RESEARCH ARTICLE

A Carbon Emission Adjustment Model Considering Green Finance Factors in the Context of Carbon Neutrality

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ABSTRACT Global climate change has led to the ecological crisis of the Earth, and achieving carbon neutrality has become a common challenge for all countries. The role of green finance in carbon emission regulation cannot be ignored. Therefore, this study aims to construct a carbon emission regulation model that integrates green finance factors and provide a scientific basis for policy makers. In this study, the influence mechanism of green finance factors on carbon emissions was first clarified, and the evaluation model of green finance indicators was constructed. Then, using econometric methods, the carbon emission adjustment model for green finance factors is constructed. The empirical analysis and test results of the model show that the development level of green finance in most provinces and cities was between 0.1 and 0.3, and the eastern region is better than the western region. In the robustness test, the first term of carbon emissions is positive, and the second term is negative, both of which pass the significance test. In the control variable section, the coefficient of green credit balance is negative, indicating that issuing green credit balance will reduce carbon emissions. Among the control variables, the non-performing loan ratio coefficient of green projects is positive, and the p-value is 0.0071(passing the significance test), indicating that the increase of the loan ratio will increase carbon emissions. The above analysis shows that carbon emission regulation models play an important role in achieving carbon neutrality goals. In the controlled variables, the coefficient of non-performing loan ratio for green projects was positive, with a P value of 0.0071 (significance test passed), indicating that increasing the loan ratio would increase carbon emissions. The above analysis indicates that carbon emission regulation models play an important role in achieving carbon neutrality goals.

INDEX TERMS Carbon neutrality, green finance, carbon emissions, entropy method, PSTR.

I. INTRODUCTION

With the acceleration of industrialization and the continuous growth of energy consumption, carbon emissions (CE) continue to increase, causing serious damage to the ecological environment [1], accompanied by problems such as

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energy shortage and environmental pollution. Therefore, carbon emission regulation (CER) has become an important task in promoting sustainable development [2], [3]. With the concept of sustainable development deeply ingrained in people's hearts, countries have begun to seek ways to achieve coordinated improvement of economy, society, and environment [4]. Given this, green finance (GF) has emerged as an innovative financial model [5], [6]. GF aims to promote

TABLE 1. The advantages and disadvantages of the model mentioned in the study.

Model	Advantage	Disadvantage	Author
Spatial Durbin model	High prediction accuracy	High operation difficulty	Liu et al. [11]
Decentralized and centralized decision models	High production efficiency	Data is not accurate enough	Wang et al. [12]
New supply chain model	Carbon emission reduction	Less platform use	Goodarzian et al.[13]
Prediction model	High accuracy of prediction results	Computationally complex	Miner et al. [14]
Analysis method based on spatial mediation and adjustment model	Comprehensive analysis	Large data demand	Dong et al. [15]
Quantile regression model	Strong flexibility	High requirements on parameters	Meo et al. [16]
Fixed effect estimation method of least square model	Simple program	There are errors in the data results	Khan et al.[17]
Content analysis	Low cost	Limited information content	Mohd et al.[18]
A novel feature selection framework based on intuitionistic fuzzy entropy	High fault tolerance	Weak anti-interference	Pandey et al.[19]
Energy poverty index prediction model	High accuracy	Large amount of calculation data	Liang et al.[20]

green economy and social growth by guiding funds towards low-carbon and environmental protection sectors. Moreover, GF has dominance in promoting sustainable economy and social development [4]. Specifically, GF can further promote the application of green technologies, optimize and upgrade the industrial structure by guiding funds towards environmental protection industries (EPI) and green projects [7], [8]. Meanwhile, GF also helps to reduce environmental pollution and resource consumption, improve resource utilization efficiency, and achieve a win-win situation of both economic and environmental benefits [9], [10].

However, current research on the relationship between GF and CE is not sufficient, lacking a systematic theoretical framework and empirical support. This goal is to explore in depth the impact mechanism of green finance factors (GFFs) on CE, construct a CER model considering GFF, and provide scientific basis for policy makers. The innovation of this study lies in incorporating GFF into the framework of the CER model, breaking through the limitations of traditional CER models that only focus on a single factor. Meanwhile, based on the analysis of China's GF level, this study constructs a CER model that is in accordance with China's national conditions, providing policymakers with more targeted methods.

II. LITERATURE REVIEW
With the change of global climate, carbon emission regulation has become a hot issue of national concern. Many domestic and foreign scholars have studied it. For example, in order to solve the problem that local governments have conducted few studies on the spatial spillover effects of environmental regulations on carbon emissions in the manufacturing industry and regional boundaries, Liu's team proposed to use the spatial Durbin model to detect the impact mechanism and spatial spillover effects on carbon emissions in the manufacturing industry. This model can clearly obtain the spatial spillover effect and regional boundary value of carbon emissions [11]. Aiming at the regulatory issues in the closed-loop

supply chain of cap-and-trade carbon emission reduction and used product recycling, Wang et al. established a decentralized and centralized decision-making model and conducted a comparison experiment with the traditional model. The experimental results showed that the government could monitor manufacturers in real time through this model, thereby reducing carbon emissions and promoting the recycling of used products [12]. In order to reduce the carbon emissions in the supply chain and minimize the total cost under the big data environment, the Goodarzian team designed a new supply chain integrated production-transport-ordering-inventory holding model. Compared with other models, it was found that the carbon emissions of the supply chain in this model were reduced by 40% and the total cost by 30%. It is much higher than other models [13]. The Miner team designed a prediction model for tracking and observing permafrost for the adjustment of carbon emissions in the melting of Arctic permafrost, and conducted a comparison experiment with other prediction models. The experimental results showed that the prediction accuracy of the model for carbon emissions in the permanent melting reached 97.67%, which was significantly better than other models [14]. In order to prove the impact of green innovation technology on carbon emission efficiency, Dong and Zhu et al. designed an analysis method based on spatial mediation model and spatial regulation model, and compared the method with traditional analysis methods. The experimental results showed that the accuracy rate of this method in analyzing carbon emission efficiency was as high as 98.67% [15].

With the development of green economy, people pay more and more attention to green finance. For example, in view of whether there is a specific relationship between the top ten green finance economies and carbon dioxide emissions, Meo et al proposed a quantile regression model based on quantile to test the quantile of carbon dioxide under different green finance, and conducted a comparison experiment with other models. The detection accuracy of this model is
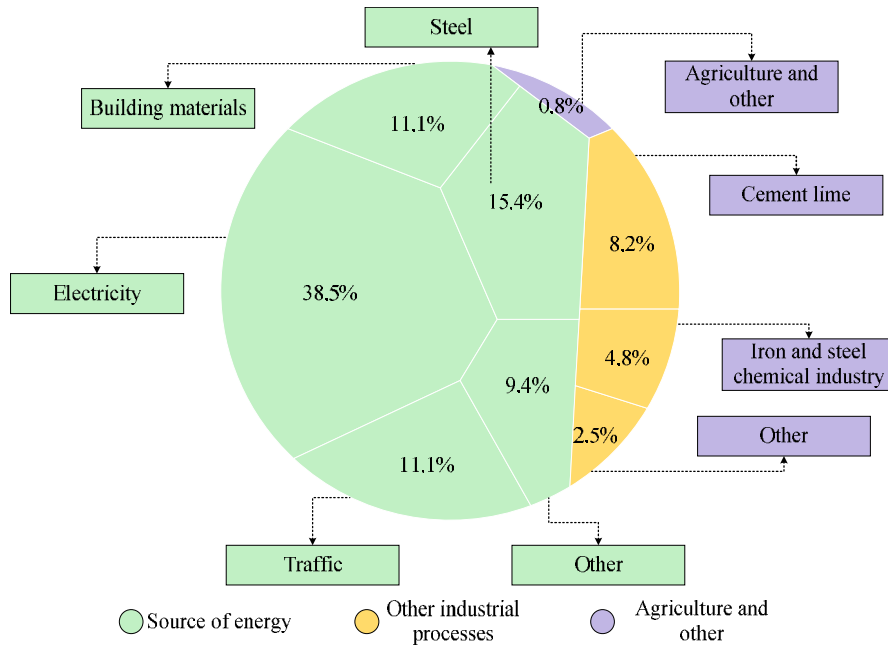
FIGURE 1. Carbon emission structure.

98.66%, which is significantly better than other models [16]. In order to study the impact of green finance on the economic and ecological footprint in Asia, Khan's team designed a fixed effect estimation method based on the least squares model, and conducted experimental analysis on this method. The results showed that green finance reduced the ecological footprint by 47.5% [17]. In order to explore the impact of green finance on ozone-depleting substances emissions and air pollution emissions, Mohd et al used content analysis to analyze ozone-depleting substances and air pollution emissions, and the results showed that green finance reduced air pollution emissions by 59.7% [18]. Due to the strong sensitivity and operability of entropy method, it has been widely used in various fields. For example, Pandey team designed a new feature selection framework based on intuitive fuzzy entropy in order to solve the interference problem of other factors in feature selection, and conducted comparative experiments on this framework. The results show that, In this framework, the interference degree of other factors on feature selection is reduced by 67%, and the anti-interference is much higher than that of other models [19]. For the problem that no consensus has been reached on the measurement of energy poverty, Liang et al. proposed to build a new multidimensional energy poverty index prediction model by using the entropy method, and conducted a comparison experiment with other models. The result shows that the prediction accuracy of the poverty index prediction model based on the entropy method is as high as 98.87%, which is significantly better than other comparison models [20]. Compare the models mentioned in the research, analyze the advantages and disadvantages of the models, and the comparison results are shown in Table 1.

To sum up, although there are a lot of studies on carbon emission regulation and green finance, there is very little discussion on the impact of green finance factors on carbon emission regulation model. Therefore, this study will deeply explore the impact mechanism of green finance factors on carbon emission, and build a carbon emission regulation model considering green finance factors.

III. CONSTRUCTION OF CER MODEL BASED ON PSTR

To construct a scientific CER model, this study first analyzes the impact mechanism between GF and CE. Subsequently, GF level evaluation indicators are constructed, and based on this, the weights of the indicators and various variables of GF are determined. Finally, a CER model based on Panel Smooth Transition Regression Models (PSTR) is constructed.

A. ANALYSIS OF THE INFLUENCE MECHANISM BETWEEN GF AND CE

Faced with the challenge of global climate change, countries have proposed the strategic decision of carbon neutrality (CN). Controlling CE is an inevitable choice for the world to achieve sustainable development, and the financial industry controls financing services and CE rights, which have a crucial impact on CE activities [21]. Therefore, to promote environmental protection and sustainable and social improvement, the GF concept has been proposed by relevant experts and scholars. To promote the leading effect of GF on CE, this study first investigates the mechanism of influence between GF and CE.

Compared with traditional finance, GF pays more attention to the living environment of human society, mainly guiding various economic entities to pay attention to the balance between natural ecology through its own financial activities [22], [23]. The main sources of CE are fossil fuels, industrial processes, and agricultural activities. Figure 1 shows the CE composition chart compiled by the National Bureau of Statistics in 2020.
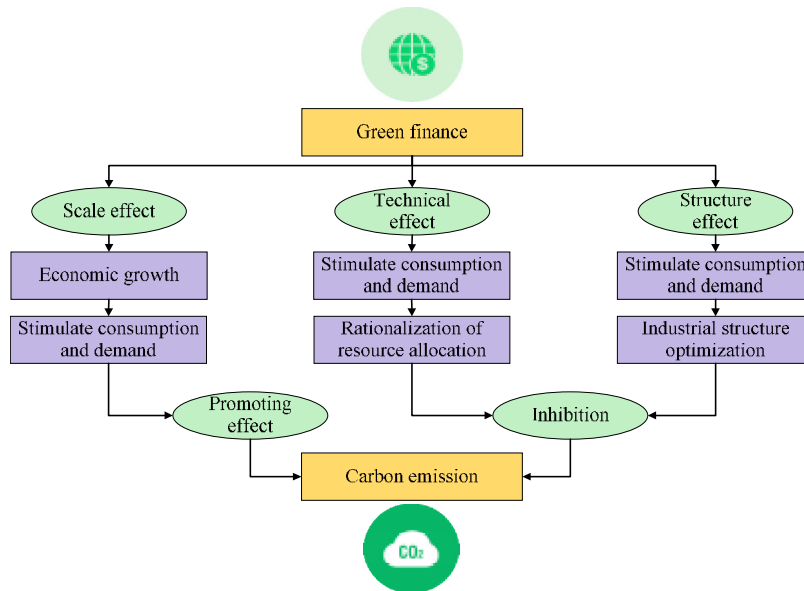
FIGURE 2. Mechanism of green finance's impact on CE.

In Figure 1, the CE structure mainly consists of three parts. The main proportion in the CE structure is energy, with electricity accounting for the largest proportion at 38.5%. Transportation, steel, and building materials all account for over 10%. Next are other industrial processes, accounting for a total proportion of 15.5%. Agricultural production activities generate the least CE, accounting for a total of 0.8%. In the process of green transformation in various industries, sufficient financial support is needed. Therefore, to achieve the "dual carbon" goal on time and efficiently, it is necessary to leverage the role of GF in CE. Figure 2 shows the mechanism of GF's impact on CE.

In Figure 2, from an overall perspective, GF has an impact on CE from three aspects. Firstly, in terms of economies of scale, the GF industry forms ecological capital by gathering and guiding funds towards low-carbon industries [24]. Secondly, there is the technological effect. GF incentivizes enterprises to strengthen the energy-saving and carbon reducing technologies, thereby improving the efficiency of resource utilization [25]. Finally, there is the structural effect. The GF industry promotes the transformation and upgrading of industrial structures in various industries, thereby increasing the proportion of green and low-carbon industries in the national economy [24], [25]. The above three aspects indicate that the GF industry has a regulatory effect on CE.

Due to the numerous factors that affect CE, to further investigate how GF drives the influencing factors of CE, this study uses the Logarithmic Mean Divisia Index (LMDI) decomposition method to analyze the influencing factors of CE. The LMDI decomposition method has been successfully applied in the research field of CE by analyzing the contribution rate of various factors to CE [26]. The decomposition formula for the influencing factors of CE in the LMDI method

is equation (1).

$$CO_2 = \sum_A \sum_B \frac{CO_{2A,B}}{E_{A,B}} \times \frac{E_{A,B}}{E_A} \times \frac{E_A}{GDP_A}$$
$$\times \frac{GDP_A}{GDP} \times \frac{GDP}{POP} \times POP \quad (1)$$

In equation (1), POP represents the population size effect. A, B represents the serial numbers of industries and energy, respectively. $\frac{CO_{2A,B}}{E_{A,B}}$ and $\frac{E_{A,B}}{E_A}$ are the CE coefficients and ratios for the B-th energy source in the A-th industry. $\frac{E_A}{GDP_A}$ is the energy intensity effect, used to represent the output or benefits obtained after investing a certain amount of resources or energy. $\frac{GDP_A}{GDP}$ and $\frac{GDP}{POP}$ represent the effects of industrial structure and economic scale, respectively. When calculating the CE quantity, the research results of Du Limin are used, and the calculation formula is equation (2).

$$CO_2 = \sum_{k=1} E_k \times CF_k \times CC_k \times COF_k \times \frac{44}{12} + m_0 \times Q$$
$$(2)$$

In equation (2), E_k represents the K-th energy consumption. $CF_k \times CC_k \times COF_k \times \frac{44}{12}$ is the CE coefficient of dioxide. Q is the cement production volume. m_0 is the CE coefficient during the cement production process. In this study, the LMDI method is utilized to analyze the impact of GF on CE, and the main driving factors of CE are analyzed from four aspects: energy, industry, technology, and economy. Next, how GF promotes the conversion of these driving factors to low-carbon effects is analyzed, thereby exerting a regulatory effect on CE.

TABLE 2. Green finance EIS.

Primary index	Secondary index	Indicator specification	Index attribute
Green credit	Amount of loans to environmental protection enterprises (EPE)	Reflects the degree of loan support of financial institutions for EPI	+
	The proportion of interest expenses of high energy-consuming industries	Measure the proportion of financial institutions' loan interest expenses to energy-intensive industries	−
Green securities	Proportion of market value of EPE	The market value of EPE in the A-share market reflects the market's recognition and support for the EPE.	+
	High energy consumption industry market value proportion	Reflects the relative position of high energy-consuming industries in the capital market	−
Green investment	The proportion of investment in environmental pollution control	Measure the proportion of investment in combating environmental pollution	+
	Proportion of government expenditure on energy conservation and EPI	Reflects the government's financial support for energy conservation and EPI	+
Green insurance	Proportion of the scale of agricultural insurance	Measure the proportion of agricultural insurance in total insurance expenditure	+
	Agricultural insurance payout rate	Reflect the compensation efficiency of agricultural insurance when dealing with risks	+
Carbon finance	CE credit intensity	The ratio of loan balance to CE was used to measure financial institutions' loan support for CE reduction projects	+

Note: The "+" and "-" in the table represent the positive and negative directions of the indicators, as well as their positive and negative impacts on the improvement of the system level.

B. CONSTRUCTION OF GF EVALUATION INDEX SYSTEM UNDER THE BACKGROUND OF CN

There is a close relationship between GF and CE, and achieving CN goals requires collaborative efforts from all parties. GF regulates CE by influencing resource input and allocation [27], [28]. After analyzing the correlation between GF and CE, this study proceeds to construct an evaluation index system (EIS) for GF. It evaluates the current development status of GF and proposes improvement measures to promote the GF industry to better serve CE.

Before constructing GF evaluation indicators, it is necessary to first clarify the principles of system. This paper is based on the research of scholars such as Li Xiaoxi to construct an EIS for GF, and combines it with published policies related to GF development to ensure that the content of GF indicators is consistent with policy objectives. The selection of evaluation indicators follows the theory of sustainable development and provides a theoretical basis for constructing EIS. Table 2 shows the EIS of the constructed GF.

The constructed indicators are divided into secondary indicators. One of the primary green indicators includes credit, securities, investment, insurance, and carbon finance. To set secondary indicators for each primary indicator. After constructing the EIS for GF, using the entropy method to calculate each indicator's weights. Firstly, the raw data is preprocessed, and the range normalization method is used to standardize the data to eliminate the impact of the positive and negative indicators on the data. The standardization formula for positive indicators is equation (3).

$$v_{ij} = \frac{x_{ij} - \min\{x_{ij}\}}{\max\{x_{ij}\} - \min\{x_{ij}\}} \quad (3)$$

In equation (3), x_{ij} belongs to the original data matrix, where i is the sample and j is the indicator [29], [30]. The formula for negative indicators is equation (4).

$$v'_{ij} = \frac{\max\{x_{ij}\} - x_{ij}}{\max\{x_{ij}\} - \min\{x_{ij}\}} \quad (4)$$

The formula for the proportion between samples and indicators is equation (5).

$$P_{ij} = \frac{x_{ij}}{\sum\limits_{i=1}^{m} x_{ij}} \quad (5)$$

In equation (5), $i = 1, 2, \ldots, m$, $j = 1, 2, \ldots, n$. Information entropy is often used as an indicator to measure uncertainty and evaluate the purity of data and the uncertainty of decision-making [31], [32]. After obtaining the proportion between indicators and samples, further to calculate the information entropy of indicators, as shown in equation (6).

$$e_j = -k \sum\limits_{i=1}^{m} p_{ij} \cdot \ln p_{ij} \quad (6)$$

In information entropy, the greater the uncertainty of variable values, the greater the information entropy. On the contrary, the more certain the value of the variable, the smaller the information entropy [33], [34]. Next, the information entropy redundancy of the indicators is calculated to obtain the average uncertainty or information content of the data information. The formula for calculating the information entropy redundancy is equation (7).

$$d_j = 1 - e_j \quad (7)$$

TABLE 3. Weight calculation results of GF indicators.

Primary index	Secondary index	Weight /%	Indicator attribute
Green credit	Amount of loans to EPE	27.42	+
	The proportion of interest expenses of high energy-consuming industries	12.33	−
Green securities	Proportion of market value of EPE	15.42	+
	High energy consumption industry market value proportion	7.23	−
Green investment	The proportion of investment in environmental pollution control	5.32	+
	Proportion of government expenditure on energy conservation and EPI	6.42	+
Green insurance	Proportion of the scale of agricultural insurance	5.23	+
	Agricultural insurance payout rate	3.53	+
Carbon finance	CE credit intensity	17.1	+

TABLE 4. Names and meanings of variables.

Variable type		Variable name	Variable symbol	Variable description
Explained variable		Carbon emission	CE	Binary CE is taken as logarithm
Explanatory variable	Quantitative variables	Green credit balance	GLC	Reflects the total amount of loans issued by financial institutions to green projects such as environmental protection and low-carbon, and is used to measure the financial support of financial institutions for green projects
		Green bond issuance	GBI	Record the total amount of green bonds issued in one year to measure the bond market's financing support for green projects
		Investment in clean energy projects	CEI	The total amount of investment received by clean energy projects is calculated to reflect the degree of capital market support for clean energy development
	Proportional type variable	Proportion of green credit	GLCR	The proportion of the balance of green credit to the total loan balance of financial institutions is used to measure the degree of greening of the loan structure of financial institutions.
		The proportion of green bonds	GBR	The proportion of green bond issuance in the total bond market reflects the proportion and importance of green bonds in the bond market
		Green insurance coverage	GIC	The proportion of risk exposure covered by green insurance products to measure the role and popularity of green insurance in risk management.
		Green return on investment	ROIG	The ratio of the benefits to the amount invested in a green investment project is used to assess the economic effectiveness and sustainability of the green investment.
	Ratio type variable	Financing satisfaction rate of carbon emission reduction projects	CFSR	The ratio between the amount of financing actually obtained by a carbon emission reduction project and the amount of financing required by the project reflects the degree of financial support of financial institutions for carbon emission reduction projects.
		Non-performing loan ratio for green projects	NPLG	The proportion of non-performing loans in green projects to the total green credit is used to assess the risk level of green credit

According to the calculation result of information entropy redundancy in equation (7), the weight of the indicators can be calculated. The formula for indicator weight is equation (8).

$$w_j = \frac{d_j}{\sum\limits_{j=1}^{n} d_j} \qquad (8)$$

Calculating the weights of various indicators of GF through the above steps, and finally the Table 3 is obtained.

In Table 3, in the GF indicator system, the overall indicator weight of green credit is the highest, with the indicator of environmental protection enterprise loan amount accounting for 27.42% and the indicator of high energy consuming industry interest expenditure accounting for 12.33%. Next

is green securities, with EPE accounting for 15.42% of the market value and high energy consuming industries accounting for 7.23% of the market value. The market value of EPE is about twice that of high energy consuming industries. In green investment, the proportion of investment in environmental pollution control is 5.32%, and the proportion of fiscal expenditure on energy conservation and EPI is 6.42%. The proportion of agricultural insurance in green insurance is about 5.23%, and the payout rate is 3.53%. In carbon finance, the proportion of CE loan intensity is 17.1%.

C. CONSTRUCTION OF CER MODEL BASED ON GFF

To further analyze the regulatory effect of GF on CE, this study constructs a CER model based on the PSTR model. The data used in model construction and indicator weight

TABLE 5. Descriptive statistics of variables.

Variable symbol	Sample number	Mean	Standard deviation	Minimum	Maximum
CE	380	5.3244	0.7822	3.2442	6.2432
GLC	380	0.3432	0.0143	0.0932	0.5322
GBI	380	0.3422	0.0334	0.3342	0.5432
CEI	380	0.4234	0.0432	0.3432	0.5722
GLCR	380	0.3532	0.0413	0.3432	0.5432
GBR	380	0.5644	0.0533	0.0533	0.6543
GIC	380	1.0653	0.1423	0.4632	1.5643
ROIG	380	5.7854	1.4536	2.5465	11.7654
CFSR	380	1.5633	0.2344	0.5432	3.8866
NPLG	380	0.4534	0.0654	0.3535	0.7865

calculation are sourced from the China Financial Yearbook, China Energy Statistical Yearbook, and China Statistical Yearbook. After obtaining the indicators' weight, the corresponding comprehensive score of a single sample can be obtained, as shown in equation (9).

$$s_i = \sum_{j=1}^{n} w_j \cdot p_{ij} \tag{9}$$

Through the above steps, this study calculates the comprehensive GF scores for each region under the constructed indicator system. In the context of CN, the GF based CE model involves multiple types of variables. To comprehensively reflect the support and promotion effect of GF on CN target activities, the impact variables related to GF have been defined and described. Table 4 shows the names, symbols, and descriptions of various variables.

In Table 4, the variables selected for this study mainly include the dependent and the explanatory variables. The former is CE, and the latter is mainly GF related sub variables. According to the properties of the sub variables, they are divided into quantitative variables, proportional variables, and ratio variables. Subsequently, data from various provinces and regions in China between 2018 and 2022 are selected as sample observations, with a total sample size of 380. Next, descriptive statistics are conducted on each variable, and Table 5 shows the results of the variable descriptive statistics.

Table 5 shows the descriptive statistical analysis results. Between 2018 and 2022, the average CE value in each region was 5.3244. In the GF related variable indicators, except for CFSR, ROIG, and GIC, the average of other variable indicators is below 1. After determining the indicator variables, the benchmark regression analysis (BRA) method is used to analyze the linear relationship between CE and other variables. Using regression coefficients in BRA to measure the degree of influence of the independent variable on the dependent variable. The expression of the BRA model is

equation (10).

$$\begin{aligned} CE_{it} = {} & a_0 + a_0 GF_{pt} + a_2 GLC_{pt}^2 + a_3 GBI_{pt} + a_4 CEI_{pt} \\ & + a_5 GLCR_{pt} + a_6 GBR_{pt} + a_7 GIC_{pt} + a_8 ROIG_{pt} \\ & + a_9 CFSR_{pt} + a_8 NPLG_{pt} + \varepsilon_{pt} \end{aligned} \tag{10}$$

In equation (10), a is the regression coefficient. ε is the random error term. p means the province or region. t represents time [45]. Then, on the basis of BRA, an interaction term between GF and environmental regulations is added to obtain a CER effect model considering GFF. The regulatory effect model is expressed as equation (11).

$$\begin{aligned} CE'_{it} = {} & \beta_0 + \beta_1 GF_{pt} + \beta_2 GLC_{pt} + \beta_3 GBI_{pt} + \beta_4 GF_{pt} \\ & \times ER_{pt} + \beta_5 GEI_{pt} + \beta_6 GLCR_{pt} + \beta_7 GBR_{pt} \\ & + \beta_8 GIC_{pt} + \beta_9 ROIG_{pt} + \beta_9 CFSR_{pt} \\ & + \beta_9 NPLG_{pt} + \varepsilon_{pt} \end{aligned} \tag{11}$$

In equation (11), $\beta_4 GF_{pt} \times ER_{pt}$ is the interaction term between GF and environmental regulations [37], [38]. After constructing the CER effect model, this study chose the PSTR model to further analyze the mechanism of action of GFF on CE [39], [40]. As a panel threshold model, PSTR can handle the matter of jumping changes well before and after the threshold value in Hansen's PTR model [41], [42]. The basic formula of PSTR is equation (12).

$$Y_{pt} = ai + \lambda_0 X_{pt} + \sum_{k=1}^{r} \lambda_k X_{pt} G(S_{pt}, \gamma_j, c_j) + \xi_{pt} \tag{12}$$

In equation (12), $G(S_{it}, \gamma_j, c_j)$ is the conversion function. λ is the regression function. k is the number of conversion functions. j is the number of threshold parameters. S_{pt} is the conversion variable. γ is the smoothing transformation parameter of the PSTR model. c is a positional parameter. ξ is a sequence of random interference terms [43], [44]. The expression of the conversion function is equation (13).

$$G(S_{pt}, \gamma_j, c_j) = \left\{ 1 + \exp\left[-\gamma_j \prod_{j=1}^{m} (S_{pt} - c_j) \right] \right\}^{-1} \tag{13}$$

After obtaining the impact mechanism of GF on CE, robustness tests are conducted on the results of the obtained impact mechanism to examine the robustness of the evaluation method and indicator interpretation ability. Firstly, the Solow residual method is used to calculate the total factor productivity of each region, and the function used is equation (14).

$$\Gamma_{pt} = \partial K_{pt}^{\Psi} L_{pt}^{1-\Psi} \tag{14}$$

In equation (14), ∂ represents total factor productivity. K is the capital stock. L represents labor input. Γ is the total output. Ψ is the elasticity of capital output [35]. Next,
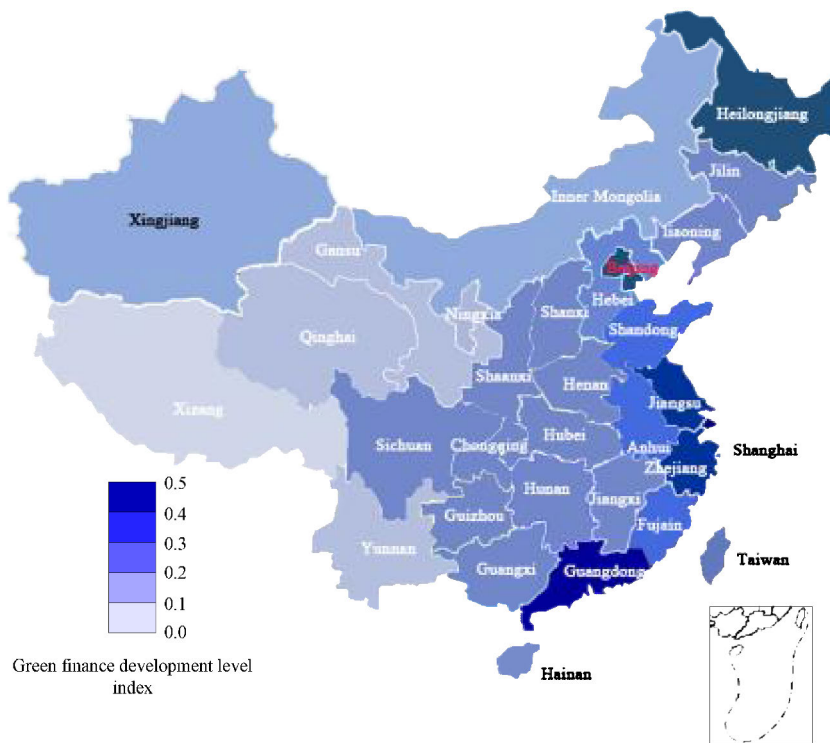
FIGURE 3. Distribution of GFD in each province in 2020.

to establish a econometric model for estimating Ψ, as shown in equation (15).

$$\ln \frac{\Gamma_{pt}}{L_{pt}} = \ln \partial + \Psi \ln \frac{K_{pt}}{L_{pt}} + \xi_{pt} \qquad (15)$$

Through the above steps, this study constructs an EIS for GF based on the analysis of the impact mechanism between GF and CE. A variable table is constructed for the regulatory mechanism of GF on CE, and variables are described and statistically analyzed based on statistical data. Finally, a CER model is constructed based on PSTR to further analyze the mechanism of GF's effect on CE.

IV. THE EFFECT OF GF ON CE UNDER THE CER MODEL
In the results section, empirical analysis is conducted from two aspects. In the first part, the development level of GF (GFD) in China is analyzed based on existing data, followed by BRA and multi-collinearity tests on the constructed variables. In the second part, BRA and robustness tests are conducted on the PSTR model, and transformation analysis is conducted based on the determination of the non-linear relationship between GF and CE.

A. DEVELOPMENT STATUS OF GF REGION AND ITS IMPACT ON CE
Before analyzing the performance of the CER model, first to study the GFD in each region. By studying the models and formulas provided, the GFD of each province and region in 2020 is calculated, and the results are exhibited in Figure 3.

In Figure 2, from a numerical perspective, the GFD in most provinces and cities (Ps/Cs) is between 0.1 and 0.3. Ps/Cs with a level between 0.2 and 0.3 include Sichuan, Chongqing, Guizhou, Shaanxi, Shaanxi, Henan, Hubei, Hunan, Jiangxi, Guangxi, etc. Ps/Cs between 0.1 and 0.2 include Qinghai, Gansu, Yunnan, Inner Mongolia, and Xinjiang. The province below 0.1 is Xizang. Provinces above 0.3 include Guangdong, Fujian, Hainan, Taiwan, Zhejiang, Shanghai, Jiangsu, Shandong, Beijing, Tianjin, Liaoning, Jilin, and Heilongjiang. Among all provinces, Guangdong has the highest GFD at 0.47, followed by Shanghai and Zhejiang. Geographically, the GFD in the eastern is higher than that in the western, while in the southern is higher than northern, and in coastal areas is higher than inland. Next, this study conducts multi-collinearity tests on the constructed control variables to determine whether there is a high degree of correlation between the explanatory variables in the model. Table 6 shows the test results.

When conducting multi-collinearity tests on control variables, the Variance Inflation Factor (VIF) method is used to measure the degree to which the variance of the estimated regression coefficients increases due to collinearity. When VIF is greater than 10, it indicates that there is collinearity between variables. In Table 6, the variable with the smallest VIF value in the control variable is 3.4633, corresponding to the issuance of green bonds. Variables with VIF values between 3 and 5 include NPLG, CFSR, GIC, GBI, and CE. In addition, the VIF values of ROIG, GBR, CEI and GLC variables are greater than 5, indicating that there is a certain

TABLE 6. Multi-collinearity test of control variables.

Variable symbol	VIF	1/VIF
CE	4.4322	0.2256
GLC	5.3568	0.1867
GBI	3.4633	0.2887
CEI	6.5321	0.1531
GLCR	4.3445	0.2302
GBR	7.3522	0.1360
GIC	3.5347	0.2829
ROIG	5.4522	0.1834
CFSR	4.7532	0.2104
NPLG	3.6352	0.2751

degree of correlation between the variables, but the VIF values of all variables are not greater than 10, which means that the model is not seriously affected by multicollinearity [46]. The highest VIF value is 7.3522, which shows a certain correlation, but it is still within the acceptable range [47]. The above results indicate that the model as a whole passes the multicollinearity test. Variables with VIF values above 5 include ROIG, GBR, CEI, and GLC. The above results indicate that the selected control variables all meet the multi-collinearity test. Next, to perform a Levin Lin Chu Test (LLC) on the control variable data to test the stationarity of time series and panel data to avoid the occurrence of "pseudo regression" phenomenon. Table 7 shows the specific results.

In Table 7, all variables are $p < 0.05$, indicating significance and meeting the LLC test. The variables with positive P-values include CE, GLC, GBI, CEI, GLCR, and GBR. The variables with negative P-values are GIC, ROIG, and CFSR. The above results indicate that each variable rejects the null hypothesis, and its panel data has stationarity without unit roots. Table 8 shows the data of the model BRA for the constructed control variable system.

In Table 9, starting from column (1) to the rightmost column represents the result values after adding control variables and conducting regression on the basis of CE2. The first term of CE is positive, and the second term of CE is negative, all of which have passed the significance test. In the control variable section, GLC is all negative, indicating that issuing green credit balance will reduce CE. Among other control variables, variables with negative coefficients and passing significance tests include GBI, CEI, GLCR, ROIG, and CFSR. Therefore, adopting the above activities in GF can effectively reduce CE. In the controlled variables, the coefficient of non-performing loan ratio for green projects is positive, P = 0.0071. Through significance testing, it is shown that increasing the non-performing loan ratio for green projects will increase CE. To ensure the model robustness, this study further conducts robustness analysis, as listed in Table 9.

The first-order terms of CE in Table 9 are all positive, while the second-order terms of CE are all negative and significant,

indicating that the model is robust. By analyzing the positive and negative values and significance of the coefficients that replace the dependent variable and shorten the sample time window, the relationship between the corresponding indicator and CE can also be determined. Among them, the coefficients of NPLG are all positive, while other indicators are negative. Therefore, an increase in NPLG will further increase CE.

B. ANALYSIS OF PSTR MODEL VALIDATION RESULTS
The constructed GF variables passes BRA and robustness analysis, followed by non-linear testing of the constructed PSTR model. Table 10 shows the test results when the number of parameters m at different positions is 1 and 2, respectively.

In Table 10, when m is 1, the values of each variable are within 100, and the P-values are all less than 1%, so the original hypothesis should be rejected. When m is 2, the values of each variable are also within 100, and the P-values are all less than 1%, indicating significance. There is a non-linear relationship between GF and CE. Table 11 presents the balance transformation analysis of the sub-technique of the PSTR model.

In Table 11, the position parameter of the model is 6.3673. All variables passes the test with t<10%. Among the variables that effectively reduce CE, GBR has the greatest overall impact, reaching −1.7202, followed by ROIG, GLC, GBI, and CFSR. The increase in NPLG will also affect the increase in CE. When NPLG increases by one unit, CE will increase by 4.4813 units. Table 12 shows the regression analysis results of the moderation model after incorporating the interaction term between environmental regulations and GF.

In Table 12, the interaction term between GF and environmental regulations has a negative coefficient at a 10% significance level, indicating that the addition of environmental regulations can promote the reduction of CE. The analysis of the coefficient value changes shows that under the influence of the interaction term between GF and environmental regulations, the inhibitory effect of GF indicators on CE has increased. Finally, based on the robustness test of the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method, the transformation function diagram of the model can be obtained, as shown in Figure 4.

In Figure 4, compared to the original model, the transformation function graph results of the current model are basically consistent. When the SER value is within 5, the G of the original and the current model are within 0.1. As the SER value increases, the G value of the model rapidly increases. When the SER value is 14, the G values of the two models approach 1.0. From the above results analysis, the constructed PSTR has robustness, and GF has a certain regulatory effect on CE.

V. MANAGERIAL AND POLICY IMPLICATIONS
Through the empirical analysis of the effect of green finance on carbon emissions under the carbon emission regulation model, the following five important management implications and policy implications are obtained. First, there are

TABLE 7. LLC test results.

Variable symbol	Statistic	p-value	Stationarity
CE	380	0.0453	Smooth and steady
GLC	380	0.0342	Smooth and steady
GBI	380	0.0346	Smooth and steady
CEI	380	0.0456	Smooth and steady
GLCR	380	0.0478	Smooth and steady
GBR	380	0.0356	Smooth and steady
GIC	380	0.0387	Smooth and steady
ROIG	380	0.0491	Smooth and steady
CFSR	380	0.0342	Smooth and steady
NPLG	380	0.0441	Smooth and steady

TABLE 8. Baseline regression analysis of control variable model.

Variable symbol	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
CE	11.3421***	13.2434***	13.3212***	13.3522***	15.3224***	13.8624***	13.6642*	12.4532***	17.4524***	13.8652***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
CE2	-12.3422***	11.3422***	11.8965***	15.5633***	11.7864***	15.6754***	-13.5432*	14.5643***	14.6432***	12.5632***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
GLC	-1.3232***	-0.2321***	-1.4321***	-0.3492**	-0.4431**	-0.4711	1.3221***	-0.3321***	-0.1342***	-1.9325***
	(0.0312)	(0.0122)	(0.0023)	(0.0312)	(0.043)	(0.0362)	(0.0023)	(0.0142)	(0.0042)	(0.0034)
GBI	-	-0.0422***	-0.4254***	-0.5326***	-0.0435***	-0.6432***	-0.0536**	-0.0432***	-0.5456***	-0.5463***
		(0.0122)	(0.021)	(0.0435)	(-0.6643)	(0.5463)	(0.0532)	(0.3555)	(0.5343)	(0.6432)
CEI	-	-	-0.3153***	-0.3984***	-0.0435**	0.6463***	0.6463***	-0.0656*	0.04535***	0.0544***
			(0.0053)	(0.0532)	(0.5463)	(-0.4324)	(-0.6433)	(-0.5363)	(-0.6533)	(-0.6643)
GLCR	-	-	-	-	-0.0435	-0.5322	0.6332	-0.3924**	-0.0532	-0.6424
					(0.5452)	(-0.5462)	(0.0093)	(0.5437)	(-0.3241)	(-0.874)
GBR	-	-	-	-	-	-0.0435*	0.5322*	0.6332	-0.3924	0.0532***
						(0.5452)	(-0.5462)	(0.0093)	(0.5437)	(-0.3241)
GIC	-	-	-	-	-	-	0.0435**	-0.5322***	0.6332***	-0.3924***
							(0.5452)	(-0.5462)	(0.0093)	(0.5437)
ROIG	-	-	-	-	-	-	-	-0.0435***	0.5322***	-0.6332***
								(0.5452)	(-0.5462)	(0.0093)
CFSR	-	-	-	-	-	-	-	-	-0.0435***	-0.5322***
									(0.5452)	(-0.5462)
NPLG	-	-	-	-	-	-	-	-	-	0.8761***
										(0.0071)
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-number	63.5533	73.5352	60.3242	80.2452	103.4222	120.4324	80.4212	169.5356	215.7422	224.4522
Observed number	380	380	380	380	380	380	380	380	380	380

Note: The values in parentheses in the table are P values. "* * *" represents 10% significance, "* *" indicates 5% significance, and "*" denotes 1% significance.

significant differences in the development level of green finance among different regions. Therefore, regional characteristics must be fully considered when promoting green finance. The eastern region has a relatively high level of green finance development, and should continue to strengthen innovation and play an exemplary and leading role. The

TABLE 9. Robustness analysis of the model.

Variable symbol	Replace the explained variable		Shorten the sample time window	
	Reference regression	Regulating effect	Reference regression	Regulating effect
CE	2.4341*** (0.0002)	2.3213*** (0.0001)	2.4023*** (0.0023)	2.3432** (0.0005)
CE2	2.4341*** (0.0002)	2.3213*** (0.0001)	2.4023*** (0.0023)	2.3432** (0.0005)
GLC	-0.2312** (0.0046)	-0.2533*** (0.0024)	-1.0253*** (0.0356)	-1.0356*** (0.0342)
GBI	-0.0134*** (0.0013)	-0.0575*** (0.0021)	-1.0353*** (0.0032)	-2.0432*** (0.0023)
CEI	-1.0043** (0.0032)	-1.0242*** (0.0034)	-2.0223*** (0.0034)	-3.0003* (0.0002)
GLCR	-0.2322* (0.0025)	-0.2567*** (0.0046)	-0.2341** (0.0003)	-0.3532*** (0.0021)
GBR	-1.0344*** (0.0018)	-1.1673 (0.0032)	-1.0214** (0.0006)	-0.2234*** (0.0017)
GIC	-2.4563 (0.0074)	-2.5322 (0.0024)	-0.5432 (0.0018)	-0.5621 (0.0001)
ROIG	-1.8542 (0.0019)	-1.9543 (0.0018)	-1.0223 (0.0002)	-1.0223 (0.0002)
CFSR	-1.0542 (0.0001)	-1.0684 (0.0016)	-2.5328 (0.0002)	-2.6542 (0.0086)
NPLG	1.7434 (0.0002)	1.7242 (0.0046)	1.6432 (0.0043)	1.5654 (0.0075)
Fixed effect	Yes	Yes	Yes	Yes
F-number	12.4367	11.5373	5.7432	4.6328
Observed number	380	380	380	380

TABLE 10. Nonlinearity test of PSTR model.

Variable symbol	m=1		m=2	
	Value	P	Value	P
CE	70.3892	0.0002	82.4786	0.0001
CE2	87.3242	0.0001	83.2452	0.0001
GLC	78.2334	0.0003	89.9137	0.0001
GBI	44.2454	0.0007	83.1478	0.0001
CEI	57.8763	0.0006	72.7865	0.0003
GLCR	78.4352	0.0002	78.8654	0.0003
GBR	75.7362	0.0002	35.2478	0.0008
GIC	24.2453	0.0009	76.5649	0.0003
ROIG	58.3597	0.0006	89.3268	0.0001
CFSR	98.2478	0.0000	78.3264	0.0002
NPLG	92.8726	0.0000	87.2367	0.0001

central and western regions need to increase policy support to improve the development speed and quality of green finance. In addition, when promoting green finance, financial institutions should strictly control the non-performing loan rate of green projects to reduce financial risks and avoid the negative impact of non-performing loans on carbon emissions. Second, the government should formulate differentiated green finance policies to adapt to the actual situation in different regions. For regions with a high level of green finance development, the government can encourage financial institutions to carry out more diversified green finance businesses, such as green bonds and green funds, to meet market demand. For regions with a lower level of development, the government should provide preferential fiscal and tax policies and guide financial institutions to increase investment in green finance in the region. Third,

TABLE 11. Analysis of fitting results of PSTR model.

Variable symbol	linearity	Nonlinearity	Total influence
GLC	2.0242***	-3.2453***	-1.2211***
	(0.0235)	(0.0289)	(0.0345)
GBI	1.2345**	-2.3532***	-1.1187***
	(0.0024)	(0.0436)	(0.0024)
CEI	2.3425	-3.4621**	-1.1196
	(0.0053)	(0.0293)	(0.0032)
GLCR	2.5748*	-3.5322***	-0.9574***
	(0.0245)	(0.0434)	(0.0935)
GBR	1.3578***	-3.4622	-2.1044
	(0.0924)	(0.0792)	(0.0034)
GIC	1.7433	-3.4635*	-1.7202**
	(0.0025)	(0.0032)	(0.0032)
ROIG	2.3535	-3.1256***	-0.7721**
	(0.0036)	(0.0042)	(0.0024)
CFSR	1.3467***	-2.3533***	-1.0066***
	(0.0046)	(0.0054)	(0.0024)
NPLG	1.2467***	3.2346**	4.4813***
	(0.0546)	(0.0035)	(0.0584)
cNPLG	2.5356		
r	6.3673		
AIC	-4.7854		
BIC	-5.6743		
RSS	2.5437		

Note: The value of t is the numerical value in parentheses. "* * *, * *, *" indicate significance of 10%, 5%, and 1%.

TABLE 12. Regression analysis.

variable	Coefficient value	T-value	P-value
GF*ER	-0.2355*	0.2452	0.0134
GLC	-1.2455**	0.2562	0.0154
GBI	-2.3455	-2.2451	0.0427
CEI	-0.2245	0.1452	0.0074
GLCR	-1.8214***	0.2582	0.0021
GBR	-1.6477	0.4356	0.0032
GIC	-5.3567***	0.8823	0.0002
ROIG	-0.8235***	0.1456	0.0235
CFSR	-4.3567	0.2145	0.0217
NPLG	2.2456***	0.2456	0.0253
Fixed effect	Controls	Controls	Controls
Individual fixation	Controls	Controls	Controls
Fixed time	Out of control	Out of control	Out of control
R2	0.4351		
F	4.5362		
Observed number	380		

the government should strengthen the regulation of green finance to ensure that it truly serves green and low-carbon development. This includes establishing a sound regulatory system for green finance, formulating clear standards and evaluation methods for green finance, and strengthening audit and information disclosure of green finance businesses. Fourth, the government should also strengthen the popularization and promotion of the concept of green finance, and improve the environmental awareness of the public and enterprises. Through publicity, education, training and seminars, more people can understand the importance and necessity of green finance, so as to form a good atmosphere for the whole society to participate in green finance. Fifth, the government should strengthen communication and cooperation with financial institutions, enterprises and other parties to jointly promote the development of green finance. The government can build a green finance cooperation platform, promote information sharing and resource integration,
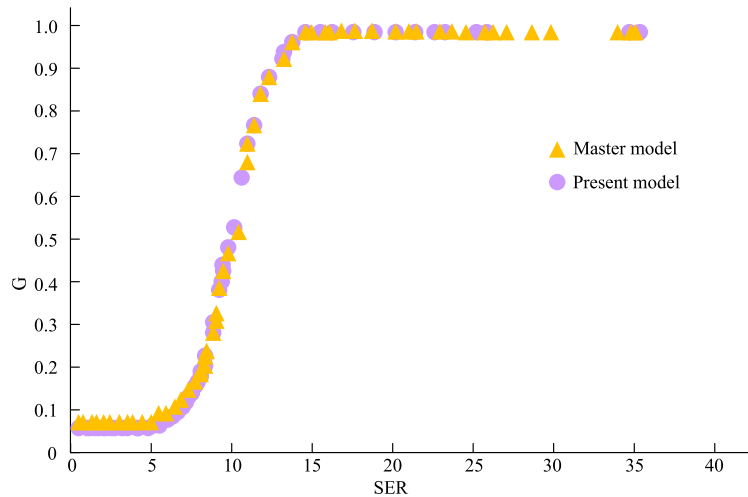
FIGURE 4. Conversion function diagram.

and provide strong support for the development of green finance.

VI. CONCLUSION

To clarify the key role of GFF in CER, this study constructed a CER model considering GFF in the context of CN. Empirical analysis showed that in the GF level analysis, Ps/Cs with GFDs ranging from 0.1 to 0.2 included Qinghai, Gansu, Yunnan, Inner Mongolia, and Xinjiang. The province below 0.1 was Xizang. Provinces above 0.3 included Guangdong, Fujian, Hainan, Taiwan, Zhejiang, Shanghai, Jiangsu, Shandong, Beijing, Tianjin, Liaoning, Jilin, and Heilongjiang. The GFD in coastal areas was higher than that in inland areas. In the LLC test results, the P-values of each variable were all less than 0.05, indicating significance and meeting the LLC test. The variables with positive P-values included CE, GLC, GBI, CEI, GLCR, and GBR. In the PSTR model testing, when analyzing the moderating model constructed in the study, when m = 1, the values of each variable were within 100, and the P-values were all less than 1%, the null hypothesis should be rejected. When m = 2, the values of each variable were also within 100, and the P-values were all less than 1%, indicating significance. From the above results, there was a nonlinear relationship between GF and CE. In the equilibrium transformation analysis, all variables passed the test with t < 10%. The variable with the greatest overall impact on reducing CE was GBR, with a total impact of -1.7202, followed by ROIG, GLC, GBI, and CFSR. From the above analysis, the constructed CER model can predict the regulatory changes of GF on CE. In the context of carbon neutrality, this study constructs a carbon emission regulation model that considers green finance factors for the first time, providing a new perspective and tool for understanding and predicting the regulatory role of green finance on carbon emissions. Specific contributions mainly include the following four points:

1. A comprehensive carbon emission regulation model is constructed by integrating green finance factors. This model not only deepens the understanding of the relationship between green finance and carbon emissions, but also provides policy makers with a new way to analyze and predict carbon emission trends.

2. Through empirical analysis, the research reveals in detail the differences in the development level of green finance in different provinces and cities, and how these differences affect carbon emissions. These findings have important reference value for the formulation of regional green finance and carbon emission policies.

3. Through the test of PSTR model, it is found that there is a nonlinear relationship between green finance and carbon emissions, which enricies the understanding of the dynamic relationship between green finance and carbon emissions, and also provides new ideas for further theoretical and empirical research.

4. Through equilibrium transformation analysis, the study identifies the key factors influencing carbon emissions and quantifies their influence. This will help policymakers to formulate emission reduction strategies more precisely.

Although this study has contributed in many ways, there are still some limitations, which also point the way for future research. First of all, the study mainly focuses on the impact of green finance on carbon emissions, without considering other possible factors, such as technological progress and industrial structure changes. These factors may also have an important impact on carbon emissions and deserve further study in the future. Second, although the research reveals the differences in the development level of green finance in different provinces and cities, the reasons behind these differences are not deeply explored. Future studies can further analyze how regional, economic, policy and other factors affect the development of green finance and its regulatory effect on carbon emissions. However, while the current model takes green finance into account, it is still possible to improve the accuracy and comprehensiveness of the forecasts by including more variables or improving the model structure. Finally, the study mainly analyzes the regulation of carbon

emissions from the perspective of green finance. In the future, comprehensive analysis can be carried out from multiple dimensions such as economy, society and environment to understand the influencing factors and regulation mechanism of carbon emissions more comprehensively.

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