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Factors Influencing Air Pollution Control of Beijing-Tianjin-Hebei Region in China

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Abstract

Background and Aim: Air pollution is one of the most concerning public events in the field of the environment in recent years. In recent years, the air pollution problem in the Beijing-Tianjin-Hebei region is more serious, which has aroused great attention in academic circles. This paper aims to use the spatial econometric model to analyze the factors influencing air pollution in Beijing-Tianjin-Hebei in China.

Materials and Methods: This literature research use time series or panel data for analysis, according to the research results of Feng, Y., et al. (2017) and Lei, J., et al. (2018), the empirical results of using the spatial econometric model to analyze the influencing factors of regional air pollution.

Results: The spatial Durbin model (SDM) is used to test the factors influencing air pollution control of the Beijing-Tianjin-Hebei region, and then the spatial lag model (SLM) and spatial error model (SEM) are used to test the robustness. The empirical results show that there is a significant positive correlation between population density, urbanization rate, car ownership rate, and PM2.5, while there is a significant negative correlation between GDP growth rate, greening rate, and PM2.5.

Conclusion: In a word, the above indicators analyze their spatial influence mechanism from the dimensions of environment, economy, and society. This shows that the causes of air pollution in the Beijing-Tianjin-Hebei region are multi-layered, and local governments need to coordinate governance from organizational relationships, safeguard mechanisms, and other aspects to fundamentally and effectively solve the above problems.

Keywords: Air Pollution; Beijing-Tianjin-Hebei Region; Influencing Factor

Introduction

Air pollution is one of the most concerning public events in the environmental field in recent years. Serious air pollution will lead to a series of consequences, such as human health damage, production, and life stagnation, biological growth delay, ozone layer destruction, global warming, and so on. Air pollution does not suddenly appear overnight but is the result of many factors such as long-term destruction of the ecological environment, extensive development mode, and backward treatment ability. The frequent occurrence and serious harm of air pollution increase the urgency of air pollution control. At the same time, the cross-domain flow characteristics of pollutants pose a great challenge to the traditional territorial control mode. Therefore, regional cooperative control, as an effective means to deal with the dilemma of cross-domain air pollution transmission, has received more and more attention.

In recent years, the air pollutants in the Beijing-Tianjin-Hebei region and surrounding cities have shown the characteristics of "small living quarters and large living quarters". The concentrated outbreak of a single pollutant and the interaction and secondary transformation among various pollutants exist simultaneously. The concentration of pollutants in the Beijing-Tianjin-Hebei region is still high, and the concentrations of six pollutants mainly monitored, such as PM2.5, PM10, and 03, are all higher than

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those in the Yangtze River Delta region. Furthermore, it is particularly important to analyze which factors will cause heavy air pollution.

Air pollution, as a worldwide problem, has attracted extensive attention from all countries and has taken corresponding control actions. Li, Liang Wei (2017) summarized and introduced the experience and practices of transboundary air pollution control in the United States, namely, effective funding guarantee mechanism, strict legal governance mechanism, and mature market-oriented operation mechanism; Including the operation mechanism of SCAQMD, a special economic zone system. The Clean Air Act provides the main legal basis for the US federal government, states, tribes, and local governments to protect air quality. Qiang, C., (2014) introduced the experience of smog control in London, England. In the process of collaborative smog control, Britain insisted on government leadership as the main support of collaborative smog control, public participation as an important means of collaborative smog control, and market regulation as a multidimensional joint force of collaborative smog control, and built a good organizational structure of collaborative smog control. Zhe, W., & Jingjing, T., (2014), by summing up the experience of foreign interregional pollution control, put forward that interregional government should transfer part of their rights, and a unified "super-power" organization beyond administrative divisions should form the transferred rights of all members, and a multi-subject cooperation mechanism should be built under the leadership of the government (Li, Liang Wei 2017; Zhe, W., & Jingjing, T., 2014; Qiang, C., 2014)

Objectives

This paper aims to use the spatial econometric model to analyze the factors influencing air pollution in Beijing-Tianjin-Hebei in China. The spatial Durbin model (SDM) is used to test the factors influencing air pollution control of the Beijing-Tianjin-Hebei region, and then the spatial lag model (SLM) and spatial error model (SEM) are used to test the robustness.

Study Scope

Through the research literature, it can be found that although some articles use time series or panel data for analysis, according to the research results of Feng, Y., et al. (2017) and Lei, J., et al. (2018), the empirical results of using the spatial econometric model to analyze the influencing factors of regional air pollution in this paper may be more robust and reliable. Therefore, this chapter will use the spatial econometric model for empirical analysis and test the robustness of the empirical results.

Empirical Analysis Process

After setting an empirical model for the influencing factors and spillover effects of air pollution in the Beijing-Tianjin-Hebei region, then we can select variables and conduct empirical tests.

1. The Establishment of The Empirical Model

According to the first law of geography, the closer the spatial distance is, the closer the properties of objects are, and the higher their correlation will be, that is, the stronger their spatial dependence will be. Through empirical research, it is found that regional air pollution has the dual characteristics of heterogeneity and dependence in spatial scope, and the evolved form of this characteristic can be analyzed by a spatial econometric model.

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In this paper, the Moran index, which measures correlation, is set as follows:

$$M = \frac{s\sum_{i=1}^{s}\sum_{j=1}^{s} W_{ij}(r_i - \bar{r})(r_j - \bar{r})}{\sum_{i=1}^{s}\sum_{i=1}^{s} W_{ij}\sum_{i=1}^{s}(r_i - \bar{r})^2} \qquad (1)$$

The formula (1), W_{ij} represents the spatial weight matrix in the model and M represents between -1 and 1. If the value of the index is less than 0, it means a negative correlation; if the value of the index is greater than 0, it means a positive correlation; and if the value of the index is equal to 0, it means no correlation. Under normal circumstances, we use the Z-value of standardized statistics to test the spatial correlation, and then further analyze the influencing factors and spillover effects through the test results. Based on the existing literature, the Z value of standardized statistics can be set as follows:

$$Z = \frac{M - E(M)}{\sqrt{VAR(M)}} \qquad (2)$$

Formula (2), $E(M)$ indicates the expectation or mean value of the Moran index, and $VAR(M)$ indicates the variance of the Moran index. When the value of the Z value is positive, it means that there is a positive correlation between air pollution in the Beijing-Tianjin-Hebei region, that is, similar observation values show the characteristics of spatial agglomeration in the spatial range; When the value of the Z value is negative, it means that there is a negative correlation between air pollution in Beijing-Tianjin-Hebei region, that is, similar observation values show the characteristics of scattered distribution in space; When the value of the Z value is 0, the similar observation values of air pollution in Beijing-Tianjin-Hebei region show the characteristics of independent random distribution.

Because the spatial econometric model can better solve the spatial dependence of some variables, but these relationships are difficult to be solved in the ordinary linear regression model, this chapter will use the spatial econometric model for empirical tests. Common spatial econometric models include spatial lag, spatial error, spatial Durbin, etc. People can choose the appropriate model to test according to the actual situation. Based on the theoretical analysis of formulas (1) and (2), a spatial metrology model can be set.

When the spatial dependence of the explained variables plays an important role in the model, and this spatial dependence also leads to spatial correlation, the model that should be used at this time is the spatial autoregressive model, which can also be called the spatial lag model (SLM). Its expression can be written as:

$$Y = \theta WY + X\varphi + e, e \sim N(0, \delta^2) \qquad (3)$$

Formula (3), Y represents the explained variable, X represents the explanatory variable, W represents the spatial weight matrix, e represents the error term of the model, and φ represents the coefficient of the explanatory variable. If you look at the matrix distribution of each variable, Y is a vector of $n \times 1$ dimensions, X is a matrix of dimensions, and W is a matrix of dimensions, and their

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distribution states are independent and identically distributed. Formula (3), θ represents the coefficient of endogenous cross-product WY, which can reflect the degree of spatial overflow or diffusion. It θ is statistically significant, it indicates that the spatial dependence is more serious.

When the error terms of the whole model have a strong spatial correlation, the model that should be used at this time is the Spatial Error Model (SEM), whose expression can be written as:

$$Y = X\varphi + \varpi Wu + e, e \sim N(0, \delta^2) \tag{4}$$

In formula (4), the representative meanings of Y 、 X 、 W 、 φ and e are the same as those in formula (3) u and ϖ represent the random error vector and spatial correlation coefficient of regression residual term.

If formula (3) is combined with formula (4), which contains both spatial lag effect and spatial error effect, the model that should be used at this time is Spatial Durbin Model (SDM). The overall model covers both exogenous and endogenous interaction effects, and its expression can be written as:

$$Y = \theta WY + X\varphi + \varsigma WX + e, e \sim N(0, \delta^2) \tag{5}$$

Formula (5), ς represents the coefficient of the exogenous interaction effect WX. When the value ς is 0, the spatial Durbin model (SDM) will evolve into the spatial lag model (SLM). The higher the significance, the stronger the spatial interaction mechanism between explanatory variables. Of course, only the numerical value ς can't judge the spatial spillover effect of the model. Only by systematically analyzing the coefficient significance of other variables can the spatial spillover effect of the model be effectively analyzed.

Theoretically, both Spatial Lag Model (SLM) and Spatial Durbin Model (SDM) can effectively analyze explanatory variables and can distinguish the direct effect from the indirect effect. The spatial Durbin Model (SDM) covers both exogenous interaction effects and endogenous interaction effects, and its empirical analysis results may be more reliable and robust. Therefore, in the empirical analysis process of this paper, firstly, the Spatial Durbin Model (SDM) is used for the empirical test, and then the spatial lag model (SLM) and spatial error model (SEM) are used for the robustness test.

2. Choice of Explained Variables and Data Sources

To describe the development of air pollution in the Beijing-Tianjin-Hebei region, this paper uses the practice of Dong, C., Cunyi, S., Jinnan, W., Hongqiang, J., Wanxin, L., & Guozhi, C., (2009) for reference and selects the annual average concentration of PM2.5 in the Beijing-Tianjin-Hebei region as the explained variable, and its data source is China National Environmental Monitoring Center. At the same time, because the PM2.5 index published by China National Environmental Monitoring Center is monthly data, the author converts it into annual data by calculating the weighted average. To reflect the situation of air pollution in the whole Beijing-Tianjin-Hebei region and its surrounding areas, the annual data of "2+26" cities are selected here for research. "2+26" cities include Beijing, Tianjin, Shijiazhuang, Tangshan, Langfang, Baoding, Cangzhou, Hengshui, Xingtai, and Handan in Hebei Province, Taiyuan, Yangquan, Changzhi and Jincheng in Shanxi Province, Jinan, Zibo, Jining, Dezhou, Liaocheng, Binzhou, and Heze in Shandong Province, Zhengzhou, Kaifeng, Anyang, Hebi, Xinxiang, and Jiaozuo in Henan Province.

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By sorting out the data of the China National Environmental Monitoring Center, we can see that in recent years, with the continuous strengthening of regional joint prevention and control, the overall atmospheric environmental quality of Beijing-Tianjin-Hebei and surrounding cities has steadily improved, and the PM2.5 concentration has gradually decreased, but it still shows a rebound trend in autumn and winter. For example, from January 2017 to May 2021, the monthly average concentration of PM2.5 in Beijing, Shijiazhuang, Taiyuan, and Zhengzhou can be seen (see Figure 1 for details). The monthly average concentration of PM2.5 in the four places has decreased rapidly, with Beijing dropping from 116 μ g/m3 to 20 μ g/m3, Shijiazhuang dropping from 200 μ g/m3 to 38 μ g/m3, and Taiyuan dropping from 100 μ g/m3. At the same time, from the heating season in October every year to around March next year, the monthly average concentration of PM2.5 will rebound, generally reaching its peak around January.

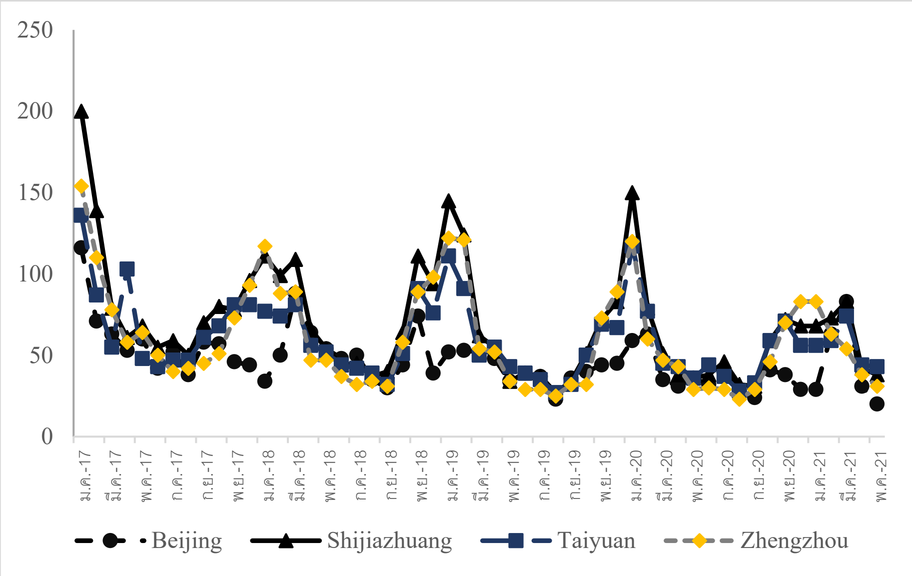

Figure 1 Monthly average concentration of PM2.5 in Beijing, Shijiazhuang, Taiyuan, and Zhengzhou from January 2017 to May 2021 (Source: China National Environmental Monitoring Center)

In terms of explanatory variables, referring to the practice of Feng, Y., et al. (2017), this paper selects three dimensions of variables to conduct research.

The first dimension is environmental change, which mainly includes three indicators: the average annual precipitation, the average humidity, and the green coverage rate of the built-up area in each city. The above data are from the websites of the National Meteorological Administration and the National Bureau of Statistics. From the point of view of the existing literature, the above three indicators may have a direct or indirect impact on the air pollution in the Beijing-Tianjin-Hebei region, because the more stable the average humidity is, the better the effect of air purification maybe, while the green coverage rate in the built-up area may have a negative correlation with the air pollution in Beijing-Tianjin-Hebei region. In addition, since all the data found on the website of the National Meteorological Administration are monthly data, to keep the dimension consistent, here, the weighted average value is calculated, and the measurement software is used to convert it into quarterly data.

The second dimension is economic development, which mainly includes three indicators: the

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economic growth rate of each city, the proportion of industrial added value to GDP, and the proportion of the secondary industry population. The data come from the websites of the National Bureau of Statistics and the statistical bureaus of various provinces and cities. According to the research results of existing literature, there may be a nonlinear relationship between the economic growth rate of a country or region and air pollution. Here, the growth rate of regional gross domestic product (GDP) is used to reflect the level of economic growth; The ratio of industrial added value to GDP is also closely related to air pollution because according to literature research, the source of air pollution in China mainly comes from coal needed by industry, so the greater the ratio of industrial added value to GDP, the more serious the air pollution in Beijing-Tianjin-Hebei region may be. At the same time, the proportion of the secondary industry population can roughly reflect the degree of the industry in the regional economic development through the number of employed people.

Third, is the dimension of social development, which mainly includes three indicators: population density, urbanization rate, and civil car ownership rate of each city. Among them, the population density reflects the population per unit area, which is expressed by dividing the resident population by the urban area. The urbanization rate reflects the level of urbanization development and the degree of agglomeration. Here, it is expressed by the proportion of the urban resident population in each city to the total resident population, and the percentage of civilian car ownership in the Beijing-Tianjin-Hebei region to the total population in this region. The above data are all from the websites of the National Bureau of Statistics and the provincial and municipal statistical bureaus. According to the research of existing literature, the increase in population density may lead to an increase in pollutant emissions and then affect air pollution. The increase in urbanization rate may lead to an increase in population density, the aggravation of automobile exhaust emissions, and so on, which will affect the degree of air pollution. (See Table 1 for details)

It should be noted that it is usually difficult to judge whether the above variables have a positive or negative impact on air pollution in cities by intuition, and the real impact should be analyzed by empirical test.

Table 1 List of variables in the spatial econometric model

Category	Symbol	Variable	Meaning	Data source
Explained variable	pm	Average annual concentration of PM2.5	Used to measure the air pollution in different cities, the greater the value of this indicator, the more serious the air pollution in this area is.	China National Environmental Monitoring Station
Explanatory variable Environmental change dimension	jyl	Annual precipitation	Used to measure the annual precipitation in different cities.	National Weather Service website
	humi	medial humidity	Used to measure the annual humidity changes in different cities.	
	lhl	Greening rate	Used to measure the green coverage rate of built-up areas in	Websites of

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Category	Symbol	Variable	Meaning	Data source
			different cities.	the National Bureau of Statistics and provincial and municipal statistical bureaus
Explanatory variable Economic development dimension	gdp	GDP growth rate	Used to measure the economic growth level of different cities.	
	gyb	Industrial added value ratio	It is used to measure the proportion of industrial-added value to GDP in different cities.	
	erb	The proportion of secondary industry population	It is used to measure the proportion of the secondary industry population in the total population.	
Explanatory variable Social development dimension	rkmd	population density	The resident population is divided by the regional area of each city to measure the population density of the city.	
	czh	Urbanization rate	It is expressed by the proportion of the urban resident population to the total resident population to measure the urbanization level of the city.	
	qzc	Car ownership rate	It is expressed by the ratio of civilian car ownership to the total population in different cities to measure the car ownership rate of the city.	

After analyzing the variables in the spatial econometric model, we test the coefficient of variance expansion (VIF) of each variable, which can analyze whether there is serious multicollinearity in the model. According to the research of existing literature, the value of the variance expansion coefficient (VIF) is generally greater than 1. The larger the value of this coefficient, the higher the probability of serious multicollinearity. If the coefficient of variance expansion (VIF) is greater than 10, it indicates that there is serious multicollinearity in the model.

Table 2 The variance expansion coefficient (VIF) test of each variable in the table model

Variable	jyl	humi	lhl	gdp	gyb	erb	rkmd	czh	qzc
VIF value	3.26	1.59	2.93	1.87	2.86	3.76	3.42	2.65	4.03

Table 2 shows the test results of the variance expansion coefficient (VIF) of each variable in the

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model. As can be seen from the table, the values of the variance expansion coefficient (VIF) of the above variables are all less than 10, which indicates that there is no serious multicollinearity problem in the model.

Autocorrelation Analysis

Before the empirical analysis of the spatial econometric model, global autocorrelation analysis is usually needed to study the local concentration of air pollution in the Beijing-Tianjin-Hebei region. This index can be measured by the global Moran index, which focuses on the aggregation of spatial series data to measure the evolution trend of air pollution in various cities. The calculation formula of the global Moran index, its formula can also be expressed by the formula (1) in the first section. At this time, the value of m in the formula (1) represents the global Moran index. When the value of the global Moran index m is greater than 0, it indicates that there is a strong positive spatial correlation between air pollution in cities, and the closer the value is to 1, the stronger the positive spatial correlation is. When the value of the global Moran index m is less than 0, it indicates that there is a strong negative spatial correlation of air pollution among cities, and the closer the value is to -1, the stronger the negative spatial correlation is. When the value of the global Moran index m is equal to 0, it indicates that the spatial distribution of air pollution among cities is random.

Figure 3 Global Moran Index Trend of Air Pollution in Beijing-Tianjin-Hebei Region from 2010 to 2019 (Data source author's calculation)

Figure 3 shows the trend of the global Moran index of air pollution in the Beijing-Tianjin-Hebei region from 2010 to 2019, calculated by the author using Stata software. As can be seen from the figure, the overall Moran index of air pollution in the Beijing-Tianjin-Hebei region increased rapidly in 2010-2013, reaching a high point of 0.356 in 2013, then dropped rapidly, with the lowest falling to 0.279 in 2015, and then increased rapidly. From the overall data, the data of the global Moran index of air pollution in the Beijing-Tianjin-Hebei region from 2010 to 2019 showed significant characteristics at a

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significant level of 1%.

Analysis of Empirical Results

After the variance expansion coefficient (VIF) test, local autocorrelation, and global autocorrelation analysis of variables, the model can be further tested and the empirical results analyzed. Here, the spatial econometric model is used to make regression analysis on the quarterly data of 2010-2019 and the annual average concentration data of PM2.5 in Beijing, Tianjin, Hebei, and surrounding areas. The specific results are shown in Table 3.

Table 3 Regression results of PM2.5 using a spatial econometric model

Model / Variable	(1)	(2)	(3)	(4)	(5)
way	OLS	OLS	OLS	SDM	SDM
jyl	0. 1075 (0.53)	0. 1223 (0.61)	0.1297 (0.63)	0. 1707 (0.76)	0. 1642 (0.69)
humi		-0.0109 (-0.61)	-0.0129 (-0.47)	-0.0098 (-0.84)	-0.0073 (-0.57)
lhl	-0. 1253* (-2.58)	-0. 1269* (-2.83)	-0. 1173* (-2.69)		-0. 1339* (-2.76)
gdp		-0.0169* (-2.49)	-0.0031* (-2.09)		-0.0022* (-1.89)
gyb		0.0045** (3.27)	0.0073** (3.42)	0.0069** (3.12)	0.0067** (3.02)
erb			0.3764 (0.52)		0.3028 (0.46)
rkmd	0.0023*** (2.71)	0.0031** (2.96)	0.0058* (1.97)		0.0071* (2.13)
czh			0.0157 (0.63)		0.0047* (1.52)
qzc			0.0097* (2.86)		0.0049* (2.73)
W* jyl				0.0034* (1.98)	0.0019* (1.93)
W* humi				-2.9564 (-0.87)	-2.8712 (-0.92)
W* lhl					-0. 1554* (-2.91)
W* gdp					-0.0037* (-2.07)
W*gyb				-0.0073	-0.0065

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Model / Variable	(1)	(2)	(3)	(4)	(5)
				(-0.28)	(-0.32)
W* erb					0.3157 (0.53)
W* rkmd					0.0067* (1.96)
W* czh					-0.0054 (-0.52)
W* qzc					0.0051* (2.84)
C	1.4753** (3.28)	1.5086 * (2.52)	1.7094 (1.01)	1.5028 (0.46)	1.7324 (0.57)
Adjusted R2	0.7656	0.7892	0.8554	0.8682	0.8913
Logarithmic likelihood ratio	71.430	80.293	82.963	87.413	92.634

Note: The values in brackets are the values of variable T, and the corresponding * * *, * *, and * respectively indicate that the estimated coefficient has passed the significance test of 1%, 5%, and 10%.

Table 3 shows the regression results of PM2.5 using a spatial econometric model. Among them, columns (1)-(3) are the regression results using OLS, and columns (4)-(5) are the regression results using the spatial Durbin model (SDM).

In column (1), explanatory variables include average annual precipitation (jyl), greening rate (lhl), and population density (rkmd); column (2) adds average humidity (humi), gdp growth rate (GDP) and industrial added value ratio (gyb) based on column (1), and column (3) is ranked first. In column (4), explanatory variables include average annual precipitation (jyl), average humidity (humi), industrial added value ratio (gyb), and the cross-product of spatial weight matrix W with average annual precipitation (jyl), average humidity (humi) and industrial added value ratio (gyb). Column (5) adds greening rate (lhl), gdp growth rate (gdp), secondary industry population ratio (erb), population density (rkmd), urbanization rate (czh), and spatial weight matrix W and greening rate (lhl), GDP growth rate (GDP), secondary industry population ratio (erb)

According to the regression results in columns (1)-(3) of Table 3, there is a significant positive correlation between industrial added value (gyb), population density (rkmd), car ownership rate (qzc), and PM2.5, while there is a significant negative correlation between gdp growth rate (GDP), greening rate (lhl) and PM2.5. The average annual precipitation (jyl According to the regression results in columns (4)-(5), the relationship between the above variables and PM2.5 has not changed significantly, and there is a significant positive correlation between spatial weight matrix W and population density (rkmd), annual average precipitation (jyl), car ownership rate (qzc) and PM2.5., There is a significant negative correlation between the cross-product of spatial weight matrix W and gdp growth rate (GDP) and greening rate (lhl) and PM2.5, but there is no significant relationship between the cross-product of

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the spatial weight matrix W and PM2.5, such as average humidity (humi), industrial added value ratio (gyb), secondary industry population ratio (erb) and urbanization rate (czh).

From the analysis of economic theory, the above empirical results are more in line with the usual intuition. When a city's GDP growth rate is high, it indicates that the region's economy is developing rapidly, and the government is more likely to invest more financial funds to control air pollution. Therefore, there is a significant negative correlation between GDP growth rate and PM2.5 The higher the green rate (lhl) is, the higher the green coverage of the built-up areas in the Beijing-Tianjin-Hebei region, and there is a significant negative correlation between it and PM2.5 The higher the ratio of industrial added value (gyb), the more developed the industrial development in Beijing-Tianjin-Hebei region, and the higher the probability of air pollution caused by the burning of coal, oil, and other raw materials. The larger the car ownership rate (qzc) and population density (rkmd), the more people are the production and living space gather, and the higher the traffic congestion, the more air pollution behaviors may occur, so the greater the probability of air pollution. Therefore, the above empirical results are in line with people's intuition in economic theory. However, to ensure the reliability of the empirical results, it is still necessary to test the robustness of the above results.

Robustness Test

After regression analysis of PM2.5 using a spatial econometric model, it is necessary to further test the robustness of the model. In the last section, the models adopted by the author are the ordinary least squares method (OLS) and the spatial Durbin model (SDM). To check the robustness, here, firstly, the original data is processed at the level of 2% by Winsor, and then the spatial lag model (SLM) and the spatial error model (SEM) are used for analysis. See Table 4 for specific results.

Table 4 Regression results of the robustness test

Model / **Variable**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
way	SLM	SLM	SLM	SEM	SEM
jyl	0. 2749 (0.73)	0. 2947 (0.62)	0.2673 (0.49)	0.2842 (0.57)	0.2067 (0.72)
humi		-0.0268 (-0.74)	-0.0267 (-0.43)	-0.0087 (-0.57)	-0.0068 (-0.59)
lhl			-0.0068* (-2.87)		-0.0073* (-2.91)
gdp		-0.0068* (-2.02)	-0.0073* (-2.87)		-0.0068* (-1.97)
gyb	0.0032* (1.67)	0.0041* (1.93)	0.0027* (1.86)	0.0059 (0.42)	0.0057 (0.39)
erb			0.2609 (0.41)		0.2672 (0.43)
rkmd	0.0043***	0.0065**	0.0053*	0.0047*	0.0057*

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Model / Variable	(1)	(2)	(3)	(4)	(5)
	(2.54)	(2.27)	(1.92)	(1.88)	(2.31)
czh			0.0268* (1.72)		-0.0042* (-1.58)
qzc			0.0068* (2.36)		0.0073* (2.28)
W*u				0.0053* (1.67)	0.0024* (1.59)
C	1.8751 ** (2.38)	1.9742 * (2.57)	1.8504 (0.82)	1.7301 (0.63)	1.6543 (0.62)
Adjusted R2	0.7862	0.7943	0.8487	0.8321	0.8794
Logarithmic likelihood ratio	75.591	83.572	88.901	87.231	90.708

Note: The values in brackets are the values of variable T, and the corresponding * * *, * *, and * respectively indicate that the estimated coefficient has passed the significance test of 1%, 5%, and 10%.

Table 4 shows the regression results of the robustness test. Among them, columns (1)-(3) are regression results using the spatial lag model (SLM), and columns (4)-(5) are regression results using the spatial error model (SEM).

In column (1) of Table 4, explanatory variables include average annual precipitation (jyl), industrial added value ratio (gyb), and population density (rkmd), column (2) adds average humidity (humi) and gdp growth rate (GDP) based on column (1), and column (3) is the basis of column (2) In column (4), explanatory variables include annual average precipitation (jyl), average humidity (humi), secondary industry population ratio (erb), population density (rkmd), and the product of spatial weight matrix W and the error term. Column (5) adds the greening rate (lhl), gdp growth rate (GDP), urbanization rate (czh), car ownership rate (qzc), and the multiplication term of the spatial weight matrix W and error term based on column (4).

According to the regression results in columns (1)-(3) of Table 4, population density (rkmd), urbanization rate (czh), car ownership rate (qzc) show a significant positive correlation with PM2.5, gdp growth rate (GDP), greening rate (lhl) show a significant negative correlation with PM2.5, and the proportion of secondary industry population (erb According to the regression results in columns (4)-(5), there is a significant positive correlation between population density (rkmd) and PM2.5, but the relationship between average annual precipitation (jyl), average humidity (humi), industrial added value ratio (gyb), secondary industry population ratio (erb) and PM2.5 is not significant. Greening rate (lhl), gdp growth rate (GDP), urbanization rate (czh), and PM2.5 showed significant negative correlation, except that the relationship between other variables and PM2.5 did not change significantly, and the cross-product of the spatial weight matrix W and error term showed a significant positive correlation with PM2.5.

Through the analysis of the regression results of the robustness test, it is found that the sign and

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significance of the main explanatory variables have not changed substantially after the regression, so it can be considered that the regression results of the model are robust.

Conclusion and Recommendations

The empirical analysis in this chapter shows that population density (rkmd), urbanization rate (czh), and car ownership rate (qzc) are positively correlated with PM2.5, while gdp growth rate (GDP), greening rate (lhl) are negatively correlated with PM2.5.

Firstly, from the empirical results of this paper, population density (rkmd) has a significant impact on air pollution. According to the data of the seventh national census, the population density of the Beijing-Tianjin-Hebei region is nearly four times that of the average population density of the whole country, and it belongs to a relatively concentrated area in the whole country. Therefore, the population density in this region has a serious impact on air pollution.

Secondly, the urbanization rate (czh) has a significant impact on the local air quality, which indicates that the Beijing-Tianjin-Hebei region should further optimize the industrial layout and urban planning and properly deal with the overloaded population and sewage industries, to play a positive role in promoting the regional air quality.

Thirdly, the car ownership rate (qzc) has a significant impact on air pollution in this area. In recent years, with the increasing rate of people's car ownership in the Beijing-Tianjin-Hebei region, they have played a certain role in promoting air pollution. For the Beijing-Tianjin-Hebei region, it is necessary to take the initiative to capture the trajectory of automobile exhaust emissions by technical means, and actively promote the development of new energy vehicles and clean energy, to effectively reduce the negative impact of automobile ownership on air pollution.

Fourthly, the GDP growth rate harms air pollution in the region. For the Beijing-Tianjin-Hebei region, it is necessary to make overall arrangements according to the "chess game" of regional development, constantly adjust and optimize the layout of industrial structure, promote the development of industries with high added value and low pollution emissions, and do a good job in the green transformation and upgrading of industries with high pollution and high energy consumption, to finally realize the sustainable and high-quality development of low-carbon cycle and achieve a win-win situation of economic development and environmental protection.

Fifth, the impact of the green rate (lhl) on air quality in this area is negative, which indicates that the green coverage rate of built-up areas in different cities harms air pollution. Therefore, actively promoting the development of green coverage in built-up areas of different cities in the Beijing-Tianjin-Hebei region has a certain positive effect on atmospheric control in the Beijing-Tianjin-Hebei region.

In a word, the above indicators analyze their spatial influence mechanism from the dimensions of environment, economy, and society. This shows that the causes of air pollution in the Beijing-Tianjin-Hebei region are multi-layered, and local governments need to coordinate governance from organizational relationships, safeguard mechanisms, and other aspects to fundamentally and effectively solve the above problems.

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References

Dong, C., Cunyi, S., Jinnan, W., Hongqiang, J., Wanxin, L., & Guozhi, C., (2009). Establishment and Empirical Analysis of Cost Function of Joint Reduction of Pollutants, Environmental Science Research, 3, 2009.

Feng, Y., Guojun, Q., & Sheng, L., (2017). Research on the Relationship between Population Agglomeration and Environmental Pollution Based on Spatial Panel Data Model, Economic Issues,7, 2017.

Lei, J., et al. (2018). On the Inefficiency of LM Test and the Choice of Spatial Measurement Model: Taking the Socio-economic Influencing Factors of China's Air Quality Index as an Example, Financial Theory Research, 5, 2018.

Li, LiangWei. (2017). Research on Spatial Characteristics and Influencing Factors of Urban Air Pollution in China: Empirical Evidence from Prefecture-level Cities, Shandong Social Sciences, 10, 2017.

Qiang, C., (2014). Advanced Econometrics and Stata Application (2nd Edition) [M], Higher Education Press. 245-260.

Zhe, W., & Jingjing, T., (2014). Air Pollution Control in Capital Economic Circle: Intergovernmental Cooperation and Multi-participation, Reform, 4, 2014.

Citation: Yang, Y., & Phromphithakkul, W., (2023). Factors Influencing Air Pollution Control of Beijing-Tianjin-Hebei Region in China. International Journal of Sociologies and Anthropologies Science Reviews (IJSASR), 3 (2), 15-28; DOI: https://doi.org/10.14456/jsasr.2023.12
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