land

Article

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

Hongjie Bao [1], Ling Shan [2], Yufei Wang [2], Yuehua Jiang [2], Cheonjae Lee [3] and Xufeng Cui [2,4,*]

[1] School of Management, Northwest Minzu University, Lanzhou 730030, China; hongjie@xbmu.edu.cn
[2] School of Business Administration, Zhongnan University of Economics and Law, Wuhan 430073, China; shanling@stu.zuel.edu.cn (L.S.); wyf@stu.zuel.edu.cn (Y.W.); jyh@stu.zuel.edu.cn (Y.J.)
[3] TUM School of Engineering & Design, Technical University of Munich (TUM), 80333 Munich, Germany; cheonjae.lee@tum.de
[4] Key Laboratory of Virtual Geographic Environment (Ministry of Education of PRC), Nanjing Normal University, Nanjing 210046, China
* Correspondence: cxf@zuel.edu.cn

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)

Citation: Bao, H.; Shan, L.; Wang, Y.; Jiang, Y.; Lee, C.; Cui, X. How Does Local Real Estate Investment Influence Neighborhood $PM_{2.5}$ Concentrations? A Spatial Econometric Analysis. *Land* **2021**, *10*, 518. https://doi.org/10.3390/land10050518

Academic Editor: Shiliang Su

Received: 7 April 2021
Accepted: 10 May 2021
Published: 13 May 2021

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 $\mu g/m^3$, the long-term mortality risk increases by about 15% compared with 10 $\mu g/m^3$. 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.

$$W_{ij}^{d} = \frac{1}{(d_{ij})^2} \tag{1}$$

$$W_1 = \begin{cases} \frac{W_{ij}^{d}}{\sum\limits_{j} W_{ij}^{d}} & ,j \neq i \\ 0, i = j \end{cases} \tag{2}$$

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.

$$W_2 = \begin{cases} \frac{1}{\left|\bar{y_i} - \bar{y_j}\right|} & ,j \neq i \\ 0, i = j \end{cases} \tag{3}$$

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.

$$W_{ij}^{e} = W_{ij}^{d} \times diag(y_1/y, y_2/y, \cdots y_n/y) \tag{4}$$

$$W_3 = \begin{cases} \frac{W_{ij}^{e}}{\sum\limits_{j} W_{ij}^{e}} & ,j \neq i \\ 0, i = j \end{cases} \tag{5}$$

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_{ij}^{d} 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].

$$I = \frac{n}{S_0} \times \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_{i=1}^{n}(x_i - \overline{x})^2} \quad (6)$$

$$S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} \quad (7)$$

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. $\overline{x}$ 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].

$$C = (n-1)\frac{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}(x_i - x_j)^2}{2nS^2 \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}} \quad (8)$$

$$S^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2 \quad (9)$$

where x_i and x_j denote $PM_{2.5}$ concentrations of city i and city j, respectively. $\overline{x}$ 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.

$$Y_{it} = \rho \sum_{j=1}^{n} w_{ij} Y_{it} + \beta_1 REI_{it} + \sum_{j} \eta_j Z_{it}^{j} + \mu_i + \xi_t + \varepsilon_{it} \quad (10)$$

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. ρ is the spatial regression coefficient; Z denotes a set of control variables; μ_i and ξ_t are the spatial-specific effect and the time-specific effect, respectively. ε_{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.

$$Y_{it} = \beta_1 REI_{it} + \sum_{j} \eta_j Z_{it}^{j} + \mu_i + \xi_{t+} \varphi_{it} \quad (11)$$

$$\varphi_{it} = \lambda \sum_{j=1}^{n} W_{ij} \varphi_{it} + \varepsilon_{it} \quad (12)$$

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, η denotes the regression coefficient of control variables, and Z denotes a set of control variables. φ_{it} represents the spatial autocorrelation error term and λ 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.

$$Y_{it} = \rho \sum_{j=1}^{n} w_{ij} Y_{it} + REI_{it}\beta + \sum_{j=1}^{n} w_{ij} REI_{jt}\gamma + \mu_i + \xi_t + \varepsilon_{it} \tag{13}$$

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_{it} are considered in the model. W_{ij} represents the spatial geographic distance weight matrix of the element in row i and column j, β represents a vector of regression coefficients, u_i denotes the individual effect, and ε_{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:

$$y_{it} = \alpha y_{i,t-1} + \theta W y_{i,t-1} + \rho \sum_{j=1}^{N} W_{ij} X_{jt} + \varepsilon_{it} \tag{14}$$

where y_{it} represents $PM_{2.5}$ concentrations in a city i at time t, θ 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].

④ 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].

⑤ 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].

⑥ 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].

⑦ 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].

⑧ 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].

⑨ 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.

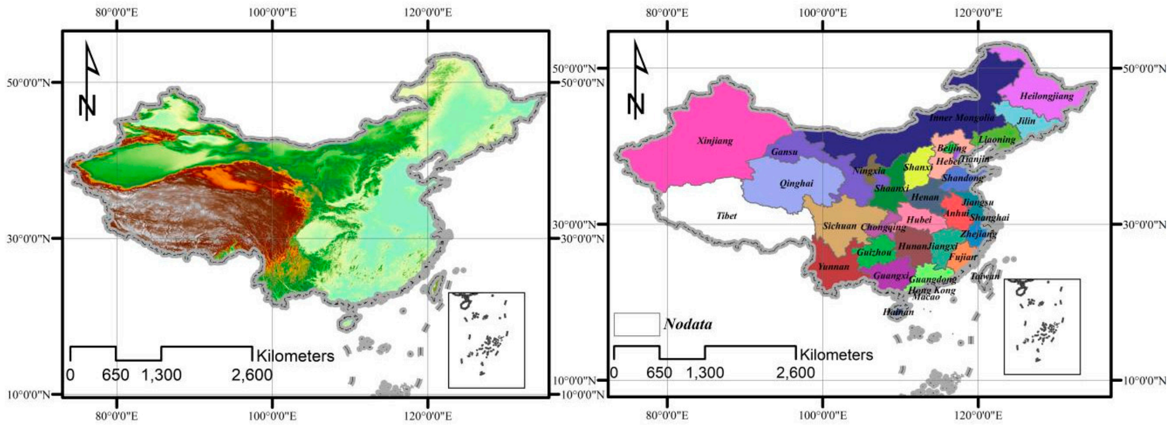

Figure 1. The location of the study area.

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.

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

Note: * means significant within 10%.

Table 2. Spatial model selection test.

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

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	
	(1)	**(2)**	**(3)**	**(4)**
	RE	**FE**	**RE**	**FE**
$lnREI_{it}$	0.409 ***	0.299 ***	0.360 ***	0.336 ***
	(10.19)	(5.30)	(9.15)	(8.79)
$(lnREI_{it})^2$	−0.0484 ***	−0.0485 ***	−0.0445 ***	−0.0341 ***
	(−10.37)	(−7.46)	(−7.20)	(−6.05)
$lnENER_{it}$	0.0567 ***	0.0797 ***	0.0734 ***	0.0637 ***
	(4.27)	(5.24)	(5.54)	(5.00)
$lnIND_{it}$	−0.598 ***	−0.346 ***	−0.168 *	−0.0173
	(−7.97)	(−3.70)	(−1.90)	(−0.21)
$lnR\&D_{it}$	0.315 ***	0.110	−0.0526	−0.0593
	(7.02)	(1.56)	(−1.25)	(−1.43)
$lnTRA_{it}$	−0.130 ***	−0.0879	−0.213 ***	−0.226 ***
	(−4.11)	(−1.57)	(−5.81)	(−6.32)
$lnEDU_{it}$	−1.310 ***	−1.157 ***	−0.800 ***	−0.882 ***
	(−8.15)	(−7.03)	(−5.69)	(−6.45)
$lnOPEN_{it}$	−0.312 ***	−0.0258	−0.0386	−0.0263
	(−8.65)	(−0.44)	(−1.02)	(−0.71)
$lnREG_{it}$	0.0986 ***	0.0445	−0.0126	0.0111
	(4.12)	(1.22)	(−0.54)	(0.50)
$lnGDP_{it}$	0.728 ***	0.880 ***	−0.821 ***	−0.913 ***
	(11.91)	(12.12)	(−4.40)	(−4.97)
$lnPOP_{it}$	−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			−849.547	−727.744
N	930	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 $PM_{2.5}$ concentration at the national level which followed the law of Kuznets curve (EKC). At the initial stage of real estate investment, $PM_{2.5}$ concentrations increased; however, with the real estate investment increasing to a certain level, $PM_{2.5}$ concentrations gradually reduced.

The coefficients of control variables showed that large-scale use of coal energy significantly increased $PM_{2.5}$ concentrations; mass use of public transportation was conducive to reducing $PM_{2.5}$ concentrations; improvements in education levels were helpful in raising public awareness of environmental protection and reducing $PM_{2.5}$ concentrations; improvement of economic development level also helped to reduce $PM_{2.5}$ concentrations; population density and $PM_{2.5}$ 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 $PM_{2.5}$ 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
$\ln REI_{it}$	0.400 ***	1.886 ***	2.286 ***
	(10.54)	(10.36)	(11.75)
$(\ln REI_{it})^2$	−0.038 ***	−0.092 ***	−0.130 ***
	(−6.84)	(−9.22)	(−13.33)
$\ln ENER_{it}$	0.079 ***	0.417 ***	0.496 ***
	(6.43)	(5.27)	(5.94)
$\ln IND_{it}$	0.048	2.026 ***	2.074 ***
	(0.58)	(5.63)	(5.08)
$\ln POP_{it}$	3.421 ***	2.178 *	5.598 ***
	(11.63)	(1.90)	(4.67)
$\ln R\&D_{it}$	−0.0593	−0.0974	−0.157
	(−1.41)	(−0.50)	(−0.76)
$\ln TRA_{it}$	−0.217 ***	0.238 **	0.020
	(−5.88)	(2.11)	(0.16)
$\ln EDU_{it}$	−0.721 ***	4.860 ***	4.139 ***
	(−4.72)	(4.47)	(3.50)
$\ln OPEN_{it}$	−0.0310	−0.230 ***	−0.261 ***
	(−0.85)	(−2.74)	(−2.66)
$\ln REG_{it}$	−0.0255	−1.111 ***	−1.136 ***
	(−1.05)	(−7.21)	(−6.68)
$\ln GDP_{it}$	−0.921 ***	−0.376	−1.297 ***
	(−5.24)	(−1.32)	(−4.95)

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 (DSDLM) 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
$\ln PM_{2.5(i,t-1)}$	0.941 ***			
	(161.99)			
$W\ln PM_{2.5(i,t-1)}$	−0.683 ***			
	(−19.28)			
$\ln REI_{it}$	0.0220 ***	0.030 **	0.145	0.175
	(2.82)	(2.56)	(1.22)	(1.36)
$(\ln REI_{it})^2$	−0.002 *	−0.003 ***	−0.014 *	−0.016 **
	(−1.92)	(−2.73)	(−1.94)	(−2.20)
$\ln ENER_{it}$	−0.000	−0.004	−0.065 **	−0.069 **
	(−0.16)	(−1.10)	(−2.22)	(−2.17)
$\ln IND_{it}$	0.031 **	0.039 **	0.153	0.193
	(2.10)	(2.16)	(1.19)	(1.35)
$\ln R\&D_{it}$	0.012 *	0.011	−0.019	−0.007
	(1.65)	(1.21)	(−0.23)	(−0.09)
$\ln TRA_{it}$	−0.021 ***	−0.026 ***	−0.102 **	−0.128 **
	(−3.20)	(−3.56)	(−2.23)	(−2.55)
$\ln EDU_{it}$	0.037	0.011	−0.573	−0.562
	(1.46)	(0.29)	(−1.47)	(−1.34)
$\ln OPEN_{it}$	−0.008	−0.010	−0.049	−0.060
	(−0.83)	(−1.02)	(−0.88)	(−1.00)
$\ln REG_{it}$	−0.003	−0.010	−0.127 *	−0.137 *
	(−0.93)	(−1.52)	(−1.72)	(−1.72)
$\ln GDP_{it}$	0.042	0.0460	0.013	0.059
	(1.41)	(1.49)	(0.14)	(0.60)
$\ln POP_{it}$	−0.095 *	−0.070	0.575	0.504
	(−1.70)	(−1.17)	(1.23)	(1.02)
ρ	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 ρ 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 DSDLM only considered the spatial correlation. However, in the DSDLM, 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
	(1)	(2)	(3)
$\ln PM_{2.5(i,t-1)}$	0.941 ***	0.947 ***	0.941 ***
	(161.99)	(159.90)	(158.67)
$W\ln PM_{2.5(i,t-1)}$	−0.683 ***	−0.654 ***	−0.511 ***
	(−19.28)	(−13.61)	(−3.18)
$\ln REI_{it}$	0.022 ***	0.016 *	0.042 ***
	(2.82)	(1.82)	(6.04)
$(\ln REI_{it})^2$	−0.002 *	−0.002 **	−0.009 ***
	(−1.92)	(−2.01)	(−10.92)
$\ln ENER_{it}$	−0.000	−0.002	−0.004
	(−0.16)	(−0.84)	(−1.25)
$\ln IND_{it}$	0.031 **	0.022	0.072 ***
	(2.10)	(1.47)	(4.24)
$\ln R\&D_{it}$	0.0123 *	0.008	0.024 ***
	(1.65)	(1.04)	(2.78)
$\ln TRA_{it}$	−0.021 ***	−0.025 ***	−0.033 ***
	(−3.20)	(−3.71)	(−4.18)
$\ln EDU_{it}$	0.037	0.042	0.027
	(1.46)	(1.53)	(0.93)
$\ln OPEN_{it}$	−0.008	−0.009	0.026 **
	(−0.83)	(−0.86)	(2.37)
$\ln REG_{it}$	−0.003	0.002	−0.003
	(−0.93)	(0.46)	(−0.82)
$\ln GDP_{it}$	0.043	0.069 **	0.046 ***
	(1.41)	(2.19)	(3.46)
$\ln POP_{it}$	−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 $PM_{2.5}$ 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)	(1)	(2)	(3)	(1)	(2)	(3)
$LnPM_{2.5(i,t-1)}$	1.004 ***	0.895 ***	0.957 ***	0.785 ***	1.195 ***	0.850 ***	1.373 ***	0.810 ***	1.402 ***
	(61.01)	(49.73)	(50.92)	(25.95)	(47.92)	(37.31)	(90.45)	(50.99)	(95.41)
$WlnPM_{2.5(i,t-1)}$	−2.650 ***	−1.201 ***	−0.450 ***	−0.493 ***	−0.930 **	−0.545 ***	−0.364 ***	−2.266 ***	−0.182 **
	(−47.88)	(−22.34)	(−10.16)	(−9.87)	(−11.15)	(−12.21)	(−5.49)	(−23.76)	(−2.27)
$lnREI_{it}$	−0.285 ***	−0.0235	−0.456 ***	0.064 *	0.248 ***	0.569 ***	−0.674 ***	−0.566 ***	−0.135 ***
	(−11.30)	(−1.08)	(−15.94)	(1.71)	(7.36)	(9.88)	(−31.78)	(−33.01)	(−9.95)
$(lnREI_{it})^2$	−0.045 ***	−0.089 ***	−0.035 ***	−0.007 *	−0.05 ***	−0.007 *	0.043 ***	0.035 ***	0.036 ***
	(−17.42)	(−37.85)	(−13.37)	(−1.71)	(−14.81)	(−1.68)	(22.81)	(18.13)	(23.16)
ρ	1.426 ***	1.301 ***	0.537 ***	0.499 ***	2.741 ***	0.968 ***	2.617 ***	2.204 ***	0.279 ***
	(30.10)	(26.96)	(12.52)	(10.99)	(40.67)	(24.77)	(40.71)	(29.48)	(3.22)
R-squared	0.004 ***	0.005 ***	0.008 ***	0.004 ***	0.001 **	0.003 ***	0.003 ***	0.003 ***	0.006 ***
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	330	330	330	240	240	240	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).

Table 8. Estimation results of the conduction mechanism.

Explanatory Variable	**Explained Variable: Land Urbanization**			**Explained Variable: $PM_{2.5}$ Concentrations**		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
$\ln LUR_{i,t-1}$	0.935 ***	0.934 ***	0.936 ***			
	(122.96)	(122.90)	(125.45)			
$W\ln LUR_{i,t-1}$	−0.149 **	−0.183 **	0.091			
	(-2.52)	(−2.10)	(0.90)			
$\ln REI_{it}$	−0.001	−0.002	−0.005 *			
	(−0.54)	(−0.71)	(−1.86)			
$(\ln REI_{it})^2$	0.000	0.000	0.001 ***			
	(0.91)	(1.24)	(3.17)			
$LnPM_{2.5(i,t-1)}$				0.929 ***	0.928 ***	0.944 ***
				(199.04)	(193.79)	(197.78)
$WlnPM_{2.5(i,t-1)}$				−0.517 ***	−0.669 ***	−0.567 ***
				(−16.66)	(−16.99)	(−14.50)
$\ln LUR_{it}$				0.216 ***	0.132 ***	0.282 ***
				(7.19)	(3.75)	(7.93)
$(\ln LUR_{it})^2$				0.047 ***	0.029 ***	0.068 ***
				(6.99)	(3.64)	(8.59)
ρ	0.158 ***	0.256 ***	0.141 ***	0.733 ***	0.770 ***	0.882 ***
	(2.69)	(3.08)	(2.42)	(23.63)	(22.31)	(25.43)
Control	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001 ***	0.001 ***	0.002 ***	0.005 ***	0.006 ***	0.006 ***
	(21.89)	(21.89)	(21.92)	(21.16)	(21.54)	(20.97)
N	900	900	900	900	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.

Author Contributions: Conceptualization, X.C.; data curation, Y.J.; formal analysis, L.S.; funding acquisition, H.B.; investigation, Y.W. and Y.J.; methodology, H.B. and X.C.; software, H.B.; supervision, X.C.; writing—original draft, H.B. and Y.W.; writing—review and editing, L.S. and C.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by MOE (Ministry of Education of PRC) Project of Humanities and Social Sciences: 20YJC850001; China Postdoctoral Science Foundation: 2019M651885; Open Project of Key Laboratory of Ethnic Information E-commerce in Universities of Gansu Province (CN): 2020-2; the Fundamental Research Funds for the Central Universities, Zhongnan University of Economics and Law (CN): 201911047, 202111023, 202111073, 202111076.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The datasets used or analyzed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Kong, Y.; Glascock, J.L.; Lu-Andrews, R. An investigation into real estate investment and economic growth in China: A dynamic panel data approach. *Sustainability* **2016**, *8*, 66. [CrossRef]
2. Chen, Y.; He, M.; Rudkin, S. Understanding Chinese provincial real estate investment: A global VAR perspective. *Econ. Model.* **2017**, *67*, 248–260. [CrossRef]
3. Chen, Q.; Kamran, S.M.; Fan, H. Real estate investment and energy efficiency: Evidence from China's policy experiment. *J. Clean. Prod.* **2019**, *217*, 440–447. [CrossRef]
4. Chang, C.; Lu, M. How has new town fever resulted in heavy debt Burden. *Acad. Mon.* **2017**, *49*, 55–65. (In Chinese)
5. Chen, Y.; Lee, C.C. The impact of real estate investment on air quality: Evidence from China. *Environ. Sci. Pollut. Res. Int.* **2020**, *27*, 22989–23001. [CrossRef] [PubMed]
6. Vanags, J.; Butane, I. Major aspects of development of sustainable investment environment in real estate industry. *Proc. Eng.* **2013**, *57*, 1223–1229. [CrossRef]
7. Clayton, J.; Devine, A.; Holtermans, R. Beyond building certification: The impact of environmental interventions on commercial real estate operations. *Energy Econ.* **2021**, *93*, 105039. [CrossRef]
8. World Health Organization. *Air Quality Guidelines for Particulate Matter, Ozone, Nitrogen Dioxide and Sulfur Dioxide*; World Health Organization Regional Office for Europe: Copenhagen, Denmark, 2006.
9. Ministry of Ecology and Environment of the People's Republic of China. China Ecological and Environmental Bulletin. 2020. Available online: http://www.mee.gov.cn/hjzl/sthjzk/zghjzkgb/ (accessed on 2 June 2020).
10. Zhao, M.; Liu, F.; Song, Y.; Geng, J. Impact of air pollution regulation and technological investment on sustainable development of green economy in Eastern China: Empirical analysis with panel data approach. *Sustainability* **2020**, *12*, 3073. [CrossRef]
11. Wang, X. Empirical test of the relationship between real estate industry and economic growth under the framework of VAR model. *Econ. Prob.* **2007**, *7*, 31–34. (In Chinese)
12. Lu, J.; Jia, Z.; Tian, H. Research on regional disparity of real estate investment and economic growth in China. *J. Wuhan Univ. Technol.* **2008**, *30*, 959–963. (In Chinese)
13. Liu, H. The dynamic economic effects of urban real estate investment in China. *Res. Econ. Manag.* **2006**, *3*, 49–53. (In Chinese)
14. Liang, Y.; Gao, T.; He, S. An empirical analysis of the coordinated development of the real estate market and the national economy. *Soc. Sci. China* **2006**, *3*, 74–84, 205–206. (In Chinese)

15. Huang, Z.; Wu, C.; Du, X. Real estate investment and economic growth: Panel data analysis at the national and regional levels. *Financ. Trade Econ.* **2008**, *8*, 56–60, 72. (In Chinese)
16. Yang, H.; Jia, J.; Zhou, Y.; Wang, S. Impact on EKC by trade and FDI in China. *China Popul. Resour. Environ.* **2005**, *15*, 99–103. (In Chinese)
17. Khalil, S.; Inam, Z. Is trade good for environment? A unit root cointegration analysis. *Pak. Dev. Rev.* **2006**, *45*, 1187–1196. [CrossRef]
18. Qiang, W.; Lee, H.F.; Lin, Z.; Wong, D.W.H. Revisiting the impact of vehicle emissions and other contributors to air pollution in urban built-up areas: A dynamic spatial econometric analysis. *Sci. Total Environ.* **2020**, *740*, 140098. [CrossRef]
19. Zhang, L.; Yang, G.; Li, X. Mining sequential patterns of $PM_{2.5}$ pollution between 338 cities in China. *J. Environ. Manag.* **2020**, *262*, 110341. [CrossRef]
20. Cesari, D.; Donateo, A.; Conte, M.; Merico, E.; Giangreco, A.; Giangreco, F.; Contini, D. An inter-comparison of $PM_{2.5}$ at urban and urban background sites: Chemical characterization and source apportionment. *Atmos. Res.* **2016**, *174–175*, 106–119. [CrossRef]
21. Ahmad, M.; Cheng, S.; Yu, Q.; Qin, W.; Zhang, Y.; Chen, J. Chemical and source characterization of $PM_{2.5}$ in summertime in severely polluted Lahore, Pakistan. *Atmos. Res.* **2019**, *234*, 104715. [CrossRef]
22. Pope III, C.A.; Burnett, R.T.; Thun, M.J.; Calle, E.E.; Krewski, D.; Ito, K.; Thurston, G.D. Lung cancer, cardiopulmonary mortality, and long-term exposure to fine particulate air pollution. *J. Am. Med. Assoc.* **2002**, *287*, 1132–1141. [CrossRef]
23. Huang, H.; Jiang, Y.; Xu, X.; Cao, X. In vitro bioaccessibility and health risk assessment of heavy metals in atmospheric particulate matters from three different functional areas of Shanghai, China. *Sci. Total Environ.* **2018**, *610–611*, 546–554. [CrossRef] [PubMed]
24. Feng, S.; Gao, D.; Liao, F.; Zhou, F.; Wang, X. The health effects of ambient $PM_{2.5}$ and potential mechanisms. *Ecotoxicol. Environ. Saf.* **2016**, *128*, 67–74. [CrossRef]
25. Chen, D.; Chen, S. Particulate air pollution and real estate valuation: Evidence from 286 Chinese prefecture-level cities over 2004–2013. *Energy Policy* **2017**, *109*, 884–897. [CrossRef]
26. Lin, X.; Wang, D. Spatiotemporal evolution of urban air quality and socioeconomic driving forces in China. *J. Geogr. Sci.* **2016**, *26*, 1533–1549. [CrossRef]
27. Liao, T.; Wang, S.; Ai, J.; Gui, K.; Duan, B.; Zhao, Q.; Zhang, X.; Jiang, W.; Sun, Y. Heavy pollution episodes, transport pathways and potential sources of PM2.5 during the winter of 2013 in Chengdu (China). *Sci. Total Environ.* **2017**, *584–585*, 1056–1065. [CrossRef] [PubMed]
28. Guo, P.; Umarova, A.B.; Luan, Y. The spatiotemporal characteristics of the air pollutants in China from 2015 to 2019. *PLoS ONE* **2020**, *15*, e0227469. [CrossRef]
29. Fan, J.-S.; Zhou, L. Impact of urbanization and real estate investment on carbon emissions: Evidence from China's provincial regions. *J. Clean. Prod.* **2019**, *209*, 309–323. [CrossRef]
30. Dong, J.; Wang, S.; Shang, K. Analysis of the influence of precipitation on air quality in some Chinese cities. *J. Arid. Resour. Environ.* **2009**, *23*, 43–48.
31. Li, L.; Qian, J.; Ou, C.; Zhou, Y.; Guo, C.; Guo, Y. Spatial and temporal analysis of air pollution index and its timescale-dependent relationship with meteorological factors in Guangzhou, China, 2001–2011. *Environ. Pollut.* **2014**, *190*, 75–81. [CrossRef]
32. Chen, M.; Guo, S.; Hu, M.; Zhang, X. The spatiotemporal evolution of population exposure to $PM_{2.5}$ within the Beijing-Tianjin-Hebei urban agglomeration, China. *J. Clean. Prod.* **2020**, *265*, 121708. [CrossRef]
33. Wang, W.; Zhang, L.; Zhao, J.; Qi, M.; Chen, F. The effect of socioeconomic factors on spatiotemporal patterns of $PM_{2.5}$ concentration in Beijing-Tianjin-Hebei region and surrounding areas. *Int. J. Environ. Res. Public Health* **2020**, *17*, 3014. [CrossRef] [PubMed]
34. Fu, Z.; Li, R. The contributions of socioeconomic indicators to global $PM_{2.5}$ based on the hybrid method of spatial econometric model and geographical and temporal weighted regression. *Sci. Total Environ.* **2020**, *703*, 135481. [CrossRef]
35. Vecchi, R.; Bernardoni, V.; Cricchio, D.; D'Alessandro, A.; Fermo, P.; Lucarelli, F.; Nava, S.; Piazzalunga, A.; Valli, G. The impact of fireworks on airborne particles. *Atmos. Environ.* **2008**, *42*, 1121–1132. [CrossRef]
36. Wu, K.; Duan, M.; Liu, H.; Zhou, Z.; Deng, Y.; Song, D.; Tan, Q. Characterizing the composition and evolution of firework-related components in air aerosols during the Spring Festival. *Environ. Geochem. Health* **2018**, *40*, 2761–2771. [CrossRef]
37. Xu, G.; Ren, X.; Xiong, K.; Li, L.; Bi, X.; Wu, Q. Analysis of the driving factors of $PM_{2.5}$ concentration in the air: A case study of the Yangtze River Delta, China. *Ecol. Indic.* **2020**, *110*, 105889. [CrossRef]
38. Ding, Y.; Zhang, M.; Qian, X.; Li, C.; Chen, S.; Wang, W. Using the geographical detector technique to explore the impact of socioeconomic factors on $PM_{2.5}$ concentrations in China. *J. Clean. Prod.* **2019**, *211*, 1480–1490. [CrossRef]
39. Ji, X.; Yao, Y.; Long, X. What causes $PM_{2.5}$ pollution? Cross-economy empirical analysis from socioeconomic perspective. *Energy Policy* **2018**, *119*, 458–472. [CrossRef]
40. Chen, J.; Zhou, C.; Wang, S.; Li, S. Impacts of energy consumption structure, energy intensity, economic growth, urbanization on $PM_{2.5}$ concentrations in countries globally. *Appl. Energy* **2018**, *230*, 94–105. [CrossRef]
41. Li, J.; Zhao, Y.; Chen, X. The grey relational analysis of chemical elements in atmospheric fine particles ($PM_{2.5}$). *Adv. Mater. Res.* **2014**, *955–959*, 1259–1262. [CrossRef]
42. Zhao, R.; Zhan, L.; Yao, M.; Yang, L. A geographically weighted regression model augmented by Geodetector analysis and principal component analysis for the spatial distribution of $PM_{2.5}$. *Sustain. Cites Soc.* **2020**, *56*, 102106. [CrossRef]

43. Wang, Y.; Duan, X.; Wang, L. Spatial-temporal evolution of $PM_{2.5}$ concentration and its socioeconomic influence factors in Chinese cities in 2014–2017. *Int. J. Environ. Res. Public Health* **2019**, *16*, 985. [CrossRef]
44. Song, Y.; Wang, J.; Ge, Y.; Xu, C. An optimal parameters-based geographical detector model enhances geographic characteristics of explanatory variables for spatial heterogeneity analysis: Cases with different types of spatial data. *GISci. Remote Sens.* **2020**, *57*, 593–610. [CrossRef]
45. Cao, L.; Li, L.; Wu, Y. How does population structure affect pollutant discharge in China? Evidence from an improved STIRPAT model. *Environ. Sci. Pollut. Res. Int.* **2020**, *28*, 2765–2778. [CrossRef]
46. Xu, F.; Huang, Q.; Yue, H.; He, C.; Wang, C.; Zhang, H. Reexamining the relationship between urbanization and pollutant emissions in China based on the STIRPAT model. *J. Environ. Manag.* **2020**, *273*, 111134. [CrossRef] [PubMed]
47. Chekouri, S.M.; Chibi, A.; Benbouziane, M. Examining the driving factors of CO_2 emissions using the STIRPAT model: The case of Algeria. *Int. J. Sustain. Energy* **2020**, *39*, 927–940. [CrossRef]
48. Zhang, Y.; Shuai, C.; Bian, J.; Chen, X.; Wu, Y.; Shen, L. Socioeconomic factors of $PM_{2.5}$ concentrations in 152 Chinese cities: Decomposition analysis using LMDI. *J. Clean. Prod.* **2019**, *218*, 96–107. [CrossRef]
49. Hwang, I.; Hopke, P.K. Estimation of source apportionment and potential source locations of $PM_{2.5}$ at a west coastal IMPROVE site. *Atmos. Environ.* **2007**, *41*, 506–518. [CrossRef]
50. Zemmer, F.; Karaca, F.; Ozkaragoz, F. Ragweed pollen observed in Turkey: Detection of sources using back trajectory models. *Sci. Total Environ.* **2012**, *430*, 101–108. [CrossRef] [PubMed]
51. Zhang, Y.; Chen, J.; Yang, H.; Li, R.; Yu, Q. Seasonal variation and potential source regions of $PM_{2.5}$-bound PAHs in the megacity Beijing, China: Impact of regional transport. *Environ. Pollut.* **2017**, *231*, 329–338. [CrossRef]
52. Yang, D.; Wang, X.; Xu, J.; Xu, C.; Lu, D.; Ye, C.; Wang, Z.; Bai, L. Quantifying the influence of natural and socioeconomic factors and their interactive impact on $PM_{2.5}$ pollution in China. *Environ. Pollut.* **2018**, *241*, 475–483. [CrossRef]
53. Shao, J.; Ge, J.; Feng, X.; Zhao, C. Study on the relationship between $PM_{2.5}$ concentration and intensive land use in Hebei Province based on a spatial regression model. *PLoS ONE* **2020**, *15*, e0238547. [CrossRef]
54. Liu, Z.; Hu, B.; Zhang, J.; Yu, Y.; Wang, Y. Characteristics of aerosol size distributions and chemical compositions during wintertime pollution episodes in Beijing. *Atmos. Res.* **2016**, *168*, 1–12. [CrossRef]
55. Demena, B.A.; Afesorgbor, S.K. The effect of FDI on environmental emissions: Evidence from a meta-analysis. *Energy Policy* **2020**, *138*, 111192. [CrossRef]
56. Yan, Y.; Qi, S. FDI and haze pollution in China. *Stat. Res.* **2017**, *34*, 69–81.
57. Martínez-Zarzoso, I.; Bengochea-Morancho, A.; Morales-Lage, R. The impact of population on CO_2 emissions: Evidence from European countries. *Environ. Resour. Econ.* **2007**, *38*, 497–512. [CrossRef]
58. Zhang, H.; Wang, K.; Xiang, B. Research on different impacts of urbanization on CO_2, emissions in provinces with different income level. *China Popul. Resour. Environ.* **2013**, *23*, 152–157. (In Chinese)
59. Zhang, X.; Yu, J. Spatial weights matrix selection and model averaging for spatial autoregressive models. *J. Econ.* **2018**, *203*, 1–18. [CrossRef]
60. Zhang, F.; Wang, Y.; Liu, W. Science and technology resource allocation, spatial association, and regional innovation. *Sustainability* **2020**, *12*, 694. [CrossRef]
61. Seya, H.; Yamagata, Y.; Tsutsumi, M. Automatic selection of a spatial weight matrix in spatial econometrics: Application to a spatial hedonic approach. *Reg. Sci. Urban Econ.* **2013**, *43*, 429–444. [CrossRef]
62. Riccioli, F.; Fratini, R.; Boncinelli, F. The impacts in real estate of landscape values: Evidence from Tuscany (Italy). *Sustainability* **2021**, *13*, 2236. [CrossRef]
63. Erdoğan, S.; Memduhoğlu, A. A spatiotemporal exploratory analysis of real estate sales in Turkey using GIS. *J. Eur. Real Estate Res.* **2019**, *12*, 207–226. [CrossRef]
64. Anselin, L.; Syabri, I.; Kho, Y. GeoDa: An introduction to spatial data analysis. *Geogr. Anal.* **2005**, *38*, 5–22. [CrossRef]
65. Shen, Z.; Baležentis, T.; Chen, X.; Valdmanis, V. Green growth and structural change in Chinese agricultural sector during 1997–2014. *China Econ. Rev.* **2018**, *51*, 83–96. [CrossRef]
66. Eyup, D.; Berna, T. CO_2 emissions, real output, energy consumption, trade, urbanization and financial development: Testing the EKC hypothesis for the USA. *Environ. Sci. Pollut. Res. Int.* **2016**, *23*, 1203–1213.
67. Shahzad, S.J.H.; Kumar, R.R.; Zakaria, M.; Hurr, M. Carbon emission, energy consumption, trade openness and financial development in Pakistan: A revisit. *Renew. Sustain. Energy Rev.* **2017**, *70*, 185–192. [CrossRef]
68. Alvarez-Herranz, A.; Balsalobre-Lorente, D.; Shahbaz, M.; Cantos, J.M. Energy innovation and renewable energy consumption in the correction of air pollution levels. *Energy Policy* **2017**, *105*, 386–397. [CrossRef]
69. Zameer, H.; Yasmeen, H.; Zafar, M.W.; Waheed, A.; Sinha, A. Analyzing the association between innovation, economic growth, and environment: Divulging the importance of FDI and trade openness in India. *Environ. Sci. Pollut. Res.* **2020**, *27*, 29539–29553. [CrossRef] [PubMed]
70. Liu, K.; Lin, B. Research on influencing factors of environmental pollution in China: A spatial econometric analysis. *J. Clean. Prod.* **2019**, *206*, 356–364. [CrossRef]
71. Hao, Y.; Zheng, S.; Zhao, M.; Wu, H.; Guo, Y.; Li, Y. Reexamining the relationships among urbanization, industrial structure, and environmental pollution in China—New evidence using the dynamic threshold panel model. *Energy Rep.* **2020**, *6*, 28–39. [CrossRef]

72. Shimadera, H.; Kojima, T.; Kondo, A.; Curci, G. Evaluation of air quality model performance for simulating long-range transport and local pollution of $PM_{2.5}$ in Japan. *Adv. Meteorol.* **2016**, *2016*, 5694251. [CrossRef]
73. Kim, C.H.; Meng, F.; Kajino, M.; Lim, J.; Jo, Y.J. Comparative numerical study of $PM_{2.5}$ in exit-and-entrance areas associated with transboundary transport over China, Japan, and Korea. *Atmosphere* **2021**, *12*, 469. [CrossRef]
74. Xiong, L.; Wei, W.; Yang, Y. Spatial effect of trade openness on regional economic growth: A study based on 1987–2009 spatial panel data in China. *China Econ. Q.* **2012**, *11*, 1037–1058. (In Chinese)
75. Xie, Q.; Sun, Q. Assessing the impact of FDI on $PM_{2.5}$ concentrations: A nonlinear panel data analysis for emerging economies. *Environ. Impact Assess. Rev.* **2020**, *80*, 106314. [CrossRef]
76. U., T.S.C.; Mitra, A. Development and degradation: The nexus between GDP, FDI, and pollution in India. *Emerg. Econ. Stud.* **2020**, *6*, 39–49. [CrossRef]
77. Shen, J.; Wei, Y.; Yang, Z. The impact of environmental regulations on the location of pollution-intensive industries in China. *J. Clean. Prod.* **2017**, *148*, 785–794. [CrossRef]
78. Abdul, J.; Mete, F. The impact of growth, energy and financial development on the environment in China: A cointegration analysis. *Energy Econ.* **2011**, *33*, 284–291.
79. Zhou, Y.; Zhou, J. Urban atmospheric environmental capacity and atmospheric environmental carrying capacity constrained by GDP–$PM_{2.5}$. *Ecol. Indic.* **2017**, *73*, 637–652. [CrossRef]
80. Wu, W.; Zhang, M.; Ding, Y. Exploring the effect of economic and environment factors on $PM_{2.5}$ concentration: A case study of the Beijing-Tianjin-Hebei region. *J. Environ. Manag.* **2020**, *268*, 110703. [CrossRef]
81. Han, S.; Sun, B. Impact of population density on $PM_{2.5}$ concentrations: A case study in Shanghai, China. *Sustainability* **2019**, *11*, 1968. [CrossRef]
82. Chen, J.; Wang, B.; Huang, S.; Song, M. The influence of increased population density in China on air pollution. *Sci. Total Environ.* **2020**, *735*, 139456. [CrossRef] [PubMed]
83. Yozgatligil, C.; Aslan, S.; Iyigun, C.; Batmaz, I. Comparison of missing value imputation methods in time series: The case of Turkish meteorological data. *Theor. Appl. Climatol.* **2013**, *112*, 143–167. [CrossRef]
84. Huang, X. Research on incomplete data interpolation method based on MCMC. *Telecom. World* **2016**, *1*, 265–266. (In Chinese)
85. Chen, M.; Dai, F.; Yang, B.; Zhu, S. Effects of urban green space morphological pattern on variation of $PM_{2.5}$ concentration in the neighborhoods of five Chinese megacities. *Build. Environ.* **2019**, *158*, 1–15. [CrossRef]
86. Ling, Q.; Fang, L.; Xiang, Z.; Tian, G. Difference of airborne particulate matter concentration in urban space with different green coverage rates in Baoji, China. *Int. J. Environ. Res. Public Health* **2019**, *16*, 1465.