How Does Local Real Estate Investment Influence Neighborhood PM$_{2.5}$ Concentrations? A Spatial Econometric Analysis

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Abstract: Real estate investment has been an important driving force in China's economic growth in recent years, and the relationship between real estate investment and PM$_{2.5}$ concentrations has been attracting widespread attention. Based on spatial econometric modelling, this paper explores the relationships between real estate investment and PM$_{2.5}$ concentrations using multi-source panel data from 30 provinces in China between 1987 and 2017. The results demonstrate that compared with static spatial panel modelling, using a dynamic spatial Durbin lag model (DSDLM) more accurately reflects the influences of real estate investment on PM$_{2.5}$ concentrations in China, and that PM$_{2.5}$ concentrations show significant superposition effects and spillover effects. Moreover, there is an inverted U-shaped relationship between real estate investment and PM$_{2.5}$ concentrations in the Eastern and Central Regions of China. At the national level, the impacts of real estate investment on land urbanization and PM$_{2.5}$ concentrations first increased and then decreased over time. The key implications of this analysis are as follows. (1) it highlights the need for a unified PM$_{2.5}$ monitoring platform among Chinese regions; (2) the quality of population urbanization rather than land urbanization should be given more attention; and (3) the speed of construction of green cities and building of green transportation systems and green town systems should be increased.

Keywords: real estate investment; PM$_{2.5}$ concentrations; spatial econometric model; dynamic spatial durbin lag model (DSDLM)

1. Introduction

Over the past two decades, the impacts of real estate investment on economic growth and urbanization development, alongside economic development policies, industrial restructuring and urbanization, have been an area of interest for recent scholarship on China [1–4]. In fact, real estate investment is the main factor influencing land urbanization. Despite the importance of real estate investment in creating positive local economic outcomes, it is increasingly being recognized as a leading cause of wastes of land, energy, water and other resources in high energy consumption and pollution in industrial sectors. Various studies have explored various impacts of real estate investment in different regions, including the relationship between real estate investment and environmental and resource issues in China [5], sustainable development in the real estate investment environment in different regions [6] and the impacts of environmental interventions on commercial real estate operations in Canada and the United States [7]. Hence, a key conclusion of the recent literature has been that real estate investment is closely related to many current environmental and resource problems. The purpose of this study is to examine the particular
consequences of real estate investment on air quality in China, using spatial econometric analysis.

In recent years, China’s “regional haze” has become more frequent, and many regions have been plagued by high levels of PM$_{2.5}$ (fine particulate matter—diameter of 2.5 µm or less), one of the key components of haze pollution. According to the *Air Quality Guidelines* [8] issued by the World Health Organization (WHO) in 2006, clean air is critical to human health and well-being, so air pollution continues to pose a significant threat to health worldwide. This can be illustrated briefly by the fact that when the annual mean PM$_{2.5}$ concentrations reach 35 µg/m$^3$, the long-term mortality risk increases by about 15% compared with 10 µg/m$^3$. Recent evidence from *China Ecological and Environmental Bulletin* [9] also showed that in 2019, among 337 cities in China, the number of days exceeding standards, with PM$_{2.5}$ as the core pollutant, accounted for 45% of the total pollution days. It is clear from the findings that PM$_{2.5}$ pollution not only poses a serious threat to human health, but also affects economic development and ecological environment protection [10], and that key issues related to PM$_{2.5}$ levels have public health implications. However, the concentration of PM$_{2.5}$ varies with real estate investment depending on the level of economic development and the city’s natural environment, alongside spillover effects across neighboring areas [5]. Therefore, it seems reasonable to study the relationships and spatial differences between real estate investment and PM$_{2.5}$ concentrations in different Chinese regions.

This study set out to investigate the impacts of real estate investment on PM$_{2.5}$ concentrations and regional differences by employing multi-source panel data from 30 provinces in China between 1987 and 2017. In this investigation, a dynamic spatial Durbin lag model (DSDLM) was designed to integrate spatiotemporal effects into the research framework, aiming to provide policy recommendations for the improvement of real estate investment quality and haze pollution control. There are several important aspects where this study makes original contributions to the current literature: (1) in exploring the impact of real estate investment on PM$_{2.5}$ concentrations by integrating spatial interaction factors into the research scope; (2) by adding spatiotemporal hysteretic effects to more accurately characterize time-space effects of real estate investment on PM$_{2.5}$ concentrations; (3) by investigating differences of spatial curve effects among the three major parts of China (i.e., the Eastern, Central, and Western Regions); (4) and tracking the conduction mechanism of land urbanization to discuss the impact of real estate investment on PM$_{2.5}$ concentrations.

### 2. Literature Review

Two important themes currently being adopted in research into real estate investment are economic growth and environmental pollution. Several attempts have been made in the literature to discuss the positive relationship between real estate investment and economic growth, highlighting significant regional differences across China [11–15]. On the question of environmental pollution, copious literature has tended to focus on the impacts of foreign direct investment (FDI), and it has been confirmed by empirical evidence that FDI has considerable positive impacts on environmental pollution emissions through panel models [16–18]. Such approaches, however, fail to address the interaction effects of real estate investment between regions, since most studies focus solely on the impacts of real estate investment over time.

Recent studies have largely been concerned with the source and chemical composition of PM$_{2.5}$ [19–21], its impact on human health [5,22–25], and its temporal-spatial distribution and driving factors [19,26–29]. When it comes to pollution sources, research identifies that natural factors [30,31] and socioeconomic factors are key contributors to levels of PM$_{2.5}$. Natural factors, such as temperature, wind speed, air humidity, topography, and the underlying surface, are notable examples. Moreover, socioeconomic factors include population density [32], GDP per capita [33], industrial structure [26], energy consumption [34], and other issues such as use of fireworks and firecrackers [22,23,35,36]. Land use patterns can also be critical. For example, Xu et al. [37] demonstrated that the physical
properties of underlying land surface have profound effects on PM$_{2.5}$ concentrations and that woodland could reduce PM$_{2.5}$ concentrations; construction land had the opposite effect. Ding et al. [38] concluded that population density was the greatest determinant of PM$_{2.5}$, showing a trend of rising first and then falling. A study by Ji et al. [39] also found income, urbanization and service industry as having significant impacts on PM$_{2.5}$. Chen et al. [40] investigated the causal links between PM$_{2.5}$ concentrations and energy consumption, energy intensity, economic growth, and urbanization in countries with different income levels, indicating that energy consumption structures were the greatest factor impacting PM$_{2.5}$ concentrations in lower-middle-income and low-income countries.

To date, a variety of methods have been used to assess impacts of real estate investment. Each has its advantages and drawbacks, but it is worth noting that current methods have proven to be measurable and with specified analysis and software. For example, a great deal of academic work has involved grey relational analysis [41], geographically weighted regression (GWR) [42], visualization and spatial measurement methods using ArcGIS, MATLAB, STARS, and others [26,28,43], geographical detector models [44], Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) models [45–47], and the Logarithmic Mean Divisia Index (LMDI) decomposition method [48]. Hybrid Single-Particle Lagrangian Integrated Trajectory Models (HYSPLIT-4), Potential Source Contribution Function (PSCF), and Concentration Weighted Trajectory (CWT) are commonly associated with the trans-regional transportation of atmospheric particulates and the identification of potential source regions. These data collection methods are widely used to understand the transmission and diffusion of various pollutants in different regions and highlight the roles of different factors, including spatial dimensions, in PM$_{2.5}$ concentrations [49–51].

In reviewing the literature, focusing on the scalability of research, recent scholarship seems to fall into three categories: the national scale [34,52], urban agglomerations [32,33], and provincial or city scale [50,53]. It is now understood that relevant research on PM$_{2.5}$ pollution characteristics and source analyses in China is mainly concentrated on the regions of Beijing–Tianjin–Hebei, the Yangtze River Delta, the Pearl River Delta and Central Plains urban agglomerations, and other complex and severely polluted areas [32,33,51,53,54].

Some Chinese regions maintain or enhance their competitiveness in attracting FDI at the expense of the natural environment [55]. Based on the environmental Kuznets inverted curve, the impact of economic growth on PM$_{2.5}$ pollution presents an inverted U-shaped curve, and the effect of FDI on improving China’s ecological environment is not obvious [56]. Additionally, previous research has demonstrated that there is an inverted U-shaped relationship between urbanization and environmental pollution (i.e., CO$_2$, wastewater, waste gas, solid waste, and SO$_2$) [57]. Further research has shown inverted U-shaped curve, non-U-shaped curve, and positive U-shaped curve relationships between CO$_2$ emissions and urbanization in different Chinese regions [58]. Generally, existing research provides a good reference for the in-depth empirical analysis conducted in this study, from both technical and theoretical angles. However, it also highlights that the impact of real estate investment on PM$_{2.5}$ concentration has been under-researched, and that a critical gap in the literature is empirical work based on surveys of multi-source panel data taking land urbanization as a transmission mechanism. Therefore, this paper discusses the relationship between local real estate investment and PM$_{2.5}$ concentration, and their spatial correlation, through a spatial weight matrix that used spatial econometric modelling. The purpose is to provide relevant policy suggestions for improving quality of real estate investment and controlling haze.

3. Methodology and Data Sources

3.1. Methodology

3.1.1. Spatial Weight Matrix

A spatial weight matrix is articulated from geographical or economic information to characterize spatial dependence [59], and reflects the spatial distances between samples,
which is the premise of spatial measurement. The spatial weight matrixes commonly used in econometric modelling are the spatial adjacent weight matrix (SAWM), the spatial geographic distance weight matrix (SGDWM), and the spatial economic distance weight matrix (SEDWM), and different statistical results may be produced based on different matrices [60,61]. This study utilized the SGDWM, the SEDWM, and the spatial economic geographic distance weight matrix (SEGDWM) to ensure the robustness of the results. Constructing the relevant spatial weights matrices involves multiple steps, summarized below.

First: constructing the SGDWM. This spatial weight matrix can be set up in two steps: the first is to take the reciprocal of the square of the geographic distance as the weight, and the second one is to directly take the reciprocal of the geographic distance as the weight. In practical operation, the reciprocal is taken from the spherical distance obtained according to the longitude and latitude of the two regions. The SGDWM is expressed through the following equations.

\[
W_{d_{ij}} = \frac{1}{(d_{ij})^2} \quad (1)
\]

\[
W_1 = \begin{cases} 
\frac{W_{d_{ij}}}{\sum_j W_{d_{ij}}}, & j \neq i \\
0, & i = j 
\end{cases} 
\quad (2)
\]

where \( W_{ij} \) is the matrix element of the \( i \)-th row and \( j \)-th column; \( d_{ij} \) is the centroid distance between province \( i \) and province \( j \), taking the reciprocal of the square of the geographical distance to accurately express the spatial relationship between different provinces. To simplify the model and explain the results easily, the SGDWM is standardized, and \( W_1 \) is the weight after standardization.

Second: constructing the SEDWM. This spatial weight matrix is expressed by the reciprocal of the absolute value of the per capita GDP difference between provinces, reflecting the economic closeness between provinces.

\[
W_2 = \begin{cases} 
\frac{1}{|y_i - y_j|}, & j \neq i \\
0, & i = j 
\end{cases} 
\quad (3)
\]

where \( y_i \) and \( y_j \) denote the average values of real per capita GDP in region \( i \) and region \( j \) during the sample period, respectively. The economic distance is introduced into the spatial weight matrix, which better reflects regional economic development. The SEDWM is standardized in this paper, and \( W_2 \) denotes the weight after standardization.

Third: constructing the SEGDWM. Considering the dual effects of economy and geography, this spatial weight matrix is helpful to judge the connections and differences between different provinces.

\[
W_{e_{ij}} = W_{d_{ij}} \times \text{diag} \left( \frac{y_1}{y}, \frac{y_2}{y}, \cdots, \frac{y_n}{y} \right) \quad (4)
\]

\[
W_3 = \begin{cases} 
\frac{W_{e_{ij}}}{\sum_j W_{e_{ij}}}, & j \neq i \\
0, & i = j 
\end{cases} 
\quad (5)
\]

where \( y_i \) represents the per capita GDP of province \( i \) during the observation period, \( y \) represents the average GDP per capita of all provinces during the observation period, and \( W_{d_{ij}} \) represents the spatial geographical distance. Similarly, the SEGDWM is standardized in this paper, and \( W_3 \) represents the weight after standardization.

3.1.2. Spatial Autocorrelation

This study supports the view that how and to what extent real estate investment affects PM\(_{2.5}\) concentrations in China depend on the spatial characteristics of urban agglomeration. Moran’s I index and Geary’s C index are used to test the stable and significant spatial
autocorrelation of PM$_{2.5}$ concentrations, determining whether a spatial econometric model could be used. The spatial autocorrelation of PM$_{2.5}$ concentrations in China is calculated using the global Moran’s I test (Moran, 1950) and Geary’s C test (Geary, 1954). The formula of Moran’s I index is as follows [62,63].

\[
I = \frac{n}{S_0} \times \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} (x_i - \bar{x}) (x_j - \bar{x})}{\sum_{i=1}^{n} (x_i - \bar{x})^2}
\]

(6)

\[S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}
\]

(7)

where $I$ is the value of the global Moran’s I; $n$ is the total number of cities; $x_i$ and $x_j$ represent the PM$_{2.5}$ concentrations of city $i$ and city $j$, respectively; $\bar{x}$ represents the average PM$_{2.5}$ concentration value of all cities, and $W_{ij}$ represents the spatial weight value. Moran’s I value is restricted to a range of $[-1, 1]$; when $I$ is greater than 0, this indicates that PM$_{2.5}$ concentrations have a positive spatial autocorrelation. When $I$ is less than 0, it indicates a negative spatial autocorrelation. Moreover, if $I$ equals 0, it indicates that the area is spatially distributed at random.

The formula of Geary’s C index is as follows [64].

\[
C = (n - 1) \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} (x_i - x_j)^2}{2nS^2 \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}}
\]

(8)

\[S^2 = \frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})^2
\]

(9)

where $x_i$ and $x_j$ denote PM$_{2.5}$ concentrations of city $i$ and city $j$, respectively. $\bar{x}$ denotes the average PM$_{2.5}$ concentration value of all cities, and $W_{ij}$ denotes the spatial weight matrix. Geary’s C value is restricted to a range of $[0, 2]$; when $C$ is greater than 1, it indicates a negative spatial autocorrelation. When $C$ is less than 1, that indicates a positive spatial autocorrelation. Moreover, if $I$ is equal to 1, it indicates no spatial autocorrelation.

3.1.3. Spatial Econometric Model

Spatial econometric models include the spatial lag model (SLM), the spatial error model (SEM), and the spatial Durbin model (SDM) [65]. The SLM model can be expressed as follows.

\[
Y_{it} = \rho \sum_{j=1}^{n} w_{ij} Y_{jt} + \beta_1 REI_{it} + \sum_{j}^{n} \eta_j Z_{ij} + \mu_i + \xi_t + \epsilon_{it}
\]

(10)

where $Y_{it}$ denotes PM$_{2.5}$ concentrations in a city $i$ at time $t$, and $REI_{it}$ denotes the amount of real estate investment at the end of each year. $\rho$ is the spatial regression coefficient; $Z$ denotes a set of control variables; $\mu_i$ and $\xi_t$ are the spatial-specific effect and the time-specific effect, respectively. $\epsilon_{it}$ is the random error term and $w_{ij}$ is the spatial weight matrix.

When the model concerning the spatial dependence is reflected in the residuals, we have the SEM, which can be expressed as follows.

\[
Y_{it} = \beta_1 REI_{it} + \sum_{j}^{n} \eta_j Z_{ij} + \mu_i + \xi_t + \phi_{it}
\]

(11)

\[
\phi_{it} = \lambda \sum_{j=1}^{n} W_{ij} \phi_{jt} + \epsilon_{it}
\]

(12)

where $Y_{it}$ denotes PM$_{2.5}$ concentrations in a city $i$ at time $t$, $REI_{it}$ denotes the amount of real estate investment at the end of each year, $\eta_j$ denotes the regression coefficient of control variables, and $Z$ denotes a set of control variables. $\phi_{it}$ represents the spatial autocorrelation error term and $\lambda$ represents the spatial autocorrelation coefficient of the error term.
When the spatial correlation is presented in both the explained and explanatory variables, we have the SDM, which can be expressed as follows.

\[ Y_{it} = \rho \sum_{j=1}^{n} w_{ij} Y_{it} + REI_{it}\beta + \sum_{j=1}^{n} w_{ij} REI_{jt}\gamma + \mu_i + \xi_t + \varepsilon_{it} \]  

(13)

where \(Y_{it}\) represents PM\(_{2.5}\) concentrations in a city \(i\) at time \(t\), and \(REI_{it}\) represents the amount of real estate investment at the end of each year; the first-order term and quadratic term of the real estate investment amount \(REI_{jt}\) are considered in the model. \(W_{ij}\) represents the spatial geographic distance weight matrix of the element in row \(i\) and column \(j\), \(\beta\) represents a vector of regression coefficients, \(\mu_i\) denotes the individual effect, and \(\varepsilon_{it}\) denotes the random error term.

When considering lag factors in the SDM, the formula of the spatial Durbin lag model (SDLM) is as follows:

\[ y_{it} = \alpha y_{i, t-1} + \theta y_{i, t-1} + \theta W y_{i, t-1} + \rho \sum_{j=1}^{N} W_{ij} X_{jt} + \varepsilon_{it} \]  

(14)

where \(y_{it}\) represents PM\(_{2.5}\) concentrations in a city \(i\) at time \(t\), \(\theta\) represents the regression coefficient of the explanatory variable, \(y_{i, t-1}\) represents the time lag term of PM\(_{2.5}\) concentrations, \(\theta W y_{i, t-1}\) represents the spatiotemporal lag term, and the other variables are the same as the above.

To avoid the endogeneity among variables and consider the dynamic effects of time and the influence of spatiotemporal diffusion, the SDM was extended into the static spatial Durbin lag model (SSDLM) and dynamic spatial Durbin lag model (DSDLM). Moreover, the likelihood ratio (LR) test and the Lagrange multiplier (LM) test were used to select a suitable spatial model. The LM test is generally used for preliminary selection, and the LR test is generally used for accurate selection, so the LR test is selected in this paper.

3.1.4. Descriptions of Variables

The outcome variable in this study is PM\(_{2.5}\) concentration. The core explanatory variable is real estate investment (REI). There are two main methods to calculate REI in the existing research. One is measured by the annual real estate investment of each province, which has strong dynamic characteristics. The other is to use the perpetual inventory method to examine the stock of REI, which is comprehensive and objective. According to the relevant literature, when taking into account the dynamic changes and comprehensive and objective characteristics of REI, the perpetual inventory method is used to calculate REI; that is to say REI is measured by the accumulative amount of real estate investment enterprises by the end of each year.

According to the relevant research, we selected some control variables. The control variables are:

1. **Energy consumption (ENER).** It is expressed by the ratio of coal consumption to total energy consumption. This indicator was selected because China’s energy consumption structure is dominated by coal, but in the process of using coal, it will produce large amounts of soot, micro-particles, and carbon dioxide, which in the long term contributes to air pollution [66,67].

2. **Research and development input (R&D).** It is reflected by the proportion of actual R&D investment to GDP. This indicator was selected because technological innovation helps to reduce the air pollution [68,69].

3. **Industrial structure (IND).** It is expressed by the ratio of the added value of the secondary industry to GDP. This indicator was selected because industrial production is one of the most important factors causing environmental pollution, and industrial production activities will inevitably cause resource consumption and pollutant
emissions, but optimization and upgrading of industrial structure are conducive to improving the environment [70,71].

Traffic volume (TRA). It is reflected by the highway passenger transport volume of each province to investigate the influences of traffic factors on the PM$_{2.5}$ concentrations. It is reflected by the highway passenger transport volume of each province to investigate the influence of traffic factors on the PM$_{2.5}$ concentrations. This indicator was selected because with rapid economic development and the improvement of people’s living standards, the number and uses of cars have increased significantly, and the large amount of vehicle emissions will aggravate the degree of air pollution [72,73].

Per capita education level (EDU). It is expressed by the ratio of the number of educated people multiply by the weighted total years of education to the total number of educated. It is expressed by the ratio of the number of educated people multiply by the weighted total years of education to the total number of educated. This indicator was selected because human capital is an important indicator of a country or region’s technological level. A higher level of education per capita will lead to greater environmental awareness and more investment in technological research and development, which in turn will help solve the region’s environmental problems [74].

Opening-up level (OPEN). It is measured by the proportion of foreign investment to GDP. This indicator was selected because the level of opening up promotes economic development, which has a certain impact on the environment. Existing studies have shown that FDI directly contributes to the reduction of PM$_{2.5}$, but indirectly contributes to the increase of PM$_{2.5}$ emissions [75,76].

Environmental regulation (REG). It is reflected by the proportion of investment in environmental pollution control to GDP. This indicator was selected because its purpose is to protect the environment and regulate all kinds of behaviors that pollute the public environment. Effective environmental regulation policies can control and prevent the expansion and growth of environmental pollution [77,78].

Per capita GDP (GDP). It represents the economic growth level in each province, and it is measured by the GDP deflator, taking the year 2000 as the base period. To reduce the heteroscedasticity of the data, all variables were adjusted with a natural logarithm, and the missing data of some indexes were supplemented by the interpolation method. This indicator was selected because the environmental Kuznets curve (EKC) proposes that the relationship between per capita income and environmental pollution level is an inverted U-shaped curve, which discusses the problem between economic development and environmental pollution [79,80].

Population density (POP). It is expressed by the ratio of the population number of each province to the area of each province. This indicator was selected because the increase of population density is an important factor in the aggravation of PM$_{2.5}$ concentrations. The increase of population density will promote the development of urbanization and the consumption of resources and environment, thereby increasing the PM$_{2.5}$ concentrations. However, consumption of clean energy and public transport services through the population can help reduce air pollution [81,82].

3.2. Data Sources

This paper was based on provincial panel data. Data for 30 Chinese provinces were gathered from multiple sources at various time points from 1987 to 2017 (shown in Figure 1), excluding Hong Kong, Macao, Taiwan, and Tibet. Data on PM$_{2.5}$ concentrations were obtained from the Center for International Earth Science Information Network (CIESIN) and the China National Environmental Monitoring Centre (CNEM). The experiments were run using ArcGIS software to adapt the raster data into the annual average PM$_{2.5}$ concentration data of 30 provinces. Since no PM$_{2.5}$ data were available before 2000, the interpolation method to calculate the fitted value of PM$_{2.5}$ from 1987 to 1999 was chosen for analysis [83,84]. Data of the core explanatory variable were from the EPS database. Data
of the above control variables were from the Chinese Statistical Yearbook (1988–2018), the Chinese Energy Statistical Yearbook (1988–2018), the Chinese Transport Statistical Yearbook (1988–2018), the Chinese Statistical Yearbook on Environment (1988–2018), and provincial statistical yearbooks.

4. Results and Discussion

4.1. Basic Empirical Results

4.1.1. Spatial Autocorrelation Test of PM$_{2.5}$ Concentrations

As shown in Table 1, the global Moran’s I index and Geary’s C index were in the range of 0 to 1 between 1987 and 2017. The global Moran’s I index was greater than 0 and fluctuated up and down around 0.2 in most years, passing the 5% significance level in most years, and it was significant at the 10% level in a few years. The global Moran’s I index was between 0 and 1, indicating that PM$_{2.5}$ concentrations presented a positive spatial agglomeration. The Geary’s C index was also significant at the 5% level between 1987 and 2017, and was between 0 and 1, indicating that PM$_{2.5}$ concentrations were positively correlated globally. Therefore, there is a strong spatial correlation between PM$_{2.5}$ concentrations in 30 provinces of China between 1987 and 2017, and the spatiality of PM$_{2.5}$ concentrations cannot be ignored.

Then the log-likelihood ratio (LR) was adopted to test the results (Table 2), showing that the SLM and the SEM were rejected at the 1% significance level, and it was appropriate to choose the SDM as the research model. Therefore, the spatial econometric model was used to obtain the unbiased estimator of the regression coefficient in this study.

Considering that PM$_{2.5}$ concentrations in the provincial area are usually related to PM$_{2.5}$ concentrations in the previous phase, there is not only a spatial autocorrelation but also temporal dynamic correlation and spatiotemporal effects of PM$_{2.5}$ concentrations in provincial areas. Therefore, the SLM was chosen in the final model, and the spatial Durbin lag model (SDLM) was the final model.
Table 1. Global spatial correlation test results.

| Variables | Test | Moran's I | E(I) | SD(I) | Z | p-Value * | Geary's C | E(c) | SD(c) | Z | p-Value * |
|-----------|------|-----------|------|-------|---|------------|-----------|------|-------|---|------------|
| 1987      | Test | 0.086     | −0.034| 0.076 | 1.593 | 0.056 | 0.829 | 1 | 0.093 | −1.842 | 0.033 |
| 1988      | Test | 0.087     | −0.034| 0.075 | 1.605 | 0.054 | 0.827 | 1 | 0.093 | −1.856 | 0.032 |
| 1989      | Test | 0.088     | −0.034| 0.075 | 1.62  | 0.053 | 0.825 | 1 | 0.093 | −1.873 | 0.031 |
| 1990      | Test | 0.089     | −0.034| 0.075 | 1.64  | 0.051 | 0.822 | 1 | 0.094 | −1.895 | 0.029 |
| 1991      | Test | 0.091     | −0.034| 0.075 | 1.666 | 0.048 | 0.819 | 1 | 0.094 | −1.922 | 0.027 |
| 1992      | Test | 0.093     | −0.034| 0.075 | 1.699 | 0.045 | 0.815 | 1 | 0.094 | −1.959 | 0.025 |
| 1993      | Test | 0.097     | −0.034| 0.075 | 1.745 | 0.041 | 0.81  | 1 | 0.095 | −2.007 | 0.022 |
| 1994      | Test | 0.101     | −0.034| 0.075 | 1.807 | 0.035 | 0.802 | 1 | 0.095 | −2.074 | 0.019 |
| 1995      | Test | 0.107     | −0.034| 0.075 | 1.896 | 0.029 | 0.793 | 1 | 0.096 | −2.168 | 0.015 |
| 1996      | Test | 0.117     | −0.034| 0.075 | 2.023 | 0.022 | 0.779 | 1 | 0.096 | −2.305 | 0.011 |
| 1997      | Test | 0.131     | −0.034| 0.075 | 2.208 | 0.014 | 0.759 | 1 | 0.096 | −2.513 | 0.006 |
| 1998      | Test | 0.152     | −0.034| 0.075 | 2.478 | 0.007 | 0.731 | 1 | 0.095 | −2.836 | 0.002 |
| 1999      | Test | 0.181     | −0.034| 0.076 | 2.85  | 0.002 | 0.693 | 1 | 0.092 | −3.333 | 0    |
| 2000      | Test | 0.218     | −0.034| 0.077 | 3.29  | 0.001 | 0.651 | 1 | 0.088 | −3.984 | 0    |
| 2001      | Test | 0.247     | −0.034| 0.077 | 3.649 | 0     | 0.624 | 1 | 0.086 | −4.382 | 0    |
| 2002      | Test | 0.212     | −0.034| 0.077 | 3.215 | 0.001 | 0.645 | 1 | 0.089 | −4.007 | 0    |
| 2003      | Test | 0.239     | −0.034| 0.076 | 3.602 | 0     | 0.65  | 1 | 0.091 | −3.85  | 0    |
| 2004      | Test | 0.177     | −0.034| 0.076 | 2.775 | 0.003 | 0.672 | 1 | 0.09 | −3.632 | 0    |
| 2005      | Test | 0.162     | −0.034| 0.076 | 2.567 | 0.005 | 0.702 | 1 | 0.089 | −3.337 | 0    |
| 2006      | Test | 0.225     | −0.034| 0.076 | 3.402 | 0     | 0.664 | 1 | 0.089 | −3.77  | 0    |
| 2007      | Test | 0.196     | −0.034| 0.076 | 3.015 | 0.001 | 0.678 | 1 | 0.089 | −3.601 | 0    |
| 2008      | Test | 0.171     | −0.034| 0.076 | 2.693 | 0.004 | 0.707 | 1 | 0.089 | −3.298 | 0    |
| 2009      | Test | 0.171     | −0.034| 0.076 | 2.704 | 0.003 | 0.714 | 1 | 0.09 | −3.172 | 0.001 |
| 2010      | Test | 0.166     | −0.034| 0.076 | 2.636 | 0.004 | 0.703 | 1 | 0.091 | −3.273 | 0.001 |
| 2011      | Test | 0.207     | −0.034| 0.077 | 3.139 | 0.001 | 0.687 | 1 | 0.087 | −3.589 | 0    |
| 2012      | Test | 0.164     | −0.034| 0.076 | 2.613 | 0.004 | 0.699 | 1 | 0.091 | −3.298 | 0    |
| 2013      | Test | 0.227     | −0.034| 0.077 | 3.392 | 0     | 0.682 | 1 | 0.087 | −3.678 | 0    |
| 2014      | Test | 0.18      | −0.034| 0.076 | 2.829 | 0.002 | 0.701 | 1 | 0.092 | −3.255 | 0.001 |
| 2015      | Test | 0.229     | −0.034| 0.076 | 3.457 | 0     | 0.68  | 1 | 0.09 | −3.565 | 0    |
| 2016      | Test | 0.246     | −0.034| 0.077 | 3.661 | 0     | 0.672 | 1 | 0.088 | −3.726 | 0    |
| 2017      | Test | −0.034    | 0.077 |       |      |      |      |     |       |     | 0.087     |

Note: * means significant within 10%.

Table 2. Spatial model selection test.

| Likelihood-ratio test | LR chi2(11) = 193.22 | Prob > chi2 = 0.000 |
|-----------------------|-----------------------|---------------------|
| (Assumption: slm nested in sdm) |              |                     |
| Likelihood-ratio test | LR chi2(9) = 212.05  | Prob > chi2 = 0.000  |
| (Assumption: sem nested in sdm) |            |                     |

4.1.2. Results of the SSDLM

The parameter estimation results of SSDLM based on PM$_{2.5}$ concentrations are shown in Table 3. In the table, columns (1) and (2) represent the results of random effects and fixed effects of ordinary panel data, respectively; the columns (3) and (4) represent the results of random effects and fixed effects of the SSDLM taking the spatial geographic distance weight matrix, respectively. From the comparison of columns (1), (3), and (4), since the spatial correlation of PM$_{2.5}$ concentrations is not taken into account, the promotional effect of real estate investment on PM$_{2.5}$ concentrations would be overestimated by the ordinary panel estimation.
Table 3. Results of the SSDLM.

| Explanatory Variables | PM SSDLM | | |
|-----------------------|-----------|-----------|-----------|-----------|
|                        | RE (1)    | FE (2)    | RE (3)    | FE (4)    |
| lnREI<sub>it</sub>    | 0.409 *** | 0.299 *** | 0.360 *** | 0.336 *** |
|                       | (10.19)   | (5.30)    | (9.15)    | (8.79)    |
| (lnREI<sub>it</sub>)<sup>2</sup> | −0.0484 *** | −0.0485 *** | −0.0445 *** | −0.0341 *** |
|                       | (−10.37)  | (−7.46)   | (−7.20)   | (−6.05)   |
| lnENER<sub>it</sub>   | 0.0567 *** | 0.0797 *** | 0.0734 *** | 0.0637 *** |
|                       | (4.27)    | (5.24)    | (5.54)    | (5.00)    |
| lnIND<sub>it</sub>    | −0.598 *** | −0.346 *** | −0.168 *  | −0.0593   |
|                       | (−7.97)   | (−3.70)   | (−1.25)   | (−1.43)   |
| lnR&DI<sub>it</sub>   | 0.315 ***  | 0.110     | −0.0526   | −0.0593   |
|                       | (7.02)    | (1.56)    | (1.25)    | (1.43)    |
| lnTRA<sub>it</sub>    | −0.130 *** | −0.0879   | −0.213 *** | −0.226 *** |
|                       | (−4.11)   | (−1.57)   | (−1.61)   | (−1.43)   |
| lnEDU<sub>it</sub>    | −1.310 *** | −1.157 *** | −0.800 *** | −0.882 *** |
|                       | (−8.15)   | (−7.03)   | (−1.66)   | (−1.65)   |
| lnOPEN<sub>it</sub>   | −0.312 *** | −0.0258   | −0.0386   | −0.0263   |
|                       | (−8.65)   | (−0.44)   | (−1.02)   | (−0.71)   |
| lnREC<sub>it</sub>    | 0.0986 *** | 0.0445    | −0.0126   | 0.0111    |
|                       | (4.12)    | (1.22)    | (0.54)    | (0.50)    |
| lnGDP<sub>it</sub>    | 0.728 ***  | 0.880 ***  | −0.821 *** | −0.913 *** |
|                       | (11.91)   | (12.12)   | (−1.40)   | (−4.97)   |
| lnPOP<sub>it</sub>    | −0.184 *** | 2.633 ***  | 2.265 ***  | 3.359 ***  |
|                       | (−6.04)   | (8.36)    | (5.84)    | (11.14)   |
| _cons                 | 3.769 ***  | −17.72 *** | −19.38 *** |          |
|                       | (6.30)    | (−8.22)   | (−4.33)   |          |
| ρ                     |           |           | 0.390 ***  | 0.352 ***  |
|                       |           |           | (6.54)    | (5.79)    |
| Log-likehood          | 930       | 930       | −849.547  | −727.744  |
| N                     | 930       | 930       | 930       |

Note: *** means significant within 1%, and * means significant within 10%.

The sign and significance of the core explanatory variable tended to be consistent. From the core explanatory variable, the coefficients of the first-order and quadratic terms of the real estate investment showed a positive correlation and a negative correlation, respectively, at the significance level of 1%, indicating that there was an inverted U-shaped curve relationship between real estate investment and PM<sub>2.5</sub> concentration at the national level which followed the law of Kuznets curve (EKC). At the initial stage of real estate investment, PM<sub>2.5</sub> concentrations increased; however, with the real estate investment increasing to a certain level, PM<sub>2.5</sub> concentrations gradually reduced.

The coefficients of control variables showed that large-scale use of coal energy significantly increased PM<sub>2.5</sub> concentrations; mass use of public transportation was conducive to reducing PM<sub>2.5</sub> concentrations; improvements in education levels were helpful in raising public awareness of environmental protection and reducing PM<sub>2.5</sub> concentrations; improvement of economic development level also helped to reduce PM<sub>2.5</sub> concentrations; population density and PM<sub>2.5</sub> concentrations had a significant positive correlation, and scale effects of population agglomeration were far greater than agglomeration effects. Other variables such as industrial structure, R&D level, and environmental regulation did not show any significant correlations with PM<sub>2.5</sub> concentrations.

Although the autoregressive coefficient ρ in Table 3 is significant, it is still necessary to further investigate its direct effects, indirect effects, and total effects in the SSDLM (Xu, 2016). These results are summarized in the following Table 4.
Table 4. Results of direct, indirect, and total effects under the SSDLM.

| Explanatory Variables | Direct Effects | Indirect Effects | Total Effects |
|-----------------------|----------------|-----------------|--------------|
| lnREI_{it}            | 0.400 ***      | 1.886 ***       | 2.286 ***    |
| (lnREI_{it})^2        | 0.038 ***      | 0.092 ***       | 0.130 ***    |
| lnENER_{it}           | 0.079 ***      | 0.417 ***       | 0.496 ***    |
| lnIND_{it}            | 0.048          | 2.026 ***       | 2.074 ***    |
| lnPOP_{it}            | 3.421 ***      | 2.178 *         | 5.598 ***    |
| lnR&D_{it}            | -0.0593        | -0.0974         | -0.157       |
| lnTRA_{it}            | -0.217 ***     | 0.238 **        | 0.020        |
| lnEDU_{it}            | -0.721 ***     | 4.860 ***       | 4.139 ***    |
| lnOPEN_{it}           | -0.0310        | -0.230 ***      | -0.261 ***   |
| lnREG_{it}            | -0.0255        | -1.111 ***      | -1.136 ***   |
| lnGDP_{it}            | -0.921 ***     | -0.376          | -1.297 ***   |

Note: *** means significant within 1%, ** means significant within 5%, and * means significant within 10%.

In Table 4, the results show that from the static point of view: (i) The local real estate investment not only affects local PM$_{2.5}$ concentrations, but also affects neighborhood PM$_{2.5}$ concentrations through spillover effects. (ii) The use of coal energy not only directly affects the increase of PM$_{2.5}$ concentrations in the local area, but also indirectly increases PM$_{2.5}$ concentrations in the adjacent area. (iii) The industrialization level of the province would increase PM$_{2.5}$ concentrations of neighboring provinces through indirect effects. (iv) The increase of population density not only directly affects PM$_{2.5}$ concentrations in the local area, but also has spillover effects on PM$_{2.5}$ concentrations in the adjacent area. (v) The research and development input and the opening-up level reduce PM$_{2.5}$ concentrations in the region and its neighboring provinces. (vi) The per capita education level reduces PM$_{2.5}$ concentrations in the region, and its indirect effect is positive, indicating that accumulation of talents in the region indirectly leads to decreasing PM$_{2.5}$ concentrations in the neighboring provincial areas. The possible reason is that people with higher levels of education have strong environmental awareness, and when they flow out from neighboring provinces, it is not conducive to the reduction of PM$_{2.5}$ concentrations in neighboring provinces. (vii) The total amount of public transport and per capita GDP restrain the increase of PM$_{2.5}$ concentrations in this region with the growth of the economy. (viii) Environmental regulation restrains PM$_{2.5}$ concentrations in neighboring provinces through indirect effects.

The above research results showed that the SSDLM studied the impact of real estate investment on PM$_{2.5}$ concentrations only from the spatial dimension, and there might be bias because PM$_{2.5}$ concentrations of a province were not only affected by the neighboring provinces but also depended on the impact of the previous PM$_{2.5}$ concentrations. Adding the time lag term to the dynamic spatial panel model was helpful for verifying whether the spatial autocorrelation of PM$_{2.5}$ concentrations was significant. In addition, the SSDLM only focused on the spatial differences of the real estate investment on PM$_{2.5}$ concentrations among different provinces at the same time point, while the dynamic spatial Durbin lag model (DSDLMM) could reflect the temporal differences of the real estate investment on PM$_{2.5}$ concentrations. PM$_{2.5}$ concentrations are a dynamic and continuous environmental...
factor, and the DSDLM should be used to investigate spatial spillover effects of PM$_{2.5}$ concentrations, so a DSDLM was constructed for further testing.

4.1.3. Results of the DSDLM

In Table 5, from the overall regression results of the dynamic model, the sign and significance of the estimated results of the core explanatory variable tended to be consistent under the spatial geographic distance weight matrix. From the explained variable, the time lag term of PM$_{2.5}$ concentrations showed a positive correlation at the 1% significance level, indicating that PM$_{2.5}$ concentrations had certain dynamic and continuous characteristics in time; that is to say, if PM$_{2.5}$ concentrations in the previous period were high, then PM$_{2.5}$ concentrations in the later period was likely to rise. The time-space lag term of PM$_{2.5}$ concentrations showed a negative correlation at a significance level of 1%, indicating that previous PM$_{2.5}$ concentrations in the neighboring provinces had an inhibitory effect on local PM$_{2.5}$ concentrations.

Table 5. Estimation results of the DSDLM.

| Variables | DSDLM | Direct Effects | Indirect Effects | Total Effects |
|-----------|-------|----------------|-----------------|--------------|
| lnPM$_{2.5}(i,t-1)$ | 0.941 *** | 0.030 ** | 0.145 | 0.175 |
| (161.99) | (1.22) | (1.36) |
| WinPM$_{2.5}(i,t-1)$ | −0.683 *** | (−19.28) | |
| lnREI$_{it}$ | 0.0220 *** | 0.030 ** | 0.145 | 0.175 |
| (2.82) | (2.56) | (1.22) | (1.36) |
| (lnREI$_{it}$)$^2$ | −0.002 * | −0.003 *** | −0.014 * | −0.016 ** |
| (−1.92) | (−2.73) | (−1.94) | (−2.20) |
| lnENER$_{it}$ | −0.000 | −0.004 | −0.065 ** | −0.069 ** |
| (−0.16) | (−1.10) | (−2.22) | (−2.17) |
| lnIND$_{it}$ | 0.031 ** | 0.039 ** | 0.153 | 0.193 |
| (2.10) | (2.16) | (1.19) | (1.35) |
| lnR&D$_{it}$ | 0.012 * | 0.011 | −0.019 | −0.007 |
| (1.65) | (1.21) | (−0.23) | (−0.09) |
| lnTRA$_{it}$ | −0.021 *** | −0.026 *** | −0.102 ** | −0.128 ** |
| (−3.20) | (−3.56) | (−2.23) | (−2.55) |
| lnEDU$_{it}$ | 0.037 | 0.011 | −0.573 | −0.562 |
| (1.46) | (0.29) | (1.47) | (1.34) |
| lnOPEN$_{it}$ | −0.008 | −0.010 | −0.049 | −0.060 |
| (−0.83) | (−1.02) | (−0.88) | (−1.00) |
| lnREG$_{it}$ | −0.003 | −0.010 | −0.127 * | −0.137 * |
| (−0.93) | (−1.52) | (−1.72) | (−1.72) |
| lnGDP$_{it}$ | 0.042 | 0.0460 | 0.013 | 0.059 |
| (1.41) | (1.49) | (0.14) | (0.60) |
| lnPOP$_{it}$ | −0.095 * | −0.070 | 0.575 | 0.504 |
| (−1.70) | (−1.17) | (1.23) | (1.02) |
| $\rho$ | 0.717 *** | | | |
| (22.38) | | | |
| Log-likelihood | 905.6915 | | | |
| N | 930 | | | |

Note: *** means significant within 1%, ** means significant within 5%, and * means significant within 10%.

Under the spatial geographic distance weight matrix, the autocorrelation coefficient $\rho$ of PM$_{2.5}$ concentrations was significant at the significance level of 1% and showed a positive correlation—namely, PM$_{2.5}$ concentrations showed a significant positive spatial spillover effect, and PM$_{2.5}$ concentration in a province was affected by the diffusion of PM$_{2.5}$ concentrations in neighboring provinces.
The autocorrelation coefficient of the explained variable was larger than that of the static model, which might because that explanatory variables of the DSDLNM only considered the spatial correlation. However, in the DSDLNM, when the time lag factor of PM$_{2.5}$ concentrations was separated from spatial correlation factors, the autocorrelation coefficient value increased significantly and was significant at the significance level of 1%. This confirmed that the SSPDM ignored dynamic and continuous characteristics of PM$_{2.5}$ concentrations, leading to estimation bias of explanatory variables for the explained variable.

From the level and significance of the time-lag term coefficient and changes in the spatial autocorrelation coefficient, dynamic spatial panel modelling confirmed that PM$_{2.5}$ concentrations were more affected by the time lag term, with the superposition effect being greater than the spillover effect. At the same time, PM$_{2.5}$ concentrations in China showed characteristics of accumulation, intersection, and continuous evolution in the spatial and temporal dimension.

Through the dynamic spatial econometric model, it was found that the real estate investment had a significant impact on PM$_{2.5}$ concentrations. The first-order and quadratic coefficients of the real estate investment showed a positive correlation and a negative correlation, respectively, at the significance level of 1%, meaning that there was an inverted U-shaped curve relationship between the real estate investment and PM$_{2.5}$ concentrations at the national level, and when the real estate investment level reached a certain level, PM$_{2.5}$ concentrations would be reduced.

4.2. Robustness Test

From the coefficients of control variables, industrial structure (IND) and research and development input (R&D) were positive at the significance level of 1%, which indicated that these variables had positive impacts on PM$_{2.5}$ concentrations; traffic volume (TRA) and population density (POP) were negative at the significance levels of 1% and 10%, respectively, which indicated that the development of population urbanization and the increase of urban public transportation would reduce PM$_{2.5}$ concentrations (Ehrhardt-Martinez, 1998).

To ensure the robustness of spatial autocorrelation of PM$_{2.5}$ concentrations, we conducted the test by changing the spatial weight matrix. As shown in Table 6, in addition to the spatial geographic distance weight matrix, the spatial economic distance weight matrix and the spatial economic geographic distance weight matrix were also used in this study. The results showed that most of the explained variable and the core explanatory variable of the three models were all at the significance level of 1%, indicating that the spatial geographic distance weight matrix model had good robustness. As mentioned above, there were some differences in different models, and differences in other control variables were not obvious.
Table 6. Results of the robustness test.

| Variables | Spatial Geographic Distance Weight Matrix | Spatial Economic Distance Weight Matrix | Spatial Economic Geographic Distance Weight Matrix |
|-----------|-------------------------------------------|----------------------------------------|--------------------------------------------------|
| lnPM₂₅(t−1) | 0.941 *** | 0.947 *** | 0.941 *** |
| (161.99) | (159.90) | (158.67) |
| WlnPM₂₅(t−1) | −0.683 *** | −0.654 *** | −0.511 *** |
| (−19.28) | (−13.61) | (−3.18) |
| lnREIᵢᵣ | 0.022 *** | 0.016 * | 0.042 *** |
| (2.82) | (1.82) | (6.04) |
| (lnREIᵢᵣ)² | −0.002 * | −0.002 ** | −0.009 *** |
| (−1.92) | (−2.01) | (−10.92) |
| lnENERᵢᵣ | −0.000 | −0.002 | −0.004 |
| (−0.16) | (−0.84) | (−1.25) |
| lnINDᵢᵣ | 0.031 ** | 0.022 | 0.072 *** |
| (2.10) | (1.47) | (4.24) |
| lnR＆Dᵢᵣ | 0.0123 * | 0.008 | 0.024 *** |
| (1.65) | (1.04) | (2.78) |
| lnTRAᵢᵣ | −0.021 *** | −0.025 *** | −0.033 *** |
| (−3.20) | (−3.71) | (−4.18) |
| lnEDUᵢᵣ | 0.037 | 0.042 | 0.027 |
| (1.46) | (1.53) | (0.93) |
| lnOPENᵢᵣ | −0.008 | −0.009 | 0.026 ** |
| (−0.83) | (−0.86) | (2.37) |
| lnREGᵢᵣ | −0.003 | 0.002 | −0.003 |
| (−0.93) | (0.46) | (−0.82) |
| lnGDPᵢᵣ | 0.043 | 0.069 ** | 0.046 *** |
| (1.41) | (2.19) | (3.46) |
| lnPOPᵢᵣ | −0.095 * | −0.124 ** | −0.133 ** |
| (−1.70) | (−2.14) | (−2.44) |
| ρ | 0.717 *** | 0.744 *** | 0.267 *** |
| (22.38) | (19.70) | (2.78) |
| Log-likelihood | 905.6915 | 873.4387 | 627.1621 |

Note: *** means significant within 1%, ** means significant within 5%, and * means significant within 10%.

4.3. Heterogeneity Test

The above research reveals characteristics of the spatial relationship between the real estate investment and PM₂₅ at the global level, so what are the characteristics locally? Is there spatial heterogeneity? First of all, after adding a quadratic term for real estate investment, the core explanatory variables of the three regions passed the significance test, so they were reserved. The dynamic spatial Durbin lag model (DSDLM) was adopted in this paper, and the results are shown in Table 6.

In Table 7, for the explanatory variables and the explained variable in different regions, differences between the estimation results and significance are not obvious under the three kinds of the spatial weight matrix, and they all had good robustness.
Table 7. Estimation results of the regional heterogeneity.

| Variable        | Eastern Region | Central Region | Western Region |
|-----------------|----------------|----------------|----------------|
|                 | (1)            | (2)            | (3)            |
| lnPM_{2.5(t-1)}| 1.004 ***      | 0.895 ***      | 0.957 ***      |
|                 | (61.01)        | (49.73)        | (50.92)        |
| WinPM_{2.5(t-1)}| -2.650 ***     | -1.201 ***     | -0.450 ***     |
|                 | (47.88)        | (-2.234)       | (-10.16)       |
| lnREI_D         | -0.285 ***     | -0.0235        | -0.456 ***     |
|                 | (-11.30)       | (-1.08)        | (-15.94)       |
| (lnREI_D)^2     | -0.045 ***     | -0.089 ***     | -0.035 ***     |
|                 | (-17.42)       | (-37.85)       | (-13.37)       |
| \rho            | 1.426 ***      | 1.301 ***      | 0.537 ***      |
|                 | (30.10)        | (26.96)        | (12.52)        |
| R-squared       | 0.004 ***      | 0.005 ***      | 0.008 ***      |
| Control         | Yes            | Yes            | Yes            |
| N               | 330            | 330            | 330            |

Note: *** means significant within 1%, ** means significant within 5%, and * means significant within 10%.

From the perspective of the explained variable, the dynamic and spatial effects of PM_{2.5} concentrations were significant in the Eastern, Central, and Western Regions. The spatial-temporal effects coefficients of the three regions were negative, and all passed the significance test. The above results showed that there was no significant difference in time between the path dependence and spatial spillover effects of PM_{2.5} concentrations in the three regions, which showed that PM_{2.5} concentrations in different regions had spatial convergence.

From the perspective of core explanatory variable, (i) the real estate investment and its quadratic term coefficients in the Eastern Region both showed negative correlations at the significance level of 1%, which indicated that there was a right tail for the inverted U-shaped relationship between the real estate investment and PM_{2.5} concentrations in the Eastern Region; (ii) the real estate investment and its quadratic term coefficients in the Central Region showed a positive and negative correlation at the significance level of 1%, which indicated that there was a left tail for the inverted U-shaped curve relationship between the real estate investment and PM_{2.5} concentrations in the Central Region; (iii) the real estate investment and its quadratic term coefficients in the Western Region showed a negative and positive correlation at the significance level of 1%, which indicated that the marginal impact of real estate investment on PM_{2.5} concentrations was gradually increasing, and the increasing relationship between the two was always relatively gentle. However, it is worth noting that pollution caused by the real estate investment was in the initial stage of the destruction of the ecological environment, and it would cause high cost of environmental remediation in the transition stage. Thus, the Western Region should pay attention to air pollution caused by industrial transfer from the Eastern and Central Region.

It was found that the impact of the real estate investment on PM_{2.5} concentrations in the three regions of China had a certain differentiation, which verified the impact of unbalanced regional development. Specifically, in recent years, with the improvement of green environmental protection technology and environmental protection awareness, the real estate investment in the Eastern Region paid more attention to the impact of PM_{2.5} concentrations under the strict environmental standards; the results showed that the Central Region tolerated the environmental pollution caused by real estate investment when pursuing economic development, but when the economic development level reached a certain level, it would improve the environmental protection standards, to alleviate the impact of the real estate investment on PM_{2.5} concentrations; the results showed that to pursue higher economic growth, the environmental impact of real estate investment in the Western Region was easy to be ignored, at the cost of rising PM_{2.5} concentrations. In general, the impact of real estate investment on regional PM_{2.5} Concentrations had a regular mechanism of decreasing and rising between the Eastern Region and the Central and Western Region.
4.4. Analysis of the Conduction Mechanism

The above results show that the impact of real estate investment on regional PM$_{2.5}$ concentrations had characteristics of differential nature, complexity, stage, and dynamism. Hence, what is the conduction mechanism of real estate investment to regional PM$_{2.5}$ concentrations? Due to the incentive of financial demand, especially land financial demand, local governments in China have a strong desire to promote the development of land urbanization. The realization of land finance needs to introduce market-oriented commercial real estate investment to obtain high land transfer fees. Considering that real estate investment influences the process of urbanization, the land urbanization mechanism is taken as the conduction mechanism of PM$_{2.5}$ concentrations on the quality of urban development for exploratory analysis in this paper. Specifically, land urbanization (LUR) is calculated by the proportion of the built-up area to the total area of the administrative region, and land urbanization is selected as the outcome variable, and the core explanatory variable and control variables remain unchanged.

In general, under the three kinds of the spatial weight matrix, the signs and significance of the variable estimation results in the whole province region were not much different, and the results had good robustness. From the perspective of the explained variable, land urbanization had obvious path dependence and spatial spillover effects, and the spatial-temporal effects were more significant (Table 8).

| Explanatory Variable | Explained Variable: Land Urbanization | Explained Variable: PM$_{2.5}$ Concentrations |
|----------------------|--------------------------------------|--------------------------------------------|
| lnLUR$_{i,t-1}$      | 0.935 ***                            | 0.929 ***                                  |
|                    | (122.96)                             | (199.04)                                   |
| WlnLUR$_{i,t-1}$     | -0.149 **                            | -0.517 ***                                 |
|                    | (-2.52)                              | (-16.66)                                   |
| lnREI$_t$            | -0.001                               | 0.216 ***                                  |
|                    | (-0.54)                              | (7.19)                                     |
| (lnREI$_t$)$^2$      | 0.000                                | 0.047 ***                                  |
|                    | (0.91)                               | (6.99)                                     |
| lnPM$_{2.5,i,t-1}$   | 0.934 ***                            | 0.928 ***                                  |
|                    | (122.90)                             | (193.79)                                   |
| WlnPM$_{2.5,i,t-1}$  | -0.183 **                            | -0.669 ***                                 |
|                    | (-2.10)                              | (-16.99)                                   |
| lnLUR$_{i,t}$        | 0.091                                | 0.132 ***                                  |
|                    | (0.90)                               | (3.75)                                     |
| (lnLUR$_{i,t}$)$^2$  | 0.001                                | 0.029 ***                                  |
|                    | (1.24)                               | (3.64)                                     |
| $\rho$              | 0.158 ***                            | 0.733 ***                                  |
|                    | (2.69)                               | (23.63)                                    |
| Control             | Yes                                  | Yes                                        |
| R-squared           | 0.001 ***                            | 0.005 ***                                  |
|                    | (21.89)                              | (21.16)                                    |
| N                   | 900                                  | 900                                        |

Note: *** means significant within 1%, ** means significant within 5%, and * means significant within 10%.

From the perspective of core explanatory variable, real estate investment positively promoted land urbanization, but the significance of its quadratic term coefficient did not pass the robustness test.

When land urbanization was the core explanatory variable, in general, under the three kinds of the spatial weight matrix, the signs and significance of the overall variable estimation results were not significantly different, and the results had good robustness. From the perspective of the explained variable, PM$_{2.5}$ concentrations also had obvious path dependence and spatial spillover effects at the national level, while the spatial-temporal effect was
negative, which indicated that PM$_{2.5}$ concentrations between neighboring provinces had a certain inhibition. The time lag term of PM$_{2.5}$ concentrations showed a positive correlation at the significance level of 1%, indicating that the path dependence of PM$_{2.5}$ concentrations also held when land urbanization was taken as the core explanatory variable. From the perspective of the core explanatory variable, land urbanization and its quadratic term coefficient showed a positive correlation, and the coefficient had passed the significance test of 1%, meaning that land urbanization was one of the main factors promoting provincial PM$_{2.5}$ concentrations. The process of land urbanization is often accompanied by a large amount of environmental pollution, which has a negative impact on the real estate investment, leading to impacts of real estate investment on land urbanization and PM$_{2.5}$ concentrations at the national level.

5. Conclusions and Policy Implications

Based on the panel data of 30 provinces in China from 1987 to 2017, the DSDLM was used to analyze the impact of the real estate investment on PM$_{2.5}$ concentrations by utilizing three kinds of spatial weight matrix. The main conclusions are as follows: (i) At the national level, there is an inverted U-shaped curve relationship between real estate investment and PM$_{2.5}$ concentrations, and a weak U-shaped curve relationship between the real estate investment and the land urbanization: the impacts of the real estate investment on the land urbanization and PM$_{2.5}$ concentrations first increase and then decrease over the period of analysis. (ii) The impact of the real estate investment on PM$_{2.5}$ concentrations shifts at the regional level; there is an inverted U-shaped curve relationship between real estate investment and PM$_{2.5}$ concentrations in the Eastern and Central Regions, which shows that PM$_{2.5}$ concentrations increased first and then decreased with the increase of the real estate investment. PM$_{2.5}$ concentrations decreased first and then increased with the increase of the real estate investment in the Western Region. (iii) Population density and the use of public transport promotes a reduction of provincial PM$_{2.5}$ concentrations, and the real estate investment driving GDP growth will hinder reduction of provincial PM$_{2.5}$ concentrations. From the perspective of dynamic development, the argument that governments should pay more attention to the quality of GDP development and its impact on provincial PM$_{2.5}$ concentrations has no statistically significant robustness. It can be seen that the national change of U shape could be related with environmental regulation and policy, and the regional differences could be related to wind stagnation and heat convection in the urban settings.

Therefore, real estate investment does have a significant impact on PM$_{2.5}$ concentrations in Chinese regions. We argue that to tackle the problems that result from haze, it is necessary to take urgent action in three areas: increasing regional-level coordination, focusing on population rather than land urbanization, and creating green transport systems. These form the basis of the following policy recommendations arising from this study.

Firstly, a unified PM$_{2.5}$ monitoring platform among regions should be established to strengthen the coordination and linkages among provinces to tackle environmental pollution and haze. The results show that the impact of real estate investment on PM$_{2.5}$ concentration has negative neighborhood spatial spillover effects, mainly generated through the channels of population attraction, talents attraction, and driving the high energy consumption and high pollution real estate related industries in the surrounding areas. In addition, relevant policies and measures should be formulated to guide high energy consumption and high-pollution industries driven by the real estate investment to regional geographic agglomeration, and alleviate and reduce PM$_{2.5}$ concentrations by improving resource allocation efficiency and technological progress.

Secondly, development quality of population urbanization rather than land urbanization should be paid more attention to, and it is necessary to reduce land waste and save the land. The real estate investment should take on enhancing the bearing capacity of the surrounding cities, strengthening infrastructure, and improving the level of the public services as the development directions, and finally improve the population absorption
capacity of the surrounding small and medium-sized cities, and reduce the negative impact of the real estate investment on the ecological environment as much as possible.

Finally, speeding up the construction of green cities and building green transportation systems and green town systems would help reduce PM$_{2.5}$ concentrations resulting from transport. Thinking sustainably about real estate investments to improve air quality in Chinese regions also requires a focus on reducing pollution resulting from rising car usage. Relevant studies show that increasing urban green spaces and implementing sustainable public transport systems can effectively reduce PM$_{2.5}$ concentrations, and that different green space coverage levels of urban green space have different effects on reducing atmospheric particulate matter [85,86], hence the need for multidimensional approaches to reducing PM$_{2.5}$ concentrations overall.

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