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Economic Growth and Urban Haze- Dynamic spatial panel data analysis based on 241 prefecture- level cities in China*

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요 약

This paper uses the spatial autoregression model (SAR) to explore the effect of foreign direct investment (FDI on haze (PM2.5) air pollution in 241 cities in China employing data published by the Socio-Economic Data and Applications Center (SEDAC) of Columbia University's Center for International Earth Science Information Network (CIESIN) Our analysis reveals an inverted U-shaped environmental kuznets curve (EKC) relationship between haze (PM2.5) pollution and China's economic growth. The appearance of China's haze (PM2.5) pollution has a time lag, and we also observed a "superposition effect" in the time dimension, as well as a spatial spillover effect. In short, the inflow of FDI has aggravated haze (PM2.5) in China, providing further evidence for the "pollution haven hypothesis (PHH)" hypothesis as it applies to China.

Keyword : Foreign Direct Investment (FDI), Economic growth, Haze (PM2.5), Pollution Haven Hypothesis (PHH), Pollution Halo Hypothesis (P-HH), Environmental Kuznets Curve (EKC)

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1. Introduction

Haze is a type of air pollution formed by solid particles, i.e., dust particles suspended in the air (known as aerosol particles). Haze contains hundreds of types of atmospheric chemical particulate matter, and if people are exposed to it for a long time, haze is known to induce a variety of physical diseases. Pm2.5 refers to particles in the atmosphere whose aerodynamic equivalent diameter is less than or equal to 2.5 microns. While small, such particles have a significant effect on air quality and visibility. According to the Regulations of the China Meteorological Administration, if the visual obstruction caused by an aerosol system formed by the non-water composition reduces horizontal visibility to less than 10 km, it can be referred to as haze or dust-haze. In 2012, China included pm2.5 in its air quality evaluation standards. The sources of haze are diverse, and include automobile exhaust, industrial emissions, construction dust, garbage incineration, and even volcanic eruptions; haze weather is usually formed as a result of a mixture of these diverse sources of pollution.

Since China's reform and opening-up in 1978, foreign direct investment (FDI) has continuously increased. According to the "Statistical Bulletin of FDI In China 2021" report by the Chinese Ministry of Commerce, in 2020, despite the significant decline in global FDI due to the effect of COVID-19, Chinese FDI still grew in 2020, despite Covid-19, to reach US$149.34 billion. The inflow of FDI fills a funding gap in China's economic growth and promotes the innovation of local technology. But the rapid economic growth has made environmental problems increasingly serious. According to the "Air Quality Database" maintained by the World Health Organization (WHO), in 2022 seventy-five in the top 100 cities (or regions) experiencing haze (pm2.5) belong to China.

The theoretical research by environmental economists shows that foreign direct investment has a complex "double" effect on environmental pollution. According to the pollution haven hypothesis, some enterprises in developed countries will transfer their polluting activities to developing countries with comparatively loose environmental regulations in order to avoid more stringent environmental rules. By this theory, it is the host country that bears the

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consequences of the environmental pollution, as foreign direct investment aggravates environmental pollution. Other scholars hold the opposite view and have put forward a Pollution Halo Hypothesis, which holds that foreign direct investment promotes technological progress, and with it the diffusion of environmental quality norms system. In this scenario, FDI has a positive effect on the ecological environment of the host country.

There is also some controversy in the academic community concerning whether China has become a "pollution haven" for developed countries. In the early 1990s, American environmental economists Grossman and Krueger found that there was also a situation between environmental quality and economic growth, insofar as the environment first went through a period of deterioration, but then improved as per capita income increased. This relationship was apparent in their developed EKC curve, which they used to describe the relative relationship between environmental quality and economic growth in a country or region. Other scholars have identified different types of curves, such as an inverted U-shaped and N-shaped curves, that apply to different regions. In recent years, between economic growth and environmental problems have become the focus of people's attention. The EKC curve is today regarded as an inevitable consideration when economic and environmental decisions are made. Building on this body of research, this paper analyzes the effect of foreign direct investment and economic growth on the average concentration of haze (PM2.5) as assessed across space.

2. Literature Review

2.1. The relationship between FDI and the environment

As concerns the relationship between FDI and the environment of the host country, three viewpoints have been developed. The deterioration theory, commonly known as the pollution haven hypothesis (PHH)was first proposed by Walter and Ugelow (1979) and posits that pollution-intensive industries tend to

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migrate from developed countries with more stringent environmental regulations to developing countries with lax environmental regulations, rendering the host state a pollution refuge, Tang, D., Li, L., & Yang, Y. (2016) used data from 31 provinces in China to examine spatial autocorrelation of haze pollution in China and how it was affected by FDI. Their work confirmed that an increase in FDI leads to an increase in haze. Jun, Wen, et al., (2018) used CO2 and SO2 emissions as variables indicating environmental pollution and used wavelet analysis tools to analyze the effect of FDI on China's environment. Their results show that FDI affects the environment over the short, medium, and long term. These works, as well as those by Cheng, L. (2013); Wang, S., Wang, H., & Sun, Q. (2020); An, T., Xu, C., & Liao, X (2021); Guo, chen, et al., (2021); Pei, Taowu, et al., (2021) support the pollution haven hypothesis as it applies to China. Other works, such as those by Hitam, M. B., & Borhan, H. B. (2012) using on Malaysia as the sample, Terzi, H., & PATA, U. (2020) using Turkey as the sample, and Baek, J., & Choi, Y. J. (2017) reviewing 17 studies from Latin America as samples, also support the pollution haven hypothesis.

A second view is known as the pollution halo hypothesis (P-HH), according to which the process of overseas investment results in technological spillover effects that result in improved local environmental protection technologies and increased environmental protection standards, the investing multinational companies having mastered the management of both. Zhang, C., & Zhou, X. (2016) examined CO2 emissions as a variable indicating environmental pollution in China and analyzed the relationship between FDI and environmental pollution using panel data from 29 provinces in China, and showed that FDI contributed to a reduction in CO2 emissions. Liu, Qianqian, et al., (2018) analyzed the relationship between FDI and environmental pollution using data from 285 Chinese cities, determining that FDI has diverse effects on various environmental substances. For example, FDI reduced soot emissions but increased SO2 and wastewater emissions. Kim, M. H., & Adilov, N. (2012) concluded that FDI promotes CO2 emissions in developed countries, but not in low-income countries. Zhu, Huiming, et al., (2016) examined the cases of FDI in Indonesia, Malaysia, the Philippines, Singapore, and Thailand and concluded that

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FDI resulted in reduced carbon emissions. The work of Demena, B. A., & Afesorgbor, S. K. (2020); Xie, Q., & Sun, Q. (2020); Li, Chenggang, et al., (2021); Ahmad, Manzoor, et al., (2021) and other scholars also supports the pollution halo hypothesis.

A third view is the synthetic environmental effect hypothesis, which holds that the effect of FDI on the environment is multidimensional and complex. According to Grossman, G. M., & Krueger, A. B. (1995), FDI can affect the environment of the host country through the channels of the economic scale effect, the structural effect, and the technology spillover effect. Bin, S., & Yue, L. (2012) analyzed panel data associated with 36 industrial sectors in China and found that FDI reduced pollution emissions through the introduction of advanced technologies. Moreover, the positive effects of this technological diffusion outweighed the negative effects associated with the scale and structure effects. According to Zhang, Yan-bo, et al., (2014), both the expansion of China's economy and the change to its economic structure caused by the infusion of FDI have played a role in worsening the environment, though the associated technology transfer has prompted some improvements to the environment.

2.2. The EKC relationship between economic growth and the environment

The Kuznets curve refers to an assumption that as the economy develops, market forces will initially increase and subsequently reduce economic inequality. This hypothesis was first proposed by economist Simon Kuznets in the 1950s and 1960s. Grossman, G. M., & Krueger, A. B. (1991) introduced the concept of the Environmental Kuznets Curve (EKC) during an analysis of the North American Free Trade Agreement (NAFTA), in which they described an inverted "U"-shaped relationship between income and environmental evolution. Shafik, N. (1994) used the World Bank's 1992 World Development Report to illustrate how increasing economic activity damages the environment, but that as income rises, so does the public demand for a healthier environment, with the result that investments in improved environmental quality will also increase. Panayotou' s analysis (1993) also supports the existence of an inverted “U“-shaped relationship between income and environment, as does the work of Song, Wenhao, et al., (2021) and Wen, H., & Dai, J. (2021) Pu, Z. (2017) took China’s key cities as samples, and found a positive N-type EKC relationship between haze pollution (PM2.5) and regional economic growth.

2.3. Research on other variables affecting the environment

Some scholars, such as Pachauri, S. (2004) believe that rising levels of urbanization alter the allocation of energy resources, and that the resulting use of clean energy and alternative energy sources lowers air pollution. Other scholars believe that in the process of rapid urbanization, the highly concentrated population and the rapid expansion of the urban spatial structure lead to problems such as urban dysfunction and traffic congestion, which in turn cause and exacerbate ecological problems (Alberti, M. 2005).

Urban greening has ecological functions such as adjusting climate, cooling and humidifying, and purifying air, and plays a significant role in controlling haze (pm2.5). Urban greening has been recognized by many scholars for its role in reducing air pollution (Jaafari, Shirkou, et al.,., 2020; Moradpour, M., & Hosseini, V. 2020). CO, NOx, SO2 and other pollutants in motor vehicle exhaust from road traffic can not only direct causes of air pollution, but also be an important source of PM2.5 formation. In this paper, these factors will be incorporated into our model analysis as control variables.

3. Methodology and Variables

3.1. Spatial econometric model construction

Building on the preexisting literature, this paper describes economic growth （GDP per capita, pgdp in primary terms and quadratic terms）, and then investigates whether there is an EKC curve relationship between economic

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growth and environmental pollution. The stock form of FDI is incorporated into the model. The model is specified below :

$$\begin{aligned}\ln pm_{i,t} &= \beta_0 + \beta_1 \ln pgdp_{i,t} + \beta_2 \ln pgdp_{i,t}^2 + \beta_3 fdi_{i,t} \\ &+ \beta_4 urban_{i,t} + \beta_5 \ln greenpop_{i,t} + \beta_6 \ln road_{i,t} + \epsilon_{i,t}\end{aligned} \quad \text{식 (1)}$$

in which "i" refers to city, "t" refers to time, and "ε" refers to the error term of regression. The following table describes the variables in greater detail.

Excepting the variable haze (PM2.5) data, all data comes from China's Economy Prediction System (EPS) data platform. The Pm2.5 data comes from the Socio-Economic Data and Applications Center (SEDAC) of Columbia University's Center for International Earth Science Information Network (CIESIN).

4. Spatial dependence analysis of FDI's effect on Haze (PM2.5) pollution in China

4.1. Global spatial autocorrelation test

Spatial autocorrelation refers to potential interdependence between observations of some variables within the same distribution area. American geographer W.R. Tobler in 1970 identified "the first law of geography: everything is related to everything else, but what is near is more related than what is far away". This relationship is also true in economics. Moran' s I index can detect the global spatial dependence of economic activities, and Moran' s I scatter plot can detect and release the local characteristics of each individual, and thus observe the spatial aggregation characteristics of the high and low observations. Moran's I index can be used to test the similarity (positive spatial correlation) or dissimilarity (negative spatial correlation) between neighboring regions in an area, as its value ranges from -1 to 1. A result greater than 0 indicates that there is a positive spatial correlation, in this case indicating that low pollution and low pollution areas are clustered together. A result less than 0 indicates that there is a negative spatial correlation, indicating low pollution. An area adjacent to a high pollution area equal to 0 would indicate that the haze (pm2.5) pollution in China is randomly distributed, and that no spatial dependence exists. The formula for calculating Moran' s I index is as follows:

$$I=\frac{\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}(x_i-\tilde{x})(x_j-\tilde{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}\sum_{i=1}^{n}(x_j-\tilde{x})^2}=\frac{\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}(x_i-\tilde{x})(x_j-\tilde{x})}{s^2\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}} \quad \text{식 (2)}$$

in which I indicates Moran' s I index, and xi and xj are the observed values of prefecture-level cities i and j, respectively. Wij refers to the spatial weight matrix, n represents the total number of level cities in the research sample, s^2 is the variance of the attribute, and x represents the average value of the attribute, that is, the average annual average concentration of pm2.5 in all prefecture-level cities. The value range of Moran's I index is [-1, 1].

Geary's C index is another commonly used index to test global spatial correlation. Here, the value of Geary's C index is between 0 and 2: > 1 indicates a negative spatial correlation, < 1 indicates a positive spatial correlation, and = 1 means no spatial correlation. The meaning of each variable in formula(3) below is the same as those in formula(2).

$$c=\frac{(n-1)\sum_{i=1}^{n}\sum_{j=1}^{n}(x_i-x_j)^2}{2\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}\sum_{i=1}^{n}(x_i-\bar{x})^2} \quad \text{식 (3)}$$

4.1.1. Establishment of the spatial matrix

The degree of interdependence between regions is typically characterized by a

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spatial weight matrix. Most empirical research uses the 0-1 adjacency standard distance to define the spatial weight matrix that determines the spatial dependence of two regions. If the two regions are only adjacent to each other without considering the economic relationship between geographical distance and non-adjacent areas, it will lead to a lower degree of fitting to the objective facts. At the same time, because FDI is a cross-regional economic behavior, it is not only affected by geographical factors but also affected by spillover and radiation effects of economic and social motivations associated with various regions. Therefore, this paper has constructed a geographic weight matrix and an economic geographic nested weight matrix to examine the spatial correlation characteristics of FDI and China's haze (PM2.5) pollution.

(1) Geographic distance weight matrix (W1)

Anything or phenomenon is usually interconnected and influenced by other things or phenomena around it; this is equally true for haze (pm2.5) levels between regions. The haze (pm2.5) of each region may have a weaker mutual influence with the farther the distance, and the opposite may have a stronger mutual influence with the closer distance. Therefore, this paper constructed a geographic weight matrix using distance attenuation. The principle of setting the geographic weight matrix (W1) is as follows:

$$w_1 = \begin{cases} \dfrac{1}{d^2} & i \neq j \\ 0 & i = j \end{cases} \quad \text{식 (4)}$$

in which d represents the distance between geographic center positions (i and j), and the inverse of the distance between the two areas is obtained using the inverse distance function. A spatial weight matrix constructed using the inverse distance function can describe any spatial effect between regions more accurately than an adjacency matrix.

(2) Economic distance weight matrix (W2)

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$$w_2 = \begin{cases} \frac{1}{|mi - mj|} & i \neq j \\ 0 & i = j \end{cases} \quad \text{식 (5)}$$

Just as the economic growth of one region will both affect and be affected by other regions (that is, economic growth has a spatial correlation) an economic distance weight matrix can be constructed according to the economic growth of each region. W2 is expressed as the reciprocal value of the absolute value of the difference in per capita GDP between region i and region j, in which mi represents the per capita GDP of region i, and mj represents the per capita GDP of region j.

(3) Economic geography nested weight matrix (w3)

$$w_3 = w_1 * w_2 \quad \text{식 (6)}$$

in which W1 is the geographic distance weight matrix, W2 is the economic distance weight matrix, and W3 is an economic-geographic nested weight matrix that considers the spatial effects of both economics and geography. After testing, the Moran I index of the economic distance weight matrix (W2) was not significant, i.e., we found no autocorrelation. The Moran I index of both geographical distance weight matrix (W1) and economic geography nested weight matrix (W3) is significant at the 1% level, with the index between 0.156 and 0.202. The range of Geary's C index was all less than 1, reflecting a significant positive spatial correlation.

4.2. Local space autocorrelation test

The test function of the global type describes the overall distribution of a phenomenon and is used to determine whether the phenomenon has aggregation characteristics in space, but it cannot indicate precisely where the aggregation occurs. If the spatial autocorrelation statistics of different spatial lags of the global type are arranged in order, a spatial autocorrelation coefficient

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correlogram can be further made to analyze whether the phenomenon has a hierarchical distribution in space. This requires the introduction of a local Moran's I index to analyze the degree and type of agglomeration in each region. This index can examine the fact that each region within a thing or phenomenon is a cluster of observations with similar properties. Or observations with dissimilar properties are clustered together. The formula used to calculate the local Moran's I index is:

$$I_i = \frac{(x_i - \tilde{x})}{s^2} \sum_{i \neq j}^{n} w_{ij}(x_i - \tilde{x}) \quad \text{식 (7)}$$

in which Ii is the local Moran' s I index, which in our case detects the degree of correlation between the average concentration of pm2.5 in an i prefecture-level city and its surrounding prefecture-level cities. When the local Moran' s I>0, the observed objects in the spatial region and adjacent regions have similar attribute values (low-low clustering or high-high clustering). When the local Moran index I < 0, the observed objects in the spatial region and adjacent regions have different attribute values (low-high clustering or high-low clustering).

A Moran scatter plot is used to study the spatial distribution characteristics of local areas of things or phenomena. The spatial lag factor Wz and z data in the Moran scatter plot represent the ordinate and abscissa, respectively. The first quadrant (HH) means that it is high in itself, and other areas around it are also high; the second quadrant (LH), means that it is low in itself, but the surrounding areas are high; the third quadrant (LL), which means that it is a high value, and the surrounding areas are all low values; the fourth quadrant (HL), which means that it is a high value, but is surrounded by low values. The first and third quadrants represent the clustering of positive spatial autocorrelation similarity values; the second and fourth quadrants represent negative spatial autocorrelation, indicating spatial anomalies. If the observations are evenly distributed in the four quadrants, no spatial autocorrelation between the examined regions exists. Moran scatterplot is shown in the Appendix at the end of this paper.

From our Moran's I scatter plot, most of the regional points are located in the first and third quadrants, both in the case of the W1 matrix and the W3 matrix. This confirmed is the existence of a positive spatial spillover effect of haze (pm2.5) pollution in China. We also note that the regional scatter distribution of haze (PM2.5) has not changed much over time.

5. Analysis method

Prior to estimating the model parameters, we had to select between the spatial auto-regressive model (SAR) or the spatial error model (SEM). Our judgment criterion was whether the model with more significant LM (Lagrange Multiplier) statistic was the most suitable. If the LM statistic of the two models has the same level of significance, then suitability needed to be determined by the significance of the robust LM (robust-LM) statistic.

In the case of the W1 geographic distance matrix, the LM test was performed on the spatial autoregressive model (SAR) and the spatial error model (SEM). As the robust LM of the spatial error model (SEM) did not pass the test, the spatial autoregressive model (SAR) was regarded as more suitable. The Wald test also supported the choice of spatial autoregressive model (SAR). Moran's I was significant, which indicated that similar to the results of the spatial correlation test above, there is a spatial effect of haze (Pm2.5) pollution. Accordingly, it was no longer appropriate to continue to use the ordinary panel model for research, so we chose the spatial panel econometric model. The LM test results of the economic geography nested weights matrix (W3) showed that both the spatial autoregressive model (SAR) and the spatial error model (SEM) were suitable for model selection. The same Wald test results supported our choice between the above two models. In order to maintain the consistency with the spatial autoregressive model (SAR) setting of the geographic distance weight matrix (W1), this model was used for the following analysis. The test results are shown in the Appendix at the end of this paper.

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Unlike traditional econometric models, spatial econometric models account for the common spatial dependence in economics (Anselin, L. 1988), that is, sample observations in one region depend on observations in other regions. Observations lack spatial independence, and the degree and pattern of spatial correlation is determined by absolute and relative positions between regions. SAR is a spatial method that describes the relationship between dependent and independent variables by considering spatial effects.

The estimation of the mixed model assumes that the haze pollution levels are the same in each region, but this assumption cannot be satisfied in reality. Time-fixed model estimates consider the effects of time, reflecting the results of time-varying variables on steady-state levels. It is mainly manifested in the influence of economic cycles, emergencies and other changes over time, but ignores the influence of spatial and regional differences. Individual models account for the effects of spatial differences, reflecting the effects of variables that vary with geographic location on steady-state levels. It is mainly reflected in the effect of economic structure, policy changes, and resource endowment on haze (PM2.5) pollution. Each of these three modeling methods will bias the estimation results, and the individual and time two-way fixed model not only controls the influence of time, but also controls the influence of spatial differences, and is therefore better able to explain the effect of haze (PM2.5) pollution. The LR test results also support our choice to employ this model.

6. Empirical Results

The results of the analysis confirm that the time lag coefficient θ of haze (PM2.5) pollution is significantly positive at the 1% level, both in the geographic distance weight matrix (W1) and the economic geographic distance weight matrix (W3). In short, China's haze (PM2.5) pollution has a lag and has a "superposition effect" in the time dimension, in which if the haze (PM2.5) pollution in a previous period was serious, then the haze (PM2.5) pollution in the following period may continue at this level. Meanwhile, spatial correlation

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coefficient ρ and its lag coefficient η also have a significant positive effect, suggesting a spatial spillover effect of haze (PM2.5) pollution in China. Finally, China's haze (PM2.5) pollution has cumulative, continuous, and overlapping evolution characteristics across the spatial, temporal and spatio-temporal dimensions, with the "spillover effect" greater than the "superposition effect".

In our model, the first-order coefficients of per capita GDP are all positive, and the quadratic coefficients are all negative. These results confirm that there is an inverted "U" relationship between haze (PM2.5) pollution and economic growth in prefecture-level cities in China. The implication is that the relationship between haze (PM2.5) pollution and economic growth in Chinese cities will eventually enter a stage of negative correlation.

Based on our empirical analysis, FDI has a promoting effect on haze (PM2.5) pollution, indicating that the "Pollution Haven Hypothesis (PHH)" applies to China. As the world's largest developing country, China receives pollution-intensive industries from developed countries along with FDI. China is still developing large-scale labor-intensive, primary factor-oriented economic growth model. In the global value chain, China, as an integral part of the production end, has undertaken the high pollution and high energy consumption part. The arrival of FDI continues to have a negative effect on haze (PM2.5) pollution.

An increasing urbanization rate has a negative correlation with the effect of haze (PM2.5) pollution. This may be rising urbanization brings a large number of permanent residents to tertiary industries, promoting their development and reducing energy consumption per unit of GDP (Liang & Zhang 2017). A reasonable urbanization spatial structure is one that not only promotes the flow of factors and optimizes the spatial allocation of resources, but also speed up the operational efficiency of regional space. For example, improvements to infrastructure, functional layout, and public transportation can effectively reduce urban traffic pollution.

Additional urban greening will inhibit haze (PM2.5) pollution and promote air purification. The same also confirmed once again that traffic pollution is one

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source of haze (PM2.5) pollution.

7. Conclusion

Moran's I and Geary's C methods were applied to spatial panel data gathered between 2004 and 2018 from 241 prefecture-level cities in China to analyze the global spatial autocorrelation and local spatial autocorrelation of PM2.5 pollution in China. The geographic weight matrix and the economic geographic weight matrix were respectively incorporated into the spatial panel model for investigation. Our results show that most haze (PM2.5) pollution in China have characteristics of high-high aggregation and low-low aggregation, with significant spatial dependence and significant positive spatial correlation. We further confirmed that a spillover effect of haze (PM2.5) pollution across space exists. The results of the dynamic spatial panel model show that haze (PM2.5) pollution is greatly affected by spatial lag term, i.e., the "spillover effect" is greater than the "superposition effect". Moreover, haze (PM2.5) pollution in China has the characteristics of intersection, accumulation and continuous evolution in the spatial dimension, the time dimension, and its spatiotemporal dimension, respectively.

The first-order coefficient of per capita GDP is positive, and the quadratic coefficient is negative. There is a significant inverted U-shaped relationship between urban haze (PM2.5) pollution and economic growth in China; as the per capita GDP increases, the concentration of haze (PM2.5) first increases and then decreases. The coefficient of FDI is significantly positive, indicating that FDI is among the influential factors that lead to an increase in the concentration of haze (PM2.5) in China. China is still far from the optimal level when attracting and utilizing FDI.

Nevertheless, the increase in urbanization has reduced haze-causing emissions. This shows that the spatial structure of China's urbanization rate improvements are reasonable, promoting the flow of factors and optimizing the spatial allocation of resources. We also confirmed that an increase in urban greening

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inhibits the growth of haze (PM2.5), and that road traffic is among of the sources of haze (PM2.5) pollution.

This paper examined the relationship between FDI, economic growth, and haze (PM2.5) in China from the perspective of spatial impact. We verified the applicability of the "pollution haven hypothesis" in China and the existence of an inverted U-shaped EKC curve to China's economic growth and haze (PM2.5) pollution situation. In recent years, China has strengthened its environmental protection policies as they relate to FDI entry. Welcoming technology-intensive investment and the development of "green energy" is an important step towards changing China's status as a polluter haven. In the future, the introduction and independent development of pollution-free new energy and pollution-free technology will be the focus of sustainable economic growth efforts. Road traffic is another source of haze (PM2.5) in China. Especially in recent years, China has strengthened its infrastructure construction efforts, including road transportation, which has brought about a rapid increase in private transportation. This has brought great pressure to improve environmental pollution. Strengthening and promoting the development of new energy-efficient vehicles and increasing the opportunities for public transportation use (reducing the use of private transportation) are also major projects for future development.

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Appendix

<Table 1> Defined Variables

Variable	Symbol	Variable Definitions	Measurement Method	Unit
Dependent Variable	Pm2.5	Haze pollution	Annual average PM2.5 concentration	$\mu g/m^3$
Core Variables	Fdi	Foreign direct investment	FDI/GDP	%
Other Control Variables	Pgdp	Level of economic growth	GDP per capita	Ten thousand yuan (RMB)
	Urban	Level of urbanization	Urban population/Total population	%
	Greenpop	Level of greening	Green space per capita	m^2
	Road	Traffic pollution	Highway mileage in this region	Km

<Table 2> Descriptive Statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
lnpm2.5	3615	3.749	0.454	1.95	4.596
lnpgdp	3615	10.423	0.764	7.764	14.586
lnpgdp2	3615	109.222	15.8	60.28	212.743
fdi	3615	0.029	0.031	0.007	0.588
urban	3615	0.793	1.913	0.103	60.413
lngreenpop	3615	3.371	0.720	0.487	6.679
lnroad	3615	6.847	0.957	4.083	9.94

<Table 3> Correlation

	lnpm2.5	lnpgdp	fdi	urban	lngreepop	lnroad
lnpm2.5	1					
lnpgdp	0.002	1				
fdi	0.035	0.105	1			
urban	0.042	0.107	-0.048	1		
lngreepop	-0.081	0.621	0.141	0.001	1	
lnroad	0.210	0.609	0.196	0.025	0.425	1

<Table 4> Unit root test

	lnpm2.5	lnpgdp	lnpgdp2	fdi	urban	lngreenpop	lnroad
llc	-22.20	-23.61	-20.27	-28.22	-31.64	-28.19	-29.78
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
breitung	-7.81	-16.86	-18.43	-11.37	-20.94	-13.65	-14.01
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
adf	1462.32	1060.13	1043.13	1723.26	1811.32	1335.82	1422.06
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
pp	1896.64	1204.17	1031.64	1744.30	1042.58	1799.25	1195.72
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

주1) () is p-value

<Table 5> Global Moran's I index and Geary's c index of PM2.5 mean concentration

	geographic distance weight matrix (W1)		economic geographic nested weight matrix (W3)	
Variables	Moran's I	Geary's c	Moran's I	Geary's c
lnpm2004	0.184***	0.727***	0.174***	0.699***
lnpm2005	0.210***	0.694***	0.188***	0.663***
lnpm2006	0.181***	0.736***	0.162***	0.694***
lnpm2007	0.199***	0.717***	0.190***	0.683***

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lnpm2008	0.156***	0.776***	0.153***	0.756***
lnpm2009	0.180***	0.746***	0.181***	0.709***
lnpm2010	0.195***	0.744***	0.188***	0.693***
lnpm2011	0.191***	0.751***	0.181***	0.711***
lnpm2012	0.194***	0.734***	0.184***	0.688***
lnpm2013	0.202***	0.759***	0.196***	0.712***
lnpm2014	0.168***	0.804***	0.181***	0.769***
lnpm2015	0.180***	0.798***	0.196***	0.753***
lnpm2016	0.189***	0.773***	0.192***	0.728***
lnpm2017	0.178***	0.800***	0.181***	0.750***
lnpm2018	0.198***	0.778***	0.198***	0.719***

<Table 6> Choice of model type (LM test in case of W1 matrix)

Test	Statistic	p-value
Spatial error		
Moran's I	101.452	0.000
Lagrange multiplier	9599.782	0.000
Robust Lagrange multiplier	0.933	0.334
Spatial lag		
Lagrange multiplier	1.0e+04	0.000
Robust Lagrange multiplier	699.570	0.000
Wald	4.09	0.664

<Table 7> Choice of model type (LM test in case of W3 matrix)

Test	Statistic	p-value
Spatial error		0.000
Moran's I	83.905	0.000
Lagrange multiplier	6551.417	0.000
Robust Lagrange multiplier	16.282	0.000
		0.000
Spatial lag		0.000
Lagrange multiplier	6908.139	0.000
Robust Lagrange multiplier	373.004	0.000
Wald	5.58	0.472

<Table 8> Choice of control type (LR Test)

	Type	CHI2	P
W1 Matrix	both or ind	118.80	0.000
	both or time	1191.66	0.000
W3 Matrix	both or ind	109.75	0.000
	both or time	11896.23	0.000

<Table 9> Estimation results of dynamic spatial panel model (SAR)

VARIABLES	W1		W3	
	Coef	z	Coef	z
$\ln pm(\theta)_{t-1}$	0.508***	20.56	0.547***	22.07
$w \cdot \ln pm(\eta)_{t-1}$	0.722***	9.67	0.570***	8.21
lnpgdp	0.305***	6.66	0.297***	6.54
$(\ln pgdp)^2$	-0.014***	-6.84	-0.014***	-6.80
fdi	1.332***	20.04	1.211***	18.77
urban	-0.003***	-6.77	-0.003***	-5.73
lngreenpop	-0.006	-1.53	-0.006	-1.58
lnroad	0.017**	2.56	0.015**	2.29
Spatial- ρ	1.039***	892.01	0.999***	1029.26
Observations	3,374		3,374	
R-squared	0.255		0.318	
Number of City	241		241	
City Fe	Yes		Yes	
Year Fe	Yes		Yes	

주1) *** $p<0.01$, ** $p<0.05$, * $p<0.1$

(1) Moran's I scatter plot of haze (PM2.5) in various prefecture-level cities in China in 2004, 2011, and 2018 under the W1 matrix

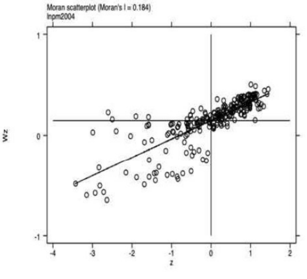

Fig1. Moran scatterplot (lnpm2004).

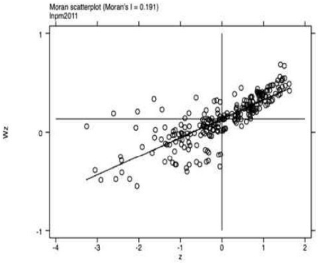

Fig2. Moran scatterplot (lnpm2011).

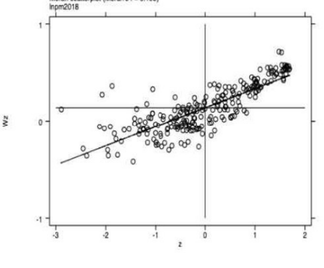

Fig3. Moran scatterplot (lnpm2018).

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(2) Moran’ s I scatter plot of haze (PM2.5) in various prefecture-level cities in China in 2004, 2011, and 2018 under the W3 matrix

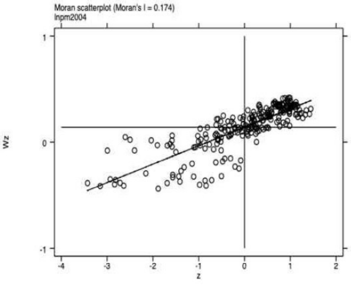

Fig4. Moran scatterplot (lnpm2004).

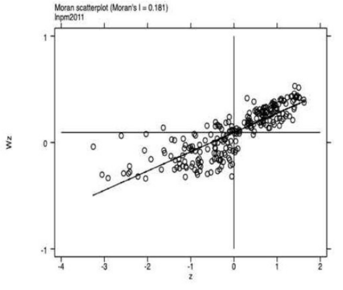

Fig5. Moran scatterplot (lnpm2011).

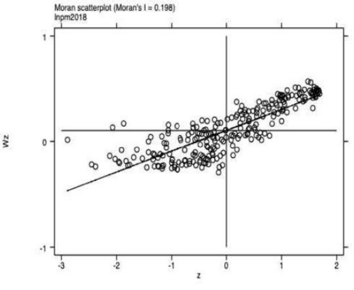

Fig6. Moran scatterplot (lnpm2018).

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FDI, 경제성장과 도시 미세먼지 오염의 관계- 중국 기반 241개 광역시의 동적 공간 패널 데이터 분석*

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Abstract

본 연구는 미국 컬럼비아 대학교 국제지구과학정보센터(CIESIN) 소속 사회적 경제 데이터·응용센터(SEDAC)에서 발표한 자료를 기초로 공간자체회귀모델(SAR)을 활용해 해외직접투자(FDI)가 중국 241개 도시의 미세먼지(PM2.5) 대기오염에 미치는 영향을 분석하였다. 그 결과 미세먼지 (pm2.5)오염과 중국의 경제발전 사이에는 역U 자형 환경쿠즈네츠곡선 (EKC)의 관계가 있는 것으로 나타났다.또한 중국의 미세먼지(PM2.5) 오염은 시차가 존재하고, 시간적 차원에서 '중첩효과'가 있고, 공간적 파급효과도 있다. 이상 분석을 의하여 FDI 유입은 중국의 미세먼지(PM2.5) 문제를 악화 시켜 중국의 '오염 대피소가설(PHH)' 가설에 추가적인 증거를 제공하고 있다.

핵심주제어: 해외직접투자（FDI）, 경제발전, 미세먼지(PM2.5), 오염 대피소가설(PHH), 오염 헤일로 가설(P-HH), 환경쿠즈네츠곡선(EKC)

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