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Original Research

What Causes $PM_{2.5}$ Pollution in China? An Empirical Study from the Perspective of Social and Economic Factors

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Abstract

Based on the Chinese provincial panel data collected from 2000 to 2014, the spatial correlation characteristics of $PM_{2.5}$ pollution are measured by using the exploratory spatial data analysis method, and then the spatial Durbin model is used to analyze the social and economic causes of $PM_{2.5}$ pollution. The results show that: (1) Both global and local spatial correlation characteristics of $PM_{2.5}$ pollution in China show positive spatial correlation, and the local spatial correlation characteristic mainly includes the two cluster areas: high-high type and low-low type. (2) The high-high cluster areas of $PM_{2.5}$ pollution are intensively distributed in the northern China plain and the Middle-Lower Yangtze plain while the low-low cluster areas are scattered throughout the Chinese northwest, southwest and northeast regions. (3) The increases of population density, industrialization level, economic development level and the number of motor vehicles will aggravate the degree of $PM_{2.5}$ pollution, while the improvement of urbanization level and technological progress can alleviate the degree of $PM_{2.5}$ pollution, but the role of environmental protection in lowering the degree of $PM_{2.5}$ pollution has not yet been revealed. (4) The increases of energy consumption can exacerbate the degree of $PM_{2.5}$ pollution in the local area, but its spatial spillover effects for the adjacent areas are not obvious.

Keywords: $PM_{2.5}$ pollution, social and economic causes, spatial Durbin model, spatial spillover effect

Introduction

China's economy has maintained a high growth speed over 40 years since implementation of the reform and opening policy. However, the extensive pattern of economic development has made China to pay a heavy environmental price for economic growth. In winter, widespread haze weather events appear in central and eastern China [1]. Among the pollutants that contribute to the hazy weather, the fine particulate matter with an aerodynamic diameter of less than 2.5 μm ($PM_{2.5}$) is

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widely considered as a culprit that induces the residents' health losses due to its characteristics of small particle size, far transmission distance, long duration of existence, rich toxic substances and the ability to destory the blood circulation system of the human body [2]. Usually, the $PM_{2.5}$ substances in the air mainly come from the industrial emission, life emission, motor vehicles emission, and centralized pollution facilities [3]. An air quality report from Peking University in 2015 noted that Beijing City experienced 437 processes of $PM_{2.5}$ pollution events, with an average duration of 70 hours from 2010 to 2014. The $PM_{2.5}$ concentrations in many cities, such as Shijiazhuang, Baoding and Zhengzhou have been extraordinary because their daily average $PM_{2.5}$ concentrations exceeded 500μg/m³. According to data released by the China Environment Monitoring Station (http://www.cnemc.cn/), none of China's 74 cities that have monitored the $PM_{2.5}$ concentrations met the air quality standard (10-20 μg/m³) recommended by the World Health Organization (WHO) in 2013, and only one out of 190 cities met the control standard in 2014. Frequent $PM_{2.5}$ pollution episodes in China cause heavy damages on a large scale, which not only hinder normal transportation and industrial production, but also seriously destroy the human health [4-7]. Therefore, it is necessary to understand the social and economic causes of $PM_{2.5}$ pollution in China.

Current researches on the driving causes of $PM_{2.5}$ pollution can be categorized into three aspects: natural factors, environmental factors and socio-economic factors. In terms of the natural factors, scholars have mainly explored the causes of $PM_{2.5}$ pollution from the perspective of land use cover changes (LUCC) and meteorological factors. Han et al. [8] analyzed the relationship between LUCC and $PM_{2.5}$ concentrations in China and draw a conclusion that the rising trend of $PM_{2.5}$ concentrations in artificial surface (represent cities) and cropland were about three times higher than in tree covered area. Su et al. [9] found that $PM_{2.5}$ concentrations were positive correlation with the air pressure and sunlight time, but negatively related to the temperature, relative humidity, wind speed and rainfall based on the monitoring data from nine air quality stations in Nanchang City. With respect to the environmental factors, scholars have tended to focus on the mechanisms of other atmospheric pollutants related to $PM_{2.5}$ pollution. Yang et al. [10] argued that in some areas with higher concentrations of particulate matter with particle size below 10μm (PM_{10}) and total suspended particulate (TSP), whose $PM_{2.5}$ concentrations tended to be relatively high. Wang et al. [11] researched the variation characteristics of air quality data came from the 35 monitoring stations in the Beijing City, finding that the change trend of $PM_{2.5}$ concentrations were consistent completely with the nitrogen dioxide (NO_2), sulfur dioxide (SO_2) and nitric oxide (NO). Xue et al. [12] used the weather research and forecasting model and community multi-scale air quality modeling system (WRF-CMAQ) to quantify the effects of ammonia emissions on the degree of $PM_{2.5}$ pollution, revealing that the ammonia emissions in Henan, Shandong, Hubei and Hebei provinces contributed more than 20 μg/m³ to their average annual $PM_{2.5}$ concentrations. In the aspect of the social and economic causes, Han et al. [13] examined and compared the $PM_{2.5}$ concentrations in urban and the surrounding regions on the Chinese county scale, and found that the $PM_{2.5}$ concentrations in the urban areas were greater than those in its surrounding areas because the urbanization process had a considerable impact on $PM_{2.5}$ concentrations. Guan et al. [14] utilized the structural decomposition analysis model (SDA) to explore the social and economic causes of $PM_{2.5}$ pollution in China, drawing a conclusion that the economic growth, capital formation and export of products could aggravate the degree of $PM_{2.5}$ pollution. Wu et al. [15] concluded that the industrialization level, number of vehicles and household consumption of natural gas could worsen the degree of $PM_{2.5}$ pollution, but the impacts of government expenditures and environmental protection on the degree of $PM_{2.5}$ pollution were not significant based on the data of $PM_{2.5}$ concentrations in 74 Chinese cities. Wu et al. [16] adopted an input and output (I-O) model to calculate the number of $PM_{2.5}$ emissions implied by the Chinese provincial trade, and got a result that the number of $PM_{2.5}$ emissions embedded in trade made up for a third of the total amounts of $PM_{2.5}$ emissions. Despite there exists a fact that some prior studies on the causes of $PM_{2.5}$ pollution have been appeared, the driving factors of $PM_{2.5}$ pollution are partly understood. Therefore, better understanding the social and economic causes of $PM_{2.5}$ pollution has become an important and challenging research focus, with various aspects included: (1) Most of scholars have mainly study the causes of $PM_{2.5}$ pollution from independent perspectives of nature, environment, or social and economic factors [17-18]. Of course, some studies have attempted to construct some models that include all of them, but the evaluation results usually present some uncertainties due to the differences existed in the aspect of statistics data [3]. (2) The traditional analysis methods of correlation and regression are common, but the spatial effects of variables may be ignored [19-20]. (3) The $PM_{2.5}$ concentrations data selected by scholars usually come from the current ground monitoring stations. However, the monitoring stations in China have been set up in 2012, meaning that most of studies are based on the cross-sectional data or short time-series panel data, which directly lower the accuracy of evaluation results. (4) Studies have paid more attention to the causes of $PM_{2.5}$ pollution on a regional scale, but the evaluation results obtained may not be applicable more broadly because each city has its own distinctive geographical characteristics [21]. The study tried to use the exploratory spatial data analysis method to measure the spatial correlation characteristic of $PM_{2.5}$ pollution in China and employed the spatial Durbin model to identify the social and economic causes of $PM_{2.5}$ pollution, which can provide a reference for relevant departments to formulate prevention measures of $PM_{2.5}$ pollution.

Data and Methods

Index Selection

The $PM_{2.5}$ pollution is affected by a variety of social and economic factors such as the population distribution characteristics, economic development level, energy consumption situation, public transport facilities, and so on. The indexes that we selected are as follows: (1) The population density (*DE*) could generate significant energy demands, especially for the traffic travel and lives of residents, which would aggravate $PM_{2.5}$ pollution situation [22]. (2) The urbanization level (*UR*) was considered as the most significant human impact on the environment because it changed energy utilization pattern and life behavior habits, ultimately causing $PM_{2.5}$ pollution [23]. The urbanization rate was chosen to reflect the urbanization level of each research unit. (3) The industrialization level (*IN*) and energy demand had a long-term stable relationship, which indirectly affected the number of $PM_{2.5}$ emissions [24]. Therefore, we used the total output value of the secondary industry to reflect the industrialization level. (4) A Map of $PM_{2.5}$ concentrations released by the National Aeronautics and Space Administration (NASA) showed that the areas with serious $PM_{2.5}$ pollution were consistent with the economically developed areas in China (https://www.nasa.gov/), so the per capita GDP was selected to represent the economic development level (EC). (5) The energy consumption (*EN*) directly was related to the amounts of $PM_{2.5}$ emissions because only the coal resources consumption currently accounted for about 70 percent of the total energy consumption in China. Considering the above situation, the total of energy consumption was reflected the condition of energy consumption [25]. (6) The Beijing environmental bulletin in 2014 reported that the contribution of motor vehicles to $PM_{2.5}$ pollution in Beijing City was about 31.1% [3]. With the popularization of cars, the impact of motor vehicles on the degree of $PM_{2.5}$ pollution was increasing, the private car ownership was selected to be an index that represented the number of motor vehicles (*MO*) due to the lack of data. (7) The environmental protection (*ENV*) measures were considered as an effective means to curb air pollution, and many studies had confirmed that the developed areas usually had greater ability to control $PM_{2.5}$ pollution [26], so the investment in the control of industrial pollution was selected as an index to reflect the intensity of environmental protection. (8) The technological progress (*TE*) played an important role in alleviating the degree of $PM_{2.5}$ pollution through the two ways of innovating production techniques and promoting energy-saving technologies [22], the research and development (R&D) funds occupied for proportion of the government expenditures was considered as an index to reflect the technological progress.

Data Sources

The paper selected 30 Chinese provinces in China (excluding Hong Kong, Macau, Taiwan and Tibet) as the basic geographical units, and the study period was selected from 2000 to 2014. The $PM_{2.5}$ concentrations data were derived by the Socioeconomic Data and Applications Center at Columbia University (SEDAC), which provided the gridded data of $PM_{2.5}$ concentrations at 35% relative humidity, at 81% accuracy (the remotely-sensed data were compared with data from 1855 ground monitoring sites), and at a spatial resolution of 0.1°*0.1°(http://fizz.phys.dal.ca/).The social and economic data that we selected mainly came from the China Statistical Yearbooks and the China Energy Statistics Yearbooks from 2001 and 2015 (http://www.stats.gov.cn/tjsj/ndsj/). It should be noted that the $PM_{2.5}$ concentrations data were three-year average value, so the gridded computational and zoning statistical tools of GIS software were needed to calculate the annual average $PM_{2.5}$ concentrations. Ultimately, the annual average data of $PM_{2.5}$ concentrations for 30 provinces in China were accessed each year.

Methods

Exploratory Spatial Data Analysis Method

The exploratory spatial data analysis (ESDA) method is used to verify whether the observation value in a certain research unit is related to the other observation values in the adjacent units. The Moran's *I* value can measure the global spatial correlation characteristic of observation object, and a local indicator of spatial association (*LISA*) map can reflect the local spatial correlation characteristic of observation object. The formulas are as follows [22]:

$$\begin{cases} I = \dfrac{\sum_{i=1}^{n}\sum_{j=1}^{n}(x_i-\overline{x})(x_j-\overline{x})}{s^2\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij}} \\ I^* = \dfrac{n(x_i-\overline{x})\sum_j w_{ij}(x_j-\overline{x})}{\sum_i (x_i-\overline{x})^2} \end{cases} \tag{1}$$

...where the I represents the Moran's I value, and I^* represents the *LISA* value. The x_i and x_j represents the $PM_{2.5}$ concentrations of *i*th and *j*th unit, respectively, and the $\overline{x}_t$ represents the annual average $PM_{2.5}$ concentrations. The s represents the variance of $PM_{2.5}$ concentrations, and the W_{ij} represents the spatial weight matrix (The paper uses a geographic adjacency matrix, where adjacent is 1, not adjacent is 0.).

Spatial Econometric Model

The spatial econometric models are established based on the traditional econometric model, which is dedicated to solve the problems of spatial dependence and heterogeneity. The commonly spatial econometric models include the spatial lag model (SLM) and spatial error model (SEM), but the spatial Durbin model (SDM) should be considered to use when the dependent variables in a certain region might have spatial correlation with the independent variable in the other regions. Their formulas are as follows [27].

$$SLM:\quad y = \rho w_{ij}y + x\beta + \mu \tag{2}$$

$$SEM:\quad \begin{cases} y = x\beta + \varepsilon \\ \varepsilon = \lambda w_{ij} + \mu \end{cases} \tag{3}$$

$$SDM:\ y = \rho w_{ij}y + x\beta_1 + w_{ij}x\beta_2 + \varepsilon \tag{4}$$

...where the y represents the dependent variable, the x represents the explanatory variable, the W_{ij} represents the spatial weight matrix that was the same as above (where adjacent is 1, not adjacent is 0), the ρ represents a spatial lagging parameter, the β, β_1 and β_2 are parametric vectors, the μ represents random disturbance term, the ε represents regression residual vector, and the λ is the auto-regression coefficient.

Results and Analysis

Spatial Correlation Characteristics of $PM_{2.5}$ Pollution in China

Global Spatial Correlation Characteristic

The $PM_{2.5}$ pollution situation faced in a certain area is not only affected by the amounts of $PM_{2.5}$ emissions in the local region, but also is related to the amounts of $PM_{2.5}$ emissions in the adjacent areas. It is necessary to analyze the spatial correlation characteristics of $PM_{2.5}$ pollution in China due to its interdependent features. Taking the annual average $PM_{2.5}$ concentrations as the dependent variables, the study took advantages of the spatial weight matrix determined based on the geographical adjacency to obtain the Moran's *I* values, *P* values and *Z* statistic values of $PM_{2.5}$ concentrations from 2000 to 2014 using the GeoDa software (Table 1).

Table 1 shows that all values of the global Moran's *I* from 2000 to 2014 in China are positive and significant at the level of 1%, indicating that the spatial distribution of $PM_{2.5}$ pollution in China has the characteristics of agglomeration development. The continuous growth of the global Moran's *I* value from 2000 to 2006 indicates that the concentrated distribution characteristic of $PM_{2.5}$ pollution in China tends to intensified due to the rapid urbanization progress, energy consumption dominated by the coal resources, and excessive emphasis on the speed of economic development. The global Moran's *I* value decreases by 0.0238 between 2006 and 2007, implying that the degree of $PM_{2.5}$ pollution concentrated is somewhat alleviated, but still very obvious. The policy measures such as the ecological compensation and environmental protection advocated by the Chinese government may be a key factor to cause this phenomenon. The global Moran's *I* value stopped falling from 2007 to 2010, implying that the phenomenon of concentrated distribution for $PM_{2.5}$ pollution in China is no longer alleviated during the period. The reason for the phenomenon is that the Chinese government tries to increase the number of investments to reverse the downward trend of economic growth speed in the context of the global financial crisis. However, the economic growth speed continues to be a priority of national development strategy without any changes in the aspect of industrial structure, which aggravates the degree of $PM_{2.5}$ pollution in different provinces. The global Moran's *I* value begins to present a downward trend after 2010, indicating that the concentrated distribution characteristic of $PM_{2.5}$ pollution in China is alleviated due to the higher awareness of the dangers generated by $PM_{2.5}$ pollution, and relevant measures are taken to slow down or mitigate its adverse effects. Meanwhile, the Chinese government also realizes that

Table 1. Moran's I value of the PM2.5 concentrations in China.

Year	Moran's I	Z-statistic	P-value	Year	Moran's I	Z-statistic	P-value
2000	0.5174	8.5144	0.001***	2008	0.6552	8.7006	0.001***
2001	0.5630	8.8419	0.001***	2009	0.6576	8.8193	0.001***
2002	0.5893	8.6714	0.001***	2010	0.6594	8.5851	0.001***
2003	0.6378	8.5567	0.001***	2011	0.6462	8.2893	0.001***
2004	0.6638	9.0507	0.001***	2012	0.6393	8.6497	0.001***
2005	0.6216	9.0113	0.001***	2013	0.6367	8.7226	0.001***
2006	0.6764	8.3901	0.001***	2014	0.6220	9.0271	0.001***
2007	0.6426	9.0271	0.001***				

Note: *** means that *P* values are significant at the level of 1%.

the economic growth speed should be supplanted by the economic growth quality with a focus on upgrading industrial structure and establishing monitoring, warning and response systems for $PM_{2.5}$ pollution, all of which effectively decrease the spatial agglomeration degree.

Local Spatial Correlation Characteristic

The Moran's *I* value can assess the global spatial distribution characteristic of $PM_{2.5}$ pollution in China, but there exists a problem that ignores the instability characteristic of local spatial distribution for $PM_{2.5}$ pollution (Shao et al., 2016). It is essential to study the local spatial correlation characteristic of $PM_{2.5}$ pollution by drawing the *LISA* maps. This study selected two years for analyzing the local spatial correlation characteristics of $PM_{2.5}$ concentrations (Fig. 1).

Fig.1 shows the two *LISA* maps of $PM_{2.5}$ concentrations in China, and can be seen that the local spatial correlation characteristic of $PM_{2.5}$ pollution mainly is divided into two cluster areas: high-high type and low-low type. The high-high cluster areas are distributed in Shandong, Henan, Hubei, Anhui and Jiangsu provinces in 2000, while the single low-low cluster area is only found in Jilin province. The two cluster areas mentioned above including the number of provinces present an increasing tread in 2014, with Beijing, Tianjin and Hebei provinces becoming the high-high cluster areas, and Heilongjiang, Gansu, Sichuan and Xinjiang provinces converting into the low-low cluster areas. Meanwhile, the high-high cluster area in Hubei province is disappeared. Taken together, the high-high cluster areas are mainly distributed in the northern China plain and the Middle-Lower Yangtze plain due to their high population densities, rapid urbanization process, and energy structure dominated by the fossil fuels, coupled with a large proportion of heavy industry and expansion of motor vehicles, which can lead to a huge amount of $PM_{2.5}$ emissions. In addition, the terrain conditions, meteorological factors and central heating in winter further enhance the degree of $PM_{2.5}$ pollution in these areas. The low–low cluster areas are distributed in China's northwest, southwest and northeast regions, but the reasons for the spatial distribution phenomenon are different. The northwest and southwest regions have the weak industrial base, low population density and limited energy consumption, leading that their amount of $PM_{2.5}$ emissions are relatively low. Although the northeast region has a better foundation for industrial development, the $PM_{2.5}$ pollution can be alleviated with industrial upgrades and better energy conservation, especially in line with China's economic development in recent years. Additionally, the northwest, southwest and northeast regions in China are under the influence of the prevailing winds, which is beneficial to transmit and diffuse the $PM_{2.5}$ pollution in the local area.

Social and Economic Causes of $PM_{2.5}$ Pollution in China

Applicability Analysis of the Models

First, we perform logarithmic processing of the selected variables in order to eliminate the variance influence of panel data. According to the decision rule proposed by Elhorst [28], the Lagrange Multiplier (LM), the Likelihood Ratio (LR), Hausman and Wald tests should be carried out based on the panel data by using the Matlab2014a software. Table 2 shows that the ordinary least square (OLS) model is the most powerful (R^2 = 0.6212) in all models that have been built, so the

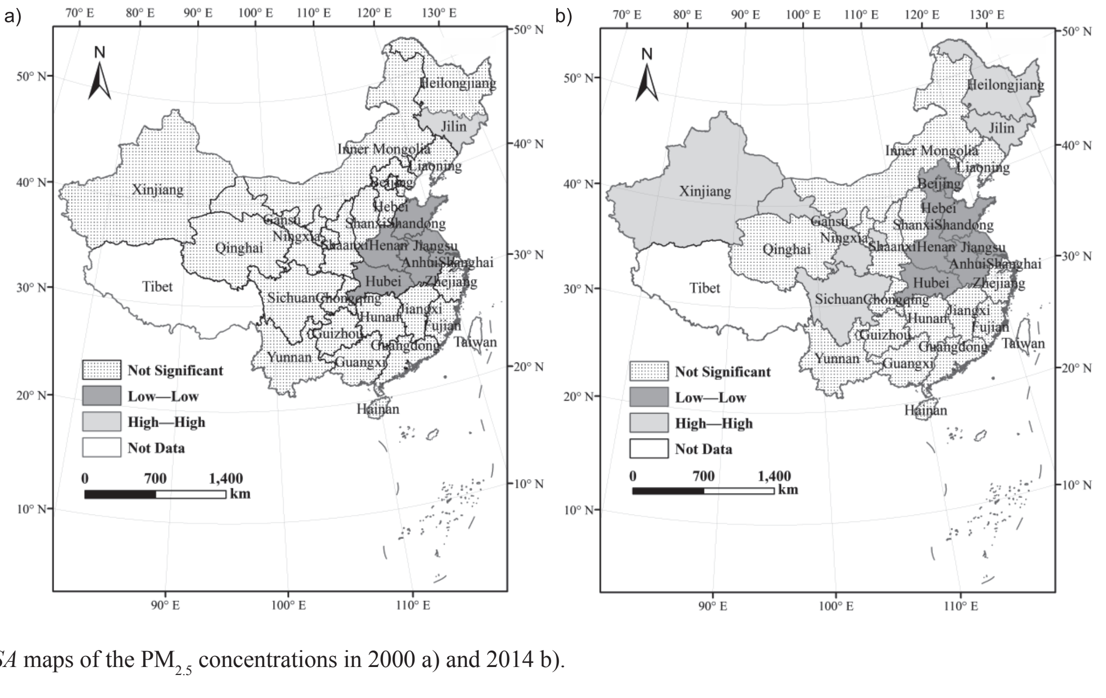

Fig. 1. *LISA* maps of the $PM_{2.5}$ concentrations in 2000 a) and 2014 b).

Table 2. LM test results for the panel data.

Variables	Mixed OLS	Spatial fixed effect	Temporal fixed effect	Spatial-temporal fixed
Ln DE	0.3129***(0.0000)	-0.1595 (0.1705)	0.2989***(0.0000)	-0.3512***(0.0022)
Ln UR	-1.0452***(0.0000)	-0.3921***(0.0012)	-1.1894***(0.0000)	-0.3839***(0.0004)
Ln IN	0.4525***(0.0003)	0.0496 (0.5813)	0.4382***(0.0005)	0.1623*(0.0733)
Ln EC	0.4210***(0.0000)	-0.0409 (0.4484)	0.4573***(0.0000)	-0.1897***(0.0050)
Ln EN	0.1784***(0.0026)	0.1758***(0.0069)	0.1997***(0.0012)	-0.0762 (0.2305)
Ln MO	0.1151***(0.0050)	0.1417***(0.0000)	-0.1552***(0.0006)	0.0714**(0.0459)
Ln ENV	-0.0155 (0.5807)	-0.0310**(0.0133)	-0.0078 (0.7953)	-0.0244*(0.0516)
Ln TE	0.0596***(0.0020)	0.0268***(0.0013)	0.1681***(0.0000)	0.0355***(0.0097)
C	-1.1657***(0.0330)	—	—	—
δ^2	0.1201	0.0167	0.1133	0.0129
R^2	0.6212	0.5047	0.6187	0.1144
Adjusted- R^2	0.6143	0.4969	0.6127	0.1004
Loglikols	-157.0588	285.7723	76.0931	343.9186
LM Spatial lag	118.7436***(0.0000)	284.5279***(0.0000)	112.9689***(0.0000)	205.6482***(0.0000)
LM Spatial error	114.4122***(0.0000)	259.0873***(0.0000)	79.0541***(0.0000)	185.6400***(0.0000)
Robust LM Spatial lag	14.7786***(0.0000)	25.4757***(0.0000)	34.3688***(0.0000)	20.2279***(0.0000)
Robust LM Spatial error	10.4472***(0.0010)	0.0351 (0.8510)	0.4540 (0.0000)	0.2198 (0.6390)

Note: (1) *P* values are given in parentheses. (2) ***, ** and * indicate that *P* values are significant at the level of 1%, 5% and 10%, respectively. (3) "-" indicates that the value does not exist.

applicability of the spatial error model (SEM), spatial lag model (SLM) and spatial Durbin model (SDM) should be determined based on the LM test results of OLS model. The LM test results of OLS model show that both SEM and SLM can be suitable for the panel data, but the test results do not determine which model to chose. Therefore, a more general form of SDM should be established first.

On the basis of the LM test results, we calculate that the Hausman test value reach 67.4238, which is significant at the level of 1%, suggesting that the SDM with the fixed-effect can accurately reflect the social and economic causes of $PM_{2.5}$ pollution in China. For the hypothesis that spatial fixed effect and temporal fixed effect are not significant for the panel data, the LR test results arrive at 535.6510 and 116.2927, respectively (Table 3). Both of them are significant at the level of 1%, meaning that we should select the Durbin model with the spatial-temporal fixed effect.

Table 3. LR test results for the panel data.

LR	Test value	P value
Spatial fixed effect	535.6510***	0.0000
Temporal fixed effect	116.2927***	0.0000

Note: *** indicates that P value is significant at the level of 1%.

Table 4 shows that the Wald test values are 19.5977 and 34.3476, at 5% and 1% significance levels, respectively, which reject the original hypothesis, implying that the Durbin model with spatial-temporal fixed effect cannot be converted to the SLM and SEM. Finally, we use the Durbin model with spatial-temporal fixed effect to analyze the social and economic causes of $PM_{2.5}$ pollution in China.

Estimation Results of the Durbin Model with Spatial-Temporal Fixed Effect

According to the Table 5, we can obtain the overall estimation results of the Durbin model with spatial-temporal fixed effect and their effect decomposition result.

As can be seen from the Table 5, the estimation results of the Durbin model with spatial-temporal fixed

Table 4. Wald test results for the panel data.

Wald	Test value	P value
Spatial lag	19.5977**	0.0120
Spatial error	34.3476***	0.0000

Note: ** and *** indicate that P value are significant at the level of 5% and 1%, respectively.

Table 5. Estimation results for the Durbin model with spatial-temporal fixed effect.

Variables	Coefficient	Direct effect	Indirect effect
Ln DE	0.5334*** (4.2655)	0.3139*** (14.4665)	0.3434*** (4.1314)
Ln UR	-0.4050*** (-4.0104)	-0.8420*** (-5.4711)	-3.3068*** (-4.6124)
Ln IN	0.0572 (0.7454)	0.6111*** (3.9576)	2.1903*** (2.7373)
Ln EC	0.1744*** (3.4944)	0.2235** (2.5623)	1.7876*** (42674)
Ln EN	0.1499*** (4.2830)	0.1442** (2.2721)	-0.3383 (-0.9504)
Ln CA	0.0108 (0.4882)	0.2281*** (4.9837)	0.8447*** (3.2378)
Ln ENV	-0.0572** (-2.2813)	-0.0044 (-0.1374)	-0.1530 (-0.9186)
Ln TE	-0.0853*** (-2.5765)	-0.1239*** (-4.1708)	-0.7191*** (-4.8067)
W Ln DE	-0.6973*** (-3.1512)	—	—
W Ln UR	0.4273* (1.8968)	—	—
W Ln IN	0.5388*** (3.9455)	—	—
W Ln EC	-0.2311* (-1.9468)	—	—
W Ln EN	0.1721** (2.0521)	—	—
W Ln CA	-0.0555 (-1.0906)	—	—
W Ln ENV	0.1920*** (4.2045)	—	—
W Ln TE	0.7020*** (21.0024)	—	—
R^2	0.8196	—	—
Log-likelihood	-26.1221	—	—

Note: (1) *T* values are given in parentheses. (2) ***, ** and * indicate that *P* values are significant at the level of 1%, 5% and 10%, respectively. (3) "-" indicates that the value does not exist.

effect show that the R^2 value reach 0.8196, which is 0.2184 higher than the R^2 of the OLS model in Table 2, confirming that the Durbin model with spatial-temporal fixed effect significantly improves the accuracy of the estimated results. In addition, the spatial lag item of economic development level (*W Ln EC*) is significant at the level of 10%, the spatial lag item of energy consumption (*W Ln EN*) is significant at the level of 5%, the spatial lag item of urbanization level (*W Ln UR*) is significant at the level of 10%, while the spatial lag items of population density (*W Ln DE*), industrialization level (*W Ln IN*), environmental protection (*W Ln ENV*) and technological progress (*W Ln TE*) are significant at the level of 1%. It is worth noting that the spatial lag item for the number of motor vehicles (*W Ln MO*) is negative, but not significant. A conclusion is drew that there exists the "feedback effect" in the Durbin model with spatial-temporal fixed effect through analyzing a series of spatial lag items mentioned above, implying that the estimated results only roughly reflect the social and economic causes of $PM_{2.5}$ pollution in China. Therefore, it is necessary to decompose the marginal effect of the independent variables on dependent variable for the local and adjacent areas, respectively.

The effect decomposition result of the Dubin model with spatial-temporal fixed effect shows that the $PM_{2.5}$ concentrations in the local area will increase by 0.3139%, while the $PM_{2.5}$ concentrations in the adjacent areas will increase by 0.3434% for each 1% increase in the aspect of population density. Each 1% increase in the urbanization level will decrease the $PM_{2.5}$ concentrations by 0.8420% in the local area and by 3.3068% in the adjacent areas. Every 1% increase in the industrialization level has a contributing of the 0.6111% increase in $PM_{2.5}$ concentrations for the local region and the 2.1903% increase for the adjacent areas. For each 1% improvement of economic development level, the degree of $PM_{2.5}$ pollution in the local area will be aggravated by 0.2235%, while be aggravated by 1.7876% in the adjacent areas, indicating that the economic development level has bigger impact on the degree of $PM_{2.5}$ pollution in the surrounding areas than in the local area. The $PM_{2.5}$ concentrations in the local area will increase by 0.1442% and its impact on $PM_{2.5}$ concentrations in the surrounding areas are not significant when the energy consumption increases by 1%. Each 1% increase in the number of motor vehicles will exacerbate the degree of $PM_{2.5}$ pollution in the local area by 0.2281%, and 0.8447% in the adjacent areas. The effect of environmental protection on the degree of $PM_{2.5}$ pollution in the local and adjacent areas are not significant, which may be due to a fact that the environmental protection measures that the government takes are lagged behind the number of $PM_{2.5}$ emissions. The $PM_{2.5}$ concentrations in the local area will fall by 0.1239%, and by 0.7191% in the adjacent areas for each 1% improvement in the aspect of technological progress. The technological progress has less effect on the degree of $PM_{2.5}$ pollution than the other the urbanization level, industrialization level and economic development level, meaning that more attention should be paid to the role of technological progress in alleviating the $PM_{2.5}$ pollution in the future.

In general, the urbanization level and technological progress are able to alleviate the degree of $PM_{2.5}$ pollution in the local and adjacent areas. The population density, industrialization level, economic development level and number of motor vehicles play the role of aggravating the degree of $PM_{2.5}$ pollution in the local area and its surroundings, while the energy consumption only influences the degree of $PM_{2.5}$ pollution in the local area, and the role of environmental protection in cutting $PM_{2.5}$ concentrations needs to be strengthened. Besides, the indirect effect of independent variables on dependent variable is greater than the direct effect on the whole, meaning that the influence of independent variables on the degree of $PM_{2.5}$ pollution is greater in the adjacent areas than in the local area. For this reason, China should pay more attention to the regional cooperation for the purpose of controlling the number of $PM_{2.5}$ emissions in the future. Of course, a comparison of the estimation results for the mixed OLS model and Dubin model with spatial-temporal fixed effect shows that the impacts of population density, industrialization level, number of motor vehicles and technological progress on the degree of $PM_{2.5}$ pollution are underestimated by 0.32%, 35.05%, 98.18% and 107.89%, while the impacts of the urbanization level, economic development level and energy consumption are overestimated by 19.44%, 46.91% and 17.17%. The environmental protection does not play a significant role in alleviating the $PM_{2.5}$ pollution in the estimation results of two models.

Conclusion and Discussion

The study describes the spatial correlation characteristics of $PM_{2.5}$ pollution in China and analyzes its social and economic causes. The conclusions can be drawn:

(1) The $PM_{2.5}$ pollution in China is strongly spatially clustered. Specifically, the global spatial correlation characteristic of $PM_{2.5}$ pollution is significantly positive, and the local spatial correlation characteristic is dominated by the high-high and low-low cluster type areas. Among of them, the high-high cluster areas are distributed in the northern China plain and the Middle-Lower Yangtze plain, while the low-low cluster areas are mainly found in the Chinese northwest, southwest and northeast regions.

(2) The population density, industrialization level, economic development level and the number of motor vehicles can aggravate the degree of $PM_{2.5}$ pollution in the local and adjacent areas, while the urbanization level and technological progress can alleviate the degree of $PM_{2.5}$ pollution. The role of environmental protection in relieving $PM_{2.5}$ pollution in the local and adjacent areas is not significant. The energy consumption only can alleviate the $PM_{2.5}$ pollution in the local area, whose spillover effect for the adjacent areas is not obvious.

(3) The impacts of population density, industrialization level, the number of motor vehicles, and technological progress on the $PM_{2.5}$ pollution are underestimated, while the impacts of the urbanization level, economic development level and energy consumption are seriously overestimated when the spatial effects of variables are not considered. More attention should be paid to identifying the functional mechanism of the technological progress, the number of motor vehicles and economic development level on the degree of $PM_{2.5}$ pollution in the future.

This paper analyzes the social and economic causes of $PM_{2.5}$ pollution in China from 2000 to 2014, but some questions are still worth pondering. First of all, the paper uses a three-year average dataset of $PM_{2.5}$ concentrations, which may have obscured extreme inter-annual variability and led to an uncertainty in analyzing the spatial correlation characteristics of $PM_{2.5}$ pollution. Therefore, a question for future research is how to make use of actual $PM_{2.5}$ concentrations data from ground monitoring stations to improve the accuracy of the gridded dataset. In addition, the social and economic causes of $PM_{2.5}$ pollution are complicated and variable because they not only involve the quantitative evaluation indexes, but also involve the non-quantitative evaluation indexes. This study only considers the impacts of the selected variables on the $PM_{2.5}$ pollution, does not consider underlying social and economic factors. Thus, future efforts should focus on selecting variables.

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Conflict of Interest

The authors declare no conflict of interest.

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