

How Does Artificial Intelligence Empower Urban Pollution Governance?

-- Evidence from the Spatial Durbin Model of 274 Cities in China

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Abstract: Against the backdrop of the "dual-carbon" goals and the green development strategy, to explore the role of artificial intelligence (AI) in local pollution and emission reduction, this study employs the Spatial Durbin Model (SDM) and uses data from 274 prefecture-level and above cities in China spanning 2013 to 2022. The explained variable is the environmental pollution index (incorporating industrial wastewater discharge, industrial sulfur dioxide emission, and industrial smoke and dust emission) constructed via the entropy weight method. The core explanatory variable is the logarithmic value of the number of AI enterprises in each city, with control variables including urbanization rate and fiscal decentralization. The results show that: AI development exerts a significantly negative impact on local pollution (the main effect coefficient is -0.011, significant at the 1% level, under both geographic distance matrix and economic-geographic nested matrix); pollution exhibits strong spatial dependence (rho value ranges from 0.828 to 0.876); the spatial spillover effect of AI is heterogeneous; both environmental pollution and AI development demonstrate significant spatial agglomeration (Moran's I index is significantly positive). This study provides a reference for leveraging intelligence to empower local pollution and emission reduction and facilitate the achievement of "dual-carbon" goals.

Keywords: Artificial Intelligence; Urban Pollution; Spatial Durbin Model.

1. Introduction

With the accelerated process of industrialization and urbanization in China, environmental pollution has become a focus of the whole society, and addressing environmental issues has also emerged as a key topic discussed by countries worldwide. Promoting green development and fostering harmonious coexistence between humans and nature have been identified as important themes during the 14th Five-Year Plan period. Carbon peaking and carbon neutrality are the core goals of China's current environmental governance, and achieving pollution and emission reduction has become a vital component of the high-quality development of China's economy. The Report to the 20th National Congress of the Communist Party of China (CPC) pointed out: "We will advance the building of a Beautiful China, adhere to the integrated protection and systematic governance of mountains, rivers, forests, farmlands, lakes, grasslands, and deserts, coordinate industrial structure adjustment, pollution control, ecological protection, and climate change response, and promote the coordinated advancement of carbon reduction, pollution reduction, green expansion, and growth. We will advance development that prioritizes ecology, is economical and intensive, and is green and low-carbon." This puts forward clear requirements for the coordinated implementation of carbon peaking and carbon neutrality efforts and clarifies the strategic path and key tasks for achieving the "dual-carbon" goals.

The Report to the 20th National Congress of the CPC proposes to promote the integrated and clustered development of strategic emerging industries and build a new batch of growth engines such as artificial intelligence. Given that AI is gradually permeating all aspects of life, this paper conducts research on the integration of AI and local pollution and emission reduction issues and proposes corresponding

solutions. With the accelerated evolution of the Fourth Industrial Revolution, the global competitive landscape is constantly reshaped, and countries around the world have taken enhancing scientific and technological innovation capabilities as the core strategy to gain competitive advantages. As a new generation of "general-purpose technology" following the Internet, AI is regarded as the key to advancing the Fourth Industrial Revolution and has become an important driving force for the new round of scientific and technological revolution and industrial transformation [1]. As the core driving force of the new round of industrial transformation, emerging information technologies represented by AI have become an engine for promoting the high-quality development of the economy and society. In 2023, the National Development and Reform Commission (NDRC) and other departments jointly issued the Implementation Plan for Green and Low-Carbon Advanced Technology Demonstration Projects, which proposes to deploy a number of projects with leading technological levels, prominent emission reduction effects, coordinated pollution and carbon reduction, and significant demonstration effects. It also clarifies the key directions, support measures, and organizational implementation methods of the green and low-carbon advanced technology demonstration projects. Currently, the application of new technologies represented by AI in industries is gradually becoming widespread, continuously penetrating all aspects of human production and life, generating new models and forming new business formats.

Scientific and technological innovation, as well as technological innovation, are the key supports for achieving the "dual-carbon" goals. The Report to the 20th National Congress of the CPC makes clear arrangements for advancing the "dual-carbon" goals in a proactive and steady manner, requiring the government to develop green and low-carbon

industries and accelerate the R&D, promotion, and application of advanced energy-saving and low-carbon technologies. The 2022 Central Economic Work Conference proposed to forge new industrial competitive advantages in the process of implementing the carbon peaking and carbon neutrality goals, elevating the dual-carbon goals from the level of environmental governance to the dimension of national industrial competitiveness restructuring, and emphasizing the cultivation of new drivers of economic growth through green and low-carbon transformation. Both the Opinions of the CPC Central Committee and the State Council on Comprehensively, Accurately and Fully Implementing the New Development Concept to Do a Good Job in Carbon Peaking and Carbon Neutrality and the Action Plan for Carbon Peaking Before 2030 issued by the State Council propose to "accelerate the R&D, promotion, and application of advanced and applicable technologies". The introduction of the above series of policies has constructed a "three-in-one" development paradigm of "environmental governance - technological innovation - industrial upgrading", striving to achieve a systematic leap in the quality of China's economy in the process of realizing the dual-carbon goals.

Lü Yue (2023) argues that AI realizes green improvement of industrial production processes through multiple aspects such as real-time monitoring of pollution emissions, precise governance, and optimization and upgrading of clean production models [2]. Therefore, promoting the intelligent development of industry may become a potentially feasible path for China to achieve green transformation. Shen Yang, Guo Xiaoyang, and Zhang Xiuwu (2022) found through research that high and new technologies such as AI manufacturing, algorithms, and industrial robots have increased enterprises' demand for high-skilled and high-knowledge labor due to the emergence of human-machine collaboration positions derived from the production processes [3]. This reduces enterprises' investment in tangible production factors such as capital and land to a certain extent, and at the same time, enables enterprises to obtain higher labor output through high production efficiency, thereby improving green total factor productivity and further empowering enterprises' green development through AI. By promoting complementary innovation through AI technology and applying it to all links and fields of production, local enterprises can quickly identify pollution sources in the production process by virtue of the advanced intelligent monitoring systems and infrared sensing technologies of intelligent manufacturing, thus shifting pollution control from end-of-pipe treatment to source governance. Solving local pollution and emission reduction issues through AI not only helps us better understand the internal mechanism of AI in assisting local pollution and emission reduction, promotes local governments to formulate more scientific and effective policies, but also drives the upgrading of local industrial structures, encourages enterprises to adopt more green production methods, achieves the "dual-carbon" goals as scheduled, and contributes to the sustainable development of the economy and society. Therefore, it is necessary to conduct in-depth discussions on the environmental effects of intelligent development and its internal mechanism, in order to provide a possible reference path for intelligence to empower green transformation and upgrading as well as local pollution and emission reduction in China, and facilitate the realization of the "dual-carbon" goals.

2. Literature Review and Research Hypothesis

2.1. Artificial Intelligence and Environmental Pollution

Since the beginning of the 21st century, China's total economic output has achieved a leap, but behind the high-speed economic development, there are also risks of excessive resource consumption and ecological damage. As a result, environmental problems such as air pollution represented by smog and water pollution represented by cyanobacteria blooms have become more prominent. With the successive emergence of such ecological problems, environmental pollution and its prevention and control have gradually become the focus of attention of the Party and the government. Since the 18th National Congress of the CPC, the Party and the government have attached great importance to environmental pollution issues and put forward the development concept that "lucid waters and lush mountains are invaluable assets". The Report to the 19th National Congress of the CPC further clearly identified environmental pollution prevention and control as one of the three critical battles for building a moderately prosperous society in all respects. In September 2020, President Xi Jinping solemnly proposed at the 75th Session of the United Nations General Assembly that China strives to reach the carbon peak by 2030 and achieve carbon neutrality by 2060, i.e., the "dual-carbon" goals. This strategic arrangement not only anchors the medium- and long-term technological roadmap for emission reduction but also transforms the concept of green development into a quantifiable institutional constraint system — through policy tools such as carbon quota trading and green finance, it forces the economic system to achieve a paradigm shift in the dynamic balance between "pollution reduction" and "growth". In this process, pollution prevention and control is entrusted with a dual mission: it is not only a rigid means to achieve the "dual-carbon" goals but also a core driver for restructuring the economic growth model. The academic focus on this issue stems from the structural support of green development for high-quality economic development: when pollution prevention and control shifts from end-of-pipe treatment to source emission control, it essentially internalizes environmental costs into a driver for improving total factor productivity through technological substitution and institutional innovation.

Existing literature on environmental pollution prevention and control mainly focuses on two levels: macro and micro. From the macro perspective, existing studies mainly focus on the establishment of environmental regulations and the optimization of industrial and energy structures. In terms of environmental legislation, Li Qiang and Liu Qingfa (2022) argue that local environmental legislation significantly inhibits environmental pollution, and the test results of lag effects also show that local environmental legislation has an inhibitory effect on environmental pollution, indicating that the emission reduction effect of local environmental legislation has a long-term mechanism [4]. In terms of environmental policies, Liu Yiwen et al. (2021) found that both phases of the Central Environmental Protection Inspection have a significant effect on improving air quality, i.e., the implementation of the Central Environmental Protection Inspection can significantly inhibit environmental pollution, which is consistent with the conclusion drawn by

Zhang Rui et al. (2023) [5, 6]. In addition, Shen Kunrong et al. (2020) also proved that the "River Chief System" plays a positive role in urban water pollution governance from the perspective of this system [7]. In terms of industrial structure, Wang Sanxing et al. (2024) analyzed the panel data of cities at or above the prefecture level and concluded that the advancement of industrial structure can improve the urban environmental situation [8]. In addition, Yang Siying et al. (2023) demonstrated the mechanism of action of industrial advancement on the green development of the industrial economy from the perspective of industrial intelligence [9]. Meanwhile, Vivanco et al. (2016) found through research that the application of AI technology in industrial production will improve the efficiency of resource utilization and pollution emission [10]; Li et al. (2022) demonstrated the contribution of AI application at the industrial level to promoting economic growth and improving the ecological environment from the perspective of industrial intelligent transformation.

From the micro perspective, existing studies mainly focus on corporate investment in pollution governance. Wang Peng et al. (2014) found through research that increasing corporate investment in pollution governance has a strong promoting effect on pollution governance, and the mechanism is that enterprises can carry out end-of-pipe treatment of pollution emissions through the construction of supporting pollution treatment facilities [11]. Through the analysis of the above literature, it can be seen that the academic community has carried out extensive research on environmental pollution prevention and control, but given the significant strategic importance of environmental pollution prevention and control, there is still broad research space in related fields.

As an important driving force for the new round of scientific and technological revolution and industrial transformation, AI has become a key layout for socialist modernization. In 2017, China issued the Development Plan for the New Generation of Artificial Intelligence, officially elevating the development of AI to the national strategic level; in recent years, generative artificial intelligence (AIGC), which has become popular, has attracted widespread attention from all sectors of society. Academic discussions on AI mainly focus on its impact effects, especially in terms of economic growth, employment, and industrial systems. Specifically, in terms of economic growth, most scholars believe that AI can promote high-quality economic development. For example, Graetz et al. (2015) found through research that AI promotes economic growth by improving labor productivity and added value [20]; Lei Chang et al. (2023) found that AI significantly promotes low-carbon economic development by optimizing the industrial structure (such as reducing the proportion of traditional high-energy-consuming industries) and promoting green technological innovation [21]; Fan Dezhi et al. (2024) found through theoretical research that large generative AI models demonstrate strong capabilities in natural language processing and generation, opening up new development paths for new drivers, new industries, and new models [12]. However, some scholars argue that the relationship between AI and urban economic resilience shows an inverted "U" shape. For example, Liu Jiaqi et al. (2023) believe that the development of AI will reduce urban economic resilience by exacerbating the digital divide, which is particularly evident in urban agglomerations such as Beibu Gulf and Harbin-Changchun, as well as in areas with low economic development levels and cities that are not comprehensive big

data pilot zones [13].

In terms of employment, some scholars hold a positive attitude towards the impact of AI on employment. For example, He Qin et al. (2024) argue that the application of AI can generally promote high-quality employment, and fiscal expenditure can positively regulate the impact of AI on employment; other scholars believe that AI has a significant substitution effect on some labor groups [14]. For example, Sun Wangshu et al. (2024) believe that the average substitution probability is higher for labor groups with low education levels [15]. In terms of the industrial system, Ye Yunling (2024) explored the relationship between AI and the externality of industrial agglomeration and found empirically that AI can promote the specialized agglomeration of industries [16]; Chai Zhengmeng (2024) found through research that industrial intelligence can promote the upgrading of China's industrial structure at the provincial level [17].

The above literature discusses the impact effects of AI from many different perspectives, but currently, few studies have deeply explored the mechanism of AI's impact on pollution emissions. Only a small number of scholars have used provincial, industrial, or enterprise panel data to empirically test the impact effects and internal mechanisms of AI on pollution emissions, and there are few studies based on urban panel data, which is one of the marginal contributions that this paper attempts to provide.

Therefore, based on the above analysis, this paper puts forward the following hypothesis:

Hypothesis 1: The development of AI helps reduce regional pollution levels.

3. Research Design

3.1. Model Design

The two-way fixed effects model effectively mitigates the problem of omitted variable bias by controlling for unobservable heterogeneity across individuals and time, laying a foundation for the reliability of the core research conclusions. However, traditional econometric models assume that research units are independent of each other, a premise that is often difficult to hold in real economic and geographical systems. When the research issue involves spatial interaction between regions, ignoring spatial dependence in estimation may lead to model specification bias and distortion of research conclusions. At the same time, introducing spatial econometric models can effectively reveal the cross-regional interaction patterns that are difficult to observe with traditional models. Therefore, this paper introduces spatial econometric models for further analysis.

There are three commonly used spatial econometric models: the Spatial Autoregressive Model (SAR), which is suitable for studying the situation where the dependent variable is directly affected by neighboring regions; the Spatial Error Model (SEM), which is used to reflect the spatial dependence of omitted variables or measurement errors; and the Spatial Durbin Model (SDM), which can be used to analyze the spillover effects of independent variables on neighboring regions. The selection of the above models can be determined through LM test, LR test, and Wald test. The specific test results are shown in Table 1.

Table 1. Test Results of Spatial Econometric Models

Test Indicator	Statistic Value	P-value
Robust LM-error	499.034	0.000
Robust LM-lag	147.321	0.000
LR test both ind	18.7	0.177
LR test both time	3151.91	0.000
LR test spatial lag	32.38	0.000
LR test spatial error	31.65	0.000
Wald test spatial lag	32.47	0.000
Wald test spatial error	31.38	0.000

$$Pollution_{it} = \alpha_i + rWPollution_{jt} + bAI_{it} + qControl_{it} + gWAI_{jt} + fWControl_{jt} + e_{it} \quad (1)$$

Among them, W represents the spatial weight matrix; $WPollution_{jt}$ represents the spatial dependence of the pollution level in neighboring regions on the local region; WAI_{jt} represents the spatial spillover effect of the AI development level in neighboring regions; α_i represents the individual fixed effect; ρ is the spatial autoregressive coefficient; β represents the direct impact of the local AI development level on local pollution; θ represents the direct impact of local control variables on local pollution; and ε_{it} is the random error term.

3.2. Indicator Selection

Explained Variable: Environmental Pollution Index ($Pollution_{it}$). To obtain a more objective and practically meaningful evaluation result, this paper draws on the indicators of Li Qiang (2018) [4]. It standardizes the data of three indicators (industrial wastewater discharge, industrial sulfur dioxide emission, and industrial smoke and dust emission), determines the weights using the entropy weight method, and then calculates the comprehensive score to measure the regional pollution level. Some missing values are supplemented using linear interpolation. The specific steps for constructing this indicator are shown in Formulas (2) to (6):

First, standardize the three negative indicators included in the environmental pollution index:

$$y_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \quad (2)$$

Then, use the standardized data to calculate the proportion of each indicator:

$$p_{ij} = \frac{y_{ij}}{\sum_{i=1}^m y_{ij}} \quad (3)$$

Next, calculate the information entropy of the j -th indicator:

$$e_j = -\frac{1}{\ln m} \sum_{i=1}^m p_{ij} \ln p_{ij} \quad (4)$$

Determine the weight of the j -th indicator:

$$w_j = \frac{1 - e_j}{\sum_{k=1}^n (1 - e_k)} \quad (5)$$

Finally, construct the comprehensive index:

$$Pollution_i = \sum_{j=1}^n w_j y_{ij} \quad (6)$$

Core Explanatory Variable: AI Development Level (AI_{it}). Considering the availability of data, this paper draws on the method of Sun Xue et al. (2022) and uses the logarithmic value of the number of AI enterprises in a city as the measure of the city's AI development level. The data are collected by searching for AI enterprises on Tianyancha (a Chinese enterprise information platform) and retaining those that are

The results in Table 1 indicate that the Spatial Durbin Model (SDM) with fixed individual effects should be used for the spatial econometric analysis in this study. The construction of the Spatial Durbin Model is shown in Formula (1):

still in operation [15].

Control Variables:

Urbanization Rate (Urban): The strength of regional development can be evaluated from multiple perspectives. The urbanization rate can represent the local industrialization level and urbanization process, and is one of the important references for foreign investment.

Fiscal Decentralization (Fd): Some scholars in the academic community have conducted research on the relationship between fiscal decentralization and environmental pollution, and most scholars tend to believe that the improvement of fiscal decentralization may lead to the deterioration of the ecological environment.

Opening-up Level (Open): Currently, there is controversy in the academic community regarding whether opening-up can promote regional pollution reduction. Hu Zongyi explored the impact of opening-up on environmental pollution from the perspective of the establishment of free trade zones and believed that the establishment of China's free trade zones can significantly reduce the concentration of urban air pollution; other scholars such as Ran Qiyang argue that trade opening and investment opening have exacerbated air pollution at this stage.

Financial Development Level (Fin): There is dynamic controversy in the academic community regarding the relationship between financial development and regional pollution.

Natural Resources (Nr): A large number of existing studies have proven that there is a positive correlation between natural resources and regional pollution. For example, Liao Hongwei's empirical study based on data from Chinese prefecture-level cities shows that resource endowment has a significant negative effect on regional environmental governance.

3.3. Data Description

This study selects data from 274 prefecture-level and above cities across China from 2013 to 2022, considering data availability. The data are obtained from the EPS platform, CSMAR database, China Statistical Yearbook, and the statistical yearbooks of various provinces and cities. For the completeness of data, cities with serious missing data (such as Changdu City, Shigatse City, and Bijie City) are excluded. The remaining data cover the entire period from 2013 to 2022. The descriptive statistical analysis of the main variables used in this paper is shown in Table 2. It can be seen from Table 2 that the mean value of the environmental pollution index ($Pollution$) is 0.9497, with a maximum value of 1 and a minimum value of 0.38, indicating that China is currently facing a relatively severe environmental pollution problem and there is a large gap in the degree of environmental

pollution between different cities; the mean value of the AI development level (AI) is 5.4235, with a maximum value of 11.29 and a minimum value of 5.23, indicating that there is a

large difference in the level of AI development between different cities in China.

Table 2. Descriptive Statistical Analysis

Variable Name	Observations	Mean	Std. Dev.	Min	Median	Max
Pollution	2740	0.9497	0.056	0.38	0.97	1
AI	2740	5.4235	1.731	0	5.23	11.29
Urban	2740	0.5833	0.142	0.18	0.56	1.08
Open	2740	0.0157	0.017	0	0.01	0.2
Fd	2740	0.0772	0.027	0.02	0.07	0.23
Fin	2740	2.6925	1.247	0.67	2.38	21.3
Nr	2740	0.0414	0.078	0	0.01	0.53

4. Empirical Analysis

4.1. Baseline Regression

Regression is conducted using Formula (1), and the regression results are shown in Table 3.

Table 3. Regression Results of the Spatial Durbin Model

Variable	(1)	(2)
	Geographic Distance Matrix	Economic-Geographic Nested Matrix
AI	-0.011*** (0.003)	-0.011*** (0.003)
W×AI	0.006* (0.004)	0.010*** (0.004)
Direct Effect	-0.011*** (0.003)	-0.011*** (0.003)
Indirect Effect	-0.032 (0.027)	0.002 (0.017)
Total Effect	-0.043 (0.027)	-0.009 (0.017)
rho	0.876*** (0.030)	0.828*** (0.032)
Sigma ²	0.001*** (0.000)	0.001*** (0.000)
Control	Y	Y
Regional Fixed Effects	Y	Y
N	2370	2370
R ²	0.268	0.132

Notes: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively; standard errors are in parentheses.

The results show that in the short term, the local AI development level has a significantly negative impact on urban pollution. The main effect coefficients under both the geographic distance matrix and the economic-geographic nested matrix are -0.011 (significant at the 1% level), indicating that AI technology effectively reduces local pollution, and the results are consistent with the baseline regression. At the same time, the short-term spatial spillover effect of AI development level is heterogeneous — the indirect effect of AI development in neighboring regions under the geographic matrix is positive and significant at the 10% level, while this effect increases to 0.010 under the economic-geographic matrix, significant at the 1% level. This suggests that inter-regional economic competition may

restrict the spillover of AI technology and even lead to local "pollution transfer"; in the long term, the negative impact of AI on urban pollution is mainly achieved through the direct effect, i.e., local AI development reduces local urban pollution. Although the spatial total effect of AI on urban pollution is negative, it is not significant, indicating that the regional synergy effect of AI in pollution prevention and control needs to be further improved. In terms of the explained variable, its spatial autoregressive coefficient rho is as high as 0.828 and 0.876, significant at the 1% level, highlighting the strong spatial dependence of urban pollution — a 1% increase in pollution in neighboring regions will push up local pollution by approximately 0.83% to 0.88%.

4.2. Robustness Test

The existence of spatial correlation is a prerequisite for using the Spatial Durbin Model for regression. This paper verifies the spatial correlation in the robustness test. In terms of spatial correlation verification, the Moran's I index is used to measure the spatial autocorrelation of the explained variable and the core explanatory variable. The calculation method of the Moran's I index is shown in Formula (7):

$$I = \frac{n}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \quad (7)$$

The results of the Moran's I index for the environmental pollution index and AI development level under the geographic weight matrix are shown in Table 7.

Table 4. Global Moran's I Index

Year	Pollution		AI	
	Moran's I	Z-value	Moran's I	Z-value
2013	0.2004***	5.572	0.161***	5.572
2014	0.21***	5.629	0.163***	5.629
2015	0.2068***	5.665	0.164***	5.665
2016	0.2064***	8.102	0.238***	8.102
2017	0.2098***	8.282	0.243***	8.282
2018	0.2154***	7.222	0.199***	7.222
2019	0.2145***	7.193	0.194***	7.193
2020	0.2487***	8.67	0.239***	8.67
2021	0.2539***	9.006	0.254***	9.006
2022	0.2515***	10.755	0.308***	10.755

It can be seen from Table 7 that the Moran's I indices of the environmental pollution index and AI development level from 2013 to 2022 are all significantly positive, indicating that the above variables all exhibit significant spatial agglomeration effects. The annual Moran scatter plots can more intuitively

depict the spatial agglomeration of variables. The annual Moran scatter plots of the AI development level are shown in

Figure 1:

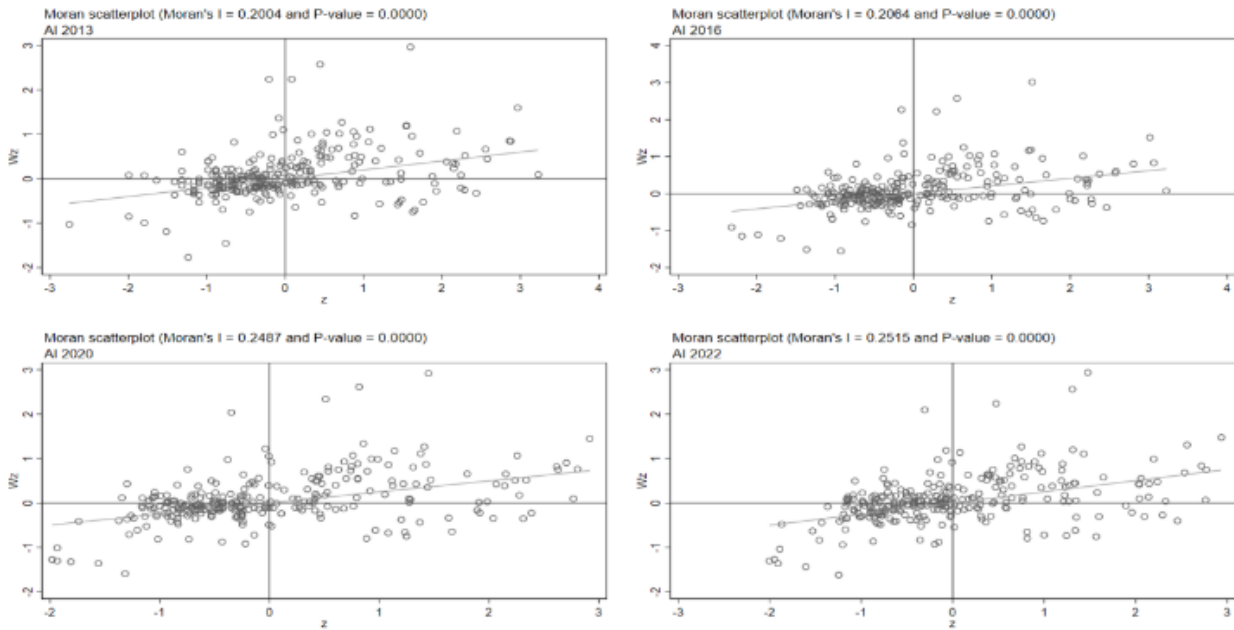


Figure 1. Moran Scatter Plots of AI Development Level

As can be seen from the figure, the AI development levels of most cities are distributed in the first and third quadrants, showing a "high-high - low-low" agglomeration pattern, which is consistent with the analysis results of the global Moran's I index, verifying the existence of spatial correlation.

5. Conclusions and Policy Recommendations

5.1. Research Conclusions

The empirical conclusions of this study are as follows: First, AI development significantly reduces local pollution levels. Under both the geographic distance matrix and the economic-geographic nested matrix, the direct effect coefficient of AI on local pollution is -0.011 (significant at the 1% level), verifying Hypothesis 1; Second, the spatial spillover effect of AI is heterogeneous. The indirect effect of AI in neighboring regions under the geographic matrix is positive and significant at the 10% level, and this effect increases to 0.010 under the economic-geographic matrix (significant at the 1% level), suggesting that inter-regional economic competition may lead to local "pollution transfer"; Third, urban pollution has extremely strong spatial dependence — a 1% increase in pollution in neighboring regions will increase local pollution by approximately 0.83% to 0.88%; Fourth, in the long term, the total effect of AI on pollution prevention and control is not significant, and the regional synergy effect needs to be improved; Fifth, the Moran's I index verification shows that both pollution and AI development exhibit a "high-high - low-low" spatial agglomeration characteristic from 2013 to 2022.

5.2. Policy Recommendations

Based on the research conclusions, the following policy recommendations are proposed: First, promote the application of AI technology in pollution governance. Support enterprises in deploying intelligent monitoring systems and infrared sensing technologies to help identify pollution sources and achieve source governance. At the same time, encourage AI to optimize clean production models and

improve green total factor productivity; Second, establish a cross-regional AI-based pollution governance synergy mechanism. Break administrative barriers, avoid "pollution transfer" through technology sharing and joint R&D, and especially promote the mutual learning of AI-based pollution governance experience in regions with close economic links to strengthen the regional synergy emission reduction effect; Third, optimize the institutional guarantee system. Balance fiscal decentralization to prevent local governments from weakening environmental protection efforts due to economic competition. At the same time, increase green financial support to guide financial resources to flow into AI-based pollution governance technology R&D and application projects, helping financial development play a role in inhibiting pollution; Fourth, implement a differentiated AI development strategy. Address the shortcomings of AI development in small and medium-sized cities, and narrow the regional gap in AI development through policy inclination and industrial cooperation, enabling them to share the dividends of AI-based pollution governance; Fifth, improve the cross-regional joint prevention and control network for pollution. Combined with the strong spatial dependence characteristic of pollution, establish a regional joint pollution monitoring and emergency response mechanism to improve the overall pollution governance efficiency.

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