Social and Economic Factors of Industrial Carbon Dioxide in China: From the Perspective of Spatiotemporal Transition

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Abstract: The reduction of CO₂ emission has become one of the significant tasks to control climate change in China. This study employs Exploratory Spatial Data Analysis (ESDA) to identify the provinces in China with different types of spatiotemporal transition, and applies the Logarithmic Mean Divisia Index (LMDI) to analyze the influencing factors of industrial CO₂ emissions. Spatial autocorrelation of provincial industrial CO₂ emissions from 2003 to 2017 has been demonstrated. The results are as follows: (1) 30 provinces in China are categorized into 8 types of spatiotemporal transition, among which 24 provinces are characterized by stable spatial structure and 6 provinces show significant spatiotemporal transition; (2) For all types of spatiotemporal transition, economic scale effect is mostly contributed to industrial CO₂ emission, while energy intensity effect is the most crucial driving force to reduce industrial carbon dioxide emission; (3) provinces of type HH-HH, HL-HL and HL-HH are most vital for CO₂ emission reduction, while the potential CO₂ emission increase of developing provinces in LL-LL, LH-LH and LL-LH should also be taken into account. Specific measures for CO₂ emission reduction are suggested accordingly.

Keywords: CO₂ emission reduction; exploratory spatial data analysis; logarithmic mean divisia index; spatial agglomeration; spatiotemporal transition

1. Introduction

Consistent growth of energy consumption in China has resulted in the massive emission of CO₂, which contributes to one of the major challenges since the 21st century—climate change [1–3]. To deal with the threat of climate change, low-carbon development has become a global consensus. China plays an important role in mitigating global climate change [4]. In 2017, the CO₂ emissions in China increased by 105.57% from 4.523 billion tons in 2003 to 9.298 billion tons [5]. At the 2009 Copenhagen Climate Change Conference, China clearly proposed that its CO₂ emission per unit of gross domestic product (GDP) in 2020 would be reduced by 40–45% compared with that in 2005. This goal was taken as a medium- and long-term plan for its national economic development [6]. Besides, at the United Nation General Assembly in 2020, China’s realization of carbon peak in 2030 and carbon neutrality in 2060 have been highly proposed. China promised its self-contribution to carbon abatement and has taken effective measures for these targets. The control of CO₂ emission, as to get a win–win achievement between the environment and economic development, has become an important goal for the sustainable economic development of China [7]. Carbon abatement in the industrial sector is crucial to the realization of China’s CO₂ emission target. The industrial sector in China has high energy consumption and CO₂ emission [8]. In 2018, the total energy consumption of China’s industrial sector was 3.11 billion tons of standard coal, accounting for 65.93% of that in China. With the rapid increase...
of the industry scale, its effect on CO₂ emissions is expected to continue to expand [9]. It is of great importance to explore issues of CO₂ emission in China’s industrial sectors.

In recent years, the issue of CO₂ emission has been widely discussed. Owing to different development levels, CO₂ emissions have significant spatial differences across regions, which is necessary to discuss from spatial perspective [5,10,11]. Studies have shown that CO₂ emission has spatial spillover effects [12,13]. Li et al., (2019) found significant spatial autocorrelation and spatial agglomeration effects of CO₂ emission in 30 Chinese provinces during the period of 2004–2016 [14]. Zhang et al., (2020) demonstrated positive spatial autocorrelation of carbon emission intensity among 281 prefecture-level cities in China [15]. Some scholars began to investigate the temporal and spatial variation of CO₂ emission [16,17]. However, most of them only analyze from temporal or spatial perspective, few traced the spatiotemporal evolution of CO₂ emission with precision [18]. The Exploratory Spatial Data Analysis (ESDA) model provides solutions to quantitively capture the dynamic changes of CO₂ emission from both temporal and spatial perspective, which has been applied into various fields, such as CO₂ emission from agriculture and water use [19,20]. Rey proposed a space-time transition classification under the framework of ESDA, which is suitable to discuss the temporal and spatial changes of CO₂ emission [21]. Zhao et al., (2017) used ESDA model to classify the spatiotemporal transition of 30 provinces in China from 1997 to 2015, which found that the spatiotemporal evolution characteristics of carbon intensity among provinces show both “agglomeration” and “differentiation” in the spatial distribution [22]. Only few researches have applied the space-time transition classification to industrial sectors in China. However, the CO₂ emission in industrial sectors is a massive part of China’s carbon abatement [23,24].

It is also important to explore the influencing factors of CO₂ emissions to obtain better carbon abatement strategies [25]. Existing studies have pointed out that population size [26], economic growth [27,28], energy consumption [29,30], energy structure [31], and industry structure [32] are the main influencing factors of CO₂ emission. The impacts of different factors vary greatly on CO₂ emissions in different industries. Lin et al., (2014) demonstrated that industrial activity is the leading force to explain emission increase in the Chinese non-metallic mineral products industry, while energy intensity is the major contributor to the emission mitigation [33]. Ma et al., (2018) illustrated that population density contributed greatly to carbon abatement of China’s commercial buildings [34]. Song et al., (2018) concluded that, in China’s iron and steel industry, economic activity was the prominent contributor to increase CO₂ emission while technology progress was the main factor of mitigated CO₂ emission [35]. Quan et al., (2020) found that economic output, population size and energy structure play a positive role in CO₂ emission in China’s logistics industry, while energy intensity plays a negative role [36]. Besides, the effects of related factors on CO₂ emissions may vary significantly in different provinces [37]. In order to mitigate industrial CO₂ emissions effectively, it is worthwhile to explore how these driving factors influence CO₂ emissions in industrial sectors of different provinces [16].

A variety of methods has been adopted to explore the influencing elements, such as Logarithmic Mean Divisia Index (LMDI) model, Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model, and Structural Decomposition Analysis (SDA) model, etc., [38–41]. LMDI has advantages on flexibility and easy access to data [42,43], which is especially suitable for provincial data in this study.

Based on existing studies, the contributions of this study are as follows. First, instead of only considering static distribution of CO₂ emission, this study adopts a ESDA method into the field of industrial CO₂ emission, which can capture the dynamic changes (both space and time) of CO₂ emission. Second, the effect decomposition of LMDI is conducted based on the classification of time-space transition of each province, which helps to identify key factors of each type and provide more targeted policy suggestions. This study evaluates the spatiotemporal transitions of industrial CO₂ emissions in China’s 30 provinces from 2003 to 2017, and explores the main driving forces of CO₂ emissions. 8 kinds of terminal industrial energy consumption at the provincial level are considered to calculate the
industrial CO$_2$ emissions, including coal, coke, crude oil, fuel oil, gasoline, kerosene, diesel oil and natural gas. Differentiated policy recommendations are proposed in line with the results and discussion.

2. Methodology and Data

2.1. Methodology

2.1.1. Calculation of CO$_2$ Emission

According to the method proposed by the Intergovernmental Panel on Climate Change (IPCC) in 2006, the industrial CO$_2$ emission can be calculated according to industrial energy consumption [44–47]. The calculation is as follows:

$$E(\text{CO}_2) = \sum_{i=1}^{8} \omega_i \times E_i = \frac{\text{NCV}_i \times \text{CEF}_i \times \text{COF}_i \times (44/12)}{c_i} \times E_i$$

(1)

where $E(\text{CO}_2)$ is the industrial CO$_2$ emission; $\omega_i$ refers to the CO$_2$ emission coefficient; $E_i$ denotes the total energy consumption; $i$ represents the 8 types of fossil energy, including coal, coke, crude oil, fuel oil, gasoline, kerosene, diesel oil and natural gas. NCV$_i$, CEF$_i$ and COF$_i$ denote the average low calorific value of energy resources, carbon emission coefficient (without conversion) and carbon oxidation factor, respectively. 44 and 22 are the molecular weights of carbon dioxide and carbon, respectively. $c_i$ is energy conversion coefficient of calorific value to standard coal.

The above parameters are from the China Energy Statistical Yearbook (2017) and the IPCC Guidelines for National Greenhouse Gas Inventories (2006). The CO$_2$ emission coefficients ($\omega_i$) of the 8 types of fossil energy are shown in Table 1.

**Table 1. The CO$_2$ emission coefficients of fuel.**

| Coefficient | Coal  | Coke  | Crude oil | Fuel oil | Kerosene | Diesel oil | Natural Gas |
|-------------|-------|-------|-----------|----------|----------|------------|-------------|
| $\omega_i$ (t/tce) | 2.741 | 2.945 | 2.147     | 2.265    | 2.104    | 2.176      | 1.642       |

2.1.2. ESDA Method

The ESDA method is introduced to measure the characteristics of spatial and temporal distributions of CO$_2$ emission. Moran’s $I$ index is used to examine the spatial agglomeration characteristics of regional carbon emission [48–50]. The calculations are as follows:

$$I = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} (X_i - \bar{X}) (X_j - \bar{X})}{S^2 \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}}$$

(2)

$$S^2 = \frac{1}{n} \sum_{i=1}^{n} (X_i - \bar{X})^2.$$  

(3)

where $n$ is the number of observed provinces; $i$ and $j$ denote city $i$ and city $j$, respectively; $X_i$ and $X_j$ are the observed values in region $i$ and region $j$; $\bar{X}$ is the average observed value of all provinces; $W_{ij}$ is the spatial weight matrix. A 0–1 matrix is used as the spatial weight matrix [51,52]. When $i$ and $j$ are adjacent, $W_{ij} = 1$; otherwise $W_{ij} = 0$. $S^2$ is the standard error of $X_i$.

2.1.3. LMDI Model

To further explore the contribution of factors influencing industrial CO$_2$ emissions, a LMDI model is adopted based on the classical Kaya identity proposed by Yoichi Kaya [53]. The effects of population, economy and energy can be evaluated in the Kaya identity:

$$CO_2 = \frac{POP}{POP} \times \frac{GDP}{GDP} \times \frac{E}{E} \times \frac{CO_2}{E}.$$  

(4)
where $CO_2$ represents total $CO_2$ emissions, $POP$ represents total population, $GDP$ denotes gross regional product, and $E$ denotes total energy consumption. Under the framework of Kaya identity, LMDI model is established to analyze the contribution of each influencing factor \[54–56\]. Due to similar properties, crude oil, fuel oil, gasoline, kerosene, and diesel oil are integrated into oil products. The 8 energy categories are simplified into 4 types. In the following calculation, Equation (4) can be extended as follows:

$$CO_2 = \sum_{i=1}^{4} \sum_{m=1}^{30} CO_{2im} = \sum_{i=1}^{4} \sum_{m=1}^{30} \left( \frac{P_m \cdot GDP_m}{E_m} \right) \cdot \frac{V_m}{E_m} \cdot \frac{GDP_m}{E_m} \cdot \frac{Em}{E_m} \cdot \frac{CO_{2im}}{E_m} = \sum_{i=1}^{4} \sum_{m=1}^{30} P \cdot G \cdot M \cdot K \cdot N \cdot S$$

(5)

where $CO_2$ refers to the total $CO_2$ emission of industrial sector; $CO_{2im}$ refers to the $CO_2$ emission generated by $i$ (energy consumption of the industrial sector) in province $m$; $P_m$ represents the total population of region $m$; $GDP_m$ represents the GDP of region $m$; $V_m$ is the industrial added value in region $m$; $E_m$ is the total industrial energy consumption in province $m$, and $E_{im}$ is the industrial energy consumption of energy type $i$ in province $m$. $P$ is resident population at the end of the year as a proxy for population size effect; $G$ represents GDP per capita as a proxy for economic scale effect; $M$ is the proportion of industrial output value in GDP, which measures the effect of industrial structure; $K$ is the energy consumption per unit industrial output value to indicate the effect of energy intensity; $N$ reflects the effect of energy structure, expressed by the proportion of energy $i$ in the total industrial energy consumption; $S$ is the $CO_2$ emission coefficient, which is indicated by the $CO_2$ emission per unit terminal energy consumption. Given that $S$ is assumed to be a constant value, only five influencing factors are decomposed, which are shown in Equations (6)–(10).

$$\Delta C^{P, -1}_p = \sum_i \frac{C_i^t - C_i^{t-1}}{\ln C_i^t - \ln C_i^{t-1}} \cdot \ln \frac{P_t}{P_t^{t-1}};$$

(6)

$$\Delta C^{G, -1}_G = \sum_i \frac{C_i^t - C_i^{t-1}}{\ln C_i^t - \ln C_i^{t-1}} \cdot \ln \frac{G_i^t}{G_i^{t-1}};$$

(7)

$$\Delta C^{M, -1}_M = \sum_i \frac{C_i^t - C_i^{t-1}}{\ln C_i^t - \ln C_i^{t-1}} \cdot \ln \frac{M_i^t}{M_i^{t-1}};$$

(8)

$$\Delta C^{K, -1}_K = \sum_i \frac{C_i^t - C_i^{t-1}}{\ln C_i^t - \ln C_i^{t-1}} \cdot \ln \frac{K_i^t}{K_i^{t-1}};$$

(9)

$$\Delta C^{N, -1}_N = \sum_i \frac{C_i^t - C_i^{t-1}}{\ln C_i^t - \ln C_i^{t-1}} \cdot \ln \frac{N_i^t}{N_i^{t-1}}.$$  

(10)

where $\Delta C^{P, -1}_p$ is the contribution of population scale effect, $\Delta C^{G, -1}_G$ is the contribution of economic scale effect, $\Delta C^{M, -1}_M$ is the contribution of industrial structure effect, $\Delta C^{N, -1}_N$ is the contribution of energy intensity effect, and $\Delta C^{S, -1}_S$ is the contribution of energy structure effect. A positive value indicates that the influencing factor is conducive to the increase of $CO_2$ emissions, whereas a negative value shows that the influencing factor reduces of $CO_2$ emissions.

2.2. Sources of Data

The data of GDP, resident population at the end of the year and industrial output value are from the China Statistical Yearbook (2004–2018). GDP is converted into real price (base year = 2003). Per capita GDP is calculated by the proportion of real GDP and resident population at the end of the year. The industrial energy consumption of coal, coke, crude oil, fuel oil, gasoline, kerosene, diesel oil and natural gas and the total province are from China Energy Statistical Yearbooks (2004–2018). Owing to data limitations, Tibet Autonomous Region, Hong Kong, Macao, and Taiwan Special Administrative Regions are excluded.
3. Analysis of Spatiotemporal Transition

3.1. Regional Distribution of Industrial CO\textsubscript{2} Emissions

The trend of total industrial CO\textsubscript{2} emissions in 30 provinces from 2003 to 2017 are shown in Figure 1. In general, the year of 2013 is a crucial turning point of CO\textsubscript{2} emission in China. Based on this, the fifteen years of CO\textsubscript{2} emission from 2003 to 2017 can be divided into two stages: the rising stage from 2003 to 2012 and the declining stage from 2013 to 2017. The industrial CO\textsubscript{2} emissions of China increased from 2.07 billion tons in 2003 to a peak of 4.37 billion tons in 2012, then showed a wavelike decrease to 3.70 billion tons in 2017. It demonstrated that the Air Pollution Control Action Plan issued in 2013 exerted a significant effect on the CO\textsubscript{2} emission, which resulted in the emission abatement directly. Moreover, China’s industrial CO\textsubscript{2} emissions grew rapidly before 2006, with a maximum growth rate of 22.6% in 2005, which is mainly caused by the overgrowth of industrialization and urbanization. During 2006–2012, the growth rate of CO\textsubscript{2} emission gradually descended from 10.39% in 2006 to 2.51% in 2012, which resulted from introducing total emission control of major pollutants in the 11th Five-Year Plan. The growth rate of total CO\textsubscript{2} emission turned negative for the first time in 2013. Although the growth rate began to rise slightly in 2014 compared with that in 2013, it is still at a low level. Since 2015, the growth rate of total CO\textsubscript{2} emission has been negative, which proves the effectiveness of relevant policies on national CO\textsubscript{2} emission reduction. During the 12th Five-Year Plan period, the Chinese government proposed the control of air pollution in key pollution areas, which directly brought about the increase of clean energy supply and control of total coal consumption in industrial sectors, thus decreased the emission of industrial CO\textsubscript{2}.

The provincial industrial CO\textsubscript{2} emissions in the starting year, turning point and ending year of this study (2003, 2013 and 2017) are shown in Figure 2. The CO\textsubscript{2} emissions of most provinces in China raised first and then decreased at the second stage, which is consistent with the overall national level in Figure 1. However, the level and distribution of CO\textsubscript{2} emissions in provinces display regional dynamic characteristics. The CO\textsubscript{2} emissions in Hebei, Shandong, Henan, and Jiangsu provinces were constantly the top 4 among provinces. The rapid economic development and flourishing industrial development in these areas lead to high carbon dioxide emissions. These high carbon emission areas with developed industries are the key areas of CO\textsubscript{2} emission reduction. Beijing and Hainan have
always been low CO$_2$ emission areas compared with others. Although economy in these regions develops fast, it is driven by the tertiary industry, rather than secondary industries. Therefore, the industrial CO$_2$ emissions in the two provinces are relatively small. The CO$_2$ emissions of Yunnan, Shanxi, Gansu, and Qinghai provinces were lower than the national average. Low economic level in these provinces leads to low industrial CO$_2$ emissions.

Figure 1. Trend of China’s industrial CO$_2$ emissions.

Figure 2. Industrial CO$_2$ emission of China’s provinces in crucial years (2003, 2013, 2017).

3.2. Spatial Autocorrelation of Industrial CO$_2$ Emission

As shown in Table 2, the global Moran’s $I$ indices of China’s industrial CO$_2$ emission from 2003 to 2017 have all passed the significance test, which ranges from 0.127 to 0.305. The results demonstrate positive spatial autocorrelation and a clustering trend of CO$_2$ emission among provinces. The industrial CO$_2$ emission of each region will be influenced by the neighboring regions, showing an “agglomeration” trend in space. Therefore, it is necessary to distinguish and analyze the geographic distribution of CO$_2$ emission.

| Year | Moran’s $I$ | Year | Moran’s $I$ | Year | Moran’s $I$ |
|------|-------------|------|-------------|------|-------------|
| 2003 | 0.225 **    | 2008 | 0.265 ***   | 2013 | 0.219 **    |
| 2004 | 0.297 ***   | 2009 | 0.244 **    | 2014 | 0.238 **    |
| 2005 | 0.301 ***   | 2010 | 0.255 ***   | 2015 | 0.203 **    |
| 2006 | 0.293 ***   | 2011 | 0.25 **     | 2016 | 0.165 **    |
| 2007 | 0.305 ***   | 2012 | 0.182 **    | 2017 | 0.127 *     |

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The global Moran’s $I$ index only reflects the overall spatial autocorrelation of an observed region. In order to further test the spatial autocorrelation of each province in China, a Moran’s $I$ scatter plot is necessary. The Moran’s $I$ scatter plots of 2003 and 2017 are shown in Figure 3. Most provinces are in the first and third quadrants, which further indicates a significant positive spatial spillover effect of industrial CO$_2$ emissions.
Table 3 displays spatial agglomeration types of industrial CO$_2$ emissions according to Moran’s $I$ scatter plot. Provinces of HH (high CO$_2$ emission in the local and neighborhood), LH (low CO$_2$ emission in the local while high CO$_2$ emission in the neighborhood), and LL (low CO$_2$ emission in the local and neighborhood) clusters account for the majority in China, while the HL (high CO$_2$ emission in the local while low CO$_2$ emission in the neighborhood) agglomeration area constitutes the minority. Specifically, provinces in the HH agglomeration area have larger economic scale and higher population density, which causes more energy consumption and CO$_2$ emission in the local. Besides, the regional agglomeration enhances economy in surrounding areas, which leads to high CO$_2$ emissions in neighboring provinces. This type mainly consists of Hebei, Shandong, and other provinces. The LH agglomeration area is mainly concentrated in Beijing, Shanghai, Tianjin, and other provinces.
regions. After rapid economic development, high carbon dioxide emission industries in local areas will be transferred to neighboring areas, demonstrating the characteristics of LH accumulation: low \( \text{CO}_2 \) emissions locally and high \( \text{CO}_2 \) emissions in the adjacent areas. The LL agglomeration area includes Yunnan, Gansu, Qinghai and other provinces, which has low \( \text{CO}_2 \) emissions both in the local and surrounding areas. Only Guangdong, Sichuan and Hunan are always in the HL agglomeration area, which has high industrial \( \text{CO}_2 \) emission in the local but low industrial \( \text{CO}_2 \) emission in the surrounding provinces. The distribution of each agglomeration type differs between 2003 and 2017, which means that some provinces transfer to other quadrants. For instance, Hubei changed from HL cluster in 2003 into HH cluster in 2017. Heilongjiang and Guizhou changed from LH cluster in 2003 to LL cluster in 2017. The spatiotemporal transition of industrial carbon emissions is necessary to be further evaluated.

### Table 3. Spatial agglomeration types of industrial \( \text{CO}_2 \) emission in China.

| Year | HH (High-High) | LH (Low-High) | LL (Low-Low) | HL (High-Low) |
|------|----------------|---------------|--------------|---------------|
| 2003 | Hebei Shandong | Tianjin Beijing | Heilongjiang Yunnan | Guangdong Sichuan |
|      | Shanxi Liaoqing Henan | Jiangxi Shaanxi Jilin | Guizhou Gansu | Hubei Hunan |
|      | Anhui Jiangsu Zhejiang | Hainan Fujian Chongqing | Qinghai Ningxia | |
|      | Inner Mongolia | Tianjin Beijing | Xinjiang Guangxi | |
|      | Hebei Shandong | Jiangxi Shaanxi Jilin | Yunnan Gansu | |
|      | Liaoning Henan Anhui | Zhejiang Chongqing | Qinghai Ningxia | |
|      | Jiangsu Shanxi Hubei | Guizhou Heilongjiang | Xinjiang Guangxi | |
|      | Inner Mongolia | | Guangxi Fujian | |
| 2017 | | | | Guangdong Sichuan |
|      | | | Hunan | |

3.3. Spatiotemporal Transition of Industrial \( \text{CO}_2 \) Emission

The spatial agglomeration characteristics of industrial \( \text{CO}_2 \) emissions in each province are evaluated according to the classification of spatiotemporal transition [19,20]. By observing the changes of 4 spatial agglomeration types (HH, LH, LL and HL) in starting and ending years (2003 and 2017), the spatial and temporal variation of \( \text{CO}_2 \) emission in different provinces can be categorized into 16 spatiotemporal transition types. It is shown in Table 4 that LH→LL, LL→HL, LH→HH, LL→HL, LH→HH, HH→HL, HL→HH, HH→LL, HH→HL, and LL→HL type have spatiotemporal transition, while LH→LL, LL→LL, HH→HH, and HL→HL type do not. The 30 provinces in China belong to 8 types: LH→LL, LL→LL, LH→LL, LL→HL, HH→HH, HL→HH, and HH→HL. To be more precise, provinces of LH→LL or LL→LL type have low \( \text{CO}_2 \) emission with no spatiotemporal transition between local and neighborhood regions. Regions in LH→LL or LL→LL type regions show low local \( \text{CO}_2 \) emission, while the spatiotemporal transition only occurs in the neighboring provinces rather than in the observed province. HH→HH and HL→HL type have high local \( \text{CO}_2 \) emission, but no significant spatiotemporal transition in the local and neighborhoods. HH→HH type areas show high local \( \text{CO}_2 \) emission, and the spatiotemporal transition only occurs in the neighboring provinces. For HH→LL type provinces, the local \( \text{CO}_2 \) emission changes from high to low and there is no spatiotemporal transition in neighboring areas.

It is concluded that the \( \text{CO}_2 \) emission in local provinces is easily influenced by that of neighboring provinces. Therefore, the provinces in LH→LL, LL→LL, HL→HH and HH→HH type should be paid more attention to promote the transition trend of \( \text{CO}_2 \) emission in China. Besides, HH→HH type provinces are supposed to have stable and high \( \text{CO}_2 \) emission in the future, which illustrates the necessity to control \( \text{CO}_2 \) emission in provinces with this transition path.
Table 4. Spatiotemporal transition of industrial CO\textsubscript{2} emission in different provinces.

| Type       | Spatiotemporal Transition | Provinces                                      |
|------------|---------------------------|-----------------------------------------------|
|            | Transition | Local | Neighborhood |                              |
| LH→LH      | I          | -     | -            | Tianjin Beijing Shanghai Jiangxi Shaanxi Jilin Chongqing                      |
| LL→LL      | I          | -     | -            | Yunnan Gansu Qinghai Guangxi Ningxia Xinjiang                                 |
| LH→LL      | II         | -     | high→low     | Fujian Hainan                                                                |
| LL→LH      | II         | -     | low→high     | Heilongjiang Guizhou                                                         |
| LH→HH      | II         | low→high | -            | -                                                                          |
| LL→HL      | II         | low→high | -            | -                                                                          |
| LH→HL      | II         | low→high | high→low     | -                                                                            |
| LL→HH      | II         | low→high | low→high     | -                                                                            |
| HH→HH      | I          | -     | -            | Hebei Shandong Shanxi Liaoning Henan Anhui Jiangsu Inner Mongolia Guangdong Sichuan Hunan |
| HL→HL      | I          | -     | -            | -                                                                            |
| HH→HL      | II         | -     | high→low     | -                                                                            |
| HL→HH      | II         | -     | low→high     | Hubei                                                                       |
| HH→LH      | II         | high→low | -            | Zhejiang                                                                   |
| HL→LL      | II         | high→low | -            | -                                                                            |
| HH→LL      | II         | high→low | high→low     | -                                                                            |
| HL→LH      | II         | high→low | low→high     | -                                                                            |

Notes: I: no spatiotemporal transition in both local and neighborhood provinces; II: spatiotemporal transition exists in local or neighborhood provinces.

4. LMDI Analysis based on Spatiotemporal Transition

4.1. Driving Factors of National Industrial CO\textsubscript{2} Emission

To further study what impacts carbon dioxide emission and how to effectively reduce carbon emission, driving factors of CO\textsubscript{2} emission are analyzed on the basis of the LMDI mode (see Figure 4). As for different factors, the economic scale always exerts a positive effect on national industrial CO\textsubscript{2} emission in 2003–2017, with the highest contribution of 658.09 million tons in 2011–2012. It shows that the effect of economic scale plays a dominant role in promoting the CO\textsubscript{2} emission, which is consistent with the result of Zhang et al. [57]. Energy intensity effect has a significant impact on the CO\textsubscript{2} emission reduction, with the highest CO\textsubscript{2} emission reduction of 645.89 million tons in 2012–2013 [58]. Population size effect makes a relatively small contribution to promoting carbon emissions. It keeps positive, except 2004–2005, with the average value of 20.86 million tons. The effect of industrial structure stays positive before 2012, except for 2009–2010. It has become negative since 2012, with the highest contribution to CO\textsubscript{2} abatement of 244.60 million tons in 2015–2016. This result illustrates that industrial structure played a significant role in promoting national industrial carbon emission before 2011–2012, whereas it became a driving force of CO\textsubscript{2} emission reduction after 2011–2012. It is necessary to adopt the industrial restructuring and upgrade as a vital means to reduce carbon emission [59]. During 2003–2017, the effect of energy structure on CO\textsubscript{2} emission stays positive except for 2012–2015, which is weaker compared to other factors. The short-term negative fluctuation may be affected by the abrupt economic decline and the environmental policy carried out during the 12th Five Year Plan. However, due to China’s traditional energy structure dominated by coal oil and natural gas, it causes the promotion of carbon dioxide emission in the long term. In terms of the tendency, the effect of economic scale was a dominant factor to the increment of CO\textsubscript{2} emission before 2012. The energy intensity effect became the strongest influencing factor instead of economic scale effect in 2012–2013 and 2015–2017. Besides, the effect of industrial structure and energy intensity has declined after 2012. To sum up, the economic development always leads to industrial CO\textsubscript{2} emission, but the improvement of energy intensity is the main driving forces of CO\textsubscript{2} abatement.
4.2. Variation of Sub-Index Contribution Degree to Different Spatiotemporal Transition Types

The effects of sub-index on carbon dioxide emission have significant differences between provinces classified by spatiotemporal transition types. Figure 5 shows the accumulative contribution degree of five influencing factors in different spatiotemporal transition types during 2003–2017. The differences of the five effects among the 8 types of provinces are as follows. For economic scale effect, the HH-LH type regions show the strongest effect (2467.51% of the total effect), which is followed by the LL-LH type (689.14%), HL-HH type (60.56%), HL-HL type (429.22%), LH-LH (426.82%), HH-HH (362.77%), LH-LL (297.59%) and LL-LL type (220.43%). For energy intensity effect, the HH-LH type regions also show the strongest effect, accounting for −2371.17% of the total effect. It is followed by the HL-HH type (−517.49%), LL-LH type (−432.43%), HL-HL type (−363.71%), LH-LH (−352.47%), HH-HH (−252.64%), LH-LL (−213.18%) and LL-LL type (−112.39%). For industrial structure effect, the type with the largest accumulative contribution degree is HH-LH (−267.11%), followed by LL-LH (−150.11%), HH-HH (−36.96%), LL-LL (−25.82%), LH-LH (−14.13%), LH-LL (−11.36%), HL-HH (−8.03%) and HL-HL (−2.26%). For population scale effect, the order of accumulative contribution degree is HH-LH (248.72%), LH-LH (34.16%), HL-HL (22.76%), LH-LL (19.58%), LL-LH (−16.31%), HH-HH (15.12%), LL-LL (13.18%), HL-HH (12.51%). For energy structure effect, the order is supposed to be: HH-LH (22.05%), HL-HL (13.99%), HL-HH (12.44%), HH-HH (11.71%), LL-LH (9.71%), LH-LL (7.37%), LL-LL (4.59%), LH-LH (5.62%).

For all spatiotemporal transition types, economic scale and energy intensity present strongest effect on CO$_2$ emission among the five influencing factors. The effect intensity of economic scale has the same trend with that of energy intensity. The spatiotemporal transition types with strong (weak) economic scale effect also have strong (weak) energy intensity effect. However, the two effects display opposite contribution to carbon dioxide emission. The economic scale effect for all spatiotemporal transition types promotes CO$_2$ emission, while energy intensity effect shows an inhibition to CO$_2$ emission. It is owing to the contradiction of regional economic development and national goal of emission reduction. For a long term, economic development has been the priority for local governments. The national goal of emission reduction will more or less impede
economic growth in a short term. Therefore, the inconsistent targets between the central government and local governments result to a counterbalance of the economic scale effect and energy intensity effect, which finally weaken the effectiveness of carbon dioxide emission. Population size, industrial structure and energy structure have less effect on CO₂ emission compared with economic scale and energy intensity. Among the three effects, the industrial structure effect decreases the CO₂ emission in all spatiotemporal transition types, while energy structure effect and population size effect (except for LL-LH type) contribute to CO₂ emissions.

Among the 8 types of spatiotemporal transition, types of HH-LH and LL-LL are typical with the highest and lowest accumulative contribution degrees respectively. The accumulative contribution degrees of each influencing factors in HH-LH type are significantly higher than that in other types. The corresponding region of this type is Zhejiang Province. Although the rapid economic growth and large population size in this province contribute a lot to CO₂ emission, the efficient energy utilization and rational industrial structure promote emission reduction. It achieves a win-win development of economy and carbon dioxide emission reduction, as maintain the CO₂ emission in a stable and relatively low level. LL-LL type regions typically have low accumulative contribution degree of each influencing factors, especially for economic scale effect and energy intensity effect. This type of provinces concentrates on Western regions of China, such as Yunnan, Gansu, Qinghai, Guangxi, Ningxia and Xinjiang. The carbon dioxide emission has still been at a low level in these provinces due to its undeveloped economy, which leads to the low accumulative contribution degrees. To better examine the difference between region types and distinguish the particularity of provinces in each type, the accumulative contribution values of each province are further discussed in the next section.

4.3. Discussion on Regional CO₂ Emission Reduction based on Spatiotemporal Transition Types

The accumulative contribution value and total carbon dioxide emission of each province based on spatiotemporal transition types during 2003–2017 are shown in Figure 6. Detailed analysis and targeted suggestion to various spatiotemporal transition type will be discussed in the following.

LH-LH type includes Tianjin, Beijing, Shanghai, Chongqing, Jiangxi, Shaanxi and Jilin, the industrial CO₂ emission of which are all ranking low in China. However, different provinces show differentiated characteristics. 4 of them are municipalities (Tianjin, Beijing, Shanghai, Chongqing) in China. In these regions, the inhibition effect of energy intensity to CO₂ is stronger than the promotion effect of economic scale compared to the other provinces. In other words, due to the rapid economic development, high efficiency of
energy utilization and the outward movement of related industries, the carbon dioxide abatement in these provinces has been carried out well and steadily during the fifteen years. Other three provinces (Jiangxi, Shaanxi and Jilin) are surrounded by several high CO₂ emission provinces, such as Hubei, Hunan, Guangdong, Anhui, Hebei, Shanxi and Liaoning. The industry of the three provinces has still been left behind the adjacent regions. Therefore, developed areas in LH-LH type, such as Tianjin, Beijing, Shanghai, Chongqing, should maintain their low emission levels as well as produce an impetus effect on neighboring provinces, as integrate resources to promote industrial transformation of the whole region; developing areas in LH-LH type, such as Jiangxi, Shaanxi and Jilin, should pay special attention for the potential environmental pollution caused by industrial undertaking from surrounding provinces.

Figure 6. The accumulative contribution value and CO₂ emission of each province based on spatiotemporal transition types during 2003–2017 (100 million tons). The provinces in LL-LL type concentrate in the western region in China, which include Yunnan, Gansu, Qinghai, Guangxi, Ningxia and Xinjiang. Since these regions fall behind both in economic and industrial development, all of the industrial CO₂ emissions are lower than the average level in China, which gradually form a LL spatial agglomeration in these provinces. However, during the current transformation of industry from the east to the west (One Belt, One Road etc.), a coordinated development should be attached importance to in LL-LL type. For instance, developing environmental conservation industries and making use of energy with high quality in the industry production. LH-LL type includes
Fujian and Hainan. The two provinces discharge low level of carbon dioxide, especially Hainan. This is because, both of them are highly dependent on the single industry of tourism, and do not take the second industry as the main development pathway. The LL-LH type consists of Heilongjiang and Guizhou. The CO₂ emission of two are not high, but the contribution of the economic scale and the industrial structure are the second highest compared to other provinces. On one side, the industry progressed fast in Guizhou. The greater the economic scale, the more CO₂ emission produced. On the other side, as a traditional industrial province, Heilongjiang has been adopting the extensive and inefficient development mode. Preventing Heilongjiang and Guizhou from becoming high CO₂ emission provinces, provinces of the LL-LH type should be emphasized as key provinces to the abatement carbon dioxide emission during economic development.

The provinces of type HH-HH (Hebei, Shandong, Shanxi, Liaoning, Henan, Anhui, Jiangsu, Inner Mongolia), HL-HL (Guangdong, Sichuan, Hunan) and HL-HH (Hubei) show higher industrial CO₂ emission over the national average, ranking the top 12 in China. Besides, the spatial agglomeration of high CO₂ emission is especially demonstrated in provinces of HH-HH type and HL-HH type during 2003–2017. As for the effects of five influencing factors, the highest promoting effect of economic scale on CO₂ emission is demonstrated in the HH-HH type, and followed by the HL-HL type. The population size positive effect in some provinces of type HH-HH (Hebei, Shandong, Shanxi) and HL-HL(Guangdong) are more intense than provinces of other types. For one thing, 75% among the 12 provinces both have large population size and economic scale, leading to more energy consumption and carbon dioxide emission. For another, many provinces are geographically adjacent, such as Huabei region (Hebei, Inner Mongolia, Shanxi), Huazhong region (Henan, Hunan, Hubei) and Huadong region (Jiangsu, Anhui, Shandong). The spatial agglomeration of adjacent provinces further strengthens the emission level of industrial CO₂ in these provinces. These provinces are supposed to break through provincial boundaries and build a coordinated mechanism, which can maximize the advantages of each province in CO₂ emission reduction, so as to realize the transformation and upgrading of low-carbon green industry, and jointly complete the target of carbon emission reduction. In HH-LH, the industrial CO₂ emission of Zhejiang has declined in 2003–2017 for the reason that, Zhejiang reinforces the energy usage and adjusts the industrial structure rationally with the economy prosperity.

5. Conclusions

By using the ESDA and LMDI methods, the study analyzes the spatiotemporal evolution of industrial CO₂ emissions among 30 provinces in China from 2003 to 2017 and further explore the impacts of five driving factors on CO₂ emissions. Corresponding conclusions and findings on the basis of different spatiotemporal transitions are as follows:

(1) China’s provinces with high industrial CO₂ emissions are mainly distributed in central and eastern regions. The industrial CO₂ emission in western provinces stays low but has an upward trend. In general, most provinces in China maintain steady spatial agglomeration types of industrial CO₂ emission. 24 provinces in China show no spatiotemporal transition of industrial CO₂ emission, while other 6 provinces have spatiotemporal transition of industrial CO₂ emission in the local or neighboring regions.

(2) For all the 8 types of spatiotemporal transition, economic scale effect is mostly contributed to industrial CO₂ emission; energy intensity effect is the most crucial factor in reducing carbon emission, which is followed by industrial structure effect; population size effect and energy structure effect both promote industrial CO₂ emission, but play little role compared with other effects.

(3) The most vital provinces for CO₂ emission abatement include provinces of type HH-HH, HL-HL and HL-HH. For provinces in HH-HH, HL-HL and HL-HH type, it is suggested to construct a particular mechanism of joint prevention and control for carbon emission reduction, so as to take the advantages of in each province, and further enhance the efficiency of emission abatement. The developing provinces in LL-LL, LH-LH and
LL-LH should also pay attention to emission control to prevent potential increase of CO₂ emission. It is important to seize the opportunity of industrial transformation, technology innovation and energy efficiency improvement. HH-LH and LH-LL type have advantages in controlling CO₂ emission. HH-LH type can be taken as an example to achieve the balance between the economy and environment protection. Provinces in LH-LL are supposed to make full use of the local superior resources to achieve prosperity such as ecological agriculture, ecological tourism and renewable resources.

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