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The spatial-temporal evolution analysis of carbon emission of China's thermal power industry based on the three-stage SBM—DEA model

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Abstract

Purpose – China has proposed two-stage goals of carbon peaking by 2030 and carbon neutralization by 2060. The carbon emission reduction effect of the power industry, especially the thermal power industry, will directly affect the progress of the goal. This paper aims to reveal the spatial-temporal characteristics and influencing factors of carbon emission efficiency of the thermal power industry and proposes policy suggestions for realizing China's carbon peak and carbon neutralization goals.

Design/methodology/approach – This paper evaluates and compares the carbon emission efficiency of the thermal power industry in 29 provinces and regions in China from 2014 to 2019 based on the three-stage slacks-based measure (SBM) of efficiency in data envelopment analysis (DEA) model of undesired output, excluding the influence of environmental factors and random errors.

Findings – Empirical results show that during the sample period, the carbon emission efficiency of China's thermal power industry shows a fluctuating upward trend, and the carbon emission efficiency varies greatly among the provincial regions. The carbon emission efficiency of the interregional thermal power industry presents a pattern of "eastern > central > western," which is consistent with the level of regional economic development. Environmental factors such as economic level and environmental regulation level are conducive to the improvement of carbon emission efficiency of the thermal power industry, but the proportion of thermal power generation and industrial structure is the opposite.

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Originality/value – This paper adopts the three-stage SBM–DEA model of undesired output and takes CO_2 as the undesired output to reveal the spatial-temporal characteristics and influencing factors of carbon emission efficiency in China's thermal power industry. The results provide a more comprehensive perspective for regional comparative evaluation and influencing factors of carbon emission efficiency in China's thermal power industry.

Keywords Thermal power industry, Carbon emission, Three-stage SBM–DEA

Paper type Research paper

1. Introduction

In 2020, the carbon emissions of China's power industry will account for 40% of the total emissions of the national energy industry, and the power industry has always been the industry with the largest carbon dioxide emissions in China and the world (Chen *et al.*, 2020). China proposes a two-stage goal of peaking carbon dioxide emissions in 2030 and achieving carbon neutrality by 2060. The emission reduction effect of the power industry will directly affect the progress of the goal.

At present, power generation based on clean and renewable energy is far from meeting China's industry power demand and daily power needs, and thermal power generation is still the main way of power supply. The China Electricity Council released the "Summary of Power Industry Operation from January to November 2020," showing that by the end of November 2020, the installed capacity of power plants with an installed capacity of 6,000 kilowatts and above in China had reached 2.02 billion kilowatts, and the installed capacity of thermal power had reached 1.23 billion kilowatts, accounting for nearly 60%. Thermal power plants that burn fossil fuels release a large amount of carbon dioxide, and carbon emission reduction in the thermal power industry is one of the key links to achieving a carbon peak in China.

As the main indicator for evaluating industry carbon emissions, carbon emission efficiency has more advantages than other indicators. Scientifically evaluate the carbon emission efficiency of the thermal power industry, conduct dynamic comparative analysis from time and space, reveal the main factors affecting carbon emissions of China's thermal power industry and put forward countermeasures and suggestions in a targeted manner, which is of great significance for promoting carbon emission reduction and sustainable development of China's power industry.

2. Literature review

At present, many scholars have carried out a lot of research on the evaluation of carbon emission efficiency from different angles. According to the existing research, it can be divided into two categories:

(1) single-factor carbon emission efficiency measurement; and
(2) multifactor carbon emission total factor efficiency evaluation.

2.1 Single-factor carbon emission efficiency measurement

It is through the traditional single-factor carbon emission efficiency measurement indicators, such as the perspective of carbon productivity, that is, the proportion of gross domestic product (GDP) to total carbon dioxide emissions during the same period (Kaya and Yokobori, 1997).

Some scholars measure and analyze carbon productivity at the national level. Jahanger *et al.* (2021) applied a panel threshold model to estimate the threshold effect of globalization on carbon productivity in China. The results show that China's carbon productivity has increased, while the pattern of economic growth has developed toward the direction of low carbon. Using the data of China's input–output table from 2002 to 2017, Guo *et al.* (2021)

measured the evolution characteristics and influencing factors of carbon productivity from the perspective of China's industrial sector's implied carbon emissions. Based on the industry level, Coderoni and Vanino (2022) used individual farm data extracted from the Italian Farm Accounting Data Network between 2008 and 2017 to analyze the relationship between carbon productivity and farm economic performance to study green growth in agricultural production. Jung *et al.* (2021) used firm-level emissions and corporate variables to investigate how the development of an emissions trading scheme affects carbon productivity. Bagchi *et al.* (2022) studied the carbon emission estimation and carbon productivity of Indian manufacturing industry from the firm level.

Another example is carbon emission intensity, which is the number of carbon emissions corresponding to a unit of GDP per capita (Sun, 2005). Ibrahim (2018) took 62 middle-income countries as samples and found that international trade and financial development played an interactive and complementary role in reducing the carbon dioxide intensity of energy use. Muttakin *et al.* (2020) studied the relationship between national election system and enterprise greenhouse gas emission intensity and discussed whether this relationship was affected by enterprise political donations. In terms of method, some scholars analyze the driving mechanism and impact of carbon emission intensity from the perspective of spatial effect by constructing a spatial Durbin model (Xiao *et al.*, 2019; Xue *et al.*, 2020; Muhammad *et al.*, 2021). Alex and Emmanuel (2019) applied artificial neural network (ANN) model to predict the growth of carbon dioxide emission intensity in Australia, Brazil, China, India and the USA. Laskar *et al.* (2022) studied the impact of carbon emission intensity of the top 100 companies listed on the Bombay Stock Exchange on corporate performance by using the system generalized method of moment model. Ali *et al.* (2022) used dynamic auto regressive distributed lag simulation technology to research and found that there is a long-term correlation between China's renewable and nonrenewable energy consumption and carbon emission intensity.

The single-factor carbon emission efficiency measurement is mostly expressed as the ratio of total carbon dioxide emissions to a certain factor. The advantage of single-factor carbon emission efficiency measurement is that the indicator data is easy to collect and easy to understand and operate. The disadvantage is that too few elements are considered, and there are inevitably relatively thin, limited and one-sided, resulting in different results from the actual situation.

2.2 Multifactor carbon emission total factor efficiency evaluation

Multifactor carbon emission total factor efficiency evaluation is evaluated by constructing a carbon emission efficiency index that includes a number of relevant factors, that is, a total factor framework system.

Some scholars have systematically and comprehensively studied carbon emissions by building a total factor framework to find out the main factors affecting carbon emissions (Loganathan *et al.*, 2020; Ngo, 2021; Pan *et al.*, 2022). The data envelopment analysis (DEA) model and its derivative models are often used in the study of carbon emission efficiency. Li *et al.* (2019) used the DEA method to evaluate the carbon emission efficiency of each province and empirically investigated the impact of urbanization on carbon emission efficiency based on the stochastic impacts by regression on population, affluence, and technology extension. Atta *et al.* (2022) evaluated the operational efficiency of Chinese listed real estate companies through SBM–DEA model and panel regression technology and studied its driving factors. To better evaluate the results, the carbon emission efficiency is measured and analyzed by constructing a super-efficiency SBM model (Zhou *et al.*, 2019; Asmita and Dharmesh, 2019). Combined with the Malmquist index, the carbon emission efficiency is evaluated from a static and dynamic point of view (Wang and Feng, 2020; Park and Kim, 2021). Zhang and Xu (2022) calculated the carbon emission efficiency of the Yellow River Basin from 2005 to 2019 based on the SBM–directional distance function model and the Malmquist–Luenberger index and measured the influencing factors of carbon emission efficiency through the Tobit model. Zaim and Taskin (2000) defined carbon emissions for the first time as undesired outputs, that is, undesired production results. Iftikhar *et al.* (2016) conducted static and dynamic analysis on energy and carbon dioxide emission efficiency of major economies based on DEA–SBM model. The carbon emission efficiency was evaluated based on the undesired output Epsilon-based measure (EBM)–DEA model, and the influencing factors were analyzed through the regression model (Zeng *et al.*, 2019; Xue *et al.*, 2021; Zhao *et al.*, 2022).

Many scholars also use the three-stage DEA model to measure and evaluate carbon emission efficiency for more accurate results (Surakiat *et al.*, 2018; Zhou and Yu, 2021). Kannan *et al.* (2021) measured the efficiency of electric power enterprises through the three-stage virtual frontier DEA (3S-VF-DEA) and then ranked electric power companies using the efficiency measurement results. Some scholars have combined the three-stage DEA model with other models to study carbon emission efficiency. Hu *et al.* (2020) measured the embodied carbon emission efficiency of China's export trade and analyzed its influencing factors by combining the three-stage DEA model with the noncompetitive I–O model. The carbon emission efficiency was measured through the three-stage DEA model, and the influencing factors of carbon emission efficiency were analyzed through the regression model (Zhu *et al.*, 2021; Zhang *et al.*, 2021). Yi *et al.* (2021) used the three-stage DEA–Malmquist model to estimate the dynamic carbon emission efficiency of China's logistics industry from 2001 to 2017 and then used the Dagum Gini coefficient method, kernel density estimation and panel vector autoregression model to analyze the regional difference decomposition and its forming mechanism. In general, domestic and foreign scholars use different types of DEA models to analyze and study China's carbon emission efficiency.

The advantage of the multifactor carbon emission fullfactor efficiency evaluation is that through a more comprehensive calculation and evaluation of carbon emission efficiency through multiple factors, the measurement results are more accurate. The disadvantage is that it is difficult to collect data because of a large number of indicators, and in terms of indicator selection, there may be correlation or intersection between indicators, resulting in unsatisfactory regression results.

Most scholars pay more attention to the research on carbon emissions in the regional power industry, but there are relatively few studies on the carbon emissions efficiency of regional thermal power generation. The traditional SBM–DEA model does not take into account the influence of environmental factors and random errors, which leads to deviations in the calculation results. Therefore, different from previous research, this paper attempts to use the three-stage SBM–DEA model of undesired output, taking CO_2 as the undesired output, to compare and evaluate the carbon emission efficiency of the thermal power industry in 29 provinces and cities in China from 2014 to 2019, revealing the spatiotemporal characteristics and influencing factors of carbon emission efficiency in China's thermal power industry and the corresponding carbon emission reduction strategies for the thermal power industry are proposed, which has important practical significance for promoting the realization of energy conservation and emission reduction in China's thermal power industry.

3. Research methods

The traditional DEA model and various DEA models derived from it measure the efficiency from the radial and angular aspects of the input–output ratio, but such models do not take into account the inefficiency caused by the slack of input and output factors. Kaoru (2001) proposed the SBM model, which solved this problem very well. Compared with the traditional DEA model, the nonradial, angle-free SBM model is dimensionless and avoids the influence of different dimensions and selection angles. Therefore, based on the interprovincial panel data of the thermal power industry in 29 provinces and cities from 2014 to 2019, this paper attempts to use the three-stage SBM–DEA model of undesired output to calculate and evaluate the carbon emission efficiency of the thermal power industry in each province and city.

3.1 First stage: SBM–DEA model of undesired output

Through the SBM–DEA model of undesired output, the initial efficiency value, input slack variable, expected output slack variable and undesired output slack variable are calculated. The model form is as follows:

$$\min\rho = \frac{1-\frac{1}{m}\sum_{i=1}^{m}{s_i}^{-}\Big/x_{i0}}{1+\frac{1}{q_1+q_2}\left(\sum_{r=1}^{q_1}{s_r}^{+}\Big/y_{r0}+\sum_{t=1}^{q_2}{s_t}^{b-}\Big/b_{t0}\right)}$$

$$s.t.\begin{cases}\sum_{j=1}^{n}x_j\lambda_j+s^{-}=x_0(i=1,\cdots,m)\\ \sum_{j=1}^{n}y_j\lambda_j-s^{+}=y_0(r=1,\cdots,q_1)\\ \sum_{j=1}^{n}b_j\lambda_j+s^{b-}=b_0(t=1,\cdots,q_2)\\ \lambda_j,{s_i}^{-},{s_r}^{+},{s_t}^{b-}\geq 0(j=1,\cdots,n)\end{cases} \tag{1}$$

In the formula: ρ is the carbon emission efficiency value to be calculated, the value range is 0–1; j is each decision-making unit; n is the number of decision-making units; m is the number of input indicators, q_1, q_2 represent the number of indicators of expected output and undesired output; ${s_i}^{-}$ is the input slack variable; ${s_r}^{+}$, ${s_t}^{b-}$ are the slack variables of expected output and undesired output; λ_j is the intensity variable; x_{j}, y_{j} and b_{j} are the m-dimensional input vector, the q_1-dimensional expected output variable and the q_2-dimensional undesired output variable of the jth decision-making unit respectively; x_0, y_0 and b_0 represent the input variables, expected output variables and undesired output variables of the evaluated decision-making unit.

The validity of the model efficiency is judged as follows:

- If <1, the evaluated decision-making unit is invalid.
- If = 1, the evaluated decision-making unit is valid, and the slack variables of input variables, expected output and undesired output variables are all 0.

It can be seen from the model that the slack variables of input and output are included in the model, which not only solves the slack problem of input and output in the traditional DEA model but also solves the problem of undesired output in the production process.

3.2 Second stage: building the SFA regression model

The efficiency values measured in the first stage include the influence of environmental factors and random errors. If all the influences are attributed to management inefficiency, the calculation relative lacks rigor, which may cause large errors in the results. Therefore, the influence of environmental factors and random noise must be eliminated. Fried *et al.* (2002) solved this problem very well by constructing the Stochastic Frontier analysis (SFA) regression model, analyzing relevant environmental variables and adjusting the initial input–output variables. Build the following regression function:

$$S_{mi} = f(Z_i; \beta_m) + \nu_{mi} + \mu_{mi}(m = 1, 2, \cdots, M; i = 1, 2, \cdots, I) \tag{2}$$

In the formula: S_{mi} is the slack variable of the m input of the i decision unit; Z_{i} represents the environmental variable and β_{m} represents the coefficient of the environmental variable; v_{mi} reflects the random noise and μ_{mi} reflects the management inefficiency, the former obeys a normal distribution, the latter assumes that it obeys a half-normal distribution truncated at 0, that is $\mu_{mi} \sim N^{+}\left(0, {\sigma_\mu}^2\right)$. Also, assume that v_{mi} and μ_{mi} are independent of each other, and their sum represents the mixed error term. To eliminate the effects of environmental variables and random noise, environmental variables, management inefficiencies and random noise need to be separated. The derivation formula of separation management inefficiency is as follows:

$$E(\mu|\varepsilon) = \sigma_* \left[\frac{\phi\left(\lambda \frac{\varepsilon}{\sigma}\right)}{\phi\left(\lambda \frac{\varepsilon}{\sigma}\right)} + \frac{\lambda\varepsilon}{\sigma} \right] \tag{3}$$

In the formula, $\sigma_* = \frac{\sigma_\mu \sigma_\nu}{\sigma}$, $\sigma = \sqrt{{\sigma_\mu}^2 + {\sigma_\nu}^2}$, $\lambda = {}^{\sigma_\mu}/_{\sigma_\nu}$, $\varepsilon = \mu_{mi} + v_{mi}$. Then, the calculation formula of the separated random error term is:

$$E\left[{}^{\nu_{mi}}/_{(\nu_{mi}+\mu_{mi})}\right] = S_{mi} - f(Z_i; \beta_m) - E\left[{}^{\mu_{mi}}/_{(\nu_{mi}+\mu_{mi})}\right] \tag{4}$$

After eliminating environmental variables and random noise, the input variables are adjusted so that all decision-making units are in the same external environment. The input variable adjustment formula is:

$$X_{mi}^{A} = X_{mi} + \left\{ \max[f(Z_i; \beta_m)] - f(Z_i; \beta_m) \right\} + [\max(\nu_{mi}) - \nu_{mi}] \tag{5}$$

In the formula: X_{mi}^{A} and X_{mi} are input variables after treatment and before treatment. $\{\max[f(Z_i;\beta_m)] - f(Z_i;\beta_m)\}$ represents the environment variable after processing, and $[\max(v_{mi}) - v_{mi}]$ represents the random noise after processing. At this time, all decision-making units will be in the same external environment, which ensures that the measured efficiency value is close to the actual value.

3.3 Third stage: the adjusted data envelopment analysis model

In the second stage, the regression analysis of the SFA model is constructed to eliminate the influence of environmental factors and random errors. The adjusted input variables and the original output variables are processed through the first-stage model again to measure all decision-making units. Compared with the first stage, the results obtained after recalculation are more accurate and true.

4. Variable selection and data collection

Given the lack of data in Tibet, Hong Kong, Macao and Taiwan regions and the particularity of the capital Beijing, they are not included in the scope of the study. By collecting and processing the relevant panel data of the thermal power industry in 29 provinces and cities across the country from 2014 to 2019, the carbon emission efficiency of the thermal power industry in each province and city is measured and evaluated. The measurement indicators of the carbon emission efficiency of China's thermal power industry are divided into input indicators and output indicators, and output indicators are further divided into expected output indicators and undesired output indicators. The specific indicators and data are selected as follows.

4.1 Selection of input variables

In the existing literature, although the research focuses of different scholars are different, the choices of input variables are generally capital, labor and energy. In this paper, the installed capacity of the thermal motor is used as the capital input; the labor input selects the number of employees in the thermal power industry, but because of the lack of special statistics, this paper replaces the number of employees in the thermal power industry with the number of employees engaged in electricity, heat production and supply and the unit is ten thousand; the total energy consumption of thermal power generation is used as energy input and the unit is ten thousand tons of standard coal.

4.2 Selection of output variables

In the production process, in addition to the expected output, there are often undesired outputs. In this paper, the power generation of thermal power generation is regarded as the expected output and the carbon dioxide emissions generated by the total energy consumption of thermal power generation in the energy balance sheet of each region are regarded as the undesired output. Since there is no direct carbon emission data in China, to calculate the carbon dioxide emissions of the thermal power industry in various provinces and cities, this paper adopts the carbon dioxide calculation formula and carbon emission coefficient proposed in the 2006 "IPCC Guidelines for National Greenhouse Gas Emission Inventory."

4.3 Selection of environment variables

The selection of environmental variables should be objective and follow the principle of influence rather than the control of decision-making units. Therefore, environmental variables that can affect the carbon emission efficiency of thermal power generation but cannot be controlled subjectively should be selected. The environmental variables selected in this paper are as follows: the level of economic development is the per capita GDP of each province and city, and the unit is yuan; the proportion of thermal power generation is expressed as the proportion of electricity generated by burning fossil fuels to the total power generation; the industrial structure is expressed by the proportion of secondary industry; the proportion of investment in environmental pollution control in each province and city in GDP represents the level of environmental regulation.

The data on the above input variables, output variables and environmental variables are all from the official website of the National Bureau of Statistics, "China Statistical Yearbook," "China Energy Statistical Yearbook," "China Labor Statistical Yearbook," "China Electricity Statistical Yearbook" and "China Environmental Statistical Yearbook."

5. Empirical analysis

5.1 First stage: analysis of empirical results of the model before adjustment

According to the undesired SBM–DEA model, this paper uses the software MaxDEA Ultra 8 to calculate the initial carbon emission efficiency value of the thermal power industry in various provinces and cities across the country from 2014 to 2019. The calculation results are shown in Table 1.

5.1.1 Empirical analysis based on time dimension. According to the evaluation results in Table 1, during the sample period, the efficiency value of all years in Jiangsu is equal to 1, indicating that the carbon emission efficiency of the thermal power industry in Jiangsu Province is effective and at the forefront of efficiency. The average efficiency values of Hebei, Ningxia and Shandong are all around 0.97, which is close to the efficiency frontier. The efficiency values of Ningxia and Hebei are all valid in other years except for some years.

In Hebei province, the carbon emission efficiency value of the thermal power industry increased from 0.767 in 2014 to 1 in 2019 and the efficiency value increased by 0.233. This is because the proportion of thermal power generation in Hebei province decreased from 92.6% in 2014 to 84.5% in 2019, a large decrease. The proportion of other clean energy

Provinces and cities	2014	2015	2016	2017	2018	2019	Mean
Tianjin	0.705	0.869	1.000	0.834	1.000	1.000	0.901
Hebei	0.767	1.000	1.000	1.000	1.000	1.000	0.961
Shanxi	0.809	0.777	0.684	0.674	0.679	0.681	0.717
Inner Mongolia	0.790	0.768	0.654	0.685	1.000	1.000	0.816
Liaoning	0.533	0.617	0.591	0.569	0.544	0.580	0.572
Jilin	0.395	0.428	0.419	0.388	0.434	0.482	0.424
Heilongjiang	0.449	0.510	0.491	0.469	0.559	0.522	0.500
Shanghai	0.786	0.946	0.926	0.816	0.791	0.874	0.856
Jiangsu	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Zhejiang	0.834	1.000	1.000	0.860	0.831	0.897	0.904
Anhui	0.807	0.847	0.798	0.820	0.811	1.000	0.847
Fujian	0.733	0.716	0.604	0.656	0.689	0.723	0.687
Jiangxi	0.597	0.700	0.767	0.738	0.764	0.809	0.729
Shandong	1.000	1.000	1.000	1.000	0.967	0.891	0.976
Henan	0.620	0.660	0.614	0.605	0.626	0.631	0.626
Hubei	0.576	0.718	0.711	0.637	0.679	0.758	0.680
Hunan	0.540	0.610	0.580	0.584	0.636	0.643	0.599
Guangdong	0.694	0.856	1.000	0.756	0.769	0.823	0.816
Guangxi	0.612	0.684	0.577	0.540	0.575	0.662	0.608
Hainan	0.794	1.000	0.696	0.611	0.643	0.697	0.740
Chongqing	0.553	0.634	0.601	0.565	0.621	0.648	0.604
Sichuan	0.465	0.520	1.000	1.000	1.000	0.565	0.758
Guizhou	0.535	0.528	0.494	0.490	0.524	0.574	0.524
Yunnan	0.369	0.382	0.346	0.312	0.329	0.351	0.348
Shaanxi	1.000	0.771	0.805	0.769	0.687	0.717	0.792
Gansu	0.500	0.580	0.539	0.481	0.515	0.533	0.525
Qinghai	0.554	0.555	0.546	0.543	0.494	0.467	0.526
Ningxia	1.000	1.000	0.777	1.000	1.000	1.000	0.963
Xinjiang	0.720	0.860	0.746	0.732	0.768	0.937	0.794
Mean	0.681	0.743	0.723	0.694	0.722	0.740	
Eastern Region	0.784	0.900	0.882	0.810	0.823	0.848	
Central Region	0.599	0.656	0.633	0.614	0.648	0.691	
Western Region	0.645	0.662	0.644	0.647	0.683	0.678	

Table 1. Carbon emission efficiency values of the thermal power industry in 29 provinces and cities in China (the first stage)

generation increased, which improved the carbon emission efficiency of the thermal power industry in Hebei Province.

The carbon emission efficiency of the thermal power industry in Shandong province was effective from 2014 to 2017, while the efficiency values in 2018 and 2019 were invalid. This indicates that although Shandong has made relevant efforts in improving efficiency, energy saving and emission reduction in these two years, the results are not satisfactory. It is likely to be caused by too much investment in thermal power energy consumption and human resources or the thermal power industry is in a relatively poor environment, there is still a lot of room for improvement in the carbon emission efficiency of the thermal power industry.

For other provinces and cities, except for Tianjin, Zhejiang, Anhui, Shaanxi and other cities whose efficiency value is equal to 1 in some years, the remaining carbon emission efficiency value is invalid. All cities should speed up the adjustment of the energy structure of the thermal power industry, strengthen regional policies for energy conservation and emission reduction, accelerate the elimination of outdated thermal power equipment and technology, and at the same time increase the technological transformation of the thermal power industry.

5.1.2 Empirical analysis based on spatial dimensions. Table 1 shows that among the 29 provinces and cities, the average carbon emission efficiency of the thermal power industry in 65.52% of the provinces and cities is less than 0.8; the average carbon emission efficiency of the thermal power industry in 31.03% of the provinces and cities is between 0.8 and 1; the average carbon emission efficiency of the thermal power industry in the remaining 3.45% of provinces and cities is equal to 1. There are fewer provinces and cities at the forefront of efficiency, and the overall level is not high.

The carbon emission efficiency of the thermal power industry shows great differences because of different regions. The maximum value of the average efficiency is 1, and the minimum value is 0.348. Among them, the provinces and cities with an average efficiency greater than 0.8 are Jiangsu, Ningxia, Shandong, Hebei, Tianjin, Zhejiang, Shanghai, Anhui, Inner Mongolia, Guangdong, except Ningxia, Anhui and Inner Mongolia, the rest of the provinces and cities are located in the eastern region.

Regionally, the carbon emission efficiency of the thermal power industry in the eastern region is generally higher than that in the central and western regions. In addition to the advantages of advanced thermal power equipment, policies such as energy conservation and emission reduction are also easier to operate and implement in the relatively economically developed eastern region.

5.2 Second stage: SFA model regression analysis

The carbon emission efficiency value of the thermal power industry in the first stage is calculated without removing environmental factors and random noise. The results may deviate from the true value and do not match the carbon emission levels of the thermal power industry, so environmental factors, random noise and management inefficiencies must be separated. In this stage, the selected environmental variables are used as independent variables to carry out SFA regression analysis on the three input slack variables of capital stock, labor and energy consumption by using Frontier4.1 software.

The results in Table 2 show that the regression coefficients of environmental variables on the slack variables of the three inputs have passed the significance test, and the likelihood ratio (LR) one-sided error test results have passed the 1% significance test, indicating that the management inefficiency item does exist. The SFA model is reasonable. The γ values of the three regression results of environmental variables on the slack variables of capital, labor and energy consumption are all around 0.7, close to 1. The results show that the variation of slack

Table 2.
Second stage SFA regression results

Slack variable	Capital stock slack variable Coefficient	*t* value	Labor slack variable Coefficient	*t* value	Energy consumption slack variable Coefficient	*t* value
Constant term	2,709.11	492.65***	43.53	2.14**	4,142.58	35.08***
Economic level	−322.29	−5.36***	−4.83	−2.73***	−550.75	−2.61***
Proportion of thermal power generation	−39.80	−0.59	0.29	0.33	597.78	2.74***
Industrial structure	436.47	2.42**	5.81	2.39**	1,098.29	1.67*
Environmental regulation level	−159.15	−2.26**	−1.93	−1.89*	838.95	3.98***
σ^2	257,303.76	206,954.56***	48.76	2.91***	2,242,487.40	1,821,358.90***
γ	0.67	17.00***	0.83	12.53***	0.69	19.37***
LR	41.73***		60.80***		46.98***	

Note: ***, ** and * in the upper right corner represent tests with significance levels of 1, 5 and 10%, respectively

variables is mainly caused by management inefficiency, so it is necessary to separate management inefficiency from environmental variables and random noises.

The positive and negative environmental variables coefficients, respectively, reflect the inhibition and promotion effect on improving the carbon emission efficiency of the thermal power industry. According to the regression results in Table 2, the effects of various environmental variables on carbon emission efficiency are different:

- *Effects of economic level.* The economic level is significantly and negatively correlated with the three input slack variables, indicating that China's economic development mode has improved at this stage. Economic development has provided financial assistance for thermal power plants, enabling thermal power plants to speed up the introduction of talents and advanced technologies and economic development has gradually eliminated high-energy consuming production equipment, improving the carbon emission efficiency of the thermal power industry.
- *Effects of the proportion of thermal power generation.* The proportion of thermal power generation is significantly and positively correlated with the slack variable of energy consumption, while it has no significant performance with the capital stock and labor slack variables. The outdated equipment in individual regions produces more carbon dioxide in the process of thermal power generation. At the same time, the increase in the proportion of thermal power generation will generate more energy consumption, which is not conducive to the improvement of the carbon emission efficiency of the thermal power industry. The government needs to optimize the energy structure of the power industry, accelerate the promotion of clean energy power generation and gradually reduce the proportion of thermal power generation in power generation.
- *Effects of industrial structure.* The industrial structure is significantly and positively correlated with the three input slack variables, indicating that the increase in the proportion of the secondary industry will lead to an increase in capital stock, labor consumption and energy consumption, resulting in more waste of input, which is not conducive to the improvement of carbon emission efficiency of the thermal power industry. Therefore, it is necessary to adjust the industrial structure and reduce the proportion of the secondary industry.

- *Effects of environmental regulation level.* The level of environmental regulation has a significant and negative correlation with the slack variable of capital stock and labor and has a significant and positive correlation with the slack variable of energy consumption, indicating that the increase in the proportion of investment in environmental pollution control in GDP is conducive to reducing capital stock and labor input. Increased investment in environmental pollution control will reduce the amount of carbon dioxide produced by thermal power generation and improve the carbon emission efficiency of the thermal power industry in general.

5.3 Third stage: analysis of the empirical results of the adjusted model

After eliminating the influence of environmental factors and random noise in the second stage, the three input variables of capital, labor and energy consumption were adjusted through SFA regression analysis and then use MaxDEA Ultra 8 to measure the adjusted variables. The results are shown in Table 3.

5.3.1 Analysis of empirical results based on time dimension. Compared with the results of the first stage, the carbon emission efficiency of the thermal power industry measured after the adjustment in the third stage has changed greatly. The efficiency values of most provinces and cities are lower than the results of the first stage, but the results are more objective and show a fluctuating increase as a whole.

Provinces and cities	2014	2015	2016	2017	2018	2019	Mean
Tianjin	0.358	0.433	0.486	0.375	1.000	1.000	0.609
Hebei	0.749	0.786	0.734	0.792	1.000	1.000	0.844
Shanxi	0.720	0.764	0.723	0.701	0.752	0.769	0.738
Inner Mongolia	1.000	0.788	0.744	0.726	0.738	1.000	0.833
Liaoning	0.525	0.582	0.560	0.518	0.569	0.585	0.557
Jilin	0.329	0.349	0.318	0.302	0.379	0.398	0.346
Heilongjiang	0.386	0.434	0.396	0.377	0.473	0.462	0.421
Shanghai	0.436	0.596	0.566	0.437	0.501	0.523	0.510
Jiangsu	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Zhejiang	0.760	1.000	1.000	0.778	0.824	0.857	0.870
Anhui	0.684	0.753	0.746	0.720	0.780	0.789	0.745
Fujian	0.557	0.568	0.471	0.498	0.619	0.630	0.557
Jiangxi	0.410	0.490	0.521	0.475	0.571	0.584	0.508
Shandong	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Henan	0.729	0.782	0.740	0.689	0.765	0.747	0.742
Hubei	0.482	0.595	0.599	0.497	0.601	0.656	0.572
Hunan	0.416	0.453	0.422	0.418	0.520	0.521	0.458
Guangdong	0.809	1.000	1.000	0.824	0.936	1.000	0.928
Guangxi	0.403	0.461	0.399	0.357	0.474	0.528	0.437
Hainan	0.167	0.244	0.164	0.141	0.195	0.197	0.185
Chongqing	0.283	0.341	0.311	0.291	0.389	0.395	0.335
Sichuan	0.326	0.319	1.000	1.000	1.000	0.390	0.672
Guizhou	0.471	0.487	0.477	0.440	0.521	0.553	0.491
Yunnan	0.242	0.214	0.166	0.154	0.223	0.237	0.206
Shaanxi	0.555	0.651	0.655	0.619	0.667	0.705	0.642
Gansu	0.386	0.435	0.395	0.356	0.443	0.442	0.410
Qinghai	0.099	0.113	0.120	0.119	0.126	0.109	0.114
Ningxia	0.483	0.508	0.469	0.457	0.561	0.569	0.508
Xinjiang	0.613	0.724	0.706	0.676	0.729	0.746	0.699

Table 3. Carbon emission efficiency values of the thermal power industry in 29 provinces and cities in China (the third stage)

The provinces with the adjusted carbon emission efficiency value of the thermal power industry equal to 1 are Jiangsu and Shandong, and the efficiency values in all years are equal to 1, indicating that the efficiency values of these two provinces are valid each year. In the first stage, although the average efficiency value of Shandong Province is close to the frontier, its efficiency value is decreasing year by year, while in the third stage, the efficiency value of Shandong Province is at the frontier of efficiency. The improvement of Shandong's efficiency value in the third stage shows that the low efficiency in the first stage is not entirely caused by its management inefficiency, but may be related to its poor external environment. The mean carbon emission efficiency of the thermal power industry in Guangdong also increased from 0.816 in the first stage to 0.928 after adjustment, indicating that the low efficiency in the first stage is similar to that in Shandong, and it may also be caused by the poor external environment.

In the results of the third stage, the average efficiency of most provinces and cities decreased. Compared with the first stage, the carbon emission efficiency of Ningxia changed greatly, and the average efficiency decreased from 0.963 to 0.508. Tianjin's average carbon emission efficiency also dropped from 0.901 to an adjusted 0.609. After removing environmental factors and random noise, the overall efficiency of these provinces and cities has decreased. This indicates that the higher efficiency in the first stage may be because of a relatively good external environment.

5.3.2 Analysis of empirical results based on spatial dimensions. Because of the different geographical locations, economic development levels and resource scarcity of different provinces and cities, there are also differences in the carbon emission efficiency of the thermal power industry in different provinces and cities. This paper divides the regions into eastern, central and western regions according to the traditional division method, to analyze the regional differences in the carbon emission efficiency of the thermal power industry. According to the carbon emission efficiency measurement results of the thermal power industry in each province and city in Table 3, the carbon emission efficiency of the thermal power industry in the three major regions from 2014 to 2019 can be obtained. The results are shown in Table 4 and Figure 1.

Figure 1 shows that, from 2014 to 2019, the carbon emission efficiency of the thermal power industry in the eastern, central and western regions kept rising with fluctuations, which shows that the national energy conservation and emission reduction work has achieved remarkable results in recent years. The carbon emission efficiency of the thermal power industry in the three major regions of the eastern, central and western regions presents a spatial pattern of "eastern > central > western," which is consistent with the economic development pattern.

The economic development level of the eastern region is relatively high, and the low-carbon concept in the eastern region is more advanced than that of the central and western regions. In the thermal power industry, the eastern region actively eliminates small- and medium-sized thermal power plants with relatively backward technology, constantly improves power generation technology, optimizes the structure of coal used for power generation and uses clean coal. Therefore, the overall efficiency is higher than that in the

Table 4. Carbon emission efficiency of eastern, central and western thermal power industry (2014–2019)

Three regions	2014	2015	2016	2017	2018	2019
Eastern region	0.636	0.721	0.698	0.636	0.764	0.779
Central region	0.519	0.577	0.558	0.522	0.605	0.616
Western region	0.442	0.458	0.495	0.472	0.534	0.516

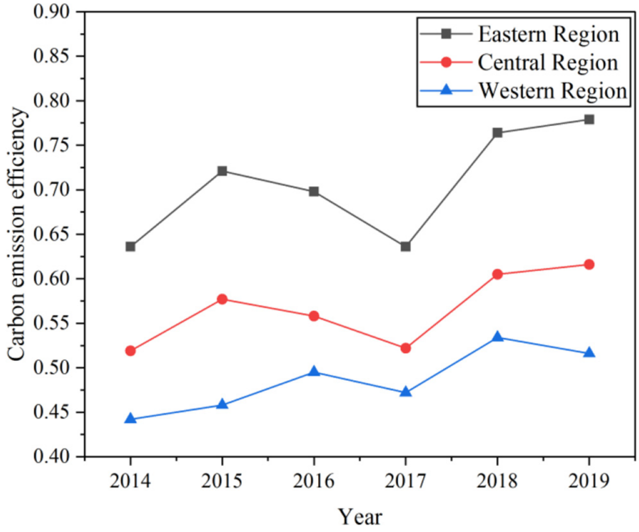

Figure 1. Carbon emission efficiency trend of the thermal power industry in eastern, central and western regions (2014–2019)

central and western regions. The economic development level of the western region is relatively low, the proportion of small- and medium-sized thermal power plants is still relatively large, and the update speed of thermal power technology is relatively slow, which hinders the improvement of the carbon emission efficiency of the thermal power industry.

6. Conclusions and recommendations

This paper analyzes the main influencing factors of carbon emission efficiency from the time dimension and space dimension, supplements the theoretical system of carbon emission efficiency and influencing factors in the thermal power industry and provides a certain reference for future research. The research on the carbon emission efficiency of the thermal power industry can help to find ways and methods to improve the carbon emission efficiency of the thermal power industry and provide a certain reference for the government to formulate and implement energy saving and emission reduction strategies of the thermal power industry with regional characteristics. The conclusions are as follows:

- Structural factors such as industrial structure and energy structure are unfavorable to the carbon emission efficiency of China's thermal power generation. During the sample period, among the external environmental factors, the economic level and the level of environmental regulation are conducive to improving the carbon emission efficiency of the thermal power industry, which are the external environmental factors of advantage. Economic development provides support for the technological transformation of thermal power plants as the mode of economic development has been improved. At the same time, the increase in the proportion of investment in pollution control promotes thermal power plants to speed up the introduction of talents and advanced technologies and eliminate high-energy-consuming production equipment, while the proportion of thermal power generation and the industrial structure are not conducive to improving the carbon emission efficiency of the thermal power industry, which are the external environmental factors of disadvantage. At this stage, the proportion of thermal power generation is still relatively large, and the use of clean energy is worthy of further promotion. The increase in the proportion of the secondary industry leads to more waste of energy consumption and other inputs, which is not conducive to the improvement of carbon emission efficiency.

- In terms of the time dimension, the carbon emission efficiency of the thermal power industry in China's provinces has been improved interactively. The carbon emission efficiency of the thermal power industry in Jiangsu and Shandong is relatively effective, and the efficiency value in each period is equal to 1, which is at the forefront of efficiency. The carbon emission efficiency value of the thermal power industry in other provinces and cities is relatively low, but it has been improved interactively. All provinces and cities should strengthen the promotion of regional energy conservation and emission reduction policies, actively eliminate small- and medium-sized thermal power plants with relatively backward technology, constantly improve power generation technology and optimize the structure of coal for power generation.
- In terms of spatial dimension, there are large differences in the carbon emission efficiency levels of the thermal power industry between regions. The carbon emission efficiency of the thermal power industry in the three regions presents a spatial pattern of "eastern > central > western," which is consistent with the economic development pattern. This is because the economic development level of the eastern region is relatively high, and the low-carbon concept should be advanced in the central region. In the thermal power industry, small and medium-sized thermal power plants with relatively backward technologies are actively eliminated, the power generation technology is continuously improved, the structure of coal used for power generation is optimized and clean coal is used. Therefore, the average carbon emission efficiency is higher than that in the central and western regions.

Based on this, this paper puts forward several suggestions:

- *Maintaining a good external environment*. The level of economic development is conducive to improving the carbon emission efficiency of the thermal power industry. The introduction of technical talents and capital investment in the thermal power industry should be increased, and the power generation technology should be continuously improved. The level of environmental regulation plays an important role in improving the carbon emission efficiency of China's thermal power industry. The promotion of relevant emission reduction measures in the thermal power industry should be strengthened and scientific and reasonable environmental regulation policies should be formulated. The government should actively eliminate small and medium thermal power plants with relatively backward technology by introducing advanced thermal power generation equipment and improving the utilization rate of coal combustion in the process of power generation, thereby reducing carbon dioxide emissions in the thermal power generation link and improving the overall carbon emission efficiency of the thermal power industry.
- *Improving the adverse external environment*. The industrial structure should be adjusted to improve power utilization efficiency, to improve the carbon emission efficiency of the thermal power industry. Optimize the structure of coal for power generation and use clean coal. At the same time, vigorously develop new clean power sources such as hydropower, wind power and nuclear power and gradually

replace the dominant position of thermal power generation in power generation, to achieve carbon emission reduction in the power industry.

- *Implementing differentiated emission reduction in different regions.* All regions should strengthen personnel exchanges and cooperation and learn from each other advanced thermal power technology and management experience based on personnel training. By introducing advanced technologies and equipment from developed regions, underdeveloped regions will gradually narrow the gap with developed regions and improve the carbon emission efficiency of the regional thermal power industry. In general, according to their actual conditions, each region should accelerate the upgrading and transformation of power generation technology in the regional thermal power industry, formulate differentiated emission reduction plans, explore new models of interregional energy cooperation and actively coordinate investment in new interregional UHV transmission channels to achieve coordinated emission reduction of the interregional thermal power industry.

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