Comparison of Regional PM$_{2.5}$ Emissions in China: Decoupling Analysis and Driving Factors

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Abstract

In recent years, dense haze has imposed a significant socio-economic cost on China. As one of the main constituent pollutants of haze, the reduction of PM$_{2.5}$ emissions is of great significance to the governance of haze. Based on characteristics of regional economic development, 30 provinces in China (excluding the Tibet Autonomous Region, and Hong Kong and Macao Special Administrative Regions) were classified into eight regions. On this basis, we compared the mechanisms of influences of growth of PM$_{2.5}$ emissions in different regions. First, the Tapio elasticity index method was used to evaluate the decoupling relationship between economic growth and PM$_{2.5}$ emissions from 2001 to 2015. We found that the decoupling relationship between China's regional economic growth and PM$_{2.5}$ emissions showed a trend of continuous optimization, but the overall degree of decoupling remained weak. Furthermore, the LMDI method was used to compare the influencing factors and regional differences in PM$_{2.5}$ emissions. The result shows that economic scale (ES) effect and technological progress (TP) effect are separately the primary driving factors for promoting and inhibiting PM$_{2.5}$ emissions, however, the influence of industrial structure (IS) effect first promotes and then inhibits regional PM$_{2.5}$ emissions. The research provides insight for the Chinese Government into formulation of regional governance policies for haze.

Keywords

Regional PM$_{2.5}$ emissions; Haze governance; Tapio decoupling model; Logarithmic mean Divisia index.

1. INTRODUCTION

In recent years, the haze disaster caused by air pollution has seriously affected the quality of China's economic growth and the health of residents. Among them, sulfur dioxide, nitrogen oxides and inhalable particulate matter (PM$_{2.5}$) are considered to be an important part of smog. Yang et al. (2016) calculated that the total economic loss of 30 provinces in 2007 due to the mortality rate and morbidity rate caused by PM$_{2.5}$ pollution was as high as RMB 346.26 billion, accounting for 1.1% of the total GDP. Another study on 9 major cities in China also showed that every 10μg/m^3 increase in the concentration of NO#, SO# and PM$_{2.5}$ within 2 days would increase the number of deaths from CHD by 0.36%-1.30% (Li et al., 2015).

Bad natural conditions may contribute to the formation of haze disasters to some extent, but the fundamental reason is that a large number of pollutants are discharged in the process of industrialization and urbanization (Lyu et al., 2016). Experience in many countries has shown that economic growth and air pollution often go hand in hand. Especially for China, a developing country, decoupling economic growth from pollutant emissions is a huge challenge (Chang et al., 2018).

In recent years, the Chinese government has been committed to changing the extensive development model and seeking the decoupling between economic growth and air pollution (Li et al., 2019). In 2018, the State Council issued a three-year action plan to win the battle against blue skies, requiring that by 2020, cities at prefecture level and above should have 80% of their air quality good, 25% lower than in 2015, and 18% lower than in cities with $PM_{2.5}$ below the standard. However, the most important thing to fully realise the decoupling of economic growth from air pollution is to identify the sources of the pollutants. Therefore, a specific study on the driving factors of pollutant emission is of great significance for completing the haze reduction plan and realizing the decoupling of economic growth from air pollution.

In addition to the serious overall pollution degree, air pollution in China also has obvious regional differences (Yang et al., 2016). Taking $PM_{2.5}$ concentration equal to 75 ug/m3(harm to human body or not) as the critical value, among the 15 Chinese cities whose annual mean $PM_{2.5}$ concentration exceeds 75 ug/m3, 13 cities are located in the northern region, only Wuhan and Hefei are located in the southern region. What factors contribute to this regional heterogeneity of air pollution? Are there differences in the main drivers of pollutant emission in different regions? Answering these questions is also important for the development of targeted and efficient regional emission reduction policies.

There are many factors that can explain the reasons behind air pollution, such as energy consumption structure, energy utilization mode and industrial structure (He et al., 2017). Since air pollutants are mainly generated by direct use of energy, Wang et al (2016) divided various driving factors into direct factors and indirect factors according to whether they are directly related to energy. The direct factor refers to energy related factors, such factors directly affect the emission of pollutants. For example, Liu et al. (2018) studied the regional differences in the impact of energy intensity and emission factors on carbon emissions. Indirect factors refer to social and economic factors, which act on factors related to energy sources first and then affect pollutant discharge. For example, Fan and Zhou. (2019) studied the impact of urbanization and real estate investment on carbon emissions.

$PM_{2.5}$ is the most important source of haze pollution. However, due to the lack of anthropogenic $PM_{2.5}$ emission data, compared with conventional air pollutants such as carbon dioxide and sulfur dioxide, the study on the driving factors of $PM_{2.5}$ is still at the initial stage. For example, Zhang et al (2019) made use of $PM_{2.5}$ monitoring concentration data at the city level to conduct factor decomposition research. However, current studies have shown that the variation of $PM_{2.5}$ concentration is greatly affected by natural factors (Yang et al., 2018). Therefore, we believe that compared with the concentration data, the total emission data of anthropogenic $PM_{2.5}$ is more suitable for the decomposition of the social and economic driving factors of $PM_{2.5}$, but the existing research is still insufficient.

Therefore, this paper first calculates the total $PM_{2.5}$ emissions from anthropo-generated sources in China from 2000 to 2015 and analyzes the decoupling status of regional economic development and $PM_{2.5}$ emissions through the TAPIO decoupling model and evaluates the overall quality of regional economic development and pollutant control. On this basis, LMDI method was further used to quantify the main driving factors of $PM_{2.5}$ emissions in different regions from two aspects of energy related factors and social and economic factors.

The contribution of this paper is to calculate the total $PM_{2.5}$ emissions from anthropogenic sources in each region and analyze the influence of energy related factors and social indirect factors on the total $PM_{2.5}$ emissions.

2. LITERATURE REVIEW

Using the decoupling model is a simple and accurate method to measure the relationship between regional economic growth and $PM_{2.5}$ emissions. When the economy develops to a certain extent, with the economic structure of the transformation or the promotion and accumulation of energy-saving technologies, it is possible to reduce environmental emissions and resource consumption while continuing to enjoy economic development. This process is called decoupling. Zhang (2000) was the first to apply the idea of decoupling to study environmental issues. The Organization for Economic Cooperation and Development (OECD) then proposed a method based on the decoupling index that divides the decoupling level into absolute and relative decoupling, to evaluate whether environmental degradation and economic growth change synchronously or not.

Since then, research into economic growth and resource environment decoupling has produced a variety of measures with which to assess the decoupling index (Wu et al. 2018). Among them, the elastic index method proposed by Tapio (2005) divided decoupling into eight grades according to the calculated elastic value and assessed the dynamic change of decoupling situation of the research object over a period of time in a more detailed and comprehensive way. In recent years, Tapio's elasticity index method has been widely used in studies evaluating the relationship between China's economic development and environmental pressure (Zhang and Bai 2018, Li et al. 2019, Wang et al. 2019b).

In conclusion, most of the existing studies on the decoupling between haze pollution and economy in China are conducted at the national, or industrial, levels, while few researchers apply such thinking at a regional level. In fact, the level of haze pollution in China varies greatly between regions. A comparative study of the decoupling relationship between haze pollution and economy at the regional level is conducive to the formulation of more targeted haze emission reduction policies by the Chinese Government. Therefore, in the present work, the Tapio elasticity index method was used to evaluate the decoupling relationship between economic growth and $PM_{2.5}$ emissions from 2001 to 2015.

After measuring the degree of decoupling, the factors driving regional $PM_{2.5}$ emissions need to be further clarified. With the development of such research tools, the decomposition method has gradually become an important method with which to study the factors driving pollutant emissions. Since the zero-value problem has been solved, the LMDI method is deemed to be the best index decomposition method at present (Liu et al. 2015, Zhao et al. 2017, Hao et al. 2018, Chen et al. 2019, Wang et al. 2019c).

Nowadays, the LMDI method is widely applied in the study of carbon emission (Chang et al. 2018, Chen et al. 2018a, Liu et al. 2019, Ma and Cai 2019, Zhang et al. 2019b), however, this method is rarely applied in the study of haze pollution. Moreover, owing to limitations affecting the data, conventional pollutants such as SO2, NOX and PM10 were selected as proxy indicators of haze pollution in most of these studies (Jia et al. 2018, Hang et al. 2019), and insufficient attention has been paid to $PM_{2.5}$ emissions. $PM_{2.5}$ is the most important component of haze. Due to the lack of total emission data pertaining to $PM_{2.5}$, the use of an IDA method is rare; Zhang et al. (2019c) first used the LMDI method to decompose the driving factors of $PM_{2.5}$ monitoring concentration data at the urban level in China, however, there are few such studies (Cheng et al. 2019, Dong et al. 2019a, Yang et al. 2019). In the present work, the total emission of $PM_{2.5}$ reflects the severity of regional haze pollution and facilitates the study of those factors driving such emissions, which is more in line with the laws of economic development.

3. METHODS AND DATA SOURCES

At present, most emission inventories have high requirements on the original data, so it is difficult to estimate the total emission of $PM_{2.5}$ at a macroscopic level. In the present work, by applying the inventory method, we selected the appropriate $PM_{2.5}$ emission coefficient and calculated the total $PM_{2.5}$ emissions in each region. The specific calculation method is as follows:

$$P = \sum_{i,j} E_{i,j} \times EF_{i,j} \times X_i(1 - \eta_i) \quad (1)$$

Where, P represents the total emission of $PM_{2.5}$; i and j respectively represent industry serial number and energy type; $E_{i,j}$ is the consumption of energy j by industry i; $EF_{i,j}$ is the emission coefficient, that is, the total amount of $PM_{2.5}$ emitted by use of energy j per unit consumed by industry i; X_i is the distribution rate (%) of pollution control technology in industry i; η_i allows for industry i having a certain technology decontamination efficiency (%).

3.1. Tapio Decoupling Model

Here, the decoupling model was used to measure the degree of decoupling, so as to get an overall understanding of the relationship between economic growth in regions and $PM_{2.5}$ emissions in the medium and long-term. The model is set as follows:

$$e_{(PM,GDP)} = \left(\frac{\Delta PM}{PM}\right) / \left(\frac{\Delta GDP}{GDP}\right) = \Delta PM \times GDP/(PM \times \Delta GDP) \tag{2}$$

Where, $e_{(PM,GDP)}$ refers to the decoupling elasticity index between the gross output value of regional economic growth and $PM_{2.5}$ emissions; PM refers to the annual total emission of $PM_{2.5}$ (10,000 t); GDP refers to the gross regional product (100 million yuan). Tapio divided the calculated decoupling elasticity index into eight decoupling states (Table 1).

Table 1. Tapio decoupling classification

Decoupling states	Decoupling index	ΔPM/PM	ΔGDP/GDP
Expansive negative decoupling	$e > 1.2$	> 0	> 0
Weak negative decoupling	$0 \leq e \leq 0.8$	< 0	< 0
Strong negative decoupling	$e < 0$	> 0	< 0
Recessive decoupling	$e > 1.2$	< 0	< 0
Weak decoupling	$0 \leq e \leq 0.8$	> 0	> 0
Strong decoupling	$e < 0$	< 0	> 0
Expansive coupling	$0.8 \leq e \leq 1.2$	> 0	> 0
Recessive coupling	$0.8 \leq e \leq 1.2$	< 0	< 0

3.2. LMDI Decomposition Model

To further study the degree of influence of each factor on regional $PM_{2.5}$ emission change, the LMDI method was introduced in the present work. Firstly, four socio-economic factors proved to have an effect on $PM_{2.5}$ emissions in many studies were selected to construct the Kaya identity as follows:

$$PM = P \times \frac{GDP}{P} \times \frac{IND}{GDP} \times \frac{PM}{IND} \tag{3}$$

Where, PM is the emission of regional $PM_{2.5}$; P represents the total population of the region; GDP is the gross regional product; IND is the added value of regional industry. Equation (3) can be simplified to:

$$PM = P \times G \times M \times I \tag{4}$$

Where, P is defined as population growth effect; G denotes per capita GDP, defined as an economic scale effect; M represents the proportion of industrial added value in GDP and is defined as the effect of industrial structure, I represents the emission of $PM_{2.5}$ per unit industrial added value, indicating the effect of technological progress.

According to the LMDI addition decomposition method, equation (4) is further decomposed, and the total variation (ΔPM) of $PM_{2.5}$ emissions in each region from period t to t + 1 can be expressed as:

$$\Delta PM = PM_{t+1} - PM_t = \Delta P + \Delta G + \Delta M + \Delta I \tag{5}$$

Where, ΔP, ΔG, ΔM, and ΔI respectively represent the variation of $PM_{2.5}$ emission caused by population growth effect, economic scale effect, industrial structure effect, and technological progress effect.

The formulae used to calculate each driving factor are as follows:

$$\Delta P = \sum_i \frac{PM_i^{t+1} - PM_i^t}{\ln PM_i^{t+1} - \ln PM_i^t} \times \ln \frac{P^{t+1}}{P^t} \tag{6}$$

$$\Delta G = \sum_i \frac{PM_i^{t+1} - PM_i^t}{\ln PM_i^{t+1} - \ln PM_i^t} \times \ln \frac{G^{t+1}}{G^t} \tag{7}$$

$$\Delta M = \sum_i \frac{PM_i^{t+1} - PM_i^t}{\ln PM_i^{t+1} - \ln PM_i^t} \times \ln \frac{M^{t+1}}{M^t} \tag{8}$$

$$\Delta I = \sum_i \frac{PM_i^{t+1} - PM_i^t}{\ln PM_i^{t+1} - \ln PM_i^t} \times \ln \frac{I^{t+1}}{I^t} \tag{9}$$

3.3. Regional Division and Data Sources

According to the principle of regional proximity and the similarity of economic development, this paper divides 30 provinces of China (excluding Tibet, Hong Kong, and Macao) into eight regions (Table 2). This division method is commonly used in the academic circles and has been recognized and applied by numerous scholars.

Data on energy consumptions of various regions were derived from China Energy Statistical Yearbook. The population and local GDP data were collected from China Statistical Yearbook. To eliminate the influence of inflation, the price in 2000 is used as the constant price, to convert the local GDP and industrial added values correspondingly.

Table 2. Regional division of China

Regions	Provinces
Beijing-Tianjin	Beijing Tianjin
Northern coastal	Shandong Hebei
Eastern coastal	Shanghai Jiangsu Zhejiang
Southern coastal	Fujian Hainan Guangdong
North-western	Shaanxi Gansu Qinghai Ningxia Xinjiang Inner Mongoria
Central region	Shanxi Anhui Jiangxi Hubei Hunan Henan
South-western	Sichuan Chongqing Yunnan Guangxi Guizhou
North-eastern	Liaoning Heilongjiang Jilin

Regional energy consumption data is from China Energy Statistical Yearbook. $PM_{2.5}$ emission coefficients is from Zhong et al. (2018). Population data and GDP in each region are from China Statistical Yearbook. To eliminate the impact of inflation, GDP and industrial added values are deflated to the level of 2000.

4. EMPIRICAL RESULTS AND ANALYSIS

4.1. Regional $PM_{2.5}$ Emissions from 2001 to 2015

$PM_{2.5}$ emissions in China increased from 2.9481×106 to 8.2758×106 tons from 2001 to 2015 at the annual average growth rate of 12.7%. Figure 1 shows the total $PM_{2.5}$ emissions and growth rates in the eight regions between 2001 and 2015.

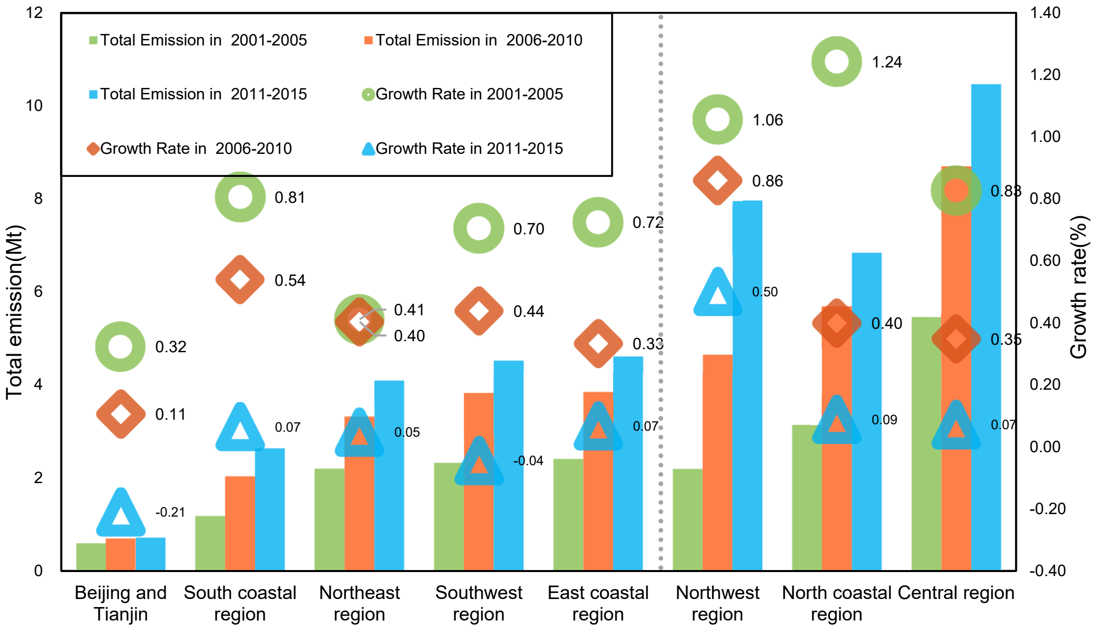

Figure 1. Total $PM_{2.5}$ emissions and growth rates in the eight regions from 2001 to 2015

From the perspective of total $PM_{2.5}$ emissions, $PM_{2.5}$ emissions in the central, northern coastal, and northwestern regions separately account for 25%, 15%, and 10% of the total emission in China. They are main regions emitting $PM_{2.5}$. Central and northern coastal regions are traditional heavy industry bases, where the industrial development promotes the large local energy consumption, thus emitting huge amounts of $PM_{2.5}$. Due to abundant reserves of fossil energy, the northwestern region undertakes the primary task for domestic energy production and supply; at the same time, the region receives a large amount of transferred heavy industry and manufacturing industry during its development, which leads to large $PM_{2.5}$ emissions.

In comparison, the other five regions have relatively low total $PM_{2.5}$ emissions, and Beijing–Tianjin region is found to have the lowest emission. This is because manufacturing sector in Beijing–Tianjin region has been transferred out early and the current economic growth of the region mainly relies on high-tech industry and financial industry. Therefore, economic growth in the region depends slightly on energy consumption. It is also worth noting that Beijing–Tianjin region is frequently covered by haze, which is probably a result of influences of haze from surrounding areas (steel producing areas in northern coast for instance).

As for growth of $PM_{2.5}$ emissions, it constantly declines in different regions. From 2010 to 2015, the growth rate of $PM_{2.5}$ emissions in almost all regions (except for the northwestern region) declined to a level below 10%. $PM_{2.5}$ emissions in Beijing–Tianjin and the southwestern regions even showed a negative growth, indicative of notable improvement of quality of economic development. While in the whole research phase, the growth rate of $PM_{2.5}$ emissions in the northwestern region kept above 50% all the time, suggesting that the $PM_{2.5}$ emissions there failed to be effectively controlled; the region exhibited low quality of economic development and faced relatively large pressure for emission reduction. The result agrees with that of Dong et al. (2019).

4.2. Decoupling Levels Between Regional Economic Growth and $PM_{2.5}$ Emissions

To more accurately evaluate the correlation between economic growth and $PM_{2.5}$ emissions of various regions, the Tapio elastic analysis is used to calculate the decoupling indexes between economic growth and $PM_{2.5}$ emissions of the eight regions and the whole country in 2001–2005, 2006–2010, and 2011–2015. As $\Delta GDP>0$, the economic growth and $PM_{2.5}$ emissions of various regions in China only show four types of decoupling: i.e. expansive negative decoupling, expansive coupling, weak decoupling, and strong decoupling.

Table 3. Decoupling index and state between $PM_{2.5}$ emissions and the economy of eight regions

Region	2001-2005		2006-2010		2011-2015	
	index	state	index	state	index	state
North-eastern	0.61	III	0.46	III	0.10	III
Beijing-Tianjin	0.39	III	0.12	III	-0.36	IV
Northern coastal	1.56	I	0.49	III	0.16	III
Eastern coastal	0.88	II	0.42	III	0.13	III
Southern coastal	1.00	II	0.66	III	0.12	III
Central	1.20	II	0.41	III	0.12	III
North-western	1.30	I	0.92	II	0.77	III
South-western	1.08	II	0.50	III	-0.06	IV
China	1.07	II	0.52	III	0.21	III

In general, the relationship between economic growth and $PM_{2.5}$ emissions in China displays a gradual decoupling trend. As shown in Table 3, the average decoupling level gradually changes from expansive coupling (growth rate of $PM_{2.5}$ emissions approaching to economic growth rate) to weak decoupling (growth rate of $PM_{2.5}$ emissions lower than economic growth rate). This manifests a process that damages and influences of economic growth to the environment gradually decrease while the quality of economic development gradually increases. It suggests that the Chinese government begins to take the control of $PM_{2.5}$ emissions into consideration while realizing economic growth, to achieve the win-win of economic growth and environment protection. The conclusion has also been confirmed by Zhan et al. (2016) and Chen et al. (2018).

However, at present, the economic growth and $PM_{2.5}$ emissions in China are weakly decoupled on the whole. At regional level, most regions still show weak decoupling, only Beijing–Tianjin and southwestern regions perform well. The two regions took the lead to achieve strong decoupling ($PM_{2.5}$ emissions reducing with economic growth) during 2011–2015. Beijing–Tianjin region was always at a leading position in terms of the decoupling effect during 2001–2015. This is mainly because the proportion of total output of the high energy-consuming secondary industry in the regional economic structure is far lower than that of the tertiary industry. As to the southwestern region, although the decoupling effect was not satisfactory in the initial period, the decoupling index constantly and stably reduced during 2006–2010 and 2011–2015 (by 58.4 and 56 percents separately). This indicates the remarkable control effect on $PM_{2.5}$ emissions in the region. The other six regions exhibited relatively low decoupling levels, and the lowest decoupling effect was found in the northwestern region, implying that the economic growth there led to great damages to the environment. Although the northwestern region also showed the weak decoupling between economic growth and $PM_{2.5}$ emissions in the late stage of the research phase, the decoupling index was still high (0.77). The result indicates that the northwestern region shows a large gap with other regions with regard to the quality of economic development.

4.3. Drivers of Regional $PM_{2.5}$ Emissions

Generally speaking, we need to achieve strong decoupling further between the economic growth and $PM_{2.5}$ emission. Therefore, to determine economic factors influencing $PM_{2.5}$ emissions and make more targeted regional emission reduction policies, drivers of $PM_{2.5}$ emissions in the eight regions are compared using LMDI method from four aspects, i.e. population, ES, IS, and TP.

Table 4. Driving effects in regional $PM_{2.5}$ emissions

Time period	Region	*PG*	*ES*	*IS*	*EI*	Total
2001-2005	North-eastern	0.36	23.05	-0.94	-6.85	15.61
	Beijing-Tianjin	1.04	6.08	0.16	-3.95	3.33
	Northern coastal	1.67	34.53	7.80	5.94	49.94
	Eastern coastal	2.96	26.20	2.93	-5.54	26.55
	Southern coastal	1.28	12.38	2.83	-2.83	13.66
	Central	0.05	56.17	15.50	-7.03	64.69
	North-western	1.26	24.60	7.64	-2.08	31.41
	South-western	-0.15	23.42	3.66	-2.20	24.73
2006-2010	North-eastern	1.16	39.25	3.16	-21.94	21.63
	Beijing-Tianjin	3.35	5.47	-1.10	-6.28	1.44
	Northern coastal	4.45	58.97	-4.49	-23.00	35.94
	Eastern coastal	5.60	37.24	-5.69	-16.06	21.10
	Southern coastal	3.82	18.92	0.16	-6.39	16.51
	Central	2.32	100.36	22.60	-75.50	49.79
	North-western	2.56	53.31	11.80	-15.12	52.55
	South-western	-0.70	46.35	13.30	-32.72	26.23
2011-2015	North-eastern	-0.05	30.65	-17.22	-9.80	3.57
	Beijing-Tianjin	1.76	4.45	-1.32	-8.05	-3.16
	Northern coastal	3.79	53.38	-18.21	-27.83	11.13
	Eastern coastal	1.72	34.53	-14.46	-16.09	5.70
	Southern coastal	1.89	19.25	-4.91	-13.16	3.07
	Central	4.38	91.64	-25.71	-56.45	13.87
	North-western	4.23	66.02	-23.37	10.09	56.97
	South-western	2.34	42.38	-14.12	-34.43	-3.83

Note: PG is the population growth effect; ES is the economic scale effect; IS is the industrial structure effect; TP is the technical progress effect.

As shown in Table 4, the ES effect is the primary positive driver for the growth of regional $PM_{2.5}$ emissions. Among the eight regions, underdeveloped areas such as the northwestern and central regions have relatively larger ES effects; while developed areas including Beijing–Tianjin, southern coastal, and eastern coastal regions present lower ES effects. The result accords with the conclusion of Shen et al. (2017). Generally, the higher the dependence of economic development of a region on energy consumption is, the larger the $PM_{2.5}$ emissions resulting from economic expansion and thereby the larger the ES effect. For economic growth, developed areas with high quality of economic development depend slightly on energy consumption; in comparison, underdeveloped areas tend to realize the rapid economic growth by developing energy-intensive industries. Besides, although the northern coastal region does not belong to an underdeveloped area, it also has a large ES effect due to high energy-consuming industries such as steel and chemical industries being dominant in the regional IS. Among the eight regions, the northwestern, central, and northern coastal regions also display the lowest decoupling level between their economic growth and $PM_{2.5}$ emissions. This indicates that the ES effect is an important factor influencing the decoupling level. The key for the central, northwestern, and northern coastal regions to realizing the strong decoupling between economic growth and $PM_{2.5}$ emissions is to facilitate the transformation of economic development from the extensive mode to the intensive mode.

The TP effect comprehensively reflects improvement of regional energy efficiency and optimization of regional energy structure and is the primary negative driver, able to effectively inhibit the growth of $PM_{2.5}$ emissions. In other words, the reduction of emission intensity attributed to progress of energy technologies is able to effectively ease pollution of haze. The TP effect contributes to large reductions of PM2.5 emissions in the central, southwestern, and northeastern regions, while low reductions in the northwestern, Beijing–Tianjin, and southern coastal regions. The energy structures were dominated by coal and the industrial technical levels were low in the central, southwestern, and northeastern regions in the early 20th century. In these regions, the energy structures and energy intensities have large potentials to be improved, so the TP effect leads to a large reduction of $PM_{2.5}$ emissions. On the contrary, the energy structures and energy intensities of Beijing–Tianjin and southern coastal regions have limited improvement potentials due to their advanced industrial technologies, so the reduction of $PM_{2.5}$ emissions attributable to TP effect is low. Owing to the characteristics of resource endowment, nearly half of the industrial enterprises in the northwestern region are high-polluting and high energy-consuming heavy chemical enterprises. Therefore, the emission intensity decreases slowly, and the TP effect contributes little to the reduction of $PM_{2.5}$ emissions.

The IS effect can either positively or negatively influence the $PM_{2.5}$ emissions in different regions, while at low influence degrees. By further studying the drivers of $PM_{2.5}$ emissions of various regions during 2001–2005, 2006–2010, and 2011–2015 (Table 4), it can be found that the IS effect first promotes and then reduces the $PM_{2.5}$ emissions.

As Table 4 illustrates, the IS effect in all of these regions led to the increase of $PM_{2.5}$ emissions from 2001 to 2005, except for the northeastern region. This is because China witnessed a fast industrialization process in the period, during which industry, especially high energy-consuming industry, occupied an increasingly larger proportion in the economy, thus resulting in huge $PM_{2.5}$ emissions. As a result, the IS effect promoted the $PM_{2.5}$ emission in the period. From 2006 to 2010, the developed areas in eastern China gradually eliminated high-polluting industry and transferred industry to backward areas in central and western China. In the period, the IS optimization in eastern China promoted the reduction of $PM_{2.5}$ emissions; while on the contrary, IS was deteriorated in central and western China, incurring increasing $PM_{2.5}$ emissions. During 2011–2015, the Chinese government began to pay much attention to the IS optimization. In the period, the proportion of secondary industry decreased in all of the regions while that of the tertiary industry began to rise continuously, thereby contributing to the remarkable reduction of $PM_{2.5}$ emissions. However, the IS optimization is a long-lasting process, and according to current implementation results, the emission reduction effect of IS optimization is not prominent enough. Therefore, to further reduce regional $PM_{2.5}$ emissions, we need to continue to tap the potential of IS in reducing $PM_{2.5}$ emissions.

The influences of the population effect on the change of $PM_{2.5}$ emissions are not evident in all of the regions. In fact, China's population growth rate has not been very high since the implementation of the Population and Family Planning Law of the People's Republic of China in 2002. At the same time, interregional migration of population is also modest because of restrictions set by the household registration system. Due to the above reasons, the population effect slightly influences the change of regional $PM_{2.5}$ emissions.

5. CONCLUSIONS AND POLICY RECOMMENDATIONS

The research explores the decoupling between economic growth and $PM_{2.5}$ emissions of various regions from 2001 to 2015 by combining the Tapio decoupling model and the LMDI based factor decomposition method. In addition, the dependence of economic development of each region on $PM_{2.5}$ emissions is measured. On this basis, the social and economic factors of $PM_{2.5}$ emissions in different regions are compared. The following conclusions are drawn:

1) Although the economic growth and $PM_{2.5}$ emissions of different regions are gradually decoupled, the decoupling is still at a low level.

2) The ES expansion and the reduction of emission intensity are separately the primary factors promoting and inhibiting $PM_{2.5}$ emissions of various regions; while IS first promotes and then reduces the emissions.

3) The northwestern, central, and northern coastal regions are relatively inferior in terms of the quality of regional economic development and the control effect on $PM_{2.5}$ emissions, which is mainly because of the extensive economic growth mode of these regions. In comparison, other regions have better quality of economic development, while IS optimization and decrease of emission intensity still present great potentials to reduce the $PM_{2.5}$ emissions.

In conclusion, the emission reduction technologies and measures used in Beijing–Tianjin, southern coastal, and eastern coastal regions, the most economically developed regions in China, exert strong demonstration effects on other regions. The northern coastal and northwestern regions need to actively change their inefficient and high-polluting economic development mode to narrow the gap with other regions in terms of reducing $PM_{2.5}$ emissions. With low quality of economic development, the central region affords a large potential in emission reduction. For the region, it is suggested to further strengthen the control over quality of industry development and construct a clean and efficient energy system to continuously decrease the industrial emission intensity. As for the southwestern region, it needs to maintain its advantages and strives to develop emerging industry, so as to facilitate the further optimization of the IS and the energy structure.

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