Revisiting China's provincial energy efficiency and its influencing factors

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ABSTRACT

Improving the energy efficiency is a fundamental way to ensure energy security and sustainable development, and is also the requirement of supply-side structural reform of China's energy. This paper uses the DEA-BCC model to estimate China's energy efficiency at the provincial level, analyzes its regional differences from 2006 to 2016, and applies a panel data model to analyze the influencing factors of energy efficiency. It selects labor, capital stock and total energy consumption as inputs and takes real GDP and comprehensive index of environmental pollution as desirable and undesirable outputs, respectively. The results show that (1) energy efficiency when undesirable output is included is generally lower than when undesirable output is excluded; (2) There is a considerable difference in energy efficiency among provinces, and China's energy efficiency, by and large, shows a trend of declining. The energy efficiency of four major regions demonstrates obvious regional differences: coastal region>northeastern region> middle region >western region; (3) The economic development level, technological progress, energy price and urbanization level are positively associated with energy efficiency, while the proportion of secondary industry and the energy consumption structure dominated by coal and oil are negatively correlated with energy efficiency.

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1. Introduction

In recent years, the improvement of energy efficiency has been the focus of sustainable development of economy and society in all countries. With the rapid development of global economy and the continuous acceleration of industrialization of all countries, the global energy consumption and the emissions of various pollutants are increasing. The low energy efficiency not only wastes limited energy, but also causes serious environmental pollution. Therefore, the issue of energy efficiency has attracted more and more attention from academia that can put forward modern, reliable and environment-friendly energy policy suggestions for different Economies and countries [1—11].

For China, the inefficient use of energy has become an important obstacle to its sustainable development. Over the past 40 years, with the rapid development of China's economy, the total amount of energy consumption and pollutant emission is increasing, and the contradiction among environment, energy and economic

growth becomes more prominent [12]. Gross domestic product (GDP) of China has increased from 364.52 billion RMB yuan in 1978—99086.5 billion RMB yuan in 2019 with approximately 9% of annual growth rate [13]. However, such great achievements in social and economic fields are primarily prompted by energy-intensive industries and infrastructure construction, which have also led to large amount of energy consumption and serious environmental pollution. According to BP Statistical Review of World Energy of 2020, China's energy consumption in 2019 reached 3417 Mtoe that was 24.3% of the world's total, and it has been the country with largest increase in energy consumption for 20 consecutive years. As China is in a stage of high-speed industrialization and urbanization, the proportion of high energy-using industries is still large, energy technology and management level relatively fall behind, and energy efficiency is low compared with developed countries [14]. The total energy consumption per $100 million of GDP is about 28000 toe, about twice that of the United States and three times that of Japan, and it is also behind developing countries such as India, Mexico and Brazil. Energy consumption mode dominated by fossil energy has brought serious environmental pollution problems to China. Now wastewater pollution, sulfur dioxide pollution, fine particle pollution and

carbon dioxide emission of China rank first in the world [15]. At present, China's economy has changed from a high-speed growth stage to a high-quality development one. For sustainable development of economy and implementation of international commitments under the Paris Agreement, Chinese government takes energy efficiency seriously and has put forward a series of development goals in terms of energy consumption and emission reduction. By 2030, energy consumption will be controlled below 6 billion tons of standard coal, that per unit GDP will reach the world average level, and carbon emissions per unit GDP will be reduced by 60%−65% compared to 2005 levels [16]. Theses energy-saving targets were allocated among the provinces and included in the performance evaluation system for local bureaucrats. Therefore, improving energy efficiency has become one of the key means for China to achieve the win-win goal of both economic growth and, at the same time, energy conservation and emissions reduction. But there are great differences in the economic development level, technological level, industrial structure, urbanization level, energy consumption structure and resource endowment of China's provinces, which may lead to differences in energy efficiency [17]. As the world's largest energy consumption country, it is necessary to analyze the differences in energy efficiency of China's provinces and its influencing factors, which has great significance for improving China's overall energy efficiency.

The rest of this paper is organized as follows: Section 2 provides a brief literature review, Section 3 introduces the methods, Section 4 presents the data and discusses the results, and Section 5 provides the conclusion and makes some suggestions.

2. Literature review

As the increasing concern on global energy conservation and emission reduction, more and more scholars are devoted to study the issue of energy efficiency, the improvement of which is considered to be the key to sustainable development of economy and society. At present, the research directions mainly focus on measurement methods of energy efficiency, selection of input-output indicators, regional differences in energy efficiency, and factors affecting energy efficiency four aspects.

Energy efficiency measurements are divided into single factor energy efficiency and total factor energy efficiency (TFEE). Single factor energy efficiency measures the relationship between energy inputs and effective outputs. The most common used indexes are the GDP energy consumption index and energy intensity [18−20]. The calculation of single factor energy efficiency is simple, which only considers energy input and ignores the effects of mutual substitution between different production factors and structural changes in the production process on energy efficiency. It cannot fully reflect real energy efficiency. Therefore, the concept of TFEE was proposed by Hu and Wang [21], which caused broad attention. The measurements of TFEE have two main methods: parametric (e.g., stochastic frontier approach, SFA) and nonparametric (e.g., data envelopment analysis, DEA). Sineviciene et al. [22]applied the SFA to an energy efficiency assessment and cause analysis of the 11 countries in Eastern Europe. Sun et al. [23] used the SFA to examine the energy efficiency performance of a sample of 71 developed and developing countries between 1990 and 2014 and evaluate the effects of both governmental institutions and green technologies on energy efficiency. Zhou et al. [24], Ouyang et al. [25], Li et al. [26] and Shao et al. [27] calculated the provincial energy efficiency in China by the SFA model. In addition, many other scholars have also applied the SFA method to analyze the energy efficiency of different industries, such as steel [28] and transportation [29]. SFA method is sensitive to the choice of function form, and the functional form is uncertain. It is usually used to study situations of multiple inputs

and single output. Compared with the SFA method, the DEA method is particularly suitable for the analysis of input-output efficiency in the case of multiple inputs and outputs. A unified unit between the indicators is not required to ensure the integrity of the information contained in the original data, and thus this method is widely used to measure energy efficiency. Jebali et al. [5] and Borozan [3] applied two-stage DEA approach to calculate the energy efficiency of Mediterranean countries and European regions. Ervural et al. [30] used traditional CCR-DEA model to analyze the energy efficiency of Turkey. Ouyang and Yang [8] analyzed the network energy and environment efficiency of 27 OECD countries by a multiplicative network DEA model. As for studies about China's energy efficiency, many different DEA models were adopted, such as game cross-efficiency DEA [17], meta-frontier super-SBM [31], three-stage data envelopment [13], etc.

When choosing input-output indicators, most scholars chose energy, labor, capital as input and GDP as desirable output. As the development of economy, people began to realize the importance of ecological environment to economic growth and social development, and bring the environmental factors into the calculation of TFEE and regard the pollutant emission as undesirable output. Most researchers applied single pollutant to express the undesirable output. For example, Apergis et al. [32], Lin and Du [33], Wang et al. [34], Wang et al. [35], Wang et al. [36], Vaninsky [37], Yu et al. [31] and Zhu et al. [14] chose CO_2 as undesirable output, while Hang et al. [38], Wang et al. [39], Wang et al. [40] and Zhao et al. [13] used SO_2 as undesirable output. Choosing single pollutant to express the undesirable output cannot thoroughly reflect the level of pollutant emissions. Therefore, recently a few researchers used CO_2, SO_2 and industrial waste gas as the undesirable output index [41,42]. Although these studies consider different indicators of undesirable output, they all emphasize that undesirable output is an important factor in determining the energy efficiency.

As for research on regional difference of energy efficiency, its research object is mainly from three aspects. The first one is Economies, mainly including European regions [3], Mediterranean countries [5], OPEC [6] and OECD countries [8]. The second is countries, involving the United States [4], Switzerland [4,43], New Zealand [11], Spain [9], Korea [7] and Finland [10]. The third one is industries, such as iron and steel industry [44], heavy and light industries [45], food and beverage sector [46]. In light of research on China's regional energy efficiency, it is mainly at the national and provincial level. Zhu et al. [14] quantitatively analyzed energy efficiency of 30 provinces in China from 2005 to 2016, and concluded that China's provincial energy efficiency is olive shaped, with obvious spatial imbalance. Yu et al. [31] found that energy efficiency of the East was the highest and that of the Middle and the West rapidly increased by estimating energy efficiency of the East, the Middle, the West, the Northeast and each province, and many regions showed the strong decoupling between energy consumption and economic growth. At the provincial level, Wu et al. [47] carried out the spatial evolution of energy efficiency in Anhui province, and noticed that the energy efficiency of cities in Anhui province showed significant spatial heterogeneity. Peng et al. [48] calculated the energy eco-efficiency of 13 prefecture-level cities in Jiangsu province from 2008 to 2017 and indicated that Nanjing was a key city to improve energy eco-efficiency. In addition, some scholars have specially evaluated energy efficiency at the industry level in China. Qi et al. [42] analyzed energy efficiency of China's 14 coal intensive industries. Feng and Wang [49] and Huo et al. [50] studied energy efficiency of China's construction industry. Zhao and Lin [51] measured the traditional energy efficiency of China's textile industry.

The research on factors affecting energy efficiency mainly focus on technical progress [52−54], industrial structure [55,56], energy

price [57,58], economic level [59], industrial agglomeration [60,61], degree of openness [62−64], urbanization level [26,65], human capital [3], policy mechanism [66] and so on. Wang et al. [67] thought that industrial structure, market factors, opening-up, energy price, energy structure, and environmental regulation exerted certain influences on energy efficiency, and industrial structure and market factors had a positive impact on energy efficiency while open-up had a negative impact on that of local and neighboring areas. Yu et al. [31] chose state intervention, urban structure, industrial structure, energy structure, market openness and environmental protection several factors and concluded that both state intervention and market openness had negative impacts on energy efficiency in different study periods. Rongdi et al. [68] studied the Yangtze River Delta city group and showed that there was a positive correlation between industrial structure, investment, scale, foreign trade and energy efficiency and government influence and system is negatively related to energy efficiency. According to the existing research, it is demonstrated that it is difficult to form a unified improvement path towards energy efficiency in the selection of energy efficiency factors.

The main information and findings of studies showed that most used TFEE to measure energy efficiency and chose labor, capital and energy as input indicators. But the selections of output were different, some only choosing GDP to be desirable output while some bringing environmental factors as undesirable output. Although there were many studies about combining environmental factors and TFEE, most scholars only considered the impacts of single or partial pollutant and chose CO_2 or SO_2 as undesirable output. It is rare to consider wastewater, SO_2, ammonia nitrogen and solid waste altogether as undesirable output in the calculation of TFEE. China is an energy consumption country dominated by fossil energy, which discharges a lot of pollutants. Therefore, introducing the above four pollutants into the energy efficiency measurement can make it more comprehensive, scientific and reasonable. Based on the above, this paper raises two major questions: How much are the differences in energy efficiency among China's provinces? What are the factors that influence the differences in energy efficiency and how do these factors affect?

The contributions of this study are as follows: (i) wastewater, SO_2, ammonia nitrogen and solid waste four pollutants are measured by the entropy method to get the comprehensive index of environmental pollution expressing the undesirable output, which overcomes the shortage of single pollutant expressing the undesirable output.(ii) According to the characteristics of regional economic development, 30 provinces and cities of China(except Hong Kong, Macao, Taiwan and Tibet) are divided into the west, the middle, the northeast and the coastal four regions. The classic DEA-BCC model is applied to calculate the energy efficiency of China's 30 provinces and cities in 2006−2016 with and without considering the undesirable output, and the differences of each China's provincial energy efficiency are analyzed and compared. (iii) The influencing factors of regional differences in energy efficiency of China's provinces are analyzed by the panel data model and some policy suggestions are put forward.

3. Methods

3.1. DEA-BCC model

DEA was firstly proposed by Charnes in 1978 [69]. It is a nonparametric method using linear programming model to evaluate the efficiency of decision-making units (DMUs). Here, this paper uses the DEA-BCC model [70] to calculate China's provincial energy efficiency. Compared with other models in DEA, such as SBM model and super-SBM model, BCC model is convenient and

feasible. Its basic principle is as follows.

Suppose that there are n decision-making units (DMU), and every decision-making unit has m input variables and s output variables. The input matrix and output matrix are $x_j = (x_{1j}, x_{2j}, \cdots, x_{mj})^T$ and $y_j = (y_{1j}, y_{2j}, \cdots, y_{sj})^T$, respectively, and the corresponding weight matrices are $v = (v_1, v_2, \cdots, v_m)^T$ and $u = (u_1, u_2, \cdots, u_s)^T$, respectively. The evaluation index of every unit can be obtained by equation (1):

$$\eta_j = \frac{u^T y_j}{v^T x_j} = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}}, j = 1, 2, \cdots, n \qquad (1)$$

where x_{ij} indicates the input amount of the jth decision-making unit to the ith input, $x_{ij} > 0$; y_{rj} indicates the output amount of the jth decision-making unit to the rth output, $y_{rj} > 0$; v_i demonstrates the weight of the ith input, and u_r means the weight of the rth output.

The BCC model is shown in equation (2), which indicates that under the condition of variable returns to scale (VRS), technical efficiency (TE) can be divided into pure technical efficiency (PTE) and scale efficiency (SE). The mathematical relationship indicates as follows:

technical efficiency (TE) = pure technical efficiency (PTE) × scale efficiency (SE)

$$(BC^2) \begin{cases} \min \theta \\ s.t. \sum_{j=1}^{n} \lambda_j x_j + s_i^- = \theta x_0, i = 1, 2, \cdots, m \\ \quad \sum_{j=1}^{n} \lambda_j y_j - s_r^+ = y_0, r = 1, 2, \cdots, s \\ \quad \sum_{j=1}^{n} \lambda_j = 1, \lambda_j \geq 0 \\ \quad s_i^- \geq 0 \\ \quad s_r^+ \geq 0 \end{cases} \qquad (2)$$

where the maximum of $\theta(\theta \leq 1)$ is the technical efficiency value of decision-making unit j_0; λ_j is the combinatorial proportion of the jth decision-making unit in the reconstituted effective decision-making unit combination; and s_i^-, s_r^+ are the slack variables of m input variables and s output variables, respectively.

The meanings of the model are as follows: (1) If $\theta = 1$ and $s_i^- = 0, s_r^+ = 0$, which means that this decision-making unit is effective, its scale efficiency and technical efficiency are effective, and the efficiency frontier is a constant return to scale; (2) If $\theta < 1$ and $s_i^- \neq 0, s_r^+ \neq 0$, which means that this decision-making unit is ineffective, perhaps as a result of the inefficiency of technical efficiency or scale efficiency or their combination; (3) If the decision-making unit is ineffective, its input and output can be adjusted and improved based on the target value until the decision-making unit mostly or completely effective.

3.2. Panel data model

Panel data are a type of two-dimensional structural data that have double properties of time series data and cross-sectional data. They may be used to study not only the differences between individuals but also changing trends for individuals over time. Because of the endogenous property of the model, the specific model should be chosen based on the assumptions of individual characteristics to determine whether the panel data model is a

fixed-effect model or a random-effect model. Its general form is shown in equation (3):

$$y_{it} = \sum_{k=1}^{k} \beta_{ki} x_{kit} + u_{it} \tag{3}$$

where i indicates the number of individuals studied in the cross section, $i = 1, 2, ..., N$; t means the known t times, t = 1, 2, ..., T; y_{it} demonstrates the observational value of the explained variable unit individual i at t time; x_{kit} indicates the observation value of the kth explanatory variable to unit individual i at t time; β_{ki} is the parameter to be estimated; and u_{it} is the random error term. Its matrix form is shown in equation (4):

$$Y_i = X_i \beta_i + U_i (i = 1, 2, \cdots, N) \tag{4}$$

in which

$$Y_i = \begin{bmatrix} y_{i1} \\ y_{i2} \\ y_{i3} \\ \vdots \\ y_{iT} \end{bmatrix}_{T \times 1} \quad X_i = \begin{bmatrix} x_{1i1} & x_{2i1} & \cdots & x_{ki1} \\ x_{1i2} & x_{2i2} & \cdots & x_{ki2} \\ x_{1i3} & x_{1i3} & \cdots & x_{ki3} \\ \vdots & \vdots & \ddots & \vdots \\ x_{1iT} & x_{2iT} & \cdots & x_{kiT} \end{bmatrix}_{T \times K} \quad \beta_i = \begin{bmatrix} \beta_{1i} \\ \beta_{2i} \\ \beta_{3i} \\ \vdots \\ \beta_{Ki} \end{bmatrix}_{K \times 1} \quad U_i = \begin{bmatrix} u_{i1} \\ u_{i2} \\ u_{i3} \\ \vdots \\ u_{iT} \end{bmatrix}_{T \times 1}$$

4. Empirical results and discussion

4.1. Measurement and regional differences analysis of energy efficiency

4.1.1. Indicators selection and display of data

According to the requirements of capital, labor, technology and environment for energy utilization in Chinese provinces, a TFEE index system is established following the principles of scientificity, maneuverability and completeness, including input indicators and output indicators, as shown in Table 1.

- Labor input. It is expressed as the human capital stock of labor quality in each province. The calculation is shown in equation (5):

$$P_{i,t} = (Coll_{i,t} \times 16 + Seni_{i,t} \times 12 + Juni_{i,t} \times 9 + Prim_{i,t} \times 6) / all_{i,t}, L_{i,t} = P_{i,t-1} \times S_{i,t-1} \tag{5}$$

where $P_{i,t}$ and $all_{i,t}$ indicate the education level aged 6 and over and total population of the ith province in the tth year, respectively; $Prim_{i,t}$, $Juni_{i,t}$, $Seni_{i,t}$, $Coll_{i,t}$ are the number of graduates from primary school, junior middle school, high school, junior college and

Table 1
Energy efficiency measurement indicators.

Types of indicators	Names of indicators
Inputs	Labor input
	Capital stock
	Energy input
Outputs	Desirable output
	Undesirable output

above of the ith province in the tth year, respectively; and $L_{i,t}$ and $S_{i,t}$ demonstrate the human capital stock of the ith province in the tth year and the total labor force of the ith province at the end of the tth year, respectively.

- Capital stock. It is measured as the fixed capital stock. Investment in fixed assets of various provinces and municipalities in China over the years is obtained from the China Statistical Yearbook. The perpetual inventory method is used to calculate the capital stock, as shown in equation (6):

$$K_{i,t} = K_{i,t-1} \times (1 - D_{i,t}) + I_{i,t} \tag{6}$$

where $K_{i,t}$, $D_{i,t}$ and $I_{i,t}$ are the capital stock, the depreciation ratio of fixed assets and investment quota of the ith province in the tth year, respectively, and $K_{i,t-1}$ is the stock of fixed capital of the ith province in the t-1st year. The nominal total fixed capital formation and

fixed asset investment price index are both obtained from the China Statistical Yearbook and the provinces' statistical yearbooks. The depreciation rate δ of fixed assets sets 10.96%. The base year is 2006, so the initial investment is the fixed stock of capital of 2006. The calculation of the initial capital stock is shown in equation (7):

$$K_{i,2006} = \frac{I_{i,2006}}{(g_{i,2006-2011} + \delta)}, g_{i,2006-2011}$$
$$= \left(\frac{\text{real fixed capital in 2011}}{\text{real fixed capital in 2006}}\right)^{0.2} - 1 \tag{7}$$

in which $K_{i,2006}$, $I_{i,2006}$ and $g_{i,2006-2011}$, respectively, indicate the capital stock, fixed investment and growth rate per annum of fixed capital of the ith province in the base year of 2006.

- Energy input. The energy consumption of coal, petroleum and natural gas in the production and daily life of provinces and municipalities in China is converted into total energy consumption indicated by standard coal (tons standard coal). Relevant data come from the Chinese Energy Statistics Yearbook and provincial statistical yearbooks.
- Desirable output. It is expressed as the real GDP of provinces (hundred million yuan). To eliminate the effect of inflation, we take 2006 as the base year and convert the nominal GDP to real GDP to ensure data comparability. The provincial nominal GDP and GDP deflator are from the China Statistical Yearbook.
- Undesirable output. It can be expressed by a comprehensive index of environmental pollution. In this paper, indexes for four pollutants (waste water discharge, SO_2 discharge, ammonia nitrogen emission and solid waste emission) are standardized, and the index weight entropy method is used to calculate the comprehensive index of environmental pollution. The specific process of the entropy method is divided into six steps:

Step 1. Preprocess the original data for standardization

$$x'_{ij} = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}} (i = 1, 2, \cdots, n; j = 1, 2, \cdots, m) \qquad (8)$$

in which x_{ij} is the jth pollutant index of a province in the ith year.

Step 2. Determine the weight of the jth pollutant index of a province in the ith year

$$y_{ij} = \frac{x'_{ij}}{\sum_{i=1}^{n} x'_{ij}} (i = 1, 2, \cdots, n; j = 1, 2, \cdots, m) \qquad (9)$$

Step 3. Ensure the entropy value of the jth pollutant index

$$e_j = -\frac{1}{\ln m} \sum_{j=1}^{m} y_{ij} \ln y_{ij} (j = 1, 2, \cdots, m) \qquad (10)$$

Step 4. Calculate the index coefficient of variation, where a smaller difference indicates a smaller influence of the index on the evaluation results

$$p_j = 1 - e_j (j = 1, 2, \cdots, m) \qquad (11)$$

Step 5. Calculate the weight of the jth pollutant index

$$w_j = \frac{p_j}{\sum_{j=1}^{m} p_j} (j = 1, 2, \cdots, m) \qquad (12)$$

Step 6. Measure the environmental pollution index of the ith year

$$c_j = \sum_{j=1}^{m} w_j x_{ij} (i = 1, 2, \cdots, n; j = 1, 2, \cdots, m) \qquad (13)$$

The comprehensive index of provinces' environmental pollution from 2006 to 2016 can be calculated using the above equations. Lower values indicate higher energy efficiency.

4.1.2. Comparative analysis of energy efficiency measurement

With and without considering undesirable output, the input production model in VRS DEAP2.0 software is used to measure and analyze the energy efficiency of 30 provinces and municipalities from 2006 to 2016. The average values are shown in Table 2.

Table 2 shows that there are significant differences in the predicted results with and without the consideration of undesirable output. There are 18 provinces in which energy efficiency when undesirable output is considered is lower than when it is not considered, and there are 12 provinces in which energy efficiency is the same under the two measurements. This result may indicate that, energy efficiency when undesirable output is considered is generally lower than when undesirable output is not considered. The measurement results for Beijing, Tianjin, Heilongjiang, Shanghai, Guangdong and Guangxi under the two conditions are 1, which means that TE, PTE and SE all implement DEA effectively. The three efficiency values of Shanxi, Inner Mongolia, Shaanxi and Ningxia without considering undesirable output are 1, whereas they are less than 1 when considering undesirable output, which is ineffective. When estimating energy efficiency, considering only desirable output while ignoring undesirable output in the production process will overestimate the actual energy efficiency. To ensure accuracy, the energy efficiency when considering undesirable output should be analyzed.

Considering undesirable output, the energy efficiency of 24 provinces is inefficient. The scale efficiency of Henan, Hainan, Qinghai and Ningxia is inefficient, and the pure technical efficiency

Table 2
Average values of energy efficiency measurement in various regions under different conditions from 2006 to 2016.

Evaluation unit-VRS	Without considering undesirable output				Considering undesirable output			
	TE	PTE	SE	Returns to scale	TE	PTE	SE	Returns to scale
Beijing	1.000	1.000	1.000	—	1.000	1.000	1.000	—
Tianjin	1.000	1.000	1.000	—	1.000	1.000	1.000	—
Hebei	0.760	0.822	0.925	drs	0.701	0.761	0.921	drs [a]
Shanxi	1.000	1.000	1.000	—	0.766	0.772	0.993	irs [b]
The Inner Mongolia Autonomous Region	1.000	1.000	1.000	—	0.649	0.650	0.998	irs
Liaoning	0.772	0.807	0.958	drs	0.685	0.721	0.950	drs
Jilin	0.885	0.896	0.987	irs	0.884	0.894	0.990	irs
Heilongjiang	1.000	1.000	1.000	—	1.000	1.000	1.000	—
Shanghai	1.000	1.000	1.000	—	1.000	1.000	1.000	—
Jiangsu	0.888	0.955	0.930	rs	0.854	0.854	1.000	—
Zhejiang	0.938	0.944	0.994	irs	0.895	0.895	1.000	—
Anhui	0.816	0.818	0.997	irs	0.816	0.818	0.997	irs
Fujian	0.932	0.942	0.989	irs	0.931	0.938	0.992	irs
Jiangxi	0.921	0.939	0.981	irs	0.758	0.777	0.976	irs
Shandong	0.736	1.000	0.736	drs	0.684	0.691	0.989	drs
Henan	0.890	1.000	0.890	drs	0.890	1.000	0.890	drs
Hubei	0.771	0.783	0.986	drs	0.771	0.783	0.986	drs
Hunan	0.878	0.940	0.935	drs	0.878	0.932	0.942	rs
Guangdong	1.000	1.000	1.000	—	1.000	1.000	1.000	—
Guangxi Autonomous Region	1.000	1.000	1.000	—	1.000	1.000	1.000	—
Hainan	0.940	1.000	0.940	irs	0.940	1.000	0.940	irs
Chongqing	0.850	0.876	0.970	irs	0.531	0.543	0.978	irs
Sichuan	0.752	0.797	0.943	drs	0.737	0.757	0.974	drs
Guizhou	0.782	0.785	0.996	irs	0.553	0.602	0.919	irs
Yunnan	0.789	0.807	0.977	irs	0.789	0.807	0.977	irs
Shaanxi	1.000	1.000	1.000	—	0.810	0.814	0.996	irs
Gansu	0.721	0.738	0.977	irs	0.603	0.659	0.915	irs
Qinghai	0.624	1.000	0.624	irs	0.512	1.000	0.512	irs
Ningxia Autonomous Region	1.000	1.000	1.000	—	0.508	1.000	0.508	irs
Xinjiang Autonomous Region	0.731	0.747	0.978	irs	0.639	0.711	0.898	irs
Mean value	0.879	0.920	0.957	drs	0.821	0.846	0.821	drs

[a] drs means that returns to scale decrease.
[b] irs means that returns to scale increase.

Table 3

Division of four major regions in China.

Regions	Provinces and municipalities	Numbers
West	Xinjiang, Qinghai, Gansu, Ningxia, Shaanxi, Guizhou, Sichuan, Chongqing, Yunnan, Guangxi, Shanxi	11
Middle	Henan, Anhui, Hunan, Hubei, Jiangxi, Inner Mongolia	6
Northeast	Heilongjiang, Jilin, Liaoning	3
Coastal areas	Beijing, Tianjin, Hebei, Shandong, Shanghai, Jiangsu, Zhejiang, Fujian, Guangdong, Hainan	10

is effective. For example, Hainan's scale efficiency is 0.940 and shows increasing returns to scale. The ratio of energy input to output is lower than the optimal production scale input-output ratio, and energy efficiency can be improved by expanding this scale. Under the same level of pure technical efficiency, in provinces with increasing returns to scale, as the value of comprehensive technical efficiency decreases, energy efficiency can be improved by increasing input factors to expand the scale. In contrast, in provinces with diminishing returns to scale, the ratio of input to output is far greater than that of the optimal production scale. Increasing inputs and increasing the scale will not improve energy efficiency.

4.1.3. Regional differences analysis of energy efficiency considering undesirable output

According to the traditional regional division, Chinese provinces and municipalities are divided into four regions: the west, the middle, the northeast and the coastal areas, as shown in Table 3.

Given the undesirable output using the BCC model, DEAP2.0 software is used to measure the regional energy efficiency from 2006 to 2016. The results are shown in Table 4, Table 5 and Fig. 1.

Table 4 demonstrates that from 2006 to 2016, energy efficiency of China's 30 provinces was quite different and the average energy efficiency showed a fluctuating downward trend. Specifically, the energy efficiency of Beijing and Shanghai were 1, achieving the

Table 5

China's regional TFEE from 2006 to 2016.

Year	West	Middle	Northeast	Coastal areas	Whole country
2006	0.731	0.767	0.886	0.973	0.839
2007	0.703	0.723	0.826	0.936	0.797
2008	0.642	0.692	0.845	0.893	0.768
2009	0.645	0.678	0.838	0.855	0.754
2010	0.619	0.675	0.811	0.857	0.741
2011	0.623	0.684	0.795	0.901	0.751
2012	0.600	0.654	0.792	0.873	0.730
2013	0.601	0.650	0.789	0.882	0.731
2014	0.632	0.635	0.767	0.841	0.719
2015	0.558	0.621	0.770	0.840	0.697
2016	0.551	0.632	0.766	0.839	0.697
Average	0.628	0.674	0.808	0.881	0.748

optimal energy efficiency and leading positions. This is because that as the most important cities in China, Beijing and Shanghai have advanced environmental management concepts and technological level and can allocate resources efficiently to maintain energy-efficient utilization in the long term. Being in the second echelon, the average energy efficiency of Guangdong, Hunan, Zhejiang, Jiangsu, Hainan, Anhui, Fujian, Jiangxi, Heilongjiang and Hubei from 2006 to 2016 were all over 0.8. These provinces are the regions with high level of economic development and emphasizing

Table 4

Provincial energy efficiency considering undesirable output.

| Province	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Average
Beijing	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Tianjin	1.000	1.000	0.930	0.899	0.820	0.720	0.630	0.559	0.503	0.482	0.443	0.726
Hebei	0.701	0.726	0.773	0.794	0.776	0.796	0.816	0.803	0.748	0.703	0.436	0.734
Shanxi	0.766	0.763	0.764	0.822	0.788	0.807	0.811	0.784	0.698	0.646	0.623	0.752
Inner Mongolia	0.649	0.675	0.663	0.667	0.657	0.596	0.553	0.502	0.446	0.419	0.423	0.568
Liaoning	0.685	0.710	0.728	0.749	0.743	0.726	0.708	0.691	0.651	0.628	0.639	0.696
Jilin	0.884	0.772	0.680	0.623	0.589	0.550	0.531	0.508	0.480	0.459	0.434	0.592
Heilongjiang	1.000	1.000	1.000	0.993	0.897	0.905	0.919	0.884	0.784	0.734	0.723	0.894
Shanghai	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Jiangsu	0.854	0.849	0.844	0.844	0.831	0.841	0.836	0.823	0.796	0.789	0.765	0.825
Zhejiang	0.895	0.893	0.887	0.895	0.872	0.903	0.921	0.929	0.911	0.896	0.873	0.898
Anhui	0.816	0.815	0.830	0.837	0.847	0.865	0.890	0.879	0.823	0.774	0.770	0.831
Fujian	0.931	0.887	0.873	0.865	0.849	0.842	0.831	0.811	0.748	0.706	0.712	0.823
Jiangxi	0.758	0.754	0.762	0.766	0.787	0.830	0.871	0.880	0.855	0.847	0.867	0.816
Shandong	0.684	0.724	0.729	0.748	0.751	0.742	0.747	0.747	0.721	0.693	0.729	0.729
Henan	0.890	0.873	0.855	0.828	0.726	0.689	0.661	0.635	0.572	0.531	0.386	0.695
Hubei	0.771	0.789	0.815	0.838	0.837	0.848	0.850	0.844	0.784	0.740	0.732	0.804
Hunan	0.878	0.895	0.913	0.920	0.956	0.961	0.991	1.000	0.942	0.903	0.775	0.921
Guangdong	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.974	0.911	0.874	0.870	0.966
Guangxi	1.000	1.000	0.976	0.893	0.744	0.682	0.638	0.583	0.549	0.524	0.373	0.724
Hainan	0.940	0.890	0.847	0.861	0.865	0.874	0.858	0.829	0.741	0.685	0.640	0.821
Chongqing	0.531	0.526	0.531	0.564	0.653	0.662	0.686	0.693	0.654	0.631	0.620	0.614
Sichuan	0.737	0.758	0.790	0.811	0.808	0.818	0.828	0.827	0.782	0.752	0.731	0.786
Guizhou	0.553	0.610	0.670	0.724	0.779	0.783	0.797	0.804	0.745	0.697	0.562	0.702
Yunnan	0.789	0.817	0.868	0.932	0.859	0.775	0.729	0.688	0.618	0.556	0.469	0.736
Shaanxi	0.810	0.868	0.813	0.782	0.783	0.760	0.718	0.675	0.727	0.859	0.817	0.783
Gansu	0.603	0.686	0.761	0.754	0.764	0.745	0.714	0.720	0.703	0.725	0.729	0.719
Qinghai	0.512	0.550	0.579	0.605	0.620	0.631	0.625	0.573	0.493	0.427	0.314	0.539
Ningxia	0.508	0.521	0.550	0.573	0.612	0.595	0.607	0.569	0.523	0.464	0.367	0.535
Xinjiang	0.639	0.700	0.711	0.751	0.718	0.791	0.814	0.771	0.686	0.612	0.576	0.706
Average	0.793	0.802	0.805	0.813	0.799	0.795	0.791	0.771	0.723	0.693	0.626	0.765
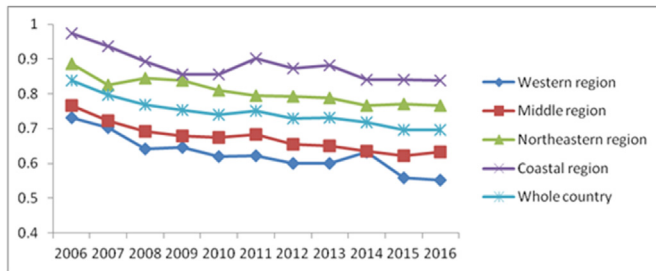
Fig. 1. The trend in energy efficiency in four major regions of China from 2006 to 2016.

environmental protection. In 2004 the strategy about The Rise of Central China brought new opportunities for the economic development of Hunan province, making its annual average energy efficiency reach 0.921. Since 2007, Hainan province has formulated and proclaimed a series of laws and regulations on ecological and environmental protection, which has a positive impact on improving the energy efficiency of Hainan province, its annual average energy efficiency reaching 0.821. While the energy efficiency of Qinghai, Ningxia, Inner Mongolia and Jilin four provinces were low, about 0.5. Especially, the energy efficiency of Qinghai province in 2016 was only 0.314, the lowest level among the whole country. These provinces are all underdeveloped areas, but they have great potential to improve energy efficiency in the future. Among the other 14 provinces, the energy efficiency of Tianjin and Guangxi decreased significantly, from 1 to 0.443 and 0.373 respectively. Tianjin is a city that short of coal, oil and other resources, with high dependence on outside. Coal consumption accounts for more than 50% of the total energy consumption, but the energy efficiency of coal is the lowest. Since 2007, Tianjin Binhai New District speeded up development, increased investment in infrastructure construction while inadequate environmental supervision, which resulted in energy efficiency reduction. While the pillar industries in Guangxi mainly focus on traditional industries with high energy consumption and emission, such as metallurgy, non-ferrous metals, sugar making, cement, etc. The energy consumption of industries with high energy consumption accounts for more than 90% of the industries above designated size, but the added value only constitutes about 50%. The contradiction between the contribution of economic growth and energy consumption is becoming more and more prominent. The way of energy utilization is extensive, thus the comprehensive utilization efficiency is not high.

In terms of the regional level, the average energy efficiency of coastal areas in 2006−2016 was the highest, up to 0.881, followed by northeastern, middle and western region, with the value of 0.808, 0.674 and 0.628, as demonstrated by Table 5. From the perspective of time dimension, the TFEE of these four regions showed a downward trend. The average energy efficiency of whole country declined 0.145 from 2006 to 2016, while that of the coastal areas and northeastern region decreased by 0.134 and 0.120, respectively, slightly less than 0.145 and the decline in the western and middle regions were 0.180 and 0.135, which was the main reason for the decrease in energy efficiency of China. These results are basically similar to those of previous studies [13,14,31,71]. The main reason for the decline of energy efficiency in 2006−2016 is that China launched an economic stimulus plan in 2008 to cope with the influence of financial crisis and large scales of investment in infrastructure construction led to environmental pollution and ecological damage, which greatly hindered the energy efficiency of China. The average value of energy efficiency in China was 0.748 in Table 5, which indicated that although China's economy developed

rapidly in 2006−2016, the average energy efficiency of most provinces did not reach the best. With the available input factors and technology level unchanged, China's overall energy efficiency has nearly 30% space for improvement.

It can be seen from Fig. 1 that in 2006−2016 there was obvious imbalance distribution on energy efficiency of China and China's TFEE showed a fluctuating downward trend. A comparison of the energy efficiency of four major regions demonstrated obvious regional differences: coastal region>northeastern region>middle region>western region. This is because that the speed of economic development of coastal region is much faster than that of the other three regions. The coastal region possesses advanced technological level and assembles a large number of material resources and excellent talents, which make resource allocation more efficient and energy utilization higher. These are the same as the conclusions of Zhao et al. [13], Zhu et al. [14] and Yang et al. [71]. In addition, energy efficiency of coastal and northeastern region were higher than that of the national average while that of middle and western region were lower than that of the national average (shown in Fig. 1). Compared with other three regions, energy efficiency of coastal region showed more volatile: declining in 2006−2009, rising in 2009−2011, slowly declining again until 2016. However, the conclusion that energy efficiency of northeastern region was higher than that of middle and western regions is different from the result of Yu et al. [31], who thought that energy efficiency of northeastern region was the lowest. The main reason is that China implemented the strategy of revitalizing the old industrial base in Northeast China in 2003, and the economic growth of three northeastern provinces began to speed up. In 2008, the economic growth rate of the three northeastern provinces was 13.7%, 0.5%, 0.5%, 0.5%, 0.3% higher than that of the whole country, coastal, middle and western regions, respectively. Meanwhile, northeastern region paid more attention to energy conservation and emission reduction to improve the energy efficiency. As shown in Fig. 1, energy efficiency of northeastern region reached a high point in 2008 and then declined slowly after 2009. While the middle region was in the middle stage of industrialization, and some backward industries in the eastern developed provinces were gradually transferring to the middle region, resulting in the rapid increase on pollutant emission. Together with the backward management and technology, energy efficiency showed a trend of declining instead of increasing. The economic development of western region relatively fell behind and the technology level was low, which caused environmental pollution and energy waste and made its energy efficiency at the lowest level. In 2014−2016 its energy efficiency decreased rapidly. However, with the implementation of the great western development strategy, the potential of energy efficiency improvement of western region is great.

4.2. Analysis of influencing factors

4.2.1. Variables selection and display of data

Based on the existing research [30,31,55,67,68], considering the reality of China's energy economy and the availability of data, the economic development level (*EDL*), technological progress (*TP*), energy price (*EP*), urbanization level (*UL*), industrial structure (*IS*), energy consumption structure (*EC*), government intervention (*GI*) and openness degree (*OD*) are selected as explanatory variables, as shown in Table 6. The energy efficiency value (*EE*) calculated by BCC model is chosen as the explained variable.

The relevant data of the above explanatory variables come from the China Statistical Yearbook (2007−2018), China Energy Statistics Yearbook (2007−2018) and China Provincial Statistical Yearbook (2007−2018). The values of all variables are expressed in logarithms of ratios or absolute values. Some missing values are

Table 6
Explanatory variables.

Variable	Description of variable	Source
Economic development level (EDL)	The natural logarithm of real GDP based on 2006	EDL is a key influencing factor. Taken from Sener and Karakas [59], who thought that there was a positive correlation between EDL and energy efficiency.
Technological progress (TP)	The natural logarithm of the number of patents authorized by provinces	Drawn from Wang and Wang [52], Zhu et al. [53] and Li and Lin [54], who believed that TP could improve the energy efficiency.
Energy price (EP)	The ratio of total energy price to output price	The change of EP will directly affect the cost and profit of energy use and indirectly influence the energy consumption behavior. Considered based on Antonietti and Fontini [58] and Wang et al. [67], who indicated a positive effect of EP on energy efficiency.
Urbanization level (UL)	The proportion of the urban population in the total population	Drawn from Li et al. [26] and Wang et al. [65], who both held that UL would influence energy efficiency, but in different directions.
Industrial structure (IS)	The proportion of secondary industry output value in regional GDP	Taken from Xiong et al. [55], Zhu et al. [56] and Rongdi et al. [68], who demonstrated that IS had a negative impact on energy efficiency.
Energy consumption structure (EC)	The proportion of coal and oil consumption in total EC	Considered based on zhao et al. [13], Yu et al. [31], and Wang et al. [67], who chose EC as one of influencing factors and thought that EC negatively affected energy efficiency.
Government intervention (GI)	The proportion of general financial expenditure in regional GDP	Drawn from Yu et al. [31] and Rongdi et al. [68], who considered that GI was negatively related to energy efficiency.
Openness degree (OD)	The proportion of foreign investment at the end of year in GDP	Taken from Imbruno and Ketterer [62], Montalbano and Nenci [63] and Pan et al. [64], whose research involved FDI, import and export.

Table 7
Fixed effects regression of panel data.

Variable	Coefficient	Standard deviation	T statistic	Probability
EDL	0.0525	0.0576	0.9100	0.0630
TP	0.0432	0.0234	1.8500	0.0660
EP	0.0418	0.1142	0.3700	0.0050
UL	0.0085	0.0158	0.5300	0.0940
IS	−0.0233	0.2066	3.9800	≤0.0001
EC	−0.0004	0.0004	0.9800	0.0100
Constant term	0.2897	0.4501	0.6400	0.0021
Goodness of fit R^2	0.8390	F statistic	8.5000	
Adjusted R^2	0.8064	probability	≤0.0001	

compensated by the average value of two adjacent years.

4.2.2. Discussion on influencing factors

The first regressions of fixed effects and random effects on panel data show that government intervention (GI) and openness degree (OD) have no significant impact on the energy efficiency of provinces in China. Therefore, these two variables are removed from subsequent regressions and then Hausman test is conducted. The test result indicates that fixed effects model and its estimation method should be used to better study the influencing factors of provincial energy efficiency in China. The regression result of fixed effects is shown in Table 7, and the regression equation is as follows:

$$\widehat{EE} = 0.2897 + 0.0525 \times EDL + 0.0432 \times TP + 0.0418 \times EP + 0.0085 \times UL - 0.0233 \times IS - 0.0004 \times EC$$

The results show the direction and degree of the impact of EDL, TP, EP, UL, IS and EC on China's energy efficiency. According to the results of the fixed effects model, fixed regression analysis has passed the goodness of fit test and F test, which indicates that the impact of each explanatory variable is significant; therefore, the regression model is established. The influence results of various variables on energy efficiency are as follows:

EDL is positively related to energy efficiency. When other variables remain unchanged, the natural logarithm of real GDP increases by 1 unit, and energy efficiency increases by 0.0525 efficiency values on average. It is indicated that with the improvement of provincial EDL, energy efficiency will be further improved, which is similar to the conclusion of Yang et al. [17] and Yu et al. [31]. For example, Guangdong, Shanghai, Beijing, Jiangsu

and other provinces with good economic development in the eastern coastal areas possess advanced infrastructure, abundant human resources, sophisticated technology and rich management experience, which can have greater ability and more opportunities to allocate resources efficiently and improve energy efficiency. Conversely, provinces with high energy efficiency can produce more economic output, thus improving the provincial EDL. Provincial EDL and energy efficiency are mutually interactive and promote each other. While Wang and Wang [52] thought that the improvement of EDL had a negative impact on energy efficiency, which promoted the development of industrialization and urbanization, increased energy consumption and weakened the positive influence of productivity improvement on energy efficiency.

TP is positively associated with energy efficiency. Keeping other variables unchanged, the energy efficiency increases by 0.0432 efficiency units for each unit of a natural logarithm of the number of patents granted in each province, which demonstrates that TP plays a positive role in improving provincial energy efficiency. This is consistent with the result of Li and Lin [54], Zhao et al. [13], Wang and Wang [52]. The increase in the number of patents for invention promotes the TP. At present, China has 1862 thousand patents for invention. The top three cities or provinces with the largest number of invention patents per 10 thousand people are Beijing, Shanghai, Jiangsu, and that of PCT international patent applications are Guangdong, Beijing, Jiangsu. Correspondingly, the energy efficiency of Beijing, Shanghai, Guangdong and Jiangsu are also very high. From the perspective of region, the level of TP also affects the differences in energy efficiency of coastal areas, Northeast, Middle and West. TP can not only improve the energy efficiency by using low energy consumption equipment, but also optimize the production process to enhance the efficiency of production factors, so as to exert a positive influence on the improvement of regional energy efficiency. But Liu et al. [72] and Gu et al. [73] held that due to the rebound effect of TP, there was a negative correlation between TP and energy efficiency.

EP has a positive impact on energy efficiency. When other factors remain unchanged, the average value of energy efficiency increases by 0.0418 efficiency units as the relative energy price increases by 1 unit. Increasing the relative EP will reduce companies' profit. To maintain their own benefits and competitive advantages, companies will increase their technology input, and fewer resources will be invested at this level of output, thus improving their energy utilization. While Yang and Wei [17], Wang et al. [67] indicated that EP could restrain the improvement of

energy efficiency, and the change of *EP* would affect the structure of energy consumption. If *EP* rises, producers will consider using poor and cheap raw materials, resulting in low efficiency and high pollution.

UL is positively related to energy efficiency. Energy efficiency increases by 0.0085 efficiency units as the proportion of urban population in the total population increases by one percentage point. The *UL* of Beijing and Shanghai is relatively high, and the proportion of the urban population in the total population is 86.5% and 82.93%, respectively, while that of Guizhou is relatively low, only 44.15%. The energy efficiency of Shanghai and Beijing is much higher than that of Guizhou. As *UL* increases, more advanced technology is introduced, and better talent is attracted. Therefore, the same input will produce more in the favorable external environment to enhance energy efficiency. This agrees with the results of Wang et al. [65] and Zhao et al. [13]. With the enhancement of *UL*, gathering of excellent talents will improve the technological level, thus exerting a positive impact on energy efficiency. While Li et al. [26] stated that the overall impact of urbanization on energy efficiency was negative in China. The reason was that along with large-scale infrastructure investment, urbanization led to the increase of energy consumption, which had a negative impact on energy efficiency.

IS has a significant negative impact on energy efficiency. When other variables remain unchanged, the energy efficiency drops by 0.0233 efficiency units as the proportion of secondary industry increases by one percentage point. *IS* inhibits the promotion of energy efficiency to some extent, which is identical with the conclusions of Zhu et al. [56], Xiong et al. [55], Guan et al. [68]. As the economic development of most provinces in China mainly depends on the secondary industry with high energy consumption, nearly 70% of China's energy consumption concentrating on the secondary industry, the increase of the proportion of the secondary industry will have a great negative impact on energy consumption and energy efficiency. The development of *IS* is unbalanced among the coastal, northeastern, middle and western regions of China, and *IS* exerts the greatest influence on the provinces in the middle region. For instance, in 2006−2016 the secondary industry of Henan accounted for the highest proportion, with an average of 54.61%, while Beijing had the lowest proportion of the secondary industry, only 23.77%. The energy efficiency of Beijing was far higher than that of Henan. However, Wang et al. [67] thought that energy efficiency belonged to the category of technology and industry can promote *TP*, so the increase of the proportion of the secondary industry helped to improve energy efficiency.

EC negatively influences energy efficiency, which is consistent with the conclusions of most studies [13,31,67]. When other factors remain unchanged, the energy efficiency will decrease by 0.0004 efficiency units for every one-percentage-point increase in the proportion of coal and oil consumption. China is a country dominated by the fossil energy consumption, and *EC* of each region is quite different. The proportions of coal and petroleum in *EC* in northeastern, middle and western China are high, while the proportion of electric power consumption in coastal areas is high. A large number of coal consumption leads to an increase in emissions of various pollutants; thus, it exerts a negative impact on the improvement of energy efficiency in various regions.

5. Conclusions

This paper uses DEA-BCC model to measure the energy efficiency of China's 30 provinces from 2006 to 2016 with and without the consideration of undesirable output, and makes a comparative analysis of regional differences. The results are as follows. (1) Under the condition of four pollutants as undesirable output, energy

efficiency considering undesirable output was generally lower than that without considering undesirable output. (2) From 2006 to 2016, China's energy efficiency, by and large, showed a declining trend. There was a considerable difference in energy efficiency among provinces. The energy efficiency values of Beijing and Shanghai were up to 1, while the lowest value about Qinghai was only 0.314. (3) From the comparison of energy efficiency in four regions, there were obvious regional differences: coastal region> northeastern region> middle region >western region. Therefore, the advantage of each region should be made full use of and the exchange of resources, funds, technology and talents among regions should be strengthened in order to promote the improvement of energy efficiency of each region. When steadily improving energy efficiency, the eastern coastal region should play a driving role in promoting energy efficiency of the other three regions. The middle region should make full use of its geographical advantage, learn the advanced technology of eastern coastal region, and adjust and optimize the industrial structure through industrial transfer. The western and the northeastern regions should fully utilize their respective energy advantages, formulate clean energy strategies, develop efficient and clean new energy, and draw lessons from the advanced technology about energy conservation and emission reduction and management experience of the eastern coastal region. Meanwhile, the characteristics of economic development, energy consumption, capital, technology and other aspects among the four major regions should be considered sufficiently, formulating corresponding energy policies according to local conditions.

Based on the energy efficiency considering the undesirable output, the panel data model is adopted to empirically analyze the influencing factors of energy efficiency. The results show that (1) Regional economic development level, technological progress, energy price and urbanization level are positively associated with energy efficiency. The higher the level of provincial economy and technological progress, the better the allocation of resources, the stronger the ability of technology transformation and diffusion, which are helpful to enhance energy efficiency. China should continuously enhance the level of regional economic development and accelerate the innovation of energy technology, such as clean low-carbon energy and key material technology. The investment in energy technology innovation and the international energy technology cooperation should also be strengthen. Besides, improving the energy price mechanism, promoting the marketization reform of energy product price and reducing the government intervention can provide a stable and healthy market environment for energy production and consumption. Enhancing the urbanization level is conductive to the industrial agglomeration and scale effect. These are also measures to improve China's provincial energy efficiency. (2) The proportion of the secondary industry and energy consumption structure dominated by coal and oil are negatively correlated with energy efficiency. Reducing the proportion of secondary industry and coal and petroleum in the ratio of energy consumption, adjusting the industry structure and energy consumption structure, encouraging clean energy consumption, increasing the proportion of natural gas, hydroenergy, solar energy, wind energy, nuclear energy and electricity consumption will also enhance the regional energy efficiency. Meanwhile, new energy can be deeply integrated with modern information technologies such as big data and artificial intelligence, forming a new mode with multi energy complementary and comprehensive energy services, in order to make the allocation of energy resources more optimal and the energy efficiency higher.

Although our research has achieved some results, this paper still has some limitations and there is still room for further development and expansion in the future. First, restricted by the factors of data acquisition, this study only uses the data from the provincial

level to measure the energy efficiency and analyze its influencing factors. Therefore, the object of study can be extended to the city level to analyze the energy efficiency difference and promotion potential of each city more accurately and more targeted. Second, when choosing the undesirable output, this paper only considers wastewater, SO_2, ammonia nitrogen and solid waste four pollutants, without considering greenhouse gas CO_2. Thus, taking CO_2 and all kinds of pollutants into account and adopting various methods can study the energy efficiency of China more fully. Third, the global energy supply and demand market will be affected by COVID-19, and the world energy market trend in the post epidemic era should be given more attention. Therefore, other factors influencing China's energy efficiency, such as global energy demand policy, Chinese energy policy, COVID-19 epidemic and so on, can be further studied.

Author contributions

H.L., Z.Z. and L.Y. designed the research. H.L. and L.Y. collected and analyzed the data. H.L., T.Z. and L.Y. wrote the paper. All authors read and approved the final manuscript.

CRediT authorship contribution statement

Haomin Liu: Conceptualization, Methodology, Software. **Zaixu Zhang:** Supervision, Methodology. **Tao Zhang:** Supervision, Writing - review & editing. **Liyang Wang:** Data curation, Writing - original draft.

Declaration of competing interest

The authors declare no conflict of interest.

Acknowledgments

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