The Energy Conservation and Emission Reduction Effects of Economic Agglomeration: A Spatial Perspective Based on China's Province-level Data

Tianyu Luo (hedwig1016@163.com)
Fudan University https://orcid.org/0000-0001-5536-3886
Hongmin Chen
Fudan University

Research Article

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The Energy Conservation and Emission Reduction Effects of Economic Agglomeration: A spatial perspective based on China's province-level data

Tianyu Luo[1], Hongmin Chen[2]

Abstract

Based on the data of 30 provinces in China from 1995 to 2017, this paper combines exploratory spatial data analysis method, dynamic spatial Durbin model, and intermediary effect model to explore the spatial influence mechanism between economic agglomeration, energy intensity, and carbon emission intensity. The research results provide a basis for China's early realization of energy conservation and emission reduction goals, economical green development, and regional development strategy selection. Firstly, the results show that China's carbon emission intensity has apparent spatial agglomeration and path dependence characteristics. Secondly, the economic agglomeration has the dual effect of energy saving and emission reduction. Furthermore, there is a significant inverted N-curve relationship between economic agglomeration and carbon emission intensity and carbon emissions, and a significant U-shaped curve relationship exists between economic agglomeration and energy intensity. Finally, economic agglomeration can indirectly affect carbon emission intensity through the mediating effect of energy intensity, and there is a significant inverted U-shaped curve relationship between energy intensity and carbon emission intensity. Therefore, promoting mutual coordination of environmental policies and building a regional collaborative governance mechanism is an effective way to achieve a win-win situation for the environment and economy of Beautiful China.

Keywords Carbon emission intensity, Energy intensity, Economic agglomeration, Exploratory spatial data analysis, Spatial Durbin Model

1. Introduction

Against the background of global warming, countries worldwide reduce greenhouse gas emissions through global agreements, and China is facing tremendous pressure to reduce carbon dioxide emissions. In 2020, China clearly stated at the United Nations General Assembly that carbon dioxide emissions should peak before 2030 and strive to achieve carbon neutrality by 2060. The carbon emission intensity index reflects the carbon emission efficiency in economic development, that is, the carbon dioxide emission caused by unit GDP growth. At present, the research on carbon emissions has been relatively sufficient, and the intensity of carbon emissions can better reflect the cost of carbon emissions (Shao et al., 2018; Zhou et al., 2018). Therefore, it is essential to study China's carbon emissions by paying attention to China's carbon emissions intensity. According to Figure 1, since 1995, although China's carbon emission intensity has shown a downward trend as a whole, the total emission intensity is still relatively large. Therefore, to achieve the goal of carbon neutrality, it is particularly critical to pay attention to the influencing factors of carbon emission intensity.

[1] Department of Environmental Science & Engineering, Fudan University, Shanghai 200433, China hedwig1016@163.com

[2] Department of Environmental Science & Engineering, Fudan University, Shanghai 200433, China chenhongmin@fudan.edu.cn

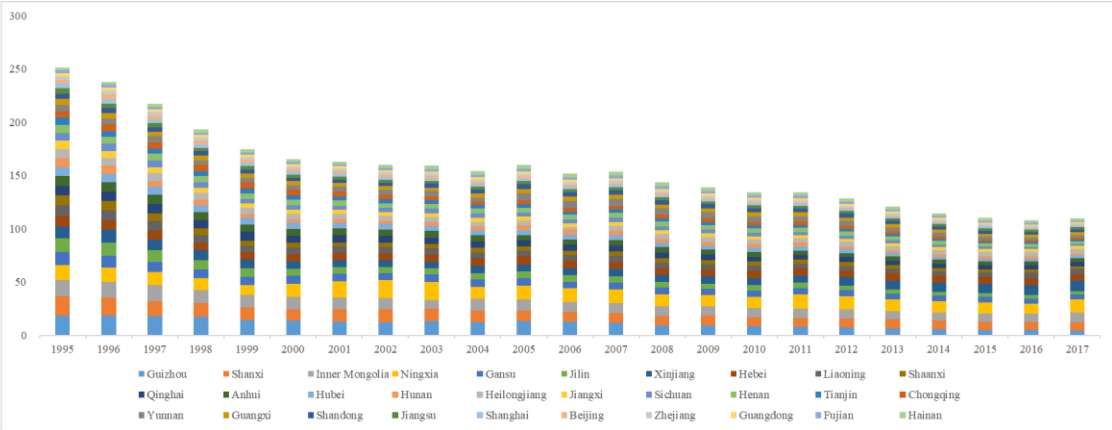

Figure 1 Carbon emission intensity in China from 1995 to 2017 (10,000 tons/100 million yuan)

The main factors affecting carbon emissions include economic growth (Asumadu-Sarkodie and Owusu, 2016; Karakaya et al., 2019; Wang and Zheng, 2021), Energy Consumption (Wang and Wang, 2019; Appiah et al., 2019), urbanization (Hanif, 2018; Pata, 2018; Wang et al., 2020) and Economic Opening (Gozgor, 2017; Cetin et al., 2018; Naz et al., 2019). With China's urban economic development, regional development strategies such as the Yangtze River Economic Belt, the Silk Road Economic Belt, the 21st Century Maritime Silk Road, and the Guangdong-Hong Kong-Macao Greater Bay Area have been implemented. Economic agglomeration improves resource utilization efficiency through technology spillover effects, and at the same time, will lead to an increase in energy consumption and carbon emissions, which will have a dual impact on energy conservation and emission reduction effects. According to the theory of external economics (Marshall, 1920) and new economic geography (Fujita et al., 1999), economic agglomeration brings positive externalities to the environment through technology spillovers and economies of scale. Enterprises can share energy-saving equipment and pollution control services (Xie and Yuan, 2016) to promote resource reuse (Ehrenfeld, 2010; Zhang and Dou, 2013; Li and Zhang, 2013). On the other hand, economic agglomeration will lead to excessive concentration of production factors, cause crowding effects, and accelerate excessive consumption of resources (Frank et al., 2001; Verhoef and Nijkamp, 2002; Zeng, 2008). Furthermore, there is an uncertain or nonlinear relationship between economic agglomeration and environmental pollution (Yan et al., 2011; Liu et al., 2018; Zhang, 2018). Therefore, to promote the coordinated development of economic agglomeration and carbon emission reduction policies and achieve a win-win effect of energy conservation and emission reduction, it is particularly critical to analyze the internal impact mechanism of economic agglomeration on carbon emissions.

The burning of fossil fuels represented by coal will directly produce pollutants such as carbon dioxide and sulfur dioxide in the production and utilization process. Therefore, energy consumption is a fundamental cause of environmental pollution, such as increased carbon emissions (Akhmat et al., 2014; Rehman and Rashid, 2017, Lai et al., 2019). The improvement of energy efficiency (Li et al., 2010; Zhang et al., 2013) and energy structure (Fu et al., 2018; Yang et al., 2019) through technological innovation can effectively reduce the level of environmental pollution. The technological progress driven by economic agglomeration can significantly improve the energy utilization efficiency in the region (Shi and Shen, 2013; Liu et al., 2017; Pei et al., 2021; Sun et al., 2021). At the same time, there is a nonlinear relationship between economic agglomeration and energy consumption (Lin et al., 2011; Shi and Shen, 2012; Zhao and Lin, 2019). Therefore, this paper takes energy consumption as an intermediary variable to comprehensively and carefully consider the impact of economic, spatial agglomeration on carbon emissions.

At present, research on carbon emissions mainly focuses on the influencing factors and control methods of total carbon emissions, and the internal relationship between carbon emissions intensity and economic agglomeration is rarely measured by including energy consumption intensity. In addition, the main research methods are decomposition analysis and standard econometric models, which can only obtain the contribution degree of influencing factors to carbon emissions but cannot explore the spatial correlation of carbon emissions and the spillover effects of influencing factors on carbon emissions. Since economic phenomena show temporal correlation and show spatial correlation to a certain extent, it is necessary and feasible to use spatial measurement methods to explore the relationship between carbon emission intensity and regional development. Therefore, focusing on China's 30 provincial-level data from 1995 to 2017, the dynamic spatial Durbin model and the intermediary effect model are used to analyze the relationship between economic agglomeration, energy intensity, and carbon emission intensity. From the perspective of spatial economic agglomeration, this article provides a necessary decision-making basis for China to effectively achieve energy conservation and emission reduction goals, economical green transformation and development, and regional development strategies.

2. Materials and methods

2.1 Data source

2.1.1 Estimation of carbon emissions intensity

The carbon emissions of China's provinces from 1995 to 2017 are represented by carbon emission intensity indicators. Carbon emission intensity is obtained by dividing the carbon emissions of each province's non-agricultural output (1). The calculation of carbon emission refers to the method provided by the Intergovernmental Panel on Climate Change (IPCC 2006), which is equal to the consumption of various energy sources converted to standard coal multiplied by the carbon emission coefficients. The formula is as follows:

$$CG = CO_2/GDP \tag{1}$$

$$CO_2 = \sum_{i=1}^{14} CO_{2,i} = \sum_{i=1}^{14} E_i \cdot NCV_i \cdot CEF_i \tag{2}$$

Where CO_2 indicates carbon emission, i indicates energy fuel, E_i indicates energy consumption, NCV_i indicates an average low calorific value of energy, CEF_i indicates carbon emission factor of energy. The formula is as follows:

$$CEF_i = CC_i \cdot COF_i \cdot (44/12) \tag{3}$$

Where CC_i represents carbon content in energy, COF_i represents carbon oxidation factor of energy. The data comes from the "China Energy Statistical Yearbook" in 1996-2018.

2.1.2 Estimation of economic agglomeration

Economic agglomeration mainly refers to the density of economic activities in the unit space. The output density reflects the spatial distribution of economic activities and the carrying capacity of economic activities per unit area, which conforms to the density characteristics of economic agglomeration (Ciccone and Hall, 1993). Therefore, this paper chooses to use non-agricultural products per unit area to measure the degree of economic agglomeration.

2.1.3 Explanatory variables

According to the STIRPAT model and the environmental Kuznets curve hypothesis, this paper sets the control variables, which are population (POP), per capita income (LY), energy consumption structure

(ES), industrial structure (IS), technological progress (RD), and economic opening rate (FDI). The specific description of each variable is shown in Table 1.

Table 1 Descriptive statistics of variables

Variable		Explanation	Unit	Mean	Min	Max
Explained variable	Carbon emission intensity (CI)	Carbon emissions per unit of non-agricultural output (constant price in 1995)	10,000 tons/100 million yuan	5.20	0.61	18.63
Core variable	Economic agglomeration (EG)	Output density (constant price in 1995)	100 million yuan/10,000 hectares	4.59	0.92	15.55
	Energy intensity (EI)	Energy consumption per unit of non-agricultural output (constant price in 1995)	10,000 tons of standard coal/100 million yuan	3.41	0.30	84.84
Control variable	Population (POP)	Population at the end of the year	Million	43.30	4.81	114.30
	Per capita income (LY)	GDP per capita (constant price in 1995)	Million yuan/person	161.73	18.26	656.36
	Energy consumption structure (ES)	Proportion of coal consumption in total energy consumption	%	0.66	0.08	0.93
	Industrial structure (IS)	Industrial added value as a proportion of GDP (constant price in 1995)	%	0.45	0.19	0.66
	Technological progress (RD)	The average number of patent authorizations per 100 R&D employees	Pieces/100 people	153.13	2.42	2489.38
	Economic opening rate (FDI)	Investment amount of foreign enterprises	100 million U.S. dollars	736.42	1.43	17622.27

Considering the availability, authority, and openness of data, this paper adopts the relevant annual statistical data of 30 Chinese provinces (excluding Tibet, Hong Kong, Macao, and Taiwan) from 1995 to 2017. The data mainly comes from the "China Statistical Yearbook," "China Compendium of Statistics," "China Energy Statistical Yearbook," "China Statistical Yearbook on Science and Technology," "China Statistical Yearbook on Environment," and province (autonomous region, municipality) statistical yearbook. Among them, various indicators are deflated and adjusted at constant prices in 1995.

2.1.4 Exploratory spatial data analysis

The Moran's I index can explain the spatial correlation of the carbon emission intensity of 30 provinces across the country very well, and the formula is as follows.

$$\mathrm{I} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(X_i - \bar{X})(X_j - \bar{X})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \quad (4)$$

Where $S^2 = \frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n}$ indicates sample variance, $\mathrm{X_i}$ and $\mathrm{X_j}$ respectively represent carbon intensity of regions i and j, n is the total number of regions, W_{ij} is the spatial weight matrix.

The spatial correlation of data is a prerequisite for building a spatial model, so the spatial correlation of core variables needs to be tested first. According to Table 2, the results show that the Moran's I index of China's carbon emission intensity in 1995-2017 is greater than 0, the p-value is less than 0.01, which indicates the carbon emission intensity of each province has a significant positive spatial correlation. Secondly, the Moran's I index from 1995 to 2017 generally shows an upward trend, indicating that the accumulation effect of inter-provincial carbon emission intensity tends to strengthen, and the differences among different provinces have gradually widened.

Table 2 Moran's I index

Year	Moran's I	Year	Moran's I
1995	0.227***	2007	0.235***
1996	0.224***	2008	0.265***
1997	0.233***	2009	0.248***
1998	0.216***	2010	0.257***
1999	0.224***	2011	0.241***
2000	0.192***	2012	0.264***
2001	0.215***	2013	0.241***
2002	0.220***	2014	0.252***
2003	0.209***	2015	0.253***
2004	0.200***	2016	0.255***
2005	0.230***	2017	0.245***
2006	0.176***	-	-

"***", "**" and "*" indicate significance at the 1%, 5%, and 10% levels, respectively, but not significant if not marked

2.2 Spatial panel model

The spatial panel model can be modified by the least-squares regression model. Therefore, this paper firstly builds the OLS model, and the model is as follows.

$$\ln \mathrm{cg} = \beta_0 + \beta_1 \ln ag + \beta_2 \ln ei + \beta_3 \ln \mathrm{pop} + \beta_4 \ln \mathrm{ly} + \beta_5 \ln \mathrm{es} + \beta_6 \ln \mathrm{is} + \beta_7 \ln \mathrm{rd} + \beta_8 \ln \mathrm{fd} + \varepsilon \tag{5}$$

Secondly, based on the OLS model, this paper constructs the spatial lag model (SLM), the spatial error model (SEM), and the spatial Durbin model (SDM). Compared with the OLS model, the SLM can better reflect the spillover effect of the carbon intensity of each province. The specific model is as follows:

$$\ln \mathrm{cg} = \beta_0 + \rho W \ln \mathrm{cg} + \beta_1 \ln ag + \beta_2 \ln ei + \beta_3 \ln \mathrm{pop} + \beta_4 \ln \mathrm{ly} + \beta_5 \ln \mathrm{es} + \beta_6 \ln \mathrm{is} + \beta_7 \ln \mathrm{rd} + \beta_8 \ln \mathrm{fd} + \mu + \lambda + \varepsilon \tag{6}$$

The superiority of the SEM is reflected in the careful consideration of other factors affecting the carbon emission intensity of each province, and the other factors are represented as random error terms. The model is as follows:

$$\ln \mathrm{cg} = \beta_0 + \beta_1 \ln ag + \beta_2 \ln ei + \beta_3 \ln \mathrm{pop} + \beta_4 \ln \mathrm{ly} + \beta_5 \ln \mathrm{es} + \beta_6 \ln \mathrm{is} + \tag{7}$$

$$\beta_7 \ln \mathrm{rd} + \beta_8 \ln \mathrm{fd} + \mu + \lambda + \varepsilon, \varepsilon = \delta W \varepsilon + \varphi$$

The explained variable itself may have spatial correlation, and the explanatory variable and error term may also have spatial characteristics. The SDM can reflect the spatial correlation from different sources and be modified into SLM and SEM by setting different coefficients. Based on this, this article chooses a more general SDM for analysis, and the SDM is as follows:

$$\begin{gathered} \ln \mathrm{cg} = \beta_0 + \rho W \ln \mathrm{cg} + \beta_1 \ln ag + \beta_2 \ln ei + \beta_3 \ln \mathrm{pop} + \beta_4 \ln \mathrm{ly} + \beta_5 \ln es + \\ \beta_6 \ln \mathrm{is} + \beta_7 \ln \mathrm{rd} + \beta_8 \ln \mathrm{fd} + \theta_1 \ln ag + \theta_2 \ln ei + \theta_3 \ln \mathrm{pop} + \theta_4 \ln \mathrm{ly} + \theta_5 \ln es + \\ \theta_6 \ln is + \theta_7 \ln rd + \theta_8 \ln fd + \mu + \lambda + \varepsilon \end{gathered} \tag{8}$$

In addition, there is a path-dependent characteristic of carbon emission changes from the time dimension, that is, the time lag effect. There may also be a two-way causal relationship between carbon emissions and factors such as economic growth and technological progress, resulting in endogenous problems (Shuai et al., 2011). Therefore, the lag phase of the carbon intensity variable was introduced into the standard static SDM. The dynamic SDM is as follows.

$$\begin{gathered} \ln \mathrm{cg} = \beta_0 + \ln cg_{-1} + \rho W \ln \mathrm{cg} + \beta_1 \ln ag + \beta_2 \ln ei + \beta_3 \ln \mathrm{pop} + \beta_4 \ln \mathrm{ly} + \\ \beta_5 \ln es + \beta_6 \ln \mathrm{is} + \beta_7 \ln \mathrm{rd} + \beta_8 \ln \mathrm{fd} + \theta_1 \ln ag + \theta_2 \ln ei + \theta_3 \ln \mathrm{pop} + \theta_4 \ln \mathrm{ly} + \\ \theta_5 \ln es + \theta_6 \ln is + \theta_7 \ln rd + \theta_8 \ln fd + \mu + \lambda + \varepsilon \end{gathered} \tag{9}$$

The weight matrix is divided into 3 categories, namely 0-1 weight matrix, geographic distance weight matrix, and economic distance weight matrix. The geographical distance weight matrix is the most common, represented as the reciprocal of the geographical distance of each province, and the formula is as follows.

$$W_{ij} = 1/d_{ij} \tag{10}$$

2.3 Intermediary effect

The mediating effect refers to the indirect effect of explanatory variables on the explained variables through intermediate variables (Mackinnon et al., 2000), tested by the widely used stepwise method (Baron and Kenny, 1999). The testing process is based on the following two conditions: the explanatory variable significantly affects the explained variable, and subsequent variables in the causal chain will be significantly affected by the previous variable. Specifically, the explanatory variable (X) has an indirect effect on the explained variable (Y) through the intermediate variable (M). Thus, the conduction process is as follows.

$$\begin{gathered} Y = cX + e_1 \\ M = aX + e_2 \\ Y = c'X + bM + e_3 \end{gathered} \tag{11}$$

3. Result and Discussion

3.1 Spatial direct effect and overflow effect

3.1.1 Model selection and comparison

In order to better construct the spatial model, the Lagrange multiplier test, likelihood ratio test, and Hausman test can empirically examine the scientific nature of the spatial panel Durbin model. The p-value of the houseman test is close to 0. At the same time, this article pays more attention to the changes of specific individuals within the region. Therefore, both test results and theory support the use of the fixed-effects model (Baltagi, 2008).

Lagrange multiplier test and likelihood ratio test provide guidance for the choice of spatial models (Anselin and Florax, 1995; Burridge and Fingleton, 2010). According to Table 3, the LM-Error is more significant than LM-LAG, and R-LM Error is more significant than R-LM Lag, so selecting SEM is more appropriate than the SLM. According to Table 4, LR-Lag and LR-Error are significant at 1% level, so SDM should not be simplified into SEM and SLM. In conclusion, based on test results, SDM should be selected.

Table 3 Lagrange multiplier test

Index	Question	Result	Conclusion
LM-Error	Whether there is spatial correlation	13.302*** （0.00）	Yes
LM-Lag	Whether there is spatial correlation	16.301*** （0.00）	Yes
R- LM error	Whether there is spatial correlation	7.432*** （0.01）	Yes
R-LM lag	Whether there is spatial correlation	10.431*** （0.00）	Yes

"***", "**" and "*" indicate significance at the 1%, 5%, and 10% levels, respectively, but not significant if not marked; p-value in parentheses

Table 4 Likelihood ratio test

Index	Assumption	Result	Conclusion
LR-Lag	SLM nested in SDM	262.900*** （0.00）	No
LR-Error	SEM nested in SDM	258.770*** （0.00）	No

"***", "**" and "*" indicate significance at the 1%, 5%, and 10% levels, respectively, but not significant if not marked; Chi^2 in parentheses

3.1.2 Spatial and temporal characteristics analysis of carbon emission intensity

ArcGIS can be used to visualize China's carbon emission intensity and economic agglomeration level in 1997-2017 (Fig. 2). In the past ten years, China's total carbon emission intensity has shown a downward trend. Divided by geographical location, carbon emission intensity decreases from west to east and from north to south. The changing trend of the level of economic agglomeration is opposite to the intensity of carbon emissions, and the degree of economic agglomeration in the eastern coastal areas has always been maintained at a relatively high level.

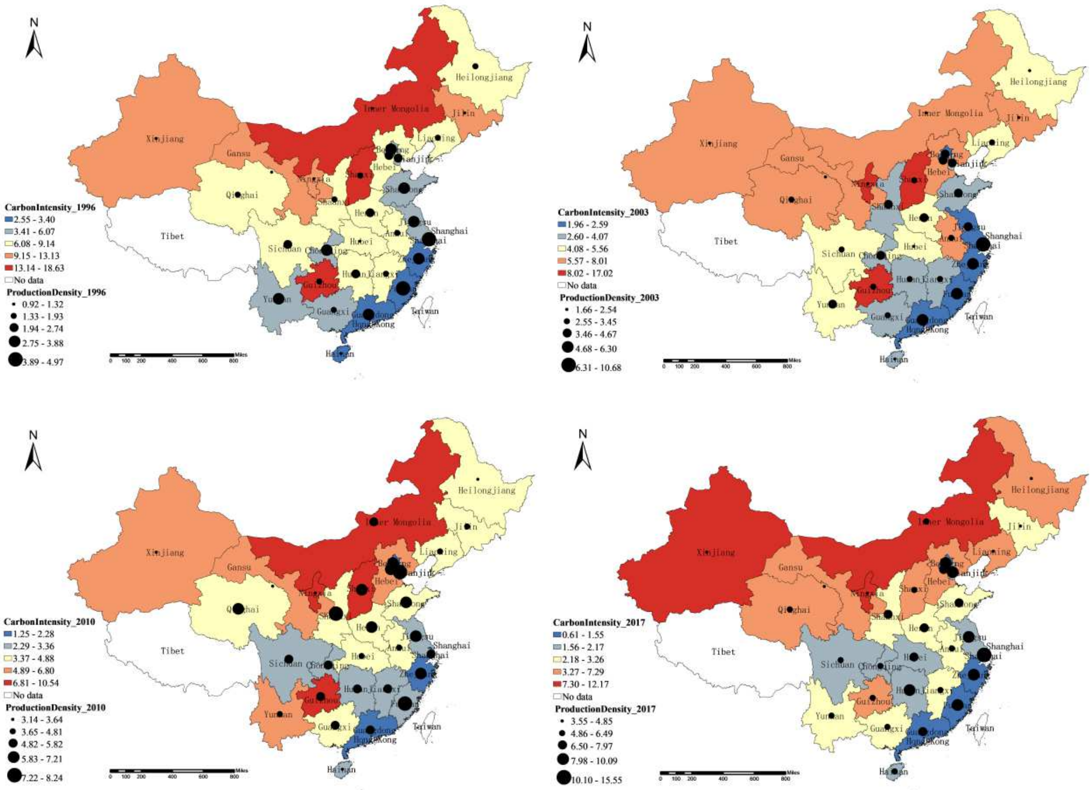

Figure 2 The spatial distribution of carbon emission intensity and economic agglomeration

3.1.3 Spatial effects of economics agglomeration

Due to regional differences and the estimation bias caused by time factors, this paper mainly adopts the dynamic spatial panel model with two-way fixed effects in time and space to estimate the parameters. For the convenience of comparison, the estimated results of the static SDM with fixed spatial effects, fixed time effects, and two-way fixed effects of time and space are reported in Table 5. In order to avoid the endogenous problem caused by economic agglomeration, the dynamic SDM with two-way fixed effects in time and space introduces a lagging one-phase variable of carbon emission intensity. Therefore, the results of this model are more reliable and will be discussed later.

The results show that the spatial lag coefficient of carbon emission intensity is significantly positive (Table. 5), indicating that carbon emission intensity has a strong path dependence and a "snowball" effect in the time dimension. In order to achieve the goal of carbon neutrality, China's carbon emission reduction work is both urgent and arduous. The spatial lag coefficient of economic agglomeration is significantly negative, indicating that economic agglomeration in neighboring provinces has a depressing effect on local carbon emission intensity. With the construction of urban agglomerations, the economic ties between neighboring regions have been continuously strengthened. Related industries and enterprises form a specialized division of labor within the entire urban agglomeration. When a central area appears in the urban agglomeration, the central area will continue to attract emerging industries to enter, thereby weakening the attractiveness of the surrounding areas due to the siphon effect. As a result, there is a negative correlation between the degree of economic agglomeration and the intensity of carbon dioxide emissions between regions.

The coefficients of the primary, secondary and tertiary terms of economic agglomeration have all passed the 1% significance level test, and there is a significant inverted-N relationship between economic agglomeration and carbon emission intensity. In the early stage of economic development, industrial gatherings had a restraining effect on carbon emission intensity. In the early days of China's reform and opening up, urbanization and industrialization were both in their infancy. When the number and scale of enterprises are limited, the scale effect promotes production efficiency, and the infrastructure can be shared. As a result, the speed of economic agglomeration greatly exceeds the intensity of carbon emissions. With the promotion of China's urbanization process, economic agglomeration plays a role in promoting carbon emission intensity. During this period, the expansion of enterprise production scale leads to an increase in the demand for production factors, so the carbon emission intensity in the production stage increases. In the period of rapid economic development in China at the beginning of the 21st century, on the one hand, the Yangtze River Delta and the Pearl River Delta have become the world's foundries.

On the other hand, environmental regulatory policies, land protection policies, and the promotion of clean technologies lag behind the growth of economic agglomeration. They are leading to economic development and increasing the intensity of carbon emissions. In the end, as the strength of enterprises increases, the division of specialization is strengthened, and environmental regulations and policies are improved—the increase in the cost of environmental pollution forces enterprises to reduce carbon emissions.

Table 5 The carbon emission intensity estimation results

Variable	Fixed spatial	Fixed time	Two-way fixed	Dynamic SDM
	Model 1	Model 2	Model 3	Model 4
L.lncg				0.210***
				（0.00）
lneg	-0.012	0.132	-0.091	-0.157***
	（0.82）	（0.89）	（-1.91）	（0.00）
lnseg	-0.051	0.118	0.029	0.124***
	（0.29）	（0.21）	（0.65）	（0.01）
lnceg	0.011	0.032	-0.010	-0.034***
	（0.38）	（0.25）	（-0.85）	（0.00）
lnei	0.803***	0.023***	0.814	0.686***
	（0.00）	（0.00）	（57.92）	（0.00）
lnsei	-0.031***	0.007***	-0.037	-0.034***
	（0.00）	（0.00）	（-9.08）	（0.00）
lnly	-0.832***	0.305***	-0.834	-0.702***
	（0.00）	（0.00）	（-5.59）	（0.00）
lnsly	0.024***	0.016***	0.022	0.018***
	（0.00）	（0.00）	（3.06）	（0.01）
lnes	0.271***	0.044***	0.232	0.174***
	（0.00）	（0.00）	（10.96）	（0.00）
lnis	0.167***	0.057***	0.291	0.261***
	（0.00）	（0.00）	（10.38）	（0.00）
lnrd	-0.009	0.012***	0.013	0.015**
	（0.27）	（0.00）	（1.75）	（0.04）
lnpop	-0.483***	0.018***	-0.345	-0.214***
	（0.00）	（0.00）	（-6.43）	（0.00）

lnfdi	0.037***	0.014	0.033	0.034***
	（0.00）	（0.25）	（4.06）	（0.00）
Wlneg	-0.343***	0.348	-0.436	-0.406***
	（0.01）	（0.39）	（-3.31）	（0.00）
Wlnei	0.045	0.09***	0.404	0.454***
	（0.4）	（0.00）	（6.56）	（0.00）
Wlnly	1.254***	0.714	1.241	0.617**
	（0.00）	（0.21）	（3.83）	（0.05）
Wlnes	0.144***	0.118**	0.020	0.043
	（0.00）	（0.04）	（0.41）	（0.34）
Wlnis	-0.059	0.131***	0.351	0.354***
	（0.28）	（0.00）	（5.15）	（0.00）
Wlnrd	-0.06***	0.038	-0.010	0.002
	（0.00）	（0.37）	（-0.48）	（0.92）
Wlnpop	0.808***	0.055	1.543	1.131***
	（0.00）	（0.18）	（11.14）	（0.00）
Wlnfdi	0.063***	0.047***	-0.009	-0.017
	（0.00）	（0.00）	（-0.37）	（0.45）
Spatial	-0.139**	0.078	-0.301***	0.441***
	（0.02）	（0.80）	（0.00）	（0.00）
R-square	0.961	0.769	0.936	0.943

"***", "**" and "*" indicate significance at the 1%, 5%, and 10% levels, respectively, but not significant if not marked; p-value in parentheses

3.1.4 Spatial effects of energy intensity

The spatial lag coefficient of energy intensity is significantly positive at the 1% level (Table 5). On the one hand, the energy intensity of neighboring provinces positively impacts the province's carbon emission intensity. On the other hand, it also confirms the existence of regional economic competition and imitation effects. When neighboring cities develop by supporting high-pollution and high-emission industries, neighboring cities will also choose to imitate. With the development of the industrial chain of urban agglomerations, energy consumption in adjacent areas tends to be similar, and carbon emission intensity also positively correlates.

The signs of the primary and secondary coefficients of energy intensity are negative and positive, respectively, and both are significant at the 1% level (Table 5), indicating a typical inverted U-shaped curve relationship between energy and carbon emission intensity. In the early stage of economic development, the expansion of production triggered by economic agglomeration promoted an accelerated increase in energy consumption and carbon emission intensity. However, with the implementation of energy-saving and emission reduction policies and technological progress, energy use efficiency has been improved, energy consumption structure has been optimized, and clean technology has been popularized. Ultimately, the carbon emission intensity will show a downward trend again.

3.1.5 Effects of the control variable

From the perspective of control variables, per capita income and its quadratic coefficient are significantly negative and significantly positive, respectively, indicating a U-shaped curve relationship between per capita income and carbon emission intensity. The coefficient of energy structure is significantly positive, confirming that China's production model of relying on coal resources limits the decline in carbon emission intensity. The coefficient of industrial structure is significantly positive, indicating that excessive dependence on the secondary industry is not conducive to reducing carbon emission intensity. The coefficient of technological progress is significantly positive, indicating that the improvement in production efficiency and the development of clean technology caused by technological progress has played a role in promoting energy conservation and emission reduction. The population size is significantly positive, indicating that population agglomeration will increase carbon emissions in the region. Finally, the coefficient of openness to the outside world is significantly positive, verifying the pollution refuge hypothesis, that is, China has attracted foreign investment in high-carbon emission industries.

3.2 Energy intensity intermediary effect

The stepwise method is a suitable method to test whether energy intensity acts as an intermediary variable for economic agglomeration and carbon emission intensity. At the same time, whether there is an energy-saving effect in economic agglomeration can also be verified.

According to Table 6, there is an inverted N-shaped relationship between economic agglomeration and carbon intensity, a U-shaped curve relationship between economic agglomeration and energy intensity, and an inverted U-shaped curve relationship between energy intensity and carbon intensity. Based on the empirical results of the intermediary effect model, it is verified that energy intensity is an intermediary variable between economic agglomeration and carbon emission intensity, and it also validates the energy-saving and emission-reduction effects of economic agglomeration. In addition, the results of models 5 and 7 also confirmed the robustness of the model 4 dynamic space Doberman model.

Table 6 Intermediary effect estimation results

Variable	EG&CI	EG&EI	EI&CI
	Model 5	Model 6	Model 7
lneg	-0.432***	-1.106***	
	（0.00）	（0.00）	
lnseg	0.233***	0.343***	
	（0.08）	（0.00）	
lnceg	-0.06***		
	（0.10）		
lnei	0.692***		0.733***
	（0.00）		（0.00）
lnsei	-0.169***		-0.181***
	（0.00）		（0.00）
lnly	-2.208***	2.864***	-2.334***
	（0.00）	（0.00）	（0.00）
lnsly	0.117***	-0.119***	0.12***
	（0.00）	（0.00）	（0.00）
lnes	0.219***	0.744***	0.245***
	（0.00）	（0.00）	（0.00）
lnis	0.448***	0.196***	0.378***

	（0.00）	（0.29）	（0.00）
lnrd	0.041***	-0.267***	0.035***
	（0.00）	（0.00）	（0.00）
lnpop	-0.075***	0.348***	-0.109***
	（0.00）	（0.00）	（0.00）
lnfdi	-0.14***	-0.306***	-0.128***
	（0.00）	（0.00）	（0.00）
constant	14.827***	-11.762***	15.581***
term	（0.00）	（0.02）	（0.00）

"***", "**" and "*" indicate significance at the 1%, 5%, and 10% levels, respectively, but not significant if not marked; p-value in parentheses

3.3 Spatial heterogeneity analysis

Table 5 shows the impact of economic agglomeration in the three regions on carbon emission intensity. Due to the time lag effect of carbon emission intensity, it is more appropriate to use the dynamic spatial Doberman model. The internal economic agglomeration and carbon emission intensity of the three regions present an "inverted N" relationship, and the energy intensity and carbon emission intensity present an inverted U-shaped relationship, which is consistent with the overall national trend. In addition, economic agglomeration and energy intensity have a significant spatial spillover effect on carbon emission intensity. Therefore, the increase in the level of economic agglomeration in the region will reduce the carbon emission intensity of the surrounding areas. In contrast, the increase in the region's energy intensity will promote the increase of the carbon emission intensity of the surrounding areas.

Comparing the differences between the three regions, economic agglomeration in the western region has the most apparent inhibitory effect on carbon emission intensity, and energy intensity also has the most significant promotion effect on carbon emission intensity. Due to geographical location and historical factors, the development of western China has always lagged behind other regions. Therefore, when policies such as the development of the Chengdu-Chongqing urban agglomeration and the New Silk Road are being promoted, attention should also be paid to energy conservation and emission reduction in the western region to China's environmental improvement.

Table 7 Spatial heterogeneity estimation results

Variable	**Eastern China**		**Central China**		**Western China**	
	SDM	**D-SDM**	**SDM**	**D-SDM**	**SDM**	**D-SDM**
	Model 8	**Model 9**	**Model 10**	**Model 11**	**Model 12**	**Model 13**
L.lncg		0.139***		0.075***		0.124***
		(0.00)		(0.00)		(0.00)
lneg	-0.268***	-0.283***	-0.437***	-0.536***	-0.786***	-0.972***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lnseg	0.176***	0.214***	0.164**	0.262***	0.729***	0.885***
	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)	(0.00)
lnceg	-0.034***	-0.045***	-0.024	-0.048**	-0.208***	-0.246***
	(0.01)	(0.00)	(0.20)	(0.02)	(0.00)	(0.00)
lnei	0.836***	0.743***	0.896***	0.844***	0.899***	0.850***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

lnsei	-0.024*	-0.028	0.005	0.012	-0.048***	-0.047***
	(0.09)	(0.11)	(0.72)	(0.41)	(0.00)	(0.00)
lnly	-1.014***	-1.028***	-1.774***	-1.969***	-0.568**	-0.568**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.02)
lnsly	0.036***	0.036***	0.081***	0.091***	-0.001	0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.94)	(0.89)
lnes	0.159***	0.130***	0.324***	0.348***	0.212***	0.182***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lnis	0.348***	0.316***	0.463***	0.437***	0.072	0.076
	(0.00)	(0.00)	(0.00)	(0.00)	(0.4)	(0.38)
lnrd	-0.003	0.001	-0.004	0.001	-0.001	0.004
	(0.67)	(0.93)	(0.71)	(0.90)	(0.92)	(0.77)
lnpop	-0.181**	-0.139	0.224	0.278*	-0.329***	-0.277**
	(0.02)	(0.11)	(0.16)	(0.08)	(0.01)	(0.03)
lnfdi	0.007	0.009	-0.052***	-0.038***	0.053***	0.050***
	(0.46)	(0.35)	(0.00)	(0.01)	(0.00)	(0.00)
Wlneg	-0.644***	-0.520***	-0.562***	-0.516***	-0.419	-0.617*
	(0.00)	(0.00)	(0.01)	(0.01)	(0.19)	(0.09)
Wlnei	0.155**	0.140*	0.209**	0.099	0.366***	0.355***
	(0.03)	(0.06)	(0.03)	(0.31)	(0.00)	(0.00)
Wlnly	0.772	0.580	-1.55**	-1.38**	-0.563	-0.262
	(0.12)	(0.29)	(0.02)	(0.04)	(0.46)	(0.73)
Wlnes	-0.061**	-0.051	0.224***	0.22***	-0.356**	-0.434***
	(0.05)	(0.14)	(0.00)	(0.00)	(0.04)	(0.01)
Wlnis	0.268***	0.222**	0.26***	0.214***	0.248	0.199
	(0.00)	(0.02)	(0.00)	(0.00)	(0.32)	(0.43)
Wlnrd	-0.022	-0.018	-0.035*	-0.039*	0.049	0.068
	(0.17)	(0.30)	(0.10)	(0.09)	(0.29)	(0.13)
Wlnpop	0.356***	0.255*	-0.076	0.079	2.329***	2.461***
	(0.01)	(0.08)	(0.83)	(0.83)	(0.00)	(0.00)
Wlnfdi	-0.029**	-0.017	-0.004	0.011	-0.049	-0.051
	(0.16)	(0.44)	(0.88)	(0.65)	(0.12)	(0.11)
Spatial	-0.102	0.105	-0.439***	0.359***	-0.165	0.229**
	(0.18)	(0.19)	(0.00)	(0.00)	(0.13)	(0.03)
R-square	0.902	0.900	0.934	0.920	0.784	0.555

"***", "**" and "*" indicate significance at the 1%, 5%, and 10% levels, respectively, but not significant if not marked; p-value in parentheses

3.4 Robust test

Finally, carbon emissions are used instead of carbon emissions intensity to test the robustness of the parameters to verify the research conclusions. According to Models 14-18 in table 8, due to the time lag effect of carbon dioxide emissions, this paper also chooses the dynamic spatial Durbin model of the two-way fixed effect of time and space to carry out the analysis. The results show that economic agglomeration and carbon dioxide emissions have an inverted N relationship, energy intensity and carbon dioxide emissions have an inverted U relationship. That is consistent with the previous conclusions, indicating that the model construction is robust.

Table 8 Carbon emission estimation results

Variable	OLS	Fixed spatial	Fixed time	Two-way fixed	Dynamic SDM
	Model 14	Model 15	Model 16	Model 17	Model 18
L.lncg					0.261***
					（0.00）
lneg	-0.326**	0.034	0.096	-0.080	-0.115**
	（0.04）	（0.53）	（0.50）	（0.12）	（0.03）
lnseg	0.209	-0.058	-0.114	0.046	0.108**
	（0.15）	（0.26）	（0.37）	（0.33）	（0.02）
lnceg	-0.066*	0.007	0.016	-0.02	-0.034***
	（0.09）	（0.63）	（0.64）	（0.12）	（0.01）
lnei	0.663***	0.774***	0.639***	0.783***	0.631***
	（0.00）	（0.00）	（0.00）	（0.00）	（0.00）
lnsei	-0.158***	-0.024***	-0.159***	-0.028***	-0.023***
	（0.00）	（0.00）	（0.00）	（0.00）	（0.00）
lnly	-1.181***	0.331*	-2.399***	0.396**	0.332**
	（0.00）	（0.06）	（0.00）	（0.01）	（0.03）
lnsly	0.122***	0.015*	0.164***	0.01	0.003
	（0.00）	（0.08）	（0.00）	（0.21）	（0.65）
lnes	0.218***	0.238***	0.156***	0.198	0.133***
	（0.00）	（0.00）	（0.001）	（0.00）	（0.00）
lnis	0.635***	0.297***	0.766***	0.414	0.34***
	（0.00）	（0.00）	（0.00）	（0.00）***	（0.00）
lnrd	0.026**	-0.015*	0.053***	0.004	0.007
	（0.02）	（0.07）	（0.00）	（0.58）	（0.37）
lnpop	0.904***	0.194***	0.759***	0.352***	0.323***
	（0.00）	（0.00）	（0.00）	（0.00）	（0.00）
lnfdi	-0.135***	0.037***	0.000	0.032***	0.034***
	（0.00）	（0.00）	（0.97）	（0.00）	（0.00）
Wlneg	5.092***	-0.462***	-0.484	-0.763***	-0.552***
	（0.00）	（0.00）	（0.20）	（0.00）	（0.00）
Wlnei		0.045	0.385***	0.476***	0.453***
		（0.42）	（0.00）	（0.00）	（0.00）
Wlnly		2.247***	1.303*	2.511***	1.69***
		（0.00）	（0.09）	（0.00）	（0.00）
Wlnes		0.089*	-0.157	0.057	0.08*
		（0.07）	（0.22）	（0.27）	（0.09）
Wlnis		-0.099	0.637***	0.427***	0.45***
		（0.10）	（0.00）	（0.00）	（0.00）
Wlnrd		-0.009	0.036	0.017	0.011
		（0.57）	（0.39）	（0.43）	（0.58）
Wlnpop		1.281***	0.052	1.953***	1.459***

		(0.00)	(0.54)	(0.00)	(0.00)
Wlnfdi		0.046**	-0.224***	-0.03	-0.034
		(0.03)	(0.00)	(0.23)	(0.15)
constant term	5.092***				
	(0.00)				
Spatial		-0.117*	-0.044	-0.474***	0.527***
		(0.06)	(0.58)	(0.00)	(0.00)
R-square	0.944	0.985	0.925	0.937	0.954

"***", "**" and "*" indicate significance at the 1%, 5%, and 10% levels, respectively, but not significant if not marked; p-value in parentheses

4. Conclusions

With the steady progress of China's new urbanization, urban agglomeration economy, and the "two belts and one road" regional development strategies, "group-style" development and industrial agglomeration have become the driving force of China's future economic growth. However, in the face of the bright future of carbon neutrality in 2060 and the reality of high carbon emissions in various provinces, achieving win-win results with energy conservation and emission reduction has become an urgent problem to be solved. This paper uses data from 30 provinces in China from 1995 to 2017, innovatively considers the time lag and spatial spillover effects of carbon emission intensity, and introduces energy intensity as an intermediary variable. It also analyzes the internal mechanism of energy conservation and emission reduction of economic agglomeration and provides policy recommendations for China's economic green transformation development and regional development strategies.

According to the research results, in the time dimension, carbon emission intensity has path-dependent characteristics, and the "snowball" effect is prominent. In the spatial dimension, both economic agglomeration and energy intensity show spatial solid spillover effects. The carbon emission intensity of this region is highly susceptible to the influence of the economic development model and energy consumption intensity of the surrounding areas. Second, economic agglomeration can play a role in energy conservation and emission reduction through positive externalities such as technology spillovers, facility sharing, centralized supervision, and specialized division of labor. Finally, with energy intensity as an intermediary variable, there are direct and indirect effects on the mechanism of economic agglomeration on carbon emission intensity.

Based on the research conclusions, this article puts forward the following policy recommendations: First, urban agglomerations have become the main spatial form of new urbanization, and the trend of regional economic integration remains unchanged. Therefore, China should pay attention to the economic development of the central and western regions and give full play to the optimal energy conservation and emission reduction of economic agglomeration effect. Second, in policy formulation, energy conservation and emission reduction policies should be coordinated with each other, and the achievement of emission reduction targets needs to be consistent with energy conservation targets. Finally, due to the significant spatial spillover effects of economic agglomeration and energy intensity, it is necessary to reach a coordinated governance mechanism for energy conservation and emission reduction policies between regions to promote the regional linkage mechanism of China's carbon market trading.

Declarations

Ethics Approval and Consent to Participate

Not applicable.

Consent to Publish

Not applicable.

Authors Contributions

Tianyu Luo and Hongmin Chen contributed to the study conception and design. Material preparation, data collection and analysis were performed by Tianyu Luo. The first draft of the manuscript was written by Tianyu Luo. Tianyu Luo and Hongmin Chen commented on previous versions of the manuscript. Tianyu Luo and Hongmin Chen read and approved the final manuscript.

Conflict of Interest

The authors declare that they have no conflict of interest.

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Availability of Data and Materials

Some or all data, models, or code generated or used during the study are available from the corresponding author by request.

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