Research on Carbon Emission Benchmark Regression Analysis Based on Spatial Durbin Model

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Abstract. The study presents a comprehensive analysis of the impact of green finance on carbon emissions in China, utilizing the Spatial Durbin Model (SDM) to account for spatial autocorrelation and spillover effects. By constructing a spatial panel data set that includes variables such as green credit, investment, and insurance, alongside provincial carbon emissions data, the research reveals that green finance significantly reduces carbon emissions both directly within provinces and indirectly through neighboring effects. The findings suggest that enhancing green finance initiatives can play a crucial role in China's carbon mitigation strategies. This work not only contributes to the understanding of green finance's role in environmental sustainability but also provides empirical evidence supporting policy formulations aimed at reducing carbon emissions.

Keywords: Spatial Durbin Modelling, Carbon Emissions, Regression Analysis, Weights-Topsis

1 Introduction

Amidst growing concerns over climate change, green finance has been identified as a key mechanism to reduce carbon emissions by channeling investments into environmentally sustainable projects. Recent research has increasingly focused on quantifying the impact of green financial mechanisms on carbon emission levels, employing various econometric models to capture the intricate relationships between financial practices and environmental outcomes. Despite these efforts, the spatial dimension of carbon emissions—an aspect critical to understanding regional disparities and spillover effects—has received relatively less attention. The spatial distribution of economic activities and environmental practices across provinces in China presents a complex landscape for the analysis of green finance's impact on carbon emissions.

This study leverages the Spatial Durbin Model (SDM) to examine both the direct and indirect effects of green finance on carbon emissions across Chinese provinces, considering the spatial interconnections between regions. By constructing a comprehensive spatial panel dataset, including variables for green credit, securities, insurance, investment, and carbon finance, this research uncovers that green finance significantly lowers carbon emissions within and across provinces. These findings underscore the importance of cross-regional cooperation and policy integration to enhance the efficacy of green finance in China's environmental strategy. This

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paper contributes to the understanding of the spatial effects of green finance on carbon emissions, offering insights for policymakers to craft more effective environmental policies that leverage the financial sector towards achieving China's sustainability goals.

2 Related works

In the literature review of green finance's impact on carbon emissions, several recent studies have contributed valuable insights: Tabash and Al-Absy [1] explored the European carbon emission trading markets and their influence on financial market returns. Their research indicated that investments focused on green energy could significantly reduce carbon risks, highlighting a vital link between financial markets and environmental sustainability. Meesaala and Mohammadi [2] conducted a systematic literature review on green finance within the MENA region. They found that green finance plays a crucial role in supporting industries with lower carbon emissions, underlining the importance of financial aid in environmental improvement efforts. Liu et al. [3] investigated how economic policy uncertainty affects carbon emissions among Chinese exporters. Their findings reveal that green finance policies are instrumental in mitigating emissions, especially in regions with economic disparities. Ren et al. [4] examined the impact of green finance on agricultural carbon efficiency in China through a quasi-experimental approach. They demonstrated that green finance significantly enhances carbon efficiency, suggesting a promising avenue for reducing agricultural carbon emissions. András and Holczinger [5] analyzed the effectiveness of preferential capital requirements for green lending, showing how such financial policies encourage investments in projects and technologies that aim to reduce carbon emissions, thereby fostering a transition towards a more sustainable economy. Furthermore, forecasting methods have applications in multiple fields [6-7]. Some scholars use prediction methods to deal with carbon emissions. Gao et al. [8] introduced a fractional grey Riccati model (FGRM(1,1)) for CO2 emission forecasting. This model enhanced prediction accuracy and provide valuable insights for atmospheric environmental governance and sustainable development, addressing gaps in modeling mechanisms present in previous studies. Together, these studies underscore the multifaceted role of green finance in reducing carbon emissions across different regions and sectors, from the financial markets of Europe to the agricultural fields of China, and the innovative landscapes of BRICS countries. They collectively affirm the critical importance of integrating financial policies with environmental objectives to achieve a sustainable future.

3 Model

3.1 Methodology for measuring indicators

3.1.1 Data positivity

Considering that only very small data need to be processed into very large data in this paper, only very small data are presented here: $\overline{x_i} = max(x) - x_i$.

3.1.2 Data normalization

In order to eliminate the effect of different magnitudes, the data also need to be standardized. If all the data are greater than or equal to 0 after standardization, then the equation can be used for standardization: $z_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}}$.

If after the standardization cannot guarantee that all the numbers are greater than or equal to 0, it is necessary to standardize with the following formula (the way of internalization, which will be controlled in the range of 0 to 1), due to the indicators in this paper each year there are values equal to 0, so they are all using the following data standardization method for data processing: $z_{ij} = \frac{x_{ij} - min\{x_{1j}, x_{2j}, \cdots, x_{nj}\}}{max\{x_{1j}, x_{2j}, \cdots, x_{nj}\} - min\{x_{1j}, x_{2j}, \cdots, x_{nj}\}}$.

3.1.3 Entropy weighting method to calculate weights

(1) Normalization is performed and the probability matrix P is calculated: $P_{ij} = \frac{z_{ij}}{\sum_{i=1}^{n} z_{ij}}$.

(2) Calculate the information entropy of each indicator:

The information entropy is related to the uncertainty of the data, if the degree of data fluctuation is large, its information entropy value is large, and conversely if the degree of data fluctuation is small, its information entropy value is small. As there may be values of 0 in the probability matrix, because ln(0) is infinite, this paper sets ln(0) to 0. $e_j = -\frac{1}{ln(n)} * \sum_{i=1}^{n} \left(p_{ij} ln(p_{ij})\right)$

(3) Calculate the information utility value as well as entropy weight calculation: $d_j = 1 - e_j$, $w_j = \frac{d_j}{\sum_{j=1}^{m} d_j}$

(4) Improvement by adding preference coefficients

Based on the entropy weight-Topsis method, a subjective factor, the preference coefficient, was introduced to combine subjective and objective weight calculations. In this study, we synthesized a large amount of information and assigned a corresponding preference coefficient H_j to each indicator based on the importance and relevant characteristics of the indicator. Similar considerations were made for the other indicators, and the preference coefficients were finally determined.

(5) Calculate optimal and worst distances

Define the maximum value: $Z^+ = \left(max(z_{11}, z_{21}, \cdots, z_{n1}), max(z_{12}, z_{22}, \cdots, z_{n2}), \cdots, max(z_{1m}, z_{2m}, \cdots, z_{nm})\right)$.

Define the minimum value: $Z^- = \left(min(z_{11}, z_{21}, \cdots, z_{n1}), min(z_{12}, z_{22}, \cdots, z_{n2}), \cdots, min(z_{1m}, z_{2m}, \cdots, z_{nm})\right)$.

Define the distance between the ith (i=1,2,⋯,n) evaluation object and the maximum value: $D_i^+ = \sqrt{\sum_{j=1}^{m} W_j * H_j * (Z_j^+ - z_{ij})^2}$.

Define the distance between the ith (i=1,2,⋯,n) evaluation object and the minimum value: $D_i^- = \sqrt{\sum_{j=1}^{m} W_j * H_j * (Z_j^- - z_{ij})^2}$.

It should be noted here that $W_j * H_j$ needs to be renormalised, and the steps are consistent with the algorithm for entropy weight normalisation.

(6) Calculate the unnormalized index as well as the normalized index

Unnormalized index: $S_i = \frac{D_i^-}{D_i^- + D_i^+}$. Normalized indices: $S = \frac{S_j}{\sum_{i=1}^{m} S_j}$.

Finally, the normalization index is then ranked to get the final result.

3.2 Benchmark regression analysis of the impact of green finance on carbon emissions

3.2.1 Description of variables

Most of the variables are obtained by formulae, and the data required for the calculations are obtained from the WIND database, the IFIND platform, and the statistical yearbooks of the National Bureau of Statistics and the provinces. The specific definitions are shown in Table 1:

Table 1. Description of variables

Type of variable	Variable Name	Variable symbol	Variable Definition
Explained Variables	Carbon Emission Intensity	CEI	Calculated
Core Explanatory Variables	Green Finance Development Index	GFI	Calculated
Explanatory Variables	Urbanisation Level	UR	Urban population/total population
	Foreign Trade Level	FT	Total import and export trade of each province/GDP
	Level of Foreign Direct Investment	FDI	Foreign direct investment/GDP
	R&D Expenditure	R&D	R&D expenditure by province/GDP
	Population Density	PD	Population per square kilometre
	Fiscal decentralisation	FD	Real per capita local financial expenditure in each region / Real per capita financial expenditure at the central level
	Energy structure	ERS	Coal energy consumption / Total energy consumption
	Economic growth	PCG	GDP per capita

3.2.2 Spatial autocorrelation test

(1) Spatial weight matrix construction

The spatial weight matrix W can reflect the spatial relationship of different individuals, and its size can reflect the strength of the spatial dependence, which has four specific forms:

a. Neighbourhood matrix

According to the rook adjacency principle (two adjacent regions have a common edge), the weights are set based on whether the provinces and cities are geographically adjacent to each other. $W_{ij} = \begin{cases} 1 & i\ is\ adjacent\ to\ j \\ 0 & other\ cases \end{cases}$.

b. Geographic distance matrix

The narrow distance usually refers to the distance between the centre of mass of two regions or the distance between administrative centres, which is constructed in the form shown in the following equation: $W_{ij} = \begin{cases} \frac{1}{d_{ij}} & i \neq j \\ 0 & i = j \end{cases}$, where d_{ij} is the spherical geographic distance between the administrative centres of region i and region j, which is obtained based on the measurement of latitude and longitude data.

c. Economic distance matrix

An economic distance matrix is a data structure used to measure economic linkages or similarities between different locations in economic space. In this paper, the economic distance between regions is measured by the difference in GDP per capita, and the economic distance matrix is constructed as in the following equation: $W_{ij} = \begin{cases} \frac{1}{|\overline{y_i} - \overline{y_j}|} & i \neq j \\ 0 & i = j \end{cases}$, where (y_i)¯and (y_j)¯denote the average GDP per capita of region i and region j, respectively, over the period 2007-2022.

d. Economic Geography Matrix

An economic geography matrix is a specific type of spatial weight matrix that combines information on geographic distances and economic linkages. It is constructed in the following equation: $W_{ij} = \begin{cases} \frac{1}{d_{ij} \times |\overline{y_i} - \overline{y_j}|} & i \neq j \\ 0 & i = j \end{cases}$.

(2) Moran index measurement

The Moran Index reflects the degree of similarity or strength of correlation between the carbon emission intensity of spatially adjacent regions.

a. Global Moran index test

Global spatial autocorrelation was performed with the global Moran index. The value of Moran index is distributed in [-1,1], when Moran index is greater than 0, it means that the carbon emission intensity of the global province has a spatial positive correlation, and the larger the carbon emission intensity the greater the possibility of agglomeration; when Moran index is less than 0, it means that the carbon emission intensity of the global province has a spatial negative correlation, and the larger the carbon emission intensity the lower the possibility of agglomeration; when Moran index is close to 0, it means that the carbon emission intensity of the global province has a spatial negative correlation, and the larger the carbon emission intensity the smaller the possibility of agglomeration; when Moran index is near to 0, it means that the global provincial carbon emission intensity has spatial randomness.

The definition formula of the global Moran index is: $I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W^*{}_{ij}(x_i-\bar{x})(x_j-\bar{x})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}}, S^2 = \frac{\sum_{i=1}^{n}(x_j-\bar{x})^2}{n}$, where n is the total number of spatial units, x_i or x_j denotes the carbon emission intensity of the ith or jth spatial unit, $W^*{}_{ij}$ denotes the spatial weight, and S^2 denotes the sample variance [7]. Time-series change of the All-area Moran Index of carbon emission intensity in China's provinces is shown in Figure 1. Its horizontal axis represents time. Its vertical axis represents the all-area Moran Index of carbon emission intensity The partial results of the global Moran index are shown in Table 2.

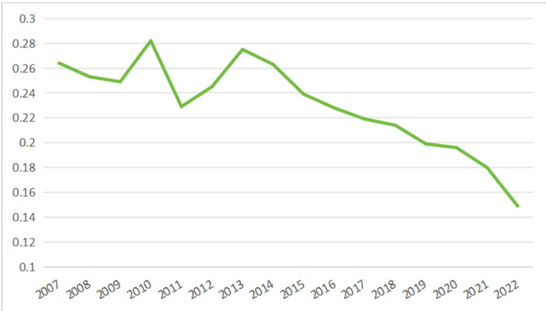

Figure 1. Time-series change of the All-area Moran Index of carbon emission intensity in China's provinces, 2007-2022

Table 2. Provincial Carbon Emission Intensity Regional Moran Index

Year	Adjacency matrix	Geographical distance matrix	Economic distance matrix	Economic geography matrix
2019	0.199**	0.030**	0.041	0.121*
2020	0.196**	0.028**	0.054	0.133*
2021	0.180**	0.015*	0.037	0.108*
2022	0.149**	0.003	0.032	0.083

P <0.01***, P<0.05**, P<0.1*

b. Local Moran index test

The local Moran index test is used to test the local spatial autocorrelation of provincial carbon emission intensity to judge the high and low situation of a province's carbon emission intensity with the average level of carbon emission intensity of the neighbouring regions, and the calculation formula of the local Moran index is: $I_i = \frac{(x_i-\bar{x})}{S^2}\sum_{j=1}^{n} W_{ij}(x_j-\bar{x})$, where is the total number of spatial units, or denotes the carbon emission intensity of the first or second spatial unit, denotes the spatial weight, and denotes the sample variance [9].

If the local Moran's index is positive, it means that there is a high and high concentration or low and low concentration of carbon emission intensity between the province and its neighbouring regions; while if the local Moran's index is negative, it means that there is a high low concentration or low high concentration of carbon emission intensity between the province and its neighbouring regions [10].

In addition, the local spatial correlation can be demonstrated by Moran scatterplot. The Moran scatterplot is divided into four quadrants, from the top right to the bottom right for quadrants one, two, three, and four, respectively, which denote high and high agglomeration (HH), low and high agglomeration (LH), low and low agglomeration (LL), and high and low agglomeration (HL), in that order.

Figures 2 and 3 show the scatter plots of Moran index based on the neighbourhood matrix and geographic distance matrix of carbon emission intensity data, respectively, and the plotting time is selected as 2007 and 2022. It can be found that in both 2007 and 2022, 60% of the provinces fall in the first and third quadrants based on either the adjacency matrix or the geographic matrix. This is similar to the results of the global Moran index, which confirms the positive spatial correlation of carbon emission intensity among provinces.

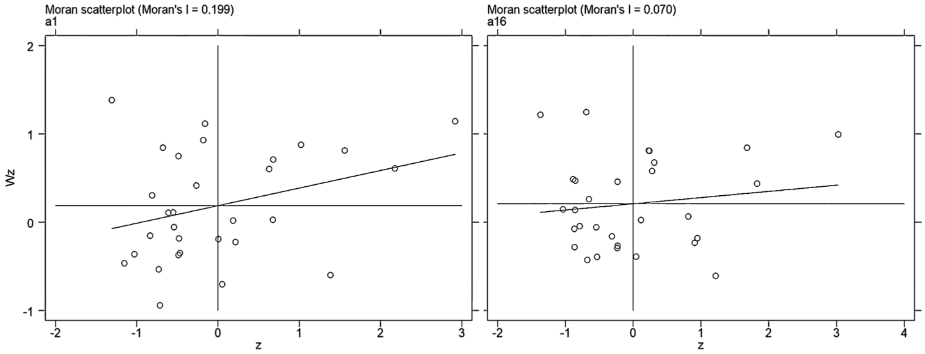

Figure 2. Moran Scatterplot of Carbon Emission Intensity Based on Neighbourhood Matrix, 2007 vs. 2022

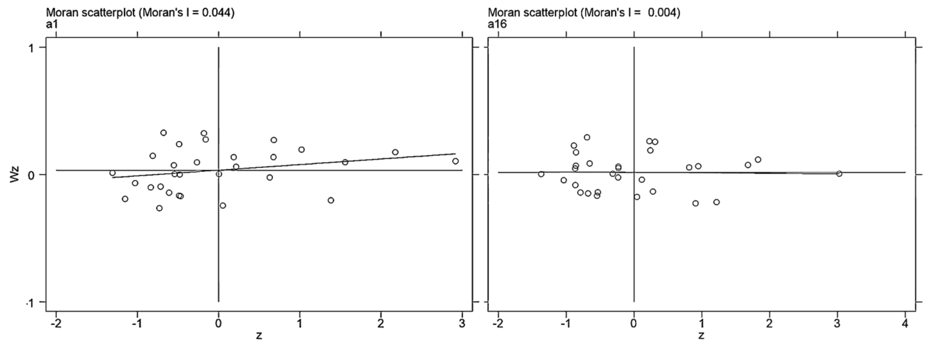

Figure 3. Moran scatter plot of carbon emission intensity based on geographic distance matrix, 2007 and 2022

3.2.3 Driving mechanism analysis based on spatial Durbin model

(1) Spatial panel model construction

The spatial Durbin model, the spatial autoregressive model, and the spatial error model are the three most commonly used spatial panel econometric models. The general measurement equation of the spatial panel measurement model is $Y_{it} = \alpha I_k + \rho W Y_{it} + \beta X_{it} + \theta W X_{it} + \varepsilon_{it}$, $\varepsilon_{it} = \sigma W \varepsilon_t + \phi_{it}$.

Y_{it} is the explanatory variable, X_{it} is the explanatory variable, α is a constant, I_k is the unit matrix, the coefficient β reflects the effect of the explanatory variable on the explanatory variable, the parameters ρ, θ, and σ are the spatial autoregressive coefficients of each term, W is the spatial weight matrix, and ε_{it} is the stochastic error term. the values of ρ, θ, and σ determine the general form of the spatial panel econometric model reduces to which specific model, such as when ρ, θ is not 0 and σ is 0, it reduces to the spatial Durbin model (SDM).

(2) Model testing

By calculating the Lagrange multipliers (LM and Robust LM), the LM test results are shown in Table 3. The test results show that LM-error and LM-lag are significant at 99% confidence level, while Robust LM-error has a p-value greater than 0.1 and fails the significance test. It indicates that it is more appropriate to choose the spatial lag model in the LM test.

Table 3. LM test results

Test	test value	p-value
Moran's I	4.752	0.000
LM-error	21.152	0.000
Robust LM-error	0.639	0.151
LM-lag	28.695	0.000
Robust LM-lag	8.183	0.089

Table 4. Wald test and LR test results

Test method	original hypothesis	statistic	p-value
Wald-SAR	SDM translatable to SAR	30.16	0.0002
Wald-SEM	SDM translatable to SEM	71.96	0.0000
LR-SAR	SDM translatable to SAR	42.52	0.0000
LR-SEM	SDM translatable to SEM	67.17	0.0000

Through the Hausman test, the test results are shown in Table 5: should be selected random effects model or fixed effects model, according to the results, the statistic is 9.74, at the 99.9% confidence level through the test, where the selection of random effects model does not meet the requirements, and therefore the selection of fixed effects model.

Table 5. Hausman test results

Test Method	Statistic	p-value
Hausman test	9.74	0.0004

In order to make the results more accurate, this paper further conducts Wald test and LR test, the results are shown in Table 4.

With individual fixed effects, the Wald test and LR test rejected the original hypothesis, indicating that the spatial Durbin model refused to degenerate into SEM or SAR, and that the spatial Durbin model (SEM) was chosen as the most appropriate, followed by further confirmation of the use of time fixed effects and regression to produce the final results.

4 Experiment and result

4.1 Data

The dataset used in this paper covers five dimensions: green credit, green securities, green insurance, green investment and carbon finance, and the specific data include the proportion of green credit scale, the proportion of interest expenses of the six high-energy-consuming industries, and the proportion of market capitalisation of environmentally friendly enterprises, etc. The data are mainly obtained from the social responsibility reports of the major banks, their financial annual reports, the database of the Choice Financial Terminal, and the "Social Responsibility Report of the Banking Industry" published by the China Association of the Banking Industry. Banking Industry Social Responsibility Report", etc. The dataset also includes data on carbon emissions, which are estimated based on the energy consumption structure and carbon emission coefficients of each province. The raw data include coal, oil and natural gas consumption of each province, etc., which are sourced from China Energy Statistics Yearbook, China Statistics Yearbook, and relevant reports such as average carbon dioxide emission coefficients of unit power supply of the provincial power grids. In addition, the dataset includes other relevant economic and social indicators, such as gross regional product (GDP), population density, urbanisation level, etc., which are mainly sourced from the National Bureau of Statistics (NBS) and other officially released statistics.

Comprehensive analyses of these data help assess the impact of green finance on provincial carbon emissions and provide a scientific basis for the formulation of relevant policies.

4.2 Regression results

In this paper, a series of tests determined that the most suitable for this study is the spatial Durbin model with fixed effects, and the following table reports the regression results based on the three spatial weighting matrices (neighbourhood matrix, geographic distance matrix, and economic geography matrix), and based on the regression results, we study the impact of green finance on carbon emissions and obtain the conclusions as follows:

In Table 6, column X can be interpreted as the local effect, which indicates the impact of local explanatory variables on local carbon emission intensity, while column WX is the spatial spillover effect, which indicates the impact of explanatory variables in the neighbouring regions on local carbon emission intensity.

Table 6. Spatial Durbin model regression results based on different spatial weight matrices

Variables	Adjacency matrix		Geographic distance matrix		Economic geography matrix	
	X	WX	X	WX	X	WX
lnGFI	-0.264*** (-2.57)	-0.125* (-1.74)	-0.159** (-1.77)	-1.010 (1.48)	-0.466*** (-3.87)	-1.158*** (-3.81)
UR	0.426* (-1.68)	-2.423** (-2.80)	1.543*** (-4.11)	9.282*** (4.45)	0.727* (1.89)	1.417 (1.09)
FT	1.152*** (10.39)	-0.656*** (-3.78)	1.034*** (12.57)	-4.145*** (-6.88)	0.770*** (7.73)	-0.977*** (-3.44)
FDI	-0.080* (1.80)	14.134*** (4.67)	-4.863*** (-3.76)	44.560*** (5.35)	0.154 (0.12)	14.272*** (3.30)

R&D	27.771*** (5.50)	10.761 (1.21)	22.286*** (5.25)	-130.504*** (-4.29)	33.806*** (6.14)	-39.500*** (-2.80)
lnPD	-0.255*** (-7.95)	0.482*** (7.91)	-0.068*** (-3.02)	1.909*** (9.72)	-0.266*** (-8.51)	0.456*** (5.21)
lnFD	-1.143*** (-10.04)	1.952*** (8.01)	-0.586*** (-6.19)	1.304** (2.22)	-1.449*** (-11.38)	1.825*** (5.37)
ERS	0.972*** (6.75)	2.008*** (5.95)	1.476*** (13.38)	19.170*** (16.65)	2.201*** (13.39)	2.329*** (4.79)
lnPCG	1.440*** (11.70)	-1.010*** (-4.31)	0.894*** (8.35)	-0.623 (0.28)	1.421*** (7.67)	-0.860 (-1.58)
rho	0.221*** (3.56)		0.209*** (-6.66)		0.058*** (3.63)	

Note: Values of Z-statistics corresponding to the regression coefficients are in parentheses; *, **, *** indicate significance at the 10 per cent, 5 per cent and 1 per cent significance levels, respectively.

The results in Table 6 do not fully reflect the impact of green finance and other explanatory variables on carbon emission intensity, nor can they accurately estimate the spatial spillover effect of green finance on carbon emission intensity in the neighbouring provinces, so the total effect is estimated by partial differentiation and decomposed into direct and indirect effects, so as to observe the impacts of the explanatory variables corresponding to the province, the explanatory variables of the neighbouring regions on the intensity of carbon emissions, and to better portray the impact of green finance on carbon emissions. The results are shown in Table 7:

Table 7. Spatial Durbin model decomposition results based on different spatial weight matrices

Variables	Adjacency matrix			Geographic distance matrix			Economic geography matrix		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
lnGFI	-0.270*** (5.19)	-0.216** (2.43)	-0.486 (-1.57)	-0.213*** (-2.64)	-0.591* (1.86)	-0.805 (1.22)	-0.468*** (6.75)	-0.188*** (-3.75)	-0.656*** (-4.48)
UR	-0.597 (-1.19)	-3.129*** (-2.87)	-3.727*8* (-3.50)	-2.093*** (-4.79)	5.350*** (5.24)	3.256*** (3.97)	0.710 (1.62)	1.366*** (1.05)	2.077* (1.65)
FT	1.143*** (10.82)	-0.048** (-2.25)	0.660*** (2.93)	1.301*** (13.79)	-2.618*** (-8.67)	1.316*** (-4.60)	0.778*** (7.91)	-0.949*** (-2.98)	-0.171 (-0.50)
FDI	-0.701 (0.48)	17.301*** (17.301)	18.002*** (3.59)	-7.224*** (-5.75)	24.226*** (6.60)	17.001*** (4.07)	0.229 (0.18)	14.351*** (3.36)	14.581*** (3.09)
R&D	28.640*** (5.92)	21.234* (1.78)	49.875*** (3.60)	29.606*** (-6.76)	-75.637*** (-4.77)	-46.030*** (-3.05)	33.525*** (6.41)	-38.362*** (-2.68)	-4.837 -0.33)
lnPD	-0.231*** (-7.52)	0.522*** (7.21)	0.290*** (3.91)	-0.160*** (-6.68)	0.947*** (8.72))	0.786*** (7.13)	-0.262*** (-8.25)	0.453*** (5.06)	0.190** (2.15)
lnFD	-1.046*** (-10.05)	2.056*** (6.74)	1.010*** (3.09)	-0.682*** (-7.07)	1.005*** (3.31)	0.322 (1.16)	-1.436*** (-11.69)	1.837*** (5.33)	0.401 (1.15)
ERS	1.094*** (8.03)	2.793*** (7.18)	3.888*** (9.38)	0.672*** (4.65)	8.215*** (10.83)	8.888*** (11.42)	2.218*** (13.61)	2.503*** (4.33)	4.721*** (6.86)
lnPCG	1.402*** (10.76)	-0.841*** (-2.86)	0.560 (-0.98)	0.987*** (8.51)	-0.898*** (-2.92)	0.089 (0.28)	1.421*** (8.42)	-0.832** (-2.43)	0.588* (1.68)

From the decomposition results, it can be seen that under three different spatial weight matrices, the direct effect of the level of green financial development after taking the logarithm are all significantly negative at the 1% level, with coefficients of -0.270, -0.213 and -0.468 in order, which once again indicates that the green finance development can directly reduce the local carbon emissions. In terms of indirect effects, the coefficients of green finance under different weight matrices are all significantly negative, with the coefficients of -0.216, -0.591 and -0.188 in turn, i.e., the green finance development in neighbouring provinces will significantly reduce carbon emissions in the province.

5 Conclusion

This study conclusively demonstrates that green finance significantly reduces carbon emissions in China, both within and across provincial boundaries, underscoring its vital role in advancing the country’s sustainability goals. The application of the Spatial Durbin Model (SDM) has highlighted the direct impact of green finance on lowering emissions within provinces, as well as its indirect, spillover effects on neighboring regions. These findings advocate for the strategic importance of incorporating spatial dynamics into the design and implementation of environmental policies. The research suggests that enhancing green finance mechanisms can serve as a critical lever for China's transition to a low-carbon economy, emphasizing the need for integrated policy efforts that transcend regional divides. As deep learning algorithms continue to advance in classification and prediction tasks [11-12], future research could try to improve the model based on deep learning algorithms and thus solve more practical problems. Future directions should focus on exploring the underlying pathways through which green finance influences environmental outcomes and the interplay with other factors like technological advances and policy frameworks. In essence, this study reinforces the case for robust support and expansion of green finance initiatives, alongside national and provincial policy alignment, to optimize the environmental benefits and propel China towards its carbon reduction targets more effectively.

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