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Evaluation on the Provincial Total Factor Energy Efficiency in China Based on the SBM-Undesirable Model

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Abstract

In this study, the theory of production economics was used to establish a reasonable input–output index system. The total factor energy efficiency (TFEE) of 31 provinces in China from 2014 to 2023 was estimated using the slacks-based measure (SBM)-Undesirable model, and the regional energy-saving potential was analyzed. Results show that: (1) The overall TFEE in China is at a high level, which first decreases and then increases and develops steadily. (2) TFEE presents regional heterogeneity, showing the distribution characteristics of high in the eastern region and low in the central and western regions, accompanied by regional σ convergence. (3) TFEE of some provinces in China has β absolute convergence and β conditional convergence, and low-efficiency provinces tend to catch up with high-efficiency provinces. The carbon emission efficiency of each province in the region verges to its own steady-state level, and the economic development level and labor input are the key factors to improve the carbon emission performance in Western China. For energy saving, most provinces have substantial energy saving potential. To improve regional energy efficiency and achieve energy-saving goals, efforts should be exerted to elevate the R&D input and strengthen technical exchanges and cooperation, optimize the industrial structure and energy consumption structure, accelerate the establishment of a smart energy management system and promote the rational flow of energy.

Keywords: Total factor energy efficiency, Energy saving potential, SBM-Undesirable model; Production economics, Carbon peaking and carbon neutrality goals

1. Introduction

Control of energy, which is an important material basis for the development of the national economy, determines the fate of a country in the future, but the unreasonable utilization of energy resources has also caused serious environmental problems. The Paris Agreement requires that nationally determined contributions (NDCs) specify energy efficiency targets. Through the principle of "energy efficiency first," the EU will promote the energy efficiency of member countries to increase by 32.5% by 2030. Such policies force countries to establish a scientific energy efficiency evaluation system [1]. The American Inflation Reduction Act encourages enterprises to improve energy efficiency through tax credits, and all of these enterprises rely on accurate total factor energy efficiency (TFEE) evaluation to guide policy design. The "14th Five-Year Plan" of China proposes the goal of reducing energy consumption per unit of gross domestic product (GDP) by 13.5%, and implements the "6 special actions" (three 500 hundred action plans, two thousand action plans and one ten thousand action plan) among key energy users. To cope with global climate change, China needs to strengthen international cooperation and exchanges; become a participant, leader, and contributor in the construction of ecological civilization; accelerate the establishment of a low-carbon economic development system focusing on recycling and sustainability; establish a clean and low-carbon energy system; promote the transformation into a low-carbon lifestyle; cooperate with other countries to cope with environmental changes; and protect the common home on which to live [2]. TFEE evaluation is an important direction in the fields of energy economics and sustainable development, with its core of comprehensively considering the relationship between multi-factor (capital, labor, technology) input and energy output, thereby scientifically evaluating energy efficiency [3]. With the continuous growth of global energy demand and increasing shortage of energy resources, improving energy efficiency has become an important way for countries to meet energy challenges and achieve sustainable development. TFEE evaluation helps to reveal the inefficient links in energy utilization and also provides a scientific basis for policy-makers to optimize resource allocation, promote energy structure transformation, and achieve low-carbon development [4].

At present, low-carbon economic transformation is an inevitable choice for the development of China, and improving the country's TFEE is the only way to achieve economic development and environmental and ecological protection [5]. On the one hand, this endeavor can effectively delay the greenhouse effect caused by the emission of greenhouse gases, such as carbon dioxide, in the process of China's economic development. On the other hand, this undertaking can promote the kinetic energy transformation for China's economic growth and achieve the goal of coordinated development. To improve energy efficiency, the influence of many influencing factors should be considered. Given the significant differences between provinces in technological level and resource endowments, regional differences, spatial linkage characteristics, dynamic evolution characteristics of TFEE among provinces, and the key factors leading to inter-provincial differences must be

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fully considered. Moreover, effective and specific energy, environmental, and industrial policies for China must be formulated to realize low-carbon economic transformation. Given the interregional differences in economic development level, industrial structure, resource endowment, energy consumption structure, and technical level in China, energy efficiency shows different performance characteristics. Therefore, of immense theoretical and practical significance is to study the variation trend of energy efficiency in different regions, analyze the energy saving potential in different regions, and propose relevant policies.

2. State of the Art

With economic development, mass energy consumption is accompanied by the increasingly severe environmental and ecological problems in recent years, thereby turning people's attention to energy efficiency improvement and development. Hence, energy efficiency has been extensively investigated by many scholars, and specific results have been achieved, mainly concentrating on the evaluation methods for energy efficiency, interregional differences in energy efficiency, and TFEE.

At present, energy efficiency is evaluated mainly through two methods: parametric and non-parametric methods. Alam et al. [6] adopted stochastic frontier analysis (SFA) as a parametric method to deal with a multi-input and single-output problem, which can be used to evaluate industrial energy efficiency; thus, this method has been proven effective in measuring energy efficiency. Lu et al. [7] analyzed and evaluated the grain production efficiency in England and Wales using the Bayesian method of SFA with a geographical additive panel. Jebali et al. [8] estimated factor productivity and its policy and economic drivers using the fixed-effect SFA method. Huo et al. [9] used the SFA method to measure the carbon emission performance and carbon emission reduction potential of various departments in the Beijing-Tianjin-Hebei region. Du et al. [10] introduced a potential quasi-SFA method to measure energy efficiency under heterogeneous technologies, applied this model in China's energy economy, and concluded that the energy efficiency of the three regions is relatively different; hence, regional characteristics should be fully considered when formulating low-carbon energy-saving policies.

Dor regional energy efficiency differences, Li et al. [11] used capital stock, energy, and labor as input indicators; and undesirable output, such as actual GDP and pollutants, to evaluate TFEE of various provinces in China via the data envelopment analysis (DEA) model. They likewise conducted a comparative analysis of the energy efficiency of various regions. The results show that China's energy efficiency was generally decreasing. Damert et al. [12] proposed a two-stage evaluation and optimization method of renewable energy development based on DEA, and discussed how to adjust the energy structure and realize the maximum efficiency of renewable energy. The study results show that this method can effectively overcome the shortcomings of the traditional model and achieve an objective evaluation, thereby providing reference for formulating the development strategies of renewable energy. Li et al. [13] discussed the efficiency of provincial power industry in China by combining DEA-judgment analysis, environmental assessment, and rank sum test. Profound differences were observed in provincial unified efficiency. Differences between provinces depend on various unified efficiency scores and dynamic changes in different periods. Czerny et al. [14] combined life cycle assessment with data envelopment analysis (DEA) to evaluate the comprehensive efficiency of the sludge-to-energy transformation system. Choi et al. [15] analyzed TFEE of provinces and eight regions in China through the optimized DEA model; the results show that the TFEE level in China was still low, and the traditional energy efficiency measurement methods would overestimate the country's actual efficiency.

For TFEE, including all factors in this study is impossible because of the numerous types of factors affecting TFEE. Scholars have particularly emphasized on the selection of influencing factors according to their own study contents. Lim et al. [16] believed that biased technological progress has an energy-saving effect between "energy–capital" and an energy rebound effect between "energy–labor," and energy efficiency can be effectively improved by informal environmental regulation. Albrizio et al. [17] thought that optimizing the energy consumption structure can promote the improvement of energy efficiency. Perkins [18] learned through that oil consumption, economic development level, and tertiary industry have significant positive effects on energy efficiency; government influence and secondary industry have significant inhibitory effects on energy efficiency; and the increase in import and export and technological progress positively affect the improvement of energy efficiency. Sueyoshi et al. [19] studied the carbon emissions of China's interprovincial transportation industry through the extended STIRPAT and the spatio-temporal geographic weighted model; they found that the impact of energy structure, industrial structure, population size, and urbanization on carbon emissions and energy efficiency of the transportation industry have regional differences, and energy intensity plays a dominant role among all driving factors. Zhang et al. [20] learned through the analysis of panel data that financial policy, investment in renewable energy, industrial production, and foreign trade have a significant impact on energy efficiency in the US, and other factors promote energy efficiency except industrial production. He et al. [21] found a significant spatial correlation between provincial TFEE, foreign direct investment can improve the technological innovation level, thereby improving TFEE, and intellectual property protection and marketization level have a positive impact on TFEE. Xiong et al. [22] investigated the impact of innovative investment in China's provincial energy industry from 1995 to 2017. Hjort et al. [23] stated that the transformation of investment to innovation and economy to sustainable energy sources can inhibit carbon emissions and retard environmental degradation. Hou et al. [24] found that R&D investment can promote the improvement of energy efficiency and the reduction of energy intensity, and then immediately realize the carbon emission reduction target of industrial sectors. Makridou et al. [25] believed that increasing energy investment can directly promote carbon emission reduction and improve energy efficiency and also exert an indirect effect through renewable energy channels and technological progress.

This study established a reasonable input–output indicator system according to theory of production economics, and capital, labor, energy, and other intermediate inputs were incorporated into the production function to construct a production frontier. This endeavor is different from other studies, in which TFEE was estimated, neglecting other intermediate inputs. With some provinces of China taken as the key objects, input indicators were selected from three aspects, namely, capital, labor, and energy; gross domestic product and total carbon dioxide emission were taken as the expected and unexpected outputs, respectively, to measure TFEE of some provinces via the SBM-Undesirable model containing unexpected outputs. In addition, the variation trends of TFEE were tested through the σ convergence, β absolute convergence, and β conditional convergence methods, expecting to provide a theoretical basis for scientifically and reasonably formulating regional differentiated policies to improve TFEE.

3. Methodology

3.1 SBM-Undesirable

Traditional DEA methods represented by the charnes-cooper-rhodes (CCR) and banker-charnes-cooper (BCC) models generally measure the efficiency of homogeneous units based on radial and angular dimensions. Given that slackness between input and output is not considered, and the efficiency level, including "undesirable output," cannot be evaluated, the results are relatively biased. To solve these problems effectively, Tone proposed the SBM-DEA model from non-radial and non-angle perspectives in 2001, incorporating slack variables into the objective function. In the current study, the provincial TFEE in China was evaluated using the SBM-Undesirable model, which is derived from the SBM-DEA model and can effectively avoid efficiency bias caused by the difference of radial and angle selection and substantially reflect the essence of agricultural carbon emission efficiency. In particular, technical efficiency value is obtained based on the constant to returns (CRS) model, and pure technical efficiency is acquired based on the variable scales to return (VRS) model. Given that the results obtained by the CRS model can better reflect the different changes of TFEE in different regions compared with the VRS model, the SBM-Undesirable model under the CRS model was adopted for evaluation and is represented as follows:

$$\rho_0 = \min \frac{1-\frac{1}{m}\sum_{i=1}^{m} s_i / x_{i_0}}{1+\frac{1}{S_1+S_2}\left(\sum_{r=1}^{s1} s_r^g / y_{r0}^g + \sum_{l=1}^{s_2} s_l^b / y_{l0}^b\right)}, \tag{1}$$

s.t

$$x_0 = X_\lambda + S^-, \tag{2}$$

$$y_0^g = Y^g \lambda - S^g, \tag{3}$$

$$y_0^b = Y^b \lambda + S^b, \tag{4}$$

$$\sum_{i=1}^{n} \lambda_j = 1, \lambda \text{Ö} 0; S^- \text{Ö} 0, S^g \text{Ö} 0, S^b \text{Ö} 0 \cdot \tag{5}$$

The assumption is that the aforementioned model contains n decision-making units, each of which includes three-aspect elements, namely, input, expected output, and unexpected output, with the following form: $\lambda \text{Ö} 0; S^- \text{Ö} 0, S^g \text{Ö} 0, S^b \text{Ö} 0 \cdot$

The matrices $X = \left[X_2, \ldots, X_n\right] \in R^{m\times n} > 0$, $Y^g = \left[y^g 1, \ldots, y^g n\right] \in R^{s1\times n} > 0$ and $Y^b = \left[y^b 1, \ldots, y^b n\right] \in R^{s2\times n} > 0$ are defined. In particular, ρ denotes efficiency; S^-, S^g, S^b represent the slack variables of the input, expected output, and unexpected output, respectively; TFEE is optimal under a slack variable of 0 and efficiency value ρ of 1, or otherwise. Whether to reduce or increase the input to improve the efficiency value should be judged through the slack variables.

3.2 Convergence method

(1) σ convergence. This study evaluated the absolute gap development trend of provincial TFEE in China using the coefficient of variation (CV) method in the σ convergence model, expressed as follows:

$$\mathrm{CV} = \frac{\sqrt{\sum_{i=1}^{n} (\mathrm{X}_i - \bar{\mathrm{X}})^2}}{n} / \bar{\mathrm{X}}, \tag{6}$$

where CV stands for the coefficient of variation in a year, X_i is the TFEE value in this year, and x denotes the mean TFEE in this year. If the standard deviation presents a declining trend according to the time sequence, then TFEE will show a σ convergence trend during this period.

(2) β absolute convergence. β absolute convergence aims to judge whether or not low-efficiency provinces tend to catch up with high-efficiency provinces during the study period (i.e., judging the presence/absence of "catch-up effect"). If the "catch-up effect" exists, then the provincial TFEE in China turns better. The β absolute convergence model is as follows:

$$\mathrm{In}(\mathrm{x}_{i,t+T}/\mathrm{X})/T = \mathrm{c} + \beta \mathrm{Inx}_{i,t} + \mu_{i,t}, \tag{7}$$

where $\mathrm{x}_{i,t}$ represents the efficiency value of the ith decision-making unit during one period, $\mathrm{x}_{i,t+\mathrm{T}}$ denotes the efficiency value of the *i*-th decision-making unit during one period, *c* is a constant term, and $\mu_{i,t}$ is the error term. If the regression result reveals $\beta < 0$ and passes the significance test, then the provincial TFEE in China exhibits the "catch-up effect."

(3) β conditional convergence. β conditional convergence aims to judge whether or not the provincial TFEE in China approaches a steady level (i.e., whether each influencing factor exerts a positive promoting effect or negative inhibitory effect on TFEE). The β conditional convergence model is as follows:

$$\mathrm{In}(x_{i,t+T} / \overline{X}) / T = c + bInx_{i,t} + \sum_{j=1}^{k} l_j m_j + m_{i,t} \cdot \tag{8}$$

Relative to the absolute β convergence model, the β conditional convergence increases the control variable *m*. That is, the effect of influencing factors is considered, and the meanings of other variables are the same as those in the conditional convergence model.

3.3 Input–output indicators

This study calculated TFEE using the SBM-Undesirable model under the TFEE framework with some provinces (districts and cities) (for the sake of data availability, not including Hong Kong, Macao and Taiwan) in China in 2014–2023 as units. Theory of production economics states that the input of production activities should keep corresponding to the output without omission or repetition. In the TFEE measurement, to keep the input–output consistency and meet the actual production status, added value (and unexpected output) should be selected for the output if capital and labor are chosen as the input indicators. That is, if capital, labor, and intermediate input are selected as input indicators, then the total output value (and unexpected output) must be chosen as output.

3.3.1 Input indicators

(1) Capital stock (*K*). When estimating the actual capital stock, the perpetual inventory method of Goldsmith is adopted by most scholars, as seen in Formula (9). In particular, K_{it} is the capital stock of province *i* in year *t*, I_{it} represents the investment of province *i* in year *t*, and δ_{it} denotes the fixed assets depreciation rate of province *i* in year *t*. The current study used the capital stock measurement method, 10.96% was taken as the fixed assets depreciation rate of each province in each year, and the capital stock of some provinces in China in 2014–2023 was calculated.

$$K_{it} = K_{i(t-1)}(1-\delta_{it}) + I_{it} \tag{9}$$

(2) Labor (*L*). In the selection of labor input indicators, the results obtained by choosing different indicators to measure the indicators may be different. Owing to the lack of actual labor time index in the study of energy efficiency in the studied area, many scholars have directly used the number of employees at the end of the year to express labor input. However, numerous scholars also think that this indicator cannot effectively represent labor capital. Therefore, labor input in different regions is estimated by combining the data of the number of employees at the end of the year, the number of years of education of each academic degree, and the proportion of each academic degree in each year. In the study on different countries and regions, some scholars have used “the number of economically active population” to express labor input, and some scholars have directly adopted the “total number of laborers at the end of the year” to measure labor input in various countries. In the current study, the number of employees (total number of laborers minus the number of unemployed people) was selected as labor input of each province.

(3) Energy consumption (*E*). Energy input in the study on energy efficiency includes coal, natural gas, oil, nuclear energy, electricity, and other energy sources. For different purposes, different scholars have also selected the consumption of different energy sources to represent the energy consumption indicator when measuring energy efficiency. Some scholars have selected the consumption of coal, petroleum, and natural gas as energy input, while others have taken total energy consumption as energy input. Considering that different energy consumption structures exist in different provinces and various energy sources are included, energy input cannot be considerably measured using the consumption of a single energy source. The current study selected the energy consumption of each province per year as energy input of the model, and data were acquired from the China Energy Statistical Yearbook.

3.3.2 Output indicators

(1) GDP. GDP was chosen as the expected output of the model based on the integrity and availability of data. As an important comprehensive statistical indicator in the accounting system, GDP can reflect the economic volume and market scale of one country (or region) and also characterize the result of production and operation activities in one country (or region). Data were derived from the China Statistical Yearbook.

(2) Carbon emissions (C). Most scholars have chosen carbon dioxide emission as the unexpected output indicator of the model. SO_2 and NO_2 emissions have also been selected by some scholars. Given the difficulty in data acquisition in each province, only carbon emission was chosen as the unexpected output of the model.

4. Results Analysis and Discussion

4.1 Descriptive statistics of indicators

Labor input is expressed by the average number of employees in each province (district and city), derived from the China Statistical Yearbook and the statistical yearbooks of each province (district and city). Energy input is expressed by the total energy consumption (ten thousand tons of standard coal) of provinces (district and city), and data come from the China Energy Statistical Yearbook from 2014 to 2023 and statistical yearbooks of provinces (district and city). Descriptive statistics of the input and output indicators are shown in Table 1.

Table 1. Descriptive statistics of the input and output indicators

Names	Samples	Minimum values	Maximum values	Mean	Standard deviations	Median
Capital stock	310	1427.89	18533.08	7118.204	3726.441	6460.195
Labor	310	40.8	2110.9	530.88	401.855	440.45
Energy consumption	310	182.8	51331.61	14965.772	12383.705	11776.96
GDP	310	2080.2	135673.2	37457.159	30343.977	29326.95
CO_2	310	8752	64247	36400.472	15125.496	42065.8

4.2 Analysis of the TFEE measurement results

4.2.1 TFEE measurement

The TFEE values (Table 2) of some provinces (cities and districts) in China were calculated using the SBM-Undesirable model and Formula (1).

Table 2. TFEE of some provinces (districts and cities) in China

Provinces	2023	2022	2021	2020	2019	2018	2017	2016	2015	2014
Beijing	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Tianjin	0.8120	1.0000	0.7300	0.7754	0.7084	0.7014	0.6571	0.6465	0.6574	0.6766
Hebei	0.4804	0.4676	0.4694	0.4996	0.5086	0.5149	0.5563	0.5274	0.5327	0.5711
Shanxi	0.4098	0.4293	0.4048	0.3952	0.3921	0.4111	0.4102	0.4038	0.4085	0.4528
Inner Mongolia	1.0000	1.0000	0.5867	0.5410	1.0000	0.5898	1.0000	1.0000	1.0000	1.0000
Liaoning	0.4786	0.4604	0.4420	0.4746	0.4911	0.4891	0.4897	0.4993	0.5175	0.4860
Jilin	0.4540	0.4573	0.4610	0.4999	0.4768	0.4640	0.4570	0.4572	0.4981	0.5057
Heilongjiang	0.3701	0.3678	0.3469	0.3697	0.3725	0.3624	0.3662	0.3862	0.4077	0.4484
Shanghai	0.8158	0.7684	0.7707	0.8073	0.8175	1.0000	1.0000	1.0000	1.0000	1.0000
Jiangsu	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Zhejiang	0.8674	0.8310	0.8475	0.8708	0.9073	0.9880	0.9616	0.9624	0.9265	1.0000
Anhui	0.6476	0.6274	0.7006	0.7903	0.7729	0.7223	0.7482	0.7534	1.0000	1.0000
Fujian	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Jiangxi	0.6793	0.6729	0.6437	0.7450	0.6840	0.7193	0.6643	0.6892	0.6981	0.7142
Shandong	0.6512	0.6684	0.6917	0.6503	0.7070	0.6818	0.6968	0.6986	0.7709	0.7510
Henan	0.6309	0.6102	0.6991	0.7322	1.0000	0.7752	0.6562	0.6377	0.7346	0.6590
Hubei	0.7293	0.7372	0.7293	0.7417	0.8182	1.0000	0.7352	0.6597	0.6677	0.7234
Hunan	0.7003	0.6881	0.6571	0.6906	0.7435	1.0000	1.0000	1.0000	1.0000	1.0000
Guangdong	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Guangxi	0.5465	0.5648	0.5388	0.5551	0.6085	0.5996	0.5888	0.5976	0.6084	0.6111
Hainan	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Chongqing	0.8057	0.7686	0.7149	0.7391	0.7193	0.7138	0.7309	0.6969	0.6648	0.6433
Sichuan	1.0000	1.0000	1.0000	1.0000	1.0000	0.8374	0.8144	0.7498	0.7643	0.7639
Guizhou	0.4241	0.4300	0.4063	0.4535	0.4492	0.4599	0.4372	0.4324	0.4424	0.4217
Yunnan	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Tibet	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Shaanxi	0.4696	0.4942	0.4724	0.4873	0.5051	0.5053	0.4940	0.5130	0.5322	0.5639
Gansu	0.4084	0.3950	0.3741	0.4030	0.4006	0.3975	0.4021	0.4138	0.4263	0.4476
Qinghai	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.8024	1.0000
Ningxia	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Xinjiang	0.4965	0.4474	1.0000	1.0000	1.0000	0.5576	0.4559	0.6978	0.5595	1.0000
Mean	0.7380	0.7383	0.7318	0.7491	0.7769	0.7578	0.7523	0.7556	0.7619	0.7884

The mean value of provincial TFEE in China has reached a high level, as shown in Figure 1. In general, the aforementioned value initially declined and increased, and declined and increased again thereafter. Since 2014, TFEE steadily decreased and reached bottom in 2017. Subsequently, TFEE increased steadily and peaked in 2019. That is, no significant effect was achieved in the improvement of provincial TFEE in China. Owing to resource endowments, the proportion of fossil energy consumption in most provinces (districts and cities) remained high, resulting in a partially substantial total energy consumption. Therefore, accelerating the construction of a reasonable and advanced industrial structure, energetically developing clean energy, optimizing the energy consumption structure, transforming the energy consumption mode, increasing the innovation input, and developing and promoting technologies and production processes to improve the TFEE are not only the important means of realizing the “carbon peak and carbon neutrality” goals; these aspects are also among the important paths to boost high-quality economic development. From the angle of single provinces, provinces with TFEE reaching 1 for a long term include Beijing, Inner Mongolia, Jiangsu, and Fujian. This finding indicates that these provinces are located at the production frontier for a long time, with optimal input–output efficiency.

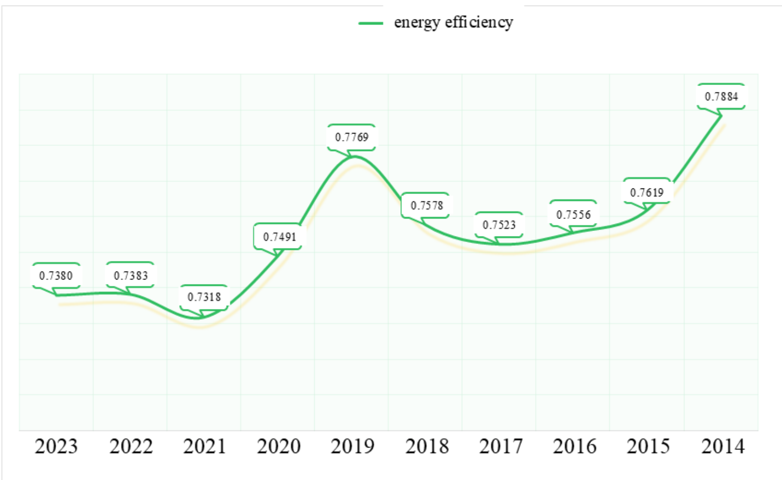

Fig.1. Mean value of the provincial TFEE in China

4.2.2 TFEE convergence analysis

(1) σ convergence. By calculating CV and forecasting the trend, the σ convergence result of TFEE is shown in Figure 2. The σ convergence test results of agricultural carbon emission efficiency in the western region show that the standard deviation of TFEE in some provinces and cities in China was on a downward trend from 2014 to 2023, indicating that the absolute gap in some provinces and cities

in China was decreasing. However, this narrowing trend does not necessarily mean that the energy carbon emission decreased definitely. Two reasons are noted for the narrowing of the gap: (1) high-TFEE areas are drawing close to low-efficiency areas and (2) low-efficiency areas are catching up with high-efficiency areas. To explore the real reasons for the narrowing gap, β absolute convergence should be conducted to determine whether or not the "catch-up effect" exists among China's provinces (i.e., whether or not low-efficiency areas are catching up with high-efficiency areas).

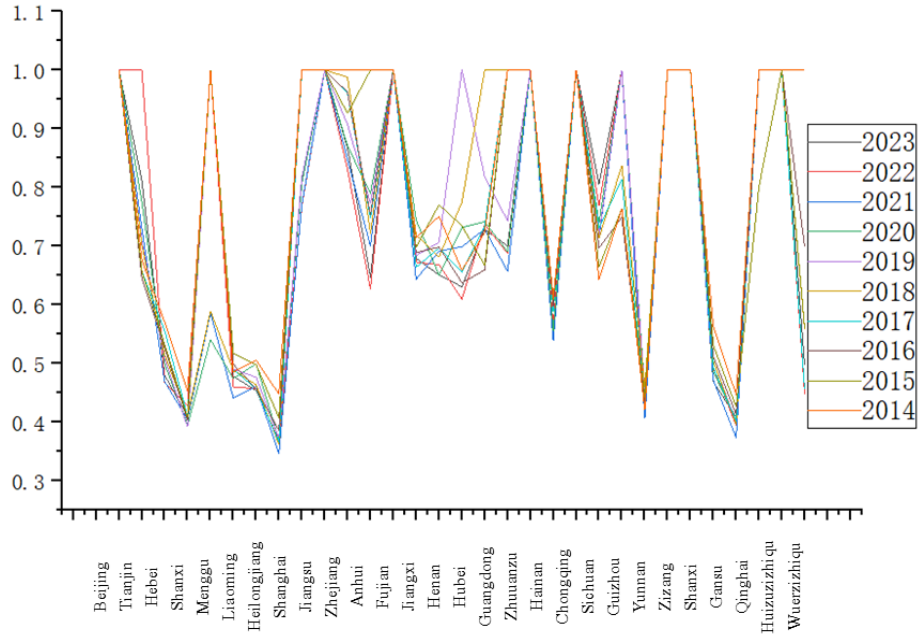

Fig.2. σ convergence results of TFEE

(2) β absolute convergence. To explore whether or not the provincial TFEE in China is inclined to their respective steady-state levels, and whether the capital, labor, and energy consumption have a positive promoting effect or negative inhibitory effect on TFEE, the β conditional convergence is needed. The β conditional convergence results were measured using the fixed and random effect (FE and RE, respectively) models; the advantages and disadvantages of the two models were tested based on the Hausman model. In this study, the consumption of capital stock, labor, and energy was taken as explanatory variable and carbon dioxide emission as the explained variable to establish the panel model. The panel model involves three models: hybrid POOL, FE, and RE models. First, the model test was performed to determine the optimal model. Table X shows that the F-test indicated a significance level of 5%, F (30,274) =190.806, p = 0.000 < 0.05. That is, the FE model outperforms the POOL model. The BP test presented a significance level of 5%, chi (1) = 1195.583, p = 0.000 < 0.05. Hence, the FE model is superior to the POOL model. The Hausman test did not show any significance, chi (2) = 0.830, p = 0.660 > 0.05. That is, the RE model outperforms the FE model. In summary, the result of RE model was taken as the final result. Table 3 shows that the β conditional convergence existed, indicating that the provincial TFEE in China was stabilized at the steady-state level with the passage of time.

Table 3. Β absolute convergence test results

Items	POOL model	FE model	RE model
Intercept	24399.532** (16.267)	24721.037** (9.576)	23266.859** (7.833)
Capital stock	1.277** (3.122)	1.739** (13.528)	1.788** (14.746)
Labor	11.635** (3.588)	−1.002 (−0.270)	1.519 (0.512)
Energy consumption	−0.370** (−5.578)	−0.087 (−1.212)	−0.114 (−1.660)
R^2	0.33	0.244	0.275
R^2 (within)	0.321	0.442	0.441
Sample size	308	308	308
Test	F (3,304) = 50.011, p=0.000	F (3,274) = 72.312, p=0.000	χ^2(3)=225.907, p=0.000

Note: Dependent variable = CO_2

*p < 0.05 and **p < 0.01 enclosed in parentheses are the t values.

5 Conclusions

5.1 Main findings

This study used theory of production economics as basis to establish a reasonable input–output indicator system, measured TFEE of some provinces (districts and cities) in China in 2014–2024 using the SBM-Undesirable model, and analyzed the energy saving potential of each province (district and city). The following conclusions are drawn. During the period, the overall TFEE in China was low, initially increasing and thereafter declining and tending to be stable. From the three major regions, TFEE in the eastern region was evidently higher than that in the central and western regions, and that in the western region was higher than that in the central region. From the perspective of provinces (districts and cities), TFEE of most provinces (districts and cities) was relatively low, presenting a distribution characteristic of high in the east and low in the west, resembling the economic development feature. From the variation characteristics of TFEE, regional heterogeneity was manifested. During the period, most provinces (districts and cities) showed significant energy saving potential study.

5.2 Policy implications

On the bases of the preceding study results and to effectively realize energy saving goals, the following suggestions are presented

(1) Strengthen regional cooperation and improve TFEE from the overall situation: Attention should be given to the spatial interaction of TFEE in the low-carbon development process. First, exchanges and cooperation between regions must be strengthened, especially exchanging carbon emission reduction policies, carbon emission reduction behavior, and technological innovation and carrying out energy-saving and low-carbon activities suitable for local areas. Second, importance should be attached to the time-dependent characteristics of TFEE in China. To implement low-carbon activities, emphasis should be on its long-term impact, and the government should consider the current and future political achievements, implement low-carbon development policies promulgated by higher authorities, and increase the emission reduction behaviors according to local conditions. Capital flow of financial institutions and the technological reform of enterprises should try to avoid carbon behavior that only focuses on current interests without considering long-term development. On the premise of ensuring enterprises' normal operation, they should concentrate on the current environmental ecology and resource protection for the long-term development of the economy and society.

(2) Formulate differentiated energy-saving policies and environmental regulation policies: TFEE and energy-saving potential of provinces (districts and cities) are relatively different. Energy and environmental policies should be formulated based on the national framework, the resource endowment and actual development of provinces (districts and cities), and the spirit of the Comprehensive Work Plan for Energy Conservation and Emission Reduction in the 14th Five-Year Plan. In addition, differentiated energy "double control" goals and energy conservation and environmental protection policies should be introduced, implementing policies according to local conditions and specific urban conditions. Meanwhile, importance should be attached to the collaborative effect between different policies, thereby strengthening mutual learning between different provinces (districts and cities), promoting the collaborative development between different regions, and realizing the energy conservation and emission reduction goals of each region.

(3) Promote technological progress in the energy industry and accelerate the development of energy: Relevant departments in China should increase investments in capital, manpower, and material resources; accelerate the technological study and development process of cleaner production in the country; improve the technical level of production; reduce production costs; and promote production efficiency. Lastly, while improving the level of cleaner production technology, attention should also be given to the development and utilization of energy, acceleration of the development of solar energy, tidal energy, nuclear energy, wind energy, and other energy sources; and reduction of dependence on traditional energy sources in the pursuit of economic development.

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