WY_{it-1} + \rho WY_{it} + \varepsilon_{it}, \varepsilon_{it} = \lambda W\varepsilon_{it} + \delta_{it} \quad (2)$$

In Eqs 1, 2, X_{it} represents the independent variable, Y_{it} denotes the dependent variable, β is the coefficient of the corresponding independent variable, ρ is the coefficient of the dependent variable, ε_{it} represents the random disturbance term, and δ_{it} represents the unobservant factor.

Based on SAR and SEM, SDM is extended by comprehensively considering the spatial lag factors of independent and dependent variables, which is constructed as follows:

$$\begin{aligned} Y_{it} = \alpha + \beta 1X_{it} + \beta 2WX_{it} + \psi WY_{it-1} + \rho WY_{it} + \varepsilon_{it} \\ + \delta_{it}, \varepsilon_{it} \in N\left(0, \sigma_{it}^2\right) \end{aligned} \quad (3)$$

Where i denotes the region, t represents time, and X_{it} represents core independent variables, namely, energy, transportation, and information infrastructure. Economic development level, industrial structure, human capital level, and government size are selected as control variables. Additionally, Y_{it} represents the dependent variable of UGSD, W represents the spatial weight matrix, WX_{it} represents the space-dependent explanatory variable, and WY_{it} is the space-dependent explained variable.

3.1.2 The mediation effect model

Referring to Wen and Ye (2014), this paper adopts the step-by-step regression method to test the mediation effects of domestic trade and opening-up on the relationship between infrastructure and UGSD. The regression model combined with the spatial weight matrix is expressed as follows:

$$Y = cWX + \beta_i WContral_i + e_1 \quad (4)$$

$$M = aWX + \beta_i WContral_i + e_2 \quad (5)$$

$$Y = c'WX + bWM + \beta_i WContral_i + e_3 \quad (6)$$

Where X denotes the independent variable, Y represents the dependent variable, M represents the mediator variable, and e_1, e_2, and e_3 represent the regression residual.

3.1.3 Spatial weight matrix

The spatial weight matrix denotes the spatial dependence characteristics of elements, which mainly consists of the geographical adjacency matrix, geographical distance matrix, and

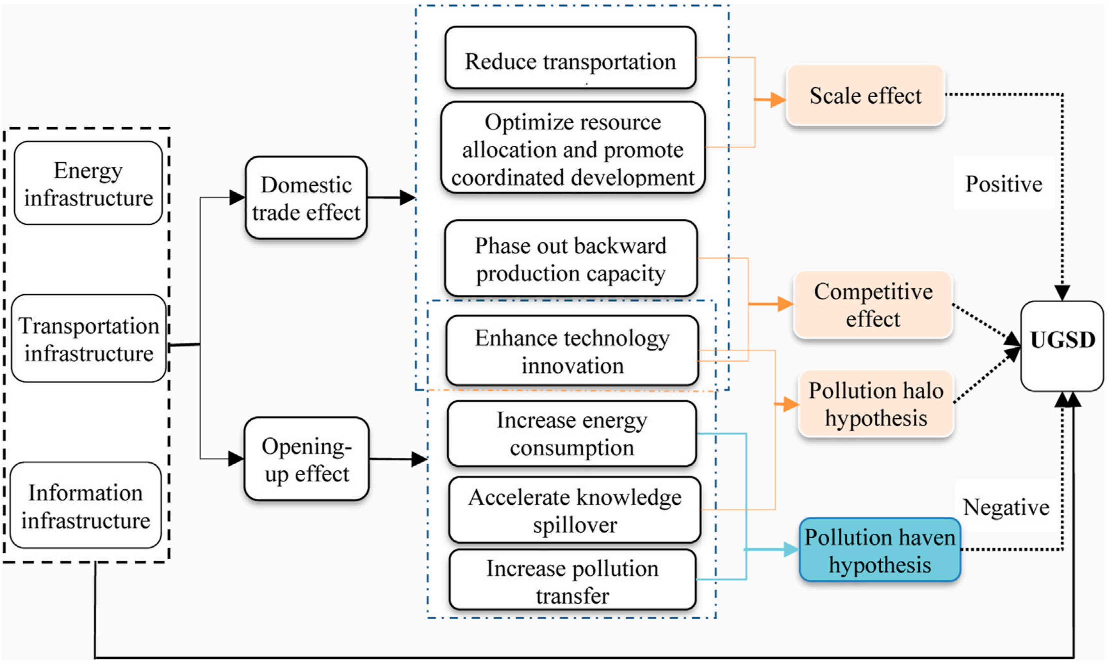

FIGURE 1
Theoretical framework diagram.

economic distance matrix. Accordingly, this paper adopts these three matrices to construct the spatial regression model and the geographical adjacency matrix is expressed as follows:

$$W_1 = \begin{cases} 1 & i \text{ and } j \text{ are adjacent} \\ 0 & i \text{ and } j \text{ are not adjacent} \end{cases} \quad i \neq j \tag{7}$$

Where the items of i and j represnet city i and city j, respectively. The geographical distance matrix is constructed as follows:

$$W_2 = \begin{cases} {}^{1}/{d_{ij}^2} & \text{when } d_{ij} \geq d \\ 0 & \text{when } d_{ij} < d \end{cases} \quad i \neq j \tag{8}$$

Where d_{ij} represents the longitude and latitude of city i and city j, which is obtained from the National Center for Basic Geographical Information. In this paper, the inverse of the square distance between city i and city j was adopted to depict their geographical distance.

The economic distance matrix is constructed as follows:

$$W_3 = \begin{cases} {}^{1}/{\left|pgdp_i - pgdp_j\right|} \\ 0 \end{cases} \quad i \neq j \tag{9}$$

Where *pgdp* is the *per capita* GDP. To make the spatial lag term include the meaning of a weighted mean, all the spatial matrices were row-normalized, and their diagonal elements were zero.

3.1.4 Moran index

The Global Moran Index (Moran's I) is widely adopted to test whether the variables have spatial agglomeration characteristics, which is calculated as follows:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} Wij\left(Yi - \bar{Y}\right)\left(Yj - \bar{Y}\right)}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} Wij} \tag{10}$$

Where $S^2 = \frac{1}{n}\sum_{i=1}^{n}(Yi - \bar{Y})^2$, and the value of Moran's I belongs to $(-1, 1)$; when Moran's I > 0, it indicates a positive spatial correlation for the variable, otherwise a negative spatial correlation. Moreover, when Moran's I $= 0$, it indicates that the spatial distribution is random and there is no spatial correlation.

3.2 Variable description and data sources

3.2.1 Primary variable

3.2.1.1 Explained variable

UGSD is calculated by the undesirable SBM model and the GML (Global Malmquist-Luenberger) index referring to Xu et al. (2021). The non-angular and non-radial SBM model containing the undesired output is as follows:

$$\min \rho = \frac{1 - \frac{1}{m}\sum_{i=1}^{m} s_i^- / xi0}{1 + \frac{1}{s_1 + s_2}\left(\sum_{i=1}^{s_1} s_r^g / y_{r0}^g + \sum_{i=1}^{s_2} s_r^b / z_{r0}^b\right)} \tag{11}$$

$$s.t.\quad X\lambda + s_i^- = xk, Y^g\lambda - s_r^g = y_0^g, Z^b\lambda + s_r^b = z_0^b$$

$$\lambda、 s_i^-、 s_r^g、 s_r^b \geq 0$$

Where ρ is the ratio of actual input-output relative to the average narrowing and expansion of technological frontier; m、$s1$、$s2$

TABLE 1 Input-output indicators of UGSD.

Indicator	Variable	Unit	Computation method
Input indicators	Fixed capital stock	100 million yuan	Perpetual inventory method
	Labor	10 thousand people	The number of urban employees at the end of the year
	Electricity consumption	10 thousand kilowatts	Total electricity consumption
	Education and technology expenditure	10 thousand yuan	Financial expenditure on science, technology, and education
Output indicators	GDP	100 million yuan	Urban GDP of the year
	International internet users	10 thousand people	The number of urban international Internet users
	Patent application quantity	Part	The number of urban patent application
	Harmless disposal rate of domestic garbage	%	Percentage of the disposal of harmless garbage
	Sewage treatment rate	%	Percentage of sewage disposed
	The green coverage rate of built-up area	%	Greening coverage rate in built-up areas of the city
	Discharge of industrial wastewater	10 thousand tons	Industrial wastewater discharge volume of the city
	Industrial smoke and dust emissions	Tons	Industrial smoke and dust emissions volume of the city
	Industrial SO_2 emissions	Tons	Industrial SO_2 emissions volume of the city

denotes the quantity of input, expected and unexpected output, respectively; and s^-、s^g、s^b are the corresponding relaxation variables. The SBM model has a defect, that is, the efficiency value calculated by the SBM model is always maintained in the interval of (0, 1). The DMU (Decision-making Unit) with a value of one is valid, while less than one will be considered invalid. This prevents us from comparing the combined technical efficiencies among cities. As such, the GML index is combined into research.

Referring to Tone (2001), a production possibility set (PPS) containing both desired output and undesired output is constructed. Assuming that N factors $x = (x1, x2, \ldots\ldots, xN) \in R_N^+$ are adopted in each DMU, then M desired output $y = (y1, y2, \ldots\ldots, yM) \in R_M^+$ and I undesired outputs $u = (u1, u2, \ldots\ldots, uI) \in R_I^+$ could be obtained. The GML index from the time serial of t to $t + 1$ is defined as follows:

$$GML^{t,t+19}\left(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}\right) = \frac{1 + D^G\left(x^t, y^t, b^t\right)}{1 + D^G\left(x^{t+1}, y^{t+1}, b^{t+1}\right)} \times \frac{1 + D^t\left(x^t, y^t, b^t\right)}{1 + D^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}\right)} \times \frac{1 + D^G\left(x^t, y^t, b^t\right)}{1 + D^t\left(x^t, y^t, b^t\right)} \times \frac{1 + D^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}\right)}{1 + D^G\left(x^{t+1}, y^{t+1}, b^{t+1}\right)} \tag{12}$$

Where $D^G(x, y, b) = max\{\beta \mid (y + \beta y, b - \beta b) \in P^G(x)\}$ denotes the global directional distance function $P^G(x)$, which is determined by the global production possibility. The $GML^{t,t+1}$ represents the variation of the UGSD level from the period of t to $t + 1$ and $GML^{t,t+1} > 1$ indicates that the UGSD level of $t + 1$ has increased since t. Referring to previous studies (Du et al., 2020; Wang and Wang, 2021; Xu et al., 2021; Xu et al., 2022), the input-output indicators are selected as shown in Table 1.

According to the research by Zhang et al. (2004), the capital stock from 2005 to 2019 is calculated by the perpetual inventory method, and the regional GDP is represented by the real GDP, in which the year 2005 is taken as the base period. Furthermore, the entropy value method with the time variable is adopted to calculate the desired output indicator by the harmless disposal rate of domestic garbage, sewage treatment rate, green coverage rate of built-up area, and undesired output indicator by discharge of industrial wastewater, industrial smoke, dust emissions, and industrial SO_2 emissions, respectively.

3.2.1.2 Explanatory variable

Considering that social infrastructure and administrative infrastructure involve the departments that provide intangible products such as culture, the relevant content cannot be defined accurately, and the data is limited, so this paper only studies the economic infrastructure. Referring to Fang et al. (2020), this paper chooses three infrastructures. ①Energy infrastructure (*ener*) is measured by the total amount of gas supply, referring to Xie (2018). ②Transportation infrastructure (*traff*). As 70% of domestic freight is transported by highway in China, the highway mileage is expressed by the proxy index of transportation infrastructure. ③Information infrastructure (*infor*). Given that telecommunication service revenue is a comprehensive index reflecting the output of information infrastructure (Liu and Hu, 2010), this paper adopts it to represent *infor*.

3.2.1.3 Mediation variable

Under the context of the double cycle, the long-term development of the economy needs to explore and expand the consumer demand of the domestic market and strengthen the domestic market trade scale. At the same time, it is necessary to promote the coordinated development of domestic trade and opening-up to optimize resource allocation and promote international cooperation, which could provide new sources of

TABLE 2 Descriptive results of data.

Variable	Mean	Std.Dev	Min	Max
UGSD	0.84	0.42	0.10	1.96
L.UGSD	0.84	0.42	0.10	1.96
lnener	12.91	1.40	7.37	16.53
lntraff	9.25	0.63	7.16	10.60
lninfor	12.50	0.98	9.62	15.88
lntrade	0.19	1.25	−3.91	2.47
lnopen	−1.00	0.28	−2.29	−0.22
lnpgdp	10.51	0.71	8.48	12.46
str	0.90	0.46	0.23	4.80
hc	201.65	250.05	2.04	1235.60
gover	0.17	0.12	0.02	1.58
scale	476	276	73	1,466
ecag	0.27	0.43	0.05	3.99

impetus for UGSD. Therefore, this paper selected domestic trade and opening-up to analyze the indirect effect of infrastructure on UGSD referring to previous research (Fan et al., 2017; Gao et al., 2022). Specifically, domestic trade (*trade*) is denoted by the ratio of total retail sales of consumer goods to GDP, and opening-up (*open*) is represented by the ratio of actually utilized foreign capital to GDP in the year.

3.2.2 Control variable

Cities with high economic development levels will have greater support for technological innovations and more investment in pro-environmental issues and infrastructure construction. As a consequence, the urban GSDL would be enhanced (Xu et al., 2021). Furthermore, industrial emissions are the main sources of pollution, which directly restrict urban green development; therefore, it is necessary to enhance the urban GSDL by innovating and upgrading the industrial structure (Xu et al., 2022). Additionally, the optimization of human capital elements is conducive to accelerating innovation and technology accumulation, and the development of the city cannot be separated from the financial support of the government. As such, based on the existing literature, this paper adopts the economic development level (*pgdp*), industrial structure (*str*), human capital level (*hc*), and government size (*gover*) to control the influence of external factors on UGSD, which are measured by per capital GDP, the proportion of the tertiary industry, the number of college students (Du et al., 2020), and the ratio of government fiscal expenditure to GDP, respectively. Table 2 shows the descriptive results of all variables adopted in this paper.

3.2.3 Data source

The data adopted in this paper were mainly obtained from the “China Urban Statistics Yearbook,” “Statistical Yearbook,” and “Science and Technology Yearbooks” of provinces and cities from the year 2006 to 2020 as well as the “Statistical Bulletin” of provinces and cities from the year 2005 to 2019. To ensure the credibility of the research results, samples with many missing data were excluded, and some missing data in the samples were supplemented by the linear interpolation method based on the variation trend. As such, these balanced panel data of 221 prefecture-level cities in China from the year 2005 to 2019 were obtained, and all the data were truncated by 1% front and back to overcome the influence of extreme data.

4 Results and discussions

4.1 Spatial correlation analysis

Based on the tools of Geoda10.1 and Stata15, the results of the global Moran index for UGSD from the year 2006 to 2019 (the year 2005 is missing because it is the default base period) were obtained, which is shown in Figure 2.

Figure 2 shows that most of the results of the global Moran index are significant with these three spatial matrices, indicating that UGSD is spatially correlated. The spatial correlation coefficients show a fluctuating and upward trend on the whole.

Furthermore, the Wald and LR tests are adopted to test the rationality of SDM, as shown in Table 3.

Theoretically, if the null hypothesis is significantly rejected, then the SDM should be adopted in further spatial regression. Table 3 shows that the results of Wald and LR tests are all significant at the level of 5% ($p < 0.05$), indicating that the SDM should be adopted in further research. Moreover, the Hausman test results show that the *p*-values are less than 0.01, indicating that SDM with fixed effects should be adopted.

4.2 Spatial spillover effect of infrastructure

As such, Table 4 shows the spatial regression results with the geographical adjacency matrix, geographical distance matrix, and economic distance matrix.

As shown in Table 4, there are positive spatial spillover effects of energy and transportation infrastructure on urban green and smart development in general. Among them, the positive spatial correlations between transportation infrastructure and urban green and smart development are more significant. The results are consistent with previous research (Liu and Hu, 2010). Transportation infrastructure could improve the accessibility and resource flow of cities, which provide opportunities to share advanced technology and deepen cooperation in production (Wang J et al., 2022). As a result, the positive spatial spillover effect of transportation infrastructure could be magnified. However, the result of the positive spillover effect of energy infrastructure on urban green and smart development is contrary to the research findings of Xie (2018). This is mainly because of the continuously optimized energy consumption structure and the development of smart energy technologies in China, which have provided a good foundation for urban sustainable development. In contrast to energy and transportation infrastructure, the positive spatial spillover effect of information infrastructure on urban green and smart development is only significant at the level of 10% with the geographical adjacency matrix and economic distance matrix,

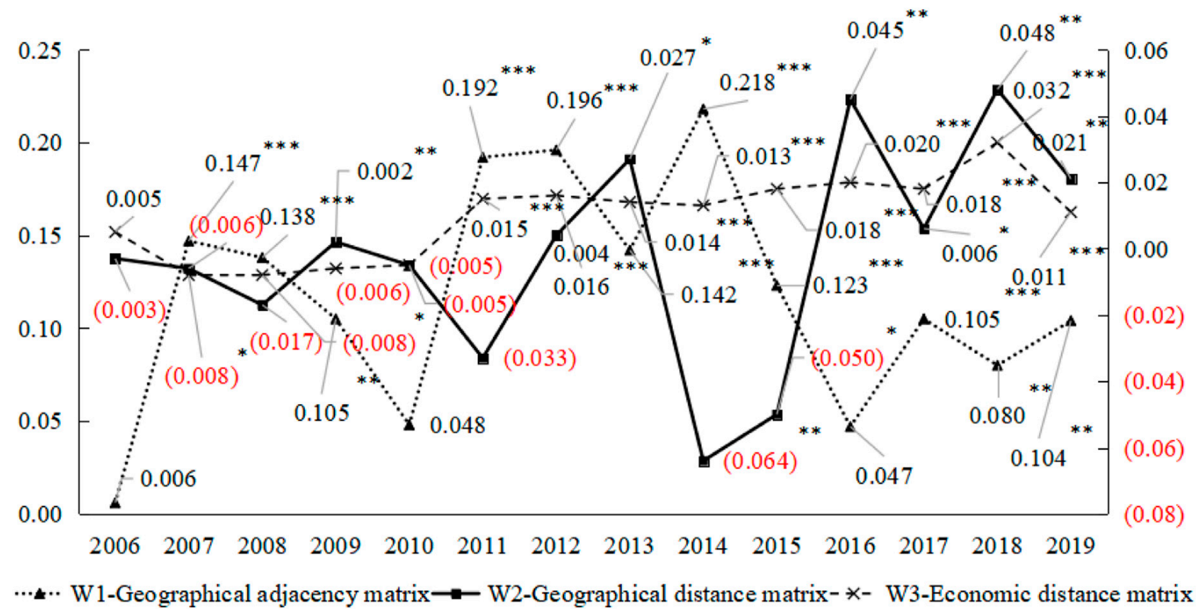

FIGURE 2
The Global Moran Index of UGSD and its significance level.

TABLE 3 Spatial model tests.

Methods	W1		W2		W3	
	Statistic	*p*-value	Statistic	*p*-value	Statistic	*p*-value
Wald lag	17.22	0.016	24.01	0.001	26.84	0.000
Wald error	17.96	0.012	20.52	0.005	27.07	0.000
LR SDM-SAR	46.42	0.000	25.31	0.000	26.73	0.000
LR SDM-SEM	48.34	0.000	22.13	0.002	26.96	0.000
Hausman test	77.04	0.000	32.75	0.000	104.04	0.000

and the coefficients are 0.0190 and 0.0543, respectively. Moreover, the spatial spillover effect of information infrastructure on urban green and smart development with a geographical distance matrix is insignificant and negative. The possible reason is that as the integration rate of information infrastructures, such as 5G base stations, and hardware facilities, such as computers, continues to increase, the large-scale use of electrical equipment will increase power and energy consumption (Pothitou et al., 2017), thus exacerbating environmental pollution. Zhang et al. (2022) pointed out that information infrastructure can effectively improve air quality though its spatial spillover effect is not obvious, which is consistent with the findings of this paper.

As for the control variables, the economic development level shows a positive spatial spillover effect on urban green and smart development with the geographical adjacency matrix, while showing an inhibitory effect with the geographical distance matrix, which is consistent with the research findings of Yuan and Liu (2019). The government size only significantly promotes adjacent cities' green and smart development with the geographical adjacency matrix, while the positive spillover effect could not be effectively released when there is a long geographical and economic distance. This is mainly because, with the increase in geographical and economic distance, less technical support and resource sharing could be obtained from cities with a larger government size, which is not conducive to the formation of a positive spatial spillover effect (Tang and Wang, 2015). Moreover, the spillover effect of the human capital level on urban green and smart development is not significant, which is mainly due to the mismatch between the structural demand for economic development and the supply of human capital (Zhang et al., 2018; Zhang and Hu, 2020).

4.3 Spatial effect decomposition

Based on the results of benchmark regression, the influence effects of energy, transportation, and information infrastructure on urban green and smart development could be further decomposed

TABLE 4 Spatial spillover effect regression results.

Variables	W1	W2	W3
L.UGSD	0.5894*** (0.0146)	0.5004*** (0.0157)	0.5000*** (0.0155)
lnener	0.0400*** (0.0046)	−0.0439*** (0.0121)	−0.0296** (0.0116)
lntraff	0.0853** (0.0366)	0.0811** (0.0365)	0.0874** (0.0372)
lninfor	0.0189* (0.0112)	0.0140 (0.0107)	0.0139 (0.0110)
lnpgdp	0.0737*** (0.0148)	0.0428* (0.0258)	0.0546** (0.0257)
str	0.0172 (0.0175)	0.0121 (0.0196)	0.0198 (0.0199)
hc	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)
gover	0.3089*** (0.1173)	0.0487 (0.0549)	0.0572 (0.0561)
WL. UGSD	−0.0839*** (0.0268)	−0.4235*** (0.0517)	−0.1014*** (0.0319)
Wlnener	0.0402*** (0.0045)	0.0545*** (0.0141)	0.0763*** (0.0125)
Wlntraff	0.0900** (0.0354)	1.0012** (0.1306)	0.2739*** (0.1008)
Wlninfor	0.0190* (0.0110)	−0.2345 (0.1472)	0.0543* (0.0292)
Wlnpgdp	0.0739*** (0.0141)	−0.2049** (0.0792)	−0.0642 (0.0374)
Wstr	0.0179 (0.0172)	0.0898* (0.0505)	0.1332 (0.0349)
Whc	0.0001 (0.0001)	0.0003 (0.0012)	−0.0001 (0.0002)
Wgover	0.3066*** (0.1177)	0.2567 (0.7104)	0.1321 (0.1632)
Log-L	277.74	365.32	275.43
rho	0.244***	0.756***	0.225***

Note: Within the parentheses is the standard error; ***, **, and * indicate the significance levels of 1%, 5%, and 10%, respectively.

TABLE 5 Spatial effect decomposition.

Variables	W1			W2			W3		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
L.UGSD	0.5136*** (0.0147)	0.0532* (0.0286)	0.5668*** (0.0299)	0.4997*** (0.0152)	−0.1812*** (0.1950)	0.3185*** (0.1949)	0.5004*** (0.0150)	0.0172 (0.0353)	0.5176*** (0.0362)
lnener	0.1045*** (0.0115)	0.0917*** (0.0185)	0.1961*** (0.0266)	−0.0431*** (0.0124)	0.0883*** (0.0319)	0.0451 (0.0302)	−0.0270** (0.0116)	0.0879*** (0.0128)	0.0610*** (0.0068)
lntraff	0.2336** (0.0919)	0.2043** (0.0882)	0.4379** (0.1758)	0.0953** (0.0375)	4.4298** (1.9755)	4.5250** (1.9905)	0.0954*** (0.0364)	0.3732*** (0.1270)	0.4685*** (0.1385)
lninfor	0.0493* (0.0285)	0.0434 (0.0265)	0.0928* (0.0543)	0.0118 (0.0110)	−0.9267 (0.6616)	−0.9148 (0.6664)	0.0169 (0.0107)	0.0717** (0.0355)	0.0886** (0.0389)
lnpgdp	0.1919*** (0.0361)	0.1678*** (0.0408)	0.3597*** (0.0707)	0.0400 (0.0247)	−0.7263** (0.3125)	−0.6862 (0.3171)	0.0527** (0.0240)	−0.0671 (0.0419)	−0.0145 (0.0404)
str	0.0463 (0.0444)	0.0392 (0.0380)	0.0855 (0.0819)	0.0145 (0.0190)	0.4147** (0.2067)	0.4292** (0.2063)	0.0253 (0.0191)	0.1747*** (0.0429)	0.2000*** (0.0420)
hc	0.0003 (0.0002)	0.0002 (0.0002)	0.0005 (0.0004)	0.0001 (0.0001)	0.0015 (0.0048)	0.0015 (0.0048)	0.0001 (0.0001)	−0.0001 (0.0002)	−0.0002 (0.0002)
gover	0.7971*** (0.3067)	0.7032** (0.3088)	1.5002** (0.6013)	0.0509 (0.0564)	1.2291 (2.9599)	1.2799 (2.9808)	0.0599 (0.0550)	0.1908 (0.2032)	0.2507 (0.2182)

Note: Within the parentheses is the standard error; ***, **, and * indicate the significance levels of 1%, 5%, and 10%, respectively.

into average direct effect, average indirect effect, and average total effect. Table 5 shows the results of spatial effect decomposition with the three spatial matrices.

As shown in Table 5, the direct and indirect effects of energy, transportation, and information infrastructure on urban green and smart development are heterogeneous with different spatial weight matrices. In general, there are positive spillover effects of energy and transportation on local and adjacent cities' urban green and smart development with the geographical adjacency matrix. This could be attributed to the construction of new energy systems and diversified transportation patterns, which are beneficial to cities' low-carbon transformation and the promotion of urban green and smart development. By contrast, the effect of information infrastructure is only positive on local green and smart development, while its spillover effect on adjacent cities is insignificant.

According to Table 5, we know that the indirect effect of energy infrastructure on urban green and smart development is positive, whereas the direct effect is significantly negative, and the total effect on urban green and smart development is insignificant with the geographical distance matrix. With regard to transportation infrastructure, the results show that the direct, indirect, and total effects are all significant, among which the indirect effect is stronger than the direct effect. However, the indirect effect of information infrastructure on urban green and smart development is insignificant, indicating that geographical proximity could not enhance the positive spillover effects of information infrastructure on urban green and smart development. The possible reason is that even though the urban information level has improved in recent years, there is still a polarization phenomenon, resulting in the unbalanced utilization of urban information infrastructure. Furthermore, there are many information islands among different industries, groups, and systems, which makes it difficult to achieve open sharing. As such, the soft environment of information including information consumption capacity, in-depth exploration, and comprehensive utilization of information resources would be the main obstacle to urban green and smart development (Wang, 2014).

With the economic distance matrix, the decomposition effect coefficients of energy infrastructure are −0.0270, 0.0879, and 0.0610, respectively. That is, energy infrastructure would suppress local urban green and smart development while promoting the green and smart development of adjacent cities. Furthermore, its spatial spillover effect offsets the negative impacts on local urban green and smart development, resulting in its positive total effect. As for transportation infrastructure, there is also a positive spatial spillover effect on urban green and smart development, which is mainly because of the efficient resource utilization, optimized transportation system, and fewer logistics cost among cities brought about by transportation infrastructure (Konno et al., 2021; Marinos et al., 2022; Wang J et al., 2022). In addition, information infrastructure shows a positive spillover effect on adjacent cities' green and smart development, while it shows an insignificant effect on local green and smart development. The reason may be that the cost of massive investment and long-term construction of local information infrastructure would not be compensated by scale and agglomeration economy in the early stage. However, the network characteristics of information infrastructure could offer opportunities for resource circulation, which could upgrade adjacent cities' innovation and technology levels, while reducing the cost of information acquisition and resource integration.

4.4 Mediation effect of domestic trade and opening-up

Based on the above theoretical analysis, the mediation effects of domestic trade and opening-up are further explored, and the results of the mediation effect of domestic trade are shown in Table 6.

As shown in Table 6, domestic trade could not mediate the impact of energy infrastructure on urban green and smart development. The possible reason is that energy infrastructure mainly serves the production of the secondary industry; as such, the role of energy infrastructure in enhancing urban development through domestic trade could be limited. In contrast, transportation infrastructure could promote green and smart development of adjacent cities by improving domestic trade with the economic distance matrix, showing a positive spatial spillover effect, which is consistent with the findings of Liu and Hu (2010). Through the diffusion and linkage effect of resource elements, transportation infrastructure could stimulate commercial trade, optimize resource allocation, and enhance the green degree of urban productivity (Ma et al., 2019). In addition, domestic trade partially mediates the impact of information infrastructure on urban green and smart development only with the economic distance matrix. This may be due to the new generation of information technologies such as blockchain and 5G technology, which have greatly transcended the constraints of time and space, resulting in economic activities being more dependent on network proximity (Yoon and Nadvi, 2018). Therefore, the advantage of urban economic proximity transcends geographical proximity in the mediation effect of domestic trade.

The results of the mediation effect of opening-up are shown in Table 7. As can be seen, there are negative spatial spillover effects of energy infrastructure on opening-up with the geographical adjacency matrix and geographical distance matrix. However, the negative spatial spillover effect of information infrastructure on opening-up is significant with the geographical distance matrix, and the spatial spillover effect of transportation infrastructure on opening-up is insignificant with all three spatial matrices. When taking opening-up as the control variable into the regression model, the spatial spillover effects of energy infrastructure on urban green and smart development turn out to be significantly positive with the geographical adjacency matrix and geographical distance matrix, while the spillover effect of information infrastructure on urban green and smart development turns to be insignificant. As such, it could be concluded that energy infrastructure could release a positive spillover effect on urban green and smart development by reducing the negative impact of opening-up. This may be due to the fact that energy infrastructure could enhance the elasticity of the energy supply chain and promote energy utilization efficiency while reducing the rigid demand for energy imports, which provides a solid foundation for domestic productivity and industrial structure upgrading. On the contrary, opening-up fails to mediate the impact of transportation and information infrastructure on urban green and smart development. The possible reason is that advantageous conditions brought by transportation and information infrastructure including advanced technology, governance experience, and high-level talents could promote the level of opening-up. However, opening-up would also cause pollution transfer and energy consumption, and when the pollution haven effect exceeds the pollution halo effect, the effects of transportation

TABLE 6 The mediation effect of domestic trade.

Variables	Domestic trade			UGSD		
	W1	W2	W3	W1	W2	W3
lnener	−0.0023 (0.0051)	0.0009 (0.0058)	0.0067 (0.0326)	−0.0167 (0.0105)	−0.0439*** (0.0121)	−0.0307*** (0.0116)
lntraff	0.0843 (0.0182)	−0.0112 (0.0177)	0.0157 (0.0175)	0.0726* (0.0372)	0.0734** (0.0367)	0.0751** (0.0372)
lninfor	0.0049 (0.0054)	−0.0051 (0.0052)	−0.0077 (0.0052)	0.0201* (0.0109)	0.0146 (0.0107)	0.0143 (0.0110)
Wlnener	0.0151*** (0.0055)	−0.0045 (0.0068)	0.0035 (0.0059)	0.0545*** (0.0113)	0.0498*** (0.0144)	0.0722*** (0.0125)
Wlntraff	0.0523* (0.0308)	0.9371*** (0.2191)	0.1664*** (0.0477)	0.0583 (0.0629)	0.6442 (0.4622)	0.2122** (0.1013)
Wlninfor	0.0148 (0.0101)	−0.1411** (0.0706)	0.0269** (0.0138)	−0.0022 (0.0207)	−0.2266 (0.1473)	0.0496* (0.0292)
lntrade				0.1708*** (0.0368)	0.0807** (0.0373)	0.1257*** (0.0381)
Wlntrade				0.0033 (0.0547)	0.2781 (0.1829)	0.2356*** (0.0771)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Log-L	2468.25	2627.84	2600.11	289.85	369.16	287.83
rho	0.327***	0.405***	0.245***	0.238***	0.737***	0.203***

Note: Within the parentheses is the standard error; ***, **, and * indicate the significance levels of 1%, 5%, and 10%, respectively.

TABLE 7 The mediation effect of opening-up.

Variables	Opening-up			UGSD		
	W1	W2	W3	W1	W2	W3
lnener	0.0218 (0.0296)	−0.0151 (0.0352)	0.0003 (0.0335)	−0.0171 (0.0105)	−0.0447*** (0.0121)	−0.0297** (0.0116)
lntraff	−0.2281** (0.1047)	0.0560 (0.1065)	−0.0731 (0.1071)	0.0899** (0.0372)	0.0857** (0.0365)	0.0861** (0.0371)
lninfor	0.0276 (0.0308)	0.0180 (0.0313)	0.0457 (0.0318)	0.0208* (0.0109)	0.0123 (0.0107)	0.0141 (0.0110)
Wlnener	−0.0025*** (0.0319)	−0.0773* (0.0402)	−0.0007 (0.0359)	0.0584*** (0.0113)	0.0575*** (0.0142)	0.0769*** (0.0125)
Wlntraff	0.2630 (0.1762)	0.7717 (1.2587)	0.2675 (0.2906)	0.0648 (0.0627)	0.8761** (0.4322)	0.2553** (0.1011)
Wlninfor	−0.0839 (0.0583)	−3.0524*** (0.4266)	−0.0618 (0.0842)	0.0079 (0.0207)	−0.2039 (0.1485)	0.0571* (0.0292)
lnopen				0.0041 (0.0064)	0.0003 (0.0062)	−0.0001 (0.0381)
Wlnopen				−0.0325*** (0.0105)	−0.2226*** (0.0721)	−0.0356** (0.0153)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Log-L	−2933.52	−2939.16	−2990.91	282.53	370.21	278.13
rho	0.289***	−0.837***	0.023	0.242***	0.707***	0.222***

Note: Within the parentheses is the standard error; ***, **, and * indicate the significance levels of 1%, 5%, and 10%, respectively.

and information infrastructure on local and adjacent cities' urban green and smart development would be negative.

4.5 Discussion

Considering the important role of infrastructure and the opportunity for the dual cycle, our research constructs a theoretical framework between infrastructure and urban green and smart development to explore the direct and indirect spatial spillover effects of different infrastructures on urban green and smart development. The main findings and hypotheses acceptance are shown in Table 8.

This research has two main findings. The first finding is the significant positive correlation between infrastructure and urban green and smart development at the city level. Heterogeneously, energy and transportation infrastructure both show positive spatial spillover effects on urban green and smart development on the whole, and the positive effect of transportation infrastructure is more significant. Therefore, there are significant differences in the impact of infrastructure on urban green and smart development. Consistent with the findings of Konno et al. (2021) and Marinos et al. (2022), transportation infrastructure provides opportunities to learn advanced technology and improve the accessibility and resource flow of cities (Wang L et al., 2022). In consequence, it plays a prominent role in releasing a positive spatial spillover effect for the green transformation

TABLE 8 Hypotheses test.

Hypothesis	W1 acceptance	W2 acceptance	W3 acceptance
H1	Yes	Yes	Yes
H2	Yes	Yes	Yes
H3	Yes	No	Yes
H4a	No	No	No
H4b	No	No	Yes
H4c	No	No	Yes
H5a	Yes	Yes	No
H5b	No	Yes	No
H5c	No	No	No

of adjacent cities. By contrast, the positive spatial spillover effect of information infrastructure on urban green and smart development is less significant. There is a possibility that as the spatial distance increases, the economic connections driven by the improvement of information infrastructure would fade gradually, thus suppressing its positive spatial spillover effect.

The second finding implies that domestic trade partially mediates the impact of transportation and information infrastructure on urban green and smart development only with the economic distance matrix. Transportation and information infrastructures show strong network features, which could break through temporal-spatial boundaries, achieve complementation of green technology and service among cities, and promote intercity trade (He and Ren, 2018; Yang and Liu, 2018), while energy infrastructure could release a positive spillover effect on urban green and smart development by reducing the negative impact of opening-up with the geographical adjacency matrix and geographical distance matrix. In line with the existing research, energy infrastructure could enhance the elasticity of the energy supply chain and promote energy utilization efficiency, while reducing the rigid demand for energy imports, which provides a solid foundation for foreign investment (Gao and Yue, 2020; Han et al., 2020). As Hu and Wang (2005) pointed out that compared with market openness, preferential policies, geographical location, and other factors, infrastructure construction is the most important factor to attract foreign direct investment.

4.6 Robustness test

In the spatial econometric model, the different weight matrices have a great influence on the estimation results. Considering the comparability of estimation results and the reliability of the conclusion, this paper adopts the following methods to conduct the robustness test. The results are shown in Table 9.

TABLE 9 Robustness test results.

Variables	W2	W3	W4
L.UGSD	0.5894*** (0.0146)	0.4958*** (0.0155)	0.4948*** (0.0157)
lnener	−0.0496*** (0.0119)	−0.0458*** (0.0113)	−0.0521*** (0.0121)
lntraff	0.0508* (0.0357)	0.0907** (0.0355)	0.0626* (0.0368)
lninfor	0.0127 (0.0103)	0.0218** (0.0104)	0.0117 (0.0106)
lnpgdp	0.0312** (0.0138)	0.0377*** (0.0137)	0.0451 (0.0288)
str	−0.0007 (0.0015)	−0.0007 (0.0016)	0.0141 (0.0199)
hc	−1.33e-07 (6.24e-06)	−1.53e-06 (6.34e-06)	0.00002 (0.0001)
gover	0.0004 (0.0010)	0.0006 (0.0010)	0.0334 (0.0548)
scale	0.0002 (0.0002)	0.0001 (0.0002)	
ecag	0.0003 (0.0004)	0.0006 (0.0004)	
WL. UGSD	−0.3712*** (0.0565)	−0.1043*** (0.0305)	−0.3871*** (0.0559)
Wlnener	0.0796*** (0.0152)	0.0848*** (0.0122)	0.0857*** (0.0166)
Wlntraff	2.0198* (0.5500)	0.1560** (0.0850)	0.1533 (0.0364)
Wlninfor	−0.1006 (0.1453)	−0.0411 (0.0253)	0.080 (0.0866)
Wlnpgdp	−0.0466 (0.0801)	−0.0757*** (0.0273)	−0.0642 (0.0374)
Wstr	0.0778*** (0.0269)	0.0776*** (0.0161)	0.0058 (0.0630)
Whc	−0.0001 (0.0001)	−0.00001 (0.00002)	0.0006 (0.0008)
Wgover	0.0662*** (0.0146)	0.0059** (0.0026)	−0.0933 (0.5320)
Wscale	−0.0099*** (0.0030)	0.0014*** (0.0005)	
Wecag	0.0225*** (0.0046)	0.0004 (0.0009)	
Log-L	352.00	290.35	389.74
rho	0.484***	0.291***	0.907***

Note: Within the parentheses is the standard error; ***, **, and * indicate the significance levels of 1%, 5%, and 10%, respectively.

(1) Adding control variables (Table 9, Column 2 and Column 3). The urban scale has been proved to be a symbol of its economic development, which was an essential condition for industrial agglomeration and acceleration of the industrialization process (Xu et al., 2022). Thus, this paper adopts the urban scale (scale) to control the potential influence of UGSD, which is measured by the urban total population at the end of the year. Cities with higher economic agglomeration tend to have more advanced and developed infrastructures. The decrease in commuting costs

and information-sharing costs makes the connection between different enterprises more convenient and faster. Therefore, this paper selects the gross domestic product per unit of land area to represent economic agglomeration.

(2) Replacing the spatial weight matrix (Table 9, Column 4). Compared with the geographical adjacency matrix, the inverse distance spatial weight matrix (W4) could measure the relationship between farther spatial units. Thus, this paper adopts the inverse of the center geographical distance between two provinces. The d_{ij} represents the geographical distance between two cities measured by latitude and longitude. The setting matrix is as follows:

$$W_4 = \begin{cases} {}^{1}/_{dij} & i \neq j \\ 0 & i = j \end{cases} \tag{13}$$

The estimation results are shown in Table 9, where we can conclude that there is no significant change in the significance and direction of the core explanatory variables, indicating that the research results are robust and credible.

5 Conclusion and implication

5.1 Research conclusion

Our research constructs a theoretical framework between infrastructure and urban green and smart development, which tries to elucidate the spatial spillover effects of different infrastructures on urban green and smart development with the three spatial matrices, reveal the multiple effects of different infrastructures on urban green and smart development from the perspectives of spatial effect decomposition, and provide new evidence for the mediation effects of domestic trade and opening-up. Based on the panel data of 221 prefecture-level cities in China from the year 2005 to 2019, urban green and smart development is measured with the undesirable SBM model and GML index, and the spatial Durbin model is adopted to explore the spatial spillover effect of infrastructure on urban green and smart development. Then, the decomposition of the spatial effect and the mediation effect of domestic trade and opening-up are analyzed. The main conclusions drawn are as follows:

First, the spatial spillover effects of three types of infrastructures on urban green and smart development are heterogeneous with the three spatial matrices. The direct effect of energy infrastructure on local green and smart development is negative, while the spatial spillover effect on adjacent cities is positive. Moreover, transportation infrastructure shows a positive effect on local and adjacent cities' green and smart development. In contrast, information infrastructure shows a less significant positive effect in promoting green and smart development of local and adjacent cities. In addition, the decomposition results of the spatial effect show that energy and transportation infrastructure promote local and adjacent green and smart development with three spatial weight matrices, while information infrastructure only promotes adjacent cities' development with the economic distance matrix.

Second, control variables show differential spatial spillover effects on urban green and smart development. In general, the economic development level shows a positive spatial spillover effect on urban green and smart development with the geographical adjacency matrix, while it shows a negative spatial spillover effect with the geographical distance matrix. Moreover, there is a positive spatial spillover effect of industrial structure on urban green and smart development only with the geographical distance matrix. Noticeably, the human capital level shows an insignificant spatial spillover effect on local and adjacent cities' green and smart development, which is possibly due to the mismatching effect between economy demand and talent supply, and the rebound effect brought by technological progress. With the geographical adjacency matrix, government size could promote green and smart development of adjacent cities through the intercity demonstration effect and the competition-cooperation effect.

Third, as for the mediation effects of domestic trade and opening-up, they play heterogeneous roles between different infrastructures and urban green and smart development. From the perspective of domestic trade, transportation and information infrastructures could promote adjacent cities' green and smart development through domestic trade with the economic distance matrix, while domestic trade does not mediate the impact of energy infrastructure on urban green and smart development with the three spatial matrices. On the contrary, energy infrastructure shows a positive spatial spillover effect on urban green and smart development by weakening the negative impact of opening-up with the geographical proximity matrix and geographical distance matrix. However, transportation and information infrastructure could not promote urban green and smart development through opening-up with the three spatial matrices.

5.2 Implications

Based on the above conclusions, the implications are put forward as follows:

First, infrastructures are required to be constructed in a reasonable way to augment their positive spatial spillover effect on urban green and smart development. In terms of energy infrastructure, a new energy system in which the green and low-carbon energy transformation is accelerated and carbon emissions responsibility is shared should be progressively implemented according to the energy production and consumption pattern of the city and its surrounding areas. Also, it is necessary to build a green and efficient transportation infrastructure, in which the proportion of railways and waterways in comprehensive transport should be increased, green logistics should be accelerated, and the concept of ecological protection should be integrated into the whole process of upgrading transportation networks. Furthermore, it is important to promote the integration of information infrastructure with the secondary and tertiary industries and promote their transformation into intelligent, digital, and networked industries. In addition, cities with advanced information infrastructure should be encouraged to spread the network effect to adjacent cities by improving the regional linkage and integration degree of information infrastructure. As such, a comprehensive driving force of energy, transportation, and information infrastructures would be formed to promote urban green and smart development.

Second, the polarization effect and siphon effect should be restrained while the positive spillover effect of intercity factors

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should be strengthened. Institutional barriers that hinder the market-based allocation of elements and the distribution of goods and services should be removed to form a unified, efficient, competitive, and open market. Furthermore, the coordinated transformation of upstream and downstream industries in energy, transportation, and information fields is supposed to be adjusted according to local conditions. Additionally, the spillover effects of high-quality talents should be enhanced to achieve integrated development of local and adjacent cities. Moreover, the administrative barriers are imperative to be broken to guide the participation of private capital in the green transformation of cities and encourage governments to establish a high-quality relationship of competition and cooperation among cities.

Third, the two-wheel driving effect of domestic trade and opening-up on the relationship between infrastructure and urban green and smart development should be promoted. On the one hand, to promote the domestic circulation of the national economy, we should optimize the supply structure and quality and strive to build a sound support policy system for expanding domestic demand. On the other hand, as the optimization of opening-up is as important as precaution of the negative spatial spillover effect on adjacent cities, thus the negative impacts of opening-up should be weakened through ecological compensation and joint innovation among cities. Moreover, it is necessary to enhance the positive interaction of infrastructures, domestic trade, and opening-up, form a coordinated development mode with multilateral cooperation, and augment the impetus of infrastructure for urban green transformation and upgrading.

This study has analyzed the spatial impacts of energy, transportation, and information infrastructures on urban green and smart development with different spatial matrices, which is meaningful in understanding the relationship between infrastructure and urban green and smart development from a more comprehensive lens. Under the context of the double cycle, the roles of domestic trade and opening-up between infrastructure and urban green and smart development have explored, and it would help China to seize the opportunities at home and abroad and promote the green transformation of cities. Although this study is conducted in the context of China, infrastructure construction and green transformation are common challenges for cities of all countries. Therefore, the research findings of this study could provide beneficial insights for countries with similar conditions. However, regardless of the positive results, there are still some limitations. Urban green and smart development is a complex system with multiple levels and structures. The level of development calculated by the undesirable SBM model and the GML index is a simple simulation of the whole system based on the input-output perspective, and further research is needed to develop a more robust evaluation method. In addition, as the indicators adopted to evaluate urban green and smart development are also closely related to sustainable development, so relative research could be further studied in the future, such as the impact of infrastructure on poverty alleviation and ecological optimization. Moreover, due to the data availability, this paper only focuses on the economic infrastructure; social infrastructure such as educational and medical infrastructures could be further studied. The indirect effect of the digitization level between infrastructure and urban green and smart development could be analyzed in future studies to extend existing research.

Data availability statement

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

Author contributions

Conceptualization, LX and JD; methodology, LX and DW; software, DW; validation, LX and JD; formal analysis, LX and DW; data checking, DW; writing—original draft preparation, DW; writing—review and editing, LX and DW; visualization, DW; supervision, LX and JD; funding acquisition, LX. 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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Inter-industrial embodied carbon transfers in a developed subnational region: a case study of Guangdong Province, China

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The close production and consumption relationship between industries leads to the embodied CO_2 transfer among industrial sectors along with the exchange of products. Thus, grasping the situation of embodied carbon transfers from the demand side is of great significance for better reducing a country or region's CO_2 emissions. This study investigates the embodied carbon transfers in Guangdong Province from 2002 to 2017 from the industrial dimension by applying a hypothetical extraction method. An enhanced generalized RAS method was utilized to predict the intersectoral carbon transfers in 2025 and 2030. The results show that, from 2002 to 2017, the average proportion of carbon emission output of 72.11% made the production and supply of electricity and heat sector the main CO_2 emission transfer exporter, while the other service and construction sectors were the leading importers. Moreover, the embodied carbon transfers between these three sectors are the main carbon transfer paths. By 2025, the other service sectors will become the largest embodied carbon importers, surpassing the construction sector. Therefore, it is necessary to control the consumption demand of other service and construction sectors on the demand side to reduce carbon emissions driven by demand.

KEYWORDS

embodied carbon transfers, hypothetical extraction method, EGRAS method, industrial sectors, Guangdong

1 Introduction

For a long time, the continuous accumulation of greenhouse gasses such as CO_2 has caused the phenomenon of global warming. Globally, China has become the country with the largest CO_2 emissions with continuous industrialization. In this regard, China has proposed a dual-carbon goal, that is, to reach carbon peak by 2030 and become carbon neutral by 2060. The secondary industry, as a crucial contributor to regional economic development, is also the main source of carbon emissions, making it an indispensable part of government carbon reduction policies. The intermediate products produced by upstream sectors with high CO_2 emissions are not entirely used by themselves. Driven by the demand of downstream sectors, some intermediate products will transfer through the industrial chain, and carbon emissions will also be transferred from the demand side to intermediate products. First, policymakers tend to focus on higher CO_2-emitting industries based on the producer principle; they believe that major carbon emitting sectors should bear a greater responsibility for reducing emissions. However, such policies may not achieve long-term carbon reductions significantly. Hence, it is essential to analyze the intersectoral carbon transfers from a consumer principle to explore how carbon emissions are transferred under demand-driven, and to help the government formulate more effective emission reduction policies.

Regarding the spatial dimension, previous studies mainly explored the CO_2 emission transfers between countries, regions, or provinces. In the study of carbon transfers from a national perspective, Wang and Han (2021) specifically analyzed the possibility of implied carbon emissions and trade decoupling between Chinese and American industries, crediting that in the US exports from high-technology industry or service industry to China, the decoupling has been best achieved. Some scholars are conducting research on the embodied emission transfers between multiple countries. Zhong et al. (2018) analyzed the carbon flows from multi-country trade, and proposed that this part of CO_2 emissions could then be lowered by increasing the proportion of clean energy in total energy consumption. Wang et al. (2020) further discussed the embodied emission transfers among major countries from the perspective of industry, and found that China's CO_2 emission inflow is largely concentrated in the electromechanical equipment and chemicals in developed countries. Huang and Zhang (2023) found that digitization can better reduce the embodied CO_2 emissions of exports under a higher global value chains (GVC) position. Some studies have explored the characteristics of carbon transfers between provinces in domestic trade. In China, the network characteristics of inter-provincial embodied emission transfers are significantly different (Sun et al. (2020)), and among them, a significant portion of the embodied carbon flows occurs between the southeastern coastal area and economically backward provinces in the central and western regions (Li and Li (2022); Tao and Wen (2022)). In addition, the generated carbon dioxide flows accordingly with industrial transfers between different provinces. Li et al. (2022) found that the paths of carbon and industrial transfers were somewhat similar but not completely coupled. Other studies explored the factors influencing inter-provincial carbon transfers. Wang and Wang et al. (2021) believed that environmental supervision and governance would inhibit the outflow of carbon emissions, whereas urbanization and energy intensity would promote its transfers. Wang and Hu (2020) found that 35.4% of carbon emissions from 2007 to 2012 came from inter-provincial demand from the production side, and this portion of carbon transfers continued to increase.

Similar to carbon emission transfers in the spatial dimension, since various industrial sectors play different roles in economic development, exploring the relationship of embodied emission transfers between industries is required, further promoting the allocation of the emission reduction responsibilities (Xia et al. (2022)). After drawing specific CO_2 transfer paths of various industries in China in 2012, Bai et al. (2018) found that the electricity and heat generation and supply industry and construction industry were the most important carbon emission exporter and importer, respectively. Zheng et al. (2022) explored the association among industrial carbon intensity, factor flow, and industrial transfers from 30 provinces. After discussing the carbon transfer path between industrial sectors, Li et al. (2021) further investigated the potential influencing factors of the main path. Sun and Fang (2022) discussed the identification and optimization of unreasonable carbon transfers from a supply-side perspective under environmental regulations.

Carbon transfers between industrial sectors are mainly based on either complex network theory or the hypothetical extraction method (HEM). In complex network theory, inter-industry CO_2 emissions are described in the form of a network, in which the industry itself is a node, and the amount of transferred CO_2 is the edge connecting the nodes (Du et al. (2018); Ma et al. (2019); Du et al. (2020); Jiang et al. (2019); Wang and Yao (2022)). Therefore, the carbon correlation between industrial sectors is reflected in several characteristics of complex networks. On basis of complex network analysis, Du et al. (2020) investigated the CO_2 transfer characteristics in 66 industries in the Yangtze River Economic Belt through network density, network connectedness, degree centrality, betweenness centrality, and other network characteristics. Wang and Yu et al. (2021) explored the significant characteristics of CO_2 emission transfers of 30 industries in China from 2002 to 2015 through complex network theory. The hypothetical extraction method analyzes the economic relationship between selected and other sectors by comparing the difference in economic performance in the presence or absence of the selected sector (Du et al. (2019); Hou et al. (2021); Dai et al. (2021); Hertwich (2021)). Hou et al. (2020) focused on the embodied CO_2 emission transfers among multiple sectors in China from 1992 to 2012 and concluded that the electricity and construction sectors were main sectors with the greatest CO_2 emission output and input, respectively. Among Pakistan's industrial sectors, Sajid (2020) found that the textile and apparel sectors were the top carbon emission importers.

Previous literature on CO_2 emission transfer mainly examined spatial dimensions, such as intercountry and interregional, while research on industrial dimensions as the entry point for carbon emission transfers is relatively insufficient. Although some studies have focused on CO_2 emission flows between industries from a national perspective, the industrial structure between regions is quite different, due to the different levels of development between regions. Thus, further exploring the carbon emission transfers among industries at the provincial and urban levels is necessary. As a result, it is better to effectively identify the carbon correlation characteristics and carbon emission transfer paths of industries in different regions. About method use, complex network analysis and hypothetical extraction method can accurately reflect the carbon correlation characteristics among sectors. However, a complex network analysis cannot show the specific carbon emission transfers between sectors because it mainly represents the carbon transfer relationship through the characteristics of the network. The hypothetical extraction method can obtain the direction and size of intersectoral carbon emission transfers by decomposing net backward and forward linkage emissions.

In this study, we used the hypothetical extraction method (HEM) as the research method to identify the main CO_2 emission exporters and importers and analyzes the intersectoral embodied carbon transfer path in Guangdong Province from 2002 to 2017. Through EGRAS method (Enhanced Generalized RAS-Method), a prediction is made for the input-output table in 2025 and 2030 and the change in carbon transfers between industrial sectors.

2 Materials and methods

2.1 Hypothetical extraction method

The basic idea of HEM is to assume that the target sector is extracted and has no economic correlation with other sectors, which was first proposed by Schultz (1977) and now applied to research fields such as carbon emissions, energy consumption, and land and water resources (Wen et al. (2022); Li et al. (2022); Fang et al. (2022); Deng et al. (2018)).

By comparing the difference in economic performance in the presence or absence of the selected sector, the impact of the selected sector on the production and its economic correlation with other sectors were analyzed.

HEM divides the industrial system M into two industrial groups, M_a and M_{-a}, where M_a is the industrial group that needs to be analyzed. The economic system can be given as:

$$\begin{bmatrix} X_a \\ X_{-a} \end{bmatrix} = \begin{bmatrix} A_{a,a} & A_{a,-a} \\ A_{-a,a} & A_{-a,-a} \end{bmatrix} \cdot \begin{bmatrix} X_a \\ X_{-a} \end{bmatrix} + \begin{bmatrix} Y_a \\ Y_{-a} \end{bmatrix} \Leftrightarrow \begin{bmatrix} X_a \\ X_{-a} \end{bmatrix} = \begin{bmatrix} W_{a,a} & W_{a,-a} \\ W_{-a,a} & W_{-a,-a} \end{bmatrix} \cdot \begin{bmatrix} Y_a \\ Y_{-a} \end{bmatrix} \tag{1}$$

where $(I-A)^{-1} = \begin{bmatrix} W_{a,a} & W_{a,-a} \\ W_{-a,a} & W_{-a,-a} \end{bmatrix}$.

Duarte et al. (2002) combined vertically integrated consumption with traditional hypothesis extraction methods and divided CO_2 emissions of the interested sector into four categories: internal, mixed, net backward linkage, and net forward linkage emissions. Moreover, vertically integrated consumption specifically reflects the CO_2 emissions from product consumption by each industry in this study. The HEM is used to find out the inter-industry carbon correlation, and the basic form is as follows:

Based on the I-O model, DCI_i, reflecting the direct carbon intensity, is calculated as:

$$DCI_i = DCE_i / X_i \tag{2}$$

where the direct CO_2 emissions of sector i is denoted by DCE_i, while X_i represents its total output.

The vertically integrated consumption of carbon emissions of sector, VIC_i, is presented as follows:

$$VIC_i = \sum_{j=1}^{n} DCI_j L_{ij} Y_i \tag{3}$$

where L_{ij} denotes the Leontief inverse matrix element, that is, the corresponding element in $L = (I-A)^{-1}$, and the sectoral final use is represented by Y_i.

By further decomposing the vertically integrated consumption of carbon emissions, we can get the following categories:

Internal emissions (IE) refer to the CO_2 emissions from the products produced and directly used by the target industrial group, M_a, for its own demand, and is shown as follows:

$$IE = DCI_a \cdot (I - A_{a,a})^{-1} \cdot Y_a \tag{4}$$

Mixed emissions (ME), which represents CO_2 emissions of the intermediate goods purchased by other industrial groups, M_{-a}, from the target industrial groups, M_a, and used in the production of M_a, are calculated as follows:

$$ME = DCI_a \cdot \left[W_{a,a} - (I - A_{a,a})^{-1}\right] \cdot Y_a \tag{5}$$

Net forward linkage emissions (NFL) reflect carbon emissions in the process of target industrial group M_a's products being purchased by other industry groups, M_{-a}, for their own use. The formula is as follows:

$$NFL = DCI_a \cdot W_{a,-a} \cdot Y_{-a} \tag{6}$$

Net backward linkage emissions (NBL) refer to the carbon emissions of products purchased from other industry groups, M_{-a}, by the target industry group, M_a, as an intermediate input. The formula is as follows:

$$NBL = DCI_{-a} \cdot W_{-a,a} \cdot Y_a \tag{7}$$

From the point of view of the whole economic system, the following relationships exist: $DCE = VIC$, $DCE = IE + ME + NFL$, $VIC = IE + ME + NBL$, and $NFL = NBL$.

By further decomposing NFL and NBL, we can obtain the specific carbon emission transfers among the industrial sectors. If sector H is a sector in other industrial groups M_{-a}, the CO_2 emissions shifted from industrial group M_a to sector H are shown as follows:

$$NFL_{a\to H} = DCI_a \cdot W_{aH} \cdot Y_H \tag{8}$$

In contrast, the carbon emission transferred from sector H to industrial group M_a can be expressed as follows:

$$NBL_{H\to a} = DCI_H \cdot W_{Ha} \cdot Y_a \tag{9}$$

By replacing the DCI in Eqs 8, 9 with the value-added rate of the industrial sectors, VAR, the embodied value transfers between industries can be presented as follows:

$$NFLV_{a\to H} = VAR_a \cdot W_{aH} \cdot Y_H \tag{10}$$

$$NBLV_{H\to a} = VAR_H \cdot W_{Ha} \cdot Y_a \tag{11}$$

2.2 EGRAS

The biproportional scaling method (RAS) was first brought forward by Stone to correct for the direct consumption coefficient. Due to the scenario analysis for 2025, 2030 and the lack of statistical data support in the preparation process, we used the EGRAS method, which was first proposed by He and Liu (2018) to estimate the intermediate inputs in 2025, 2030. This method has several advantages including number preservation, convexity preservation, zero preservation, being unbiased, avoiding positive and negative term offsets, and effectively retaining the prior information. The model is shown as follows:

$$\begin{aligned} & EGRAS = \min \sum_{ij} \left(a_{ij} - 1\right) \ln a_{ij} \\ & \text{s.t.} \sum_j a_{ij} \cdot X_{ij}^0 = u_i, \text{for all } i \\ & \sum_i a_{ij} \cdot X_{ij}^0 = v_j, \text{for all } j \\ & a_{ij} \geq \varepsilon \geq 0, \text{for all } i, j \\ & X_{ij} = a_{ij} \cdot X_{ij}^0, \text{for all } i, j \\ & \varepsilon = e^{-30}, \text{exogenous variable} \end{aligned} \tag{12}$$

where $X^0{}_{ij}$ and X_{ij} are the intermediate input in the reference period and the target period, respectively; a_{ij} is defined as the ratio of X_{ij} to $X^0{}_{ij}$; u_i and v_j are the total intermediate output of industry i and the total intermediate input of industry j in the target period, respectively.

2.3 Data

2.3.1 Industrial CO_2 emissions

Industrial CO_2 emissions caused by energy use can be presented as follows:

$$CE_i = \sum_{k=1}^{n} e_{i,k} \times ACV_k \times \theta_k \, (k = 1, 2, \cdots, n) \tag{13}$$

where CE_i denotes the CO_2 emissions generated by the fuel consumption of industry i; $e_{i,k}$ is consumption of fuel k in industry i, and fuel k's average lower heating value is expressed by ACV_k. θ_k, the fuel k's emission factor, is presented as follows:

$$\theta_k = C_k \times O_k \times \frac{44}{12} \tag{14}$$

where C_k represents carbon content per unit calorific value of fuel k, and its carbon oxidation rate is represented by O_k.

The industrial energy consumption data in Guangdong Province were collected from Carbon Emissions Accounts and Datasets (CEADs), while the average lower heating value was obtained from the associated table of China Energy Statistical Yearbook. Carbon content per unit calorific value and carbon oxidation rate were obtained from the Guidelines for the Preparation of the Provincial Greenhouse Gas Inventory (Trial). See Supplementary Appendix S1 for carbon emission factor and average lower heating values for some fuels.

In order to maintain consistency of sector classification in different data, this study divided the industries in I-O table into 28 sectors, then further adjusted and merged the sector in carbon emission accounting accordingly. The corresponding relationship between the sectors is shown in Supplementary Appendix S2.

2.3.2 Compilation of comparable prices input-output table

Referring to the compilation method of Li and Xue (1998), Liu and Peng (2010), Xu (2016) and Lu (2019), this study compiles the comparable price I-O tables for 2002, 2007, 2015, and 2017, with 2012 as the benchmark year. The price index of all sectors was obtained from the National Bureau of Statistics of China and the Guangdong Statistical Yearbook. The I-O tables in Guangdong Province from 2002 to 2017 was taken from Guangdong Provincial Bureau of Statistics.

2.3.3 Compilation of non-competitive input-output table

With reference to Weber et al. (2008), we further adjust the comparable price I-O table to a non-competitive I-O table with comparable prices. It is assumed that both imports and domestic products or services from outside the province flow to intermediate input and final demand within the province (including exports and domestic and external outflows).

2.3.4 Future change setting of carbon intensity

Based on the Action Plan for Carbon Peak before 2030 and "The 14th Five Year Plan" for Guangdong Province to Address Climate Change, assuming that the carbon intensity of Guangdong Province will decrease by 20.5% in 2025 compared with 2020, and by 18.5% in 2030 compared with 2025, then carbon intensity in 2025 and 2030 were calculated on the basis of 2002–2017. See Supplementary Appendix S3 for more details.

2.3.5 Compilation of input-output tables of Guangdong Province in 2025 and 2030

According to the input-output tables from 2002 to 2017, the components such as added value, total intermediate, final use and other components in the input-output table for 2025, 2030 can be simply estimated. Finally, on basis of the intermediate demand of the 2017 input-output table, the EGRAS method was referenced to estimate the intermediate input and complete the compilation of the 2025, 2030 input-output tables (Zhang et al. (2021)). See Table 1 for the main assumptions and Supplementary Appendix S4 for detailed compilation steps.

3 Results

3.1 Inter-industrial carbon emission transfers from 2002 to 2017

The direct consumption of carbon emissions represents the sectoral CO_2 emissions on the supply side, while the vertically integrated consumption represents it from a demand side. If the sectoral direct consumption is greater than its vertically integrated consumption, then it means a part of the CO_2 emissions is shifted to other industries along with the products, and *vice versa*. The direct consumption and vertically integrated consumption in 28 industrial sectors are presented in Table 2, taking the data of 2012 as a case. The production and supply of electricity and heat sector (S22), metal smelting and rolling sector (S14), and the transport, storage and post sector (S26), these three sectors consumed a great deal of energy, causing direct carbon emissions with 311.51, 33.21, 56.99 Mt respectively. However, for these sectors, due to higher vertically integrated consumption, carbon emissions from a supply side were greater than those driven by their own needs, making them the main embodied emission exporters. As for direct consumption of S22, 84% of carbon emissions came from products provided to other industries rather than from intermediate products required for its own production. This part of CO_2 emissions was generated under the demand of other industries and was transferred among various sectors. In the other two sectors with embodied carbon emission outputs (i.e., S14 and S26), this proportion was 64% and 47%, respectively. The direct consumption of other service sectors (S28), electrical, mechanical, and equipment manufacturing sector (S18), the construction sector (S25), and manufacturing of communication equipment, computers, and other electronic equipment sector (S19) were less than the vertical integration consumption, which indicated that the net CO_2 emissions were transferred into these sectors. From

TABLE 1 Main assumptions for the compilation of input-output tables in 2025 and 2030.

	2025	2030
Average annual change rate of GDP	+6%	+5%
Change in the proportion of added value		
Manufacturing industry	−2.5%	−1.7%
Manufacturing of communication equipment, computers and other electronic equipment	+0.6%	+0.4%
Transportation Equipment	+0.4%	+0.2%
General and special equipment manufacturing	+0.3%	+0.18%
Service	+4.5%	+2.8%
Finance	+3.5%	+2.5%
Information transmission, software and information technology services	+2%	+1.2%

The average annual change rate of the GDP, in 2025 and 2030 is relative to that in 2020 and 2025, respectively, and the proportion of added value in 2025 and 2030 is relative to that in 2017 and 2025, respectively.

the point of view of demand, the CO_2 emissions of other service sectors for their own production were 46.94 Mt, while from the supply side, the carbon emissions were only 1.86 Mt. Approximately 45.09 Mt of carbon dioxide was hidden in the intermediate products purchased by other service sectors from other industries, which was 24.29 times the CO_2 emissions from its own production. The net carbon inflows of construction sector were only 4.79 times that of the supply side, but the embodied carbon emission input was 56.24 Mt, which made itself the largest embodied CO_2 importer.

3.1.1 Embodied carbon emission output and input

The NFL and NBL of the various sectors reflect their embodied CO_2 emission output and input between industries, respectively. As shown in Figure 1A, from 2002 to 2017, five major industries with the largest proportion of NFL among industrial sectors in Guangdong Province were S22 (production and supply of electricity and heat sector, ~72.11%), S26 (transport, storage and post sector, ~10.83%), S14 (metal smelting and rolling sector, ~5.54%), S13 (non-metallic mineral products sector, ~3.51%), and S11 (petroleum processing, coking and nuclear fuel processing, ~1.64%), with the total carbon emission output accounting for more than 90%. As the main energy production and supply sector, the production and supply of electricity and heat sector is an important upstream industry in economies, providing other industries with the necessary electricity and heat to meet their basic productive activities. Therefore, the important position of this sector in the industrial chain makes it the largest exporter of carbon.

The proportion of embodied carbon outputs of the transportation, storage, and post sector rose from 9.11% in 2002 to 12.71% in 2017. By further decomposing the NFL of the transportation, storage, and post sectors, we obtained the specific carbon emissions transferred from this sector to another industrial sector. As seen in Figure 2A, the embodied carbon transferred from the transportation, storage and post sector to S28 (other service sectors), S25 (construction sector), S27 (wholesale, retail and accommodation, catering sector) increased significantly from 2.04, 2.93 and 0.67 Mt in 2002 to 8.97, 7.37 and 6.03 Mt in 2017, respectively. In 2017, these three paths accounted for more than 50% of the CO_2 emission outputs of the transportation, storage, and post sector. Continuously strengthening domestic and international trade, such as the rapid development of express services in the postal industry, has promoted economic links between the transportation, storage, and post sector, other service sectors, and the wholesale, retail, accommodation, and catering sector, then further improved the carbon linkage among them.

In addition, the proportion of embodied CO_2 output of the metal smelting and rolling sector increased significantly, from 2.60% in 2002 to 8.17% in 2017. As a major manufacturing province in China, the development of advanced manufacturing in Guangdong Province has increased the demand for ferrous and non-ferrous metal materials in the electrical, mechanical and equipment manufacturing sector, metal products sector, and general and specialty equipment manufacturing sector. This increased embodied carbon output of metal smelting and rolling sector, as shown in Figure 2B, from which carbon emission transferred to S18 (electrical, mechanical, and equipment manufacturing sector) increased from 0.43 Mt in 2002 to 6.49 Mt in 2017. The proportion of this part of the carbon emission output of the metal smelting and rolling sector also increased from 10.80% to 24.56%.

The CO_2 emission input of the industries is expressed by NBL; that is, the carbon emissions implied in the goods are transferred as a result of purchasing products from other sectors. Figure 1B shows that S25 (construction sector), S28 (other service sectors), S19 (manufacturing of communication equipment, computers, and other electronic equipment sector), S8 (leather, furs, down, and related products sector), S27 (wholesale, retail and accommodation, catering sector), and S18 (electrical, mechanical, and equipment manufacturing sector) were the top six sectors in Guangdong Province with the highest CO_2 emission input, transferring more than 55% of the total CO_2 emissions.

From 2002 to 2017, S25 (construction sector) was the top embodied carbon importer. The share of transferred CO_2 rose from 18.46% in 2002 to 25.76% in 2007, decreased to 15.56% in 2012, and rose steadily to 17.02% in 2017. The proportion of carbon emissions input of S29 (other service sectors) decreased from 12.46% in 2002 to 7.23% in 2007 and increased to 15.92% in 2017, with a trend of surpassing the construction sector as the largest embodied CO_2 emission importer. The large amounts of construction materials and mechanical equipment required for construction

TABLE 2 Direct consumption and vertically integrated consumption of industrial sectors in Guangdong Province in 2012.

Sectors	DCE ($MtCO_2$)	VIC ($MtCO_2$)	(DC-VIC)/DC
S3	0.79	0.07	0.90
S22	311.51	48.54	0.84
S14	33.21	11.88	0.64
S26	56.99	30.38	0.47
S21	5.29	3.03	0.43
S11	8.95	7.49	0.16
S23	1.27	1.29	−0.02
S13	17.77	19.60	−0.10
S1	4.67	7.60	−0.63
S7	3.89	6.39	−0.65
S27	9.69	24.94	−1.57
S5	0.17	0.52	−2.08
S12	5.90	21.37	−2.62
S10	6.42	30.35	−3.73
S25	11.75	68.00	−4.79
S6	1.81	11.00	−5.09
S4	0.18	1.28	−6.10
S20	0.23	2.30	−9.03
S24	0.07	0.82	−10.99
S15	1.69	22.63	−12.39
S19	1.97	26.54	−12.48
S16	1.25	17.53	−13.08
S8	1.48	22.21	−14.06
S17	0.77	12.62	−15.46
S18	1.71	37.09	−20.69
S9	0.39	9.22	−22.84
S28	1.86	46.94	−24.29
S2	0.00	0.00	—

and installation activities in the construction sector cannot be met by their own production. The same is true for other service sectors, such as the tertiary industry. These two sectors are more likely to purchase the products and services required for their intermediate inputs from other industries during production. Therefore, despite the large proportion of transferred CO_2 emissions, they exhibited lower carbon emissions on the supply side. As important advanced manufacturing industries in Guangdong Province, S19 (manufacturing of communication equipment, computers and other electronic equipment sector) and S18 (electrical, mechanical and equipment manufacturing sector) have also been taking a high proportion in carbon emission transfers, and their carbon emission input increased from 12.92 and 9.72 Mt in 2002 to 31.19 and 24.03 Mt in 2017.

3.1.2 The main paths of embodied carbon emission transfers

By decomposing the NFL and NBL of the various industries, the specific CO_2 emission transfer amount between industrial sectors can be obtained to further analyze the key embodied emission transfer paths. Figure 3 summarizes the top 15 paths with the largest carbon emission transfers in each year from 2002 to 2017, with a total of 20 paths. The sum of the carbon emission transfers from these pathways made up over 70% of the total. Among them, S22 (production and supply of electricity and heat sector) accounted for 17 routes as carbon emission exporters. In the other three paths, the carbon emission exporters were S13 (non-metallic mineral products sector) and S26 (transportation, storage, and post sector). As main embodied carbon exporters and importers, the carbon correlation between S22, and S25 (construction sector) or S28 (other service sectors) naturally became the two most important carbon emission transfer paths. However, it is noteworthy that in 2017, the embodied CO_2 emission input of S28 from S22 was 38.92 Mt, that exceeded the 37.73 Mt transferred by S25 from S22 and became the largest CO_2 emission transfer path. Moreover, the proportion of CO_2 emissions transferred from S22 to basic manufacturing sectors like S6 (food manufacturing and tobacco processing sector), S7 (textile sector), and S14 (metal smelting and rolling sector) decreased significantly from 2.36%, 2.28%, and 1.97% in 2002 to 1.56%, 1.47%, and 0.62% in 2017, respectively. In contrast, there was still a strong carbon emission correlation with S19 (manufacturing of communication equipment, computers, and other electronic equipment sector), S18 (electrical, mechanical, and equipment manufacturing sector), and S22.

The changes in the proportion of embodied emission transfers and the proportion of value-added transfers in the main carbon emission transfer paths were shown in Supplementary Figure A1, respectively, from 2007 to 2017. Among the six main paths, there was an obvious correlation between the changes in the proportion of carbon transfers and the change in the proportion of value-added transfers. It shows that the embodied CO_2 transfers between industries was, to a certain extent, the embodiment of the value of products circulating in the industrial chain, reflecting changes in the industrial structure. Therefore, the changes of the main carbon emission transfer path reflect that Guangdong Province is continuously developing advanced manufacturing industry and striving to promote its structural transformation and upgrading.

3.2 Inter-industrial carbon emission transfers in 2025 and 2030

After a simple prediction of the carbon intensity of various industries and using the EGRAS method to compile the I-O tables of Guangdong Province in 2025 and 2030, then the CO_2 emissions in these two periods were obtained, as shown in Supplementary Figure A2. According to China's Action Plan for Carbon Peak before 2030, Guangdong Province is expected to realize the carbon peak target between 2025 and 2030, with estimated carbon emissions of 523.78 and 519.53 Mt in 2025 and 2030, respectively.

3.2.1 Embodied carbon emission output and input

The main CO_2 emission exporters among the industrial sectors in 2017–2030 are shown in Figure 4A, including S22 (production and supply of electricity and heat sector), S26 (transportation, storage, and

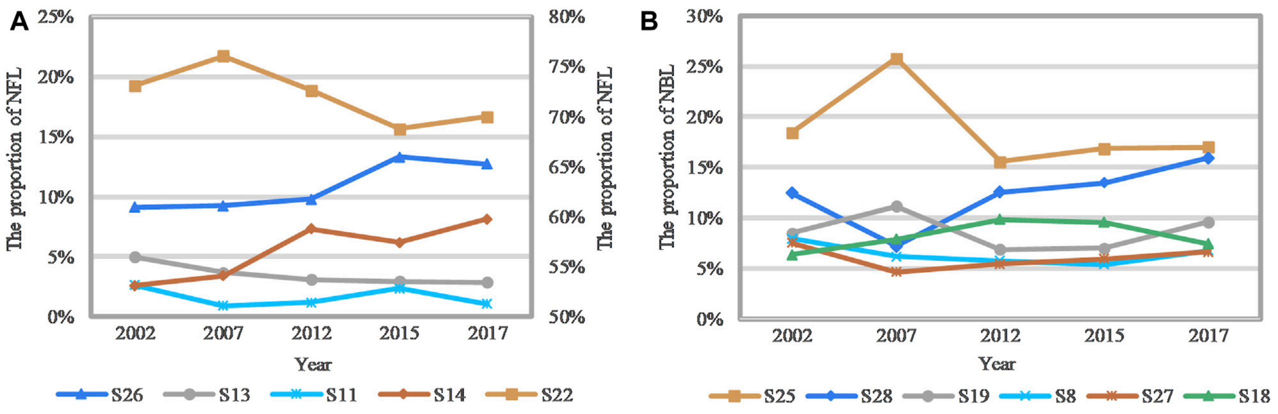

FIGURE 1
The proportion of NFL/NBL of sectors in Guangdong Province from 2002 to 2017. **(A)** The top five sectors with the largest proportion of NFL. **(B)** The top six sectors with the largest proportion of NBL. Notes: In **(A)**, the broken line of production and supply of electricity and heat sector adopts the secondary ordinate on the right-hand side.

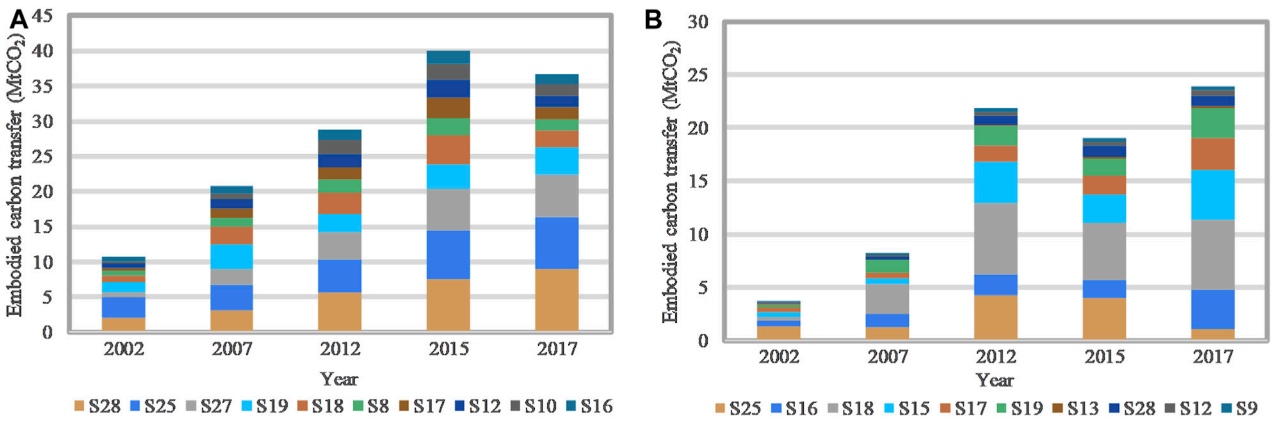

FIGURE 2
Ten main carbon emissions transfer paths from major sectors in Guangdong Province from 2002 to 2017. **(A)** The transport, storage, and post sector. **(B)** The metal smelting and rolling sector.

post sector), S14 (metal smelting and rolling sector), S5 (non-metallic mineral products sector), and S27 (wholesale, retail, accommodation, and catering sector). Furthermore, S22 remains the most important sector with the largest embodied CO_2 emission output; however, the proportion of carbon emission output will decrease from 69.97% in 2017 to 55.73% in 2030, owing to the reduction in its own carbon intensity and its reduced dependence of other industrial sectors on electricity and heat. The embodied CO_2 emission output of the transportation, storage, and post sector and the metal smelting and rolling sector will continue to increase from 2002 to 2017, from 12.71% to 8.16% in 2017 to 17.32% and 13.55% in 2030, respectively.

In 2017–2025, the main sectors with embodied carbon inputs in Guangdong Province were still S25 (construction sector), S28 (other service sectors), S19 (manufacturing of communication equipment, computers, and other electronic equipment sector), S18 (electrical, mechanical, and equipment manufacturing sector), S8 (leather, furs, down, and related products sector), and S27 (wholesale, retail, accommodation, catering sector). The difference is that, in 2025, the share of CO_2 emission input of the other service sectors will begin to exceed that of the construction sector and rise to 31.02% by 2030, becoming the largest embodied CO_2 emission importer, as presented in Figure 4B. As Guangdong Province strives to accelerate industrial structural transformation and hope to build a new system of modern service industry, the share of GDP of other service sectors, mainly the finance, information transmission, software, and information technology service sectors, will continue to increase, and economic ties with other industrial sectors will also strengthen. Additionally, it will lead to increased input of carbon emissions.

3.2.2 The main paths of embodied carbon emission transfers

The first 10 carbon emission transfer paths of Guangdong Province in each year in 2017, 2025, and 2030, totaling 14 paths, were analyzed, and the results are shown in Figure 5. The carbon linkages between S22

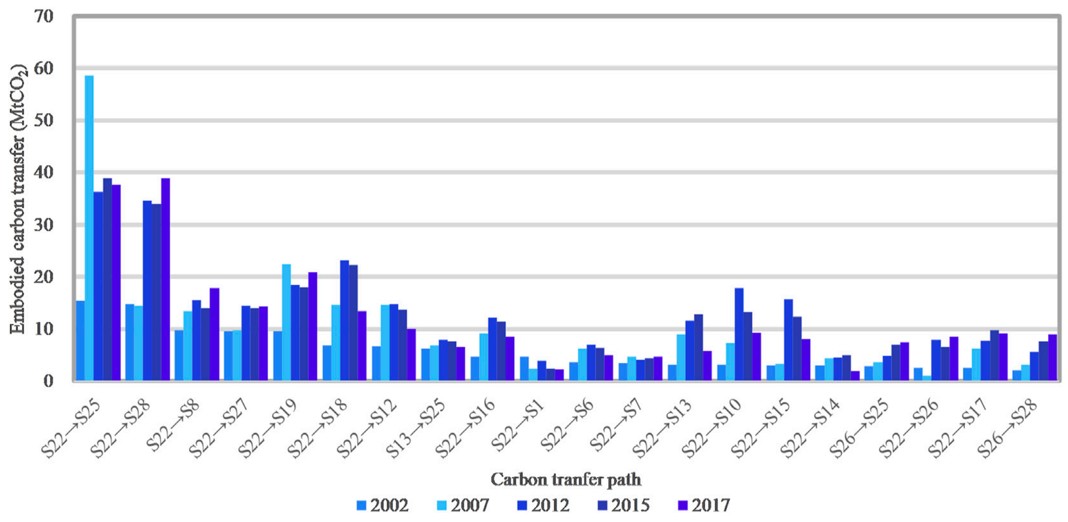

FIGURE 3
The top 15 carbon emission transfer paths among industrial sectors in Guangdong Province from 2002 to 2017.

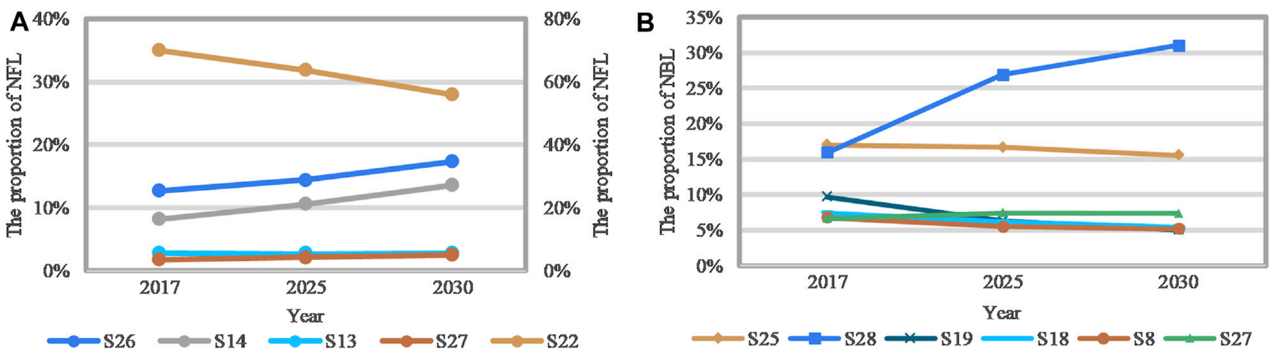

FIGURE 4
The proportion of NFL/NBL of sectors in Guangdong Province from 2017 to 2030. **(A)** The top five sectors with the largest proportion of NFL **(B)** The top six sectors with the largest proportion of NBL. Notes: In **(A)**, the broken line of production and supply of electricity and heat sector adopts the secondary ordinate on the right-hand side.

(production and supply of electricity and heat sector) and S28 (other service sectors), and between S22 and S25 (construction sector) remain the most critical carbon transfer paths. The share of transferred CO_2 emissions in these two pathways increases from 23.72% in 2017 to 27.94% in 2030. In addition, the proportion of embodied emission transfers between S22 and S28 increased from 12.08% in 2017 to 19.31% in 2030, which is far higher than the 8.63% between S22 and S25. As Guangdong Province enters the stage of high-quality development, the productive service sector is becoming increasingly specialized, promoting its integration with primary and secondary industries, and the value-added rate of the service industry will constantly increase, further promoting the economic development. Therefore, the demand in the service sector for transportation and logistics has been increasing, and the industry relationship between the service sector and the transport, storage, and post sector has become closer. The carbon emission transfers between S26 (transport, storage, and post sector) and S28, and S26 and S27 (wholesale, retail and accommodation, catering sector) has increased significantly from 8.99 and 6.00 Mt in 2017 to 20.03 and 8.66 Mt in 2030. In addition, the proportion of carbon emission transfers in these three paths between S16 (general and special equipment manufacturing sector), S17 (transportation equipment sector), S15 (metal products sector) and S14 (metal smelting and rolling sector) respectively increased from 1.17%, 0.93% and 1.46% in 2017 to 2.58%, 2.39% and 2.33% in 2030. This change is mainly due to the increase in the proportion of added value of advanced manufacturing industry during the “Fourteenth Five-Year Plan” period, which further strengthened the carbon emission linkages between the above-mentioned industrial sectors.

4 Discussion

This study first compiles a non-competitive I-O table with comparable prices in Guangdong Province from 2002 to

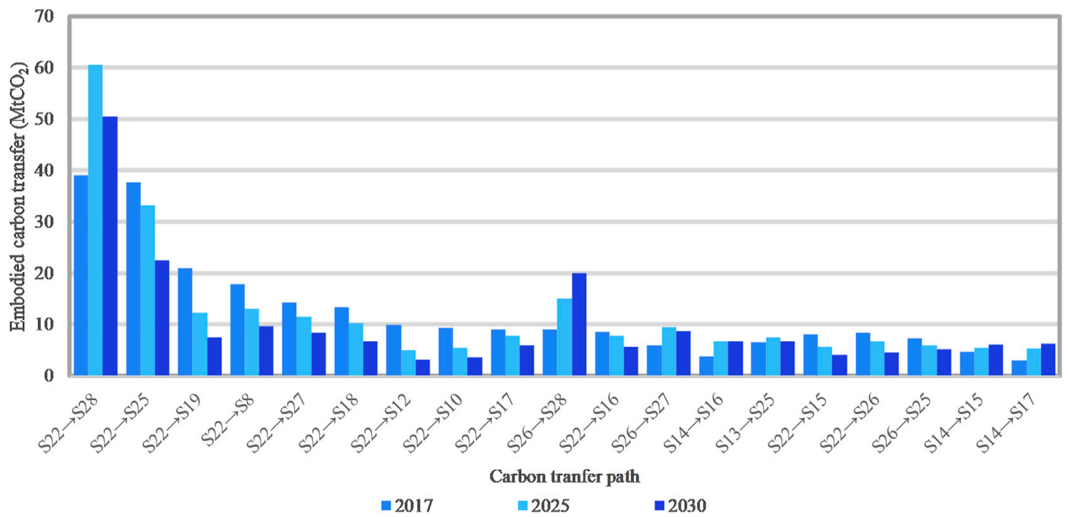

FIGURE 5
The top 15 paths of carbon emission transfer among sectors in Guangdong Province from 2017 to 2030.

2017 and then uses EGRAS to roughly compile the I-O table in Guangdong Province in 2025 and 2030. Finally, we analyzed carbon emission transfers from 2002 to 2017 and from 2017 to 2030 using HEM. Some findings are as follows:

1) From 2002 to 2017, the average proportion of carbon emission output of the production and supply of electricity and heat sector reached 72.11%, that remains the most important CO_2 emission exporter. In 2017, the proportion of embodied emission input of construction sector reached 17.02%, while that in other service sectors was 15.92%. Among the carbon transfer paths, the carbon linkage between the production and supply of electricity and heat sector as exporter, and construction sector and other service sectors as importers are the most critical carbon transfer paths. In 2017, the other service sector transferred 38.92 Mt of carbon emissions from the production and supply of electricity and heat sector, surpassing the path between the construction sector and the production and supply of electricity and heat sector as the largest carbon emission transfer path.
2) In 2017–2030, the production and supply of the electricity and heat sector was still the main exporter with the highest CO_2 emission output, but the proportion of carbon emission output will decrease significantly, mainly because of decreased dependence on electricity and heat and lower carbon intensity. In 2025, the proportion of embodied emission input of other service sectors will exceed that of the construction sector and will become the leading CO_2 emission importer. By 2030, the carbon transfer path between the production and supply of electricity and heat sector, and other service sectors will account for 19.31% of carbon emissions.

Carbon transfers between industrial sectors shows that carbon emission reduction policies cannot be targeted only at industries that directly emit higher CO_2. An increase in the demand of downstream industrial sectors also results in increased carbon emissions from upstream industries. Therefore, we put forward relevant suggestions on the carbon emission reduction policies of industrial sectors from the supply side and the demand side respectively, hoping to scientifically realize carbon emission reduction from the perspective of the whole industry chain.

On the supply side, most CO_2 emission outputs are from the important basic industries such as the energy supply, transportation, and metal processing. Thus, there is a real need to limit direct CO_2 emissions reasonably. Second, for the most important embodied CO_2 emission exporter, it is also essential to optimize energy structure, and promote the construction of wind power and photovoltaic bases, further improving the exploitation and utilization of renewable energy. In addition, key carbon emission exporters can also improve the energy utilization rate in their own production processes, which reduces energy consumption to a certain extent, thereby achieving the goal of carbon emission reduction. The government can also encourage relevant sectors to adopt green and clean technology for production and accelerate the technological development of clean energy to directly reduce CO_2 emissions.

On the demand side, it is also required to reduce the demand of these sectors such as the construction sector and other service sectors on the premise of maintaining the stable development of the industry. This eases CO_2 reduction pressure on the upstream production industries. Specifically, the industrial sector can improve the efficiency of electricity usage and reduce unnecessary losses.

Overall, it is required to scientifically monitor the carbon transfer path among the main carbon emission exporters and importers, especially the path involving the energy supply sector, pay close attention to the carbon correlation changes among industries, and further explore the main drivers behind the path. Thus, corresponding measures can be taken to address different carbon transfer paths to achieve more scientific and efficient carbon emission reductions while maintaining stable economic growth.

This study mainly studies the carbon emission transfer between industrial sectors in Guangdong Province based on the input-output table, and analyzes the main carbon emission transfer sectors and paths. In this study, the industrial sectors such as the metal smelting and rolling sector are the main carbon emitters, while other studies have shown that industrial land use affects economic performance and regional carbon emissions (Pan et al. (2021); Shu and Xiong (2019)). Therefore, in the future, we can further explore how to achieve urban carbon emission reduction more effectively from the perspective of land use and industrial space layout.

Data availability statement

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

Author contributions

JJ and WL contributed to the conception and design of the study. WL analyzed the model and drafted the manuscript. XL provided data and method support. 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

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2023.1216279/full#supplementary-material

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Research on the impact of fiscal environmental protection expenditure on agricultural carbon emissions

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China's agricultural and rural greenhouse gas emissions account for about 15% of its total emissions. Studying how to reduce China's agricultural carbon emissions (ACEs) is of great strategic significance. Based on the panel data of 31 provinces (cities) in China from 2007 to 2020, this paper empirically tests the impact of fiscal environmental protection expenditure (FEPE) on ACEs. The results reveal that: FEPE has significant negative impacts on ACEs; FEPE has a heterogeneous impact on ACEs in different regions, which shows that it has a significant impact on the eastern and central regions and provinces with relatively "high" carbon emissions, while it has no significant impact on the western regions and provinces with relatively "low" carbon emissions; Further the results of mechanism analysis show that the impact of FEPE on ACEs is mainly manifested in its inhibiting effect on agricultural diesel, fertilizer and film use of carbon emissions. In light of these findings, it is imperative for the government to ensure steady and substantial investments in environmental protection. Moreover, implementing region-specific measures is essential to effectively curbing ACEs. The findings of this study offer invaluable insights that can guide the formulation of policies aimed at effectively reducing ACEs.

KEYWORDS

fiscal environmental protection expenditure, agricultural carbon emissions, policy research, China, greenhouse effect

1 Introduction

Over an extended period, the excessive depletion of agricultural resources has led to a notable rise in agricultural non-point source pollution. This escalation in pollution has triggered a warning signal for the ecological environment, signifying a critical state (Abbas et al., 2022a; Elahi et al., 2022a; Abbas et al., 2022b). Consequently, this situation is closely associated with the occurrence of extreme weather events (Elahi et al., 2022b). Relevant evidence shows that the total emissions of agricultural greenhouse gases account for about 25% of the global emissions, which have exceeded the carbon emissions of the transport industry, and even close to the carbon emissions of electricity production. As an open ecosystem, the agricultural system needs a lot of auxiliary inputs such as fertilizer and agricultural machinery from the outside to continuously promote the smooth flow of energy, material and information and maximize the economic value flow. These inputs are becoming a source of ACEs and contributing to global warming and greenhouse effect. As a large agricultural country, China's agricultural and rural greenhouse gas emissions account for about 15% of its total emissions. Therefore, studying whether FEPE can reduce ACEs, whether there are any heterogenous impacts among different regions and how FEPE affects ACEs are of great strategic significance. We gathered panel data at the provincial level in China and used the ordinary least squares methods to examine the impacts of FEPE on ACEs.

Our paper is mainly related to three branches of research: firstly, the research on the intensity and efficiency of agricultural carbon emissions. Carbon emissions from agricultural production account for nearly 15% of the total human carbon emissions (Laborde et al., 2021). ACEs accounted for 20% of the global total carbon emissions in 2017 (Zhang et al., 2019a), with 17% of total carbon emissions for China (Guan et al., 2008). As the largest agricultural country in the world, China's ACEs account for 11%–12% of the world's total (Guo et al., 2022) and are about twice those of the United States (Bai et al., 2019). How to measure ACEs is also a topic that scholars have been paying attention to. West and Marland (2002) divided ACEs into fertilizer, pesticide, irrigation and seed cultivation. Johnson, et al. (Johnson et al., 2007) also divided ACEs into four categories. In contrast, Mosier et al. (1998) divides ACEs into land use, plant growth and animal breeding. Certainly, these definitions are quite close with slight differences. And Liu, et al. (Liu et al., 2021a) found ACEs in China showed an inverted-"U" trend, with the overall growth rate declining gradually. Li and Wang (2023) also demonstrated that China's ACEs started to fall after 2015.

Secondly, our research is also relevant to the influencing factors of agricultural carbon emissions. Northrup et al. (2021) believed that advances in agricultural technology could reduce agricultural carbon emissions. Zhao et al. (2018) found that water resource utilization efficiency has a greater impact on reducing ACEs, and Hinz et al. (2020) demonstrated that agricultural production efficiency can significantly reduce ACEs. Some scholars have also found that compared with the situation in 1975, the ACEs have decreased by more than one-half due to the reduced agriculture areas (Ali and Nitivattananon, 2012). Also scholars found that land use change can lead to great decrease in fertilizer and pesticide use (Ren et al., 2019; Haider et al., 2020). Holka et al. (2022) demonstrated that the mineral fertilizer is the main source of the ACEs, and organic farming has the potential for reducing ACEs. Yang, et al. (Yang et al., 2022a) discovered that quality improvement projects can reduce ACEs. Scholars also found agricultural management practices can also reduce ACEs (Yu et al., 2013; Peter et al., 2017).

However, the role of agricultural technology progress in agricultural carbon emissions is uncertain. Under the background of smallholder farming, it is assumed that agricultural environmental pollution can be reduced through moderately expanding the farm size, but it is not suitable for agricultural carbon emissions (Wang et al., 2022). In recent years, scholars have also begun to pay attention to the impact of green credit policies on agricultural carbon emissions. For example: Qin et al. (2023) have studied the inhibition effect of green credit on agricultural carbon emissions. Guo, Zhao, Song, Tang and Li (Guo et al., 2022) found that, fertilizer consumption and ACEs have a positive correlation, but green finance can significantly reduce ACEs. In essence, green credit policy is also an environmental regulation policy. Furthermore, we try to examine the impact of FEPE (as one kind of environmental regulation policy) on ACEs, which is innovative.

Thirdly, our research also tries to explore the impact of FEPE (short for fiscal environmental protection expenditure) on the ecological environment, which is controversial. Most scholars support the positive role of fiscal expenditure. For example, López et al. (2011) had proved the positive effect of public expenditure on air quality and water quality. He et al. (2018) noted that FEPE in China was not conducive to air quality. Xie et al. (2021) found that increasing financial expenditure in China did help improve energy and carbon emission efficiency. Huang (2018) found a negative link between FEPE and SO2 emission in China. Xu et al. (2023) also confirmed the relation between FEPE and CO2, but found the expenditure efficiency stayed at a relatively low level. However, Moshiri and Daneshmand (2020) found that FEPE had no significant impacts on environmental protection in Iran. Adewuyi (2016) believed that the government expenditure can show the opposite effect in the short term and long term. Galinato and Galinato (2016) showed that fiscal expenditure increases forest land clearing for agricultural production, which leads to more carbon dioxide emissions. Therefore, the impacts of FEPE on ACEs are still worth empirical testing. Moreover, we examine the heterogeneous impacts of FEPE on agricultural carbon emissions, which can enable us to have a deeper understanding of the applicability of FEPE policies in different regions; Although lots of scholars have confirmed the effect of FEPE on environmental pollution, the mechanism how FEPE affected ACEs have not been explored yet, which is also our research topic.

2 Theoretical analysis

Known as the Porter Hypothesis (PH), the proposition that appropriate environmental regulation will stimulate technological innovation was proposed by Porter (1991); Porter and Vanderlinde (1995). Lots of scholars have demonstrated that environmental regulation can promote innovative behavior of enterprises (Ambec and Barla, 2002; Hamamoto, 2006; Yang et al., 2012; Rubashkina et al., 2015).With the concept of green development, Chinese governments have continuously increased financial investment in energy conservation and emission reduction, greatly promoting the green development. The data from the National Bureau of Statistics reveal that the expenditure on energy conservation and environmental protection showed a steady and rapid growth trend from 2007 to 2020. In 2019, it reached the maximum of 739.02 billion yuan, accounting for 3.09% of the national public expenditure in that year.

As an environmental regulation policy, FEPE can reduce carbon emissions from two aspects: The first is regulation and prevention of pollution sources. Fan et al. (2020); Halkos and Paizanos (2013) demonstrated that FEPE can effectively promote energy conservation and reduce carbon emissions. The second is the treatment of discharged pollutants. Chinese government has established natural forest protection and pollution reduction accounts under the FEPE account. The pollution reduction account is used to measure the funds spent on various types of pollutant treatment, including pollution reduction facilities, emission reduction technologies, R&D investment, and emission reduction costs. Government can improve environmental quality by punishing environmental pollution behavior (Raza, 2020; Zhang et al., 2022). Of course, as a fiscal expenditure item, the increase in FEPE may also indirectly affect carbon emissions by affecting economic development. Due to the non-linear relationship between economic development and carbon emissions, this indirect effect is uncertain. But according to Fan, Li, Wang and Li (Fan et al., 2020), the direct effect of FEPE will outweigh the indirect effect, which will have an inhibitory effect on carbon emissions. Therefore, this paper proposes:

Hypothesis 1. FEPE can reduce ACEs.

The impact mechanism of FEPE on ACEs is through two pathways. The first is to reduce ACEs through the agricultural non-point source pollution. In China, chemical oxygen demand emissions in agricultural pollution exceed the industrial sector and become the main source of chemical oxygen demand emissions (Chen et al., 2021). And agricultural non-point source pollution has always been the most important factor affecting agricultural carbon emissions (Zhang et al., 2019b; Zou et al., 2020). The long-term irrational use of agricultural chemical inputs such as fertilizers, pesticides and agricultural films has made agricultural non-point source pollution more serious, aggravated soil pollution on cultivated land, and thus affected ACEs.

The second aspect of our research focuses on enhancing agricultural productivity. Through advancements in agricultural technology, particularly the widespread adoption of agricultural mechanization, we can not only elevate the efficiency of agricultural production but also facilitate the optimal utilization of agricultural infrastructure, fertilizers, pesticides, agricultural film, and other material resources. This, in turn, contributes to a reduction in agricultural carbon emissions. Studies have confirmed that a bundle of AGPTs (agricultural green production technology) are applied to maximize total yield and products quality, such as weed and pest control, soil and water conservation technology. Abdulai and Huffman (2014) argued that the adoption of this technology increases rice yields and net returns significantly. Besides, Midingoyi, et al. (Midingoyi et al., 2018) found that farmers who adopt integrated pest management have higher mango yields, and also use lower quantities of insecticide and cause less damage to the environment.

From the perspective of causality, both agricultural technology progress and agricultural non-point source pollution (fertilizer, pesticide, agricultural film) emerge as pivotal factors that can either contribute to the escalation or mitigation of agricultural carbon emissions. However, existing research has not definitively established the dominant mechanism in this regard. Building upon these considerations, this paper proposes:

Hypothesis 2. FEPE will inhibit ACEs by reducing agricultural non-point source pollution (fertilizer, pesticide, agricultural film).

Hypothesis 3. FEPE will inhibit ACEs by improving agricultural technology progress.

3 Models, variables and data sources

3.1 Model design

This paper mainly formulates the following econometric models:

TABLE 1 The source, coefficient and reference of ACEs.

Source	Coefficient	References
fertilizer application	0.8956	West and Marland, (2002)
pesticide input	4.934	Li et al., (2011)
agricultural film utilization	5.18	Li et al., (2011)
diesel consumption	0.5927	IPCC, (2007)
tillage	312.6kg/km2	Wu et al., (2007)
irrigation	20.476 kg/ha	Dubey and Lal, (2009)

$$C_{it} = \beta_0 + \beta_1 \times FEPE_{it} + \sum_{k=1}^{n} \beta_k \times Control_{kit} + \mu_i + \lambda_t + \nu_{it} \quad (1)$$

Among (1), C_{it} represents agricultural carbon emissions, Fin_{it} means FEPE, and we are concerned about the coefficient in front of the variable FEPE, and if β_1 is significantly negative, it means that FEPE can significantly reduce agricultural carbon emissions. $Control_{kit}$ represents other control variables. Additionally, we incorporate individual fixed effect and time fixed effect to exclude the influence of unchanging individual characteristics and temporal trends.

3.2 Variable description

3.2.1 Dependent variable

ACEs are the carbon emissions generated by the input of factors in the production process of planting industry in a relatively narrow sense. Referring to the relevant literature (Zhang et al., 2019a), the sources of ACEs are mainly defined in the six aspects of fertilizer application, pesticide input, agricultural film utilization, diesel consumption, tillage and irrigation in the agricultural production process. The corresponding coefficients are 0.8956, 4.934, 5.18, 0.5927, 312.6kg/km2 and 20.476 kg/ha, respectively, which is shown in Table 1. Then we can calculate agricultural carbon emissions according to formula (2). We collect the data of fertilizer application, pesticide input, agricultural film utilization and diesel consumption from China's rural statistical yearbook. Tillage and irrigation are respectively expressed by the actual planting area and irrigation area of crops in China.

$$C_t = \sum\nolimits_{k=1}^{k} c_{kt} = \sum\nolimits_{k=1}^{k} \delta_k \omega_k \quad (2)$$

Among (2), C_t represents the total ACEs of each province; k and t represent the type and year of carbon emission sources respectively; c_{kt} represents the carbon emissions from all kinds of sources; δ_k and ω_k represents the carbon emission coefficient and corresponding element input from all kinds of sources.

3.2.2 Core explanatory variables

FEPE is measured by the proportion of the fiscal expenditure on energy conservation and environmental protection in the total fiscal expenditure. In 2006, China officially established the subject of expenditure on environmental protection in the

TABLE 2 Variables and data sources.

Variable	Calculation formula	Data sources
ACEs	The calculation formula is shown in Eq. 2	China Rural Statistical Yearbook
FEPE	Proportion of financial energy conservation and environmental protection expenditure in total financial expenditure	Provincial Statistical Yearbook
Agricultural mechanization	The ratio of total mechanical power to the number of employees in the primary industry	China Rural Statistical Yearbook
Multiple crop index	Proportion of total sown area of crops to cultivated area	Provincial Statistical Yearbook
Scale management of agricultural land	The ratio of total sown area of crops to the number of employees in the primary industry	
Planting structure	Proportion of grain sown area to total crop sown area	
Urbanization level	Proportion of urban permanent population to total permanent population	
Consumption level of rural residents	Per capita consumption expenditure of rural residents	

classification of budget expenditure. In 2007, the "environmental protection" category of expenditure was set up in the general public budget expenditure, which is uniformly used for the expenditure of funds related to environmental protection. In 2011, the "Environmental protection" subject was renamed "Energy Conservation and Environmental Protection" subject. Therefore, the ratio of fiscal expenditure on energy conservation and environmental protection to total fiscal expenditure can be used to reflect the importance of the government to energy conservation and environmental protection (Fan et al., 2022; Sheng et al., 2022).

3.2.3 Control variables

Referring to the research of Raihan and Tuspekova (2022); Bashir et al. (2023); Li et al. (2023), and considering the data availability, we select the following six control variables.

- *Agricultural mechanization,* which is measured by the ratio of total mechanical power to the number of employees in the primary industry to control the impact of agricultural labor input on agricultural carbon emissions.
- *Multiple cropping index.* It is characterized by the ratio of the total planting area of crops to the cultivated land area, which has effects on ACEs by affecting the scale of agricultural planting.
- *Scale management of agricultural land,* which affects the agricultural planting scale, is measured by the ratio of the total planting area of crops to the number of employees in the primary industry.
- *Planting structure,* which is measured by the ratio of grain sown area to total crop sown area so as to reflect the "grain-oriented" characteristics of planting structure.
- *Urbanization level is* characterized by the ratio of urban population to regional permanent population.
- *Consumption level of rural residents* have an impact on ACEs by influencing the scale of agricultural planting and other aspects, which is measured by the *per capita* consumption expenditure of rural residents.

3.3 Data sources

As China designated environmental protection as a fiscal expenditure category in 2007, this article mainly collected panel data of 31 provinces (cities) in mainland of China from 2007 to 2020. The original data pertaining to fertilizer application, pesticide input, agricultural film utilization, diesel consumption and agricultural mechanization are sourced from China's rural statistical yearbook. Other relevant original data including financial energy conservation and environmental protection expenditure, total financial expenditure, total power of agricultural machinery, number of employees in the primary industry, *per capita* consumption level of rural residents, grain planting area, crop planting area, cultivated land area, urbanization level, etc. are extracted from China's statistical yearbook. Detailed sources are provided in Table 2. Any instances of missing data were supplemented using the moving average method. Descriptive statistical outcomes are presented in Table 3.

3.4 The spatiotemporal evolution characteristics of agricultural carbon emissions in China

Using the natural breakpoint classification method, China's agricultural carbon emissions are categorized into five distinct levels and visually represented on a map, as depicted in Figure 1.

From Figure 1, several conclusions can be drawn: firstly, prior to 2014, ACEs in various regions of China showed an upward trend. However, in recent years, these emissions in different regions of China have exhibited a consistent downward trend; notable and persistent disparities in agricultural carbon emissions are evident among China's diverse regions. Substantial differences exist between major agricultural provinces and non-agricultural provinces, as well as between the eastern, central, and western regions. Thirdly, ACEs in prominent agricultural provinces such as Henan, Shanxi, and Heilongjiang are positioned at a high level, while emissions in regions such as Fujian, Zhejiang, and Tibet remain at a lower level.

TABLE 3 Descriptive statistical results of main variables.

Variable	Number of samples	Mean	Standard deviation	Min	Max
ACEs	434	5.361	1.108	2.293	6.903
FEPE	434	0.030	0.011	0.008	0.068
Agricultural mechanization	434	4.150	2.069	0.864	12.59
Planting structure	434	0.655	0.135	0.328	0.971
Scale management of agricultural land	434	6.834	3.559	2.090	27.71
Urbanization level	434	1.289	0.376	0.488	2.324
Multiple crop index	434	55.34	14.27	21.50	93.77
Consumption level of rural residents	434	8,460	4,232	2080	22,449

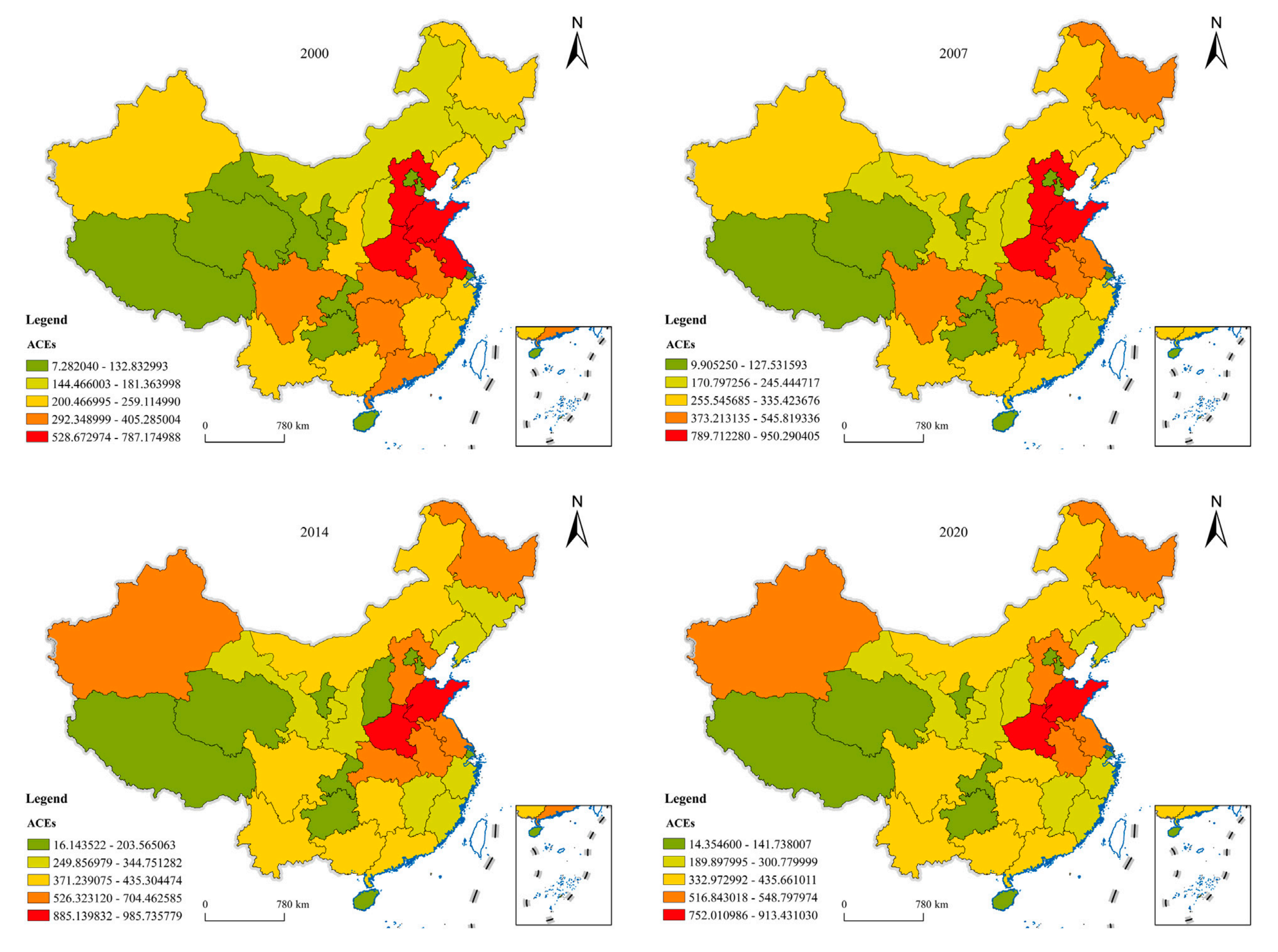

FIGURE 1
The spatiotemporal evolution trend of ACEs in various regions of China.

4 Results

4.1 Benchmark regression analysis

Prior to conducting the regression analysis, a Pearson correlation analysis was performed on the primary variables to mitigate the potential issue of severe multicollinearity. The outcomes of this analysis are presented in Table 4.

Table 3 indicates noteworthy correlations between ACEs and several variables. ACEs display a significant negative correlation with variables like FEPE, Urbanization level, and Consumption level of rural residents. Conversely, ACEs exhibit a significant

TABLE 4 Correlation coefficient of main variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) ACEs	1							
(2) FEPE	−0.105*	1						
(3) Agricultural mechanization	0.036	0.055	1					
(4) Planting structure	0.216*	0.285*	0.400*	1				
(5) Scale management of agricultural land	0.251*	0.116*	0.586*	0.405*	1			
(6) Urbanization level	0.271*	−0.350*	−0.118*	−0.334*	−0.151*	1		
(7) Multiple crop index	−0.218*	−0.102*	0.222*	−0.034	0.243*	0.098*	1	
(8) Consumption level of rural residents	−0.111*	−0.048	0.344*	−0.149*	0.222*	0.183*	0.717*	1

Note: * indicates significant at 5% level.

TABLE 5 The impact of FEPE on ACEs.

	(1)	(2)	(3)	(4)
FEPE	−7.18***	−4.74***	−5.30***	−4.20***
	(−11.86)	(−8.20)	(−8.68)	(−7.87)
Agricultural mechanization		0.04***		
		(9.13)		
Planting structure		−0.28**	−0.25**	−0.21**
		(−2.45)	(−2.11)	(−2.01)
Multiple crop index		0.04	0.04	0.04
		(1.20)	(1.12)	(1.31)
Urbanization level		0.01***	0.01***	
		(5.45)	(4.28)	
Scale management of agricultural land			0.02***	0.02***
			(5.37)	(5.06)
Consumption level of rural residents				−0.00***
				(-11.80)
Year Fixed Effect	Yes	Yes	Yes	Yes
Province Fixed Effect	Yes	Yes	Yes	Yes
N	434	434	434	434
adj. R^2	0.994	0.996	0.995	0.996

Note: The values in brackets are t statistics, $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

positive correlation with variables such as Planting structure and Agricultural land scale management. Additionally, ACEs show a significant positive correlation with the Multiple cropping index while having no significant correlation with Agricultural mechanization. Notably, a robust correlation exists between Urbanization level and Consumption level of rural residents, evidenced by a correlation coefficient of 0.717. Similarly, a strong correlation of 0.586 emerges between Agricultural mechanization and Scale management of agricultural land. This highlights the necessity of excluding these highly correlated variables from the model simultaneously to avert severe multicollinearity, which could compromise the stability of regression coefficients. As a solution, we adopt stepwise regression analysis to scrutinize the impact of FEPE on ACEs. The outcomes of this analysis are presented in Table 5.

Table 5 shows that FEPE has significant negative impacts on ACEs. Specifically, in the model (1)–(4), the coefficients of FEPE are significantly negative, which has confirmed the hypothesis 1: FEPE can reduce ACEs. The reason may be that FEPE can bring more the use of environmental protection facilities, equipment, and materials. The coefficients of variable Agricultural mechanization and Agricultural scale management are both significantly positive, indicating that agricultural mechanization and agricultural scale management will increase ACEs. The main reason of the finding may be that the use of agricultural machinery and equipment will cause the increase of carbon emissions. The coefficient of Planting structure is significantly negative, indicating that the "grain-oriented" planting structure will reduce ACEs. This may be due to the relatively less use of pesticides, agricultural films, fertilizers, etc. In food crops compared with other crops. The coefficient of Urbanization level is significantly positive, indicating that with the further acceleration of urbanization, the ACEs will also increase. The reason may be that urbanization makes the rural labor force show the characteristics of aging, feminization, and part-time employment. In order to avoid agricultural production reduction, farmers have invested a large amount of alternative production factors such as fertilizer, pesticide, agricultural film and mechanical facilities, resulting in large amount of ACEs. The coefficient of Consumption level of rural residents is significantly negative, indicating that with the improvement of rural residents' consumption capacity, ACEs will be reduced. The reason may be that with the improvement of rural residents' consumption capacity, there is a higher demand for the safety and quality of agricultural products, which urges farmers to adopt green low-carbon agricultural technology and reduce the input of pesticides and fertilizers, and thus it will improve agricultural green production efficiency and reduce ACEs.

TABLE 6 Heterogeneous impacts: different physical and geographical locations.

	(1)	(2)	(3)
	East area	Centre area	West area
FEPE	−3.83***	−2.08**	−1.57
	(−3.80)	(−2.37)	(-1.65)
Planting structure	−0.57***	−0.39	0.67**
	(−3.30)	(−1.45)	(2.20)
Scale management of agricultural land	0.03***	0.02***	0.01
	(3.61)	(4.70)	(0.99)
Multiple crop index	0.06	−0.18***	0.08
	(1.14)	(-2.80)	(1.63)
Consumption level of rural residents	−0.00***	−0.00	−0.00***
	(−4.04)	(−0.78)	(-6.51)
Year Fixed Effect	Yes	Yes	Yes
Province Fixed Effect	Yes	Yes	Yes
N	154	126	154
adj. R^2	0.996	0.987	0.998

Note: The values in brackets are t statistics, $*p < 0.1$, $* *p < 0.05$, $* * *p < 0.01$.

4.2 Heterogeneity analysis

4.2.1 Based on natural geographical location

First of all, according to the division of the China Bureau of Statistics, 31 provinces and cities in China can be divided into the eastern, central, and western regions based on their geographical location and economic development level (Nie et al., 2019). According to the degree of economic development, they are divided into the eastern, central, and western regions. The environmental Kuznets theory tells us that there may be an inverted U-shaped relationship between the degree of economic development and carbon emissions. Therefore, it is necessary to distinguish three major regions and examine the heterogeneous impacts of FEPE on ACEs.

Table 6 reveals that FEPE exhibits a significant inhibitory effect on ACEs within the eastern and central regions, while its inhibitory effect is not statistically significant in the western regions. Specifically, in model (1) and model (2), the coefficients in front of the FEPE variable are −3.83 and −2.08 respectively, both of which are significant. In contrast, in model (3), the coefficients in front of the FEPE variable are both insignificant, which indicates that for the eastern and central regions, FEPE has a significant inhibitory effect on ACEs. However, this inhibitory impact is not discernible in the western regions. This variation can potentially be attributed to the heightened policy responsiveness of farmers in the central and eastern regions, owing to improved Internet infrastructure and expedited information dissemination. Consequently, as fiscal allocation towards environmental protection increases, farmers in these regions are more inclined to adopt corresponding technological measures aimed at diminishing ACEs.

4.2.2 Based on whether it is the main grain producing area

The main grain producing areas include Jiangsu, Inner Mongolia, Hebei, Henan, Shandong, Heilongjiang, Jilin, Liaoning, Anhui, Hubei, Hunan, Jiangxi and Sichuan. We also divide the samples into main grain producing areas and non-main grain producing areas and investigate potential heterogeneous impacts.

Table 7 shows that although the impact of FEPE on ACEs in major grain-producing areas is higher than that in non-major grain-producing areas, the difference is insignificant. It reveals that there are no differences among the impacts of FEPE on ACEs.

4.2.3 Based on different degree of ACEs

This paper further discusses the heterogeneous impacts of FEPE on ACEs under different quantiles of ACEs, which is shown in Table 8.

Table 8 shows that, the negative impact of FEPE on ACEs is significant at the high point, not at the low point. The coefficient of FEPE is significant at the 0.5, 0.7, and 0.9 quantiles, while not significant at the 0.1 and 0.3 quantiles. This shows that in provinces with relatively “high carbon emissions”, the FEPE policy plays a significant role in reducing carbon emissions. The possible explanation lies in the agricultural production mode’s susceptibility to path dependence. In provinces with relatively low carbon emissions, the scope for further ACE reduction is considerably constrained, rendering emissions reduction a challenging endeavor. At this time, the carbon emission reduction will also rely more on coordinated policies other than FEPE.

TABLE 7 Heterogeneous impacts: main grain producing areas and non-main grain producing areas.

	(1)	(2)	(3)
	Grain producing area	Not grain producing area	All samples
FEPE	−4.03***	−3.51***	−4.09***
	(−5.09)	(−4.84)	(−6.56)
Planting structure	−0.69***	−0.13	−0.21**
	(−3.27)	(−0.84)	(−1.99)
Scale management of agricultural land	0.02***	0.01**	0.02***
	(5.73)	(2.28)	(5.06)
Multiple crop index	−0.17***	0.07	0.04
	(−3.08)	(1.65)	(1.32)
Consumption level of rural residents	−0.00	−0.00***	−0.00***
	(−1.14)	(−10.99)	(−11.61)
FEPE*Grain production area			−0.37
			(−0.34)
Year Fixed Effect	Yes	Yes	Yes
Province Fixed Effect	Yes	Yes	Yes
N	182	252	434
adj. R^2	0.981	0.995	0.996
Inter-group coefficient difference test (*p*-value)	0.527 (0.35)		

Note: The values in brackets are t statistics, $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$, the inter-group coefficient difference test adopts Fisher combination test.

TABLE 8 Heterogeneity effect: distribution effect.

	(1)	(2)	(3)	(4)	(5)
	0.1	0.3	0.5	0.7	0.9
FEPE	−5.144	−5.039	−21.446***	−5.487**	−15.997**
	(−0.614)	(−0.614)	(−9.945)	(−2.339)	(−2.041)
Planting structure	5.986	−0.851	2.804***	2.046***	−0.539
	(1.281)	(−0.503)	(16.310)	(8.746)	(-0.619)
Scale management of agricultural land	−0.251*	−0.062	0.035***	0.052***	0.061**
	(−1.673)	(−1.221)	(9.171)	(2.715)	(2.209)
Multiple crop index	−0.231	0.370	0.932***	0.529***	0.092
	(−0.225)	(0.783)	(34.530)	(10.425)	(0.257)
Consumption level of rural residents	0.000	−0.000	−0.000**	−0.000*	0.000
	(0.485)	(−0.505)	(−2.415)	(−1.762)	(1.132)
N	434	434	434	434	434

Note: The values in brackets are t statistics, $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

TABLE 9 Mechanism analysis: agricultural non-point source pollution.

	(1)	(2)	(3)	(4)	(5)	(6)
	Chemical fertilizer	Agricultural film	Diesel oil	Pesticide	Turn	Irrigate
FEPE	−331.93***	−245.47***	−334.43***	−55.13**	−1.19*	−27.48
	(-3.07)	(-5.29)	(-4.65)	(-2.20)	(-1.81)	(-0.59)
Planting structure	−63.92***	−23.10**	−55.94***	−26.74***	−0.28**	34.71***
	(−3.00)	(−2.52)	(−3.94)	(−5.40)	(−2.18)	(3.78)
Scale management of agricultural land	1.67**	0.08	0.74*	−0.13	0.06***	2.12***
	(2.58)	(0.28)	(1.71)	(−0.86)	(14.28)	(7.60)
Multiple crop index	−14.01**	0.68	0.68	−2.75**	−0.02	−7.19***
	(−2.36)	(0.27)	(0.17)	(−2.00)	(−0.62)	(−2.82)
Consumption level of rural residents	−0.00***	−0.00**	0.00**	−0.00***	−0.00**	−0.00**
	(−5.59)	(−2.24)	(2.36)	(−5.26)	(−2.21)	(−1.98)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Province Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	434	434	434	434	434	434
adj. R^2	0.988	0.969	0.936	0.977	0.995	0.980

Note: The values in brackets are t statistics, $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

4.3 Mechanism analysis

Furthermore, we explore the mechanism how FEPE affects ACEs from two aspects: agricultural technological progress and agricultural non-point source pollution.

4.3.1 Agricultural technological progress

Our paper mainly uses the total agricultural machinery power to measure the progress of agricultural technology. We construct the panel intermediary effect model to test the impact of agricultural technology progress. The study found that fiscal expenditure on environmental protection could not significantly affect the progress of agricultural technology. Therefore, this paper believes that FEPE cannot affect ACEs by affecting agricultural technology progress (Because it is not significant, we do not list the results here). This may be due to the fact that in response to environmental regulation, farmers may increase their expenditure on pollution abatement, which implies that their investment in mechanization would be crowed out (Palmer et al., 1995; Greenstone, 2002).

4.3.2 Agricultural non-point source pollution

Table 9 shows that among the six sources of ACEs, FEPE has the largest inhibiting effect on ACEs from the use of agricultural diesel, fertilizer and film, followed by the use of pesticides and tillage, and has no significant inhibiting effect on ACEs from irrigation. Specifically, in the model (1)–(3), the coefficients in front of the variable FEPE are −331.93, −245.47, and −334.43, respectively, all of which are significant, while in the model (4)–(5), the coefficients in front of the variable FEPE are −55.13 and −1.19, respectively, and have passed the 5% and 10% significance test, which shows that the FEPE has higher inhibitory effect on the ACEs from agricultural diesel, fertilizer and film use than that from the use of pesticides and tillage. The coefficient in front of the FEPE variable in model (6) lacks significance, indicating that FEPE has no significant effect on ACEs from irrigation.

5 Discussion

This article collects panel data at the provincial level in China to illustrate the efficacy of FEPE in mitigating ACEs. The findings affirm that FEPE indeed leads to a reduction in ACEs. This consistency aligns with prior research, including the works of Xu et al. (Yang et al., 2022a; Fan et al., 2022) and so on, reinforcing the credibility of the Porter hypothesis and providing further affirmation of the effectiveness of government environmental governance within the agricultural domain. The government supports environmental infrastructure construction or some application construction projects, which may stimulate enterprises to engage in subsequent pollution control or energy conservation and emission reduction activities. Cooperating with mandatory means, local FEPE has a strong guiding role for enterprise environmental protection investment (Yang et al., 2022b). On the one hand, the increase of local FEPE will promote technological progress (Guo and Zhang, 2023; Wei et al., 2023), provide specialized environmental protection services to industry, reduce industrial environmental protection costs, and improve industrial technological efficiency (Deng et al., 2023); On the other hand, it will strengthen the environmental awareness of industrial enterprises and encourage them to build green industrial chains (Liu et al., 2021b), internalizing environmental protection costs. This not only helps to solve environmental externalization, but also can improve the production efficiency of industrial enterprises, enhance the competitiveness of the entire industry, and achieve industrial technology upgrading.

Based on previous studies (Fan et al., 2022), we also find that FEPE has heterogeneous effects across different regions, and the effectiveness of policy implementation is mainly in the eastern and central regions with high carbon emissions, rather than western regions with low emissions. The possible reason is that in regions with relatively backward economies, local governments still place promoting economic growth before environmental governance; the reason is that the regions with high carbon emissions receive government attention have more pressure to reduce carbon emissions. As for the mechanism how FEPE affects ACEs, this article finds that FEPE mainly affects ACEs through agricultural diesel, fertilizer, and film use, rather than the level of agricultural mechanization. This is also different from previous studies (Luo et al., 2023), which argued that environmental regulation can promote technology innovation. We find the impact of FEPE on ACEs in major grain-producing areas is higher than that in non-major grain-producing areas, but these differences are not statistically significant. In addition, the heterogeneous impacts of FEPE on ACEs at different quantiles are manifested as significant at the high point, but insignificant at the low point, which reveals that only in provinces with relatively "high carbon emissions", FEPE can play a significant role in reducing ACEs. It is consistent with the research of Hong et al. (2022), which argues that the negative impact is more pronounced for non-heavily polluted regions.

Considering the spatial spillover effect of environmental pollution, we can collect more abundant data in the future (such as data from more segmented regions). This expanded dataset can then be used to formulate spatial econometric models to investigate the influence of FEPE on ACEs. In addition, policy evaluation is also one of the leading research directions, and to explore the impact of specific FEPE policies on ACEs can provide reference for government to formulate corresponding fiscal policies. Studying the impact of FEPE policies on farmers' behavior is a more worthwhile study, and we will further explore this aspect in the future.

6 Conclusion

To investigate whether FEPE can reduce ACEs, whether there are any heterogenous impacts among different regions and how FEPE affects ACEs, we have gathered panel data at the provincial level in China from 2007 to 2020 and used the ordinary least squares method to examine the impacts of FEPE on ACEs. The conclusions are as follows: To investigate whether FEPE can reduce ACEs, whether there are any heterogenous impacts among different regions and how to reduce ACEs, we have gathered panel data at the provincial level in China from 2007 to 2020 and used the ordinary least squares method to examine the impacts of FEPE on ACEs. The conclusions are as follows: FEPE has significant negative impacts on ACEs; And in different regions FEPE has heterogeneous impacts on ACEs, which shows that it has a significant impact on the eastern and central regions and provinces with relatively "high" carbon emissions, while it has no significant impact in the western regions and the "low" carbon emissions regions; Further mechanism analysis shows that the impact of FEPE on ACEs is mainly manifested in its inhibiting effect on agricultural diesel, fertilizer and film use of carbon emissions. The research findings hold substantial significance in guiding practical efforts aimed at diminishing ACEs.

Building upon the aforementioned conclusions, we put forward the following policy recommendations:

- First of all, Chinese government should guarantee the enduring stability of investments in environmental protection. It is imperative to secure an unbroken stream of funding for environmental safeguarding, originating from local government sources. There is a growing need to gradually augment financial allocations for environmental protection at all administrative tiers, thereby enhancing the proportion of such allocations within the broader framework of government budgetary disbursements.
- Secondly, it is essential to streamline the framework of fiscal allocations designated for environmental protection. To optimize the efficacy of environmental protection funding, a more nuanced approach is warranted in the ongoing execution of energy conservation and emission reduction initiatives. This could involve creating distinct funds for carbon emission control and specialized management interventions. Concurrently, the allocation structure for environmental protection expenditure should remain attuned to contemporary imperatives, forging a close alignment with China's present ecological context. Timely inclusions of essential projects and the pruning of superfluous elements are imperative, with a parallel consolidation of duplicate accounts for a more efficient system.
- Thirdly, it is imperative to develop viable strategies for mitigating ACEs that take into account the regional disparities in resource endowment. These strategies should involve adjusting the grain planting structures in primary grain-producing regions and harnessing the resource advantages of non-primary grain-producing areas. In the eastern plain region, expanding the scale of grain cultivation could be advantageous, while also leveraging the carbon reduction potential of the digital economy. In the southwestern region, the promotion of intercropping corn and soybeans can enhance soybean production capabilities, concurrently facilitating nitrogen fixation and fertilizer utilization. Additionally, attention should be directed towards the role of FEPE in stimulating the advancement of agricultural scientific and technological innovation.

In addition, this article also has several limitations: Firstly, the fiscal decentralization system in China is usually described as a three-level fiscal decentralization, which refers to the decentralization relationship between the central government, provincial governments, and local governments. Focusing solely on analyzing the influence of FEPE at the provincial level is insufficient. These limitations impel me to undertake further research in the future. Secondly, this study predominantly conducts empirical analysis of the FEPE's impact on ACEs from a macro perspective, lacking a comprehensive examination of micro mechanisms. These limitations will serve as a foundation for guiding my subsequent research endeavors.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found in the article/Supplementary Material.

Author contributions

Conceptualization, SW and XC; methodology, SW and XC; software, SW and XC; validation, SW and XC; formal analysis, SW and XC; investigation, SW and XC; resources, SW and XC; data curation, SW and XC; writing—original draft preparation, SW and XC; writing—review and editing, SW and XC; visualization, SW and XC; supervision, SW and XC; project administration, SW and XC; funding acquisition, SW and XC. 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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Analysis of influencing factors of industrial green and low-carbon transformation under the background of "double carbon": evidence from Sichuan province, China

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Introduction: Industrial green and low-carbon transformation is the key to improve economic development and necessary process to achieve the goal of the carbon peaking and carbon neutrality. Few studies have been done on the decomposition of carbon emission factors in industries and sub-industries and the impact of green and low-carbon transformation about carbon emission in each industry quantitatively. However, the study of industries and sub-industries can comprehensively analyze the development path of green and low-carbon transformation from a more detailed perspective, and provide scientific reasons for the optimization of industrial structure and energy structure.

Methods: The extended Kaya identity for industrial carbon emission is constructed to obtain four factors influencing industrial carbon emission: economic output effect, industrial structure effect, energy intensity effect, carbon consumption intensity in this paper. Then, the LMDI decomposition method is combined with the above identity to innovatively obtain the contribution value of carbon emissions from the perspective of overall, industrial sector and tertiary industry. Then, based on the results of factor decomposition, a multi-index scenario prediction model is constructed. On this basis, the extreme learning machine model optimized by particle swarm optimization (PSO-ELM) was used to predict the influence of the changes in the driving factors on the reduction of industrial carbon emissions. By setting the baseline and industrial green and low-carbon transformation scenarios, it is predicted that industrial carbon emission in Sichuan Province.

Results and discussion: (1) Economic output effect always promotes the growth of industrial carbon emissions, and with the adjustment of industrial structure and energy structure, the other three factors begin to restrain the growth of carbon emissions. (2) Scenario prediction shows that without considering the economic costs of transformation, improving carbon emission reduction efficiency can be obtained through accelerating the rate of change of industrial structure of the secondary and tertiary industries, increasing the proportion of energy intensity reduction, and strengthening the proportion of non-fossil energy use.

KEYWORDS

double carbon, green and low-carbon transformation of industry, the extend Kaya identity, LMDI decomposition method, scenario prediction method, PSO-ELM model

1 Introduction

Green and low-carbon development is an important proposition to promote the harmonious coexistence between man and nature, and it is also the only way to achieve a balance between economic development and environmental quality (Gu, 2016). In recent years, extreme meteorological disasters have intensified significantly. Facing the pressure of climate crisis, it is in the common interest of all countries in the world to realize economic recovery and cope with climate change through green and low-carbon development (Renhou et al., 2023). The European Union has reached the peak of carbon emissions in 1990. On 15 March 2021, the European Commission published the "Horizon Europe" Strategic Plan 2021–2024, in which the first phase of strategic investment priorities includes climate, energy, industry, transport and other areas, as well as the realization of carbon neutral emerging technologies. In 2020 and 2021, the United Kingdom has released the 10-point Plan for Green Industrial Revolution, the Green Hydrogen Energy Strategy and the Net Zero Strategy. In 2021, France issued the "France 2030 Plan" to promote the development of small nuclear reactors, green hydrogen energy, industrial decarbonization, green cars, low-carbon aircraft and other related technologies and industries in the next 5 years. Since 2021, the United States has actively implemented the Green New Deal, increased investment in clean technology research and development.

At present, China's energy-intensive industry and carbon-intensive energy are still the main reasons for the increase in carbon emissions (Research Group of National Institute of Development Strategy at Wuhan University, 2022). With the proposal of the "double carbon" goal, the industry needs to carry out green and low-carbon transformation development to reduce industrial carbon emissions. The "14th Five-Year Plan" period is an opportunity for China's industrial green and low-carbon transformation. In recent years, clean energy and green industries in Sichuan Province have been developing rapidly, which make Sichuan Province play an increasingly significant role in the national industrial landscape. Simultaneously, the industrial and economic development of Sichuan province is similar to that of most inland provinces in China. Though the industrial structure is gradually changing to the "3-2-1" transformation, the balance issues of the industrial structure, energy structure, economic and ecological development have not been resolved. Among them, "1", "2", and "3" represent the primary industry, the secondary industry and the tertiary industry respectively (Research Group of National Institute of Development Strategy at Wuhan University, 2022).

In order to achieve the "double carbon" goal as soon as possible, Sichuan issued the "Sichuan Province Carbon Peak Implementation Plan," "Sichuan Province "14th Five-Year" Comprehensive Work Plan for energy conservation and emission reduction" and other policies. In 2021, Sichuan province released the vision of enabling green and low-carbon industries to achieve the goal of "double carbon," which pointed out that because industries with large resource consumption, strong environmental pollution, energy-intensive, and less added value have stricter resource and environmental constraints under the carbon neutral vision, the deep transformation of energy-intensive industries will face significant challenges. Therefore, how to achieve green and low-carbon industrial development is an urgent problem for China to solve under the background of "double carbon".

In essence, the transformation of industrial green and low-carbon is the transformation of industrial structure, energy structure and consumption structure. At the same time, industrial development cannot do without energy supply, and green and sustainable development depends on a clean and sustainable energy structure (Yu et al., 2022). Industrial transformation is the key support to achieve green and low-carbon economic development. Therefore, for clarifying the development mode of industrial green and low-carbon transformation, we must determine the important factors affecting industrial carbon emissions firstly.

Given that there are few analyses on industrial carbon emissions and green and low-carbon development from the perspective of the whole industry, taking Sichuan Province as an example, this study explores the influencing factors of industrial green and low-carbon transformation under the "double carbon" background. This paper innovatively studies the influencing factors of industrial carbon emissions from the carbon emissions of perspective of overall, industrial sectors and three industries. The LMDI decomposition method is used to study the influencing factors of industrial carbon emissions from 2005 to 2019 at different stages and clarify the development paths of green and low-carbon transformation of different industries and industrial sectors. Meanwhile, based on the results of factor decomposition and combined with policy documents, a multi-indicator scenario prediction model is built. The PSO-ELM model combined the scenario prediction indexes is constructed to forecast industrial carbon emissions in Sichuan from 2020 to 2025, verifying whether adjusting the above-mentioned influencing factors can effectively reduce industrial emissions. From the perspective of theoretical value, this study comprehensively analyzes the influencing factor of industry carbon emissions from the perspective of overall, industrial sector and tertiary industry. In addition, this paper expands the application range of PSO-ELM prediction model and provides a new choice for carbon emission prediction model. In terms of practical value, positioning the role of Sichuan Province in realizing the "double carbon" goal in China can not only promote the green and low-carbon transformation of Sichuan Province, but also provide an important reference for the industrial transformation and clean energy utilization of cities in China and international community.

2 Literature review

2.1 Industrial green low-carbon transformation and carbon emission

With the Copenhagen Climate Conference was held in 2009, low-carbon concept has gradually become the subject of the development of various industries and fields, and there has been a shift from the traditional carbon-intensive economy to low-carbon economy. Various industries have also begun to explore their transformation paths and development modes. Low-carbon transformation refers to changing the existing economic growth mode based on fossil energy through mechanism innovation, institutional arrangement and technological innovation, and realizing a sustainable economic development form supported by low carbon or zero carbon energy. Aiming at carbon emission reduction, low-carbon transformation takes the optimization of industrial structure, the change of industrial organization, and the transformation of economic development mode and system as an important content. Therefore, the purpose of industrial green low-carbon transformation is to reduce carbon emissions by adjusting industrial structure and energy structure. As a result, it is very important to analyze the influencing factors of industrial green and low-carbon transformation.

Foreign scholars mainly studied the formulation and realization of carbon emission targets, carbon locking issues, etc., and explored low-carbon transition from the perspective of industry. For example, Rietbergen et al. (2015) participated in the goal-setting process of the carbon performance ladder in the Netherlands. They concluded that the current goal-setting process of the carbon performance ladder did not set the optimal carbon emission reduction target. The goal-setting was necessary to consider the minimum performance level of the low-carbon transformation of the industry to maintain the carbon performance ladder as an effective tool for green public procurement. In addition to relevant studies on carbon targets, the issue of carbon locking has also begun to attract attention. Janipour et al. (2020) explored the potential carbon locking in the Dutch chemical industry through semi-structured interviews with 11 key industries. The results showed that low-carbon options have high operating costs, low risk of capital providers and shareholders to accept, and some barriers will inhibit the process of carbon emission reduction. Different from foreign studies, domestic studies focus on exploring the influencing factors of carbon emission change (Yan and Fang, 2015). On this basis, many scholars have studied the historical track and characteristics of carbon emission of China's manufacturing industry, and explored the low-carbon transformation potential of carbon emission of China's manufacturing industry based on scenario analysis. In addition, some scholars have explored the impact of industrial structure changes on China's carbon emissions in recent years from different dimensions. Meanwhile, they have analyzed the carbon emission reduction potential of each industry, some possible hidden carbon emission pathways and their industry share (Dan et al., 2016).

2.2 Factor decomposition of industrial carbon emissions

At present, some research mainly use quantitative methods to study the linear or nonlinear impact of green and low-carbon transformation development on economy and green innovation in specific industries such as petrochemical industry, agriculture, financial industry and construction industry (Yuan, 2014; Yue et al., 2022; Haitao et al., 2023; Luo et al., 2023). Others mainly make qualitative analysis on the green development path of an industry under the background of "double carbon" goal (Jiang et al., 2022; Xueting and Junbiao, 2022). Meanwhile, the impact of different industrial development on carbon emissions by decomposition method has gradually become an important research (Hu and Gui, 2017).

Few studies have been done on the decomposition of carbon emission factors in industries and sub-industries and the impact of green and low-carbon transformation about carbon emission in each industry quantitatively, while researches on carbon emissions mainly focuses on a specific industry (Song, 2012; Abul et al., 2015; Mikko et al., 2016; Long and Han, 2020; Yuan et al., 2020) and the measures of energy saving and emission reduction (Liu et al., 2015; Hu J. B. et al., 2021; Song et al., 2022). In reality, the change of a target variable is caused by a variety of factors, but there are big differences between the influences of these factors. Thus, it is necessary to find out the main influencing factors that cause the change of the target variable from the numerous influencing factors, and then analyze the main factors to make the target variable develop in a good direction, so as to put forward targeted policy suggestions. Therefore, it is important to find and decompose the main influencing factors. Factor decomposition models are commonly used in studies of greenhouse gases (Hu and Gui, 2017; Yue, 2021). The LMDI method decomposes several influencing factors that cause changes in a target variable and forms a combination, discerning the magnitude of the influence of each driver on the changes in the target variable. Thus, the LMDI method has become the mainstream method adopted in analyzing energy consumption, GHG emissions, etc. (Ediger and Huvaz, 2006; Hatzigeorgiou et al., 2008; Hu and Gui, 2017). LMDI decomposition method can clarify the role of other factors on the carbon emissions of energy sources such as electricity, coal, and oil (Hwang et al., 2020; Reema, 2022), which can provide a scientific path to improve the energy structure and environmental quality. In addition, in order to optimize the industrial structure and clarify the influencing factors of industrial carbon emissions, LMDI decomposition method is also commonly used to study the influencing factors of carbon emissions in industrial sectors such as industry, tourism, and transportation (Hu and Gui, 2017; Sun et al., 2017; Liu and Ding, 2020; Chen et al., 2022). Meanwhile, the carbon emissions of a country or region are affected by various factors such as economic effects, energy intensity, industrial structure, energy mix, and population changes. Therefore, in order to analyze and quantify the effect of the influencing factors of carbon emissions on a certain country and region, and provide a reference basis for national or regional emission reduction policies, LMDI decomposition method is also widely applied in this field (Dalia and Tomas, 2016; Fu et al., 2019; Dong et al., 2020). Some scholars have also combined LMDI decomposition method with scenario prediction methods to predict the impact of a province or regional driver on carbon emissions, which can provide different development paths for regions to achieve peak carbon neutrality (Yue, 2021; Liu et al., 2022; Wang et al., 2022).

Through analyzing the above literature, although many scholars have made more researches in carbon emission factor decomposition and extended the application of LMDI decomposition method and Kaya identity, there are still some unexplored directions. At present, most studies mainly focus on the decomposition of a certain industry, an industry or a factor that affects carbon emissions, but t few studies are involved in the decomposition of carbon emission factors for the whole industry and sub-industries, and the quantitative analysis of the impact of green and low-carbon transformation on carbon emissions in each industry. Meanwhile, most of the literatures on carbon emission forecasting based on LMDI method focus on the changes of carbon emission during the whole sample period, without considering the degree of influence of each driver on carbon emission changes in different stages. In addition, most scholars construct scenario analysis indicators only, lacking comprehensive analysis of policies and China's development status.

Therefore, in this paper taking Sichuan for an example, the LMDI method and the extended Kaya identity are used to classify the drivers of carbon emissions into various effects from the overall, sub-industry and three major industry perspectives, and the impact of each industry development on carbon emissions is quantified by conducting empirical analysis at different stages. At the same time, combined with the scenario analysis method, the impact of changes in industrial carbon emission factors on carbon emissions in Sichuan Province is predicted analyzed under different scenarios. Further research was carried out about the impact of industrial green and low-carbon transformation under the background of double carbon, which provides reference value the transformation and development of green and low-carbon industries in cities similar to Sichuan's energy structure and industrial structure.

3 Model construction and data sources

3.1 LMDI model of industrial carbon emissions

Based on Kaya identity, the extended Kaya identity of carbon emissions is constructed, which is shown as Formula 1.

$$C = \sum_{i=1}^{n} C_i = \sum_{i=1}^{n} GDP \times \frac{GDP_i}{GDP} \times \frac{E_i}{GDP_i} \times \frac{C_i}{E_i} \tag{1}$$

Where, C indicates the total industrial carbon emissions. C_i indicates carbon emissions of the ith industry. GDP indicates total industrial output. GDP_i indicates the output of the ith industry. E_i indicates the energy consumption of the ith sector.

The Kaya identity was proposed by Japanese scholar Yoichi Kaya in 1989 (Kaya, 1989). Although the Kaya identity can only explain the change of carbon emission flow, and the driving factors are mostly superficial factors, the Kaya identity is still widely used in carbon emission. This is because the Kaya identity has the advantages of simple mathematical form, no residual decomposition, and strong explanatory power for driving factors of carbon emission change.

In order to make Eq. 1 has a clearer way to represent the impact of each factor on the industry's carbon emissions, Formula 1 is expressed as Formula 2.

$$C = \sum_{i=1}^{n} Q \times I_i \times S_i \times M_i \tag{2}$$

Where, $Q = GDP$ indicates total outputs, i.e., total output of the industrial sector. $I_i = GDP_i/GDP$ indicates the industrial structure of ith sector, i.e., the proportion of the output of each sector to total output. $S_i = E_i/GDP_i$ indicates the energy intensity of the ith sector, i.e., energy consumption by the sector as a proportion of output by the industry. $M_i = C_i/E_i$ indicates carbon consumption intensity, i.e., share of each carbon emission in energy consumption.

The specific meaning of Formula 2 is that carbon emissions (C) are influenced by changes in economic output effect (Q), industrial structure effect (I), energy intensity effect (S), and carbon consumption intensity effect (M).

On the basis of Formula 2, the result of factor decomposition was obtained by using logarithmic mean divisia index (LMDI) decomposition method, as shown in Formula 3. About the LMDI decomposition method it is proposed by Ang and Liu, (2007), which can not only decompose various factors affecting carbon emissions, but also solve the problem of zero residual (Dong et al., 2020).

$$\Delta C = \Delta C^t - \Delta C^0 = \Delta C_Q + \Delta C_I + \Delta C_S + \Delta C_M \tag{3}$$

Where, ΔC is defined as the total effect of the change in industry carbon emissions from the base year to the tth year.

Correspondingly, the contribution values of each influence factor are obtained by decomposition, which are Formula 4, 5, 6, 7.

$$\Delta C_Q = \sum_{i=1}^{n} \frac{C_i^t - C_i^0}{InC_i^t - InC_i^0} In\left(\frac{Q^t}{Q^0}\right) \tag{4}$$

$$\Delta C_I = \sum_{i=1}^{n} \frac{C_i^t - C_i^0}{InC_i^t - InC_i^0} In\left(\frac{I^t}{I^0}\right) \tag{5}$$

$$\Delta C_S = \sum_{i=1}^{n} \frac{C_i^t - C_i^0}{InC_i^t - InC_i^0} In\left(\frac{S^t}{S^0}\right) \tag{6}$$

$$\Delta C_M = \sum_{i=1}^{n} \frac{C_i^t - C_i^0}{InC_i^t - InC_i^0} In\left(\frac{M^t}{M^0}\right) \tag{7}$$

Where, ΔC_Q indicates the impact of economic output on carbon emissions. ΔC_I indicates the impact of industrial structure on carbon emissions. ΔC_S indicates the impact of energy intensity on carbon emissions. ΔC_M indicates the impact of carbon consumption intensity on carbon emissions.

3.2 PSO-ELM prediction model

PSO-ELM prediction model means the extreme learning machine (ELM) model optimized by particle swarm optimization (PSO). The ELM model has a faster learning speed and better generalization performance compared with traditional neural networks, and the weights and thresholds of the ELM model are optimized by a particle swarm optimization algorithm, which can further improve the prediction accuracy and convergence speed of the network (Chen, 2021).

ELM is a fast-learning algorithm for single hidden layer neural networks that can randomly initialize the input weights and biases and obtain the corresponding output weights (Cao et al., 2010). Let the single hidden layer feed-forward neural network have m neurons, N hidden layer nodes and 1 output neuron. Then the output of the ELM is Eq. 3:

$$y = \sum_{j=1}^{N} g\left(a_j^T x + b_j\right)\beta_j \tag{8}$$

Where: $x = [x_1, x_2, \ldots, x_m]^T$ is the m inputs; $a_j = \{a_{1j}, a_{2j}, \ldots a_{mj}\}$ is the connection weights of all input layers to the jth neuron, a_{ij} is the connection weight of the ith neuron to the jth hidden layer node; b_j represents the bias value of the jth hidden layer node; $g(\ )$ is the hidden layer excitation function; B_j is the connection weight of the jth hidden layer to the output layer (Huang et al., 2006).

The traditional neural networks are more complex to solve for a_j, b_j, and B_j in practice. While the ELM model is based on a single hidden layer feed-forward neural network, which directly assigns values to a_j and b_j, and only needs to learn B_j. At the same time, compared with the traditional feed-forward neural network, it adds an undertaking layer. The ELM model not only has excellent generalization and approximation capabilities, but also has the advantages of fast operation and low complexity (Chen, 2021).

Particle Swarm Optimization (PSO) is a classical heuristic algorithm whose basic idea is to use the sharing of information by individuals in a population to produce an evolutionary process from disorder to order in the solution space to obtain the optimal solution to the problem. As the prediction accuracy of the ELM model is affected by the weights and thresholds, the use of PSO to optimize the weights and thresholds can improve the prediction accuracy of the ELM model (Liu et al., 2023).

3.3 Data sources and processing

The data include China's total GDP, each industry and sub-industries sector's GDP, energy consumption and carbon emissions. All data concerning GDP and energy consumption were obtained from energy and national economic accounts of Sichuan Statistical Yearbook (2005–2020). In order to ensure the accuracy of industrial carbon emission data calculation and the accuracy of research results, the data of carbon emissions of each sector in Sichuan Province are taken from the Provincial Emissions Inventory (2005–2019) of the CEADs (China Carbon Accounting Database). The database's carbon emissions data is currently only updated until 2019. By the relevant literatures (Hu and Gui, 2017; Dong et al., 2020; Yue, 2021; Wang et al., 2022) and the classification criteria of each industrial sector in the Sichuan Provincial Statistical Yearbook, the data caliber is unified between different types of industrial sectors. Finally, the industries in Sichuan Province are divided into three main categories, among which agriculture, forestry, animal husbandry and fishery are the primary industries, industry and construction are the secondary industries, and transportation, warehousing, postal service, wholesale, retail, accommodation, catering industry and others are the tertiary industry.

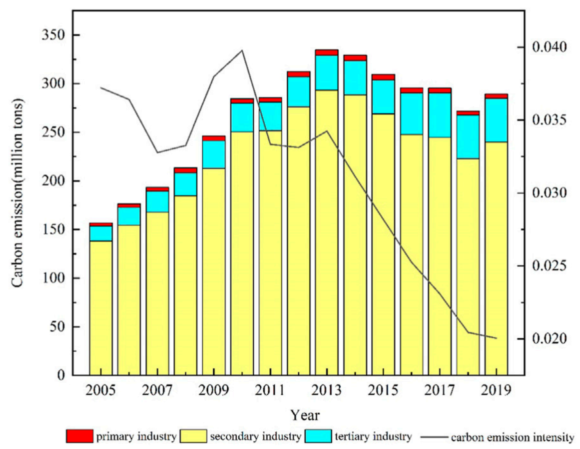

FIGURE 1
Changes in total industrial carbon emissions and carbon emission intensity in Sichuan from 2005 to 2019.

4 Empirical analysis

4.1 Carbon emission characteristics of industry in Sichuan province

In this paper, according to the data on carbon emissions of each industry, the trends of total industrial carbon emissions are analyzed in Sichuan province from 2005 to 2019. As can be seen from Figure 1, from 2005 to 2013, carbon emissions continued to rise, and from 2015 to 2019, they declined and remained stable. From 2005 to 2019, total carbon emissions of final energy consumption by various industries increased by 13.257 million tons, with an average annual growth rate of 4.48%. The secondary industry was the main output sector of the total carbon emissions in Sichuan Province, and it played a dominant role in the composition of carbon emissions. In terms of growth rates, the average annual growth rates of carbon emissions from the primary, secondary and tertiary industries were 2.22%, 4.03%, and 7.91%, respectively. Among the three industries, the tertiary industry had the highest average annual growth rate, but the total carbon emissions of the tertiary industry were still less than that of the secondary industry, and there was a big gap. In terms of carbon emission intensity, although the total carbon emission increased continuously from 2010 to 2013 and reached the peak, the carbon emission intensity showed a downward trend, which indicated that the amount of carbon dioxide emitted by per unit of output in Sichuan province was declining while its economy was growing. Especially since 2013, carbon emission intensity has continued to decrease, meaning that industries have gradually entered a low-carbon development mode in Sichuan Province. This indicates that if the industrial economic level remains unchanged, industrial carbon emissions continue to decrease, and the trend of green and low-carbon development continues to emerge.

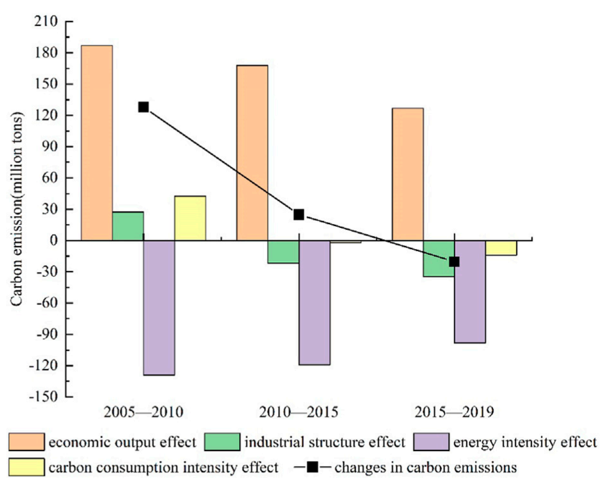

FIGURE 2
Results of phased decomposition of industrial carbon emissions changes in Sichuan.

4.2 Results of the decomposition of industrial carbon emission factors based on different perspectives

4.2.1 Overall perspective

Firstly, from the overall perspective, the change of the contribution value of the four main factors mentioned above to industrial carbon emissions at different stages (2005–2010, 2010–2015, and 2015–2019) in Sichuan Province was analyzed to determine the impact of these factors on carbon emissions. As can be seen from Figure 2, the decomposition of industrial carbon emissions in the three stages reveals that economic output effect was the main driving factor of carbon emissions growth, with the most prominent effect from 2005 to 2010. However, on the whole, the promoting impact of economic output effect on carbon emissions was gradually decreasing. In addition, the energy intensity effect restrains the growth of carbon emissions consistently. Furthermore, both the industrial structure effect and the carbon consumption intensity effect promoted the increase of carbon emissions from 2005 to 2010, and inhibit the increase of carbon emissions in the following two stages, but the energy intensity effect was more significant. In the three stages, the change of carbon emissions always showed a downward trend. Based on the decomposition results of specific industrial carbon emissions in Table 1, the conclusions are as follows.

(1) In the whole time periods, the economic output effect was always positive values and showed a decreasing trend, which indicated that although the impact of economic growth on carbon emissions in Sichuan Province had decreased, the rapid economic growth was still the dominant factor leading to the increase of carbon emission.
(2) The industrial structure effect promoted the increase of carbon emissions from 2005 to 2010, but turned negative after entering 2010, indicating that the industrial structure effect began to restrain the growth of emissions. The cumulative contribution value of industrial structure effect from 2005 to 2019 was −13.31 million tons, which reflected that the industrial structure adjustment has played a positive role in Sichuan province. At the same time, it is still necessary to further optimize and upgrade the industrial structure and carry out green and low-carbon transformation according to the current deployment.
(3) Energy intensity refers to the level of energy consumption per unit of GDP, which reflects the efficiency of energy in economic development (Dong et al., 2020). In the whole three stages, the influence of energy intensity effect on carbon emissions in Sichuan Province had always been negative, and its cumulative contribution value was −286.917 million tons. Therefore, the reduction of energy intensity can effectively restrain the increase of carbon emissions, which will bring a new upgrading path for the industrial green and low-carbon development of Sichuan Province in the future.
(4) The carbon consumption intensity effect represents the level of CO_2 output per unit energy consumption. The carbon consumption intensity effect promoted carbon emissions from 2005 to 2010 and inhibited them after 2010, which was the same as the industrial structure effect on carbon emissions. However, in the whole three stages, the cumulative contribution

TABLE 1 The results of the factor decomposition of industrial carbon emissions.

Effect	2005–2010		2010–2015		2015–2019		2005–2019	
	Contribution value (million tons)	Rate (%)	Contribution value (million tons)	Rate (%)	Contribution value (million tons)	Rate (%)	Contribution value (million tons)	Rate (%)
Economic output effect	187.023	146.18	168.066	674.81	126.699	−624.86	400.384	303.80
Industrial structure effect	27.383	21.40	−21.851	−87.74	−34.585	170.57	−13.310	−10.10
Energy intensity effect	−129.111	−100.91	−119.135	−478.35	−98.242	484.51	−286.917	−217.70
Carbon consumption intensity effect	42.649	33.33	−2.174	−8.73	−14.148	69.78	31.637	24.00

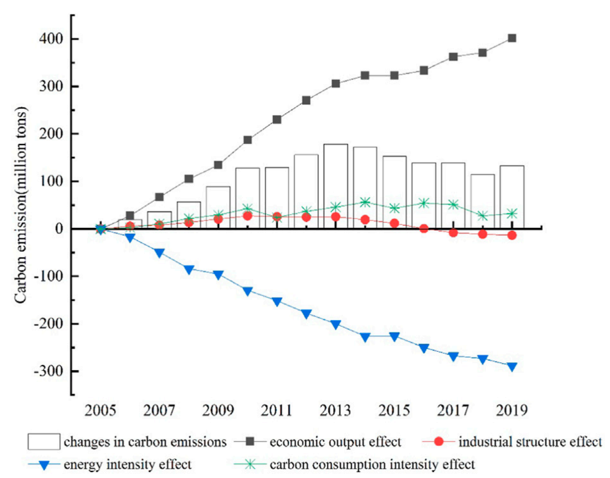

FIGURE 3
The cumulative contribution of the driving factor of industrial carbon emissions in Sichuan.

value of carbon consumption intensity effect was 31.637 million tons, which indicated that the energy efficiency and quality of the industry were not high in Sichuan Province. In the future, it is still necessary to optimize the energy structure by increasing the proportion of clean energy.

Further, the cumulative contribution of each driving factor is studied from the overall perspective, and the dynamic impact of each driving factor on carbon emissions in Sichuan province is analyzed. With 2005 as the base period, the cumulative contribution of the driving factors of industrial carbon emissions was obtained, as shown in Figure 3. As can be seen from Figure 3, from 2005 to 2013, the variation of carbon emissions in Sichuan Province increased year by year, reaching the maximum in 2013. From 2013 to 2019, the variation of carbon emissions showed a trend of fluctuating growth. From the analysis of the four driving factors, it can be seen that economic output effect, carbon consumption intensity effect and industrial structure all promoted the growth of carbon emissions, among which economic output effect was the main driving factor, and showed an upward trend on the whole. The energy intensity effect restrained the growth of carbon emissions effectively, which was an important driving factor for achieving the "double carbon" goal. Moreover, the influence of energy intensity effect on carbon emissions continued to strengthen, so it is necessary to focus on the low-carbon development effect of the secondary industry in the future.

4.2.2 Industrial sectors perspective

In this paper, based on the classification of industrial sectors in China Statistical Yearbook and Sichuan Provincial Statistical Yearbook, Sichuan's industrial sectors are divided into six types, as shown in Table 2. Here, other industries include information transmission, software and information technology service industry, financial industry, real estate industry, leasing and business service industry, scientific research and technology service industry, etc. Different industrial sectors produce different products, resulting in different energy demand, labor productivity, technology level and output. The detailed analyses are shown in Table 2.

(1) According to the ΔC_Q in Table 2, it can be seen that the contribution value of the economic output effect to carbon emissions was positive contribution value for six types of industrial sectors during the three stages. Meanwhile, except for individual sectors, the contribution value of economic output effect in the majority of industrial sectors decreased gradually in the whole three stages, mainly including agriculture, forestry, animal husbandry, fishery, industry, construction, transportation, storage and postal industry, which indicates that these four industrial sectors are also keeping CO_2 emissions under control during the process of economic growth. In the whole three stages, the industrial sector with the largest reduction in carbon emissions on account of economic output effect was industry. The main reason for this phenomenon is that the industrial low-carbon development, the construction of industrial Internet, and the industrial digital transformation are promoted effectively in Sichuan Province, so that the green and low-energy industrial production keeps increasing. Therefore, the impact of the industrial sector on carbon emissions shows a downward trend.

TABLE 2 Decomposition of carbon emission influencing factors in 6 types of industrial sectors in Sichuan.

Industrial sector	2005–2010				2010–2015				2015–2019			
	ΔC_Q	ΔC_I	ΔC_S	ΔC_M	ΔC_Q	ΔC_I	ΔC_S	ΔC_M	ΔC_Q	ΔC_I	ΔC_S	ΔC_M
Agriculture, forestry, animal husbandry and fishery	3.280	−1.287	−2.042	1.511	2.855	−0.694	−1.643	0.529	2.056	−0.735	−0.343	−2.379
Industry	162.804	33.559	−118.429	33.665	145.709	−36.872	−89.703	0.106	106.414	−55.183	−76.269	−6.517
Construction	1.864	0.052	−0.404	−0.722	1.243	0.212	−0.717	−1.422	1.249	0.180	−0.263	1.333
Transportation, storage and postal	13.065	−7.945	3.895	−0.154	11.062	1.276	−7.921	−5.006	10.276	0.563	−5.348	5.292
Wholesale, retail trade and accommodation, catering	3.718	−0.116	−1.534	0.911	4.070	0.518	−1.548	−0.334	3.591	1.035	−3.000	−1.939
Others	2.270	0.233	−1.286	1.039	3.015	0.448	−0.978	0.702	2.939	1.367	−2.071	−2.522

TABLE 3 The factor decomposition of carbon emissions of three industries.

Years	Effect	Primary industry		Secondary industry		Tertiary industry	
		Values (million tons)	Rate (%)	Values (million tons)	Rate (%)	Values (million tons)	Rate (%)
2005–2010	Economic output	3.280	224.36	164.677	146.52	19.066	135.28
	Industrial structure	−1.287	−88.03	29.394	26.15	−0.724	−5.14
	Energy intensity	−2.042	−139.66	−114.110	−101.53	−12.960	−91.96
	Carbon consumption intensity	1.511	103.32	32.427	28.85	8.711	61.81
2010–2015	Economic output	2.855	272.78	146.968	792.05	18.244	343.99
	Industrial structure	−0.694	−66.30	−26.158	−140.97	5.000	94.28
	Energy intensity	−1.643	−157.03	−99.677	−537.19	−17.814	−335.89
	Carbon consumption intensity	0.529	50.55	−2.578	−13.89	−0.126	−2.37
2015–2019	Economic output	2.056	−146.78	107.759	−370.86	16.883	165.83
	Industrial structure	−0.735	52.46	−40.519	139.45	6.668	65.49
	Energy intensity	−0.343	24.51	−87.657	301.67	−10.241	−100.59
	Carbon consumption intensity	−2.379	169.82	−8.640	29.74	−3.129	−30.73
2005–2019	Economic output	5.326	1,621.16	343.340	336.98	51.719	174.86
	Industrial structure	−2.107	−641.49	−19.239	−18.88	8.036	27.17
	Energy intensity	−2.165	−659.18	−245.793	−241.24	−38.958	−131.71
	Carbon consumption intensity	−0.724	−220.49	23.580	23.14	8.781	29.69

(2) According to the ΔC_I in Table 2, it can be seen that the contribution value of the industrial sector to the increase of carbon emissions changed from positive to negative, and the contribution value of the agriculture, forestry, animal husbandry and fishery sectors to the increase of carbon emissions was always negative, which indicated that the industrial structure of Sichuan Province began to optimize gradually, and to some extent inhibited the rapid growth of carbon emissions. Meanwhile, with the acceleration of urbanization and the improvement of the living standard, the contribution value of transportation, storage and postal services, wholesale, retail and accommodation, catering and other industries to carbon emissions shows an increasing trend, which indicates that the scale of the tertiary industry is expanding in Sichuan province, and the rapid development of the tertiary industry will inevitably promote the increase of carbon emissions.

(3) According to the ΔC_S in Table 2, it can be seen that the energy intensity effect was negative for all industrial sectors in the whole three stages, except for transportation, storage and postal industry, which had a positive energy intensity effect from 2005 to 2010. Among them, the energy intensity effect of agriculture, forestry, animal husbandry, fishery and industry has a gradually decreasing influence on controlling the growth of carbon emissions. As a whole, the energy intensity effects of all industrial sectors restrain the increase of carbon emissions effectively. Therefore, the decrease of energy intensity is a key factor to restrain the increase of carbon emissions, which poses a challenge to the development of green and low-carbon economy in Sichuan Province.

(4) According to the ΔC_M in Table 2, it can be seen that the carbon consumption intensity effects of some industrial sectors are positive value and some are negative value among the six industrial sectors in the three stages. From the perspective of contribution value, agriculture, forestry, animal husbandry, fishery, industry and other industry sectors play a significant role in restraining the increase of carbon emissions, among which the industrial sector has the strongest inhibitory effect. With the change of carbon consumption intensity effect during the whole three stages, the number of sectors with negative contribution values gradually increases, indicating that the share of non-fossil energy in each industrial sector has increased. At the same time, the change of carbon consumption intensity effect will also promote the industrial energy conservation and emission reduction to zero carbon (Wang et al., 2022), resulting in significant carbon emission reduction effect.

4.2.3 Three industries perspective

In order to grasp the direction of green and low-carbon industrial development in Sichuan province, the impact of each

TABLE 4 Scenario indicators for each driver factor in Sichuan.

Parameter setting	Scenario mode	2020–2025
Rate of change of gross industrial product	Baseline	6%
	Green and low-carbon transformation	6%
Rate of change of industrial structure of primary industry	Baseline	−3.72%
	Green and low-carbon transformation	−3.72%
Rate of change of industrial structure of secondary industry	Baseline	−3.91%
	Green and low-carbon transformation	−4.11%
Rate of change of industrial structure of tertiary industry	Baseline	4.28%
	Green and low-carbon transformation	4.48%
Rate of change of energy intensity	Baseline	−2.86%
	Green and low-carbon transformation	−3.20%
Non-fossil energy rate of change	Baseline	12.76%
	Green and low-carbon transformation	14.29%

driving factor above on carbon emissions is analyzed from the perspective of three industries. The detailed decomposition results were shown in Table 3.

(1) For the economic output effect, the contribution values of the three industries were positive during the three stages. From 2005 to 2010, carbon emissions from the secondary industry increased by 328.03 million tons due to the economic output effect, accounting for 88.05% of the increase in industrial carbon emissions caused by economic output effect. Therefore, in terms of economic output effect, the secondary industry has the strongest promoting effect on carbon emissions.
(2) For the industrial structure effect, the contribution values of the primary and tertiary industries were negative, while the secondary industries were positive contribution values in the first stage (2005–2010). The reason is that the proportion of the primary and tertiary industries in the three industries is not high, while the secondary industry dominates. From 2010 to 2015 and 2015 to 2019, the contribution values of the primary and tertiary industries were negative, and the tertiary industry was positive. This is because the tertiary industry developed rapidly as the income of the residents had improved and the demand of services had increased. At the same time, with the continuous adjustment of the three industrial structures, the proportion of secondary and primary industries decreased and the proportion of tertiary industries significantly increased. Therefore, the industrial structure effect of the secondary industry showed a negative influence on the growth of carbon emissions.
(3) For the energy intensity effect, the contribution values of the three industries were negative during the three stages, which showed that the energy intensity effect led to the reduction of industrial carbon emissions, and the industry with the largest reduction was the secondary industry. In a comprehensive view, the energy intensity effect on carbon emission reduction was the secondary industry, the tertiary industry, and the primary industry in descending order. The main reason for this is that the secondary industry consumed more energy. When controlling the energy intensity of the secondary industry can effectively promote the reduction of carbon emissions and help the development of the low-carbon economy.
(4) For the carbon consumption intensity effect, the contribution values of the three industries were similar to the industrial structure. From 2005 to 2010, the contribution values of carbon consumption intensity effect on the three industries were all positive values, indicating that the three industries used fossil energy extensively and energy inefficiently. From 2010 to 2015 and 2015 to 2019, the contribution values of the carbon consumption intensity effect on the secondary industry were negative, while the primary industry and tertiary industry had positive and negative contribution values. The reason for these is that the secondary industry focused on the adjustment of energy structure and gradually developed the use of clean energy during the period, but the utility for the reduction of carbon emissions was low, and that the industry in Sichuan province was still very dependent on coal and other fossil energy, and the technology of developing clean energy was still relatively backward.

5 The development impact of industrial green and low-carbon transformation

5.1 Scenario setting of industrial green and low-carbon transformation

According to the emission reduction situation of Sichuan Province during the “13th Five-Year” Plan period, combined with the relevant policies and measures of the 14th Five-Year Plan period, related parameter values and the change rate of the driving effect factors of carbon emission are set under the two scenarios respectively, namely, baseline and green and low-carbon transformation. Accordingly, the impact of industrial green and low-carbon transformation on the realization of the “double carbon” goal is analyzed in Sichuan Province. The parameters of each scenario were shown in Table 4.

(1) Economic output effect. The economic output effect is mainly affected by the gross industrial product. Meanwhile, according to the indicators of "the 14th Five-Year Plan for Sichuan's National Economic and Social Development and the Outline of the Long-term Goals for 2035," combined with the fact that the COVID-19 epidemic will slow down the overall economic growth rate, the average annual growth rate of industrial GDP at 6% was set under the two scenarios set above in this paper.
(2) Industrial structure effect. The industrial structure effect refers to the proportion of the output values of the three industries in the total output values. Therefore, the effect of the industrial structure effect was converted into the effect of the industrial structure of each industry on carbon emissions in this paper. In the scenario of baseline, it is assumed that the changes of three industrial structure maintain the annual average change rate in the past 5 years, that is, in the primary, secondary, and tertiary industries it is −3.72%, −3.91% and 4.28% respectively. Under the green and low-carbon transformation scenario, it is set in this paper that the average annual change rate of the industrial structure of the primary industry remains unchanged, the secondary industry decreases by 0.2%, and the tertiary industry increases by 0.2%, namely, the average annual growth rate of the three industries is −3.72%, −4.11%, and 4.48% respectively, based on the literatures (Fu et al., 2019; Yue, 2021) and the following reasons. On the one hand, the adjustment of industrial structure will affect the green and low-carbon transformation of industry. On the other hand, from the LDMI decomposition results above, it can be concluded that the proportion of the industrial structure, which declines in the secondary industry and increases in the primary and tertiary industries, will help to restrain the increase of carbon emissions. In addition, compared with the secondary and tertiary industries, the industrial structure effect of the primary industry has less impact on carbon emissions. Therefore, the change rate of the industrial structure of the primary industry is set to remain unchanged.
(3) Energy intensity effect. According to the "14th Five-Year Plan for Energy Development in Sichuan Province," the energy intensity was set to decrease by 13.5% in the baseline scenario compared with 2019, with an average annual change rate of −2.86%. Energy intensity is an effective factor to restrain the increase of carbon emissions. Therefore, the energy intensity was set to decrease by 15% compared with 2019, with an average annual change rate of −3.20% in the green and low-carbon transformation scenario.
(4) Carbon consumption intensity effect. The carbon consumption intensity is influenced by the energy consumption structure. At the same time, the increase of the use of clean energy such as non-fossil energy will effectively reduce industrial carbon emissions, especially in the secondary industry. Carbon consumption intensity scenarios are based on the average annual change rate of the share of non-fossil energy (Wang et al., 2022). In 2022, According to the "14th Five-Year Plan" for Energy Conservation and Emission Reduction in Sichuan Province," the share of non-fossil energy consumption will reach about 41.5% by 2025. Therefore, under the baseline scenario, the proportion of non-fossil energy is set at 41.5% in 2025, with an average annual growth rate of 12.76% in this paper. After the low-carbon transformation of the industry, energy efficiency and the proportion of non-fossil energy will be further improved. Meanwhile, combined with related literatures about the setting of carbon emission intensity scenarios (Wang et al., 2022), the proportion of non-fossil energy is set at 41.5% in 2025 under the scenario of green and low-carbon transformation, with an average annual growth rate of 14.29%.

5.2 Impact analysis of industrial green and low-carbon transformation

Under the baseline and green and low-carbon transformation scenarios, we forecasted and analyzed the change of industrial carbon emissions in Sichuan from 2020 to 2025, and determined the impact of industrial green and low-carbon transformation on the trend of carbon emissions change, which based on the extreme learning machine model optimized by particle swarm optimization (PSO-ELM) prediction model in this paper.

The data from 2005 to 2015 were used as the training set and the data from 2016 to 2019 were used as the test set to build the PSO-ELM prediction model. The prediction values and simulation errors of the model are shown in Table 5. As can be seen from Table 5, compared with the simulation results of data, the simulation of PSO-ELM has higher prediction accuracy, and its mean relative error is 0.968%. The MSE, RMSE and MAE reflect the degree of deviation between the predictive values and the true values, and the smaller the value, the higher the prediction accuracy (Yue, 2021). In this paper, the MSE, RMSE and MAE are 9.599, 3.098, and 2.769, respectively, and the three values are small. Therefore, PSO-ELM combined prediction model has better prediction accuracy. When the indicators of the two scenarios were input into the PSO-ELM model respectively, the corresponding scenario predictive values of Sichuan Province from 2020 to 2025 were obtained. The trend of industrial carbon emission in Sichuan Province is obtained accordingly, as shown in Figure 4.

As can be seen from Figure 4, the Scenario predictive values of industrial carbon emissions in Sichuan province decreased under the baseline and green and low-carbon transformation scenarios. Under the baseline scenario, industrial carbon emissions will be reduced by 5.885 million tons compared with 2019, with an average annual decline rate of 3.2%. Under the green and low-carbon transformation scenario, industrial carbon emissions in 2025 will be reduced by 8.830 million tons compared with 2019, with an average annual decline rate of 5.07%. Therefore, the total industrial carbon emissions can be reduced effectively under the two scenarios. But the emission reduction efficiency is stronger under the scenario of industrial green and low-carbon transformation. The results showed that the keys to promoting the reduction of industrial carbon emissions are optimizing the industrial structure, especially the secondary industry and tertiary industry, reducing

TABLE 5 The prediction values and simulation errors of the PSO-ELM prediction model.

Years	Actual values (million tons)	Prediction values (million tons)	Mean squared error (MSE)	Root mean squared error (RMSE)	Mean absolute error (MAE)
2016	295.637	295.149	9.599	3.098	2.769
2017	295.360	291.163			
2018	271.587	275.012			
2019	289.217	286.249			
Mean relative error (%)			0.968		

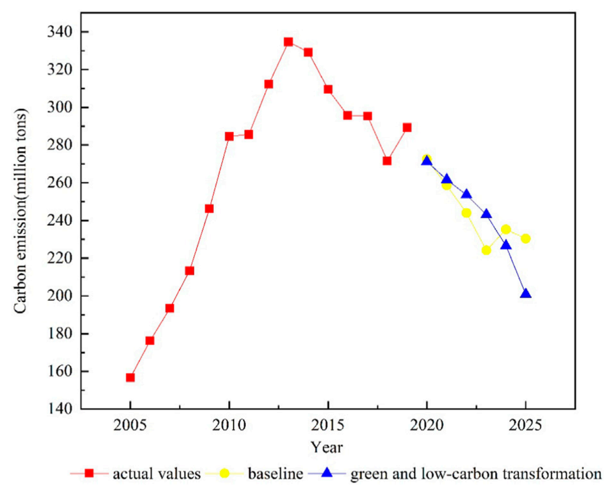

FIGURE 4
Industrial carbon emissions trends in Sichuan, 2005–2025.

the proportion of energy per unit of GDP, and strengthening the proportion of non-fossil energy under the economy keep a steady rise. Therefore, the green and low-carbon transformation of the industry can effectively restrain the increase of carbon emissions and help Sichuan achieve the "double carbon" goal as soon as possible.

6 Discussions and conclusion

6.1 Discussions

In terms of the results above, for Sichuan Province the control effect of industrial carbon emissions is obvious in recent years. In this paper, the change trend of industrial carbon emissions predicted under two scenarios is similar to the results of Liao's research (Liao et al., 2022), which predicted that under baseline, low-carbon and the economic slowdown scenarios, carbon emissions in Sichuan province will show a downward trend from 2020 to 2025 gradually. Compared with Liao's research which only selected three factors affecting carbon emissions in Sichuan Province, more scenario indicators based on the results of factor decomposition are set up to improve the practicability of the results in this paper. At the same time, the adjustment of industrial structure is one of the important means to promote the reduction of carbon emissions, so we incorporate changes in industrial structure and carbon consumption intensity into the forecast of industrial carbon emissions specially. The scenario prediction results show that an effective reduction of carbon emissions can be achieved by a 0.2% decrease in the rate of structural change of secondary and tertiary industries in Sichuan Province in this paper, While Qiaochu et al. (2022) also believes that the improvement of low-carbon efficiency in Sichuan Province is largely due to the optimization of industrial structure. In addition, the energy intensity effect and carbon consumption intensity effect can inhibit the increase of industrial carbon emissions, and the main factors influencing these two effects are the proportion of non-fossil energy and the efficiency of fossil energy use. Therefore, the carbon consumption intensity and energy intensity are added to make the existing studies more comprehensive.

The situation that the carbon emissions show a decreasing trend, but the overall decrease is small in Sichuan, is consistent with that of the whole country obtained in Liu and Ding (2020) 's research. From the perspective of economic policy and industrial policy, the results of the study, as shown in Figure 1, confirm that the secondary industry is the main source of carbon emissions in Sichuan province, and the economic output effect consistently promotes the rise of carbon emissions in the overall, industrial sector and three industry perspectives, which indicate that the economic growth mode at the expense of the environment and the irrational industrial structure lead to the increase of industrial carbon emissions in Sichuan Province. The conclusion accords with the current situation of industrial development in China and is consistent with the existing research (Hu and Gui, 2017; Fu et al., 2019; Ma et al., 2019; Dong et al., 2020). Therefore, all industries should strengthen the efficient use of fossil energy, reduce unnecessary energy consumption, control the growth rate of energy consumption in the secondary industry, take the advantage of new energy technologies, and reduce the total industrial carbon emissions.

In terms of method, the LMDI decomposition method has been widely used in the research of carbon emissions. At present, most studies of industrial carbon emissions mainly focus on the individual industries, not the whole industry (Ma et al., 2019; Sun and Yang, 2020). And there is a lack of further analysis of how changes in these factors will affect carbon emissions, after obtaining the influencing factors of industrial carbon emissions. Although some scholars have studied the factors influencing industrial carbon emissions from a holistic perspective, such as Hu and Gui (2017), who decomposed the factors of industrial carbon emissions from three perspectives. However, they used a small amount of data and did not consider the role of non-fossil energy use on industrial carbon emissions. Therefore, more factors is added to the Kaya identity and these factors combined with the LMDI method are analyzed by the PSO-ELM prediction model to quantify the effect of factor changes on industrial carbon emissions in this paper. At the same time, the application of LMDI method combined with scenario prediction expands the existing methods further.

In terms of the reliability, the carbon emission data of provincial industries calculated is used directly in this paper, according to the IPCC method in the CEADs database. On the one hand, the IPCC method considers almost all GHG emission sources comprehensively, and provides specific emission principles and detailed calculation methods. At the same time, this method is also the most authoritative and reliable method recognized internationally (Zhang et al., 2022). In this paper, data from CEADs database is directly used, while other studies (Hu and Gui, 2017; Hu X. W. et al., 2021; Wang et al., 2022) made some estimates using online data or literature data. This is because that although the data of CEADs database is accurate, the update speed is slow. Therefore, using other data would reduce the accuracy of the results. On the other hand, the scenario forecast indicators used in this paper are all derived from the policy documents related to the green and low-carbon transformation of industries. Therefore, the results analyzed and predicted can be used as a reference for government departments.

6.2 Research conclusions

According to the research results, the following conclusions are obtained.

(1) From the viewpoint of the economic output effect, the economic output effect always contributes to the increase of carbon emissions under the overall, industrial sector and three industries' perspectives. From the overall perspective and the three industrial perspectives, the contribution of economic output effect to industrial carbon emissions is decreasing, indicating that the effectiveness of green economic development in the three major industries is beginning to be significant. From the perspective of industrial sectors, the economic output effect of the industrial sector has the strongest contribution to carbon emissions, followed by transportation, storage, and postal industry. The rest of the industrial sectors have a smaller impact. This indicates that industry is still the pillar industry of economic development.
(2) From the industrial structure effect, the change in industrial structure begins to inhibit the growth of carbon emissions. The inhibiting effect of the secondary industry is the most obvious. From the perspective of industrial sectors, the inhibiting effect of industrial structure in the industrial sector is increasing, while the effect of industrial structure in the tertiary industries, such as transportation, storage, postal service, and wholesale, is gradually promoting the increase of carbon emissions. This indicates that the industrial structure is changing to "3-2-1," which is in line with the trend of industrial structure change in China at this stage.
(3) From the energy intensity effect, the energy intensity effect consistently restrains the growth of carbon emissions under the three perspectives, and the inhibitory of energy intensity effect shows that the energy consumption of various industries is decreasing, the quality of economic development is increasing, and the dependence of economic development on energy is also weakening.
(4) In terms of the carbon consumption intensity effect, the carbon consumption intensity effect shifts from positive to negative values in the overall perspective and begins to suppress the increase of carbon emissions in industries. Except for the carbon intensity effect of construction, transportation, storage, and postal industries, which began to promote the increase of carbon emissions, the carbon intensity effect of agriculture, industry, wholesale and retail industries all gradually suppressed the increase of carbon emissions. The rapid development of urbanization in recent years, which has led to the rapid development of construction, transportation, logistics, and other industries, resulting in an increase in demand for energy use and thus the increase in carbon emissions is the main reason for this phenomenon.
(5) Through the quantitative analysis of the impact of the industrial green and low-carbon transformation in Sichuan province, combined with the indicator settings of the scenario analysis, it is concluded that without considering the economic cost of transformation, accelerating the rate of change of industrial structure of secondary and tertiary industries, increasing the proportion of decrease in energy intensity, strengthening the proportion of non-fossil energy use, and optimizing the industrial structure and energy intensity can effectively improve the efficiency of carbon emission reduction and help Sichuan province achieve the goal of "double carbon" as soon as possible.

6.3 Enlightenment and suggestions

Based on the above research results, this paper provides the following suggestions for the green and low-carbon industrial transformation development of Sichuan Province and other regions at home and abroad.

Firstly, promoting the development of clean energy and take the path of green and low-carbon development. Sichuan Province and other regions should give full play to its huge potential in the development and use of clean energy, and increase the proportion of clean energy consumption.

Secondly, speeding up the transformation of energy-intensive industries and take the path of energy conservation and carbon reduction. Sichuan Province should focus on the transformation of energy-consuming industries. Meanwhile, other regions should actively promote the transformation and upgrading of energy-consuming industries and energy technology innovation.

Thirdly, strengthening policy support and control, and take the path of ecological development first. Sichuan Province and other regions should introduce precise policy support for resources, environment, technology research and development, finance and other aspects at the provincial level to encourage social capital to enter green and low-carbon industries.

In the paper, firstly, the extended Kaya identity was constructed, and then, combined with LMDI method, the four factors affecting industrial carbon emissions and their contribution values were decomposed. Secondly, from the perspectives of the overall, industrial sector and tertiary industry, the PSO-ELM method is used to predict industrial carbon emissions and the influence trend of adjustment of the above influencing factors on industrial carbon emissions in Sichuan Province by setting scenario prediction indicators. It provides a reference to realize the development path of industrial green and low-carbon transformation. However, there are still some shortcomings in this paper. First of all, the influencing factors of industrial green and low-carbon transformation are complex and diverse. In order to improve the research, more influencing factors should be added in the future, such as industrial transformation cost, industrial innovation level and other factors. Secondly, industrial sectors are divided into six categories in this paper, and it is impossible to analyze the influence of a specific industry in more detail, such as manufacturing, financial industry, etc., so industrial sectors should be divided in more detail in the future.

Data availability statement

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

Author contributions

BL: Conceptualization, Data curation, Funding acquisition, Methodology, Project administration, Supervision, Validation, Writing–review and editing. HC: Conceptualization, Data curation, Formal Analysis, Methodology, Writing–original draft, Writing–review and editing. YL: Conceptualization, Data curation, Funding acquisition, Methodology, Project administration, Supervision, Validation, Visualization, Writing–review and editing. YZ: Conceptualization, Data curation, Formal Analysis, Methodology, Software, Writing–review and editing.

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Conflict of interest

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

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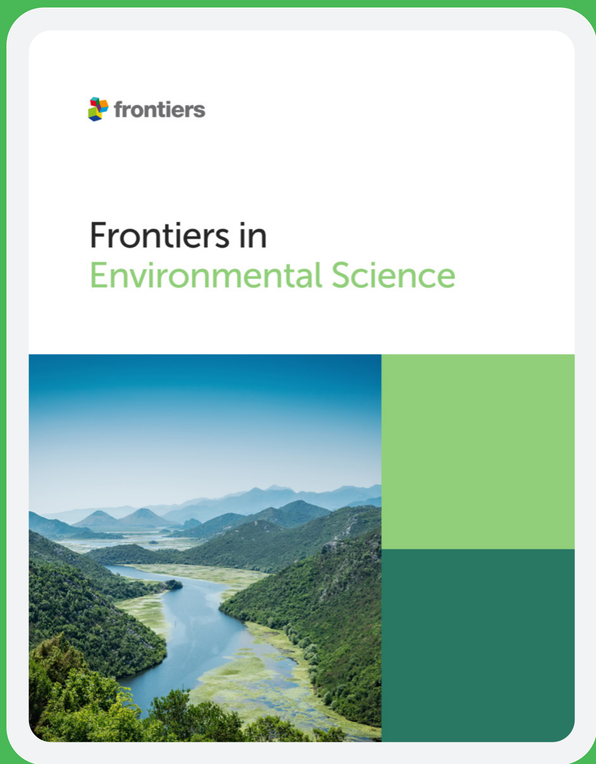

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