Original Research

Provincial Contributions Analysis of the Slowdown in the Growth of China's Industrial CO$_2$ Emissions in the "New Normal"

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Abstract

The industrial sector has been the largest CO$_2$ emitter in China. The purpose of this paper is to explore the reasons for the slowdown in the growth of industrial CO$_2$ emissions (ICE) since China's economy entered a new development model in 2012 – the "new normal". First, we overviewed the ICE status in China from 2007 to 2017. Then, we utilized the Tapio model to analyze the decoupling relationship between ICE and industrial economy. Finally, the Logarithmic Mean Divisia Index (LMDI) was used to explore the related driving factors of ICE change and the contributions of each province to China's ICE increase. The results showed that: (1) the growth rates of China's ICE were 41.34% and 6.7% in 2007-2012 and 2012-2017, respectively, a signal that the growth of ICE has significantly slowed down in the "new normal". The spatial distribution in ICE has gradually evolved from high emissions in northern coastal regions and low emissions in other regions to high emissions in northern regions and low emissions in southern regions. In addition, the gap of ICE has gradually widened among provinces. (2) The decoupling elasticity between China's ICE and industrial economy decreased from 0.53 in 2007-2012 to 0.29 in 2012-2017. That may be related to a strong decoupling state in the central and southwestern provinces and the decline of the elasticity in the coastal provinces. (3) From 2007 to 2012, energy intensity was the main inhibiting factor in China's ICE. From 2012 to 2017, industrial structure was the primary contributor to ICE reduction, followed by energy intensity. The central and eastern provinces with large-scale industrial economies, such as Hebei, Sichuan, Hubei, and Shandong, have significantly reduced the increment of ICE, making the main contribution to the decline in the growth rate of China's ICE.

Keywords: industrial CO$_2$ emissions, decoupling elasticity, driving factors, provincial contributions

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Introduction

Global warming has been well recognized as one of the serious challenges facing humankind in the 21st century. The main cause is that human activities have consumed a large amount of fossil fuels in the past century and a great quantity of greenhouse gases such as CO_2 have been emitted [1-2]. At present, China has become the largest CO_2 emitter in the world. The emissions have surpassed the sum of those in the US and EU, putting China under enormous pressure to reduce emissions and address global warming in the international community [3]. In December 2015, the 21st United Nations Climate Change Conference was officially held in Paris, France, where the Paris Agreement was adopted. That limited the global average temperature increase compared with the pre-industrial level to less within 2ºC [4]. Accordingly, the Chinese government promised to reduce CO_2 emissions per unit gross domestic product (GDP) by 60-65% from 2005 levels by 2030; it requires substantial reduction in CO_2 emissions for China [5].

Since the reform and opening up in 1978, urbanization and industrialization in China have developed rapidly. The industry holds a key position not only in China's economy but also in China's total energy consumption. The industrial value added accounts for more than 30% of GDP in China [6]. Approximately 70% of China's total energy is used by various industrial activities [7], proving that the industrial sector can play a major role in reducing CO_2 emissions. Moreover, the industrial sector in China is the largest CO_2 emitter, and its CO_2 emissions have continued to increase in recent years [8]. However, since China's economy entered the "new normal" in 2012, the economic structure has been constantly adjusted, and the level of economic growth has shifted from high speed to medium-high speed. According to the calculation, the growth rate of China's ICE experiences a significant slowing trend since 2012. Thus, it is of a certain reference significance to explore

its reasons for the formulation of China's ICE reduction policies in the future. Further, there is a large gap in the industrial structure and development level among 30 provinces, which leads to various characteristics in ICE in different provinces. Meantime, different provinces account for different share of China's overall ICE (Fig. 1), and the influencing factors in their ICE change exhibit some differences. Therefore, it is very urgent to reveal ICE status in different periods at the national and provincial scales, and to carry out the research on the influencing mechanism of ICE change and the contributions of each province to the national ICE change. The studies can reveal the reasons for the slowdown of China's ICE growth in the "new normal", so as to provide theoretical reference for the policy adjustment of energy conservation and emission reduction in China's industrial sector.

Literature Review

The decoupling theory has been widely used in studying the relationship between economic growth and environment [9-11]. Meanwhile, the theory, proposed by the OECD, is used as a basic theory to describe the relationship between economic growth and resource consumption or environmental pollution, and it is divided into absolute decoupling and relative decoupling [12]. Zhang et al. [13] introduced the decoupling index into energy and environment field in 2000. Freitas and Kaneko [14] used this method to explore the decoupling situation between economic activity and CO_2 emissions from energy consumption in 2004-2009 in Brazil, and found absolute decoupling in 2009. Moreover, Tapio et al. [15] presented a theoretical framework for decoupling in 2005, defining the difference between decoupling, coupling and negative decoupling, and then divided them into weak, strong, and expansive or recessive degrees of decoupling. The Tapio decoupling model has been adopted by many scholars [16-18].
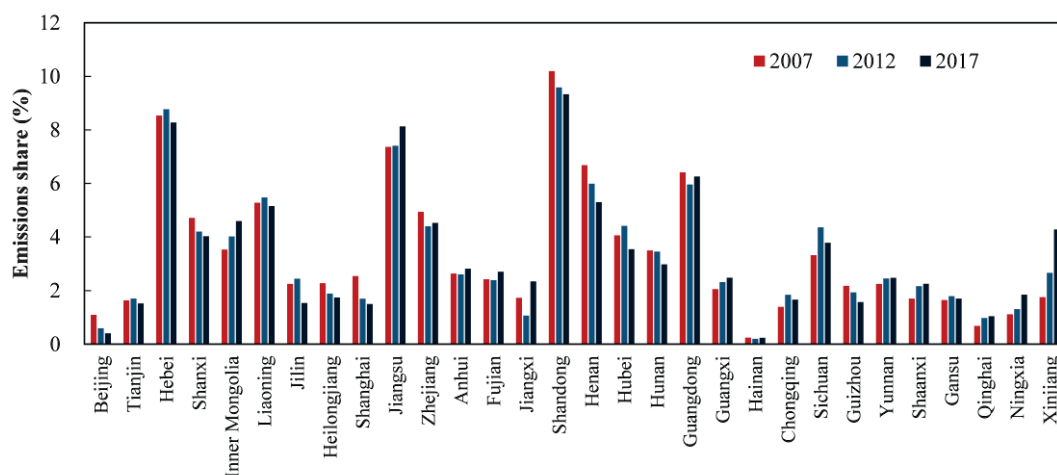

Fig. 1. The share that ICE of each province accounted for the national ICE.

For instance, Wang et al. [19] utilized the method to quantify the decoupling elasticity between China's economy and CO_2 emissions. The decoupling results indicated that the elasticity had a downward trend during the whole period, with two types of states: expansive negative decoupling (2002-2005) and weak decoupling (2000-2002 and 2005-2014). Based on the Logarithmic Mean Divisia Index (LMDI) theory, Zhang et al. [20] decomposed the decoupling indicator between the economic growth and energy consumption in China, and found the deep reason leading to the decoupling state. Zhou et al. [1] quantitatively analyzed the decoupling relationship between carbon emissions and economic growth in eight major regions of China between 1996 and 2012 by applying the Tapio extended model. The result revealed that a weak decoupling relationship between industrial energy carbon emission and economic growth was found in most regions. In order to explore a more accurate decoupling relationship, the Tapio decoupling model was applied in this study.

However, the decoupling analysis between ICE and industrial economy is not enough to find out the reasons for the slowdown of China's ICE growth in the "new normal". Thus, we often combined it with the decomposition analysis to investigate the causes of change in CO_2 emissions.

The decomposition analysis usually included three major decomposition methods: production theory decomposition analysis method (PDA) [21], structure decomposition analysis method (SDA) [22], and index decomposition analysis method (IDA) [23]. The PDA method combined the distance function and the Malmquist index to decompose the target variables and used the DEA model to calculate the distance function to determine the effect of all influence factors on the target variables [1]. Compared with the PDA method, the other two methods are more widely used. The SDA approach is based on the input-output model in quantitative economics to decompose the changes in energy or CO_2 emissions by using the input-output tables in specific years [24-25]. For example, Chang et al. [22] employed SDA method to examine emission trends and influencing factors in ICE changes in Taiwan during 1981-1991. The results showed that the level of domestic final demand and exports was the primary factor in the increase of CO_2 emissions, and the effect of decreasing industrial CO_2 intensity was a main reducing factor. SDA has been widely used in the environment field by many scholars [26]. Moreover, SDA can only analyze years with input-output tables, while IDA can analyze all years and have a lower requirement for data. Therefore, IDA is more widely used. IDA usually has two common methods [27]: the Laspeyres index and the Divisia index, where the Laspeyres index uses percentage change whereas the Divisia index uses logarithmic change. Meanwhile, the Divisia index approach is more practical and preferred in general use. It mainly includes two methods: the

arithmetic mean Divisia index (AMDI) [28] and LMDI [29]. However, AMDI not only contains the residual problem, but it cannot solve the problem of "zero value" data. The LMDI method can solve the problem of "zero value" by replacing a small positive value, and there is no unexplained residual term [30]. Therefore, the method is applied in a large number of studies [31-32]. For example, Zhang et al. [33] explored the influencing factors of CO_2 emissions from electricity generation in China during 1991-2009 based the LMDI method. The results indicated that the economic activity effect was the main driving factor, but the electricity generation efficiency effect was the leading inhibiting factor. Due to the theoretical foundation, adaptability, ease of use, and result interpretation of the LMDI method [34], this paper also adopted it to analyze the main influencing factors of ICE change in China and its 30 provinces.

At present, much literature has discussed the influencing factors of China's ICE changes [35-37]. The studies can be divided into three research scales: nation [38-39], province [40] and city [41-42]. At the national scale, the analysis of the influencing factors in ICE change was mainly concentrated in the entire industrial sector [43], industrial sub-sectors [44], and multiple sectors [45]. For example, Ouyang et al. [46] discussed the driving factors of China's ICE changes from 1991 to 2010 by using the LMDI method. Their study suggested that industrial activities made the main contribution to China's ICE growth, and energy intensity made the leading contribution to China's ICE decrease. Yang et al. [47] investigated the influencing factors of CO_2 emissions in China's thermal power industry. The decomposition results demonstrated that power intensity and economic activities were the main factors in promoting CO_2 emissions; inversely, energy efficiency was the chief factor in inhibiting CO_2 emissions. Dong et al. [48] combined the PDA and LMDI methods to analyze 10 influencing factors in China's 23 industrial sectors. Their results showed that GDP was the key factor in promoting CO_2 emissions, and energy intensity and technological advantages exerted a significant inhibiting effect on CO_2 emissions. At the province and city scales, the analysis of the influencing factors in ICE change was mainly concentrated in multiple sectors. For example, Liu et al. [49] used the LMDI decomposition method to explore the main driving factors of CO_2 emissions based on the calculation in CO_2 emissions of 36 industrial sectors in Henan Province. The results demonstrated that the economic scale played a decisive role in CO_2 emissions' growth. Structure and energy intensity produced the major inhibiting effects on CO_2 emissions. Jia et al. [50] conducted a decomposition analysis in CO_2 emissions of industrial sector and its 32 subsectors in Nanchang. The results revealed that economic output made a leading contribution to ICE growth, and energy intensity made the main contribution to ICE reduction. Further, some scholars also analyzed China's ICE by combining the decoupling model with the LMDI decomposition

method [51]. For instance, Wang et al. [52] carried out the decoupling and decomposition analysis for China's ICE from 1994 to 2013 by employing the Tapio decoupling model and the LMDI method. The results indicated that "weak decoupling" and "expansive decoupling" were the main decoupling states at this stage. Per capita wealth was the decisive driving force of ICE, and energy intensity was the main determinant of ICE reduction. Ren et al. [53] calculated the trend of decoupling effects in China's manufacturing industry from 1996 to 2010. The decoupling results figured out that China's manufacturing industry has gone through four decoupling stages: strong negative decoupling stage (1996-1999), weak decoupling stage (2000-2001), expansive negative decoupling stage (2002-2004), and weak decoupling stage (2005-2010). Lu et al. [54] investigated the decoupling of CO_2 emissions in multiple sectors in Jiangsu Province, and found that most of important industrial sectors appeared a weak decoupling state. Wang et al. [55] analyzed the decoupling situation of ICE in Taiwan. The results demonstrated that the energy intensity promoted decoupling, and the energy structure and industrial structure inhibited decoupling. In addition, in order to show a clearer picture of the main status of the research on the influencing factors of China's ICE, the relevant literature has been listed in Table 1.

In a nutshell, a number of studies have explored the influencing factors of CO_2 emissions at the regional level [56-58]. It should be noted that these studies tend to make the study area independent in exploring the reasons of ICE changes. Thus, their spatial interaction effect is often ignored. In the meanwhile, some few scholars have noticed this problem. For example,

Wang et al. [6] utilized an extended LMDI approach to decompose the changes of China's ICE from three scales: national, regional and provincial, and figured out that different factors exerted different effects in different periods and regions. However, there is no specific discussion on the contributions of each province to the national ICE change, which may lead to unfair allocation in the share of emission reduction among provinces. Further, there is little research on the relation between ICE and industrial economy at the provincial scale, perhaps leading to a lack of analysis of the development status between ICE and industrial economy in different provinces when exploring the causes of ICE change. This paper tries to fill these gaps. Besides, there is no clear purpose in the division of study stages in most researches, dividing them based on the individual subjectivity or "five-year plan". Therefore, in order to explore the reasons for the slowdown of ICE growth since China's economy entered the "new normal", the research period is divided into 2007-2012 and 2012-2017 in this paper.

Based on the above analysis, we first reveal the spatio-temporal evolution characteristics of China's ICE. Then, the Tapio model is used to investigate the decoupling relationship between ICE and industrial economy at the national and provincial scales. Second, the LMDI decomposition method is used to probe the influencing factors of ICE change. Third, the contribution of each province to the change of China's ICE is explored. The results can find out the reasons for the slowdown of China's ICE growth in the "new normal", and also provide a theoretical basis for China's industrial sector to formulate emissions reduction policies according to local conditions.

Table 1. The relative literature on the analysis of influencing factors in China's ICE.

Sector	Region	Method	The main promoting factors to ICE	The main inhabiting factors to ICE	Reference
Main heavy and light industrial sectors	Shanghai	LMDI	Industrial output	Energy intensity, and energy and industrial structure	[30]
Industrial sector	Chongqing	LMDI	Industrial output	Energy structure perform	[31]
35 industrial sectors	Tianjin	LMDI	Economies scale	Energy utilization efficiency	[25]
32 industrial sectors	Shanghai	LMDI	Output scale	Industrial structure	[48]
35 industrial sectors	Tianjin	LMDI	The scale of production	Intensity of energy	[46]
32 industrial sectors	Nanchang	LMDI	Economic output	Energy intensity	[39]
34 sectors	Zhuhai	LMDI and decoupling	Economic output	Energy intensity	[40]
13 major sectors	Henan	LMDI	Economic scale	Internal structure, and energy intensity	[38]
38 sub-sectors	Jiangsu	LMDI and decoupling	Industrial output	Energy efficiency	[43]
20 industrial sectors	Taiwan	LMDI and decoupling	Energy structure and industrial structure	Energy intensity	[44]

Table 1. Continued.

35 industrial sector	Jiangxi	LMDI	Output, R&D intensity, and investment intensity	The R&D efficiency, energy intensity, and industrial structure	[47]
Four energy sectors	Liaoning	LMDI	Economic growth, and investment structure	Energy intensity, and energy technology	[29]
The secondary industry sectors	Yangtze River Delta	Panel model	Gross industrial output value	Energy structure, energy intensity, and the structure of industrial enterprises	[26]
Industrial sector	China	LMDI	Industrial activity	Energy intensity	[35]
Manufacturing industry	China	LMDI and decoupling	Economic output	Energy intensity	[42]
Power industry	China	LMDI	Electricity intensity, and economic activity	Energy efficiency	[36]
19 industrial sectors	China	Econometric regression model	FDI, and trade comparative advantage	Trade openness, environmental regulation, and technology	[24]
36 industrial sectors	China	LMDI	Industrial output	Energy intensity and structure	[49]
38 industrial sectors	China	LMDI	Emission coefficient	Energy intensity	[34]
energy-intensive industries	China	LMDI	Emission coefficient	Energy intensity	[33]
Industrial sector	China	LMDI and decoupling	Per capita wealth	Energy intensity	[41]
Industrial sector	China	LMDI	Investment intensity	R&D intensity, and energy intensity	[32]
Heavy industry	China	LMDI and Decoupling	Labor productivity	Energy intensity	[45]
23 industries	China	Combining LMDI, PDA	GDP	Energy intensity, and technological advances	[37]
Metal industrial sectors	China	Combining IDA, PDA and Decoupling	Investment scale	Potential energy intensity, investment efficiency, and production technological progress	[28]
Industrial sector	China	LMDI	Industrial activity	Energy intensity	[27]
Industrial sector	China (a provincial level)	Spatial econometric models	Energy consumption structure, and ownership structure	energy efficiency, and scale structure	[50]
Industrial sector	China (national, region and provincial level)	LMDI	Industrial activity	Energy intensity	[6]
Industrial sector	China (national and provincial level)	LMDI and decoupling	Economic level	Industrial structure, and energy intensity	This study

Material and Methods

CO$_2$ Emissions' Estimation

The energy consumption data in the industrial sector of each province is collected from China Energy Statistical Yearbook. The data including industrial value added, GDP, and population are obtained from the China Statistical Yearbook and Statistical Yearbook of each province. The study period ranges from 2007 to 2017. The industrial value added and GDP are deflated at the 2007 constant prices by using the corresponding price indices. The CO$_2$ emissions' factor is collected from IPCC [62]. China's ICE is represented by the sum of the ICE of 30 provinces.

In this study, the ICE is derived from the final fossil energy consumption (directly used) and electricity & heat consumption (indirectly used). The electricity and heat are transformed by other energy, and it is hard to determine the CO$_2$ emissions' coefficient. Among them, the heat transformed by fossil energy is generally used in the local area. Therefore, the average heat CO$_2$

coefficient is a value that the CO_2 emissions from fossil energy used by heat production divided by the heat produced. However, the thermal power generation is divided into local thermal power and external thermal power. The energy data of external thermal power is difficult to collect. Therefore, the CO_2 emissions' coefficient of electricity employed the data released by China [63]. According to the calculation method of CO_2 emissions in IPCC [51], we compute the ICE by using Equation (1):

$$C_i = \sum_j E_{ij} \cdot NCV_j \cdot CC_j \cdot O_j \cdot \frac{44}{12} + EL_i \cdot \kappa + H_i \cdot \frac{C_i^h}{h_i}$$

(1)

...where: C_i denotes the CO_2 emissions from energy uses in province i. E_{ij} denotes the final consumption of fuel j in mass units in province i. NCV_j denotes the net calorific value (NCV) of fuel j. CC_j denotes the carbon content (CC) of fuel j. O_j denotes the carbon oxidation factor of fuel j. EL_i denotes the final consumption of electricity in province i. κ denotes the CO_2 emissions' coefficient of electricity. H_i denotes the final consumption of heat in province i. h_i denotes the heat produced by fossil energy in province i. C_i^h denotes the CO_2 emissions from fossil energy used by heat production in province i, and it is expressed in Equation (2):

$$C^h = \sum_j E_{hj} \cdot NCV_j \cdot CC_j \cdot O_j \cdot \frac{44}{12}$$

(2)

...where: E_{hj} represents the final consumption of fuel j for heat production.

Kernel Density Estimation

Kernel density estimation can analyze the overall spatial differences in ICE, and directly express the distributional dynamic and evolution trend of ICE through the change of function's curve convergence and convergence range. This method has been applied in studying uneven distribution of CO_2 emissions [47], and it can be described as Equation (3):

$$f(x) = \frac{1}{Nh} \sum_{i=1}^{N} K\left(\frac{x_i - x}{h}\right)$$

(3)

...where: N denotes the number of observation. h represents the bandwidth. $K(\cdot)$ represents the kernel function. x_i denotes the observation value obeying independent and identically distributed. This paper employed the Gaussian kernel function to study the distributional dynamic and evolution trend in ICE and ICE intensity in China's 30 provinces. The function is defined as Equation (4):

$$K(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right)$$

(4)

Therefore, this paper can analyze the evolution of ICE distribution in China's 30 provinces by observing distributional position, scalability, and morphological changes of kernel density function map.

Decoupling Model

According to the Tapio decoupling model [16], this paper can explore the relationship between CO_2 emissions (C) and industrial value added (IVA) in the industrial sector. The decoupling elasticity can be written as Equation (5):

$$D(C, IVA) = \frac{\Delta C/C}{\Delta IVA/IVA}$$

(5)

...where: D denotes the decoupling elasticity. C denotes the CO_2 emissions. ΔC denotes the change of CO_2 emissions from a base year to a target year. IVA denotes the industrial value added. ΔIVA denotes the change of IVA from a base year to a target year. Based on the studies of Tapio [15] and Vehams [64-65], the results yielded eight logical possibilities (Fig. 2): weak decoupling (WD), expansive coupling (EC), expansive negative decoupling (END), strong negative decoupling (SND), weak negative decoupling (WND), recessive coupling (RC), recessive decoupling (RD), and strong decoupling (SD).
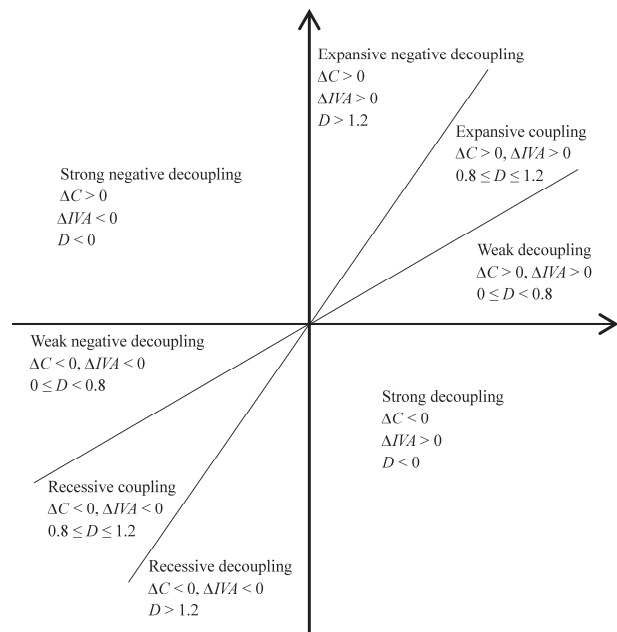

Fig. 2. The decoupling framework between ICE and industrial economy.

Decomposition Model of CO_2 Emissions

The LMDI method is preferred because all zeros in the data set can be replaced by a small positive constant [27]. Ang [23] concluded that the LMDI is the preferred method, due to their theoretical foundation, adaptability, ease of use, and result interpretation. Moreover, Ang [29] gave a practical guide that includes the general formulation process and summary tables for easy reference and examples. The decomposition of ICE is expressed as Equation (6):

$$C = \sum_j C_j = \frac{C_j}{E_j} \cdot \frac{E_j}{E} \cdot \frac{E}{Q} \cdot \frac{Q}{G} \cdot \frac{G}{P} \cdot P =$$

$$\sum_j Coe_j \cdot ES_j \cdot EI \cdot IS \cdot EL \cdot P \tag{6}$$

...where: C_j denotes the CO_2 emissions of energy j. E_j denotes the energy consumption of energy j. E, Q, and P denote the total energy consumption, industrial value added and population, respectively. Moreover, Coe represents the CO_2 emissions' coefficient. ES represents the energy structure. EI represents the energy intensity. IS represents the industrial structure. EL represents the economic level.

According to the LMDI method [23, 66], we decomposed the changes of ICE (ΔC_{tot}) through the additive decomposition method. The ΔC_{tot} can be written as Equation (7):

$$\Delta C_{tot} = \Delta C^t - \Delta C^0 = \Delta C_{Coe} + \Delta C_{ES} + \Delta C_{EI} +$$

$$\Delta C_{IS} + \Delta C_{EL} + \Delta C_P \tag{7}$$

...where: CO_2 emissions' coefficient effect (ΔC_{Coe}) denotes the changes of CO_2 emissions every unit of energy consumption, and the coefficient of fossil energy is unchanged [6] ($\Delta C_{Coe}=0$). Energy structure effect (ΔC_{ES}) denotes the changes of share of different energy in total energy consumption in China's industry. Energy intensity effect (ΔC_{EI}) denotes the changes of ratio of industrial energy consumption to industrial value added. Industrial structure effect (ΔC_{IS}) denotes the changes of the share of industrial value added in GDP. Economic level effect (ΔC_{EL}) denotes the changes of per capita GDP. Population effect (ΔC_P) denotes the changes of population.

Accordingly, the effects of each factor can be estimated by Equations (8-13):

$$\Delta C_{Coe} = \sum_j \frac{C_t - C_0}{InC_t - InC_0} \cdot In \frac{Coe_t^j}{Coe_0^j} = 0 \tag{8}$$

$$\Delta C_{ES} = \sum_j \frac{C_t - C_0}{InC_t - InC_0} \cdot In \frac{ES_t^j}{ES_0^j} \tag{9}$$

$$\Delta C_{EI} = \sum \frac{C_t - C_0}{InC_t - InC_0} \cdot In \frac{EI_t}{EI_0} \tag{10}$$

$$\Delta C_{IS} = \sum \frac{C_t - C_0}{InC_t - InC_0} \cdot In \frac{IS_t}{IS_0} \tag{11}$$

$$\Delta C_{EL} = \sum \frac{C_t - C_0}{InC_t - InC_0} \cdot In \frac{EL_t}{EL_0} \tag{12}$$

$$\Delta C_P = \sum \frac{C_t - C_0}{InC_t - InC_0} \cdot In \frac{P_t}{P_0} \tag{13}$$

Results and Discussion

Evolution Characteristics of ICE

As shown in Fig. 3, China's ICE rose from 5509.43 Mt in 2007 to 7787.15 Mt in 2012, and slightly increased to 8308.78 Mt in 2017. From 2007 to 2012, the growth rate of ICE was as high as 41.34%. That may be explained by many resource-element-driven industrial enterprises in industrial sector and a large amount of energy consumption caused by the fast-growing industrial economy during this period. However, the growth rate of ICE was only 6.7% from 2012 to 2017. That may be related to "Keep to the new path of industrialization with Chinese characteristics" put forward at the 18th National Congress of the Communist Party of China and "Coordinated progress in advancing the new type of industrialization" proposed by the central government and the state council in 2015. The industrial structures have continued to change from resource-element-driven industries to green-innovation-driven industries [67]. In addition to a slight increase in 2017, China's ICE intensity has continuously decreased from 4.46 tons/10,000 yuan in 2007 to 2.90 tons/10,000 yuan in 2016. That may be attributed to the upgrading of industrial structures and the
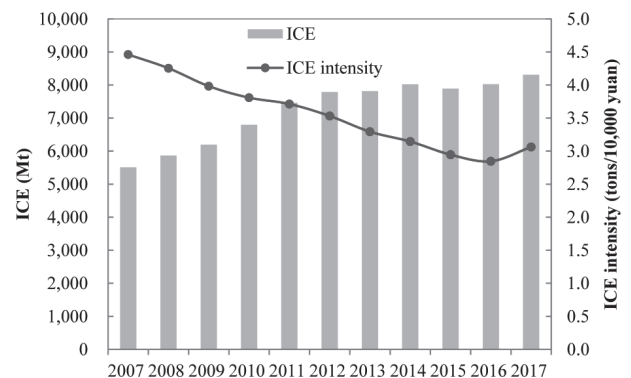

Fig. 3. The ICE status in China from 2007 to 2017.

improvements of energy utilization technology in China's industrial sectors.

Spatio-Temporal Evolution Characteristics of ICE at the Provincial Level

Based on the characteristics of rapid growth before 2012 and weak fluctuations after 2012 in China's ICE, this paper described the spatial distribution of China's ICE in 2007, 2012, and 2017 (Figs 4, 5). As shown in Fig. 4, China's ICE rose on the whole over the study period, with an obvious spatial difference. In 2007, the ICE in the eastern coastal provinces was significantly higher than that in other provinces, among which Shandong, Hebei, Jiangsu, Henan, and Guangdong were the top 5 industrial CO_2 emitters. However, the ICE intensity in Guangdong and Jiangsu was significantly lower than that in other provinces (Fig. 5). Meanwhile, the ICE in the Northwest regions was significantly lower than that in other regions, but their ICE intensity was significantly higher (Fig. 5). That may be due to the characteristic of small-scale and extensive development in industrial sector in northwest China. In 2012, the ICE of most provinces increased to different degrees, and the number of the provinces with ICE of

level 3-5 increased significantly. That may be resulted from a large amount of energy consumption caused by the continuous industrialization and urbanization in different provinces. What calls for special attention is that the focus of China's ICE had a trend to spread to the mainland provinces. The ICE level in Shanxi, Hubei, and Sichuan shifted from level 2 to level 3, and the level in Shaanxi, Gansu, Ningxia, and Xinjiang shifted from level 1 to level 2. That may be due to the transfer of labor-intensive and resource-intensive industries from the eastern regions to the central and western regions. In addition, the ICE intensity of each province has declined to different degrees from 2007 to 2012 (Fig. 5). In 2017, the ICE in most provinces increased by a small margin, and the ICE in the northern regions was generally higher than that in the southern regions. However, the ICE intensity in the northwest regions, such as Ningxia, Xinjiang, and Qinghai, has increased (Fig. 5), and their intensity was significantly higher than that in other provinces. The major cause was that the industrial production in the northwest regions was still highly dependent on energy and resource inputs, undertaking some resource-intensive industries from the central and eastern regions. Therefore, it is vital for the northwest regions to ensure the transformation
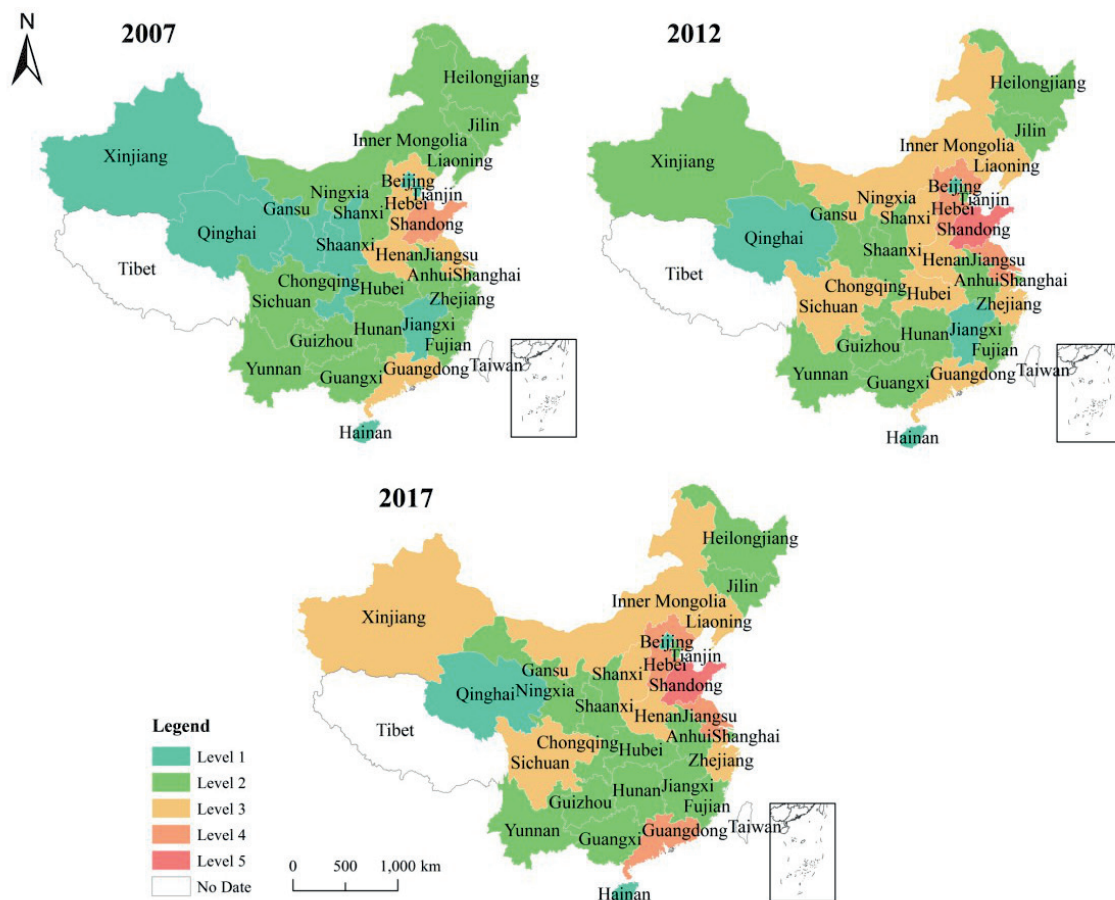

Fig. 4. The spatio-temporal evolution characteristics of ICE at the provincial level. Level 1-5 represent different ranges of ICE, which in turn are 0-100 Mt, 100-300 Mt, 300-500 Mt, 500-700 Mt, and >700 Mt, respectively.
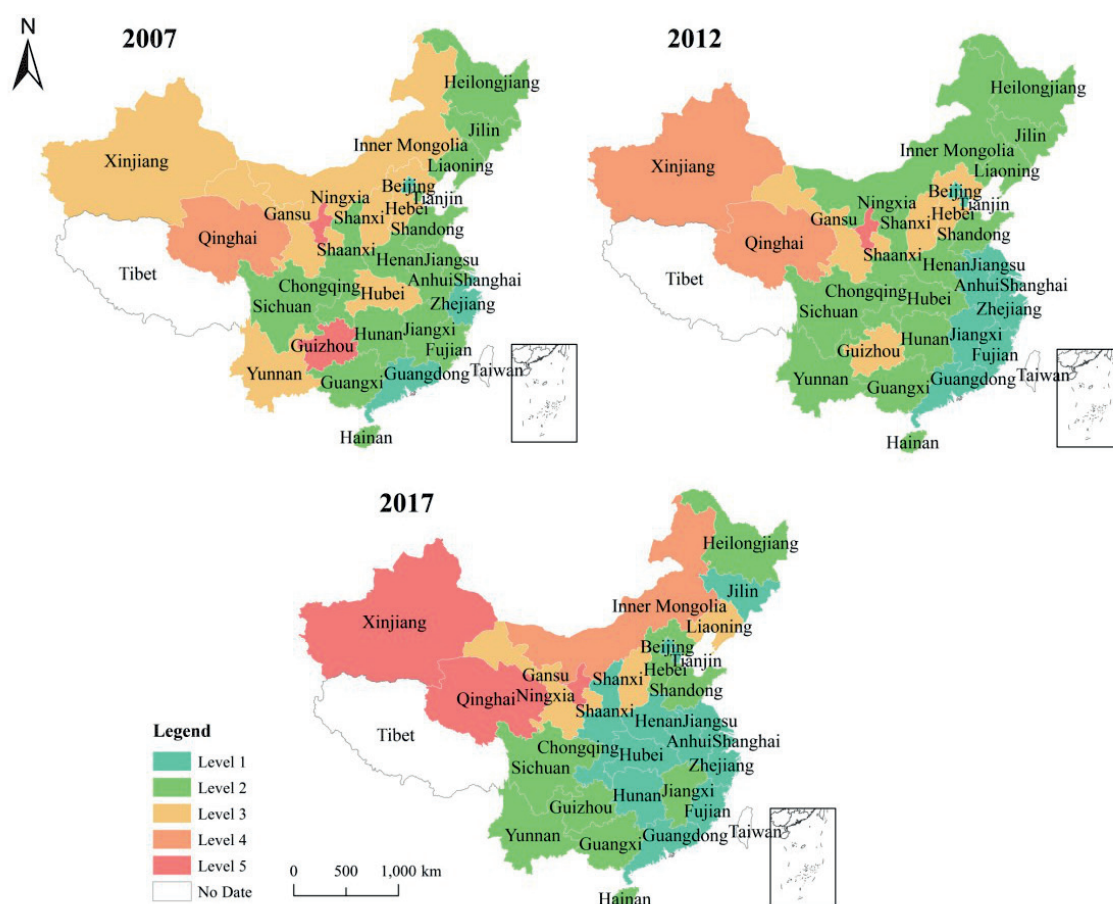
Fig. 5. The spatio-temporal evolution characteristics of ICE intensity at the provincial level. Level 1-5 represent different ranges of ICE intensity, which in turn are 0-3 tons/10,000 yuan, 3-6 tons/10,000 yuan, 6-9 tons/10,000 yuan, 9-12 tons/10,000 yuan, and >12 tons/10,000 yuan, respectively.

of industrial production to environmentally friendly, low-carbon, energy-saving, and high-tech processing type, so as to achieve the dual goals of industrial economic growth and low-carbon emissions [68]. Coastal provinces such as Shandong, Guangdong and Jiangsu were still the major industrial CO_2 emitters, and their ICE intensity was still at a relatively low level, suggesting that their industrial economic volume and quality improved synchronously.

Evolution Trend of ICE Distribution Based on Kernel Density

To further clarify the evolution characteristics of ICE among 30 provinces, this paper applied R (Gaussian kernel density function) to plot a graph of evolution trend of ICE and ICE intensity among 30 provinces in 2007, 2012, and 2017. The results are shown in Fig. 6.

Specifically, the crest of ICE has moved to the right and the slope had a slowing trend during 2007-2012, namely, the ICE in 30 provinces have significantly increased as a whole. In addition, the variation range of the curve has increased, implying that the gap of ICE has become larger among 30 provinces. That may be explained by the growing gap of the industrial economy

volume in different provinces. Compared with 2012, the curve in 2017 moved slightly to the right, meaning that the ICE in most provinces increased slightly during this period. Fig. 6 also showed the evolution trend of ICE intensity. On the contrary, the crest of ICE intensity has moved to the left and had a steep slope during 2007-2012, illustrating that the intensity has declined overall and clustered at lower values. That may be resulted from the upgrading of industrial structures and the improvement of energy utilization technology in China. In the meantime, the range of the curve has narrowed significantly, suggesting that the difference of ICE intensity has further reduced among 30 provinces. In 2017, the crest of the curve moved further to the left, showing that ICE intensity of different provinces has further decreased and concentrated at the lower values. However, the crest of the curve has widened in 2017, demonstrating that the ICE intensity among 30 provinces was more polarized. It is noticeable that the density of ICE intensity within the range of 10-20 tons/10,000 yuan increased. That was the result of the continuous deterioration of ICE in northwest China. Thus, more policies should be made and more measures should be taken to reduce their ICE intensity.
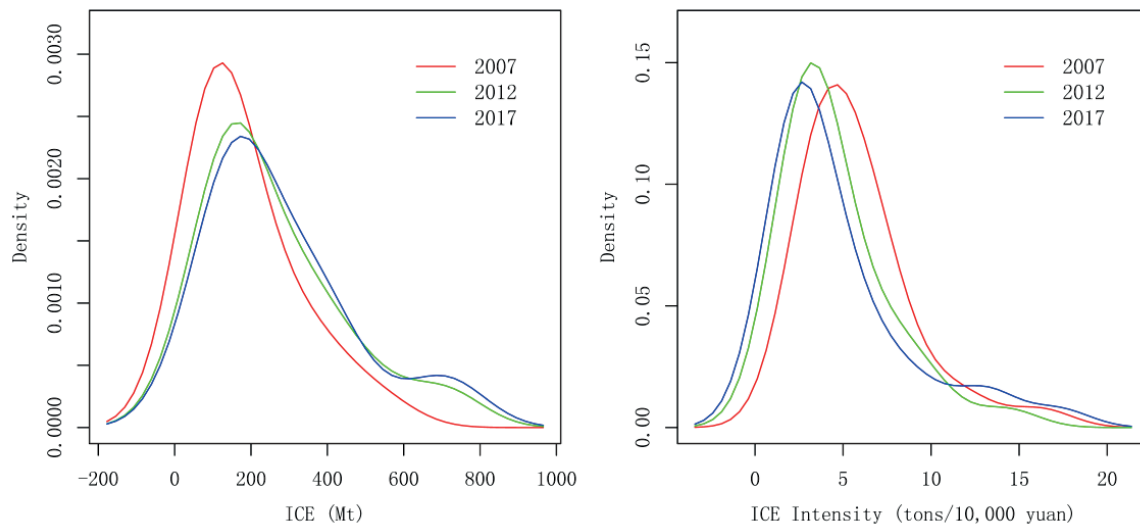
Fig. 6. The evolution trend of ICE and ICE intensity among 30 provinces.

The Results of the Decoupling Analysis

The Decoupling Analysis at the National Level

As shown in Fig. 7, from 2007 to 2012, the decoupling elasticity between ICE and industrial economy was relatively high up to 0.53. Moreover, the decoupling state was WD with the elasticity between 0.4 and 0.8 each year. During this period, the Chinese government promoted the rapid increase of industrial investment. At the same time, the rapid growth of industrial economy was accompanied by the inefficiency of energy use and relatively high decoupling elasticity, producing the rapid growth of ICE. From 2012 to 2017, the decoupling elasticity was relatively low, reaching 0.29. Three decoupling states, WD, SD (2014-2015), and SND (2016-2017), were found in this period. Moreover, the elasticity showed an "M" curve trend in different years, that is, an unstable but good decoupling state as a whole, which was conductive to a significant decline of the growth rate in China's ICE. That may be related to "Keep to the new path of
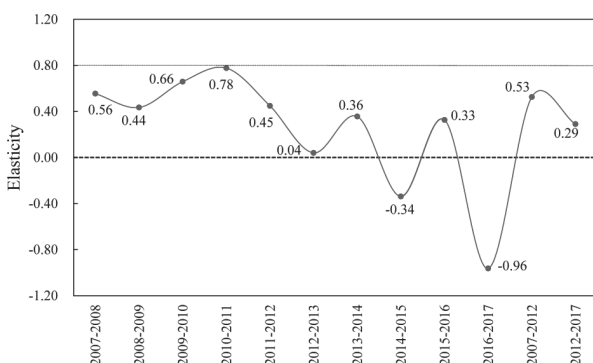
industrialization with Chinese characteristics" proposed by China and the transformation of industrial type from resource-driven industries to green innovation-driven industries. However, the SND state appeared in 2016-2017, in other words, the industrial economy declines while ICE increases. Therefore, China's industrial sector should continue to adjust the industrial structure and improve energy efficiency, comprehensively strengthen scientific and technological innovation, and promote the decoupling between ICE and industrial economy.

Decoupling Analysis at the Provincial Level

The Fig. 8 shows four decoupling states occurred among 30 provinces during 2007-2012, namely, SD, WD, EC, and END. The relationship between ICE and industrial economy presented a WD state in most provinces. That is to say, the growth rate of ICE was lower than that of the industrial economy. The EC state was found in Gansu, with a decoupling elasticity of 0.83, which indicates that ICE and industrial economy increased almost simultaneously. Xinjiang displayed an END state with the decoupling elasticity of 2.48. Although the WD state was found in other provinces, their decoupling elasticity was still large, especially in the central and western regions. During this period, the industrial scale in most provinces was at the stage of rapid expansion, and the share of advanced industries such as high-tech, green and innovative industries was small, resulting in a large decoupling elasticity in China's industrial sector as a whole (Fig. 7). In contrast, Beijing, Shanghai, and Jiangxi were the only three provinces displaying an SD state. In other words, their ICE decreases with the growth of industrial economy. However, the three provinces only accounted for 3.35% of China's total ICE in 2012 (Fig. 1), which indirectly indicates that their industrial scale was not large enough to change the overall undesirable decoupling status in China.

Fig. 7. The decoupling elasticity between ICE and industrial economy at the national level.

From 2012 to 2017, the decoupling situation of China's ICE changed greatly in space. Compared with the previous period, the decoupling state in the northern regions was significantly worse in this period. Nevertheless, the state was more ideal in the central and southwest regions. Five decoupling states were found among 30 provinces, namely, SD, WD, END, WND, and SND. Specifically, there were 10 provinces presenting an SD state, and they are Beijing, Tianjin, Jilin, Shanghai, Henan, Hubei, Hunan, Chongqing, Sichuan, and Guizhou. Compared with the previous period, the number of provinces with an SD state increased significantly in this period. Meanwhile, it is noteworthy that these provinces were mainly located in the Beijing-Tianjin, central and southwest China. The number of provinces displaying a WD state was significantly fewer than that in the previous period, and they were mainly concentrated in eastern China. Among them, the decoupling elasticity of the major industrial CO$_2$ emitter such as Shandong, Hebei, Guangdong, Jiangsu, and Zhejiang has significantly declined. These provinces and some provinces with an SD state accounted for a large share of the national ICE (Fig. 1), making an important contribution to the reduction of national decoupling elasticity to 0.29 (Fig. 7). The END state was found in Guangxi, Hainan, Jiangxi, Ningxia, and Xinjiang. Heilongjiang was the only province in WND state. That is to say, both ICE and industrial economy were in decline, and the decline rate of the former was less. SND state, the worst decoupling relation, occurred in Inner Mongolia, Liaoning, Gansu, and Qinghai, namely, ICE increased with the decrease of industrial value added. It is worth noting that END, WND, or SND state was mainly found in the northern regions, and their industrial economy was a mainly resource-oriented type. Although ICE in these provinces accounted for a low share of the national ICE (Fig. 1), they still produced a certain inhibiting effect on the further reduction of national decoupling elasticity. Meantime, the industrial economies in these provinces depended on energy consumption. Nevertheless, the

importance of traditional industries in the economy has declined, leading to a significant reduction in demand for their industrial products. Therefore, it is urgent for these provinces to improve the technological level and energy utilization efficiency of related industries, to shut down high-polluting and energy-consuming enterprises whose production equipment does not meet the standards, and to develop some high-tech industries with low emissions and high value added.

The Results of the Decomposition Analysis

Decomposition Analysis at National Level

As shown in Table 2, China's ICE increased by 2277.72 Mt from 2007 to 2012, with the growth rate of 41.34%, caused by economic level, population, and industrial structure. Among them, economic level was the decisive contributor to ICE increase, with an increase of 3424.85 Mt. That may be due to the rapid growth of China's economy and the 4 trillion yuan investment of the central government in response to the financial crisis in 2008 to expand domestic demand during this period [69]. Meanwhile, the industrial structure contributed 57.78 Mt to ICE increase. Population always played a positive role in ICE increase, leading to 214.20 Mt. Energy intensity was the largest curbing factor in ICE, and the curbing effect was 1,469.80 Mt. That may be attributed to the improvements of energy utilization technology and industrial structure in China's industrial sector. Energy structure exhibited a marginal inhibiting effect on ICE.

From 2012 to 2017, China's ICE only increased by 521.63 Mt, with the growth rate of 6.7%. Economic level contributed most to the ICE growth, with an increase of 2825.77 Mt. The major cause was that China's economy has been growing steadily and the market for industrial products has been expanding. Population was a minor contributor to ICE growth, resulting in 234.27 Mt. Nevertheless, it is noticeable that industrial structure was the largest contributor to ICE reduction during
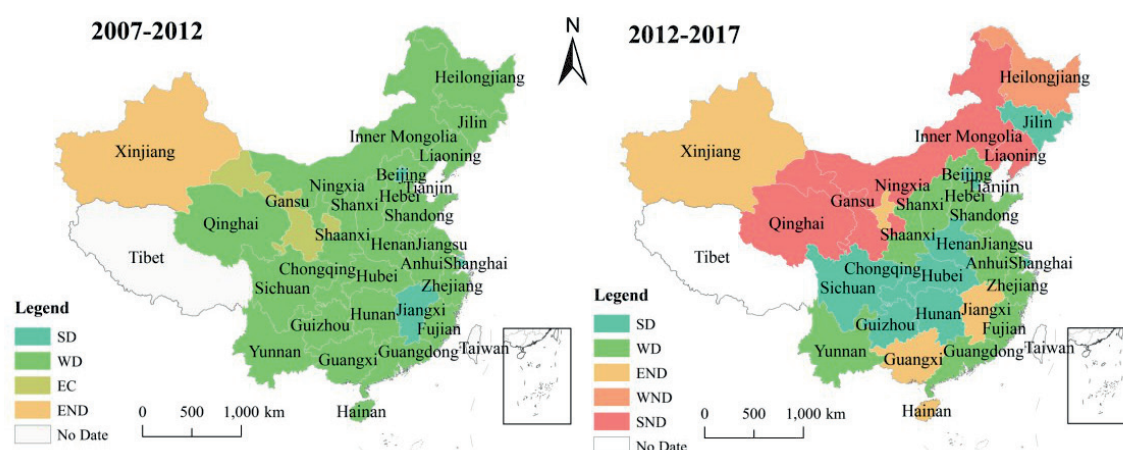

Fig. 8. The decoupling states between ICE and industrial economy at provincial level.

Table 2. The decomposition results of different factors in ICE change at the national level.

Stage	ΔC_{ES}	ΔC_{EI}	ΔC_{IS}	ΔC_{EL}	ΔC_P	ΔC
2007-2008	3.35	−274.14	−14.36	597.00	45.27	357.13
2008-2009	−6.15	−391.02	58.35	617.62	46.03	324.84
2009-2010	−79.91	−210.55	93.24	752.66	45.75	601.19
2010-2011	46.76	−227.69	59.07	756.17	35.02	669.34
2011-2012	−15.45	−366.41	−36.45	701.40	42.13	325.22
2007-2012	−51.39	−1469.80	159.86	3424.85	214.20	2277.72
2012-2013	−185.07	−359.27	−134.87	661.22	41.87	23.88
2013-2014	−22.90	−343.61	−49.69	584.90	42.29	210.99
2014-2015	−11.49	−505.18	−214.55	549.00	48.58	−133.64
2015-2016	−17.75	−254.54	−154.25	510.46	51.68	135.59
2016-2017	50.63	540.78	−876.65	520.20	49.85	284.82
2012-2017	−186.58	−921.82	−1430.01	2825.77	234.27	521.63

the period, with figure of 1430.01 Mt, the primary contributor to the decline in the growth rate of China's ICE. That may be due to the "Keep to the new path of industrialization with Chinese characteristics" proposed by China. Accordingly, the industrial type has been transforming from labor-intensive industries and raw material heavy chemical industries to capital-intensive, technology-intensive manufacturing industries and modern service industries to meet the needs of products and living. Energy intensity was a minor contributor to ICE reduction, leading to 92.82 Mt. However, it brought an increase of 540.78 Mt in 2016-2017, indicating that more attention should be paid to the upgrading of industrial structure within the industry. Energy structure exerted a restraining effect on ICE, with an emission reduction of 186.58 Mt, showing that China's energy consumption structure has improved in recent years.

It is particularly worth mentioning that the slowdown of China's ICE growth was mainly caused by industrial structure and energy intensity during 2012-2017. The decline in the proportion of industrial value added in GDP was the reason for the large amount of emission reduction caused by the industrial structure in this period, which is different from ICE reduction mainly caused by energy intensity during 2007-2012. More to the point, although the reduction in the share of industrial economy in the national economy is conducive to ICE reduction, it is unhealthy for the steady development of national economy to blindly reduce the proportion of industrial economy, and to vigorously develop the tertiary industry such as finance. Therefore, the next emission reduction target in China's industrial economy should also be focused upon the development of the green and innovative industries with low energy consumption and high value added.

Provincial Contribution to China's ICE Change

As shown in Fig. 9, the decrease or growth of ICE caused by driving factors overall was larger in 2007-2012 than that in 2012-2017 in most provinces. With the development of the social economy, technology, and industrial structure, the contributions to the national ICE and the driving direction of influencing factors in ICE in the different provinces have changed in 2012-2017. The specific changes are as follows:

From 2007 to 2012, Hebei, Shandong, and Jiangsu contributed most to China's ICE growth, with the contributions of 213, 185 and 171 Mt, respectively. Meanwhile, their ICE was among the top 3 of all provinces. Economic level played the main role in their ICE growth. However, the decoupling elasticity of the three provinces was relatively high in this period, suggesting that the improvement of their economic level was relatively extensive. Energy intensity in Hebei and Jiangsu was the largest inhibiting factor in ICE, but the figure for the ICE reduction was only 74 and 72 Mt, respectively, which also indicates that energy intensity still has a great potential for their ICE reduction. Industrial structure and energy intensity in Shandong made the main contributions to ICE reduction. Whereas, their contributions to ICE reductions was only 87 and 72 Mt, respectively, implying that Shandong still needs to pay attention to the upgrading of industrial structure and the innovative and green development of industry. Moreover, Xinjiang, with END state, contributed 111 Mt to China's ICE increase. The economic level and energy intensity were the crucial promoting factors in its ICE growth; meantime, its ICE share in the country also increased from 1.75% in 2007 to 2.66% in 2012 (Fig. 1). That may be due to its vigorous development of the traditional resource-intensive industries and a high level of the ICE intensity (Fig. 5). Hence, energy
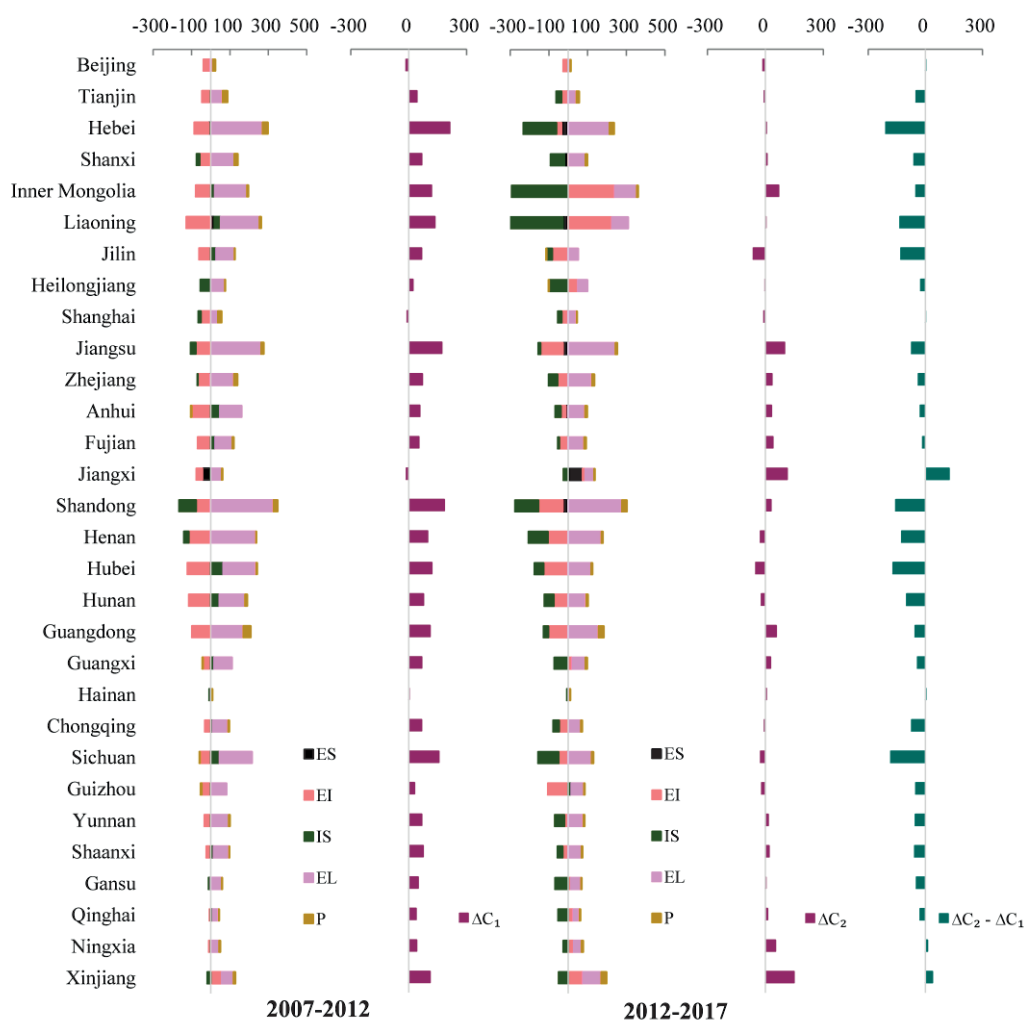
Fig. 9. The decomposition results of different factors in ICE change at the provincial level (Mt). ΔC_1 denotes the ICE change in different provinces from 2007 to 2012. ΔC_2 denotes the ICE change in different provinces from 2012 to 2017. $\Delta C_2 - \Delta C_1$ denotes the change of ICE increment from 2007-2012 to 2012-2017.

utilization technology and industrial transformation and upgrading should be improved to reduce its ICE intensity and restrain the rapid growth of ICE.

Compared with the previous period, the contributions of most provinces to the national ICE growth decreased to different degrees during 2012-2017, which led to a significant decline in the growth rate of China's ICE at this stage. Xinjiang was the largest contributor to China's ICE growth, with figures of 148 Mt, and its ICE share in the country has further increased from 2.66% in 2012 to 4.28% in 2017. Economic level and energy intensity were still the main promoting factors in its ICE. In the meanwhile, its decoupling state was END. Therefore, it is necessary to facilitate its improvement of energy efficiency and technological advancement to curb the continuous rapid ICE growth. Jiangxi contributed 112 Mt to the growth of national ICE, and its ICE share in the country increased from only 1.06% in 2012 to 2.35% in 2017. Energy structure and economic level played the leading roles in ICE increase. That may be explained by the relatively extensive

industrial economy such as ceramics in Jiangxi. Thus, specific attention should be paid to the improvement of its energy structure and energy utilization efficiency. Jiangsu contributed 99 Mt to the national ICE growth, and its ICE share in the country increased from 7.41% in 2012 to 8.13% in 2017. Economic level was the main promoting factor in its ICE growth, and energy intensity was the main curbing factor in its ICE. Industrial structure contributed only 11 Mt reductions to its ICE. Hence, the tertiary industry such as finance can be appropriately developed to reduce its ICE growth. Jilin and Hubei contributed most to China's ICE reduction, with figure of 62 and 50 Mt, respectively. Energy intensity was the decisive inhibiting factor in their ICE growth. Meanwhile, their ICE reduction from energy intensity has been greater than the ICE growth caused by the economic level, thereby presenting a good decoupling state.

Moreover, comparing the change of ICE increment in two phases, there was a larger increment reduction in the central and eastern provinces with large-scale

industrial economy (Figs 1, 9), playing the main role in the increase of only 521.63 Mt in China's ICE during 2012-2017. Hebei and Sichuan were the two provinces with the largest reduction in ICE increment, with figures of 208 and 182 Mt, respectively. The primary driving factor in curbing their ICE has changed from energy intensity to industrial structure, and their decoupling elasticity was relatively low. That may be the result from the transformation and upgrading of their industrial structure as well as the improvement of energy utilization technology, making a great contribution to the substantial decline of the growth rate in China's ICE. Hubei and Shandong followed with the reductions of 170 and 156 Mt, respectively. Meantime, in the provinces as Liaoning, Jilin, and Henan with a large reduction in ICE increment, energy intensity and industrial structure played the main roles in restraining their ICE growth. Furthermore, although the industrial structure effect brought a large amount of ICE reductions in the provinces with large-scale traditional industries, they should also avoid blindly shifting the industry to the development of the tertiary industry. Meanwhile, more attention should be given to the improvement of energy utilization efficiency and the upgrading of industrial structure within industry to reduce their energy intensity. Beijing, Shanghai, Jiangxi, Hainan, and Xinjiang were the only provinces with the growth of ICE increment. Among them, except for Xinjiang, other provinces accounted for a small share of the national ICE, producing a weak curbing effect on the slowdown of China's ICE growth.

Conclusions

In order to figure out the reasons for the slowdown of China's ICE growth in the "new normal", we first explored the evolution characteristics of ICE. Secondly, the Tapio decoupling model was introduced to analyze the decoupling relationship between ICE and industrial economy. Finally, we further explored the related driving factors of ICE change, and the contributions of each province to China's ICE in 2007-2012 and 2012-2017 by using the LMDI method. The main conclusions are as follows:

China's ICE rose from 5509.43 Mt in 2007 to 7787.15 Mt in 2012, and slightly increased to 8308.78 Mt in 2017. The growth rate of ICE was 41.34% from 2007 to 2012, while it significantly decreased to 6.7% from 2012 to 2017. On the whole, the spatial difference of China's ICE has gradually evolved from high emissions in the northern coastal regions and low emissions in other regions to high emissions in the northern regions and low emissions in the southern regions. Meanwhile, the gap of ICE has gradually widened among provinces. Moreover, ICE intensity continued to decrease in the central and eastern provinces, but remained consistently high in the resource-intensive industrial areas such as Northwest and Northeast. The gap of ICE intensity

has decreased among provinces, converging on lower values.

From 2007 to 2012, the decoupling elasticity between China's ICE and industrial economy was relatively high, reaching 0.53. Most provinces displayed a WD state. From 2012 to 2017, the elasticity dropped to 0.29, which was conducive to the decline of the growth rate in China's ICE. Compared with the previous stage, the decoupling state in the northern regions was significantly worse during this period. Nevertheless, the state was more ideal in the central and southwest regions. Meanwhile, the SD state mainly appeared in central and southwest China, and their ICE accounted for a large share of the national ICE, making a significant contribution to the decline of China's overall decoupling elasticity. It is noteworthy that the northern regions mainly experienced the END, WND, or SND state, and their ICE accounted for a low share of the national ICE (Fig. 1). Thus, they exhibited a certain inhibiting effect on the further reduction of national overall decoupling elasticity.

China's ICE increased by 2277.72 Mt from 2007 to 2012. Economic level was the main contributor to ICE growth, and energy intensity was the main determinant of ICE reduction. Hebei, Shandong, and Jiangsu contributed most to China's ICE increase. From 2012 to 2017, the ICE only increased by 521.63 Mt. Economic level played a decisive role in ICE growth. It should be noted that industrial structure was the primary curbing factor in China's ICE, while energy intensity was the minor inhibiting factor, with an emission reduction of 1430.01 Mt and 921.82 Mt, respectively, which is the main reason for the slowdown of China's ICE growth. Further, the reductions of ICE increment in the central and eastern provinces with large-scale industrial economies, such as Hebei, Sichuan, Hubei, and Shandong, were relatively large. Hence, they made the main contribution to the decline in the growth rate of China's ICE. Industrial structure and energy intensity were the main inhibiting factors in their ICE growth.

Based on these results, we recommend some specific countermeasures and suggestions for China's ICE reduction.

(1) Improve the energy utilization structure and reduce the proportion of high-carbon energy sources such as coal. The excessive proportion of coal consumption can be replaced by some measures such as the conversion from coal to electricity and increasing the proportion of natural gas consumption. Meanwhile, particular attention should be paid to the Northwest regions and the provinces with a weak industrial base, such as Jiangxi and Hainan. With abundant sunshine and natural resources in the northwest regions and rich natural-gas reserves in the southwest regions, more efforts should be made to introduce or develop advanced techologies, incease the development of clean and renewable energy in these regions, and increase the proportion of clean energy such as wind, electricity and nuclear power [1].

(2) Research and popularize energy utilization technology to improve the utilization efficiency. Increase investment in the research and development of energy utilization technologies. Priority should be given to technological upgrading in the northwest regions and some provinces with high ICE intensity, such as Shanxi and Liaoning. Meanwhile, they should strengthen technological exchanges with the developed eastern regions, and introduce and absorb advanced high-efficiency technologies, energy-saving technologies and renewable energy technologies to reduce energy intensity. Moreover, more stringent reduction policies should be formulated for energy-intensive industries to promote the use of energy-saving technologies and equipment, while phasing out some high-energy-consuming and high-polluting enterprises.

(3) Adjust the industrial structure and optimize the industrial production. The northeast and central regions should accelerate the optimization of their industrial structures. While promoting the transformation and upgrading of traditional industries, they should implement key projects, strengthen technological support and accelerate the development of strategic new industries and advanced manufacturing. However, the eastern provinces can't blindly de-industrialize. "De-industrialization" often leads to the loss of industrial support and stagnation in economic development. Reasonable optimization of industrial policies is an important support for industrial low-carbon development. When undertaking resource-intensive industries in the central and eastern regions, the western regions should also obtain advanced energy-saving equipment and technologies from the eastern regions. Further, some enterprises with high pollution, high emission, and low efficiency should be eliminated, and the low-carbon and technology-based manufacturing should be vigorously developed.

(4) Decompose the goal of ICE reduction into different factors and provinces, and establish a mechanism of sharing regional responsibility and a compensation system for emissions' reduction. Allocate more reduction to the provinces with a larger ICE share in the country, such as Shandong, Jiangsu, and Hebei. Meanwhile, actively increase the ICE reduction caused by the main inhibiting factor in the provinces with a larger ICE increment, such as Xinjiang, Jiangxi, and Jiangsu. In addition, the underdeveloped areas in the central and western regions should be encouraged to strengthen cooperation with the developed areas along the eastern coast to continue to narrow the gap in CO_2 emissions' intensity.

Acknowledgements

Conflict of Interest

The authors declare no conflict of interest.

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