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Research article

Exploring the effect of green finance on green development of China's energy-intensive industry—A spatial econometric analysis

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ABSTRACT

An indispensable part of the green revolution is the green development of the Energy-intensive Industry (EII), which is crucial for China to achieve its "double carbon" target. EII is one of the key sectors bound by the green finance policy, whose development level is susceptible to regional conditions. Therefore, this research constructs a spatial Durbin model using provincial panel data (2001-2019) to empirically examine the impact of green finance on EII's green total factor productivity (GTFP). Evidence shows that green finance boosts EII's GTFP significantly and there is a spatial spillover effect. Specifically, the results demonstrate that the spatial spillover effect's regional heterogeneity is positive in the eastern, central and northeastern regions, and negative in the weatern region. Furthermore, there is a spatial inhibitory effect on two subindustries of EII, i.e., Manufacture of Non-metallic Mineral Products industry and Smelting and Pressing of Non-ferrous Metals industry, proving the spatial spillover effect's sectoral heterogeneity for green finance. This research provides experimental evidence and policy suggestions for enhancing the promotion impact of green finance on EII's GTFP.

1. Introduction

With accelerated industrialization and continuing economic growth, the massive consumption of energy and natural resources, as well as the resulting environmental damage, has become increasingly significant (Homaeigohar and Elbahri, 2017). China is the world's top carbon producer at current levels, contributing to 29.1% of the overall global emissions of CO_2 (Lee and Lee, 2022). With a solemn pledge to "aim for 2023 as the carbon peak and 2060 as the carbon neutral year" in 2020, China demonstrated its resolve to make significant progress in the country's green transformation. How to reduce energy consumption, while maintaining sustainable economic development and increasing productivity growth, has become a serious challenge for China. Based on national conditions, the country needs to concentrate on the industrial sector's green development. Energy-intensive industry (EII), also known as an energy-consuming industry, refers to the industry with substantial energy usage and emission per unit in the production process (including six subsectors, i.e., the Processing of petroleum, coal and other Fuels (PPCO), Manufacture of raw chemical materials and chemical products (MRCMCP), Manufacture of non-metallic mineral products (MNMP), Smelting and pressing of ferrous metals (SPFM), Smelting and pressing of non-ferrous metals (SPNM), and Production and supply of electric power and heat power (PSEH) NBSC, 2011). EII was first introduced by the National Development and Reform Commission (NDRC) in the National Economic and Social Development Report in 2010 (NBSC, 2011). 50.5% of the total energy consumed by society came from EII and 75.7% of overall industrial energy use in 2019 (Lin and Zhang, 2022). Therefore, encouraging EII's green development is essential to achieving the "double carbon" objective.

How to make economic growth less dependent on environmental pollution and resource depletion is now an important task shared by countries around the world. There has been in-depth discussion of this issue globally, with one of the core issues being the integration of "green" concepts into policy agendas. Countries such as the United States, the European Union and Japan have formulated green economy development strategies for greening economies aimed at reducing environmental impacts while promoting sustainable economic development through policy interventions (Altenburg and Rodrik, 2017; Rodrik, 2015). In 2003, 'The Equator Principles' incorporated corporate environmental responsibility into the assessment criteria, and with the introduction of this principle, countries began to combine this concept with banking development, which has gradually made finance an important means of promoting energy conservation and emission reduction and high-quality economic development (WB, 2012). In China, green finance was described as an economic activity in *The Guidance on Building a Green Financial System*, published in 2016 by the People's

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List of abbreviations

EII	Energy-intensive Industry
GTFP	Green total factor productivity
SBM	Slacks-Based Measure
DMU	Decision-Making Unit
GECH	Global changes in efficiency
GTCH	Global changes in technology
GML	Global Malmquist-Luenberger
SEM	Spatial Error Model
SAR	Spatial Autoregressive Model
SDM	Spatial Durbin Model
GFI	Green finance level
DEV	Industrial development level
EI	Energy intensity
ER	Environmental regulation intensity
R&D	Technology investment level
TI	Technology innovation level
PPCO	Processing of petroleum, coal and other fuels
MRCMCP	Manufacture of raw chemical materials and chemical products
MNMP	Manufacture of non-metallic mineral products
SPFM	Smelting and pressing of ferrous metals
SPNM	Smelting and pressing of non-ferrous metals
PSEH	Production and supply of electric power and heat power

Bank of China and seven other departments and commissions (PBOC, 2016), that supports resource efficiency, climate change mitigation, and environmental enhancement. Financial services are provided for project investment, project operation, and risk management related to environmental protection, energy conservation, and other environmental initiatives. As a vital element in the expansion of green economy, green finance has progressively grown to be a potent tool for low-carbon development in China through market-based financial instruments, such as equity products, bond products, private equity capital funds, venture capital funds, etc., to curb polluting investments and promote technological progress involving energy efficiency and environmental protection (Wang and Wang, 2021).

EII is one of the key sectors bound by the green finance policy. On one hand, aim to obtain loans from financial institutions, EII's enterprises must upgrade and optimize their energy structures and equipment technologies, thus improving energy efficiency and ultimately enhancing green development (Wang and Wang, 2021; Zhang et al., 2021a). On the other hand, the growth of green finance raises the possibility of facing administrative punishment and reputation risk of financial institutions that provide financing support to EII's enterprises by strengthening the supervision of investments, thus making it more challenging for EII's enterprises to access to financing and inhibiting their green total factor productivity (GTFP) improvement, which refers to the overall efficiency of production, considering both economic output and environmental sustainability (Yu et al., 2021). It is then worth exploring whether the advancement of green financing has considerably influenced the green development of EII (measured by GTFP in this research).

Due to the vastness of China's territory, different regions possess the varied abundance of natural resources, and their economic development level show significant differences. This variability has led to the heterogeneities on the implementation of green financial policies, the development level of EII, the spatial distribution of energy consumption, and the intensity of carbon emissions (Lin and Zhang, 2023). Moreover, factors like the size, diversity and habits of China's population may also have an impact on the implementation of green finance policies and the development of the industry (Rasoulinezhad and Taghizadeh-Hesary, 2022). These factors present both challenges and opportunities. For instance, the large size of the population implies huge market demand and potential, but it also increases the complexity and difficulty of policy implementation (Jiakui et al., 2023). Therefore, China's EII must pay close attention to and give full consideration to these differences in the process of promoting green development. Furthermore, since green finance is a market measure for green development, the process of its implementation is susceptible to regional economic conditions, degree of financial development and other related factors. It is shown that remarkable regional heterogeneity exists in the level of financial regulatory capacity and development level, and financial development gradually shows the characteristics of geographical agglomeration (Wang, 2018). To advance green finance policies and the environmentally friendly expansion of EII, it is therefore important theoretically and practically to explore how green finance affects the GTFP of EII in China, to explain the mechanism underlying it, and to investigate the impact's spatial spillover effects more thoroughly.

The main research questions are (1) to explore the spatio-temporal characteristics of GTFP of EII in China; (2) based on the spatial perspective, to explore the impact and spillover effect of green finance on GTFP in China's EII; (3) to analyze the variability of the impacts in different regions and for different industries of EII. The perspective of this study is EII and its subsectors in each province (cities and autonomous regions). It can not only study the regional differences in the impact of green finance on the GTFP of EII from the provincial level, but also from the perspective of subindustries. By constructing a spatial econometric model, this study explores the implementation of green finance policies and their interaction and impact on EII at regional level, aiming to provide a theoretical basis for regions to formulate green finance policies tailored to the green development of EII.

This paper will be divided into the following parts: Section 2 Literature review, Section 3 Data and methodology, Section 4 Results and discussion, and Section 5 Conclusion and policy implications. The research results will contribute to an improved comprehension of how China's EII is affected by the implementation of green finance policy, offering theoretical direction and policy implications for China to green EII and further reach the "double carbon" objective.

2. Literature review

Literature review includes Effect of green finance on industrial development, Impact of green finance on EII, and Spatial effects of industry development. Initially, literatures on the impacts of green finance on both the economy and the environment were reviewed. Then relevant studies on green finance and EII were sorted out. Ultimately, by reviewing the research on the spatial effects of green finance and industrial green development, the research gaps in the existing literature were identified, thus determining the research questions and providing a theoretical support and empirical evidence for the research.

2.1. Effect of green finance on industrial development

Cowan (1998) contended that green finance is the result of integrating traditional finance and the emerging green economy, which bridges the environment and the economy. Green finance aims to assist industrial enterprises in achieving greater economic and environmental benefits while consuming less energy and resources by judicious allocation of financial resources (Gu et al., 2021), which can significantly contribute to the reduction of emissions, energy conservation and green development of industries (Le et al., 2020). As a key tool for promoting sustainable development, it has been proven to be of indispensable importance in enhancing environmental quality, driving economic growth and accelerating the development of financial institutions (Scholtens and Dam, 2007). The discussion of green finance in these literatures mainly presents three perspectives. Firstly, green finance, as a financial service model, is committed to solving practical environmental problems, such as environmental protection, pollution management and resource conservation, as well as promoting other environmentally friendly initiatives (Badar et al., 2022). Secondly, another viewpoint considers green finance as a form of financial innovation, leveraging diverse economic products to manage and mitigate environmental risks (Hafner et al., 2020). Finally, the most recent view defines green finance as a financial framework that promotes environmentally friendly investments and aims to build an environmentally conscious society based on carbon finance (Amighini et al., 2022).

In China, the main focus is on the contribution of green finance to economic growth and environmental protection. Green finance has been proved in studies to protect economic growth potential. For the time being, green finance policy may result in the inability of green investment returns to fully compensate for revenue reductions caused by decreasing investments in energy-intensive projects (Shi et al., 2022). But over time, green finance will speed up technical advancement and increase productivity, thus achieving environmental improvements and stable economic growth (Zhang et al., 2022b). At the same time, regional and sector-specific specified development policies are impacted by green finance (Li et al., 2023).

Researchers were also interested in green finance in light of its environmental impact. Huang and Zhang (2021) drew the conclusion that there is some degree of inhibitory effect on environmental pollution associated with the establishment of pilot zones for green finance reform and innovations based on quasi-experiment research. Lee and Lee (2022) suggested that the level of regional GTFP is greatly raised by the evolution of green finance. Based on the micro-level research, green finance guides the flow of financial resources to cleaner production companies in a motivating way, thus achieving environmental governance goals, and helping to reduce Sulphur dioxide and wastewater emissions (Zhang et al., 2021b). Yu et al. (2021) claimed that the growth of green finance could alleviate financial constraints facing businesses engaged in environmental protection, new energy, new materials, and other related fields. It can also provide more environmental protection products and support the growth of environmentally friendly firms. In addition, scholars have researched the mechanisms of green finance's effects on the environment, which include capital investment, resource allocation, and technological innovation (Huang et al., 2021; Zhang et al., 2022a). Zhang et al. (2021a) stated that green credit policies improve company profitability, encourage corporate innovation and modernize the industrial structure to reduce environmental pollution.

2.2. Impact of green finance on EII

More research has been carried out into the extent of EII's green development (Feng et al., 2019; Lin and Zhang, 2022), while relatively few studies examine how green finance affects the green development of EII. Limited studies evaluated the impact of green credit (a part of green finance policies) on this industry. Some have claimed that green credit may ultimately promote the green development of EII by providing external credit assistance for green technological innovation activities and green transformation of EII enterprises (Aizawa and Yang, 2010; Schmidt, 2014). However, Su and Lian (2018) and Sun and Zeng (2023) both concluded that green credit reduced pollution emissions by limiting the supply of funds to heavily polluting enterprises, thus pushing them to make technological improvements and upgrades or scale down their production. Some scholars hold different views on its effect, arguing that green finance increased the lending thresholds for operations with excessive pollution and emissions, causing serious credit financing constraints and a significant increase in financing costs for EII, leading to a significant reduction in total financing and investment in the industry (Xu and Li, 2020). Businesses that lack funding will spend less in projects with high risk and unclear returns, particularly those involving green innovation (Cecere et al., 2020). And some studies concluded that the adoption of green credit policies not only significantly reduced the amount of money invested in EII, but also significantly curbed companies' interest-bearing debt financing and long-term liabilities (Wang et al., 2020). Accordingly, it is reasonable to assume that green credit policies will influence the green development of EII.

2.3. Spatial effects of industry development

Anselin (1988) noted that almost all spatial data are characterized by spatial dependence or spatial autocorrelation. Ordinary econometric methods are incapable of dealing with data difficulties such as spatial dependence. Therefore, spatial econometric methods were developed (Krugman, 1998; Paelinck and Klaassen, 1979). There exist significant geographical variations in the expansion of green finance, along with improvements in financial regulatory capacity (Yin and Xu, 2022). Based on enterprise data, Zhang et al. (2018) calculated the degree of green financial development and concluded that uneven development exists among regions. From a spatial perspective, Zhu et al. (2021a) investigated the influence on environmental pollution of synergistic effects involving green finance and other elements including technical advancement, industrial structure as well as environmental legislation. Guo et al. (2023) explored the mechanism by which green finance affects energy efficiency from the standpoint of spatial spillovers.

Spatial effects analysis has gradually become an important perspective in the efficiency estimation of different industries. In China's logistics industry, Bai et al. (2021) explored the spatial effects and motivating elements of eco-efficiency and concluded that it has a positive spillover effect; Zhong (2020) measured agricultural GTFP and explored the influence of agricultural informatization on agricultural GTFP; Du et al. (2022) measured the construction industry's carbon emission efficiency, on the basis of which they constructed a spatial panel econometric model to investigate its contributing variables. From a spatial standpoint, EII's carbon emission efficiency indicators were examined (Zhu et al., 2021b).

To investigate the influence of green finance on GTFP at the regional level, some researchers opted to use the dynamic Spatial Durbin Model (SDM). Based on provincial data, green technology innovation efficiency was found to be enhanced by green credit and green financial products, with the degree of green financial development being the primary factor causing the difference in regional innovation efficiency (Li et al., 2022; Yin et al., 2021) concluded that green finance significantly affects GTFP of China and there exists a spatial spillover effect.

Studies on how green finance affects industrial growth spatially are scarce. Some researchers concluded that green finance has been instrumental in growing China's tourism industry (Ip et al., 2023; Zhang and Xing, 2022). In addition, green finance has been shown to be positively associated with low-carbon development in the manufacturing industry with spatial spillover effects (Xu et al., 2023). Some researchers assessed how green finance policies like green credit affected green development of organizations in high-pollution industries (Ge and Zhu, 2022; Tian et al., 2022). There are few studies involving how green finance affects GTFP in EII and whether it has spatial effects.

In summary, the existing research results have provided more reference for this study, but some fields are yet to be further explored and deepened. Firstly, most of the existing literature focuses on the relationship between green finance and regional economic growth, and the impact of environmental regulations on EII, while less on the impact of green finance on the green development of EII and its spatial spillover effects. Secondly, in terms of research methodology, the existing literature on the impact of green finance on EII mostly uses qualitative research, and it is worthwhile to carry out research on the spatial spillover effects of green finance and green development

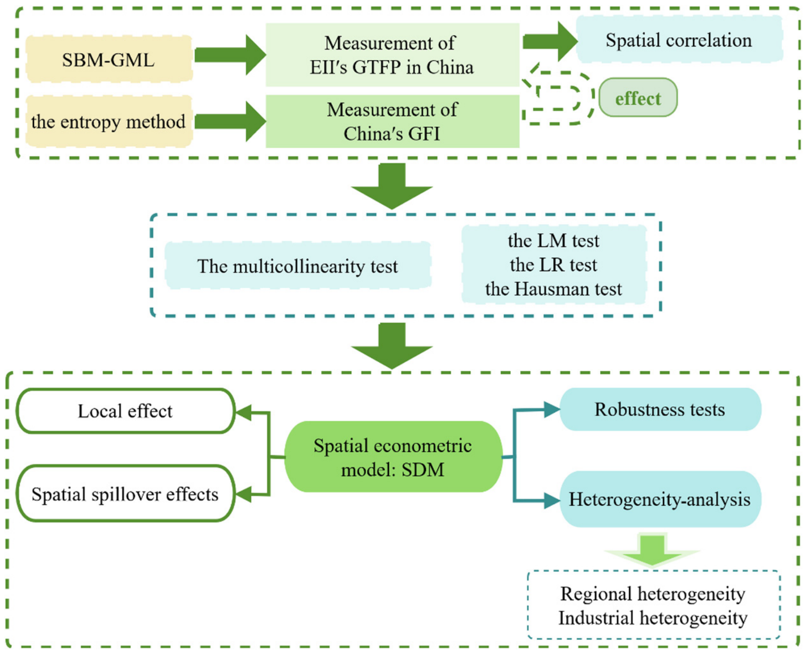

Fig. 1. The flow chart of the research.

of EII. Finally, most existing studies use green credit to measure the level of green finance, but from the connotation of green finance, green investment, green insurance and green securities are also an important part of green finance (Eyraud et al., 2013). Above all, based on the spatial perspective, this research empirically analyses the impact of green finance on the green development of China's EII, and combines the empirical results with policy recommendations for better implementation of green finance policies and promotion of the green development of EII.

3. Data and methodology

To explore the spatial spillover effect of green finance on GTFP of China's EII, this research firstly measures EII's GTFP and green finance level (GFI) based on SBM-GML and the entropy method, respectively. On this basis, a series of tests are carried out to select appropriate econometric models. Finally, a spatial panel econometric model is used to empirically investigate the spatial effect of green finance on GTFP in EII and to test the robustness of its effect. This research also explores regional heterogeneity and industrial heterogeneity of the impacts. Fig. 1 shows the flow chart of the research.

3.1. The measurement of GTFP in EII

Tone and Tsutsui (2011) proposed the global DEA models based on slacks variables with undesirable outputs, i.e., Slacks-Based Measure (SBM), which were adopted to measure the GTFP of EII and its six subsectors. It improved efficiency measurement precision and resolved the problem of lack of variables in the conventional radial model's inefficiency rate calculations. A Decision-Making Unit (DMU) of production is the EII of each province. This is the equation (refer to Tone and Tsutsui (2011) and Zhang and Choi (2013)):

$$\min \rho = \frac{1 - \frac{1}{n}\sum_{i=1}^{n}\frac{s_i^x}{x_{i0}}}{1 + \frac{1}{u+v}\left(\sum_{r=1}^{u}\frac{s_r^y}{y_{r0}} + \sum_{l=1}^{v}\frac{s_l^b}{b_{l0}}\right)}$$

$$\text{s.t.} x_{i0} = \sum_{j=1}^{k} x_{ij}\lambda_j + s_i^x, i = 1, 2, \ldots, n$$

$$y_{r0} = \sum_{j=1}^{k} y_{rj}\lambda_j - s_r^y, r = 1, 2, \ldots, u$$

$$b_{l0} = \sum_{j=1}^{k} b_{lj}\lambda_j - s_l^b, l = 1, 2, \ldots, v$$

$$\sum_{j=1}^{k}\lambda_j = 1, \lambda, s^x, s^y, s^b \geq 0 \tag{1}$$

ρ in Eq. (1) is the GTFP of a DMU. Assuming that there are $k(k = 1, \ldots, K)$ DMUs, n various kinds of inputs $(x \in R_n^+)$ are used, and u kinds of desired outputs $(y \in R_u^+)$ are generated along with v kinds of undesirable outputs $(b \in R_v^+)$. s_i^x, s_r^y, s_l^b respectively stand for the related slack variables for slack input, slack desirable output, and slack undesirable output. In order to investigate the underlying causes of the GTFP trends, this paper separated GTFP into two factors, namely global changes in efficiency (GECH) and global changes in technology (GTCH), using a combination of SBM and the Global Malmquist-Luenberger (GML) (refer to Lin and Zhang (2022) for details).

The number of employees, capital stocks, and energy consumption of EII were selected as input indicators, the gross output values of EII as desirable output, and the comprehensive environmental index including CO_2 emissions, wastewater, waste gas, and solid waste selected to be the undesirable output indicator (refer to Lin and Zhang (2022) for selection of indicators). The relevant statistics were gathered from the China Energy Statistical Yearbook (NBSC, 2020a), the China Statistical Yearbook on Environment (NBSC, 2020c) and the provincial statistical yearbook (2001–2019). The IPCC Guidelines for National Greenhouse Gas Inventories were employed to calculate CO_2 emissions (IPCC, 2006).

3.2. Spatial econometric methods

3.2.1. Spatial correlation

Having spatial correlation is a prerequisite for advancing spatial effect studies, therefore, for provincial EII, the global Moran's index is utilized to investigate the global spatial agglomeration of GTFP by following equations (Moran, 1953; Zhao et al., 2020):

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(x_i - \overline{x}\right)\left(x_j - \overline{x}\right)}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \tag{2}$$

I represents the global Moran's index. Moran's I is a common method to test spatial correlation: its value interval is [−1,1], and the signs indicate the positive and negative spatial correlation of the study objects in adjacent areas; the degree of geographical connection increases as the absolute value of the index approaches 1, and when the value is 0, it represents spatial random distribution. $S^2 = \frac{1}{n}\sum_{i=1}^{n}\left(x_i-\overline{x}\right)^2$; n is the number of provinces, and x_i and x_j represent the specific GTFP values of province i and j, respectively; the value of the spatial weight matrix element, denoted by w_{ij}, will be interpreted in Section 3.2.2.

3.2.2. Spatial weighting matrix

In spatial analysis, spatial effects will be reflected by geographic proximity, geographic distance, geographic distribution density, etc. Prior to investigating spatial impacts, a suitable spatial weight matrix must be chosen. The link connecting units in terms of geography or economy is shown using the spatial weight matrix (W), and three spatial weight matrices were selected to construct the model separately in this paper. Firstly, from the perspective of physical geography, W is created using the criterion of whether each province is contiguous to another to examine the spatial influence of natural geographic location, which is called the geographic adjacency spatial matrix (W^1) (Guan and Xu, 2016); the economic distance matrix (W^2) based on the average GDP was constructed (Wang et al., 2021); in addition, the average GDP and the distance of each province were selected to comprehensively construct the economic geographic weight matrix (W^3), considering geographical conditions and the state of economic growth (Mu et al., 2021). The concrete construction equations of the spatial matrix are as follows.

$$W=\begin{bmatrix} w_{11} & \cdots & w_{1j} \\ \vdots & \ddots & \vdots \\ w_{i1} & \cdots & w_{ij} \end{bmatrix} \tag{3}$$

$$w_{ij}^1=\begin{cases} 1, & unit\ i\ is\ adjacent\ with\ unit\ j \\ 0, & unit\ i\ is\ not\ adjacent\ with\ unit\ j\ or\ i=j \end{cases} \tag{4}$$

$$w_{ij}^2=\begin{cases} \dfrac{1}{\left|\overline{gdp_i}-\overline{gdp_j}\right|}, & i\neq j \\ 0, & i=j \end{cases} \tag{5}$$

$$w_{ij}^3=w_d * diag\left(\frac{\overline{gdp_1}}{\overline{gdp}},\frac{\overline{gdp_2}}{\overline{gdp}},\ldots\ldots,\frac{\overline{gdp_n}}{\overline{gdp}}\right) \tag{6}$$

$$w_d=\begin{cases} \dfrac{1}{d_{ij}}, & i\neq j \\ 0, & i=j \end{cases} \tag{7}$$

where $\overline{gdp_i}$ represents the average GDP of unit i during the sample period and $\overline{gdp}$ stands for the overall average GDP; w_d is a matrix generated according to distance; d_{ij} is derived using the longitude and latitude between units i and j.

3.2.3. Spatial econometric model

Cross-sectional and panel data's spatial correlation and heterogeneity are incorporated into the research model via spatial econometric models. There are generally three spatial econometric models: the Spatial Error Model (SEM), the Spatial Autoregressive Model (SAR), and the Spatial Durbin Model (SDM) (Elhorst, 2010). SDM incorporates both dependent and independent spatial lag terms, but statistical tests are necessary to determine whether the SDM deteriorates into a SAR or SEM model before selecting the model.

The SEM assumes that the model's error term exhibits spatial correlation, meaning that a portion of the error term in a specific area is influenced by the error terms in neighboring areas. The model can be expressed as:

$$\begin{cases} Y=X\beta+u_i+\delta_t+\varepsilon_{it} \\ \varepsilon_{it}=\lambda W\varepsilon_{it}+\upsilon_{it} \end{cases} \tag{8}$$

The explanatory variable matrix, which includes the core explanatory variable and control variables, is represented by the letters X; Y is the explained variable; W represents the spatial matrix; the spatial error coefficient of the explained variable λ, which measures the impact of errors in nearby areas on a specific local area; β shows the influence of the explanatory variable on the explained variable; u_i, δ_t and υ_{it} represent the space-fixed effect, time-fixed effect and the error term, respectively.

The SAR incorporates spatial dependent variable lags, which assume that through spatial interactions, the dependent variable's growth has an impact on the dependent variable's growth in other places. The model is expressed as follows:

$$Y=\rho WY+X\beta+u_i+\delta_t+\varepsilon_{it} \tag{9}$$

WY is the variable that can be explained by space-lagged, and is the spatial regression coefficient that reflects diffusion and spillover between nearby spatial units; ε_{it} indicates distributed random terms independently. u_i and δ_t are the same as in Eq. (9).

The SDM not only can analyze the impact of independent variables in adjacent domains on its own dependent variables, but it can also examine the impacts of independent variables in adjacent domains on its own dependent variables. The SDM is given by

$$Y=\rho WY+X\beta+\theta WX+u_i+\delta_t+\varepsilon_{it} \tag{10}$$

θ is the explanatory variable's spatial spillover coefficient; ε_{it} indicates distributed random terms independently. When $\theta=0$ and $\rho\neq 0$, the SDM would simplify degenerate into the SAR; when $\theta+\rho\beta=0$, the SDM model will be degenerated to the SEM. Therefore, the applicability of SDM is wider than the other two models.

3.3. Variables and data

To analyze how green finance would affect EII's GTFP, the main variables are chosen as follows.

(1) Explained variable: GTFP for EII measured by SBM-GML model is selected as an explanatory variable for the empirical analysis to reflect the green development of EII and its subsectors.

(2) Core explanatory variable: Green finance level (GFI). It is a comprehensive index of green finance that includes environmental support, green credit, green investment, green insurance and green securities (Huang et al., 2022; Wang et al., 2022). According to data availability, this paper calculated provincial GFI during the sample period by using the entropy method. Table 1 provides detailed indicators for the construction of GFI.

(3) Control variables: the factors affecting the GTFP of EII are considered from the three aspects, i.e., the economy, the environment, and science and technology. The control variables are selected as industrial development level (DEV), energy intensity (EI), environmental regulation intensity (ER), technology investment level (R&D), and technology innovation level (TI). The China Statistical Yearbook (NBSC, 2020b), each province's statistical yearbook, the China Industrial Statistical Yearbook (NBSC, 2021), and the China Energy Statistical Yearbook (NBSC, 2020a) were used for collecting the data for the years 2001 to 2019.

DEV is expressed as the ratio of EII's output value to the total industrial output value, which reflects the degree of EII's technology development level in the province; meanwhile, provinces with high DEV are also more likely to have inter-industry resource appropriation (Wang et al., 2021). EI reflects the industry's energy dependence in its development process, and is measured in terms of energy consumption

Table 1
Indicator system of GFI.

	Index	Index Description
Green finance level (GFI)	Green credit	Percentage of interest expense of Energy-intensive industry
	Green investment	Proportion of investment in environmental pollution control in GDP
	Green insurance	Revenue from environmental pollution liability insurance divided by total insurance revenue
	Green securities	The market capitalization of green companies divided by the total market capitalization
	Environmental support	Proportion of fiscal environmental protection expenditure to fiscal general budget expenditure

Table 2
Descriptive statistics of variables.

Variable	Sign	Unit	Mean	Std.	Min.	Max.
Explained variable	GTFP	/	0.3495	0.2163	0.1015	1.0000
Core explanatory variable	GFI	/	0.1406	0.0930	0.0418	0.7930
Control variables	DEV	/	0.3798	0.1279	0.1434	0.8092
	EI	/	1.5573	1.3565	0.1636	10.0379
	ER	/	0.0014	0.0012	0.0000	0.0096
	R&D	/	0.0476	0.0397	0.0009	0.1755
	TI	million items	2.9349	5.7961	0.0070	52.7390

per unit of output, which is measured as a percentage of energy use to total output value. A high EI indicates that the industry will produce more carbon emissions. ER could raise the cost of production for the industry, while on the other hand, it also promotes technological innovation and productivity improvement. Then, ER is expressed as the industrial pollution control investment divided by total industrial output. Technological progress is a key driver of low-carbon transition and GTFP growth (Zhao et al., 2023). R&D is expressed as the share of industrial enterprises' expenditure on science and technology to fiscal expenditure. Investment in R&D influence the industry's GTFP by improving the research environment, increasing the motivation of R&D staff, bringing about the development of clean energy and environmental technologies, and in turn reducing emissions. TI is expressed by the number of domestic patents granted in each province. The variables' descriptive statistics are shown in Table 2.

4. Results and discussion

4.1. Spatiotemporal variations of GTFP in EII

In order to scientifically reflect the variations of GTFP in EII in different regions, the country is divided into four regions: Eastern Region, Central Region, Western Region, and Northeastern Region (this division will also be used in this way subsequently). Fig. 2 shows the average regional GTFPs of EII during different Five-Year Plan (FYP) periods. It can be seen that during 2001–2005, EII's GTFP in China was still at a comparatively low level, it was improved remarkably thereafter. The Chinese government was dedicated to encouraging pollution reduction and energy conservation since the 11th FYP (2006–2010), and with the launch of the 12th FYP in 2011, the country has set environmental goals to actively address climate change, providing policy constraints to ensure pollution emission reduction and encourage the modernization and transformation of polluting companies through technology. Then EII, one of the key targets that receive significant policy attention, demonstrates how the government's efforts have assisted EII in making steady progress toward greener growth. The western region got the least improvement in the GTFP of EII among all regions during the study period.

Technological progress was the key driver of GTFP improvements for EII while declining efficiency was a deterrent over the 10th to 13th FYP. Over the past four FYPs, EII has been undergoing a transformation in its development pattern, with some achievements in technological innovation and green development. However, GTFP decreased in the eastern region earlier in the study period and declined in the western region for the entire sample period, and only the central region had a GECH consistently greater than 1. In other words, management or allocation inefficiencies inhibited the improvement of GTFP in EII, particularly in the western region.

4.2. Impact of green finance on EII's GTFP

4.2.1. Spatial correlation analysis

Due to the energy dependence and geographic attachment of EII, the geographic adjacency spatial matrix (W^1) is selected. The spatial weight matrix data are derived from the China Statistical Yearbook and the Centre for Constructing Geographic National Geographic Information; EII's GTFP is calculated by Eq. (1). Corresponding global Moran's I values are shown in Table 3. The Moran indices of GTFP in EII from 2001–2019 are significantly positive with distribution intervals of [0.465,0.884], which indicates a relatively strong positive spatial correlation between the study subjects. Thus, an empirical analysis of spatial effects using spatial econometric models is an appropriate choice (Moran scatterplot is shown in Supplementary Material Figure A).

4.2.2. Statistical tests and selection of spatial econometric model

The multicollinearity test is initially conducted using the correlation coefficient and variance inflation factor (VIF) to assess the relationship between explanatory variables (shown in Table 4). Considering all of the explanatory variables' correlation coefficients are all less than 0.8 and the VIF values are less than 10, there is no issue of multicollinearity among them.

According to the spatial correlation analysis, the selection of spatial econometric models was carried out (The results of the tests displays in Supplementary Material Table A). First, the LM test was used to compare the spatial panel regression model with the Ordinary Least Squares (OLS) panel model, and it was found that the statistics of the LM-Lag and LM-error tests are both significant at the 1% level, indicating that this empirical study can be modeled by the spatial panel econometric model. To ascertain whether the SDM degraded to SAR or SEM, the LR test was used, and according to Elhorst (2014), if both LM_lag and LR_spatial_lag were significant at 1%, as well as the LM_error and LR_spatial_error tests, the SDM was more appropriately selected for empirical analysis. The fixed effects model has been selected, and the SDM with both fixed time and space fixation is more appropriate for this investigation because the Hausman test results demonstrate that the model rejects the initial hypothesis at the 1% level.

4.2.3. Regression results analysis

In Table 5, the results of the OLS and spatial model regression estimation are shown. Regression (4) is the SDM regression result in focus. Regression (3) without control variables, SEM of regression (5) and SAR of regression (6) are used as robustness tests, separately. First, the R-squared values of SDM are higher than those of OLS regression when compared to the OLS estimate's (2) values, indicating that the spatial econometric model fits better. Secondly, there are differences in the regression coefficients between the OLS model and the SDM, which may be due to the lack of consideration of spatial factors. This spatial spillover effect must therefore be taken into consideration. Finally, regressions (4), (5), and (6) all show that the regression coefficients are significant and have the same sign, indicating that the conclusions are robust.

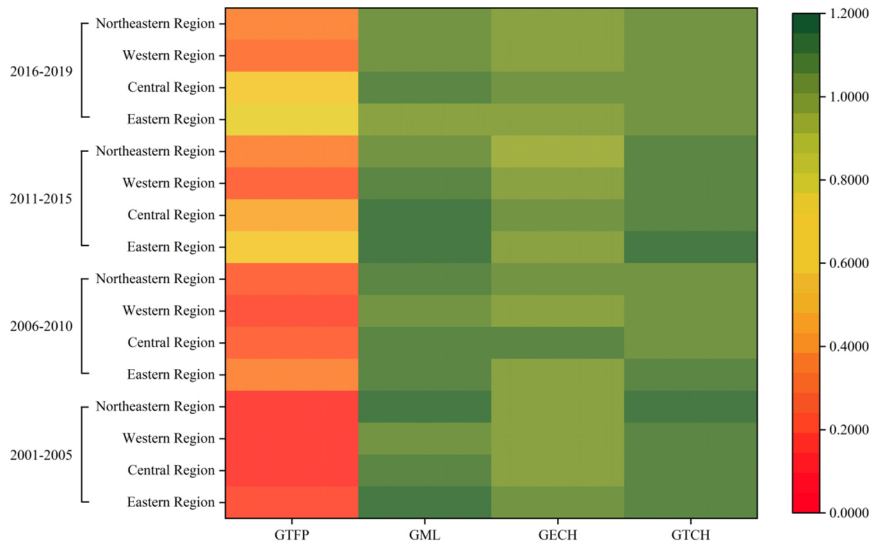

Fig. 2. Heat map of the regional time-averaged GTFP of China's EII.

Table 3
Global Moran's I index and z statistics of EII's GTFP from 2001 to 2019.

Year	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Moran's I	0.884	0.525	0.775	0.707	0.757	0.749	0.872	0.851	0.815	0.834
z	13.060	6.411	10.536	7.691	8.054	7.885	12.152	10.325	9.319	9.446
Year	2011	2012	2013	2014	2015	2016	2017	2018	2019	
Moran's I	0.800	0.764	0.561	0.575	0.540	0.584	0.538	0.540	0.465	
z	8.622	7.687	5.295	5.471	5.109	5.409	5.148	5.127	4.483	

Table 4
Results of multicollinearity test.

	$\ln GFI$	$\ln DEV$	$\ln EI$	$\ln ER$	$\ln R\&D$	$\ln TI$
$\ln GFI$	1					
$\ln DEV$	−0.3989	1				
$\ln EI$	−0.7836	0.2798	1			
$\ln ER$	−0.6319	0.4373	0.6880	1		
$\ln R\&D$	0.5318	−0.5568	−0.5295	−0.3950	1	
$\ln TI$	0.7876	−0.5056	−0.7945	−0.6288	0.7590	1
VIF	3.33	1.77	4.16	2.27	2.79	5.87

As shown in Table 5, the results of the empirical tests were collated to analyze the spatial effect of GFI on GTFP of EII in China. Overall, EII's GTFP has a strong positive spatial spillover effect, as evidenced by the overall spatial autoregressive coefficients 0.1217 and 0.4220 in models (4) and (6), respectively (significant at the 5% level and above). In other words, the enhancement of GTFP in EII within a province shows a favorable spatial impact on adjacent regions. The coefficient of the direct term of GFI in the two-fixed SDM, $\ln GFI$, is 0.4196 and satisfies the test at 1% significance level, demonstrating that GFI has a beneficial contribution to the improvement of GTFP in EII. Following the addition of control variables, the coefficient of $\ln GFI$ slightly decreases, suggesting that the impact of GFI on EII's GTFP was influenced by other factors. The spatial lag coefficient $W * \ln GFI$ of GFI under the adjacency matrix is significantly positive, showing that enhancing GTFP in EII was significantly impacted spatially by the rise of green finance, i.e., there are substantial benefits to the development of green finance because it not only supports green growth in EII within the region but also in the neighboring areas.

Regarding the control variables, the estimated coefficient of R&D is significantly positive, while the enhancement of the GTFP of EII is significantly hampered by EI and ER, while DEV and TI are not significant. The significant negative spatial effect coefficient of DEV and EI shows that when industry development and energy intensity rise, the GTFP of EII in the surrounding area decreases. ER's spatial effect coefficient is noticeably positive, indicating that the neighborhood's GTFP for EII is positively impacted by increased environmental regulation.

To be clear, the marginal utility of associated explanatory variables is not directly reflected in the coefficients of the SDM (Lesage and Pace, 2009). The decomposition effects are therefore calculated using partial differential methods (Ke et al., 2021; Zhang and Wang, 2018). Table 6 presents the outcomes of the spatial spillover effects of SDM.

The direct effect of GFI is significant with a coefficient value of 0.7591, the indirect effect is significant with a coefficient value of 1.1416, and the total effect is significant with a coefficient value of 1.9007, indicating that for every 1 percentage increase in the level of GFI in one province, the GTFP of EII in the province will increase by 0.7591 percentage, the GTFP of EII in neighboring areas will increase by 1.1416 percentage, while the overall GTFP will increase by 1.9007 percentage. Due to the positive spatial spillover of GFI and EII's GTFP, local EII's GTFP will also be influenced by GFI and EII's GTFP in other areas. Possible reasons can be interpreted as follows. First, in the beginning phases of developing green finance, the government typically takes the initiative. Since local governments compete with one another, the practices of local provinces' environmental regulation will "infect" the neighboring regions. Second, EII's enterprises have raised the interest rates on their loans owing to the financing limitations of green finance, forcing them to transform and reduce their pollution emissions. In addition, due to the "warning effect", EII in neighborhoods will also cause a reduction in carbon emissions. Therefore, when local green finance develops, so will the GTFP of EII in the surrounding areas, encouraging them to adopt stronger green financing strategies and stimulating the improvement of the GTFP of EII.

In terms of the contribution of control variables, although DEV's direct effect was insignificant, nonetheless, its total effect and the indirect effect were both significantly negative, which indicates that the provinces with higher EII industrial output have a repressive influence on EII's GTFP growth in surrounding areas, which may be due to the

Table 5
Estimation results of OLS and spatial models.

Variable	OLS		SDM		SEM	SAR
	(1)	(2)	(3)	(4)	(5)	(6)
	NO	YES	NO	YES	YES	YES
$\ln GFI$	0.9060***	0.8705***	0.7225***	0.4196***	0.1688***	0.7233***
$\ln DEV$	/	−0.3911***	/	0.0442	0.0763	0.1345
$\ln EI$	/	−0.3177***	/	−0.3709***	−0.4528***	−0.3989***
$\ln ER$	/	−0.0583***	/	−0.0952***	−0.1272***	−0.0713***
$\ln R\&D$	/	0.1347***	/	0.1258***	0.1473***	0.1045***
$\ln TI$	/	−0.1842***	/	−0.0188	−0.1386***	−0.0423*
$W * \ln GFI$	/	/	1.1583***	1.2491***	/	/
$W * \ln DEV$	/	/	/	−0.4156***	/	/
$W * \ln EI$	/	/	/	−0.3291***	/	/
$W * \ln ER$	/	/	/	0.0932**	/	/
$W * \ln R\&D$	/	/	/	−0.0454	/	/
$W * \ln TI$	/	/	/	−0.0794	/	/
Rho	/	/	0.3629***	0.1217**	/	0.4220***
R^2	0.4958	0.5789	0.5766	0.6329	0.6217	0.5979

Note:
* Indicate significance at the 10% level.
** Indicate significance at the 5% level.
*** Indicate significance at the 1% level.

Table 6
Spatial effect decomposition results.

Variable	Direct effect	Indirect effect	Total effect
$\ln GFI$	0.7591***	1.1416***	1.9007***
	(8.10)	(7.22)	(10.75)
$\ln DEV$	−0.0654	−0.3605***	−0.4259***
	(−1.15)	(−3.80)	(−4.57)
$\ln EI$	−0.4631***	−0.3295***	−0.7926***
	(−12.82)	(−5.38)	(−11.10)
$\ln ER$	−0.0740***	0.0726**	−0.0014
	(−5.60)	(3.01)	(−0.05)
$\ln R\&D$	0.1175***	−0.0278	0.0897*
	(4.36)	(−0.62)	(1.81)
$\ln TI$	−0.0378	−0.0717	−0.1095
	(−1.41)	(−1.49)	(−1.04)

Note: The value in parentheses is the T statistic.
* Indicate significance at the 10% level.
** Indicate significance at the 5% level.
*** Indicate significance at the 1% level.

occurrence of "resource squeeze" or "pollution transfer", thus reducing the overall provincial EII's GTFP. EI's decomposition effects were all significantly negative, implying that the GTFP of provincial EII was significantly impacted negatively by EI and had a spatial spillover effect. EII's energy consumption and reliance on energy are positively correlated with EI. Moreover, only a small percentage of the energy consumed by EII is generated by clean energy sources; the majority derives from traditional energy sources like coal, gasoline, kerosene, and diesel. Therefore, low energy use efficiency in EII and high emissions restrict EII's ability to develop sustainably. There was a strong negative direct effect of ER EII's GTFP, but the overall effect on GTFP in EII remains undetermined. This may be explained by the fact that inappropriate environmental regulation constrains part of the profits of EII and increases the operating costs, while the implementation of environmental regulation legislation results in compliance costs that outweigh the benefits of innovation. However, environmental regulation may cause some mature EII enterprises to move to the surrounding area, increasing the total output of EII in the surrounding area, thus increasing its GTFP. R&D contributed to the local GTFP as well as the overall EII, which indicates that the enhanced R&D activities provide strong technical support for energy saving and emission reduction, and increased economic benefits in EII; however, the spillover effects on the surrounding areas were not significant. All effects of TI were not significant yet.

4.3. Robustness tests

To explore whether the regression results are impacted by differences in regional economic development, the robustness test was conducted by changing the spatial weight matrix. The economic distance matrix (W^2) and the economic geographic weight matrix (W^3) were consecutively substituted for W^1. Correlations all pass the 10% significance test and maintain a high consistency with earlier estimation results, verifying that the outcomes of the regression are robust (The detailed results of the robustness tests are presented in Supplementary Material Table B).

4.4. Heterogeneity analysis

Considering the effect of GFI on GTFP of EII may differ depending on the region, this research then separated all provinces into four regions, namely, the Eastern, Central, Western and Northeastern regions, and examined the spatial spillover of GFI impacting GTFP in EII in different regions.

Based on the total effect shown in Table 7, it is evident that the development of the GTFP of EII is significantly influenced favorably by GFIs in the Eastern, Central, and Northeastern regions, and the direct and indirect effects are notably positive in the Eastern and Central regions. The western region was in any case reflected as the obstacles to GTFP in EII, probably due to the negative effects of the "race to the bottom" problem in the industry between provinces caused by the green finance policies (Kan et al., 2023).

EII contains six subsectors, the model parameters were then determined on the basis of completing the model test independently to study the impact of GFI and its spatial spillover effect in subsectors (in Table 7). The majority of subsectors' GTFP is significantly promoted by GFI, while MNMP and SPNM demonstrated a negative spatial spillover effect, i.e., the GTFP of MNMP and SPNM in the surrounding areas are negatively impacted by the local GFI improvement. Besides, PSEH was the subsector with the least pronounced direct effect (0.2398).

5. Conclusion and policy implications

A SDM was built based on provincial panel data (2001–2019) to investigate the effect of green finance on the GTFP of EII in China, with the following conclusions: (1) GTFP of EII showed spatial and temporal variations. (2) GFI has a significant beneficial impact on EII's GTFP and has a spatial spillover effect, i.e., it significantly contributed to the green development of EII in local and neighboring provinces.

Table 7
Results of heterogeneity analysis.

	$\ln GFI$	$W * \ln GFI$	Direct effect	Indirect effect	Total effect
Eastern region	0.4085***	1.6867**	0.3999***	1.6495***	2.0494***
	(3.89)	(2.34)	(8.72)	(3.73)	(5.58)
Central region	0.4191	0.5990*	0.4265**	0.6516*	1.0781***
	(1.52)	(1.70)	(2.25)	(1.82)	(3.11)
Western region	−0.5611	−1.1171**	−0.5373	−1.1079**	−1.6452***
	(−1.42)	(−2.04)	(−1.31)	(−2.10)	(−3.45)
Northeastern region	−0.4665	0.3628*	−0.4526	0.4632*	0.0106**
	(−1.48)	(1.75)	(−1.54)	(1.96)	(2.55)
PPCO	0.4431***	0.8166**	0.5812***	0.5498**	1.1310***
	(4.31)	(2.54)	(3.91)	(2.48)	(4.08)
MRCMCP	0.5871***	0.4836***	0.7059***	0.6602***	1.3661***
	(8.18)	(3.28)	(8.34)	(4.22)	(6.59)
MNMP	1.0330***	−0.1257	1.0641***	−0.3629*	1.3661***
	(9.24)	(−0.48)	(8.91)	(−1.71)	(6.59)
SPFM	0.6520***	0.7966***	0.6789***	0.9481***	1.6270***
	(4.58)	(3.52)	(4.73)	(4.07)	(7.14)
SPNM	0.8934***	−0.6685**	0.8770***	−0.5914**	0.2856
	(6.21)	(−2.95)	(6.06)	(−2.41)	(1.18)
PSEH	0.1880	0.3965**	0.2398**	0.4632*	0.7030**
	(1.63)	(1.98)	(2.01)	(1.96)	(2.55)

Note: The value in parentheses is the T statistic.
* Indicate significance at the 10% level.
** Indicate significance at the 5% level.
*** Indicate significance at the 1% level.

(3) GFI has a beneficial impact on EII's GTFP in Eastern, Central and Northeastern regions, among which the strongest impact occurs in Eastern region. The barriers to GTFP in EII are shown in Western region. (4) From a subsector perspective, green finance has a smaller influence on PSEH's GTFP than other subsectors, and it has a spatial inhibitory effect on MNMP and SPNM.

The following recommendations are made in light of the aforementioned findings:

Firstly, the contribution of green finance to EII's green development needs to be fully utilized to indicate policy direction. The government ought to make efforts to strengthen green finance regulations and provide relevant institutions stronger responsibility and authority to supervise and review, and promote industrial transformation of EII through policy tools like green credit. In addition, adjusting the development of environmental laws and regulations linked to green finance to encourage the synergistic between green finance and environmental regulation would support the long-term growth of EII. Policies on green finance can collaborate with R&D to jointly develop the promotion of GTFP in EII, for example, guiding the industry's R&D investment through green capital to improve the overall technology level.

Secondly, since green finance has a large spatial spillover impact on EII's GTFP, it is crucial to fully utilize this effect in order to actualize regional green finance linkage and enlarge its spatial spillover effect on the GTFP of EII. Cooperation and communication between provinces and regions on the green development of EII should be strengthened, and efficient cooperation and improvement of regional linkage mechanisms should be carried out between regions. The Eastern region, which has distinct advantages in the green development of EII, ought to take the lead. The government should establish a cooperation platform to optimally allocate market resources and guide the green capital elements to flow more to the EII's enterprises that need to be upgraded. Balanced development of green financial growth in different regions need to be emphasized so that the GTFP of EII in the whole region could finally be improved and realize the benign interaction to ensure the maximization of common interests. Besides, due to the industry development level's spatial inhibitory effect on EII, the "resource occupation" and "pollution transfer" and other issues in some areas of EII need to be emphasized to prevent the blind expansion of the industry and eliminate regional unbalanced development as much as possible.

Thirdly, as green finance policies related to EII are being implemented, the actual conditions of different regions should be taken into account to lessen the policy effects' asymmetry. According to the results of the heterogeneity study, green finance is less effective at fostering GTFP in EII in the Western region, which is far from the East. Thus, the government and relevant organizations should take into account the industry's variations with regard to the regional market environment, and formulate specific measures in accordance with EII's situations in different regions.

Finally, in order to create specialized environmental control measures and assessment indicators for subsectors of MNMP, SPNM, and PSEH, the government should take into account the characteristics of industrial disparities. Particular emphasis should be given to directing the credit threshold of enterprises in these sectors in response to green finance's detrimental spatial spillover effect on MNMP and SPNM. Regional specified credit assessment indicators on enterprises can be formulated to coordinate the uneven regional green development of the sectors. As for PSEH, it is a reasonable initiative to reduce CO_2 emissions by directing the deployment of renewable energy sources, particularly wind energy, through green finance, instead of conventional energy sources for power generation (Wang et al., 2023). In addition, increased efforts can be made to develop insurance products that support green transformation, the anti-risk ability of enterprises should be improved in response to the long R&D cycle of emission reduction technology.

Due to the limitation of the disclosure of data such as the number of energy and employees in subdivided EII industries at the provincial level, the data related to the measurement of EII's GTFP is only updated to 2019, so that although the study of the relationship between green finance on EII's GTFP can reflect the general trend, it lacks the timeliness to a certain extent. Therefore, we suggest conducting further research after the updated provincial-level data on EII and green finance data are disclosed to obtain more precise and comprehensive results. In addition, it is necessary to further conduct a path analysis on how green finance impacts EII's GTFP.

CRediT authorship contribution statement

Jinxian Lin: Conceptualization, Resources, Software, Writing – original draft. **Ling Zhang:** Formal analysis, Investigation, Methodology, Writing – review & editing. **Zhanfeng Dong:** Project administration, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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