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The Environmental Pollution Effects of Industrial Agglomeration

A Spatial Econometric Analysis Based on Chinese City Data

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ABSTRACT

To analyze the environmental pollution effects elicited by industrial agglomeration, a spatial econometric model is constructed based on the Green Solow model. Using data derived from 285 Chinese cities between 2003and 2014, the global Moran'I and local bivariate LISA agglomeration map demonstrates that there is significant correlation between industrial agglomeration and industrial pollution discharge. Then, the spatial Durbin model (SDM) is built and the empirical results are as follows. First, inter-city industrial pollution discharge has a demonstration effect. Cites in the same region should take measures to cooperate to lower industrial pollution discharge. Second, the relationship between the local cities' industrial agglomeration and the local cities' industrial pollution discharge fits the inverted "U" curve. While the neighboring cities' industrial agglomeration will decrease the local cities' industrial pollution discharge. So, measures should be taken to increase the industrial agglomeration degree in the long run.

KEYWORDS

China, Demonstration Effect, Industrial Pollution, LISA, Moran's I, Spatial Correlation, Spatial Durbin Model, Spatial Spillover

INTRODUCTION

Industrial agglomeration contributes a lot to spur economic growth of China mainly through Marshall-Arrow-Romer (MAR) externalities or Jacobs externalities. While with the enhancing of industrial agglomeration and rapid economic growth, China now has been noted for not only its high economic growth but also its severe environmental degradation (Sun &Yuan, 2015). According to the "Towards the environmentally sustainable future: national environmental analysis of the People's Republic of China" issued by Asian development bank 2013, only less than 1% of the 500 large cities in China are up to the world health organization (WHO) air quality standards. In 2012, 33 out of 113 key environmental protection cities achieved the National Air Standard II level (Ministry of Environmental Protection, 2012).

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The industrial pollution also leads to China's agricultural losses by reducing yields and reducing areas suitable for crops. The concentrations of SO_2 and fluoride typical for some Chinese cities and industrial areas in the 1980s can reduce the growth and yield of local crops and vegetables by 5-25% (Cao, 1989). Wei et al. (2014) noted that an agricultural loss of $1.43 billion was caused by industrial SO_2 pollution in China, which accounted for approximately 0.66% of the total agricultural added value of 899 countries. Monterroso-Rivas et al. (2018) estimates the double impact of climate change and soil loss over crops and gets the result that with climate change caused by environmental pollution, potential crop yields suffer a generalized decrease.

As the environmental pollution appeared with the industrial agglomeration, the relationship between industrial agglomeration and industrial pollution discharge has received high attention within the field of environmental economics. Most of the literature use Chinese provincial panel data to do empirical research and contradictory findings have been reported. The industrial agglomeration may aggravate industrial pollution discharge due to the industrial production expansion (Fagbohunka, 2012; Sun & Yuan, 2015) and the "pollution haven" effects (Zeng & Zhao, 2009; Wagner & Timmins, 2009). By contrast, research also provides evidence that industrial agglomeration is conducive to abate industrial pollution discharge because of the scale effect in pollutant treatment (Copeland & Taylor, 2004), more stringent environmental regulations in the industrial agglomeration (Lu & Feng, 2014; Milani, 2017), the knowledge and technology spillover effect (Porter, & Van, 1995; Popp, Newell, & Jaffe, 2010) and the industrial symbiosis effects in the industrial agglomeration (Cheng, 2016). There are also research gets the conclusion that the relationship between industrial agglomeration and environmental pollution is nonlinear because of the effect of the intermediate variables such as city size, marketization level, industrial agglomeration degree, industrial structure and technological innovation (Zhang & Dou, 2015; He, Huang, & Ye, 2014).

Although previous studies make this topic clearer, there are still deficiencies. One is that the existing literatures based on China used the provincial data. As a large country, the industrial agglomeration level is quite different in different region of a province, so the research using provincial data cannot reflect the real relation between industrial agglomeration and environmental pollution. In addition, most of the existing research ignored the spatial correlation and spillover effects of industrial agglomeration and industrial pollution. In reality, the flow of contaminated water, the diffusion of air pollution, and the spread of dust all lead to spatial correlation and spatial dependence of regional environmental pollution levels (Wang, Kang, Wu, & Xiao, 2013; Li, 2014). Furthermore, spatial correlation could also result from endogenous interactions in plant behavior in the industrial cluster, which could generate both the "selection effect" and "demonstration effect" (Gray & Shadbegian, 2007). So the research results without considering the spatial correlation may be biased.

Compared with previous researches, the contributions of this study are mainly embodied in the following two aspects. First, the study uses panel data of 285 prefecture level cities' annual data from 2003-2014 to investigate the relationship of industrial agglomeration and industrial pollution discharge in China. Second, The Moran's I and bivariate LISA is used to estimate the spatial autocorrelation of industrial agglomeration and industrial pollution discharge in China. Furthermore, spatial Durbin model (SDM) is applied to estimate the effect of industrial agglomeration on industrial pollution discharge to ensure that the spatial autocorrelation effect and spatial spillover effect be taken into consideration.

The rest of this paper is organized as follows. Section 2 describes the variables, methodology and builds the spatial econometric model. Section 3 does empirical estimation using the panel data of 285 prefecture level cities of China from 2003-2014. Section 4 concludes the paper with a brief summary of findings and discussion of policy implications.

METHODOLOGY AND SPATIAL ECONOMETRIC MODEL

Variables and Data description

The explained variable is the amount of industrial pollutant discharge (P), while now there is not a unified statistic indicator to measure. As SO_2 is the most typical pollutant in industrial pollution emissions, this paper chooses the amount of industrial SO_2 emission (Ton) as the proxy of industrial pollutant emission (P) (Yang, 2015; liu, Zhu, & Du, 2017). The core independent variable is the degree of manufacturing agglomeration (ag). There are several methods to measure the degree of industrial agglomeration, such as the economic density, the location quotient and EG index. While the location quotient and EG index does not fully reflect the economic development differences and the geographical area differences among the cities. So, this article uses industrial density (Ten thousand RMB Yuan per square Km), which is the industrial output per unit area to measure the degree of agglomeration. A number of studies in industrial agglomeration have used this index, including Ciccone and Hall (1996) and Martin (2011).

Besides the explained variable and the core independent variable, there are also four control variables. The first control variable is the economic development level, which is an important factor influences the pollutant emission. Per capita GDP (RMB Yuan) is used to measure the level of economic development. The second control variable is foreign direct investment, which plays an important role in China and influences the industrial pollutant emission. This paper uses the actual annual foreign investment[1] (ten thousand RMB Yuan) to measure foreign direct investment. The third control variable is the investment on research and development. Domestic research and development is a main channel of technological progress, which can help enterprises to adopt environmental-friendly technologies and then reducing pollutant emissions. In this study, the annual spending on research and development (ten thousand RMB Yuan) is used to measure. The last control variable is environmental regulation degree. There is not direct statistic data to reflect the environmental regulation degree. The quantity of employment in the environmental department of a city can reflect the environmental regulation degree. Considering of the available of the data, this paper choose the quantity of employment in the environmental department of a city (person) as the proxy of the city's environmental regulation degree.

To reflect the spatial autocorrelation and spatial spillover effect, this study uses the spatial model, so the spatial weight matrix W_{ij} need to be defined. W_{ij} is a $n \times n$ matrix with components w_{ij}. This matrix is the formal expression of spatial dependence between observations (Anselin, 1988). In this study, geographic distance is used to determine the spatial weight matrix. We let $w_{ij} = 1 / d_{ij}$, where d_{ij} is the Euclidean distance between city i and city j. In addition, the matrix W is commonly row-standardized such that the elements of each row sum to one.

Exploratory Spatial Data Analysis (ESDA)

Tobler (1970) put forward the First Law of Geography that any object is related to other objects with special consideration of distance, which shows that the more closely located the objects are, the stronger the correlation that exists between them. It is called spatial autocorrelation. ESDA is a method of describing spatial autocorrelation, which is employed to detect spatial properties of a phenomenon (Anselin, 1995). It can be divided into global spatial autocorrelation analysis and local spatial autocorrelation analysis. Global spatial autocorrelation analysis is used to describe spatial distribution characteristics in the entire study area, while local spatial autocorrelation analysis is used to evaluate spatial agglomeration, spatial heterogeneity or spatial regimes among regions. This study uses Moran's I, one of the most widely used spatial autocorrelation statistics (Anselin, 1995; Getis, 2007) to measure the spatial correlation of industrial agglomeration and industrial pollution emission.

The global Moran's I of industrial pollution emission is calculated using the following formula (Moran, 1948):

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

Where I^P is the global spatial autocorrelation index of industrial SO_2 emission, n is the total number of geographic units (i.e., cities), x_i^P and x_j^P are the standardized industrial SO_2 emission degree of city i and j. $\overline{x}^P = \frac{1}{n}\sum_{i=1}^{n} x_i^P$, w_{ij} is the spatial weight matrix, which is defined by the inverse distance between different cities. The values of global Moran's I range from -1 to 1. Equation (1) suggests that the calculation of I^P is based on a comparison of industrial SO_2 emission values in neighboring geographical units. The values of I^P vary between -1 and 1. If $I^P > 0$, there is positive spatial correlation between the industrial SO_2 emission of different regions, which means that the neighboring units have similar values over the entire study area. The larger the value is, the stronger the correlation will be. Inversely, if Moran's I<0, negative spatial correlation exists. Negative spatial correlation means that dissimilar values are observed among neighboring units, or the regions with high industrial SO_2 emission are neighbored with regions with low industrial SO_2 emission.

Similar to the global Moran's I of industrial SO_2 emission, the global Moran's I of industrial agglomeration is calculated using the following formula:

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

Where I^{ag} is the global spatial autocorrelation index of industrial agglomeration, x_i^{ag} and x_j^{ag} are the standardized industrial agglomeration degree of city i and j. $\overline{x}^{ag} = \frac{1}{n}\sum_{i=1}^{n} x_i^{ag}$. w_{ij} is the spatial weight matrix, which is defined by the inverse distance between different cities. If $I^{ag} > 0$, there is positive spatial correlation between the industrial agglomeration of different cities; Inversely, if I^{ag} <0, different cities have negative spatial correlation of industrial agglomeration.

Local Moran's I, which is often called LISA, is applied to measure local clustering phenomenon between region i and j. the bivariate LISA agglomeration map illustrates the relationship between the values of the chosen attribute at a given location and the average value of another attribute at neighboring locations at a certain significance level (Chakravorty, Koo, & Lall, 2003; Chi & Zhu, 2008). To visualize local spatial correlation, the bivariate LISA agglomeration map is drawn using the software Geoda.

Model Building

Based on the Green Solow model (Brock & Taylor, 2010), this paper assumes that industrial production discharges pollution and has negative effects on environment. The government will set a certain level of environmental regulation to achieve social welfare maximization. Enterprises have to invest part of their outputs on pollution control to meet environmental regulation requirements. So the final production function can be expressed as equation (3).

$$Y_{it} = A_{it} K_{it}^{\alpha_{it}} L_{it}^{1-\alpha_{it}} \left(1-\theta_{it}\right) \tag{3}$$

In equation (3), Y_{it} is the net output of city i in period t, K_{it} and L_{it} is the capital and labor used in production of city i in period t respectively. A_{it} is the total factor productivity, α_{it} is the input ratios of capital in production, which is a constant between 0 and 1. 1-α_{it} is the input ratios of labor. θ_{it} is a constant between 0 and 1 too. It is the fraction of economic output dedicated to pollution emission abatement. By using the framework of Xie & Yuan (2016), the enterprises' pollution discharge (P) is given by equation (4).

$$P_{it} = A_{it}^{-1} Y_{it} (1-\theta_{it})^{\beta_{it}-1} \tag{4}$$

Where A_{it} , Y_{it} and θ_{it} denote the same meaning as in equation (3), β_{it} is a constant and $\beta_{it} > 1$ ensures the effectiveness of the production in technology, which means that the output is positive after deducting pollution emissions. $P_{it}'(\theta_{it}) < 0$ indicates that pollution emission $\left(P_{it}\right)$ is the decreasing function of the pollution emission abatement investment fraction $\left(\theta_{it}\right)$. While θ_{it} is the increasing function of the environmental regulation degree, so the pollution emission is inversely proportional to the environmental regulation degree. The total factor productivity $\left(A_{it}\right)$ is negatively related to the pollution emissions. While the total factor productivity is mainly up to the technology and the economies of scale, both of these two aspects are affected by industrial agglomeration. On the one hand, industrial agglomeration changes the spatial distribution of economic activities and influences the scale economy effects. On the other hand, industrial agglomeration influences technology level through technological spillover (Zhu, 2009). Besides the industrial agglomeration effects, developing countries also obtain technological advance through independent research and development $\left(rd_{it}\right)$ and foreign direct investment $\left(fdi_{it}\right)$. So the total factor productivity can be expressed as equation (5).

$$A_{it} = h(ag_{it}, rd_{it}, fdi_{it}) \tag{5}$$

Where ag_{it} is the industrial agglomeration level of city i in period t, rd_{it} is the research and development level, and fdi_{it} is the amount of foreign direct investment. Combine equation (4) and equation (5), the pollution discharge equation can be rewritten as equation (6) .

$$P_{it} = h\left(ag_{it}, rd_{it}, fdi_{it}\right)^{-1} Y_{it} \left(1-\theta_{it}\right)^{\beta_{it}} \tag{6}$$

According to environmental Kuznets curve (EKC) hypothesis, there are inverse U shape relationship between industrial pollution and economic development. To test whether there is EKC effect in the research period and whether there is the likely relationship between industrial agglomeration and industrial pollutant emission, this paper constructs the model with quadratic term of industrial agglomeration and the quadratic term of economic development level. The econometric model is set as equation (7). To avoid the heteroscedasticity of variables, all variables are taken the logarithm form.

$$\ln p_{it} = \alpha + \beta_{11} \ln ag_{it} + \beta_{12} \ln ags_{it} + \beta_2 \ln rd_{it} + \beta_3 \ln fdi_{it} + \beta_{41} \ln pgdp_{it} + \beta_{42} \ln pgdps_{it} + \beta_5 \ln envr_{it} + \varepsilon_{it} \tag{7}$$

In equation (7), P_{it} is the industrial pollutant emission of city i in year t. ag_{it} is the industrial agglomeration level, ags_{it} is the quadratic term of industrial agglomeration, rd_{it} is the investment on research and development, fdi_{it} is the amount of foreign direct investment, $pgdp_{it}$ denotes the economic development level, $pgdps_{it}$ denotes the quadratic term of economic development level and $envr_{it}$ denotes environmental regulation level. α is the city-specific effect, and ε_{it} is the random error term.

While in Equation (7), spatial autocorrelation and spatial heterogeneity of industrial agglomeration and industrial pollution emission among cities are neglected. Following Anselin (1995), this study uses spatial panel-data econometric models, which combines the spatial econometric method and the panel-data method. This approach improves the accuracy of estimation results by introducing both temporal and spatial characteristics into the research system. There are three kinds of spatial panel-data econometric models: the Spatial Autoregressive Model (SAR), the Spatial Error Model (SEM) and the Spatial Durbin Model (SDM) (Croonenbroeck & Ambach, 2014). SAR contains endogenous interaction effects; the SEM contains interaction effects among the error terms; while the SDM includes terms in which the W matrix interacts with the regressors. The SDM model is built first before deciding whether it can be simplified into SAR or SEM according to the results of the Wald and LR tests. The SDM model is set as equation (8).

$$\ln p_{it} = \alpha + \rho W \ln p_{it} + \beta_{11} \ln ag_{it} + \beta_{12} \ln ags_{it} + \beta_2 \ln rd_{it} + \beta_3 \ln fdi_{it} + \beta_{41} \ln pgdp_{it} + \beta_{42} \ln pgdps_{it} + \beta_5 \ln envr_{it} + \alpha_{11} W \ln ag_{it} + \alpha_{12} W \ln ags_{it} + \alpha_2 W \ln rd_{it} + \alpha_3 W \ln fdi_{it} + \alpha_{41} W \ln pgdp_{it} + \alpha_{42} W \ln pgdps_{it} + \alpha_5 W \ln envr_{it} + \varepsilon_{it} \tag{8}$$

Where ρ is the spatial autoregressive coefficient and W is the spatial weight matrix of size $n \times n$.

EMPIRICAL RESULT AND DISCUSSION

Existing Statistics

Panel data of 285 Chinese prefecture cities[2] from 2003 to 2014 is used to explore the relationship between industrial agglomeration and industrial pollutant discharge. All the data are sourced from the Chinese City Statistical Yearbook and the China City Environment Yearbook (2002-2015). All the currency data are adjusted to the comparable price by taking 2003 as base period. For the individual missing data, this paper uses statistical methods to supplement the missing data. Table 1 reports the descriptive statistics of the variables.

Spatial Correlation Analysis

The global Moran's I of industrial SO2 emission for 285 cities in China during 2003-2014 is shown in table 2. Table 2 reports that industrial SO_2 emission in China exists positive spatial autocorrelation. The high z values and low p values suggest that Moran's I Values are highly statistically significant for industrial SO_2 emission. In other words, industrial SO_2 emission in China is not distributed randomly, but show spatial clustering phenomenon between some regions. The regions with high

Table 1. Descriptive statistics

Variables	Unit	Mean	Standard deviation	Minimum	Maximum
Industrial SO_2 discharge	Ton	61874	60982.77	0.47	683162
Industrial agglomeration (ag)	Ten thousand RMB Yuan per square Km	1939	4824.30	2.406	75783
GDP per capita (pgdp)	RMB Yuan	20992	18894	73.84	294213
spending on R&D (rd)	Ten thousand RMB Yuan	22014	95585	29.46	1713539
actual annual foreign direct investment (fdi)	Ten thousand RMB Yuan	288628	680175.9	0	7078742
Employment in environmental department (envr)	people	6948	8226	100	99202

industrial SO_2 emission are adjacent to other high industrial SO_2 emission regions. The Moran's I increase gradually during 2003-2014, which indicates a tendency of increased concentration of industrial SO_2 discharge in China.

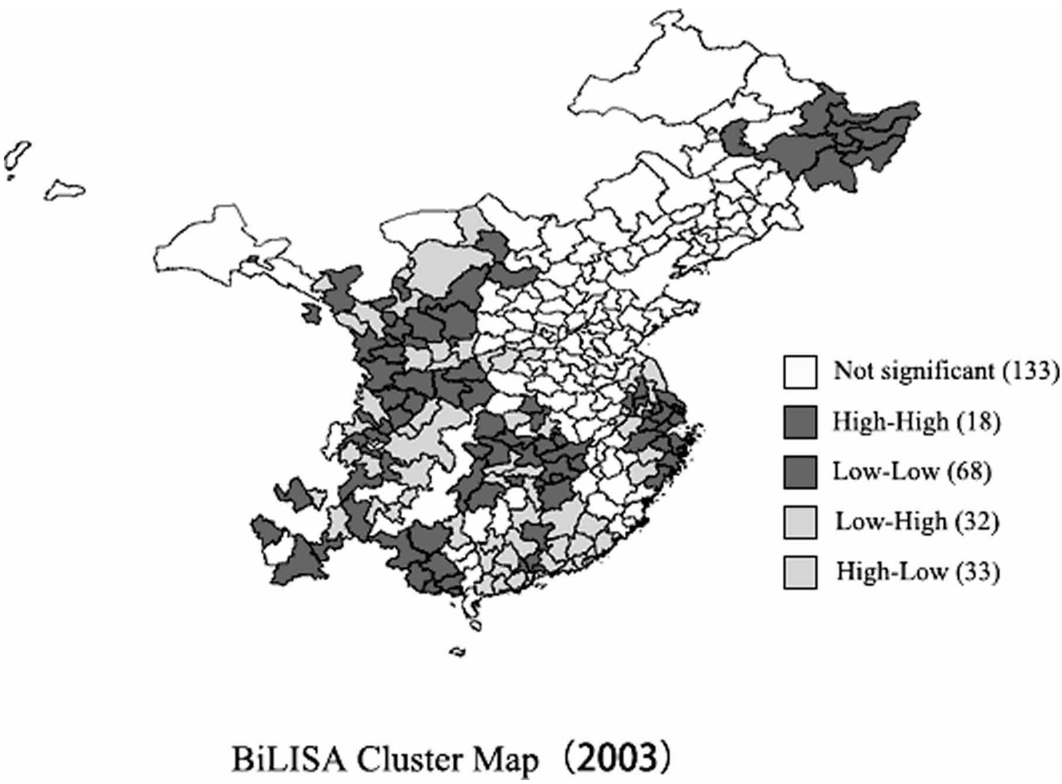
To visualize local spatial correlation, the bivariate LISA agglomeration map is drawn using the software Geoda. There are four types of local spatial autocorrelation. High-high type (HH) and Low-low type (LL) indicate positive spatial correlation. HH type indicates high industrial agglomeration values are surrounded by high industrial SO_2 emission value, LL indicates low industrial agglomeration values are surrounded by low industrial SO_2 emission values. High-low type (HL) and Low-high type (LH) indicate negative spatial correlation. HL indicates that high values are surrounded by low values and LH indicates low values are surrounded by high values. Figure 1-3[3] present BILISA agglomeration maps between industrial agglomeration and industrial SO_2 emission in 2003, 2009 and 2014.

Table 2. The global Moran's I of industrial agglomeration and industrial SO2 emission

year	industrial agglomeration		industrial SO2 emission	
	I^{ag}	Z-value	I^{P}	Z-value
2003	0.246***	11.83	0.105***	4.576
2004	0.246***	11.68	0.103***	4.477
2005	0.246***	12.19	0.112***	4.856
2006	0.248***	12.35	0.105***	4.548
2007	0.262***	12.73	0.086***	3.809
2008	0.264***	13.24	0.096***	4.236
2009	0.281***	13.24	0.096***	4.275
2010	0.288***	13.41	0.102***	4.512
2011	0.285***	13.24	0.163***	6.875
2012	0.287***	13.32	0.177***	7.493
2013	0.297***	13.75	0.188***	7.983
2014	0.284***	13.21	0.182***	7.727

The results are calculated by Arcgis 10.2; ***Statistical significance at 1% level.

Figure 1. BILISA agglomeration maps between industrial agglomeration and industrial SO_2 emission in 2003



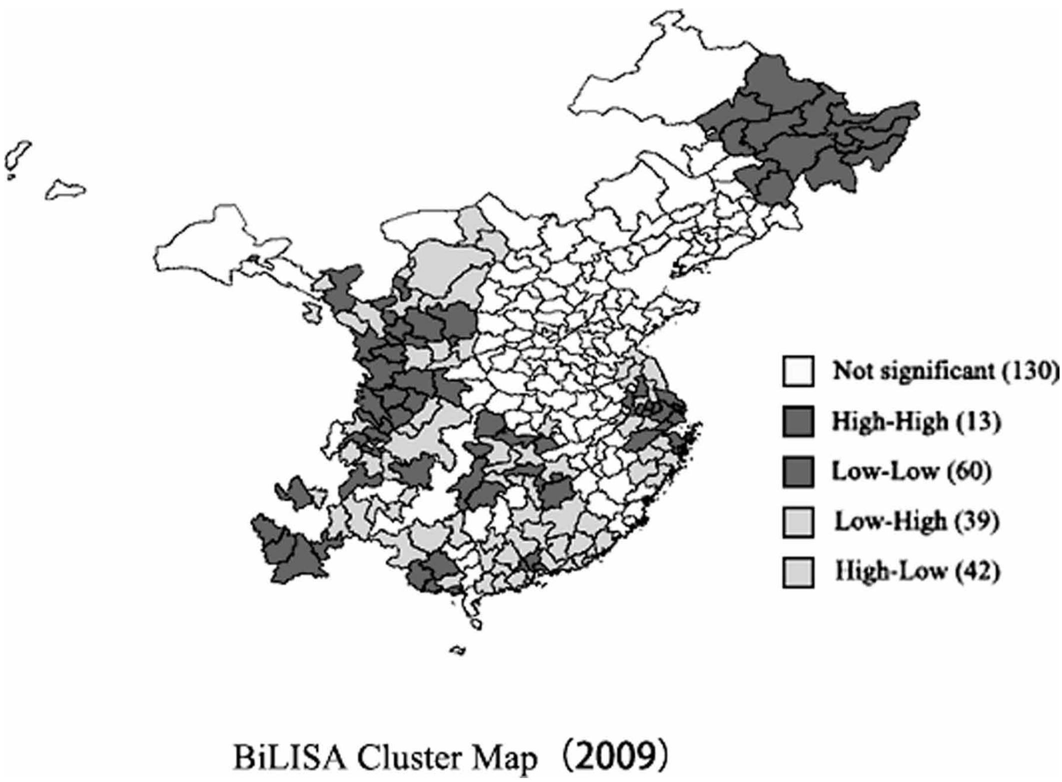
The LISA maps demonstrate that HH regions are mainly concentrated in eastern coastal regions. This indicates that high industrial agglomeration in eastern regions of China probably leads to high industrial pollution. LL regions are mainly distributed in western and northern regions of China. Industrial development is relatively backward in these areas and the industrial pollution is also small. LH regions, which represent regions with high industrial agglomeration, but low industrial pollution, are mainly located in the southern and eastern areas of China. The number of LH type cities increases from 32 to 43 during 2003-2014. This indicates that more cities are developing environmental friendly industrial agglomeration. HL regions means high industrial pollution and low industrial agglomeration are mainly located in the western and northern regions of China.

To conclude, the global spatial analysis shows that both the industrial agglomeration and industrial SO_2 emission are significant spatial autocorrelation. The local spatial analysis indicates there are spatial heterogeneity between industrial agglomeration and industrial SO_2 emission. Consequently, it is important to incorporate the spatial autocorrelation and spatial heterogeneity into the model when analyzing the environmental effects of industrial agglomeration.

Spatial Econometric Test Results

To further test the spatial effect of industrial agglomeration on industrial pollution emission, this research utilizes the LM test for spatial panel data. In these tests, whether the non-spatial model can be rejected is determined by the significance of the statistics. If the results of both the SEM and SAR are not statistically significant, the traditional panel model should be chosen; if any of them is significant, then the spatial econometric model should be utilized to capture the spatiality. To set the proper spatial panel data model, the following three steps should be taken. First, the general panel data model without considering the spatial interaction is built to determine whether the model

Figure 2. BILISA agglomeration maps between industrial agglomeration and industrial SO_2 emission in 2009

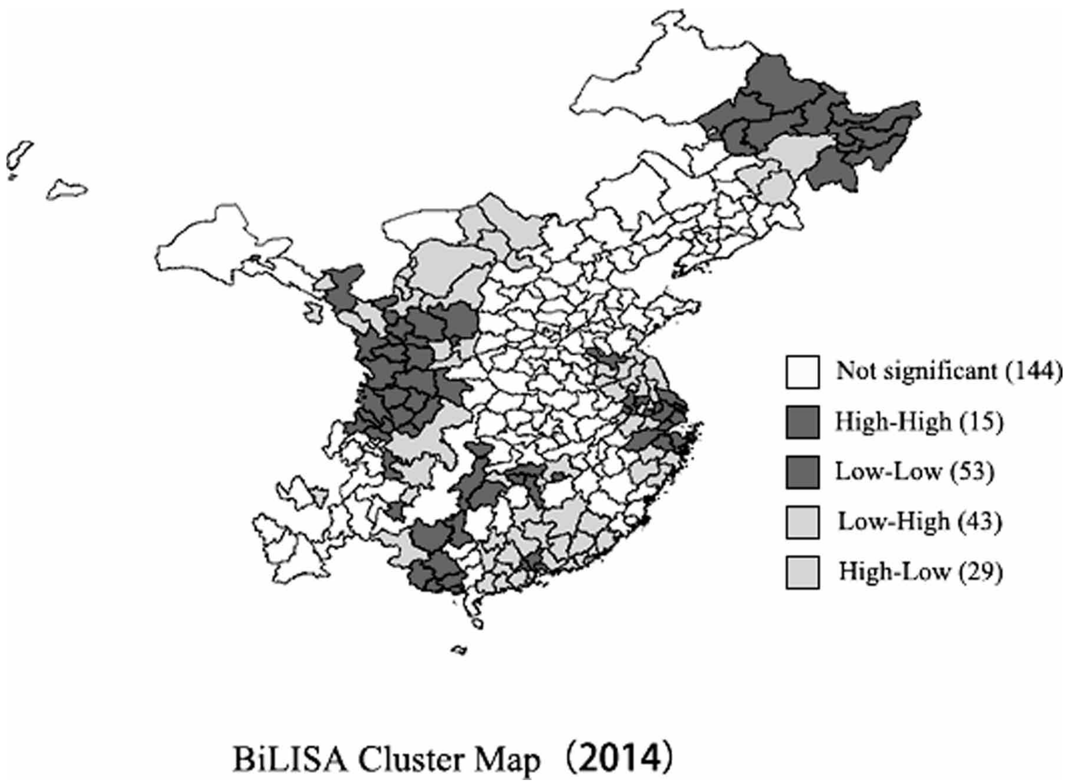


is time fixed, space fixed, both time and space fixed, or none of time and space fixed. Second, the statistical test is carried out according to the model determined in the first step to determine which type of spatial interaction existed in the model. Third, the SDM model is constructed based on the fixed effect model and the postulated conditions to determine whether the SAR, SEM or SDM is more proper (Ding, Zhao, & Zhi, 2012).

Table 3 reports the regression results of the four types of non-spatial panel data models. Taking the estimation results of pooled OLS as an example, the impact coefficient of industrial agglomeration on industrial pollution is 0.5650, which is significant at the level of 1%. The regression coefficient of some other control variables can also pass statistical tests. But the value of R^2 is only 0.2270. This indicates that the model fits the interpreted variables only in a low degree, which may be due to the omission of spatial factors. LM (SAR) and Robust LM (SAR) are 155.2851 and 43.0331 respectively. LM (SEM) and Robust LM (SEM) are 554.4807 and 442.2288 respectively, and all values could pass the significance tests of 1%, which indicates that the Pooled OLS should be rejected and the spatial econometric model should be adopted for analysis. The estimation results of the other three non-spatial models are similar to the estimation results of pooled OLS. The LM (SAR), the robust LM (SAR), the LM (SEM) and the robust LM (SEM) tests of the models without fixed effects, with space-fixed effects, with time-fixed effects and with space-and-time fixed effects are all significant. Hence, the LM tests prove the existence of spatiality. It is thus more appropriate than the traditional panel data model for analyzing the impact of industrial agglomeration on industrial pollution from the perspective of spatial econometrics.

The joint LR test of space-fixed effects and time-fixed effects (listed in table 4) rejects the null hypothesis of no space-fixed and no time-fixed effects; either the space-fixed effects model or the time-fixed effects model can more accurately capture the impact of industrial agglomeration on the industrial pollution than traditional panel data model.

Figure 3. BILISA agglomeration maps between industrial agglomeration and industrial SO_2 emission in 2014



The empirical result of the SDM is shown in table 5. The Wald and LR test results of the bias-corrected space-and-time-fixed effects SDM are all significant. This means that the model cannot be simplified into the SAR or SEM.

The bias-corrected estimation results of the space-and-time fixed effect SDM are reported in table 5. As shown in table 5, the coefficient of the spatial effect is positive and significant, which means that the demonstration effect exists in inter-regional industrial pollution emission. 1% increase of the industrial pollution discharge in the neighboring cities will lead to a 0.5495% increase in the local city. As for the impact of industrial agglomeration on industrial pollution emission, a 1% increase in the industrial agglomeration will lead to a 0.4888% increase in the industrial pollution emission of the local city. The coefficient of the quadratic term of industrial agglomeration is negative, which means that the impact of the industrial agglomeration on the industrial pollution emission fits the inverted "U" curve. While the coefficient of W*lnag is -1.3497, which is the spatial spillover effect of the neighboring cities' industrial agglomeration on the local industrial pollution emission. The neighboring cities' industrial agglomeration increases 1%, the local cities' industrial pollution emission will decrease 1.3497%.

The coefficient of GDP per capita (pgdp) is positive, and the quadratic term of GDP per capita (pgdp) is negative. This means that the relationship between GDP per capita and industrial pollutant emission accords with the environmental Kuznets curve. The industrial pollutant emission first increases with the economic development, while after reaching a turning point, the industrial pollutant emission will decrease with the economic development. The coefficient of W*lnpgdp is not significant. The investment on research and development (rd) is negatively related to industrial pollution discharge. 1% increase in rd will lead to 0.0872% decrease in industrial pollution discharge. The result is accordance with the theoretical hypothesis. With the technological innovation, more and

Table 3. The LM test for choosing the spatial model

	Pooled OLS	Space-fixed Effects	Time-fixed Effects	Space-and-time Fixed Effects
lnag	0.5650*** (9.4824)	0.5533*** (10.1453)	0.6637*** (11.0672)	0.4262*** (7.7886)
lnrd	-0.0775*** (-4.8293)	-0.0227** (-2.1256)	0.0327 (1.3731)	-0.1032*** (-6.5058)
lnfdi	-0.0065 (-0.7664)	0.0073 (0.9573)	-0.0253*** (-2.9480)	0.0062 (0.8361)
lnpgdp	0.6223 (1.4577)	0.7610*** (3.1627)	0.8258* (1.9362)	0.4271* (1.7921)
lnenvr	0.4024*** (14.3009)	-0.0334 (-0.8837)	0.3606*** (12.2722)	-0.0116 (-0.3030)
lnags	-0.0321*** (-6.5089)	-0.0333*** (-7.3320)	-0.0423*** (-8.3930)	-0.0288*** (-6.2812)
lnpgdps	-0.0205 (-0.9290)	-0.0438*** (-3.4320)	-0.0266 (-1.2053)	-0.0254** (-1.9769)
con	1.6014 (0.7992)			
σ^2	1.0192	0.2004	0.9826	0.1916
R^2	0.2270	0.0562	0.2481	0.0471
LogL	-4881.3	-2100.9	-4819.3	-2024.2
LM (SAR)	155.2851***	445.8708***	160.6597***	32.3612***
LM (SEM)	554.4807***	423.9386***	179.2077***	41.4444***
Robust LM (SAR)	43.0331***	27.8121***	5.4722**	5.2039**
Robust LM (SEM)	442.2288***	5.8799**	24.0202***	14.2871***

Note: t –values are in the parentheses. *represents significance level at 10%, ** represents significance level at 5%, and *** represents significance level at 1% respectively.

Table 4. Joint LR test results of space-fixed effects and time-fixed effects

	LR Statistics	Degree of Freedom	P-value
Space-fixed Effect	5590.2178	285	0
Time-fixed Effect	153.4164	12	0

more environmentally friendly technologies will be used in industrial production and less industrial pollutant will be discharged. The impacts of other control variables are not significant.

Decomposition the Industrial Agglomeration Effects on Industrial Pollution Discharge

By introducing spatial effects into traditional panel data model, the impact of industrial agglomeration on industrial pollution discharge is no longer represented only in the variables' coefficient; instead, the spatial effect allows decomposing the impact into direct and indirect effects.

Table 5. The bias-corrected estimation result of the space-and-time fixed effect SDM

Variable	Coefficient	Variable	Coefficient
lnag	0.4888*** (7.8811)	**w*lnag**	-1.3497** (-2.2328)
lnrd	-0.0872*** (-4.9174)	**w*lnrd**	-0.1775 (-1.3973)
lnfdi	0.0125 (1.5886)	**w*lnfdi**	-0.2165*** (-2.8935)
lnpgdp	0.7914*** (3.0074)	**w*lnpgdp**	-2.8917 (-1.0740)
lnenvr	0.0008 (0.0212)	**w*lnenvr**	-0.5177 (-1.1521)
lnags	-0.0323*** (-5.7747)	**w*lnags**	0.0536 (1.4026)
lnpgdps	-0.0440*** (-3.0384)	**w*lnpgdps**	0.1685 (1.2828)
w*lnp	0.5495*** (7.3170)	σ^2	0.2039
Corr^2	0.0572	R^2	0.8579
LogL	-1991.127	**LR test (SAR)**	35.9346***
Wald test (SAR)	33.1492***	**LR test (SEM)**	29.4169***
Wald test (SEM)	27.4615***	**Hausman test**	150.8535**

Note: t –values are in the parentheses. *represents significance level at 10%, ** represents significance level at 5%, and *** represents significance level at 1% respectively.

The decomposition results are reported in table 6. The direct effects of industrial agglomeration (ag) on industrial pollution discharge is 0.4811 and significant at 1%. The indirect and total effects are negative, but not significant. This means that the industrial agglomeration will aggravate the industrial pollution discharge of the local city, while the effect of neighboring cities' industrial agglomeration on the local cities' industrial pollution emission is not remarkable.

The direct effect of the investment on research and development (rd) is -0.0895 and significant at1%. The indirect effect is negative too but not significant. The total effect is negative and significant at 10%. This means that the investment on rd can lower the industrial pollution discharge of the local city. The direct effect of the foreign direct investment is positive but not significant, while the indirect effect is -0.4955 and significant at 5%. This indicates that the foreign direct investment of the neighboring cities is conducive to reduce the local cities' industrial pollution emission. The direct effect of the per capita GDP is 0.7644 and significant at 1%, while the indirect and total effects are not significant. This means that with the per capita GDP increases, industrial pollution also increases, while the spillover effect is not significant.

CONCLUSION

The conclusions of this study are as follows. First, inter-city industrial pollution discharge has a certain demonstration effect: when adjacent cities increase 1% industrial pollution discharge, the local city will increase 0.5495% industrial pollution discharge. So the cites in the same region should take measures to cooperate to lower industrial pollution discharge. The consistent environment protection policies should be taken among the neighboring cities. As the central government, measures should be taken to cultivate the environmental demonstration cities in different regions to drive other cities to lower industrial pollution discharge.

Second, the local cities' industrial agglomeration exacerbates industrial emission. While the coefficient of the square term of industrial agglomeration is negative, which means that with the increase of the industrial agglomeration degree, the industrial pollution discharge will increase first,

Table 6. Effects decomposition of the influencing factors

Variables	Direct Effects	Indirect Effects	Total Effects
$\ln ag$	0.4811*** (7.9629)	-2.5187 (-1.5490)	-2.0377 (-1.2554)
$\ln rd$	-0.0895*** (-5.1649)	-0.5453 (-1.4975)	-0.6348 * (-1.7595)
$\ln fdi$	0.0109 (1.4223)	-0.4955** (-2.0530)	-0.4846** (-2.0062)
$\ln pgdp$	0.7644*** (2.9390)	-5.9852 (-0.8171)	-5.2208 (-0.7138)
$\ln envr$	-0.0054 (-0.1331)	-1.2473 (-1.0842)	-1.2526 (-1.0864)

Note: t –values are in the parentheses. *represents significance level at 10%, ** represents significance level at 5%, and *** represents significance level at 1% respectively.

after the industrial agglomeration degree up to a certain point, the industrial pollution discharge will decrease. So industrial agglomeration strategy should be further implemented and policies should be taken to improve the quality of the industrial agglomeration. The spatial analysis results show the neighboring cities' industrial agglomeration will decrease the local cities' industrial pollution discharge. The city with higher industrial agglomeration level will attract more industries from the neighboring cities, while the cities around the city with higher industrial agglomeration level may experience the "shadow effect" and has weak industrial development, the less industrial pollution discharge. According to the decomposition of the effects of industrial agglomeration on industrial pollution discharge, the total effect is negative. So measures should be taken to increase the industrial agglomeration degree in the long run. In the short run, industrial agglomeration may lead to the local cities' industrial pollution discharge increase too, while in the long run, industrial agglomeration is not only an effective way to develop economics, but also an effective way to lower industrial pollution discharge.

Third, the coefficient of per capita GDP is positive and the coefficient of the square term of per capita GDP is negative, which meets the environmental Kuznets curve. So to solve the environmental problems in China, the effective measure is still further developing the economics. The environmental pollution problem in China now is the stage problems accompany with the economic development. Any measures to solve the environmental problems at the cost of economic development are not desirable. The investment on research and development (rd) is conducive to lower industrial pollution discharge. On one hand, the government should further take measures to increase the government investment on rd. On the other hand, measures should be taken to stimulate the private investors to invest more on the new technology research.

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ENDNOTES

1. The data unit of FDI in China's city book is million US dollar, in order to weed out exchange rate fluctuating, we first convert the data unit into RMB using the annual average exchange rate.
2. There are 292 prefecture level cities in China now. In order to meet the integrity of the data, this article just uses data of 285 cities, excluding Zhongwei, Longnan, Chaohu, Bijie, Tongren, Sansha and Lasha.
3. This is not the complete map of China, it just demonstrates the regions of the research sample.

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