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Analysis of Regional Differences in Energy-Related $PM_{2.5}$ Emissions in China: Influencing Factors and Mitigation Countermeasures

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Abstract: China's rapid economic development has resulted in a series of serious environmental pollution problems, such as atmospheric particulate pollution. However, the socioeconomic factors affecting energy-related $PM_{2.5}$ emissions are indistinct. Therefore, this study first explored the change in $PM_{2.5}$ emissions over time in China from 1995 to 2012. Then the STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) model was adopted for quantitatively revealing the mechanisms of various factors on energy-related $PM_{2.5}$ emissions. Finally, the Environmental Kuznets Curve (EKC) hypothesis was adopted to examine whether an EKC relationship between affluence and energy-related $PM_{2.5}$ emissions is present from a multiscale perspective. The results showed that energy-related $PM_{2.5}$ emissions in most regions showed an increasing trend over the study period. The influences of the increase in population, energy intensity, and energy use mix on energy-related $PM_{2.5}$ emissions were positive and heterogeneous, and population scale was the major driving force of energy-related $PM_{2.5}$ emissions. The effects of the increase in the urbanization level and the proportion of tertiary industry increased value to GDP on energy-related $PM_{2.5}$ emissions varied from area to area. An inverse U-shape EKC relationship for energy-related $PM_{2.5}$ emissions was not verified except for eastern China. The conclusions are valuable for reducing $PM_{2.5}$ emissions without affecting China's economic development.

Keywords: energy-related $PM_{2.5}$ emissions; STIRPAT model; influence factors; Environmental Kuznets Curve

1. Introduction

The rapid advancement of China's industrialization has led to a deterioration of air quality in China. Severe air pollution has spread from developed regions, especially in the developed eastern provinces, to the whole country. The frequency of hazy weather showed a significant upward trend, and air pollution has increasingly become a core issue that constrains sustainable development and ecologically friendly urban development [1,2]. Therefore, effective control of pollutant emissions and effective improvement of urban environmental air quality have become important targets for the Chinese government [3]. Fine particulate matter ($PM_{2.5}$) can not only be suspended in the air, but also generates new pollutants through chemical reactions and reduces atmospheric visibility [4]. In addition, $PM_{2.5}$ pollution can seriously affect human health [5–7]. Many medical studies have shown that long-term exposure to air containing $PM_{2.5}$ can cause respiratory diseases and cardiovascular diseases, damage the body's immune system, and increase the risk of death in exposed populations [8–11]. The number of premature deaths per year in China due prolonged exposure to polluted air exceeds 1.25 million [12]. In the winter of 2013, the maximum concentration of $PM_{2.5}$ in Beijing exceeded 1000 μg/m^3 [13]. Therefore, the $PM_{2.5}$ pollution problem has increasingly become the focus of China's air pollution prevention and control, and is also one of the hotspots of atmospheric environment research.

Many scholars have carried out a large number of studies on $PM_{2.5}$ pollution in recent years. The research has mainly focused on the transboundary diffusion of $PM_{2.5}$ [14–16], the health effects of $PM_{2.5}$ [17–20], source analysis of $PM_{2.5}$ pollutants [21–24], simulation of $PM_{2.5}$ concentration [25–28], spatiotemporal changes and patterns of $PM_{2.5}$ pollution [29–31], contributing factors analysis of $PM_{2.5}$ concentration [32–35], establishing a $PM_{2.5}$ emissions inventory [36,37], and determining the dispersion of PM [38–40]. Total pollutant discharge control is a measure for environmental management, so reducing $PM_{2.5}$ emissions will be a commendable means of preventing $PM_{2.5}$ pollution. In 2012, new air quality standards were formulated, and $PM_{2.5}$ concentration was listed as a routine key environmental monitoring index for the first time. In 2013, the Chinese government published 10 air pollution control measures to cope with serious and persistent $PM_{2.5}$ pollution. The Chinese government is also trying to expand the scope of air quality monitoring. The monitoring sites for $PM_{2.5}$ concentration have increased from 612 in 2013 to 1436 in 2016. After that, a couple of studies tried to quantify the socioeconomic factors contributing to $PM_{2.5}$ emissions and reveal the dynamic relationship between these variables in recent years. For instance, Guan et al. [41] adopted the input-output method and the structural decomposition analysis (SDA) method to quantify influencing factors on China's primary $PM_{2.5}$ discharge from 1997 to 2010. Meng et al. [42] applied an input-output model for revealing the influence of trade contributing to primary PM discharge in Beijing. Lyu et al. [43] employed the Logarithmic Mean Divisia Index (LMDI) method for exploring the major driving force of primary $PM_{2.5}$ discharge from 1997 to 2012 in China. Xu et al. [44] applied the SDA method for identifying the socioeconomic factors contributing to China's primary air pollutant discharge.

The concept of the Environmental Kuznets Curve (EKC) hypothesis is that environmental quality initially deteriorates with economic growth, and then increases as economic development reaches a certain level. In recent years, this hypothesis has been used to empirically study the relationship between environmental quality and per capita income. For instance, the EKC hypothesis was applied by Brajer et al. [45] to test whether air pollution presented an inverted-U-type EKC relationship with economic growth. The EKC hypothesis for CO_2 and SO_2 emissions' relationship with economic growth in the United Kingdom was verified by Fosten et al. [46]. In Malaysia, the EKC hypothesis for carbon dioxide emissions' correlation with increasing income was discovered by Saboori et al. [47]. Shahbaz et al. [48] discovered evidence supporting an inverted-U-shaped nexus between financial development and carbon dioxide emissions. Hao et al. [49] verified an inverted-U-shaped EKC relationship for $PM_{2.5}$ concentrations in 73 Chinese cities with economic growth. The research by Wang et al. [50] confirmed that sulfur dioxide emissions had an inverted-U-shaped link with economic growth. The EKC hypothesis for three pollutant emissions (carbon dioxide, industrial wastewater, and industrial waste solid) in China was examined by Li et al. [51] and the results approved this hypothesis. Chen et al. [52] applied the EKC hypothesis to explore the nexus between affluence and Air Pollution Index (API) in China.

In summary, there are still some limitations in the existing literature. Firstly, the input-output method, the SDA method, and the LMDI method are often used in the existing research, but the econometric analysis method is seldom used. Secondly, there are few papers analyzing the factors contributing to $PM_{2.5}$ discharge, especially about the regional differences in China's energy-related $PM_{2.5}$ emissions influencing factors. Thirdly, although a lot of researchers have studied the EKC relationship between pollution and economic development, this paper is different because it examines primary $PM_{2.5}$ emissions for the first time. The main contributions of this study are: (1) filling the gap in that the econometric analysis method is seldom used to reveal the influencing factors of energy-related $PM_{2.5}$ emissions. It can also be regarded as an example of using the STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) model to examine the influencing factors of energy-related $PM_{2.5}$ emissions. (2) The EKC hypothesis is used to study the relationship between energy-related $PM_{2.5}$ emissions and GDP for the first time, and this paper contributes to the empirical literature. (3) The study can improve the public's understanding of the changes of $PM_{2.5}$ emissions with economic growth, which is valuable for harmonizing economic growth and $PM_{2.5}$ emissions reduction.

This paper has three main objectives: (1) exploring the change in $PM_{2.5}$ emissions over time; (2) revealing quantitatively the influencing factors of energy-related $PM_{2.5}$ discharge from a multiscale perspective; (3) examining whether an EKC relationship between affluence and energy-related $PM_{2.5}$ emissions is present from a multiscale perspective.

2. Research Area and Data

2.1. Research Area

In order to analyze the socioeconomic factors affecting energy-related $PM_{2.5}$ emissions from different scales, two research areas with different administrative scales were chosen in this paper. Mainland China was the first research area (Figure 1). With the start of Chinese economic reform in 1978, China's economy underwent rapid development that resulted in a series of serious environmental problems and massive energy-related $PM_{2.5}$ emissions. However, the influence mechanism of socioeconomic factors contributing to energy-related $PM_{2.5}$ emissions is still ill-defined. The eastern region, central region, and western region were together chosen as the second research area. Due to natural conditions and policy factors, eastern China took the lead in development and formed a relatively complete industrial economic system, while the development of central and western China was relatively slow, which makes China's regional economic development imbalanced. Regional differences in China are becoming more and more prominent, mainly in the following three aspects: (1) the difference in regional economic development level; (2) the difference in regional economic structure; (3) the difference in per capita income level. Different regions inevitably have different socioeconomic factors contributing to energy-related $PM_{2.5}$ emissions.

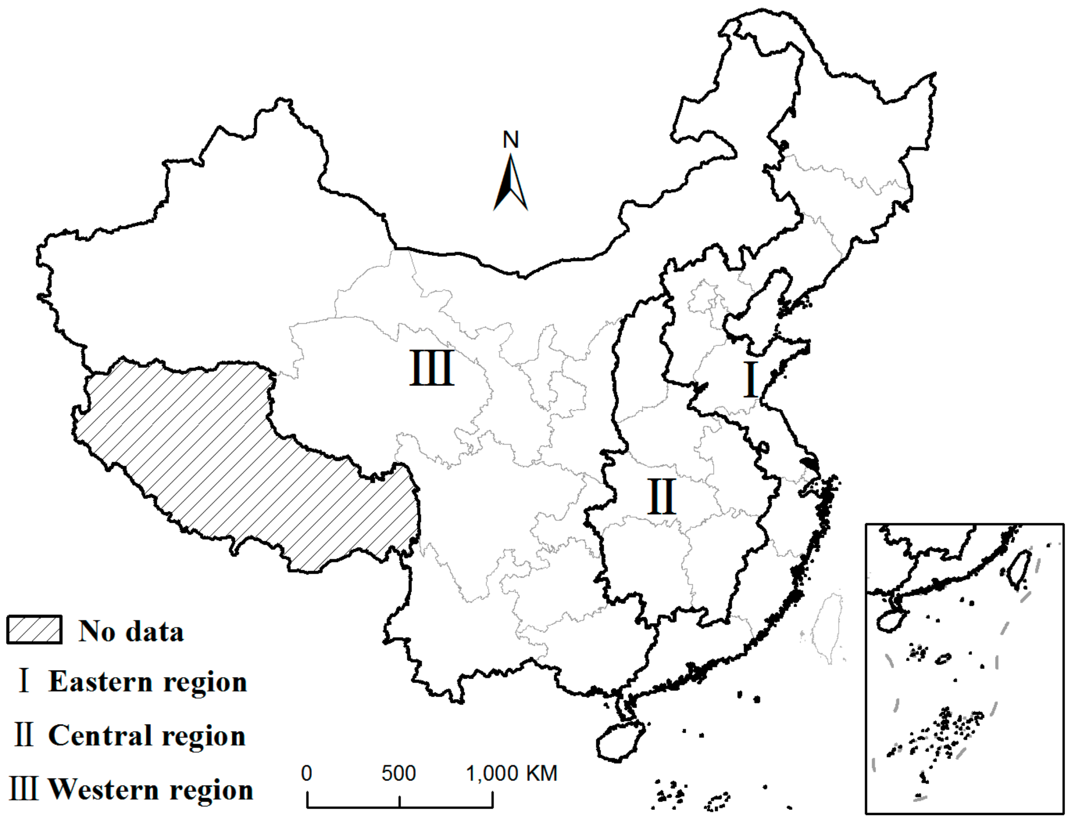

Figure 1. The spatial distribution of the research areas.

2.2. Data Sources

Based on data availability, this study selected the time series dataset of 30 provinces in China in 1995–2012, excluding Hong Kong, Macao, Taiwan, and Tibet. The provincial primary energy-related $PM_{2.5}$ emissions data in China were downloaded from the Multi-resolution Emission Inventory for China (MEIC). The data of the provincial gross domestic product (GDP), provincial total population, urban population, coal use, energy use, and the tertiary industry (primary industry refers to industry for the production of food and other biological materials, including planting, forestry, animal husbandry, aquaculture, etc.; secondary industry refers to industry that reprocesses the basic materials provided by the primary industry and nature, including mining, manufacturing, power, gas and water production and supply, construction, etc.; tertiary industry refers to the service industry, mainly including transportation, communications, commerce, catering, financial industry, education industry, etc.) increased value were all obtained from the National Bureau of Statistics of China. In order to eliminate inflation, GDP was calculated at a constant price in 1995. The detailed description of the data used in this study are shown in Table 1.

Table 1. Description of the data used in this study.

Data	Data Description	Year	Unit	Source
Provincial $PM_{2.5}$ emissions data	Including $PM_{2.5}$ emissions data of 30 provinces	1995–2012	ton	http://www.meicmodel.org/dataset-meic.html
Provincial GDP	Including GDP of 30 provinces	1995–2012	10^8 yuan	http://www.stats.gov.cn/
Provincial total population	Including the total population of 30 provinces	1995–2012	10^4 persons	http://www.stats.gov.cn/
Provincial urban population	Including urban population of 30 provinces	1995–2012	10^4 persons	http://www.stats.gov.cn/
Provincial coal use	Including coal use of 30 provinces	1995–2012	ton of standard coal	China Energy Statistics Yearbook
Provincial energy use	Including energy use of 30 provinces	1995–2012	ton of standard coal	China Energy Statistics Yearbook
the tertiary industry increased value	Including the tertiary industry increased value of 30 provinces	1995–2012	10^8 yuan	http://www.stats.gov.cn/

3. Methodology

3.1. Time Variation Trend (Slope)

The simple linear regression model is a method frequently used to detect the time variation trends of observation data. The equation is as follows:

$$Slope = \frac{n\sum_{a=1}^{n} aI_a - \sum_{a=1}^{n} a \sum_{a=1}^{n} I_a}{n\sum_{a=1}^{n} a^2 - \left(\sum_{a=1}^{n} a\right)^2}, \tag{1}$$

where n denotes the time span and is equal to 18, and I_a represents the energy-related $PM_{2.5}$ emissions in a year.

3.2. STIRPAT Model

The formula is as follows:

$$I = a\, P^b\, A^c\, T^d\, e, \tag{2}$$

where I denotes energy-related $PM_{2.5}$ emissions, P indicates the total population, A expresses the affluence, T represents the technology level, a denotes the model coefficients, b, c, and d represent the simulation coefficient of independent variables, and e means the error value sustainability-425450.

After taking natural logarithm, Equation (2) was transformed into:

$$ln(I) = ln(a) + b\ ln(P) + c\ ln(A) + d\ ln(T) + ln(e). \quad (3)$$

As the STIRPAT model gives consideration to the individual impact of different changes in P, A, and T on the pollutant emissions and can be extended by incorporating other factors and appropriately decomposing each factor, this method is widely applied to reveal the factors affecting pollutant discharge. For instance, Li et al. [53,54] utilized a STIRPAT model for exploring the influence of different factors on China's CO_2 emissions. A STIRPAT model was utilized for detecting the major factors affecting Beijing's carbon dioxide emissions [55]. Shafiei et al. [56] explored the determinants of carbon emissions in the Organization for Economic Co-operation and Development (OECD) countries based on the STIRPAT model. Shahbaz et al. [57] explored the determinants of Malaysian energy use based on the STIRPAT model and found that urbanization was the major factor affecting Malaysian energy use growth. Laureti et al. [58] explored the determinants of Madrid's NOx discharge based on an augmented STIRPAT model. Zhang et al. [59] utilized a STIRPAT model for revealing the relationships between population aging and CO_2 emissions from multiscale perspective. Wang et al. [60] attempted to combine the STIRPAT model with a semi-parametric regression model for revealing the link between the income/urbanization and industrial CO_2 discharge. Xie et al. [61] employed an improved STIRPAT model for exploring the transportation infrastructure and urban carbon emissions nexus. Chai et al. [62] adopted a comprehensive LMDI-STIRPAT-PLSR model for analyzing influencing factors with regard to natural gas consumption. Wang et al. [63] quantified the major driving factors for Xinjiang's CO_2 emissions from different development stages. Zhang et al. [64] utilized an STIRPAT model for identifying the inherent relation between urbanization and CO_2 emissions. Yang et al. [65] utilized a STIRPAT model to quantify the influences of natural and socioeconomic parameters for CO_2 emissions.

Therefore, some factors, namely, U (Urbanization), S (Industrial mix), and E (Energy use mix), were incorporated to build the extended STIRPAT model for quantitatively revealing the influencing factors on energy-related $PM_{2.5}$ emissions in 1995–2012. The $ln(A)$ in Equation (3) was decomposed into $ln(A)$ and $(lnA)^2$ for testing whether there was an EKC relationship between energy-related $PM_{2.5}$ emissions and wealth growth [66,67]. Detailed information on variables is displayed in Table 2. The final STIRPAT model can be described by the following equation:

$$ln(I) = ln(a) + \beta_1\ ln(P) + \beta_{21}\ ln(A) + \beta_{22}\ (lnA)^2 + \beta_3\ ln(T) + \beta_4\ ln(U) + \beta_5\ ln(E) + \beta_6\ ln(S) + ln(e), \quad (4)$$

where U refers to urbanization; E means energy use mix; and S represents the industrial mix. β_1, β_{21}, β_{22}, β_3, β_4, β_5, β_6 are all fitting coefficients. When P, A, T, U, E and S are varied by 1%, 'I' will wave by β_1%, $\beta_{21} + 2\beta_{22}\ lnA$%, β_3%, β_4%, β_5% and β_6% respectively. Moreover, if $\beta_{21} > 0$ and $\beta_{22} < 0$, this indicates that an inverse-U-shaped EKC relationship is present between energy-related $PM_{2.5}$ emissions and economic development [68].

Table 2. Description of variables.

Variables	Symbol	Definition	Unit
Primary $PM_{2.5}$ emissions	*I*	Energy-related $PM_{2.5}$ emissions accounting	ton
Population size	*P*	Provincial total population	10^4 persons
Affluence	*A*	GDP divided by population	Yuan per capita
Technology level	*T*	Energy use per unit GDP	ton of standard coal/10^4 Yuan
Urbanization	*U*	Urban population divided by total population	%
Energy use structure	*E*	The ratio of coal use to total energy use	%
Industrial structure	*S*	The tertiary industry increased value divided by GDP	%

3.3. Multicollinearity Testing

Multicollinearity represents a situation in which there is a strong and linear correlation between independent variables. If multicollinearity is present among explanatory variables in the linear regression model, it will lead to: (1) an OLS estimator with large variance and low precision; (2) the individual effects of variables not being judged; (3) a nonsense significance test; and (4) an unstable regression model [69]. These unstable alterations will bring about an unreasonable regression model, thus providing unreliable results for variables.

There are many methods to assess “strong and linear correlations” between factors, such as the variance inflation factor (VIF) and correlation matrix. VIF, calculated by the ordinary least square (OLS) regression method, is the most commonly used method to evaluate whether there is multicollinearity between independent variables in regression models. The larger the VIF, the more serious the multicollinearity. It is generally believed that there is serious multicollinearity if a VIF is greater than 10 [70–72].

3.4. Ridge Regression

Ridge regression is an improved OLS estimation method because it abandons its unbiased property and can effectively decrease the standard error. Ridge regression is a more practical and reliable way to obtain fitting coefficients at the cost of precision loss. If there is multicollinearity between independent variables, the value of determinant of X′X matrix is approximately 0 (X is an n×b matrix (rank b) of independent variables). Therefore, matrix $(X'X)^{-1}$ will be hypersensitive to tiny changes in the data. If X′X is added to the constant matrix KI under the condition $K \geq 0$, the sensitivity of $(X'X + KI)^{-1}$ will be improved (K is the constant). Therefore, the coefficients estimation of ridge regression is more stable than the OLS regression method. Its estimator is as follows:

$$\beta(K) = (X'X + KI)^{-1}\, X'Y. \tag{5}$$

If K = 0, its estimator is the result of OLS regression; if $K \rightarrow \infty$, its sustainability-425450 is close to 0, so K should not be too large.

4. Results

4.1. The Variation Trend of Energy-Related $PM_{2.5}$ Emissions

The energy-related $PM_{2.5}$ emissions in 1995–2012 in China and the three economic zones are displayed in Figure 2. During the period from 1995 to 2006, the energy-related $PM_{2.5}$ emissions in the three economic zones showed an increasing trend. The rise of energy-related $PM_{2.5}$ emissions in western China was the fastest. The growth rate of energy-related $PM_{2.5}$ emissions in central China was the second highest. Energy-related $PM_{2.5}$ emissions in the eastern regions grew slowly and remained basically unchanged. During the period from 2006 to 2012, there were obvious differences in the changes of energy-related $PM_{2.5}$ emissions. Energy-related $PM_{2.5}$ emissions in eastern China featured a downward trend, while energy-related $PM_{2.5}$ emissions in central and western China showed an upward trend. A simple linear regression model was used to calculate the slopes of energy-related $PM_{2.5}$ emissions from 1995 to 2012. The slope was 5.29×10^4 tons/year in China, and the energy-related $PM_{2.5}$ emissions were fluctuating upward. The slope was -4.21×10^4 tons/year in the eastern region, indicating a downward trend from 1995 to 2012. The slope of central and western China were 3.61×10^4 tons/year and 5.89×10^4 tons/year respectively, which showed that energy-related $PM_{2.5}$ emissions had an upward trend in 1995–2012.

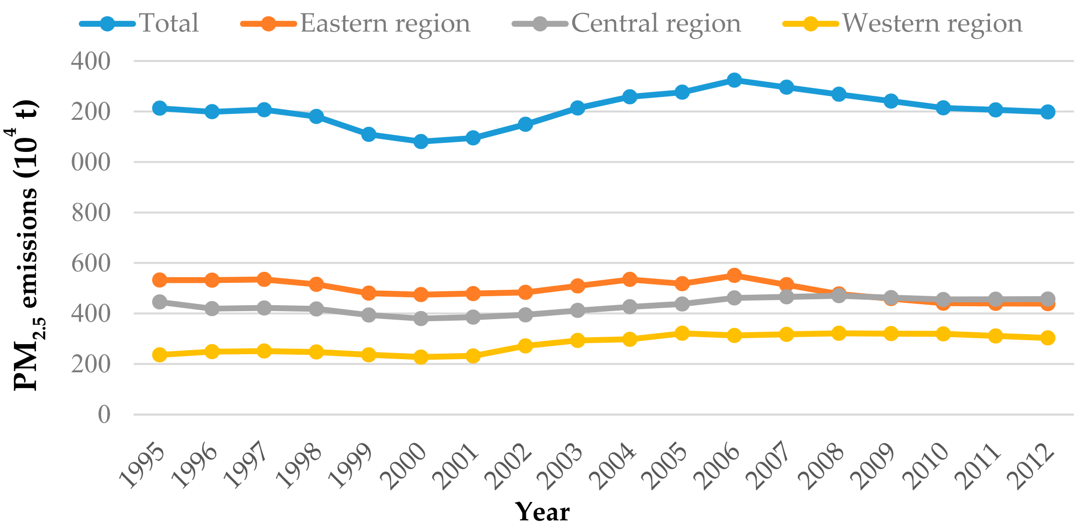

Figure 2. The variation trend of energy-related $PM_{2.5}$ emissions.

4.2. Results of Multicollinearity Inspection

According to the data collected, OLS regression was adopted in SPSS to determine whether multicollinearity is present (OLS results are displayed in Table 3). Several VIFs were much higher than 10, which implied that multicollinearity between independent variables was present. Therefore, the coefficients fitted by the OLS regression method cannot be guaranteed and the OLS results cannot be applied to quantify the factors affecting energy-related $PM_{2.5}$ emissions. Obviously, in order to get reliable regression results, the multicollinearity between independent variables must be eliminated.

Table 3. OLS results.

	Whole of China		**Eastern Region**		**Central Region**		**Western Region**	
	Unstandardized Coefficients	**VIF**	**Unstandardized Coefficients**	**VIF**	**Unstandardized Coefficients**	**VIF**	**Unstandardized Coefficients**	**VIF**
lnP	1.015	2.052	1.004	1.789	1.085	3.764	1.050	2.709
lnGDP	3.057	518.962	2.784	918.240	−0.582	1792.491	1.679	929.583
(lnGDP)2	−0.160	510.146	−0.144	901.297	0.040	1751.724	−0.081	926.299
lnT	0.361	2.503	0.360	2.575	0.573	3.110	0.315	17.961
lnU	0.352	15.351	−0.108	14.333	0.234	9.384	0.314	24.376
lnE	0.396	2.005	0.354	3.520	0.534	3.682	0.264	2.143
lnS	−0.449	1.779	−0.174	4.096	0.161	2.182	−0.107	1.498
C	−11.637	2.052	−9.415		1.692	3.764	−6.455	2.709
R^2	0.972		0.950		0.936		0.969	
F test	1315.992		619.027		207.514		413.653	
Sig.	0.000		0.000		0.000		0.000	

Notes: P (Population), T (Technology level), U (Urbanization), S (Industrial mix), and E (Energy use mix).

4.3. Ridge Regression Estimation

The ridge regression method was applied to fit Equation (4) for reducing the impact of multicollinearity between independent variables; the simulation coefficients are shown in Table 4. Its estimation coefficients are selected according to the ridge trace. When K = 0.1 (whole of China), K = 0.05 (eastern region), K = 0.08 (central region), K = 0.1 (western region), the ridge trace is almost stable. The specific coefficients are displayed in Table 4.

Table 4. Ridge regression results.

Coefficient	Whole of China	Eastern Region	Central Region	Western Region
lnP	0.864 *** (58.868)	0.936 *** (42.164)	0.839 *** (22.985)	0.828 *** (42.464)
lnGDP	0.081 *** (7.713)	0.033 * (1.695)	0.089 *** (6.976)	0.112 *** (8.337)
$(\ln GDP)^2$	0.001 ** (1.977)	−0.002 * (−1.725)	0.005 *** (6.669)	0.006 *** (7.769)
lnT	0.174 *** (7.144)	0.288 *** (5.848)	0.420 *** (9.862)	0.419 *** (3.108)
lnU	0.213 *** (5.206)	−0.122 (−1.548)	0.052 * (1.625)	−0.031 (−0.607)
lnE	0.526 *** (13.409)	0.453 *** (6.642)	0.511 *** (18.221)	0.286 *** (7.769)
lnS	−0.679 *** (−9.775)	−0.242 *** (−2.128)	−0.073 * (−1.841)	−0.063 (−0.517)
C	4.348 *** (12.201)	4.319 *** (7.691)	4.490 *** (13.899)	3.483 *** (6.387)
R^2	0.919	0.944	0.913	0.918
F test	864.446	545.495	150.587	304.106
Sig.	0.000	0.000	0.000	0.000
K	0.1	0.05	0.08	0.1

Notes: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level. T statistics are in parentheses. P (Population), T (Technology level), U (Urbanization), S (Industrial mix), and E (Energy use mix).

4.4. Empirical Analysis

4.4.1. The Whole of China

For the whole of China, population scale, energy intensity, urbanization, and energy use mix all had a positive and statistically effects on energy-related $PM_{2.5}$ emissions, whereas the negative effects of industrial mix on energy-related $PM_{2.5}$ emissions was significant. The fit coefficients of energy-related $PM_{2.5}$ emissions to population scale, energy intensity, urbanization, and energy use mix were 0.864, 0.174, 0.213, and 0.526 respectively, which showed that energy-related $PM_{2.5}$ emissions increased with the increase of total population, technology level, urbanization level, and ratio of coal use to total energy use. The fit coefficients of energy-related $PM_{2.5}$ emissions to industrial mix was −0.679, indicating that China's energy-related $PM_{2.5}$ emissions declined with the increase of the proportion of added value of tertiary industry to GDP. Moreover, the fit coefficients of energy-related $PM_{2.5}$ emissions to per capita GDP and its square were all positive and significant at the level of 5%. This indicated that an EKC relationship between wealth and energy-related $PM_{2.5}$ emissions was not present in China during this study period.

4.4.2. The Eastern Region of China

For the eastern region, energy-related $PM_{2.5}$ emissions were positively and statistically significantly correlated with the population scale, energy intensity, and energy use mix. The fit coefficients of energy-related $PM_{2.5}$ emissions to population scale, energy intensity, and energy use mix are 0.936, 0.288, and 0.453, respectively. This implied that the influences of the increase the increase in the total population, technology level, and ratio of coal use increased the energy-related $PM_{2.5}$ emissions in the eastern region. The proportion of tertiary industry increased value to GDP showed a negative correlation with the energy-related $PM_{2.5}$ emissions, and was statistically significantly under the level of 5%. The proportion of increased value of tertiary industry to GDP increased by 1%, which resulted in a 0.242% decrease in the energy-related $PM_{2.5}$ emissions. Moreover, the sensitivity of energy-related $PM_{2.5}$ emissions production in eastern China to urbanization was minus but statistically not significant. Interestingly, the fit coefficients of energy-related $PM_{2.5}$ emissions to per capita GDP and its square value were found to be statistically significant with a positive and negative correlation at the level $\alpha = 0.1$, respectively. Energy-related $PM_{2.5}$ emissions first increased sharply and then decreased with wealth growth, indicating that an EKC relationship between economic level and energy-related $PM_{2.5}$ emissions was present in the eastern region during this study period.

4.4.3. The Central Region of China

For the central region, the simulated elasticities were all statistically significant under the level $\alpha = 0.1$ or lower. Similar to the national scale, population size, energy intensity, urbanization, and energy use mix all positively influenced energy-related $PM_{2.5}$ emissions, whereas industrial mix negatively affected energy-related $PM_{2.5}$ emissions. The proportion of increased value of tertiary industry to GDP increased by 1%, which resulted in a 0.073% decrease in the energy-related $PM_{2.5}$ emissions. The elasticities of energy-related $PM_{2.5}$ emissions to population scale, energy intensity, urbanization and energy use mix were 0.839, 0.420, 0.052, and 0.511, respectively, indicating that the impacts of the decrease in the total population, technology level, urbanization level and ratio of coal use to total energy use all decreased the energy-related $PM_{2.5}$ emissions in the central China. Moreover, the elasticities of energy-related $PM_{2.5}$ emissions to per capita GDP and its square value were significant at the level $\alpha = 0.1$ and showed a positive correlation. This demonstrated that the existence of an inverted-U-type EKC relationship between wealth and energy-related $PM_{2.5}$ emissions in central China was not validated during this study period.

4.4.4. The Western Region of China

For the western region, the effect of the total population, technology level, and percentages of coal use to total energy use on energy-related $PM_{2.5}$ emissions were positive. The positive sensitivity of total population, energy use per unit GDP, and percentages of coal use on energy-related $PM_{2.5}$ emissions were 0.828, 0.419, and 0.286, respectively, which implied that the effects of the decrease in total population, energy use per GDP and percentages of coal use fell by energy-related $PM_{2.5}$ emissions. The effects of the urbanization level and the ratio of tertiary industry increased value to GDP on energy-related $PM_{2.5}$ emissions were all not significant even at the 10% level. Besides, the simulated elasticities of energy-related $PM_{2.5}$ emissions to per capita GDP and its square value were all statistically significant with a positive correlation under the level of 1%, demonstrating no EKC relationship between affluence and energy-related $PM_{2.5}$ emissions in western China during the study period.

5. Conclusions and Policy Recommendations

This study explored the change in $PM_{2.5}$ emissions over time in China. Then, an extended STIRPAT model was adopted for quantitatively revealing the various socioeconomic factors on energy-related $PM_{2.5}$ emissions from multiscale perspective in 1995–2012. Finally, the EKC hypothesis was adopted to test whether there is an EKC relationship between affluence and energy-related $PM_{2.5}$ emissions from multiscale perspective and some conclusions have been drawn.

The results showed that energy-related $PM_{2.5}$ emissions in most regions showed an increasing trend over the study period. The effects of the increase in population size, energy intensity and energy use mix on energy-related $PM_{2.5}$ emissions were positive and heterogeneous in China, population size was the major driving force of energy-related $PM_{2.5}$ emissions. Higher urbanization increased energy-related $PM_{2.5}$ emissions for the whole of China and central China, whereas the effects of urbanization level on energy-related $PM_{2.5}$ emissions in eastern and western China were statistically insignificant even at the level $\alpha = 0.1$. The proportion of tertiary industry increased value to GDP had negative influences on energy-related $PM_{2.5}$ emissions for the whole of China and eastern and central China, whereas the effects of the proportion of tertiary industry increased value to GDP on energy-related $PM_{2.5}$ emissions of western China was statistically insignificant even at the level $\alpha = 0.1$.

Moreover, the EKC relationship for energy-related $PM_{2.5}$ emissions has not been verified, excluding eastern China.

Population size had a significant positive effect on $PM_{2.5}$ emissions. In general, an increase in population size can affect $PM_{2.5}$ emissions in two ways: (1) the agglomeration effect—increasing population size often produces an agglomeration effect, which will improve technological level, public transport sharing efficiency, and energy efficiency to reduce $PM_{2.5}$ emissions; (2) the scale effect—the increase in population size will directly or indirectly lead to an increase in energy consumption, which will result in the increase of energy-related $PM_{2.5}$ emissions. The results showed that the scale effect of population size was significantly higher than its aggregation effect during the study period. Therefore, in the future, the government should pay more attention to the role of the population agglomeration effect for mitigating its scale effect on primary $PM_{2.5}$ emissions. For example, the government should use the media for publicizing the concept of a green life, striving to raise public awareness of low energy use, advocating a low-energy lifestyle, and promoting sustainable consumption patterns for households.

The eastern region demonstrated an EKC relationship as GDP increased. Most regions of China have levels of $PM_{2.5}$ emissions that are still increasing, that is to say, the $PM_{2.5}$ emissions will continue to be positively correlated with economic growth for some time. The "decoupling" stage between $PM_{2.5}$ emissions and economic growth has not yet arrived, which again illustrates the urgency of energy conservation and emissions reduction. Therefore, the government should emphasize sustainable development and further guide residents' green travel and consumption in order to achieve a win-win situation of stable economic growth and continuous decline of $PM_{2.5}$ emissions. For example, advocating "low-energy transportation" is also an effective measure to reduce $PM_{2.5}$ emissions.

The effect of the increase in energy intensity on energy-related $PM_{2.5}$ emissions was positive. Technological progress can often affect $PM_{2.5}$ emissions through production technology and emissions reduction technology, that is to say, technological progress can reduce $PM_{2.5}$ emissions, but also can promote economic growth, resulting in an increase in $PM_{2.5}$ emissions. The results showed that the effect of production technology is significantly higher than that of emissions reduction technology during the research period. Therefore, the government should accelerate research and development of energy conservation technology, develop new energy-efficient products, implement incentive policies, and guide enterprises to improve energy efficiency.

The effects of the increase in energy use mix on energy-related $PM_{2.5}$ emissions were positive, indicating that the increase of coal proportion increased primary $PM_{2.5}$ emissions. Therefore, it is necessary to adjust the energy use mix for mitigating its positive impact on energy-related $PM_{2.5}$ emissions. The Chinese government should actively develop clean, green energy to reduce the proportion of coal use.

Higher urbanization increased energy-related $PM_{2.5}$ emissions for the whole of China and the central region, whereas the impact of urbanization on energy-related $PM_{2.5}$ emissions in the eastern and western region was not significant. In the process of urbanization, building new buildings will consume a large amount of energy. Therefore, the government should advocate the use of more environmentally friendly materials instead of traditional cement and improve the quality of buildings for reducing energy use.

The proportion of tertiary industry increased value to GDP had negative influences on energy-related $PM_{2.5}$ emissions, excluding the western region. This is because the leading industry in the western region is secondary industry, and the tertiary industry accounts for a relatively low proportion and develops slowly. Therefore, the government should promote the optimization, transformation, and upgrading of industrial structures, and develop tertiary industry.

Our conclusions have improved the public's understanding of the changes of $PM_{2.5}$ emissions with economic growth, and are valuable for harmonizing economic growth and $PM_{2.5}$ emissions reduction. However, many influencing factors such as foreign direct investment, population age structure, and consumption mode will be valuable to explore in further research.

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