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Driving Forces of Industrial Water Pollutant Emission from Spatial-Dynamic Perspective in China: Analysis Based on Kaya Equation and LMDI Decomposition

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Abstract

The identification of the driving forces of industrial water pollutant emissions in China is conducive to its effective abatement. It also promotes the coordinated development of China's economic growth and the environment protection. Utilizing the Kaya equation and China's provincial panel data from 1999 to 2015, this paper investigates the spatial-dynamic driving forces governing industrial water pollutant emission. We decompose and quantify the heterogeneous effects of different drivers, that is, technology, energy consumption, and economic size distribution. Applying the LMDI decomposition method, this paper also calculates the contribution of the three drivers to the abatement of industrial water pollutant emissions. The analysis indicates that the most important contribution to pollutant abatement is the development of technology, followed by energy consumption, and the least affected is the distribution of economic scale. In the future, the Chinese government should pay more attention to the impact of energy consumption on pollution abatement. This paper suggests that the Chinese government should improve the clean use of fossil fuel, optimize the energy consumption structure, and develop the use of more clean energy.

Keywords

Driving Force, Kaya Equation, LMDI Decomposition, Technology, Energy Consumption

1. Introduction

Since the implementation of the policy of reform and opening up, China's economy has maintained a relatively fast growth trend. However, the rapid economic development of China has been accompanied by the emission of a great number of pollutants, which in turn have caused severe environmental problems [1]. The extraordinary economic growth, industrialization and urbanization coupled with inadequate investment in basic water supply and treatment infrastructures, have resulted in increasing industrial water pollution [2]. Industrial wastewater pollution has a strong destructive effect on the ecological environment and ecosystem, and thus cause environmental and human health [3] [4]. The continuous improvement of industrial water pollution is an important prerequisite for sustainable economic and social development. Therefore, it is necessary to explore the driving forces of industrial water pollution emission by decomposing and analyzing its spatial evolution trend. This paper is aimed to explore the key factors and variables for achieving industrial water pollution reduction, so as to provide certain policy recommendations for sustainable economic development and high quality development.

Chemical Oxygen Demand (COD) is a measure of the amount of reductive substances that need to be oxidized in water samples. It reflects the extent to which water is contaminated with reductive substances [5]. The time trend of industrial COD emissions per unit of GDP in China from 1999 to 2015 is shown in **Figure 1** [6]. It can be seen from **Figure 1** that the industrial COD emissions per unit of GDP have always maintained a downward trend. Then, it is necessary for us to decompose and analyze the industrial COD emission per unit of GDP, and quantitatively measure which factors lead to the decline of industrial COD emissions per unit of GDP. Our main goal is to analyze the driving force of reduction of industrial water pollution. Which aspects we can further work from in the future in order to further promote the reduction of industrial water pollution.

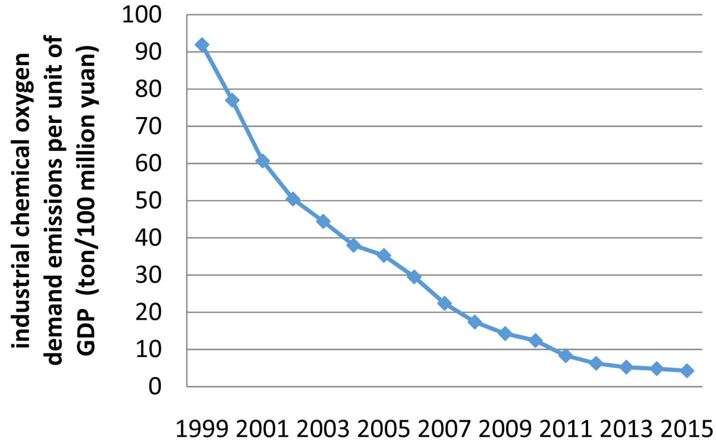

Figure 1. The time trend of industrial COD emissions per unit of GDP in China from 1999 to 2015.

The existing literature has conducted extensive research on industrial wastewater and exhaust gas decomposition. Ma (2016) built the Kaya Equation between Chinese industrial pollutants discharge with industrial scale, industrial structure (the proportion of high-pollutant loaded sectors in gross industrial output), pollution productive efficiency (the waste discharge per unit of gross industrial output) and waste discharge source structure from 2001 to 2013. The contribution rates of four factors to the change of pollutants discharge were calculated with the approach of LMDI [7]. Ling and Zhang (2017) used the Kaya identity to divide the industrial waste influencing factors into cleaner production technology level, energy consumption per unit industrial GDP, industrial economy level and population scale [8]. Wen *et al.* (2018) explored the main impact factors of industrial air pollutant emissions in Beijing-Tianjin-Hebei region and surrounding areas from 2011 to 2015 based on Logarithmic Mean Divisia Index (LMDI) [9]. Shapiro and Walker (2018) analyzed the pollution reduction of US manufacturing industry from the perspectives of environmental regulation, productivity, and trade by decomposing US industry pollution emissions into three factors: scale, structure, and technology [10]. Geng *et al.* (2014) analyzed the spatial-temporal characteristics and driving forces of industrial wastewater emission variations in China's 31 provinces during the years 1995-2010. The results showed that economic factors are the main driving factors of industrial wastewater emission changes and found that technology improvement considerably offsets emission increases [2]. Chen *et al.* (2016) utilized the Exploratory Spatial Data Analysis (ESDA) method to analyze the characteristics of the spatio-temporal distribution of the total wastewater discharge among 31 provinces in China from 2002 to 2013. It also discussed about the driving factors affected the wastewater discharge through the Logarithmic Mean Divisia Index (LMDI) method [11]. Chen *et al.* (2017) analyzed the evolution of spatial-temporal pattern of industrial wastewater in the Yangtze River Economic Zone from 2002 to 2013 and the main driving factors affecting industrial wastewater discharge. The results showed that the economic development effect and the technological development effect are the main factors which lead to the increase and decrease of industrial wastewater discharge respectively [12]. Yao *et al.* (2016) identified the main driving forces for SO_2 and COD emission reduction in China's industrial system. The results indicated that Engineering Emission Reduction and Supervision Emission Reduction have made the greatest contributions to reducing COD emissions; but Structure Emission Reduction has not had an obvious effect [1]. However，less attention is paid to the research of driving forces of industrial water pollutant emission from spatial-dynamic perspectives in China in the existing literature.

To explore the driving forces of industrial water pollutant emission from spatial-dynamic perspective in China, this paper applies the provincial panel data from 1999 to 2015 to decompose the industrial COD emissions per unit of GDP (*i.e.* the intensity of pollution emissions). Based on the Kaya equation, the pollution emission intensity is decomposed into three factors: technology effect, energy consumption intensity, and regional distribution of economic scale. The contribution rate of each factor is quantitatively determined by applying the LMDI decomposition method. At last, rational and effective policy recommendations are drawn in order to achieve high-quality development goals to control water pollution emissions while developing the economy.

2. Data Sources and Research Methods

1) Data Sources

This paper applies the provincial panel data from 1999 to 2015 in China to decompose the industrial COD emissions per unit of GDP into technology effect, energy consumption intensity, and regional distribution of economic scale the three factors. The industrial COD emissions of each province comes form *China Environmental Yearbook* from 1999 to 2015. GDP of the whole country and each province comes from *China Statistics Yearbook* from 1999 to 2015. Energy consumption of the whole country and each province comes from *China Energy Statistics Yearbook* from 1999 to 2015. The total sample in the paper is divided into four regions according to the commonly used regional division. The eastern region includes Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The central region includes Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan. The western region includes Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang. The Northeast region includes Liaoning, Jilin and Heilongjiang. Due to the difficulty of data collection, this paper only studies the industrial COD emission in mainland China, and does not include data and analysis of Tibetan autonomous regions. It is analyzed from five dimensions that are the national, eastern, central, western and northeast regions in this paper.

2) Kaya Equation

Kaya's identity was originally proposed by Japanese scholar Kaya to break down greenhouse gas emissions into four driving factors: energy carbon intensity, energy consumption per unit of GDP, GDP per capita, and population [13] [14]. In order to analyze the factors affecting the industrial COD emission per unit of GDP, we build the Kaya equation and apply the research method of Shapiro and Walker (2018) [10]. The industrial COD emissions are decomposed according to the spatial dimension firstly, which is shown in Formula (1).

$$Industrial\ COD\ Emission = \sum_{i=1}^{30} Industrial\ COD\ Emission_i \tag{1}$$

In Formula (1), $Industrial\ COD\ Emission$ represents industrial COD emissions across China. $Industrial\ COD\ Emission_i$ stands for industrial COD emissions of province i in China. Due to the difficulty of data collection, this paper only contains data from 30 provinces in mainland China. Tibet, Hong Kong, Macao and Taiwan of China do not include in the sample.

Furthermore, industrial COD emissions across China are decomposed according to Formula (2).

$$\begin{aligned}&\textit{Industrial COD Emission}\\&=\sum_{i=1}^{30}\frac{\textit{Industrial COD Emission}_i}{\textit{Energy}_i}\cdot\frac{\textit{Energy}_i}{\textit{GDP}_i}\cdot\frac{\textit{GDP}_i}{\textit{GDP}}\cdot\textit{GDP}\end{aligned} \tag{2}$$

In Formula (2), industrial COD emissions of province *i* are decomposed into three factors: technology effect, energy consumption intensity, and regional distribution of economic scale. Technology effect is measured by industrial COD emission per unit of energy consumption; energy consumption intensity is measured by energy consumption per unit of GDP; regional distribution of economic scale is measured by the ratio of GDP in province *i* to the whole country.

It is divided by GDP on both sides of Formula (2), and we can obtain the Formula (3).

$$\begin{aligned}&\frac{\textit{Industrial COD Emission}}{\textit{GDP}}\\&=\sum_{i=1}^{30}\frac{\textit{Industrial COD Emission}_i}{\textit{Energy}_i}\cdot\frac{\textit{Energy}_i}{\textit{GDP}_i}\cdot\frac{\textit{GDP}_i}{\textit{GDP}}\end{aligned} \tag{3}$$

Formula (3) is abbreviated as Formula (4).

$$\text{ICODEG}=\sum_{i=1}^{30}\textit{ICODEE}_i\cdot EG_i\cdot GG_i \tag{4}$$

In Formula (4), ICODEG represents the industrial COD emission per unit of GDP; $ICODEE_i$ represents the technology effect of province *i*; EG_i represents energy consumption intensity of province *i*; GG_i represents regional distribution of economic scale of province *i*.

At first, the decomposition results of industrial COD per unit of GDP in the baseline case are obtained. Then, one factor is controlled (maintaining the value of 1999 unchanged), and the other two factors change with the real situation. The time trend of industrial COD per unit of GDP after controlling one factor is obtained, and compared with the time trend of the baseline (the three influencing factors are not controlled). The greater the deviation of the two time trends, the greater the impact of this factor.

3) Logarithmic Mean Divisia Index (LMDI) Model

The DI index decomposition analysis method and Laspeyres index decomposition analysis method were put forward in the 1980s. LMDI represents Logarithmic Mean Divisia Index method in DI's index decomposition analysis method, and it is a digital model produced by Ang [14] [15] [16]. This model was used to learn more about the contribution of people's activities to pollution discharge [17] [18]. The model is suitable for problems in factor decomposition and widely used in analyzing forces [17].

According to the LMDI method put forward by Ang, the change of industrial COD emission per unit of GDP between a base year *m* and a target year *t*, is denoted by $\Delta\text{ICODEG}^{t-m}$

$$\Delta \text{ICODEG} = \Delta ICODEE_i + \Delta EG_i + \Delta GG_i \tag{5}$$

The contribution rate of each factor to industrial COD emission per unit of GDP can be calculated by the following formulas:

$$\Delta ICODEE_i = \frac{ICODEG_i^t - ICODEG_i^0}{\ln ICODEG_i^t - \ln ICODEG_i^0} \cdot \left(\ln \frac{ICODEE_i^t}{ICODEE_i^0} \right) \tag{6}$$

$$\Delta EG_i = \frac{ICODEG_i^t - ICODEG_i^0}{\ln ICODEG_i^t - \ln ICODEG_i^0} \cdot \left(\ln \frac{EG_i^t}{EG_i^0} \right) \tag{7}$$

$$\Delta GG_i = \frac{ICODEG_i^t - ICODEG_i^0}{\ln ICODEG_i^t - \ln ICODEG_i^0} \cdot \left(\ln \frac{GG_i^t}{GG_i^0} \right) \tag{8}$$

3. Empirical Analysis

1) Kaya equation and decomposition analysis

Based on the provincial panel data from 1999 to 2015, the Kaya equation and the decomposition method of Shapiro and Walker (2018), the industrial COD emissions per unit of GDP are decomposed into three factors: technology effect, energy consumption intensity, and regional distribution of economic scale. At first, the decomposition results of industrial COD per unit of GDP in the baseline case are obtained. Then, one factor is controlled (maintaining the value of 1999 unchanged), and the other two factors change with the real situation. The time trend of industrial COD per unit of GDP after controlling one factor is obtained, and compared with the time trend of the baseline. It is analyzed from five dimensions that are the national, eastern, central, western and northeast regions in this paper. Decomposition results of industrial COD emissions in the eastern region, central region, western region and northeastern region in China are shown in **Figures 2-6** respectively. As can be seen from **Figures 2-6**, the technology effect has the greatest impact on industrial COD emissions per unit of

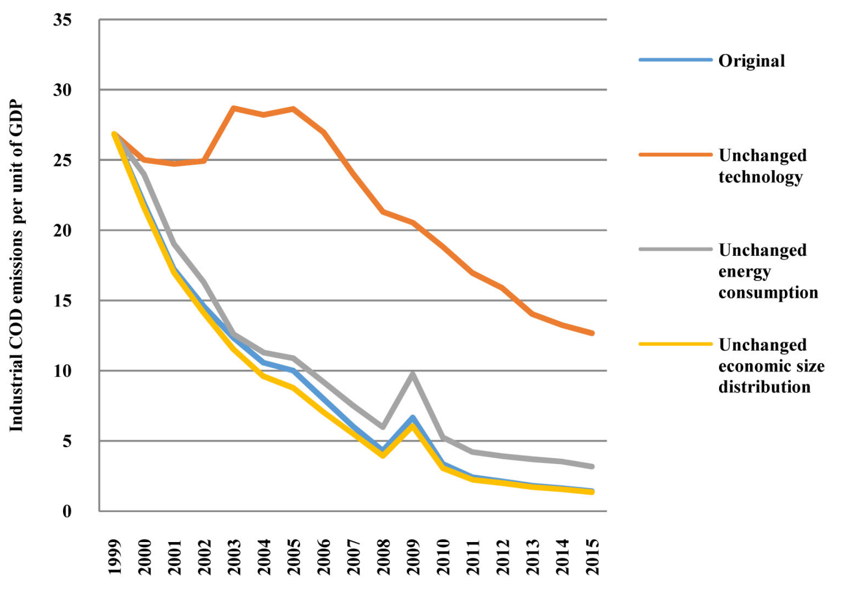

Figure 2. Industrial COD emissions decomposition results in the eastern region.

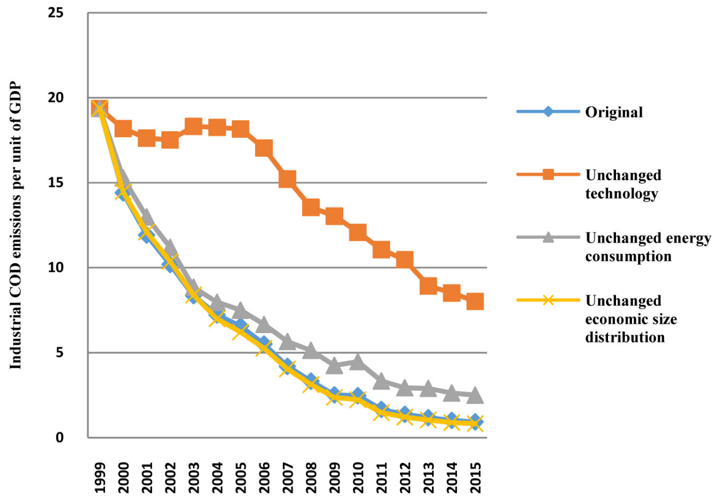

Figure 3. Industrial COD emissions decomposition results in the central region.

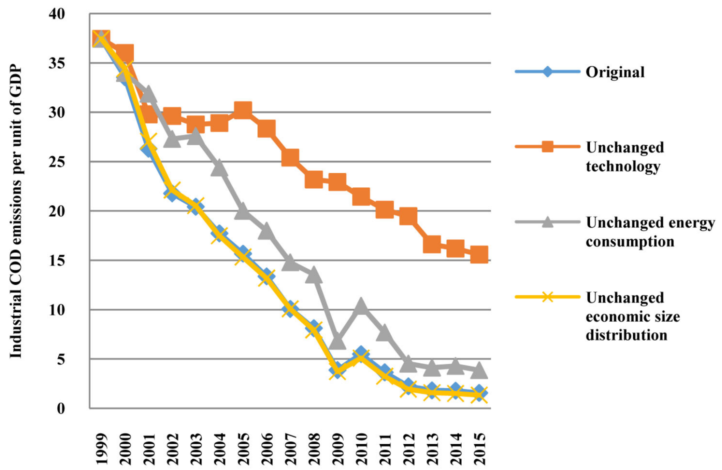

Figure 4. Decomposition results of industrial COD emissions in the western region.

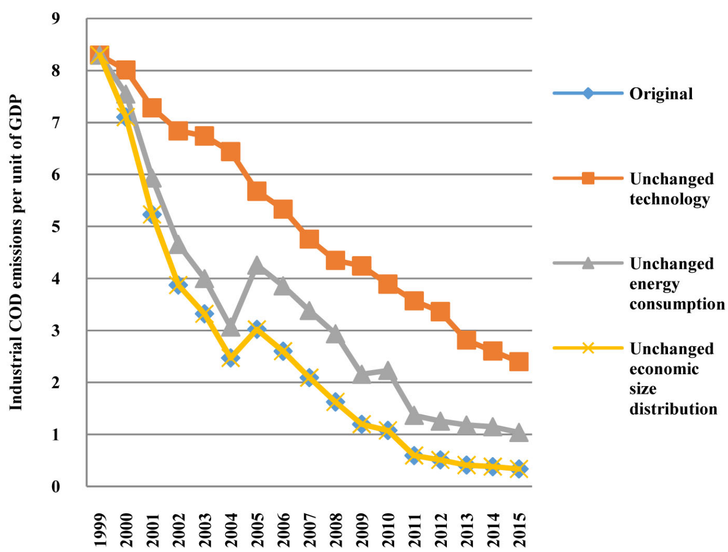

Figure 5. Decomposition results of industrial COD emissions in Northeastern China.

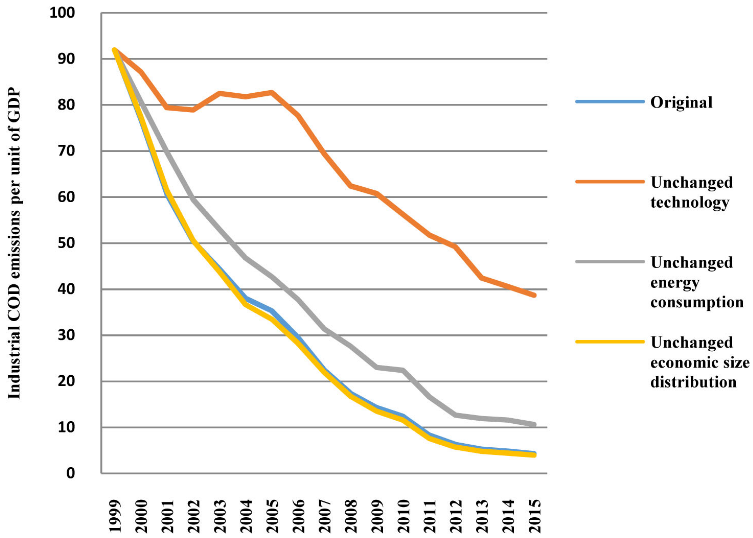

Figure 6. Decomposition results of industrial COD emissions for the whole country.

GDP, because controlling one factor will result in the largest deviation from the time trend of the baseline. It is found that the impact of energy consumption intensity on industrial COD emissions is the second, and the impact of economic scale distribution on industrial COD emissions is the minimal.

2) LMDI decomposition analysis

According to the LMDI decomposition model, the contribution rates of three factors to industrial COD emissions are quantitatively explored. Contribution rate of three factors in the eastern region is shown in **Figure 7**.

In **Figure 7**, contribution rate of technology effect in eastern China is within the range of 0.6 to 1.15, and the growth rate is relatively fast from 2000 to 2003, and reached a peak of 1.03461 in 2003. The contribution rate from 2003 to 2015 is relatively stable and slightly decreases, but it is always above 0.8. Therefore, the technology effect is the main driving force of industrial COD emissions in the eastern region. The contribution rate of energy consumption intensity in eastern China is in the range of 0.01 to 0.44. However, it dropped rapidly from 2000 to 2003, from the highest value of 0.426721 in 2000 to the lowest value of 0.0117249 in 2003. Its contribution rate has been slowly rising since 2003. Energy consumption intensity is another driving force of industrial COD emissions in the eastern region. The contribution of economic scale distribution in eastern China to industrial COD emissions is very little.

Contribution rate of three factors in the central region is shown in **Figure 8**. Contribution rate of three factors in the western region is shown in **Figure 9**. Contribution rate of three factors in the northeastern region is shown in **Figure 10**. Contribution rate of three factors for the whole country is shown in **Figure 11**. As can be seen from **Figures 8-11**, the technology effect of China's whole country, central, western and northeastern regions are the main drivers of industrial COD emissions. Energy consumption intensity is another driving force of industrial COD emissions. The results is similar to that of the eastern region.

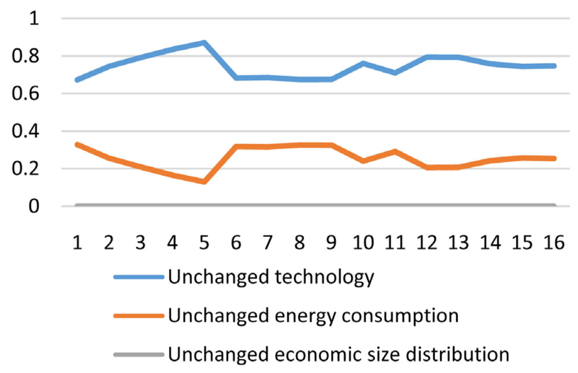

Figure 7. Contribution rate of three factors in the eastern region.

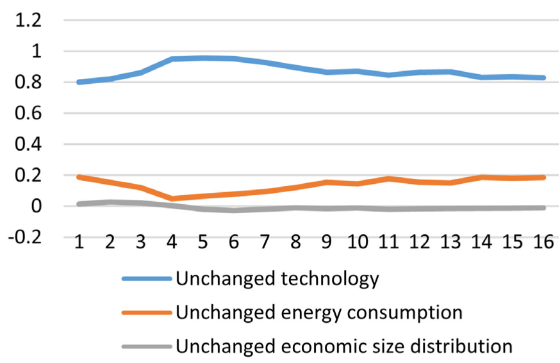

Figure 8. Contribution rate of three factors in the central region.

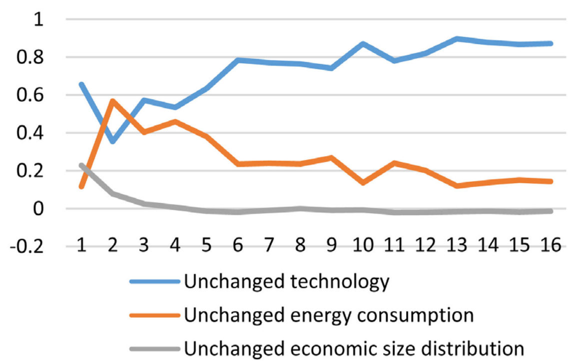

Figure 9. Contribution rate of three factors in the western region.

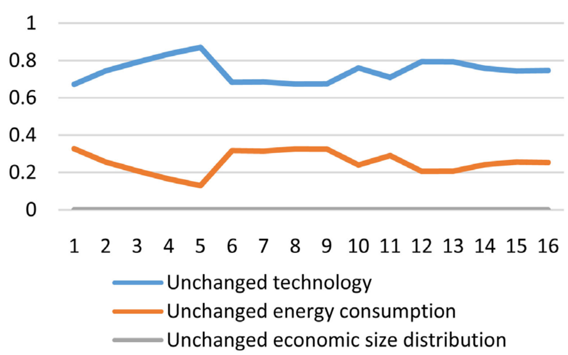

Figure 10. Contribution rate of three factors in the Northeastern China.

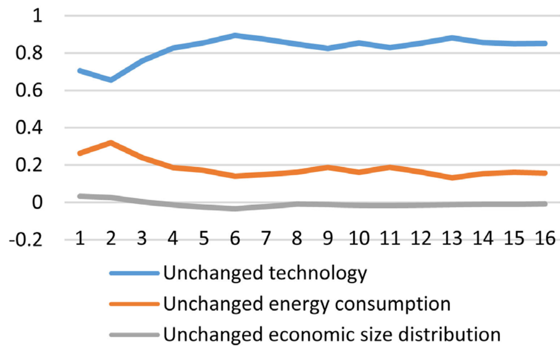

Figure 11. Contribution rate of three factors for the whole country.

4. Conclusions

Utilizing the Kaya equation and China's provincial panel data from 1999 to 2015, this paper investigates the spatial-dynamic driving forces governing industrial water pollutant emission. We decompose and quantify the heterogeneous effects of different drivers, that is, technology, energy consumption, and economic size distribution. Applying the LMDI decomposition method, this paper also calculates the contribution of the three drivers to the abatement of industrial water pollutant emissions. The analysis indicates that the most important contribution to pollutant abatement is the development of technology, followed by energy consumption, and the least affected is the distribution of economic scale.

From the results of analysis, it can be seen that if we want to reduce China's industrial COD emissions, the most important thing to improve the technical level, that is, the pollution discharge per unit of energy consumption. We should develop more clean energy technologies to improve the technical level. Second, we should reduce energy consumption intensity. In order to achieve this goal, we should vigorously develop modern high-end tertiary industries. A more advanced tertiary industry means more efficient output and more GDP with less pollution, thus achieving the goal of a green economy. In addition, the impact of economic scale distribution in the four major regions of China is subtle. It can be seen that China's market liquidity is relatively good and the market is not lack of competition. In the future, the Chinese government should adopt more clean coal combustion technology to reduce emissions, reduce the energy consumption intensity, optimize the energy consumption structure and develop the use of more clean energy.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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