



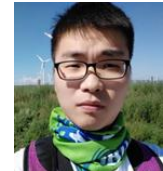
THE IMPACT OF INDUSTRIAL AGGLOMERATION ON CARBON EMISSIONS: EMPIRICAL EVIDENCE FROM CHINA

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ABSTRACT

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Based on panel data of China from 2004 to 2016, this paper explored the spatial spillover effect in industrial agglomeration and carbon emissions by using a spatial econometric model. Our results showed that industrial agglomeration significantly increases the carbon emissions in the local region, while inhibits the carbon emissions in the neighboring areas. After considering the choice of different spatial weight matrices, the conclusion is still robust. Further tests show that, on the one hand, industrial agglomeration can increase local carbon emissions and restrain them in the neighboring regions by increasing the industrial scale. On the other hand, industrial agglomeration suppresses the carbon emissions of local and neighboring areas by influencing the intensity of energy consumption. Moreover, the emission decrease effect of industrial agglomeration on the local part through the energy intensity is stronger than that in the vicinity. We propose that the government should coordinate the impact of industrial agglomeration on pollution emissions through both scale and energy effects. Maximize the role of energy saving and emission reduction in industrial agglomeration.

Contribution/Originality: This study contributes to the existing literature that greenhouse gases, such as carbon emissions, which have an important impact on global temperature rise, have the characteristics of the transboundary transfer. Developing countries can reduce carbon emissions by promoting the scale effect and energy effect of local industrial agglomeration.

1. INTRODUCTION

The Chinese economy is shifting from an extensive model of aiming for growth to an intensive model of structural adjustment. High-quality development has undoubtedly become the central theme of China's current economic expansion. The traditional view is that foreign direct investment provides China with an opportunity to access innovative green technology. However, in recent years, the vicious pollution incident involving foreign capital has occurred often. To maintain or strengthen its economic competitiveness, some regions of China have attracted more foreign investment, and have relaxed the standards for environmental regulation, which has led to "race to the bottom." As the world's largest developing country, China is leading the "Made in China 2025" by speeding up promoting industrial agglomeration. Since it is challenging to improve China's environmental quality by attracting foreign investment from developed countries, can China achieve energy conservation and emission reduction by turning its attention to the economic agglomeration effects triggered by large-scale industrial agglomeration?

The results of the present investigation suggest that industrial agglomeration can produce agglomeration effects through the reallocation of economic factors, which in turn have a dual impact on pollution emissions. On the one hand, the compact spatial fiscal behavior of agglomeration economy can achieve technology spillover and improve the efficiency of factors utilization through various positive externalities triggered by agglomeration. So, we can conclude that agglomeration economy has a positive influence on reducing pollution emissions. On the other hand, agglomeration may trigger a "crowding effect" by expanding the production scale and factor input of the agglomeration area, increasing energy consumption and producing more carbon emissions. Therefore, in the context of China's commitment to reducing emissions under the framework of the Paris Agreement, an in-depth analysis of the impact mechanism of industrial agglomeration on carbon emissions has rich policy implications and practical implications.

2. LITERATURE REVIEW

The relationship between agglomeration economies and environmental pollution has traditionally been a hot topic for governments and academics. The expansion of output scale and the increase in consumer demand are the essential characteristics of the spatial agglomeration of economic activities. In particular, the gathering of pollution-intensive industries has resulted in the deterioration of environmental quality. On the one hand, economic gatherings promote regional economic growth and capacity expansion, resulting in more pollution emissions; On the other hand, the economies of scale formed by agglomeration can reduce the cost of unit pollution treatment of enterprises, which is conducive to the improvement of environmental quality (Shi and Shen, 2013; Wang and Nie, 2016). Therefore, the relationship between agglomeration and environmental pollution is quite complicated (Yang, 2015; Liu *et al.*, 2018; Wang *et al.*, 2018; Shao *et al.*, 2019). Economic agglomeration is aggravating environmental pollution or inhibiting environmental pollution. The academic community does not reach a consensus conclusion.

One view is that the agglomeration economy exacerbates environmental pollution (Virkanen, 1998; De Leeuw *et al.*, 2001). The expansion of output scale and the increase in energy consumption demand accompanying the gathering will result in an increase in environmental pollution. Wang and Nie (2016) used the data of China's establishment of development zones and found that the scale expansion of enterprises significantly increased the deterioration of the environment. The concentrated discharge of polluting enterprises in space is the source of environmental pollution (Wang and Nie, 2016). Bai *et al.* (2019) used panel data from 64 cities in China to find that population agglomeration and urban expansion have resulted in an increase in carbon dioxide emissions, due to the expansion of public demand for energy (Bai *et al.*, 2019). Chen *et al.* (2018) based on panel data of 187 cities in China from 2005 to 2013, found that the scale effect of industrial agglomeration aggravated urban carbon dioxide emissions, while the intensity effect was conducive to the reduction of carbon dioxide emissions (Chen *et al.*, 2018). Furthermore, many studies also believe that economic agglomeration exacerbates carbon dioxide emissions by expanding output scale (Anderson, 1979; Ciccone and Hall, 1996; Zhang and Dou, 2013; Han *et al.*, 2018).

Another point of view is that agglomeration alleviates environmental pollution because the positive externality of agglomeration promotes green technological progress (Krugman, 1998). Many studies believe that FDI agglomeration can improve environmental conditions (He, 2006; Xu and Deng, 2012; Shao *et al.*, 2019). Jun *et al.* (2017) conducted a study on 285 cities in China from 2014 to 2013 by constructing a dynamic spatial econometric model. It was noted that industrial agglomeration could promote energy efficiency (Jun *et al.*, 2017). Deng and Xu (2016) used a spatial econometric model to find that FDI can reduce the intensity of regional pollution emissions, while Mar externality and Jacobs externality enhance the emission reduction effect of FDI (Deng and Xu, 2016). By reviewing the literature, we find that the relationship between agglomeration economies and environmental pollution is uncertain. We speculate that agglomeration economies can have an impact on environmental pollution through the scale effect and the energy effect. On the one hand, we will analyze the total effect of agglomeration

economy on environmental pollution; on the other hand, we also will examine the influence of agglomeration economy on environmental pollution through scale effect and energy effect.

3. METHODOLOGY AND DATA

3.1. Spatial Econometric Models

Influenced by the natural climate and human activities, carbon emissions have spatial correlation effects and will spread between regions. The current literature consistently proves the significant spatial dependence of carbon emissions in various areas of China (Jun *et al.*, 2017; Wang *et al.*, 2018; Wang *et al.*, 2019). At the same time, the new economic geography believes the multiple externalities of the agglomeration economy have spatial diffusion characteristics that decay with geographical distance (Fingleton and Lopez-Bazo, 2006). Besides, with the closer economic linkages and social activities between regions, factors such as competition, imitation, and spillover between geographically close areas will also lead to spatial interaction between domains. Therefore, any empirical research that ignores spatial correlation will not cause a consistent estimate. So, this paper analyzes the spatial correlation effect of China's interprovincial carbon emissions and industrial agglomeration by modeling a spatial econometric model. The base model is expressed as:

$$\begin{aligned} Carbon_{it} &= \rho W Carbon_{it} + \beta_1 agg_{it} + \beta_2 X_{it} + \delta_1 Wagg_{it} \\ &+ \delta_2 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \quad (1)$$

$$\varepsilon_{it} = \theta W \varepsilon_{it} + e_{it}$$

Where i and t represent the region and year respectively; $Carbon$ is the explained variable, indicating carbon emissions. agg is the key explanatory variable, indicating industrial agglomeration. X is the set of control variables; W is the spatial weight matrix; $WCarbon$ is the spatial lag term of the explained variable, which represent the spatial spillovers of carbon emissions; $Wagg$ and WX are the spatial lag terms of industrial agglomeration and control variables, respectively, indicating the interaction between different regions. μ_i indicates the individual effect that does not change with time; λ_t indicates the temporal effect that does not change with the individual; ε_{it} is the random disturbance term.

If both ρ and θ are zero, Equation 1 is a Spatial Error Model (SEM); if both δ and θ are zero, Equation 1 is the Spatial Lagged Model (SLM); if θ is zero, Equation 1 is the Spatial Dubin Model (SDM). Referring to the practice of LeSage and Pace (2009) this paper uses the Lagrange multiplier (LM) test and the robust LM test to choose the correct model and use the Maximum Likelihood Estimation (MLE) to estimate the parameters of the model (LeSage and Pace, 2009).

Considering the carbon emission and the agglomeration characteristics of industrial agglomeration in this paper, we refer to the method of Feng and Rui (2017); Jun *et al.* (2017) and draws on the construction idea of the gravity model (Anderson, 1979) to define the spatial weight matrix as:

$$W = \begin{cases} \bar{Q}_i \times \bar{Q}_j / d_{ij}^2 & (i \neq j) \\ 0 & (i = j) \end{cases} \quad (2)$$

Where, \bar{Q}_i and \bar{Q}_j represent the average real GDP per capita of area i and area j in 2004–2016, respectively; d_{ij} is the distance between area i and area j , which is the geographical spherical distance calculated according to the latitude and longitude coordinates of the provincial capital cities.

LeSage and Pace (2009) pointed out that the use of point estimation coefficients in the spatial econometric model to test whether there is a spatial spillover effect may lead to wrong conclusions (LeSage and Pace, 2009). The partial differential interpretation of the variables in the spatial regression model can be used as an effective way to test whether there is a spatial spillover effect. Hence Equation 2 can be rewritten as:

$$Carbon = (I - \rho W)^{-1}(\beta X + WX\delta) + R \tag{3}$$

In Equation 3, R is the residual term including the intercept and disturbance term. X is the explanatory variables including the key variable agg . The partial derivatives of the expectation of $Carbon$ to the k th explanatory variable can be written as:

$$\begin{aligned} \left[\frac{\partial E(Carbon)}{\partial x_{1k}} \quad \dots \quad \frac{\partial E(Carbon)}{\partial x_{Nk}} \right] &= \begin{bmatrix} \frac{\partial E(Carbon_1)}{\partial x_{1k}} & \dots & \frac{\partial E(Carbon_1)}{\partial x_{1k}} \\ \vdots & \ddots & \vdots \\ \frac{\partial E(Carbon_N)}{\partial x_{Nk}} & \dots & \frac{\partial E(Carbon_N)}{\partial x_{Nk}} \end{bmatrix} \\ &= (I - \rho W)^{-1} \begin{bmatrix} \beta_k & w_{12} \delta_k & \dots & w_{1N} \delta_k \\ w_{21} \delta_k & \beta_k & \dots & w_{2N} \delta_k \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1} \delta_k & w_{N2} \delta_k & \dots & \beta_k \end{bmatrix} \end{aligned} \tag{4}$$

Where, the direct effect is the diagonal elements of the partial derivative matrix in Equation 4, which indicates the influence of the explanatory variables of the local area on the explained variables. The indirect effect is the mean of the sum of the non-diagonal elements of the partial derivative matrix in Equation 4, indicating the impact of the explanatory variables of adjacent regions on the explained variables. The partial derivative matrix is the total effect, which is the sum of the direct effect and the indirect effect.

3.2. Definitions of Variables

(1) Explained variables: carbon emissions ($Carbon$)

The carbon emission data from 30 provinces, municipalities directly under the central government, and the autonomous regions are from the China Emission Accounts and Datasets (CEADs) (Shan et al., 2016; Shan et al., 2018).

(2) Key explanatory variables: industrial agglomeration (agg).

The location entropy should be selected for the industrial agglomeration measure in a specific area, which is not affected by the size of the area and can better reflect the spatial distribution of the elements. Considering that industry is a vital source of carbon emissions. We use industrial agglomeration level as a proxy variable for industrial agglomeration. The location entropy is defined as:

$$agg_i = (q_i/q)/(Q_i/Q) \tag{5}$$

In Equation 5, q_i is the number of industrial employees in the region i , q is the total number of industrial employees in the nation; Q_i is the total number of employed people in area i , and Q is the total number of working people in the country.

(3) Control variables

The other control variables include ① Foreign direct investment (fdi), using the logarithmic representation of the actual use of foreign investment in each region. ② Environmental regulation ($regu$), using the proportion of environmental governance investment in each region as a percentage of GDP. ③ Industrial structure (is), using the added value of the secondary industry in each region as a percentage of GDP. ④ R&D investment (RD), expressed in proportion to the R&D investment in each region as a percentage of GDP.

3.3. Data Sources

This paper covers 30 provinces, autonomous regions, and municipalities directly under the central government (excluding Tibet) in the Chinese mainland and the period between 2004–2016. Table 1 shows the primary data sources and related explanations. Table 2 presents the descriptive statistics of variables.

Table-1. Data description.

Symbol	Variable	Unit	Source
<i>Carbon</i>	Carbon emissions	10 kt	China Emission Accounts and Datasets (CEADs)
<i>agg</i>	Industrial agglomeration	-	Calculated by author
<i>lnfdi</i>	Foreign direct investment	Billion us\$	China Statistical Yearbooks 2005–2017
<i>regu</i>	Environmental regulation intensity	%	China Statistical Yearbooks 2005–2017
<i>is</i>	Industrial structure	%	China Statistical Yearbooks 2005–2017
<i>rd</i>	R&D expenditure	%	China Statistical Yearbooks 2005–2017

Table-2. Descriptive statistics of variables.

Variable	Number of Samples	Mean	Standard Deviation	Minimum	Maximum
<i>Carbon</i>	390	265.3	181.3	16.5	855.6
<i>agg</i>	390	0.916	0.57	0.159	2.9
<i>lnfdi</i>	390	5.135	1.613	-0.007	7.72
<i>regu</i>	390	0.0137	0.0104	0.00174	0.0601
<i>is</i>	390	0.467	0.0786	0.193	0.59
<i>rd</i>	390	5.135	1.613	-0.007	7.72

4. RESULTS AND DISCUSSION

4.1. Base Regression

This paper proceeded to a series of tests to screen the model. In Table 3, both the LM test and the robust LM test of the spatial lag model and the spatial error model significantly reject the null hypothesis that there is no spatial correlation, which indicates that the introduction of the spatial econometric method is reasonable. The LR test under the condition of the spatial Dubin model shows that the spatial Dubin model cannot be reduced to the spatial lag model and the spatial error model. In summary, this paper sets the econometric model as a spatial Dubin model.

Table-3. Tests of model identification.

Test	Spatial Lag Model	Spatial Error Model
Lagrange multiplier (LM) test	225.919***	238.537***
Robust LM test	8.647***	21.265***
Likelihood-ratio (LR) test	88.93***	135.74***
Wald test	30.85***	276.90***

Note: z statistics in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01.

Table 4 reports the results of the regression of Equation 5. The result of the Spatial Dubin Model(SDM) is located in column (5) and used as the base model of this paper. For comparison, column (1) and column (2) report the pooled least squares estimation (POLS) and the fixed effects (FE) estimation for Equation 1 without considering spatial interaction effects, respectively. Moreover, column (3) and column (4) report the spatial lag model and the spatial error model, respectively.

Table-4. Estimation results of the spatial econometric models.

Explanatory Variables	POLS	FE	MLE		
	(1)	(2)	(3)	(4)	(5)
<i>agg</i>	35.26*** (3.66)	35.26*** (3.66)	33.49*** (3.72)	40.87*** (4.24)	50.86*** (5.44)
<i>lnfdi</i>	8.383* (1.71)	8.383* (1.71)	6.493 (1.40)	4.479 (0.94)	6.337 (1.40)
<i>regu</i>	1053.9** (2.38)	1053.9** (2.38)	978.3** (2.37)	892.2** (2.16)	1019.9*** (2.58)
<i>is</i>	13.85 (0.19)	13.85 (0.19)	-0.355 (-0.01)	5.951 (0.09)	-24.22 (-0.36)
<i>rd</i>	3167.8*** (2.75)	3167.8*** (2.75)	3024.6*** (2.81)	2968.9*** (2.61)	1877.3 (1.52)
<i>WCarbon</i>			0.121** (2.02)		0.153** (2.54)
<i>Wagg</i>					-48.75*** (-3.98)
<i>Wlnfdi</i>					15.72** (2.17)
<i>Wregu</i>					1562.6** (2.15)
<i>Wis</i>					-87.25 (-0.81)
<i>Wrd</i>					797.8 (0.49)
<i>Wε</i>				0.165*** (2.60)	
Spatial effects	Control	Control	Control	Control	Control
Temporal effects	Control	Control	Control	Control	Control
Hausman test					-4.85
R^2	0.9580	0.6975	0.2461	0.3782	0.6500
Log-L			-1961.1007	-1959.7306	-1942.2325
Obs	390	390	390	390	390

Note: z statistics in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01.

As shown in Table 4, the Hausman test has a negative statistic, which means that the explanatory variables in the model are related to individual effects, which can be regarded as signals rejecting the null hypothesis. This implies that the model should be estimated for fixed effects. It can be seen that the significance and the symbol direction of the regression coefficients of the key explanatory variable *agg* in column (1)-column (5) have not changed, and the estimation results of most control variables are also consistent, which indicates the results in this paper are robust. Next, based on the estimation results of column (5), the spatial spillover effect of industrial agglomeration on carbon emissions is estimated by Equation 4. The estimated results are shown in Table 5.

Direct effect aspect. The coefficient of industrial agglomeration is significantly positive, which indicates that industrial agglomeration has a positive impact on carbon emissions in the local area. The higher the number of industrial enterprises in the region, the higher the concentration, and the carbon emissions in the region will also rise. The coefficient of foreign direct investment is positive, but it has not passed the 10% significance level test, which means that the introduction of foreign capital has little impact on the carbon emissions of the region. The coefficient of environmental regulation is substantially positive, which means that as the intensity of ecological governance increases, carbon emissions in the local area are not suppressed, but instead increase. The coefficient of industrial structure is negative, but not significant, which indicates that the development of the secondary industry has not caused more carbon emissions, but has a tendency to inhibit emissions potentially. The coefficient of R&D investment is significantly positive, which indicates that R&D investment and technological innovation have not played the role of suppressing Carbon emissions, but have intensified the emissions. Because the R&D investment can be divided into R&D for production technology and reduction, according to the results of this paper, the current R&D investment in China is mainly biased towards production technology, which aims to increase productivity and thus exacerbate carbon emissions.

Table-5. Results of spatial spillover effect.

Variables	Direct effect	Indirect effect	Total effect
<i>agg</i>	48.80***	-45.62***	3.182
	-5.13	(-3.60)	-0.21
<i>lnfdi</i>	7.128	18.81**	25.94***
	-1.64	-2.25	-2.59
<i>regu</i>	1161.9***	1909.4**	3071.3***
	-3	-2.36	-3.2
<i>is</i>	-29.45	-95.31	-124.8
	(-0.43)	(-0.77)	(-0.75)
<i>rd</i>	1969.4*	1287	3256.4*
	-1.68	-0.74	-1.86

Note: z statistics in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01.

Indirect effects. The coefficient of industrial agglomeration is significantly negative, indicating that the higher the level of industrial agglomeration in the local region, will contribute to the suppression of carbon emissions in adjacent areas. The coefficient of foreign direct investment is considered positive, which indicates that the introduction of foreign capital in the local region will aggravate the carbon emissions in neighboring areas. The coefficient of environmental regulation is significantly positive, which indicates that the increase of environmental pollution in the local region will promote the rise of carbon emissions in neighboring areas. So, governance of carbon emissions requires coordination and cooperation between local governments, and any unilateral management will be futile. The coefficient of industrial structure is negative, but not significant, which indicates that the adjustment of industrial architecture in the local region has a potential inhibitory effect on carbon emissions in neighboring areas. The coefficient of R&D investment has not passed the 10% significance level test, but its coefficient is positive, which also indicates to some extent that the main direction of R&D investment may lie in the improvement of productivity, at least not directly reflected in the progress of energy saving and emission reduction technology.

4.2. Robustness Test

The result of the parameter estimation of the spatial econometric model is strongly influenced by the selection of the spatial weight matrix. It is necessary in order to estimate the robustness of the estimation under different spatial weight matrices. Therefore, this paper uses 0-1 adjacency matrix, geographic distance matrix, and economic distance matrix, and employs the linear weighted matrix of economic distance and geographic distance to estimate the spatial Durbin model represented by formula (1) based on the maximum likelihood estimation method. The

estimation results are presented in Table 6. Where, column (1) is 0-1 adjacent weight, column (2) is economic distance weight, column (3) is geographic distance weight, and column (4) is economic and geographic distance nesting weight.

It is found that the symbol direction and significance of the coefficients of the key explanatory variable(*agg*) have not changed, and the symbol direction and significance of most control variables are also consistent, which indicates that the estimation results in this paper are robust.

4.3. Mechanism Test

From the previous analysis, it can be seen that industrial agglomeration have a significant positive effect and a significant negative indirect effect on carbon emissions. Then, what mechanism does industrial agglomeration affect carbon emissions? Studying this will contribute to understanding more deeply the intrinsic relationship between industrial agglomeration and pollution emissions. In this paper, the industrial scale and energy intensity are selected as mediator variables, and the mediation effect model is constructed to test the possible influence channels.

Table-6. Estimation of different spatial weight matrices.

Effects	Variables	(1)	(2)	(3)	(4)
Direct effects	<i>agg</i>	40.57*** (4.53)	40.02*** (4.20)	39.08*** (4.15)	37.02*** (3.96)
	<i>lnfdi</i>	7.423* (1.71)	6.923 (1.48)	7.379* (1.72)	6.531 (1.55)
	<i>regu</i>	1320.7*** (3.43)	1069.3*** (2.75)	1352.9*** (3.44)	1358.7*** (3.48)
	<i>is</i>	106.6 (1.61)	-9.684 (-0.15)	-34.96 (-0.50)	-31.42 (-0.47)
	<i>rd</i>	2573.6** (2.19)	1852.3* (1.74)	2609.1** (2.29)	2703.7** (2.38)
Indirect effects	<i>agg</i>	-66.81*** (-3.25)	34.26 (0.91)	-30.99** (-2.10)	-25.17 (-1.47)
	<i>lnfdi</i>	-30.31*** (-2.62)	-72.09*** (-3.76)	29.52*** (3.53)	46.91*** (4.71)
	<i>regu</i>	1743.9 (1.61)	-1813.7 (-1.12)	3047.0*** (3.55)	3718.1*** (3.37)
	<i>is</i>	297.2* (1.79)	366.7 (1.40)	-22.94 (-0.19)	-48.66 (-0.34)
	<i>rd</i>	7857.9*** (3.45)	4344.3 (0.95)	-423.4 (-0.24)	-102.2 (-0.05)

Note: z statistics in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01.

(1) Mediation Variables

1. Industrial scale(*scale*). This paper selects the industrial added value of each region as the proxy variable of industrial scale to test the scale effect of industrial agglomeration.
2. Energy intensity(*ei*). We examine the energy effect by selecting the unit GDP energy consumption as a proxy variable of energy intensity.

(2) Model Setting

Referring to the general practice of the existing literature, a mediating effect model of the following form is set to examine the mechanism by which industrial agglomeration affects carbon emissions through scale effects and energy effects.

$$Carbon_{it} = \rho W Carbon_{it} + \beta_1 agg_{it} + \beta_2 X_{it} + \delta_1 W agg_{it} + \delta_2 W X_{it} + \lambda_t + \mu_i + \varepsilon_{it} \tag{6}$$

$$\begin{aligned}
 \lnscale_{it} &= \rho W \lnscale_{it} + \beta_1 agg_{it} + \beta_2 X_{it} + \delta_1 Wagg_{it} \\
 &+ \delta_2 WX_{it} + \lambda_t + \mu_i + \varepsilon_{it}
 \end{aligned}
 \tag{7}$$

$$\begin{aligned}
 \ln ei_{it} &= \rho W \ln ei_{it} + \beta_1 agg_{it} + \beta_2 X_{it} + \delta_1 Wagg_{it} \\
 &+ \delta_2 WX_{it} + \lambda_t + \mu_i + \varepsilon_{it}
 \end{aligned}
 \tag{8}$$

$$\begin{aligned}
 Carbon_{it} &= \rho W Carbon_{it} + \beta_1 agg_{it} + \beta_2 \lnscale_{it} + \beta_3 \ln ei_{it} + \beta_4 X_{it} \\
 &+ \delta_1 Wagg_{it} + \delta_2 W \lnscale_{it} + \delta_3 W \ln ei_{it} + \delta_4 WX_{it} + \lambda_t + \mu_i + \varepsilon_{it}
 \end{aligned}
 \tag{9}$$

Among them, *lnscale* represents production scale; *ln ei* represents energy intensity. Other variables are the same as Equation 1.

Table-7. Results of mechanism test.

		Carbon	lnscale	ei	Carbon
		(1)	(2)	(3)	(4)
Direct effects	<i>agg</i>	48.80***	0.0237**	-0.144*	52.79***
		-5.13	-1.96	(-1.95)	-5.72
	<i>lnfdi</i>	7.128	0.00442	-0.160***	10.93**
		-1.64	-0.83	(-4.94)	-2.37
	<i>regu</i>	1161.9***	1.348***	-6.174**	589
		-3	-2.85	(-2.14)	-1.54
	<i>is</i>	-29.45	0.551***	1.020**	45.81
		(-0.43)	-6.71	-2.35	-0.57
	<i>rd</i>	1969.4*	-3.543**	2.265	3580.6***
		-1.68	(-2.36)	-0.25	-2.92
<i>lnscale</i>				149.8***	
<i>ln ei</i>				-3.87	
				14.22**	
				-2.12	
Indirect effects	<i>agg</i>	-45.62***	-0.0251*	-0.00709	-27.34**
		(-3.60)	(-1.69)	(-0.08)	(-2.16)
	<i>lnfdi</i>	18.81**	-0.00492	-0.222***	26.11***
		-2.25	(-0.51)	(-3.88)	-2.74
	<i>regu</i>	1909.4**	-1.143	1.391	1520.2*
		-2.36	(-1.24)	-0.25	-1.88
	<i>is</i>	-95.31	0.802***	1.058	1.917
		(-0.77)	-5.83	-1.58	-0.01
	<i>rd</i>	1287	-3.414	11.15	2286.9
		-0.74	(-1.64)	-0.93	-1.22
<i>lnscale</i>				-197.7***	
<i>ln ei</i>				(-2.64)	
				-16.82	
				(-0.29)	
	Spatial effects	YES	YES	YES	YES
	Temporal effects	YES	YES	YES	YES
	<i>R</i> ²	0.65	0.0565	0.2328	0.7084
	<i>Log-L</i>	-1942.23	664.6826	-55.5908	-1917.58
	<i>N</i>	390	390	390	390

Note: z statistics in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01.

The mechanism of industrial agglomeration compact on carbon emissions

Table 7 shows the results of the test for the mechanism of industrial agglomeration affect carbon emissions. Where, column (1) is the estimation result of the benchmark model (5); columns (2) and (3) are the estimation results of Equations 7 and 8; column (4) reports the estimated result of Equation 9.

Direct effect aspect. From the regression results of columns (2)-(3), it can be seen that the regression coefficient of industrial scale to industrial agglomeration is significantly positive, which indicates that industrial agglomeration can increase the size of industrial output in the local region and has a significant role in promoting industrial development. The energy intensity has a significant negative regression coefficient for industrial agglomeration, which indicates that industrial agglomeration significantly inhibits the improvement of energy intensity in the local area. From the regression results in column (4), it can be seen that the coefficient of industrial agglomeration is significantly positive, which means that industrial agglomeration significantly increases the carbon emissions of the local region. The regression coefficients of industrial scale and energy intensity are significantly positive, which indicates that with the increase of industrial output value and the rise in energy intensity, the carbon emissions in this region will have a significant increasing trend. Compared with the regression results of column (1), the coefficient of industrial agglomeration increases slightly after adding the mediator variables of industrial scale and energy intensity, which preliminaries indicates that industrial scale and energy intensity have a particular "mediation effect" in the direct effect.

Indirect effects aspect. From the regression results of columns (2)-(3), it can be seen that the regression coefficient of industrial scale to industrial agglomeration is significantly negative, which means that industrial agglomeration has a significant inhibitory effect on the industrial scale of neighboring regions. The agglomeration of enterprises in the surrounding areas of the central region will reduce the industrial output value of the surrounding areas. The regression coefficient of energy intensity of industrial agglomeration is negative, but not significant, which means that industrial agglomeration has less impact on the energy intensity of adjacent areas, at least will not aggravate the improvement of energy consumption level in neighboring areas. The regression results in column (4) show that the regression coefficient of industrial agglomeration is significantly negative, which shows that industrial agglomeration has a significant inhibitory effect on carbon emissions in adjacent areas. Both industrial scale and energy intensity have a negative impact on carbon emissions. The regression coefficient of industrial scale has passed the 1% significance level test, but the regression coefficient of energy intensity is not significant, which means that compared with energy intensity, the inhibition effect of industrial scale on carbon emissions in adjacent areas is more prominent. Compared with the regression results of column (1), the coefficient of industrial agglomeration declines considerably after the introduction of mediator variables such as industrial scale and energy intensity, which indicates preliminaries that in terms of indirect effect, the "mediation effect" should not be ignored.

In summary, industrial agglomeration can indeed affect carbon emissions in the local region and adjacent areas through industrial scale and energy intensity. We further understand the reason why industrial agglomeration aggravates the carbon emissions in the local areas is that industrial agglomeration has increased the industrial output value, expanded the industrial scale. At the same time, industrial agglomeration has promoted energy in the local area. However, the reason why industrial agglomeration has a significant inhibitory effect on carbon emissions in adjacent regions lies in the transfer and flow of elements in the agglomeration process. Specifically, the agglomeration of enterprises in the local region has resulted in the continuous decline of industrial scale and the reduction of energy consumption demand in the neighboring areas, thus reducing carbon emissions in the nearby areas.

5. CONCLUSIONS

Based on the 2004-2016 Chinese provincial panel data, this paper uses spatial econometric models to analyze the impact of industrial agglomeration on carbon emissions. The study found that industrial agglomeration has a

positive effect on local carbon emissions, but can reduce carbon emissions in neighboring regions. This conclusion is still robust after considering the choice of different spatial weight matrices. We further use industrial scale and energy intensity as the mediator variable to test the mechanism of industrial agglomeration affecting carbon emissions. We find that, on the one hand, industrial agglomeration exacerbates local carbon emissions by promoting industrial scale expansion, but it can suppress carbon emissions in neighboring regions; on the other hand, industrial agglomeration inhibits carbon emissions in local and neighboring areas by affecting energy intensity. We also found that industrial agglomeration has a stronger effect on reducing emissions in the local region through energy effects than in adjacent areas.

In this regard, we suggest that the government should make full use of the restraining effect of industrial agglomeration on carbon emissions through energy effect. Since industrial agglomeration can affect carbon emissions by affecting energy intensity, the mediating effect of energy intensity indicates that there is a direct correlation between carbon emission reduction and energy-saving policies. When formulating energy conservation and emission reduction policies, the government should fully consider the mutual coordination of the two strategies, and at the same time realize the energy conservation and emission reduction effects of economic agglomeration. At the same time, we should be vigilant about the positive spillover effect of industrial agglomeration on carbon emissions in nearby areas. Local governments should form a coordinated governance model to prevent industrial agglomeration and increase carbon emissions in the surrounding regions. Also, the government should formulate preferential policies, actively encourage the introduction of foreign-invested enterprises with high environmental protection technologies, and at the same time use the spillover effects of foreign capital and agglomeration economies to promote green technology advancement in the agglomeration areas.

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