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Research Article

Effect of Energy Development and Technological Innovation on $PM_{2.5}$ in China: A Spatial Durbin Econometric Analysis

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Using the panel data of 29 provinces and regions in China, this paper analyzes the temporal and spatial characteristics of $PM_{2.5}$ concentration. The spatial Durbin model is used to empirically examine the impact of energy development and technological innovation on $PM_{2.5}$. The results show that the interprovincial $PM_{2.5}$ in China showed an inverted "N" trend. There is a spatial agglomeration of interprovincial $PM_{2.5}$, and the spatial autocorrelation is significant. The spatial autoregression coefficients of adjacent weights and distance weights are significantly positive, and $PM_{2.5}$ pollution in adjacent areas has a positive effect on the region. From the view of energy development, the increase in energy intensity will significantly increase the concentration of $PM_{2.5}$ in adjacent areas, which will increase the global $PM_{2.5}$ concentration. The increase in the proportion of coal consumption increases the concentration of $PM_{2.5}$ in the region and globally. The increase in energy consumption prices will reduce the $PM_{2.5}$ concentration in the region and globally. From the view of technological innovation, the increase in sales revenue of new products of industrial enterprises above the scale will reduce the concentration of $PM_{2.5}$ in the region by 0.1285 percentage points and the concentration of $PM_{2.5}$ in adjacent areas by 0.3058 percentage points, which will reduce the global $PM_{2.5}$ concentration by 0.4343 percentage points. The increase in the number of granted patent applications will reduce the $PM_{2.5}$ concentration of the adjacent regions and globally. The increasing level of infrastructure for technological innovation in the region will reduce the concentration of $PM_{2.5}$ in adjacent areas. The increase in technical market turnover will reduce the concentration of $PM_{2.5}$ in the region and the concentration of $PM_{2.5}$ in adjacent areas, which will reduce the global $PM_{2.5}$ concentration. In order to reduce the concentration of $PM_{2.5}$ in China, we should continue to promote $PM_{2.5}$ regional collaborative governance. In terms of energy development, it is necessary to reduce energy intensity, optimize energy structure, implement energy substitution, and rationalize energy prices. In terms of technological innovation, it is essential to increase sales revenue of new products of industrial enterprises, raise number of granted patent applications, vigorously improve level of infrastructure for technological innovation, and enhance technical market turnover.

1. Introduction

In the first quarter of 2013, China experienced severe hazy weather that affected 1.3 million square kilometers and 800 million people. Since then, this haze has continued to shroud most parts of China. Energy consumption, directly or indirectly, increases the degree of haze pollution. How does energy development affect haze pollution? At the same time, China is speeding up the construction of an innovative country. Studying energy development and technology innovation on haze pollution have important implications for building a beautiful China.

The main components of haze pollution are $PM_{2.5}$ and PM_{10}. Particles with an aerodynamic equivalent diameter of $10\mu m$ or less are called PM_{10}. Particles with diameters less than $2.5\mu m$ are called $PM_{2.5}$. Energy development includes energy intensity, energy structure, and energy prices. The literature has studied the impact of energy intensity on haze pollution. For example, Cheng et al. (2017) found that China's energy intensity has a significant positive impact on $PM_{2.5}$ and should limit the rapid growth of energy intensity [1]. Liu and Jiang (2017) found that a decrease in energy intensity would reduce PM_{10} concentrations in the region [2]. Regarding energy structure contamination with

haze, Ma and Zhang (2014) asserted that in the long run, changing the energy consumption structure and optimizing the industrial structure are the keys to controlling haze. In the short term, reducing the use of inferior coal is an effective method [3]. Hao and Liu (2015) indicated that to reduce haze pollution in China, the energy structure in secondary industries should be improved by reducing coal consumption and increasing the consumption of clean energy, such as natural gas and renewable energy [4]. Wei and Ma (2015) pointed out that adjusting energy structure and technological progress are the fundamental means to control haze [5]. Li (2016) found that the cause of haze pollution in China was the backwardness of energy technologies, the higher proportion of coal consumption, and the greater proportion of heavy industries [6].Wang X et al. (2018) found that clean energy consumption had negative effects on PM2.5 concentrations in China [7].

Technological innovation is the introduction of new products, services, or elements in the production process or service operations [8]. Technological innovation accelerates economic growth by increasing productivity and reduces energy consumption in the production process by increasing energy efficiency, ultimately reducing pollution emissions [9]. The literature has investigated the impact of technological innovations on atmospheric pollution. For example, Popp (2003) used patent data to study the innovation of the United States' flue gas desulfurization devices ("scrubbers") and showed that technological innovations since 1990 increased scrubber removal efficiency [10]. Shi and Lai (2013) found that the diffusion of low-carbon and green technological innovations promotes regional economic development but saves energy through low-carbon dioxide emissions or zero energy emissions [11]. Yang and Li (2017) studied the relationship between technological change and carbon emissions based on China's 1997–2010 panel data for 30 provinces and found that technological progress is the greatest contributor to CO_2 emission reductions [12]. Wang et al. (2018) estimated the impact of Chinese technical knowledge on the intensity of industrial air pollutants based on the learning curve and environmental learning curve theories and found a causal relationship between technical knowledge and the intensity of industrial air pollutants [13].

The literature has also investigated the impact of technological innovations on haze. For example, Chang et al. (2017) applied regional optimization methods to analyze the impact of technological development in Shanghai on $PM_{2.5}$ pollution and found that decreased fossil energy consumption and increased use of clean energy can reduce $PM_{2.5}$ contamination [14]. Xu and Lin (2018) believe that China's energy-saving emission reduction technology continues to lag behind developed countries, which makes reducing $PM_{2.5}$ pollution in China is a difficult problem to overcome [15]. Zhang et al. (2016) suggested that technological innovation should be strengthened to prevent and control haze pollution in Beijing [16]. Liu (2018) found that technological innovation reduces PM_{10} at a regional level and indirectly reduces PM_{10} in adjacent regions through knowledge spillover effects [17].

The literature has also discussed the impact of energy development and technological innovation on haze pollution, but the following deficiencies have been observed. Firstly, from the perspective of energy development, the literature on the impact of energy structure on haze pollution is abundant but investigations of the impact of energy development combined with technological innovation on the haze pollution are scarce. Secondly, the literature on the impact of technological innovation on environmental pollution has been increasing, but the literature on the impact of technological innovation on haze pollution, especially on $PM_{2.5}$, is relatively scarce. Thirdly, from the perspective of research methods, most of the literature has analyzed the impact of technological innovation on haze pollution from the perspective of ordinary panels, but investigations from the perspective of spatial measurement are still lacking. Finally, there is a dearth of literature on the use of technical innovation infrastructure indicators to measure technological innovation, which is usually measured by patents or R&D input indicators.

Based on the deficiencies in the literature, this paper intends to expand on the following aspects. First, energy development and technological innovation are included in the same framework to examine the impact of energy development and technological innovation on $PM_{2.5}$. Secondly, the spatial Durbin model with an adjacent weight matrix and distance weight matrix is used to analyze the impact of energy development and technological innovation on $PM_{2.5}$. Finally, indicators such as technological innovation infrastructure are used to refer to technological innovation.

2. Methodology and Data

2.1. Global Spatial Autocorrelation. The global spatial autocorrelation can effectively describe the overall situation of $PM_{2.5}$ changes at the interprovincial level and is usually analyzed by the Global Moran's I index. This index was first proposed by Moran (1950) [18]. The Global Moran's I index reflects the similarities between units in each region and adjacent regions through a spatial weight matrix (Anselin, 1988) [19]. Its calculation formula is as follows:

$$\begin{aligned} Moran's\ I &= \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(x_i-\overline{x}\right)\left(x_j-\overline{x}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i=1}^{n}\left(x_i-\overline{x}\right)^2} \\ &= \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(x_i-\overline{x}\right)\left(x_j-\overline{x}\right)}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \end{aligned} \tag{1}$$

where $S^2 = (1/n)\sum_{i=1}^{n}(x_i-\overline{x})^2$ is the variance of the observations. $\overline{x} = (1/n)\sum_{i=1}^{n} x_i$ is the average of all spatial unit observations. x_i and x_j represent the ith and jth spatial unit observations, respectively, and n is the total number of spatial units. w_{ij} is a spatial weight matrix. The range of the Global Moran's I Index is [-1, 1]. I>0 indicates a positive spatial autocorrelation of interprovincial $PM_{2.5}$ in China. The larger the value is, the stronger the agglomeration is; that is, the high value zone is adjacent to the high value zone, and the low value zone is adjacent to the low value zone. I<0 indicates a negative autocorrelation of the interprovincial $PM_{2.5}$ in China; that is, the high value zone is adjacent to the low

value zone. I=0 indicates no spatial autocorrelation in the provincial $PM_{2.5}$ in China.

The significance was tested using a standardized statistic, Z, with the following formula:

$$Z = \frac{I - E(I)}{\sqrt{VAR(I)}} \tag{2}$$

In (2), E(I) and VAR(I) are the expected values and variances of Moran's I index, respectively. At a significant level of 5%, if $|Z| > 1.96$, there is a significant spatial autocorrelation.

Anselin (1996, 2002) [20, 21] believes that the Global Moran's I index scatter plot can show the spatial autocorrelation. The first and third quadrants illustrate the positive spatial correlation of the observations. The second and fourth quadrants describe the negative spatial correlation of observations.

2.2. Spatial Regress Models. The spatial panel model mainly includes spatial lag model SLM, spatial error model SEM, and spatial Durbin model SDM (Anselin et al., 2008) [22]. According to Elhorst (2012), the spatial lag model SLM formula is as follows [23]:

$$y_{it} = \delta \sum_{j=1}^{N} w_{ij} y_{jt} + \alpha + x_{it}\beta + \mu_i + \lambda_t + \varepsilon_{it}, \quad i = 1, \ldots, N, \; t = 1, \ldots, T \tag{3}$$

where $y_{it} = (y_{1t}, y_{2t}, y_{3t} \ldots, y_{Nt})^T$ it is an N×1 dimensional vector composed of explanatory variables. $\sum_{j=1}^{N} w_{ij} y_{jt}$ is the interaction effect between the interpreted variable y_{it} and the adjacent elements y_{jt} and w_{ij} are an N×N nonnegative spatial weight matrix. δ is the response parameter of the endogenous interaction effect. α is a constant item. x_{it} is an N × K exogenous explanatory variable matrix. β is the matching response parameter. ε_{it} is an independent identical distribution error term, subject to $(0, \sigma^2)$ distribution. μ_i represents the spatial effect. λ_t is the time fixed effect.

This paper uses two types of spatial weight matrices. One is the traditional binary spatial adjacent matrix, hereinafter referred to as the adjacent matrix.

$$w_{ij} = \begin{cases} 1 & \text{for } i \neq j \text{ and neighboring} \\ 0 & \text{for } i \neq j \text{ and not - neighboring} \\ 0 & \text{for } i = j \end{cases} \tag{4}$$

The other is the distance weight. d_{ij} is the distance between the geographical centers of the two regions.

$$w_{ij} = \begin{cases} \dfrac{1}{d_{ij}^{\,2}} & i \neq j \\ 0 & i = j \end{cases} \tag{5}$$

where d is the distance between the geographical center of the two regions.

The spatial error model, SEM, which describes the spatial disturbance correlation and spatial overall correlation, is given by

$$\begin{aligned} y_{it} &= \alpha + x_{it}\beta + \mu_i + \lambda_t + \phi_{it} \\ \phi_{it} &= \rho \sum_{j=1}^{N} w_{ij}\phi_{it} + \varepsilon_{it} \end{aligned} \tag{6}$$

where ϕ_{it} is the spatial autocorrelation error and ρ is the spatial error correlation coefficient which estimates the degree of influence of the error shock of adjacent units with regard to the dependent variable on the observation value of the unit. The other parameters are the same as defined above.

The spatial Durbin model, SDM, which includes the spatial lag value of the explanatory variables is given by

$$y_{it} = \delta \sum_{j=1}^{N} w_{ij} y_{jt} + \alpha + x_{it}\beta + \sum_{j=1}^{N} w_{ij} x_{ijt}\theta + \mu_i + \lambda_t + \varepsilon_{it} \tag{7}$$

where both θ and β are $K{\times}1$ dimensional parameter vectors. The other parameter implication is the same as above. Due to the introduction of the spatial weight matrix, the spatial econometric may produce endogenous variables. If the ordinary least squares estimation is still used in the spatial econometric model, a bias factor will be produced; thus, the maximum likelihood method is used for estimation.

2.3. Model Specification. To analyze the impact of energy development, technological innovation, and other factors on interprovincial $PM_{2.5}$ in China, the following model was constructed:

$$\begin{aligned} \ln(PM_{2.5it}) = \alpha &+ \beta_1 \ln(Ei_{it}) + \beta_2 \ln(Cs_{it}) \\ &+ \beta_3 \ln(Ppi_{it}) + \beta_4 \ln(Npi_{it}) \\ &+ \beta_5 (\ln Patent) + \beta_6 \ln(Infra_{it}) \\ &+ \beta_7 \ln(Market_{it}) + \varepsilon_{it} \end{aligned} \tag{8}$$

In formula (8), $PM_{2.5}$ is the particulate matter that can enter the lung, or fine particulate matter. Ei is the energy intensity, which is the ratio of the energy consumption of each province to the regional GDP. Cs is the energy structure, which is the proportion of coal consumption in energy consumption. Ppi is the price of energy consumption, which is represented by the producer price index of industrial producer. Npi is the sales revenue of new products of industrial enterprises above the scale. Patent is the amount of patent application authorization. Infra is technological innovation infrastructure that is characterized by internet penetration rate. Market is the turnover of the technology market.

2.4. Data. This article examines 29 provincial administrative regions in mainland China. Due to the lack of data on Tibet and Chongqing, it does not consider Tibet and Chongqing. The sources of the raw data are the 2004–2017 China Statistical Yearbook, China Energy Statistical Yearbook, China Science and Technology Statistical Yearbook, statistical yearbooks of various provinces and districts, and statistical bulletins on the national economic and social development of various provinces and districts over the years. China's monitoring of $PM_{2.5}$ started late, that is, well after

Table 1: Descriptions of all variables in econometric model.

Variable	Unit	Mean	Maximum	Minimum	Std. Dev.	Observation
$PM_{2.5}$	$\mu g/m^3$	37.5951	154.00	2.170	22.5786	406
Ei	Tce/10^4 Yuan	1.194	4.520	0.270	0.705	406
Cs	%	72.776	4518.000	9.810	221.860	406
Ppi	No unit	101.991	125.250	82.410	6.185	406
Npi	10^4 Yuan	27244930	2.87E+08	38551.00	44506476	406
Patent	piece	24258.41	269944.0	70.000	45273.93	406
Infra	%	30.420	77.830	2.150	19.767	406
Market	10^4 Yuan	1518325	39409752	1885.000	4029395	406

Table 2: Correlations analysis and VIF tests.

	VIF	$PM_{2.5}$	*Ei*	*Cs*	*Ppi*	*Npi*	*Patent*	*Infra*	*Market*
$PM_{2.5}$	-	1.000							
Ei	3.7015	-0.3579***	1.000						
Cs	1.0148	-0.0440	0.1386***	1.000					
Ppi	1.4093	-0.4122***	0.3714***	0.0706	1.000				
Npi	6.4635	0.3280***	-0.4463***	-0.0366	-0.2206***	1.000			
Patent	6.9443	0.2866***	-0.4200***	-0.0364	-0.2164***	0.9335***	1.000		
Infra	5.6643	0.4299***	-0.5900***	-0.0857*	-0.5087***	0.5298***	0.5305***	1.000	
Market	1.3815	0.2702***	-0.3164***	-0.0488	-0.1736***	0.2619***	0.3321***	0.4799***	1.000

Note. *, * * * indicates significance at 10% and 1% levels, respectively.

the problem began. Therefore, to acquire $PM_{2.5}$ data, the annual mean value data from 2003 to 2010 was mainly based on the measurement of global aerosol optical depth from satellite-borne equipment operated by a Columbia University research team and the Battle Research Institute (Donkelaar et al. 2010) [24]. The data of the population-weighted average annual $PM_{2.5}$ for all provinces of China from 2003–2010 are also derived from these sources. $PM_{2.5}$ data from 2011–2012 were calculated based on monitoring data from the China Environmental Monitoring Center. The years 2013–2016 are from the China Statistical Yearbook (2014–2017). Referring to Ma et al. (2016), provincial capital data are used instead of provincial data [25]. The descriptive statistics of the relevant variables are shown in Table 1.

The correlation coefficient and multicollinearity test of the variables are shown in Table 2. It can be observed that, in addition to the correlation coefficient between Patent and Npi being as high as 0.9335, other correlation coefficients are lower than 0.6, and some correlation coefficients do not pass the significance test. Using the variance inflation factor VIF to test for multicollinearity, the results show that a VIF greater than 1 is less than 6.95, and the mean is 3.797. Since the VIF values are all less than 10, there is no multicollinearity.

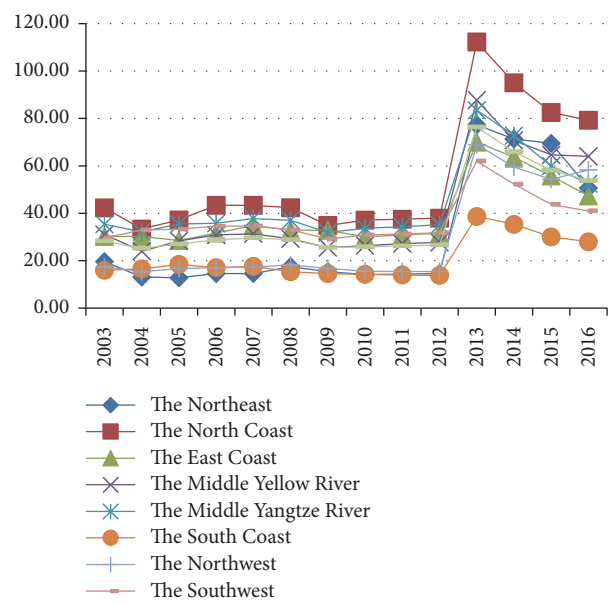

Figure 1: Time change trend of $PM_{2.5}$ in China.

3. Temporal and Spatial Characteristics of Interprovincial $PM_{2.5}$ in China

3.1. Temporal Variation Characteristics of the Interprovincial $PM_{2.5}$. From the perspective of the temporal characteristics, the interprovincial $PM_{2.5}$ in China showed an inverted "N" trend, that is, a slow downward trend before 2012, an upward trend after 2012, a peak after reaching a peak in 2013, and then a downward trend. These trends are in line with China's situation. China's haze pollution showed a major increase in 2013. Since then, the country has committed to the management of haze pollution, and haze pollution has shown a downward trend.

According to the traditional eight regional division methods, the interprovincial $PM_{2.5}$ in China is divided into eight regions (Figure 1). The descriptive statistics of $PM_{2.5}$

Table 3: Descriptions of $PM_{2.5}$.

Region	Mean	Maximum	Minimum	Std. Dev.	Observations
Northeast	29.9595	81.000	7.530	24.8257	42
North Coast	54.1728	154.000	27.700	27.6504	56
East Coast	39.3197	78.000	21.510	16.2013	42
Middle Yellow River	40.6401	108.000	11.430	24.7028	56
Middle Yangtze River	44.1114	94.000	26.870	17.2208	56
South Coast	20.6838	53.000	2.170	12.9610	42
Northwest	29.0419	88.000	12.530	20.8145	56
Southwest	37.1357	96.000	19.360	14.0458	56

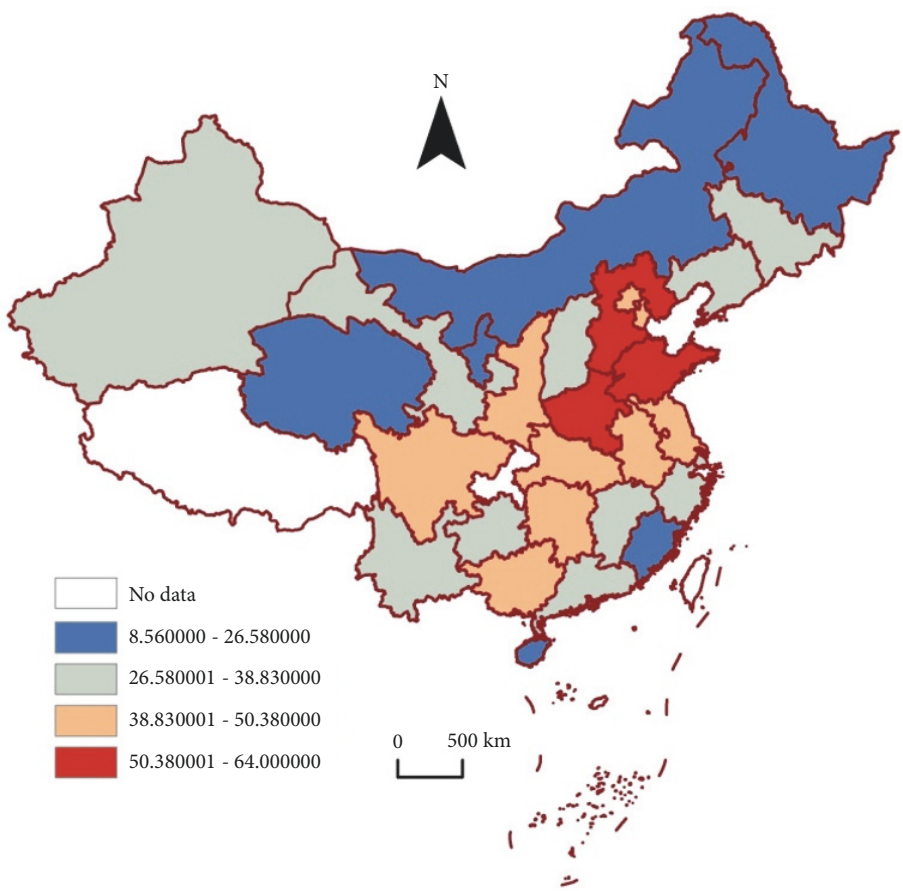

Figure 2: Spatial distribution of $PM_{2.5}$ average value in China.

concentrations in the eight regions are shown in Table 3. The average $PM_{2.5}$ concentrations in the northern coast and middle Yangtze River are higher than the national average. Except for 2009, the average $PM_{2.5}$ concentration in the middle Yellow River is higher than that of the whole country. The mean value of $PM_{2.5}$ in the southern coastal areas is lower than the national average. As presented in Table 3, the average annual $PM_{2.5}$ concentration in China is $37.5951 \mu g/m^3$. In the eight regions, the mean concentration of $PM_{2.5}$ in the northern coast is 54.1728, ranking first. The average concentration of $PM_{2.5}$ in the middle Yangtze River and middle Yellow River was higher than $40 \mu g/m^3$, ranking second and third, respectively. The average concentration of $PM_{2.5}$ in the eastern coast ranks fourth. The mean $PM_{2.5}$ concentrations in these four regions are higher than the national average. The average concentration of $PM_{2.5}$ in the southern coastal areas is the lowest, from low to high, followed by the northwest, northeast, and southwest regions, in that order. The $PM_{2.5}$ concentrations in these four regions are lower than the national average.

3.2. Spatial Differentiation Characteristics of the Interprovincial $PM_{2.5}$

3.2.1. Spatial Distribution Pattern of the Interprovincial $PM_{2.5}$. Using ArcGIS10.2 software, according to the quartile method, the distribution map of $PM_{2.5}$ in China from 2003 to 2016 is plotted (Figure 2).

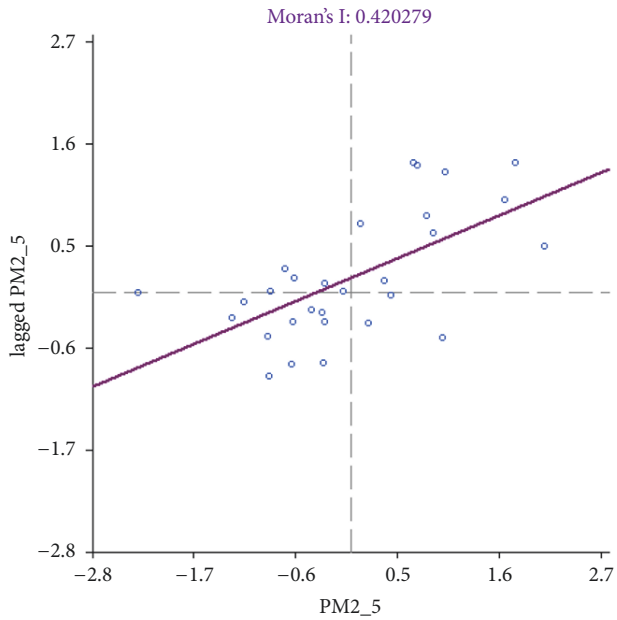

Figure 3: Moran's I index scatter plot of $PM_{2.5}$ average in China.

From low to high, the interprovincial $PM_{2.5}$ average is divided into four levels. The first-level provinces are Hainan, Fujian, Inner Mongolia, Ningxia, Heilongjiang, and Qinghai. The second-tier provinces are Guizhou, Jilin, Gansu, Yunnan, Guangdong, Zhejiang, Xinjiang, Shanghai, Liaoning, Jiangxi, and Shanxi. The third-level provinces are Guangxi, Shaanxi, Hunan, Tianjin, Beijing, Anhui, Hubei, Sichuan, and Jiangsu. The fourth level is Henan, Shandong, and Hebei. It can be observed that the mean values of $PM_{2.5}$ in the northern coast and middle Yellow River are relatively high and that of Guizhou, Yunnan, and the northeast in the south coast and southwest regions are relatively low. The interprovincial $PM_{2.5}$ in China shows a trend of high and low in the east, and there is a spatial agglomeration.

3.2.2. Global Spatial Autocorrelation Analysis of the Interprovincial $PM_{2.5}$. By using GeoDA9.5 software and rook neighboring, Moran's I index of the interprovincial $PM_{2.5}$ average value in China from 2003 to 2016 is 0.4203. After 999 permutations, the P value is 0.0020, and the normal statistic Z value is 3.6473, which is larger than the critical value 1.96 of the normal distribution function at the 0.05 significant level and indicates that the interprovincial $PM_{2.5}$ average value spatial autocorrelation is significant.

Moran's I index scatter plot is used to further examine the state of spatial agglomeration (Figure 3). The first quadrant is the H–H agglomeration. Ten provinces and autonomous regions, namely, Hebei, Shaanxi, Shandong, Henan, Jiangsu, Beijing, Tianjin, Anhui, Hubei, and Shanxi, are in this quadrant, account for 34.48% of all the investigated provinces, and are mainly located in the north coast and middle Yellow River. The third quadrant is the L–L agglomeration. Ten provinces and autonomous regions, namely, Inner Mongolia, Fujian, Guangdong, Zhejiang, Shanghai, Gansu, Ningxia, Heilongjiang, Jilin, and Xinjiang, are in this quadrant, together with Hainan, which spans the second and third quadrants and accounts for 37.93% of all the provinces. These provinces are mainly located in the southern coast, the eastern coast, and the northeast. The second quadrant is L–H, with five provinces and regions in Jiangxi, Liaoning, Yunnan, Guizhou, and Qinghai, and Hainan. The fourth quadrant is an agglomeration of H–L, and Sichuan, Hunan, and Guangxi are located in this quadrant. In general, the proportion of provinces with the same spatial autocorrelation in the H–H and L–L quadrants is 72.41%. In the L–H quadrant and the H–L quadrant, the provinces with different spatial autocorrelations accounted for only 31.03%. Based on these results, it can be observed that the interprovincial PM2.5 regional integration in China is significant.

4. Empirical Research

Based on the spatial agglomeration of $PM_{2.5}$, the spatial econometric model is used to analyze the impact of energy development and technological innovation on $PM_{2.5}$.

4.1. Spatial Diagnostic Test. In Section 2, as aforementioned, there are generally three types of spatial panel models. To determine which model to use, a nonspatial interaction model is used for spatial diagnostic tests based on the model selection mechanism proposed by Anselin (2005) [26]. The results are shown in Table 4. For the adjacent weights, the LM-lag and LM-error tests show that both the hypothesis of no spatially lagged dependent variable and the hypothesis of no spatially auto-correlated error term must be rejected at 1% significance. The time fixed effect did not pass the robust LM-lag test. The spatial fixed effect did not pass the significance test of robust LM-error. According to Elhorst (2014) [27], the spatial Durbin panel model was chosen. The measurement method is the maximum likelihood estimation proposed by Elhorst (2003) [28].

For the distance weight, the LM-lag and LM-error tests show that both the hypothesis of no spatially lagged dependent variable and the hypothesis of no spatially auto-correlated error term must be rejected at 1% significance. The robust LM-lag test shows that the pooled OLS and time fixed effects do not pass the significance test. Similar to the robust LM-error test, only the pooled OLS passes the significance test; thus, the spatial Durbin panel model is chosen in the same way as the adjacent weights. The LR test is used to select the fixed effects. The results indicate that at the 1% level of significance the null hypothesis that the spatial fixed effects are jointly insignificant must be rejected. Similarly, the null hypothesis that the time-period fixed effects are jointly insignificant must be rejected. According to Baltagi (2005) [29], the two-way fixed effects model is selected, which is also known as the two-way fixed effects model.

4.2. Empirical Analysis. The results of the spatial Durbin model with two-way fixed effects are shown in Table 5. The Wald and LR tests of the two weights show that at the 1% level of significance, the null hypothesis of the spatial Durbin

Table 4: Estimation results of nonspatial panel model.

Variables	Pooled OLS	Spatial fixed effects	Time-period fixed effects	two-way fixed effects
		Adjacent weight		
Intercept	11.5064*** (0.0000)	—	—	—
ln *Ei*	0.3473*** (0.0001)	-1.1951*** (0.0000)	0.5160*** (0.0000)	0.3958*** (0.0078)
ln *Cs*	0.2146*** (0.0037)	0.1257* (0.0722)	0.0781(0.1749)	0.0851** (0.0395)
ln *Ppi*	-2.5530*** (0.0000)	-2.3159*** (0.0000)	-1.1728* (0.0781)	-1.2583*** (0.0009)
ln *Npi*	-0.0179(0.6843)	-0.1685*** (0.0009)	0.1261*** (0.0006)	-0.1664*** (0.0000)
ln *Patent*	0.2509*** (0.0000)	0.2093*** (0.0015)	0.1263*** (0.0024)	-0.0204(0.6597)
ln *Infra*	-0.0352(0.4382)	-0.2274*** (0.0007)	-0.3931*** (0.0000)	0.0364(0.5603)
ln *Market*	0.0776*** (0.0017)	-0.0598(0.1106)	0.1053*** (0.0000)	-0.0565** (0.0112)
R^2	0.4091	0.4705	0.4592	0.1661
LM-lag	201.7888*** (0.000)	340.0601*** (0.000)	70.4194*** (0.000)	66.6052*** (0.0000)
Robust LM-lag	4.6368** (0.031)	36.9528*** (0.000)	1.2878(0.256)	60.7071*** (0.0000)
LM-error	219.8807*** (0.000)	303.1079*** (0.000)	82.2136*** (0.000)	39.3528*** (0.0000)
Robust LM-error	22.7288*** (0.000)	0.0006(0.980)	13.0820*** (0.000)	33.4547*** (0.0000)
		Distance weight		
Intercept	11.5064*** (0.0000)	—	—	—
ln *Ei*	0.3473*** (0.0001)	-1.1951*** (0.0000)	0.5160*** (0.0000)	0.3958*** (0.0078)
ln *Cs*	0.2146*** (0.0037)	0.1257* (0.0722)	0.0781*** (0.1749)	0.0851** (0.0395)
ln *Ppi*	-2.5530*** (0.0000)	-2.3159*** (0.0000)	-1.1728*** (0.0000)	-1.2583*** (0.0009)
ln *Npi*	-0.0179(0.6843)	-0.1685*** (0.0009)	0.1261*** (0.0006)	-0.1664*** (0.0000)
ln *Patent*	0.2509*** (0.0000)	0.2093*** (0.0015)	0.1263*** (0.0024)	-0.0204(0.6597)
ln *Infra*	-0.0352(0.4382)	-0.2274*** (0.0007)	-0.3931*** (0.0000)	0.0364(0.5603)
ln *Market*	0.0776*** (0.0017)	-0.0598(0.1106)	0.1053*** (0.0000)	-0.0565** (0.0112)
R^2	0.4091	0.4705	0.4592	0.1661
LM-lag	102.2239*** (0.000)	323.1789*** (0.000)	13.6513*** (0.000)	35.8038*** (0.000)
Robust LM-lag	0.6919(0.406)	46.2787*** (0.0000)	1.1820(0.277)	10.4315*** (0.001)
LM-error	136.6806*** (0.0000)	276.9055*** (0.0000)	12.9372*** (0.0000)	27.6293*** (0.000)
Robust LM-error	35.1486*** (0.0000)	0.0053(0.942)	0.4678(0.0494)	2.2570(0.133)
	Fixed effects	Statistics	DOF	P value
LR-test	Spatial fixed effects	538.5783	29	0.0000
	Time-period fixed effects	441.7073	14	0.0000

Note. *, **, * * * indicates significance at 10%, 5%, and 1% levels, respectively.

model SDM into the spatial lag model SLM is rejected, and the spatial Durbin model SDM is also rejected as the spatial error model SEM; therefore, a spatial Durbin model SDM is used. The estimated value of the Hausman test of the adjacent weight is 95.6264, the degree of freedom is 15, and the value of P is 0. Therefore, the random effect is rejected, and the two-way fixed effect model is used. Elhorst (2014) indicated that the coefficients of the spatially lagged dependent variable and independent variables are quite sensitive to bias corrections. Therefore, in the following analysis of adjacent weights, the two-way fixed effect model with bias correction is selected (the third column of data in Table 4). The estimated value of the distance weight Hausman test is 60.0659, the degree of freedom is 15, and the value of P is 0. Therefore, the model also rejects the random effect and selects the bi-directional fixed effect model. That is, distance weights are used to describe the third column of the second half of Table 5.

Comparing the estimation results in Tables 5 and 4, it can be observed that the R^2 of the noninteractive effect model is smaller whether it is the adjacent weight or the distance weight. The noninteractive effect of an adjacent weight and distance weight two-way fixed model R^2 are both 0.1661. The two-way fixed effect of the spatial Durbin model R^2 is 0.9398, and the distance weight error correction two-way fixed effect Durbin model R^2 is 0.9297. This paper illustrates that the use of a spatial Durbin model to analyze the impact of energy development and technical innovation on $PM_{2.5}$ is reasonable. The spatial auto-regression coefficients of adjacent weights and distance weights are 0.4268 and 0.5168, respectively; all pass the 1% level significance test, indicating that the $PM_{2.5}$ of adjacent regions have a positive impact on local region. A decrease of one percentage point in $PM_{2.5}$ in adjacent regions results in a decrease in $PM_{2.5}$ in this area by 0.4268, 0.5168 percentage points, respectively. $PM_{2.5}$ has a spatial spillover effect. This is consistent with the robust LM test of the spatial autocorrelation of Table 4. Additionally, the auto-regression coefficient of the distance weights is significantly larger than the adjacent weight because the

Table 5: Estimation results of spatial Durbin model.

Variables	Two-way fixed effects	Two-way fixed effects (with bias correction)	Random spatial effects and time-period fixed effects
		Adjacent weight	
δ	0.3679*** (0.0000)	0.4268*** (0.0000)	0.4329*** (0.0000)
ln *Ei*	0.1058(0.4343)	0.0980(0.4896)	0.0411(0.7629)
ln *Cs*	0.0899*** (0.0089)	0.0880** (0.0147)	0.0882** (0.0143)
ln *Ppi*	-1.0526*** (0.0018)	-1.0389*** (0.0003)	-1.0866*** (0.0021)
ln *Npi*	-0.1079*** (0.0000)	-0.1043*** (0.0002)	-0.0893*** (0.0015)
ln *Patent*	0.0626(0.1363)	0.0657(0.1356)	0.0905** (0.0310)
ln *Infra*	0.0410(0.4668)	0.0454(0.4419)	0.0467(0.4255)
ln *Market*	-0.0452** (0.0170)	-0.0439** (0.0000)	-00471** (0.0161)
$W*$ ln *Ei*	1.0147*** (0.0004)	0.9882*** (0.0010)	0.4913* (0.0676)
$W*$ ln *Cs*	0.0696(0.2970)	0.0608(0.3844)	0.0434(0.5334)
$W*$ ln *Ppi*	-0.4512(0.4771)	-0.3386(0.6104)	-0.5460(0.4074)
$W*$ ln *Npi*	-0.1558*** (0.0076)	-0.1414** (0.0206)	-0.0786(0.1850)
$W*$ ln *Patent*	-0.3095*** (0.0000)	-0.3052* (0.0000)	-0.2093*** (0.0016)
$W*$ ln *Infra*	-0.2437** (0.0474)	-0.2467* (0.0557)	-0.2543** (0.0463)
$W*$ ln *Market*	-0.0869** (0.0252)	-0.0802** (0.0486)	-0.0864** (0.0312)
Teta	—	—	0.0701*** (0.0000)
R^2	0.9391	0.9398	0.8902
log-likelihood	141.4070	141.4070	-840.5862
Wald spatial lag	71.8978*** (0.000)	61.5451*** (0.000)	46.1114*** (0.000)
LR spatial lag	67.7774*** (0.000)	67.7774*** (0.000)	—
Wald spatial error	87.6175*** (0.000)	75.3315*** (0.000)	54.5307*** (0.000)
LR spatial error	81.6844*** (0.000)	81.6844*** (0.000)	—
Hausman test	Statistics	*DOF*	*P* value
	95.6264	15	0.0000
		Distance weight	
Δ	0.4449*** (0.0000)	0.5168*** (0.0000)	0.4399*** (0.0000)
ln *Ei*	0.4862*** (0.0000)	0.4867*** (0.0011)	0.3066** (0.0245)
ln *Cs*	0.0752** (0.0421)	0.0737* (0.0570)	0.0795** (0.0426)
ln *Ppi*	-0.8146** (0.0282)	-0.7859** (0.0431)	-1.1188*** (0.0030)
ln *Npi*	-0.1472*** (0.0000)	-0.1441*** (0.0000)	-0.1198*** (0.0000)
ln *Patent*	0.0152(0.7189)	0.0160(0.7184)	0.0646(0.1287)
ln *Infra*	0.0163(0.7785)	0.0203(0.7379)	0.0219(0.7171)
ln *Market*	-0.0591*** (0.0006)	-0.0579*** (0.0057)	-0.0492** (0.0187)
$W*$ ln *Ei*	-0.4203(0.2145)	-0.4437(0.2106)	-0.5212* (0.0864)
$W*$ ln *Cs*	0.3411* (0.0764)	0.3277(0.1039)	0.3314(0.1030)
$W*$ ln *Ppi*	-1.0727(0.1067)	-0.9562(0.1689)	-0.0258(0.9525)
$W*$ ln *Npi*	-0.2430*** (0.0013)	-0.2238*** (0.0046)	-0.1340* (0.0685)
$W*$ ln *Patent*	-0.2628** (0.0210)	-0.2619** (0.0280)	-0.0715(0.5086)
$W*$ ln *Infra*	-0.2226(0.1075)	-0.2215(0.1261)	-0.0901(0.5263)
$W*$ ln *Market*	-0.0024(0.9589)	0.0021(0.9653)	-0.0085(0.8572)
teta	—	—	0.0782*** (0.0000)
R^2	0.9287	0.9297	0.8679
log-likelihood	105.4847	105.4847	-649.7897
Wald spatial lag	24.3571*** (0.0000)	20.5623*** (0.0045)	9.7989(0.2003)
LR spatial lag	23.2803*** (0.0015)	23.2803*** (0.0015)	—
Wald spatial error	33.2143*** (0.0000)	28.4091*** (0.0000)	14.7569** (0.0392)
LR spatial error	30.2017*** (0.0000)	30.2017*** (0.0000)	—
Hausman test	Statistics	*DOF*	*P* value
	60.0659	15	0.0000

Note. *, **, *** indicates significance at 10%, 5%, and 1% levels, respectively.

Table 6: Decomposition estimates of the direct, indirect, and total effects.

Variables	Direct effect	Indirect effect	Total effect
		Distance weight	
ln *Ei*	0.2323(0.1155)	1.6573*** (0.0010)	1.8896*** (0.0006)
ln *Cs*	0.1012** (0.0158)	0.1616(0.1815)	0.2628* (0.0718)
ln *Ppi*	-1.1418*** (0.0062)	-1.2932(0.2219)	-2.4350* (0.0507)
ln *Npi*	-0.1285*** (0.0003)	-0.3058*** (0.0055)	-0.4343*** (0.0012)
ln *Patent*	0.0270(0.5692)	-0.4464*** (0.0006)	-0.4194*** (0.0040)
ln *Infra*	0.0153(0.7962)	-0.3766* (0.0806)	-0.3613(0.1181)
ln *Market*	-0.0560** (0.0183)	-0.1605** (0.0250)	-0.2165** (0.0136)
		Adjacent weight	
ln *Ei*	0.4738*** (0.0059)	-0.3154(0.6591)	0.1584(0.8446)
ln *Cs*	0.1243** (0.0180)	0.7165* (0.0894)	0.8408* (0.0663)
ln *Ppi*	-0.9929** (0.0159)	-2.6540** (0.0396)	-3.6469** (0.0114)
ln *Npi*	-0.1819*** (0.0000)	-0.5782*** (0.0011)	-0.7601*** (0.0001)
ln *Patent*	-0.0189(0.6949)	-0.5025** (0.0443)	-0.5214* (0.0559)
ln *Infra*	-0.0126(0.8562)	-0.4191(0.1590)	-0.4317(0.2006)
ln *Market*	-0.0595** (0.0164)	-0.0442(0.6603)	-0.1037(0.3700)

Note. *, **, * * * indicates significance at 10%, 5%, and 1% levels, respectively.

spillover of $PM_{2.5}$ is related to the geographical location. Even when not geographically adjacent, a certain area affects other areas. Therefore, this paper uses two types of weight matrix, namely, the adjacent weight and distance weight, to analyze the spatial spillover effect of provincial $PM_{2.5}$ in China in order to reflect the objective reality comprehensively and accurately.

Since the significance of each variable estimation coefficient in the nonspatial model is not the same as in the spatial econometric model, the coefficient in Table 5 cannot be compared with the Table 4. LeSage and Pace (2009) believe that direct and indirect effects explain the true spatial spillover effect of each variable. Therefore, this paper decomposes the direct and indirect effects of explanatory variables. The results are shown in Table 6. Due to the feedback effect, the direct effects of the variables in Table 6 are different than in Table 5. Elhorst (2014) believes that the feedback effect is partly due to the coefficient estimate of the spatially lagged dependent variable and partly to the coefficient of the spatially lagged value of the explanatory variable itself. The decomposition result of the adjacent weight is better than the distance weight, and the coefficient signs are roughly the same. Therefore, the results of the adjacent weights are used for analysis.

The direct effect of energy intensity is positive, but it has not passed the significance test, indicating that the positive effect of energy intensity on haze pollution in the region is not obvious. The indirect effects and total effects of energy intensity are significantly positive. The increase in energy intensity will significantly increase the concentration of $PM_{2.5}$ in adjacent areas, and subsequently increase the global $PM_{2.5}$ concentration. The direct effects and total effects of energy structure are significantly positive. The increase in the proportion of coal consumption increases the $PM_{2.5}$ concentration in the region and globally. The proportion of coal consumption increase 1 percentage will increase the $PM_{2.5}$ concentration in the region by 0.1012 percentage points and increase the global $PM_{2.5}$ concentration by 0.2628 percentage points. Therefore, in order to reduce $PM_{2.5}$ concentrations, China should reduce the proportion of coal consumption.

The direct effect and total effect of energy consumption price are significantly negative. The increase in energy consumption price decreases the $PM_{2.5}$ concentration in the region and globally. The energy consumption price increase 1 percentage will reduce the concentration of $PM_{2.5}$ in the region by 1.1418 percentage points and reduce the global $PM_{2.5}$ concentration by 2.4350 percentage points. It shows that the rise of energy consumption price can effectively reduce the $PM_{2.5}$ concentration. The direct, indirect, and total effects of the sales revenue of new products of industrial enterprises are significantly negative. The increase in sales revenue of new products will reduce the concentration of $PM_{2.5}$ in the region by 0.1285 percentage points, reduce the concentration of $PM_{2.5}$ in adjacent regions by 0.3058 percentage points, and reduce the global $PM_{2.5}$ concentration by 0.4343 percentage points. It shows that the sales revenue of new products of industrial enterprises has achieved remarkable results in reducing $PM_{2.5}$ concentration. The indirect effects and total effects of patents are significantly negative. The increase in the number of patent applications granted in the region will reduce the $PM_{2.5}$ concentration of the adjacent regions and globally. The indirect effect of Infra is significantly negative, indicating that the increase in infrastructure for technological innovation in the region will reduce the concentration of $PM_{2.5}$ in adjacent areas. The direct, indirect, and total effects of the turnover of the technology market are significantly negative. The increase in the turnover of the technology market will not only reduce the concentration of $PM_{2.5}$ in the region but also the concentration of $PM_{2.5}$ in the adjacent region through the spillover effect, significantly reducing Global $PM_{2.5}$ concentration.

Therefore, in order to reduce $PM_{2.5}$ concentration, it is necessary to increase the number of patent applications granted, expand technological innovation infrastructure and increase turnover of the technology market in China.

5. Conclusion and Policy Implications

This paper uses the panel data of 29 provinces and regions in China (excluding Tibet and Chongqing) to analyze the spatial and temporal characteristics of $PM_{2.5}$. The spatial Durbin model is used to empirically examine the impact of energy development and technological innovations on $PM_{2.5}$. The following are the main findings of this research.

From the perspective of temporal characteristics, the interprovincial $PM_{2.5}$ in China shows an inverted "N" trend. The average concentrations of $PM_{2.5}$ in the northern coast, middle Yangtze River, middle Yellow River, and eastern coast are higher than the national average. The average concentrations of $PM_{2.5}$ in the south coast, northwest, northeast, and southwest regions are lower than the national average. The interprovincial $PM_{2.5}$ in China is high in the east and low in the west, and a spatial agglomeration is observed. The $PM_{2.5}$ has a significant autocorrelation, and the regional integration trend is significant. The spatial autoregression coefficients of adjacent weights and distance weights are significantly positive, and haze pollution in adjacent regions has a positive impact on local region. There is a spatial spillover effect of interprovincial $PM_{2.5}$ in China. The indirect effects and total effects of Energy intensity are significantly positive. The increase in energy intensity will significantly increase the concentration of $PM_{2.5}$ in adjacent areas, and subsequently increase the global $PM_{2.5}$ concentration. The direct effects and total effects of Energy structure are significantly positive. The increase in the proportion of coal consumption increases the $PM_{2.5}$ concentrations in the region and globally. The direct effect and total effect of energy consumption price are significantly negative. The increase in energy consumption price reduces the $PM_{2.5}$ concentration in the region and globally. The direct, indirect, and total effects of the sales revenue of new products of industrial enterprises are significantly negative. The increase in sales revenue of new products in local region will reduce the concentration of $PM_{2.5}$ in the region by 0.1285 percentage points and that in adjacent regions by 0.3058 percentage points, which will reduce the global $PM_{2.5}$ concentration by 0.4343 percentage points. The indirect effects and total effects of patents are significantly negative. The increase in the number of patent applications granted in the region will reduce the $PM_{2.5}$ concentrations of the adjacent regions and globally. The indirect effect of Infra is significantly negative, indicating that the increase in infrastructure for technological innovation in the region will reduce the concentration of $PM_{2.5}$ in the adjacent areas. The direct, indirect, and total effects of the turnover of the technology market are significantly negative. The increase in the turnover of the technology market will not only reduce the concentration of $PM_{2.5}$ in the region but also reduce the concentration of $PM_{2.5}$ in the adjacent region through the spillover effect, significantly reducing global $PM_{2.5}$ concentration.

Based on the main findings of this study, this paper proposes the following recommendations for China. First, continue to promote the regional collaborative management of $PM_{2.5}$. Based on the spatial spillover effect of $PM_{2.5}$, the control of $PM_{2.5}$ requires joint prevention [7]. After the outbreak of smog pollution, the Chinese government implemented strong measures to control haze pollution, including joint prevention and control of the Beijing–Tianjin–Hebei region. The inverted "N" curve of China's $PM_{2.5}$ indicates that these governance measures are effective. Additionally, continue to promote regional collaborative governance and form a joint force to control haze pollution. The concentrations of $PM_{2.5}$ in the southern coastal and southwest regions are relatively low, and these regions can work together to consolidate existing achievements and present these positive effects throughout the country. The concentrations of $PM_{2.5}$ in the northern coastal areas and the middle Yellow River are relatively high. The provinces and regions within these regions must negotiate, cogovern, work together, share resources and information, and reduce their respective concentrations of $PM_{2.5}$.

Secondly, reduce energy intensity [30]. An increase in energy intensity will increase the concentration of $PM_{2.5}$; thus, it is necessary to increase energy efficiency and reduce energy intensity through technological innovations, that is, directly by reducing the concentration of $PM_{2.5}$ and indirectly by improving the level of technological innovation, to reduce $PM_{2.5}$ pollution. Taxation and other economic means will encourage enterprises to carry out technological transformations to improve their technological level and reduce energy intensity; research and develop clean technologies; implement clean production processes; and eradicate the generation and emission of $PM_{2.5}$ from the source.

Again, optimize energy structure and implement energy substitution. An increase in the proportion of coal consumption increases the concentration of $PM_{2.5}$ in the region and globally. Therefore, China should reduce its proportion of coal consumption and optimize its energy structure. Although the rapid reduction of China's coal consumption is a difficult task in the short term, it is possible to manage the pollution control of bulk coal by formulating coal quality standards, using gasification and purification methods to generate electricity, and employing liquid fuels to utilize coal in a cleaner manner [31]. Additionally, as soon as possible, achieve coal-fired power generation on behalf of coal while improving coal quality, reducing the use and supply of coal, optimizing its energy consumption structure, increasing the ratio of clean energy and renewable energy, implementing energy alternatives, supporting the development of new energy, and promoting the consumption of new energy.

Thirdly, increase energy prices. The consumption of energy is in line with the law of demand, that is, an increase in energy prices will reduce energy consumption and, subsequently, reduce $PM_{2.5}$ concentrations. At present, the price of energy in China is low, and this price distortion does not reflect the cost of energy. This phenomenon is one of the reasons for the high energy consumption in China. Therefore, China should completely change the phenomenon of lower energy prices and play a regulatory role in the

market mechanism: the price should reflect the cost of energy use [32, 33]. Along with the overall advancement of China's resource tax reform, China must speed up the implementation of environmental protection tax legislation, establish an environmental tax system, and realize the combined effect of resource taxes, energy taxes, and environmental taxes.

Finally, improve the level of technological innovation. As mentioned, the sales revenue of new products of industrial enterprises, patent, turnover of the technology market, and other factors can directly or indirectly reduce the concentration of $PM_{2.5}$, and technological innovation is an effective method of reducing $PM_{2.5}$. Therefore, China must seize the opportunity to build an innovative country, enhance disruptive technological innovation, and improve the level of technological innovation. China can learn from the literature on developed countries and consider effective and advanced governance technology that can be absorbed and reformed and applied to China's $PM_{2.5}$ governance [34]. Talent is the basis of technological innovation; thus, it is possible to increase technological innovation personnel through incentive measures. Efficiency improves the level of technological innovation and the capital scale of technological innovation. Technological innovation requires financial support; thus, the financing channels for technological innovation must be broadened. Additionally, expanding the scale of technological innovation capital also promotes the expansion of technological innovation and production scale.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares that they have no conflicts of interest.

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