What Is the Regional Differences in Carbon Emission Performance: Evidences From Energy-intensive Industries in China?

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What is the regional differences in carbon emission performance: evidences from energy-intensive industries in China?

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Abstract

As the major energy consumers, energy-intensive industries are the key players in achieving carbon emission reduction targets. Grasping the carbon emission reduction potential has a direct impact on the implementation of the carbon emission reduction policies of China. The paper builds a super-Slack Based Model(SBM) considering this undesirable output, and calculates the carbon emission efficiency. Then, the Meta-Frontier Malmquist-Luenberger productivity index (MF-MLPI) is constructed to dynamically analyse the growth rate changes of the carbon emission efficiency and the regional differences in energy-intensive industries. Furthermore, the carbon emission reduction potential of the energy-intensive industries in various economic regions of China is discussed and the conclusions are as follows: there is a big difference in the carbon emission Technology Gap Ratios (TGRs) of the energy-intensive industries in different economic regions; the growth rate of the carbon emission efficiency of energy-intensive industries shows a trend of first declining and then slowly recovering while the carbon reduction potential generally shows a trend of decreasing and then rising; and the carbon emission reduction potential in the eastern region keeps decreasing. The following is recommended: the government should rationally distribute energy-intensive industries, promote industrial structure adjustment, optimize the energy structure according to the regional industrial advantages; increase investment in R&D, promote energy technology innovation in energy-intensive industries; prioritize the promotion of carbon peaks on key emission industries and regional, formulate differentiated plans for the regions and industries with different carbon emission reduction potentials.

Keywords Energy-intensive industries, Carbon emission efficiency, Carbon emission reduction potential, Meta-Frontier-Malmquist-Luenberger productivity index

Introduction

The establishment of the National Independent Contribution (INPC) mechanism in the Paris Agreement has opened a new stage of global climate change governance. Green and low carbon have become the core concepts of global climate governance in the future. With the largest carbon emissions in the world, China is facing huge pressure to conduct carbon emission reductions, which has restricted the industrial green development of China. The Chinese government promises to reach its peak carbon dioxide (CO₂) emissions at approximately 2030 and strives to reduce CO₂ emissions per unit of GDP by 60%-65% compared to 2005. The proportion of CO₂ emissions from global fossil fuel energy to the greenhouse gas emissions is 81%, with industry accounting for 50% in 2013 (IEA 2015). From 2001-2014, the carbon emissions of China increased at a rate of 8.18% per year, the industry was the largest carbon emitting sector, and the CO₂ emissions of the industrial sector accounted for 83.95%-96.21% of the total (Liu 2017). Energy-intensive industries are typical representatives of industry. “The 2010 National Economic and Social Development Statistical Report” identified six energy-intensive industries including the following: chemical raw materials and chemical products manufacturing, the petroleum processing coking and nuclear fuel processing industry, the non-metallic mineral products industry, the ferrous metal smelting and rolling processing industry, the non-ferrous metal smelting and rolling processing industry, and the electric power heat production and supply industry.

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As shown in Figure 1, from 2005 to 2017, the energy consumption of energy-intensive industries rose from 1.12 to 2.17 billion tons of standard coal, increased by 94.84%; and energy consumption of energy-intensive industries accounted for about 72.95% of industrial energy consumption. Here, the proportion was significantly reduced in year 2005 and year 2010 due to a relatively large increase in industrial energy consumption compared to other years. During the research period, the proportion of energy consumption in energy-intensive industries gradually increased from 42.94% to 48.74%, with a growth of 11.11%.

Fig. 1 Energy consumption of Energy-intensive industries from 2005 to 2017

As shown in Figure 2, the proportion of CO₂ emissions in energy-intensive industries with respect to all industry rose from 59.34% to 76.51%, which increased by 28.93% (it strongly fluctuated in the Years 2005 and 2010). In terms of specific industries, the CO₂ emissions of the ferrous metal smelting and rolling processing industry were relatively large, accounting for approximately 35% of the CO₂ emissions of energy-intensive industries. The CO₂ emissions of the ferrous metal smelting and rolling processing industry increased by 89.36% from 2005 to 2014 (with the largest increase) while it steadily decreased after 2015. The change of the CO₂ emissions in the non-metallic mineral products industry is similar to that in the ferrous metal smelting and rolling processing industry. The CO₂ emissions of the chemical raw materials and chemical products manufacturing industry, the non-ferrous metal smelting and rolling processing industry, the petroleum processing coking and nuclear fuel processing industry, and the electric power thermal production and supply industry all showed gradual upward trends. The increase of the CO₂ emissions in the chemical raw materials and chemical product manufacturing industry was the largest, rising by 1.17 times; meanwhile, after 2015, the CO₂ emissions of chemical raw materials and chemical product manufacturing stabilized and had a slight downward trend.

Fig. 2 CO₂ emissions of energy-intensive industries and their proportions from 2005 to 2017

As the major energy consumers, energy-intensive industries are the key players in achieving carbon emission

reduction targets. At the end of 2017, the National Development and Reform Commission officially launched the national carbon emissions trading system for the power industry; however, it is difficult to calculate the quotas for other key industries such as petrochemicals, building materials, and iron and steel due to the lack of basic carbon emissions data for most companies. In addition, the adjustment of the industrial distribution has led to energy-intensive industries gradually shifting from the southeast coast to the central and western regions; therefore, establishing the carbon market can not only effectively reduce the "pollution paradise" effect, but it can also improve the economic growth of the industrialized transition regions in the central and western regions (Tang et al. 2016). It can be seen that as an important part of the carbon market, the data of energy-intensive industries directly affect the improvement of the national carbon emissions trading system, and the carbon productivity of energy-intensive industries directly affects the carbon productivity of downstream industries and the entire economic system. The carbon emission reduction potential of their industries also directly influences the achievement of the carbon emission peak control goals of China. Therefore, the green development dynamics and carbon emission reduction potential of enterprises in energy-intensive industries need to be widely studied by academics and departmental decision makers.

Literature review

Scholars have been devoted to the research of carbon emission reduction potential and the achievement of carbon emission reduction goals (Wei et al. 2013; Xu and Zhang 2013; Fu and Yuan 2017). Recently, they have been more concerned with departments and industries, and the most commonly used approach is scenario analysis. Can and Price (2008) conducted a scenario analysis of the energy consumption and CO₂ emissions of the global industrial, transportation and construction sectors. Cai et al. (2008) explored the carbon emission reduction capabilities of five major emission industries in China, Özer et al. (2012) evaluated the emission reduction potential of the Turkish power sector, and Branger and Quirion (2015) used anti-scene methods to predict the European Cement Industry's emission reduction potential. Yang et al. (2018) believed that the scale effect was the main factor that promoted the continuous increase of carbon emissions in energy-intensive industries while the effects of energy technology progress and factor substitution had formed a certain degree of suppression of the increase in carbon emissions in energy-intensive industries. Based on an input-output table and the structural decomposition model, Shao and Li (2018) found that after 2007, the declines in export contributions and technological changes led to a decline in the demand for energy-intensive products, which ultimately led to the industry's overcapacity and the value-added rate continued to decline.

Xie et al. (2017) calculated the environmental efficiency and emission reduction costs of the industrial sectors and considered that it was necessary to consider the heterogeneity of the industry when proposing carbon emission reduction strategies. Guo (2014) estimated that after peaking in 2030, industry would continue to make positive contributions to carbon emission reductions; the cumulative emission reduction potential from 2030 to 2050 would be 6.59 billion tons, of which structural emission reduction would be 2.48 billion tons and intensity emission reductions would be 4.12 billion tons. Wen (2015) predicted that the peak inflection points of the carbon emissions in the steel and cement industries that were desirable for 2015 to 2020. The peaks that were desirable were 1.2 billion to 1.3 billion tons of CO₂ equivalent and 1.26 billion to 1.33 billion tons of CO₂ equivalent, respectively; furthermore, under the scenario of strong emission reductions, the peak of the power industry would reach 4.7 billion tons and 4.4 billion tons of CO₂ equivalent, respectively. By establishing and utilizing the environmental learning curve (ELC) model of carbon intensity, Yu et al. (2016) estimated that the average carbon intensity reduction potential of 43 Chinese economic sectors in 2020 would be 33.0% and 39.0% in 2020 compared of that in 2012 in two different scenarios. Some scholars evaluate the global industry or national industrial sector from the perspective of carbon capture and storage (CCS). Rootzen and Johnsson (2015) showed

how to implement CCS in the oil refining, steel and cement industries to measure carbon emission reduction prospects, and believed that the large-scale introduction of CCS was costly and expensive. Saygin et al. (2013) predicted that the CCS of seven industrial sectors in the Netherlands would increase the peak industrial carbon emissions by 39% to 47% from 2008 to 2040. Kang et al. (2020) considered the large-scale deployment of CCS for power industry maybe around 2030, and long term break-even CO₂ prices for implementing CCS, ranging from approximately \$46-62 per ton CO₂. By the end of 2017, Norway, Abu Dhabi, Germany, Japan and other countries implemented large-scale CCS projects in energy-intensive industries such as steel, power, petrochemicals, etc., and effectively achieved carbon emission reduction targets (IEA 2017). A series of studies on energy-intensive industries have been conducted to assess their carbon emissions efficiency and carbon emissions reduction potential. The carbon dioxide emissions of energy-intensive industries account for 64% of the total EU industrial emissions. To achieve the emission reduction targets of the EU by 2050, the scientific community and industry have conducted in-depth cross-industry technical decarbonisation research in key areas (Gerres et al. 2019). Research found that the proportion of energy-intensive industries in Korean manufacturing was large, which meant that the energy efficiency was relatively low; and it also found that R&D intensity had a positive impact on the innovation of energy-intensive industries (Song and Oh 2015). Lin and Tan (2017) and Du et al. (2018) both believed that the industry scale and labour productivity were the dominant forces for CO₂ emissions changes in energy-intensive industries, and energy intensity was the main factor that promoted CO₂ emission reduction. In addition, Tan and Lin (2020) believed that from the perspective of energy and factor substitution, the collection of carbon taxes could help reduce CO₂ emissions in energy-intensive industries and improve the energy eco-efficiency of China. Liu et al. (2019) found that the energy-intensive industries of China had a significant downward trend in their carbon emission intensity, showing spatially differentiated patterns of "West High East Low" and "North High South Low" and significant spatial correlation; and Sueyoshi et al. (2020) took power industry as an example to verify the regional heterogeneity of energy efficiency in China. Guo et al. (2018) found that the economic efficiency of coal in energy-intensive industries was greater than the environmental efficiency of coal, and the empirical results showed the potential for energy savings and emission reduction in the industries. In addition, Qi et al. (2020) found that the coal efficiency of the major coal-intensive industries of China was mainly derived from technological progress, and there were differences in the driving factors of coal efficiency in different industries. Different from the existing literatures, which mainly discuss the carbon emissions of energy-intensive industries as a whole or a single carbon-intensive industry, the main contribution of the paper is to analyse the regional heterogeneity of the CO₂ emissions of energy-intensive industries of China, evaluate the carbon efficiency and further calculate the carbon emission reduction potential of energy-intensive industries. Considering regional heterogeneity factors such as the level of economic development and resource endowments among different provinces in China, we can avoid deviations in the assessment of the overall carbon emission efficiency of energy-intensive industries and dynamically predict the state of the carbon emission reduction potentials of different provinces. The rest of this paper is organized as follows. The third part states the main methods adopted in this paper, including the data processing and data resources. In the fourth part, we show our results and the related discussion. Finally, we conclude this paper and put forward some policy recommendations.

Methods and Data

Research methods

Super-SBM model considering undesirable output

The multi-objective decision model is used to evaluate the relative efficiency of the decision-making unit in the

Data Envelopment Analysis (DEA) model. Since the model does not need to consider the input and output function relationships, it has been widely used in the field of environmental and energy efficiency assessment in recent years.

Tone (2001) proposed a slack-based measure (SBM) model, which solves the problem that the traditional radial DEA model does not include the slack variable to measure the inefficiency, and makes up for the deviation caused by the selection difference between the radial and angle. In actual industrial production, a "good" output is usually accompanied by "bad" outputs such as sewage and exhaust gas. Tone (2014) defined the SBM-DEA model including the undesired output and better solved the problem of slack variables and the effect of undesired output on efficiency values in efficiency evaluation. In the analysis results of DEA, there are usually cases where multiple decision-making units are invalid, and it is unable to further distinguish decision-making units with the same efficiency value. To solve this problem, Andersen and Petersen (1993) proposed the Super-Efficiency model, which can further evaluate and rank the results of SBM-DEA. Thence, based on an undesired output, the paper builds an SBM super-efficiency model (Super-SBM). Compared with other DEA models, it can more truly reflect the essence of the carbon emission efficiency evaluation of energy-intensive industries.

Suppose that the low-carbon economic production system has "n" decision-making units (DMU_i, where i=1, 2...n), and each decision-making unit has 3 vectors of input, desirable output, and undesired output. Each vector is represented as $x \in R^{m \times n}$, $y^g \in R^{s_1 \times n}$, and $y^b \in R^{s_2 \times n}$. Then, define the input-output matrix as follows:

$$\begin{cases} X = (x_1, x_2, \dots, x_n) \in R_+^{m \times n} > 0 \\ Y^g = (y_1^g, y_2^g, \dots, y_n^g) \in R_+^{s_1 \times n} > 0 \\ Y^b = (y_1^b, y_2^b, \dots, y_n^b) \in R_+^{s_2 \times n} > 0 \end{cases} \quad (1)$$

Under the assumption of constant returns to scale, the possible production sets of production units are as follows:

$$p = \{(x, y^g, y^b) | x \geq X\lambda, y^g \leq Y^g\lambda, y^b \geq Y^b\lambda\} \quad (2)$$

where λ is the weight vector. The Super-SBM model considering undesired output is as follows:

$$\text{Min} \rho_{SE} = \frac{1 + \frac{1}{m} \sum_{i=1}^m \frac{s_i^-}{x_{ik}}}{1 - \frac{1}{s_1 + s_2} \left(\sum_{r=1}^{s_1} \frac{s_r^g}{y_{rk}^g} + \sum_{v=1}^{s_2} \frac{s_v^b}{y_{vk}^b} \right)} \quad (3)$$

$$\text{s. t.} \begin{cases} \sum_{j=1, j \neq k}^n x_{ij} \lambda_j - s_i^- \leq x_{ik} \\ \sum_{j=1, j \neq k}^n y_{vj}^b \lambda_j - s_v^b \leq y_{vk}^b \\ 1 - \frac{1}{s_1 + s_2} \left(\sum_{r=1}^{s_1} \frac{s_r^g}{y_{rk}^g} + \sum_{v=1}^{s_2} \frac{s_v^b}{y_{vk}^b} \right) > 0 \\ s^-, s^g, s^b, \lambda \geq 0, i = 1, 2 \dots q; j = 1, 2 \dots n (j \neq k) \end{cases} \quad (4)$$

In the model, ρ_{SE} is the target efficiency value, k is the decision-making unit being evaluated, x_{ij} refers to the input, y_{vk}^b refers to the undesirable output, s_r^g represents the shortage of the desirable output of the decision-making unit, s_v^b represents the excess of the undesired output of the decision-making unit, s^- represents the input relaxation variable, s^g represents the relaxation variable of the desirable output, and s^b represents the undesirable output. The resulting relaxation variable ρ_{SE} is strictly monotonically decreasing with respect to s^-, s^g , and s^b , and it satisfies $0 \leq \rho_{SE} \leq 1$; and when $\rho_{SE} = 1$ and s^-, s^g , and $s^b = 0$, the decision-making unit is effective. If $\rho_{SE} < 1$, it means that the decision-making unit is ineffective and the input-output variables of the model needs to be optimized.

Meta-Frontier Malmquist-Luenberger Productivity Index (MF-MLPL)

In addition to measuring the carbon emission efficiency of energy-intensive industries, this paper will also dynamically analyse the changes in the carbon emission performance of energy-intensive industries. Considering the regional heterogeneity of the production technology of different decision-making units, combined with the Directional Distance Function (DDF), this paper proposes the MF-MLPL considering undesirable output. Hayami (1969) proposed the meta-frontier technology to solve the problems that may arise from a single production frontier. It divides the decision-making units into different groups as needed, and each group constitutes a production frontier as a group frontier. Afterwards, the envelope curves formed by different groups of production frontiers obtain a common frontier (Meta-Frontier), and the technological gap between the group frontier and the common frontier is the Technology Gap Ratio (TGR). To distinguish different decision-making unit groups containing undesirable outputs, based on the environmental technology (the Environmental Technology) of Fare et al. (2007), the group production technology is set as follows (TE^G): $T^G = \{(x, y^g, y^b): x \text{ produce } (y^g, y^b)\}$. Assuming that the production frontier is the optimal production frontier of the evaluated decision-making unit, its production technology can be expressed as all groups' Union of production technology sets (TE^M): $TE^M = \{TE^1 \cup TE^2 \dots \cup TE^G\}$. Drawing on Chung et al.'s (1997) Directional Distance Function, the Directional Distance Function (DDF) for the group frontier production technology and the common frontier production technology is as follows:

$$\vec{D}_0^G(x, y^g, y^b; g) = \max\{\beta: (y^g + \beta y^g, y^b - \beta y^b) \in P^G(x)\} \quad (5)$$

$$\vec{D}_0^M(x, y^g, y^b; g) = \max\{\beta: (y^g + \beta y^g, y^b - \beta y^b) \in P^M(x)\} \quad (6)$$

$$TGP(x, y^g, y^b; g) = \frac{TE^M(x, y^g, y^b; g)}{TE^G(x, y^g, y^b; g)} = \frac{\frac{1}{[1 + \vec{D}_0^M(x, y^g, y^b; g)]}}{\frac{1}{[1 + \vec{D}_0^G(x, y^g, y^b; g)]}} \quad (7)$$

The Malmquist index is usually decomposed into the efficiency change (EC) and technology change (TC). Learning from the meta-Frontier approach of Oh and Lee (2010), the Group-Frontier Malmquist-Luenberger Productivity Index (GF-MLPL) is decomposed into the following:

$$\begin{aligned} GF-MLPL_t^{t+1} &= \frac{1 + \vec{D}_0^G(x^t, y^{gt}, y^{bt}; g^t)}{1 + \vec{D}_0^G(x^{t+1}, y^{g(t+1)}, y^{b(t+1)}; g^{t+1})} = EC \times BPC \\ &= \frac{1 + \vec{D}_0^{Gt}(x^t, y^{gt}, y^{bt}; g^t)}{1 + \vec{D}_0^{G(t+1)}(x^{t+1}, y^{g(t+1)}, y^{b(t+1)}; g^{t+1})} \\ &\quad \times \frac{1 + \vec{D}_0^{G(t+1)}(x^{t+1}, y^{g(t+1)}, y^{b(t+1)}; g^{t+1})}{1 + \vec{D}_0^G(x^{t+1}, y^{g(t+1)}, y^{b(t+1)}; g^{t+1})} \\ &\quad \times \frac{1 + \vec{D}_0^{Gt}(x^t, y^{gt}, y^{bt}; g^t)}{1 + \vec{D}_0^G(x^t, y^{gt}, y^{bt}; g^t)} \end{aligned} \quad (8)$$

The Meta-Frontier Malmquist-Luenberger Productivity Index (MF-MLPL) is decomposed into the following:

$$\begin{aligned}
1 \quad \text{MF} - \text{MLPL}_t^{t+1} &= \frac{1 + \vec{D}_0^M(x^t, y^{gt}, y^{bt}; g^t)}{1 + \vec{D}_0^M(x^{t+1}, y^{g(t+1)}, y^{b(t+1)}; g^{t+1})} = \\
2 \quad &= \frac{1 + \vec{D}_0^{Gt}(x^t, y^{gt}, y^{bt}; g^t)}{1 + \vec{D}_0^{G(t+1)}(x^{t+1}, y^{g(t+1)}, y^{b(t+1)}; g^{t+1})} \times \frac{1 + \vec{D}_0^{G(t+1)}(x^{t+1}, y^{g(t+1)}, y^{b(t+1)}; g^{t+1})}{1 + \vec{D}_0^M(x^{t+1}, y^{g(t+1)}, y^{b(t+1)}; g^{t+1})} \\
3 \quad &= \frac{1 + \vec{D}_0^{Gt}(x^t, y^{gt}, y^{bt}; g^t)}{1 + \vec{D}_0^{G(t+1)}(x^{t+1}, y^{g(t+1)}, y^{b(t+1)}; g^{t+1})} \times \frac{1 + \vec{D}_0^{Gt}(x^t, y^{gt}, y^{bt}; g^t)}{1 + \vec{D}_0^M(x^t, y^{gt}, y^{bt}; g^t)} \\
4 \quad &\times \frac{1 + \vec{D}_0^G(x^{t+1}, y^{g(t+1)}, y^{b(t+1)}; g^{t+1})}{1 + \vec{D}_0^M(x^{t+1}, y^{g(t+1)}, y^{b(t+1)}; g^{t+1})} = EC \times BPC \times TGC \quad (9)
\end{aligned}$$

Among them, the BPC (Best Practice Change) is the gap between the current frontier and the global frontier within the group from period t to t+1, that is, the global Malmquist technology change (TC); and the TGC is the change in the technical gap ratio from period t to t+1 (TGR).

Indicators and data

This paper selects the basic data of 30 provinces of China in the period of 2005-2017 (considering the availability of data, the Hong Kong, Macao and Taiwan regions of China and Tibet have not been included). The economic regions are divided as follow: The Northeast region, including Liaoning, Jilin and Heilongjiang; the East Region, including Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; the central region, including Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan; and the western region, including Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. To eliminate the influence of price factors, the economic indicators are adjusted using 2005 as the base year. Based on the theoretical model analysis, this paper selects the capital stock (Capital), the fossil energy consumption of energy-intensive industries (FE), and industrial employees (Labour) as the input variables; the industrial value-added (Yield) as the desirable output; and the CO₂ emissions (E-CO₂) of energy-intensive industries as the undesired output. The industrial value-added and energy consumption data of the six energy-intensive industries come from the "China Statistical Yearbook", the "China Industrial Economic Statistical Yearbook", the "China Energy Statistical Yearbook" and the statistical yearbooks of the provinces over the years. The data characteristics of each input-output variable are shown in Table 1.

Capital stock. Drawing on the estimation method of the capital stocks in various provinces of Shan (2008), the capital stock is adjusted using constant 2005 prices with the economic depreciation rate of 9.6%. The calculation formula is as follows:

$$C_{t,i} = I_{t,i} + (1 - \delta_{t,i})C_{(t-1),i} \quad (10)$$

$C_{t,i}$ and $C_{(t-1),i}$ refer to the capital stock of area i in the current year and the previous year, respectively; $I_{t,i}$ refers to the fixed asset investment in the current year; and $\delta_{t,i}$ refers to the depreciation rate of fixed assets.

Energy consumption. The fossil energy consumption of the energy-intensive industries of various regions is taken as the input element, including raw coal, coke, natural gas, crude oil, gasoline, kerosene, fuel oil, liquefied petroleum gas, diesel and other fossil energy sources. Since the data of Shanghai, Jiangsu, Zhejiang, and Sichuan provinces cannot be directly obtained, we treat these provinces using data from those with similar energy

consumption structures by following Lin and Tan (2016): the energy consumption structures of Shanghai and Sichuan refer to Beijing and the energy consumption structures of Chongqing, Jiangsu and Zhejiang refer to Guangdong.

labour force. Considering the availability of data and the methods of most studies, this paper uses the number of industrial employees to measure the labour input.

Industrial added-value. The industrial value-added of the energy-intensive industries during the research period is used as the desirable output, and the figures are adjusted using 2005 prices.

CO₂ emissions. Based on the types of fossil energy consumption in energy-intensive industries, the average low calorific values and carbon oxidation rates of different fossil energy sources using the "2006 IPCC Guidelines for national greenhouse gas emission Inventories" are adopted to calculate CO₂ emissions (IPCC 2006).

Table 1 Descriptive statistics of the input-output variables

Variable	Capital (Billion Yuan)	FE (Million Ton Standard Coal)	Labour (Million Person)	Yield (10 billion Yuan)	E-CO ₂ (Million Ton)
Max	15301.93	260.60	15.68	3529.18	640.80
Min	151.67	5.13	0.097	15.62	12.60
Ave	3179.89	72.30	2.97	692.08	177.78
STD	2843.10	52.74	3.22	659.91	129.68

Results and Discussion

Based on the model analysis and data processing, the paper estimates the carbon emission efficiency technology gap of the energy-intensive industries in various provinces and four economic regions of China during the period of 2005-2017, and analyses the carbon emission reduction potential of the energy-intensive industries in various provinces and four economic regions.

Carbon emission technology gap ratio of energy-intensive industries

There are large differences in the carbon emission Technology Gap Ratios(TGRs)of the energy-intensive industries in different economic regions, as shown in Fig. 3. The northeast is one of the regions of China rich in comprehensive mineral and energy resources, and energy-intensive industries are important pillar industries in the region. Heilongjiang is the largest energy producing area in the northeast region; therefore, the technology gap between the meta-frontier and the group-frontier of carbon emissions in Heilongjiang is large. The technology gap ratio of each province in the eastern region is close to 1, indicating that there is basically no technological gap between the meta-frontier and the group-frontier of the energy-intensive industries in the eastern region. With profound economic strength, natural geographical advantages and industrial advantages, the eastern region has long been the most socially and economically developed region in China, and so its carbon emission efficiency has always been at the forefront of the four major economic regions. The TGR of the meta-frontier and group-frontier of the energy-intensive industries in the central region is approximately 0.88, and the technical gap between the meta-frontier and group-frontier of the energy-intensive industries in the western region fluctuates slightly, from 0.83 to 0.95. Since the "Eleventh Five-Year Plan", due to being in the process of rapid industrialization, a high proportion of heavy industries and low energy efficiency have occurred in the Mid-western region, resulting in a large gap between the meta-frontier and group-frontier of the energy-intensive industries. Especially for Hunan, Hubei, Sichuan, Chongqing, Guangxi, Shanxi and other provinces, most of them belong to the Yangtze River Economic Belt and have regional advantages and development potential.

Driven by industrial transformation, the economic growth rates of these provinces are higher than the average level; furthermore, loose policy also provides wide energy and carbon emission spaces for them. After 2000, due to international industrial transfer, resource and environmental constraints, and increased labour costs, the spatial distribution of the energy-intensive industries in China has experienced the characteristic of “agglomeration to diffusion to aggregation” (Liu et al. 2019a). By transferring industry from eastern coastal regions to the central and western regions, industrial transfer brings economic development and production technology, but it also brings a lot of carbon flow, stimulating the further development and growth of energy-intensive industries in the central and western regions. In the "Eleventh Five-Year Plan" and "Twelfth Five-Year Plan", the government has accelerated the energy conservation and emission reduction processes, and has controlled energy consumption and carbon emissions from experiencing excessively rapid growth by setting energy consumption intensity targets and carbon emission intensity targets, respectively. During the period of 2005-2017, the average TGR of all energy-intensive industries was approximately 0.93, as shown in Figure 4, and the TGR each year in the eastern region was 1. During the period of the "Eleventh Five-Year Plan", the technological gaps of the carbon emission efficiency in the northeast and western regions have gradually decreased, and the technological gap in the central region is relatively large. Under the western development policy, the urbanization process and industrial transformation and upgrading have also brought more industrial agglomeration and economic development space for energy-intensive industries in the central region, which also undertake lighter emission reduction tasks. However, this industrial migration trend could not promote technological innovation, and it unavoidably brings about the “pollution paradise” effect, leading to a larger gap between the meta-frontier and the group-frontier in the central region. The global financial crisis in 2008 greatly affected global economic development, and the rapid industrialization of the central region caused the technology gap of carbon emission efficiency to decrease to 0.8. After 2011, the global economy has gradually recovered, most energy-intensive industries have adopted destocking management, and the carbon emission indicators have also been included in the “Twelfth Five-Year Plan”. With the process of industrialization, the central and western regions pay more attention to the technological innovation and industrial restructuring of energy-intensive industries to improve the carbon emission efficiency and the technology gap is constantly narrowing. After 2011, the technological gap of carbon emission efficiency in the Northeast region has gradually improved and decreased from 0.95 to 0.79.

Fig. 3 Average technology gap ratio of the carbon emission efficiency in energy-intensive industries

Fig. 4 Technology gap ratio of the carbon emission efficiency of energy-intensive industries in different regions

Meta-Frontier Malmquist-Luenberger Productivity Index (MF-MLPL)

Based on the meta-frontier, figure 5 presents the changes in the carbon emission performance in energy-intensive industries. The growth rate of the carbon emission efficiency of energy-intensive industries in different economic regions shows a trend of first declining and then slowly recovering. During the "Eleventh Five-Year Plan" period, the Chinese government attached great importance to energy conservation and emission reduction and regarded energy conservation and emission reduction as an important tool for adjusting the economic structure, thus changing the development mode, responding to climate change, and promoting scientific development. They put forward the constraint targets of reducing energy consumption per GDP by 20% and reducing the total pollutant emissions by 10%. Therefore, the growth rate of the carbon emission efficiency of energy-intensive industries fell sharply before 2010, and the average MF-MLPL decreased by 18.93%. The efficiency growth rate in western regions is relatively high, and the gap in the MF-MLPL of different economic regions was the smallest in 2009-2010. During the "Twelfth Five-Year Plan" period, due to the reduction in the elasticity of energy consumption, the energy-saving and emission reduction policies of energy-intensive industries were adjusted. The policy focused on improving energy efficiency, adjusting the industrial structure, strengthening green and low-carbon technological innovation, and improving market restraint mechanisms; thence, the overall growth rate of the carbon emission efficiency of energy-intensive industries had slowed down. After 2014, the MF-MLPL has been gradually improved, especially for the eastern region. The growth rate of the carbon emission efficiency of energy-intensive industries has rebounded since 2012 and increased by 7.15%.

Further analysis of the causes of the fluctuations in the growth rate of the carbon emission efficiency of energy-intensive industries is presented in table 2. We decompose the growth rate (MF-MLPL) of the carbon emission efficiency of energy-intensive industries into carbon emission efficiency changes (EC), carbon emissions best practice technology changes (BPC), and technology gap ratio changes (TGC). Before 2010, compared with other economic regions, the efficiency of the energy-intensive industries in the central and north eastern regions increased rapidly, and the EC reached 1.01. That in the central region may be due to the rapid industrialization process and the spatial distribution of energy-intensive industries since the rapid development has also increased carbon emissions. Meanwhile, the strategies of revitalizing the Northeast and the old industrial base policies have also contributed to the improvement of the northeast region. After 2010, with the advancement of energy saving and emission reduction policies, the carbon emission efficiency of the eastern region increased

significantly from 1.0074 to 1.016 while the carbon emission efficiency of the energy-intensive industries in the northeast region dropped to 0.9819. The BPC in different economic regions has shown a downward trend, and the technological innovation capacity in the eastern region is relatively high. The BPC in the western region has decreased from 1.0491 to 0.9986 since 2010. The possible reason is that the continuous increase in R&D innovation investment in the eastern region has been effective. The energy-intensive industries in the western region are mostly heavy industries with low energy efficiency, resulting in an insufficient technological innovation capability.

Fig. 5 Meta-Frontier Malmquist-Luenberger Productivity Index (MF-MLPL)

Table 2 MF-MLPI and its decomposition rate from 2005 to 2017

	MF-MLPL		EC		BPC		TGC	
	2005-2010	2010-2017	2005-2010	2010-2017	2005-2010	2010-2017	2005-2010	2010-2017
Northeast	1.0349	0.9866	1.0113	0.9819	1.0386	1.0016	0.9935	1.0138
East	1.0565	1.0345	1.0074	1.0160	1.0592	1.0279	0.9921	0.9985
Central	1.0509	0.9903	1.0131	1.0121	1.0591	1.0141	0.9815	0.9858
West	1.0828	1.0034	1.0030	1.0047	1.0491	0.9986	1.0371	0.9988
Average	1.0629	1.0095	1.0080	1.0077	1.0534	1.0118	1.0066	0.9976

Analysis of the carbon emission reduction potentials in energy-intensive industries

(1) Carbon emission reduction potential in energy-intensive industries (relative value)

As shown in Figure 6, the carbon reduction potential of energy-intensive industries generally shows a trend of decreasing and then rising, with an average score of 29.74%. The carbon emission reduction potential of energy-intensive industries in the eastern region keeps decreasing, falling from 34.05% to 15.31%. After 2000, energy conservation and emission reduction have been constraints in the "Eleventh Five-Year Plan", and the government has proposed specific requirements for controlling greenhouse gas emissions. Figure 5 shows that the carbon emission reduction potential of energy-intensive industries in China has been declining since 2005, indicating that during the period of the "Eleventh Five-Year Plan", energy conservation and emission reduction policies have achieved remarkable results. Affected by the financial crisis in 2008, the carbon emission reduction potential of energy-intensive industries rebounded slightly in 2009. From 2005 to 2012, the carbon emission reduction potential of energy-intensive industries in the western region was relatively high, with an average score of 37.73%; the reduction potential of energy-intensive industries in the eastern region was relatively low, with an average score of 27.16%; and the reduction potentials in the northeast and central regions are both close to

the national level. After 2011, energy conservation and emission reduction policies were adjusted accordingly by emphasizing industrial optimization, upgrading energy-intensive industries and adjusting the energy structure; establishing and improving the economic structure adjustment guarantee mechanism; and promoting the accountability mechanism for energy conservation and emission reduction. After 2012, except for the eastern region, the carbon emission reduction potentials of energy-intensive industries greatly increased, and the reduction potential in the northeast region rose from 26.94% to 39.51%. The carbon emission reduction potentials in the central and west regions increased by 27.92% and 26.17%, respectively. The results indicate that the reconstruction plans of the old industrial bases in the Midwest and Revitalizing the Northeast Strategy have been effectively implemented. With the urbanization and industrialization in the Midwest, more emphasis has been placed on upgrading, transforming and adjusting the energy structure of energy-intensive industries. From the perspective of provinces, the carbon emission reduction potentials of energy-intensive industries in the eastern region are polarized, those in the central region is more even, and the reduction potential in the western region is highly fluctuant. The carbon emission reduction potentials of energy-intensive industries in Tianjin and Guangdong are relatively low, all within 10%; and the provinces such as Hainan, Guizhou, Gansu, and Ningxia have high reduction potentials, approximately 40%.

Under the group-frontier technology in Figure 7, the trends of the carbon emission reduction potentials of energy-intensive industries in different economic regions are similar to that of the meta-frontier. Except for the eastern region, the carbon emission reduction potentials of energy-intensive industries are lower than that of the meta-frontier. The average carbon emission reduction potential of energy-intensive industries nationwide is 23.94%. The carbon emission reduction potential of energy-intensive industries in the central region is significantly lower than those of other economic regions. It decreased from 30.48% in 2005 to 9.62% in 2012, and later rose to 20.90%. The carbon emission reduction potential of energy-intensive industries in economic regions differed from each other before the year of 2009. After 2009, the reduction potentials of the northeast and western regions gradually approached the national level.

Fig. 6 Carbon emission reduction potential of energy-intensive industries under meta-frontier

Fig.7 Carbon emission reduction potential of energy-intensive industries under group-frontier

(2) Carbon emission reduction potential values of energy-intensive industries in different provinces

The carbon emission reduction potential values of different provinces in energy-intensive industries under the meta-frontier from 2005 to 2017 are illustrated in table 3. From the provincial perspective, the top five cities with the lowest potential values of energy-intensive industries under the meta-frontier are Tianjin (3.46 Million Tons, 9.36%), Hainan (7.44 Million Tons, 41.99%), Beijing (10.74 Million Tons, 24.29%), Chongqing (15.01 Million Tons, 27.19%) and Heilongjiang (17.03 Million Tons, 24.60%); meanwhile, the five cities with the largest potential values are Liaoning (208.30 Million Tons, 37.26%), Hebei (119.68 Million Tons, 30.74%), Shandong (118.09 Million Tons, 27.56%), Henan (101.99 Million Tons, 30.49%) and Shanxi (86.11 Million Tons, 35.16%). Liaoning is the city with the highest potential value in the northeast region. Since the "Eleventh Five-Year Plan", the growth rate of the energy-intensive industries in Liaoning has slowed down, and the potential value of energy-intensive industries has increased year by year. This indicates that Liaoning Province has achieved significant effectiveness in the compression of energy-intensive industries and the adjustment of economic structure.

During the research period, the carbon emission reduction potential values of the energy-intensive industries in the eastern region showed a tiered fluctuation trend, and the potential values in Hebei and Shandong are similar and high as they are both provinces with relatively concentrated energy-intensive industries. Hebei is an industrial province with steel, cement, and glass as the economic mainstays while Shandong is dominated by petrochemicals and electricity. The total output values of the energy-intensive industries in Hebei and Shandong account for approximately 40% and 50%, respectively, and the proportion of the energy consumption of the energy-intensive industries with respect to the total industrial energy is up to 75%; therefore, the carbon reduction trends of the two provinces are similar in the implementation of the energy saving and emission reduction policy. Shanghai, Jiangsu, Zhejiang and Guangdong in the eastern region are located in the Yangtze River Economic Belt with the strongest comprehensive strength and are pioneers of the ecological civilization construction of China. Meanwhile, Shanghai, Jiangsu and Zhejiang rank as the top three in the green development of the Yangtze River Economic Belt. With the gradual increase in the energy consumption, the carbon emission reduction potential in the eastern region is decreasing yearly, and the actual potential value of each province fluctuates less. The innovation-driven effect in Guangdong has been improved the fastest, and the potential value of the energy-intensive industries in Guangdong has changed significantly.

The carbon emission reduction potential values of the energy-intensive industries in the central region differ in each province, among of which the potential values in Henan, Shanxi, and Anhui are relatively high and rising slowly while the potential values in Hunan, Hubei, and Jiangxi show a downward trend. Combined with the

carbon reduction potential trend of the energy-intensive industries in the central region, it is obvious that there are differences in the economic development among provinces in the central region due to resource endowments and comparative advantages. Henan and Shanxi are provinces in the central region with relatively concentrated energy-intensive industries. The output value of their energy-intensive industries accounts for approximately 45% of the province while the proportion of the energy consumption of their energy-intensive industries is up to 87-90%. Therefore, with the urbanization and industrial transformation and upgrading, the governments of the central and western regions should actively improve their energy use efficiency, optimize their industrial structures, regard low-carbon industrial development as the key direction for energy conservation and emission reduction, and apply technological innovation to suppress carbon dioxide emissions in order to jointly achieve economic development, energy savings and emission reduction potential values. The carbon emission reduction potential values of the energy-intensive industries in the western region are relatively concentrated, and the potential values in Xinjiang, Inner Mongolia, and Shaanxi provinces have changed significantly. After 2000, energy-intensive industries gradually shifted from the eastern coastal region to the central and western regions. In 2016, the proportion of energy-intensive industries in the central and western regions increased by 4.97% and 3.49%, respectively; and the industrial shares of most provinces in the western region increased with the growth in Guangxi and Shaanxi exceeding 1% (Liu et al., 2019b). The policies of Western Development and urbanization have effectively promoted the economic development of the western region and strengthened the attractiveness of the central and western regions to energy-intensive industries, which also intensified the accumulation of energy consumption and carbon emissions in these areas.

Table 3 Carbon emission reduction potential values of energy-intensive Industries under meta-frontier (million tons)

Province	Area	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Mean
Liaoning	NE	172.45	183.19	187.28	176.96	196.66	206.18	192.24	197.93	206.12	202.28	214.95	291.63	280.01	208.30
Jilin	NE	60.00	62.28	68.14	95.83	94.56	79.07	79.49	77.45	79.60	73.16	71.22	57.12	62.35	73.87
Heilongjiang	NE	12.30	15.33	10.41	12.01	19.71	15.14	0.00	13.75	17.08	20.94	21.94	29.47	33.27	17.03
Beijing	E	24.93	22.88	21.59	17.81	16.74	9.34	8.90	6.72	4.42	2.94	2.67	0.65	0.00	10.74
Tianjin	E	6.54	7.46	7.89	5.93	7.96	4.35	0.00	2.21	0.30	0.00	0.72	1.65	0.00	3.46
Hebei	E	102.70	114.73	119.75	106.45	117.04	114.99	112.67	121.60	129.16	127.37	117.71	135.98	135.63	119.68
Shanghai	E	33.62	33.73	34.73	32.71	34.92	20.49	26.34	24.36	28.44	25.84	26.24	22.16	15.63	27.63
Jiangsu	E	48.01	51.66	56.94	51.75	59.12	65.97	56.22	63.36	71.19	64.22	58.18	48.75	35.60	56.23
Zhejiang	E	46.00	50.04	52.48	49.03	57.46	60.59	56.07	63.22	67.85	64.24	63.77	57.90	61.78	57.73
Fujian	E	20.02	22.63	27.99	28.65	33.03	29.06	36.28	27.72	43.74	43.07	27.64	19.09	23.86	29.45
Shandong	E	113.34	111.09	122.90	109.46	120.84	124.21	117.05	123.11	126.34	121.51	118.44	112.90	113.95	118.09
Guangdong	E	30.48	27.65	17.87	0.00	35.69	23.06	16.70	32.71	26.97	19.77	14.65	4.18	0.00	19.21
Hainan	E	7.42	6.42	6.00	5.98	6.75	6.38	7.24	7.68	8.33	8.84	9.59	8.30	7.79	7.44
Shanxi	M	70.08	76.76	78.14	71.15	81.59	81.26	74.74	78.03	83.86	96.85	100.38	114.18	112.32	86.11
Anhui	M	55.74	60.84	66.17	71.16	79.10	77.26	70.87	72.48	80.44	83.48	64.24	83.28	90.32	73.49
Jiangxi	M	33.08	36.45	38.76	37.18	40.07	38.86	36.14	35.51	37.69	38.06	41.19	43.85	43.62	38.50
Henan	M	93.57	91.02	99.57	94.84	103.28	103.22	104.95	105.08	108.35	112.05	110.52	103.49	95.95	101.99
Hubei	M	44.56	42.78	37.28	31.32	30.94	28.66	25.98	20.18	22.69	20.68	17.69	12.59	10.38	26.60
Hunan	M	52.69	55.34	61.25	59.14	55.94	54.56	49.69	46.69	38.93	33.57	39.99	40.65	43.66	48.62
Inner Mongolia	W	75.81	57.06	61.18	59.90	62.25	48.43	36.09	35.86	43.62	43.84	29.67	86.45	107.94	57.55
Guangxi	W	27.77	27.95	28.86	29.74	35.27	28.98	29.35	26.54	33.19	37.58	31.66	34.35	45.42	32.05

Chongqing	W	17.38	19.23	21.60	19.48	14.01	13.74	11.76	10.80	12.95	15.56	14.47	12.43	11.66	15.01
Sichuan	W	60.62	67.06	73.25	65.70	66.65	65.53	75.45	65.87	67.39	60.83	63.20	67.17	63.97	66.36
Guizhou	W	39.87	42.78	44.46	39.92	42.97	43.44	47.17	47.62	43.26	35.27	27.48	31.47	26.93	39.43
Yunnan	W	10.66	9.96	10.14	40.37	44.19	46.70	49.98	59.12	51.10	52.07	51.34	53.23	56.71	41.20
Shaanxi	W	31.16	38.39	42.01	42.61	48.61	51.92	41.54	46.33	40.51	44.85	72.99	76.13	73.87	50.07
Gansu	W	34.01	34.81	35.30	35.34	37.79	36.10	34.70	38.10	40.59	42.37	51.00	48.51	53.92	40.20
Qinghai	W	14.24	14.84	15.31	13.39	14.48	15.09	16.11	17.77	20.04	24.05	24.97	26.13	30.14	18.97
Ningxia	W	18.53	20.35	22.92	22.36	23.85	25.96	33.16	37.95	42.64	45.08	49.25	47.30	62.47	34.76
Xinjiang	W	21.88	18.23	21.31	24.20	30.87	29.84	30.95	40.27	52.11	72.72	90.83	99.87	100.02	48.7

Conclusions and policy implications

The paper describes the CO₂ emissions of the energy-intensive industries of China, builds a Super-SBM model considering undesirable outputs, and calculates the carbon emission efficiency. Then, Meta-Frontier Malmquist-Luenberger Productivity Index (MF-MLPI) is constructed to dynamically analyse the growth rate changes of the carbon emission efficiency and the regional differences among energy-intensive industries; furthermore, the carbon emission reduction potential of the energy-intensive industries in various economic regions of China are discussed. Conclusions are drawn as follows.

- (1) From the perspective of the province, there is a big difference in the carbon emission Technology Gap Ratio (TGR) of energy-intensive industries in different economic regions. The technology gap between the meta-frontier and the group-frontier of carbon emissions in Heilongjiang is large. The technology gap ratio of each province in the eastern region is close to 1. The TGR of the meta-frontier and group-frontier of energy-intensive industries in central regions is around 0.88, and the technical gap between the meta-frontier and group-frontier of energy-intensive industries in the western regions fluctuates slightly, among 0.83 to 0.95. During the period of 2005-2017, the average TGR of total energy-intensive industries was around 0.93. After 2011, with the process of industrialization, the central and western regions pay more attention on the technological innovation and industrial restructuring of energy-intensive industries, and the technology gap is constantly narrowing, while the gap in the Northeast region has gradually expanded.
- (2) The growth rate of carbon emission efficiency of energy-intensive industries in different economic regions shows a trend of first declining and then slowly recovering. The growth rate of carbon emission efficiency of energy-intensive industries fell sharply before 2010. and the growth rate in western regions is relatively high. After 2014, the MF-MLPL has been gradually improved, especially for the eastern region, the growth rate of carbon emission efficiency of energy-intensive industries has rebounded since 2012, increased by 7.15%. Compared with other economic regions, the efficiency of energy-intensive industries in the central and northeastern regions increased rapidly before 2010. After 2010, with the advancement of energy saving and emission reduction policies, the carbon emission efficiency in the eastern region increased significantly, while that in the northeast region dropped to 0.9819.
- (3) Carbon reduction potential of energy-intensive industries generally shows a trend of decreasing and then rising, with an average score of 29.74%. The carbon emission reduction potential in the eastern region keeps decreasing. From 2005 to 2012, the carbon emission reduction potential of energy-intensive industries in the western region was relatively higher than that in the eastern region was relatively low. After 2012, except for the eastern region, the carbon emission reduction potentials of energy-intensive industries in other economic regions have greatly increased. From the perspective of provinces, the carbon emission reduction potentials of energy-intensive industries in the eastern region are polarized, the central region is more even, while the reduction potentials in the western region are highly fluctuant. The carbon emission reduction

potential in Tianjin and Guangdong is relatively low, all within 10%; provinces such as Hainan, Guizhou, Gansu, and Ningxia have high carbon emission reduction potential, around 40%.

- (4) During the research period, the carbon emission reduction potential values of energy-intensive industries in the central regions differ in each province, among of which the potential values in Henan, Shanxi, and Anhui are relatively high and rising slowly, while the potential values in Hunan, Hubei, and Jiangxi show a downward trend. The carbon emission reduction potential values of energy-intensive industries in the western region are relatively concentrated, and the potential values in Xinjiang, Inner Mongolia, and Shaanxi provinces have changed significantly.

Based on the research conclusions, policy recommendations are drawn as follows:

- (1) According to the industrial advantages of different regions, the government should rationally distribute energy-intensive industries, promote industrial structure adjustment and optimize the energy structure. As the agglomeration region of energy-intensive industries, the eastern region has experienced a gradually weakened resource carrying capacity. It is necessary to further improve environmental regulations, implement various environmental standards, and strengthen the application of energy-saving and environmental protection technologies in energy-intensive industries. During the rapid industrialization and urbanization process, the central and western regions have transferred some energy-intensive industries. Hence, we should pay attention to the harmonious development of industry, regional resources and the environment; strengthen the energy efficiency to avoid the “pollution paradise” effect in the central and western regions. Furthermore, the growth of the value-added of the energy-intensive industries in the central and western regions should be controlled to avoid overcapacity.
- (2) The government should increase R&D investment and promote energy technology innovation in energy-intensive industries. It is necessary to strengthen low-carbon technological innovation and achieve transformation in the eastern region, effectively support the development of high-tech industries and modern service industries, and increase the value added of energy-intensive industries. The energy efficiency of the energy-intensive industries in the central and western regions is relatively low, and the government should actively eliminate outdated industries and promote the upgrading of the industrial structure. Through the development of energy technology, we can help to improve the energy-consumption efficiency, thereby promoting the transformation of energy-intensive industries from extensive to intensive.
- (3) The government should formulate differentiated emission reduction plans according to the characteristics of regions and industries. Energy-intensive industries in China are still currently dominated by coal-based energy structures, which contain huge potential for energy structure optimization to promote carbon emission reduction. The scope of resource tax collection for fossil energy such as coal should be appropriately expanded, complete environmental protection tax system could be established, and the competitiveness of the market prices of renewable energy should be enhanced in the meantime. The government should give priority to promoting carbon peaks of key emission industries and regional, formulate differentiated carbon emission reduction plans for the regions and industries with different reduction potentials, and gradually complete scientific and efficient carbon emission reduction targets for energy-intensive industries.

Declarations

Ethics approval and consent to participate: All studies did not involve human or animal ethics.

Consent for publication: This manuscript hasn't contained any individual person's data in any form.

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