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An assessment of energy efficiency based on environmental constraints and its influencing factors in China

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Abstract

The super-efficiency directional distance function (DDF) with data envelopment analysis (DEA) model (SEDDF-DEA) is more facilitative than to increase traditional method as a rise of energy efficiency in China, which is currently important energy development from Asia-pacific region countries. SEDDF-DEA is promoted as sustained total-factor energy efficiency (TFEE), value added outputs, and Malmquist-Luenberger productivity index (MLPI) to otherwise thorny environmental energy productivity problems with environmental constraint to concrete the means of regression model. This paper assesses the energy efficiency under environmental constraints using panel data covering the years of 2000–2015 in China. Considering the environmental constraints, the results showed that the average TFEE of the whole country followed an upward trend after 2006. The average MLPI score for the whole country increased by 10.57% during 2005–2010, which was mainly due to the progress made in developing and applying environmental technologies. The TFEE of the whole nation was promoted by the accumulation of capital stock, while it was suppressed by excessive production in secondary industries and foreign investment. The primary challenge for the northeast of China is to strengthen industrial transformation and upgrade traditional industries, as well as adjusting the economy and energy structure. The eastern and central regions of the country need to exploit clean- or low-energy industry to improve inefficiencies due to excessive consumption. The western region of China needs to implement renewable energy strategies to promote regional development.

Keywords Energy efficiency · Super-efficiency directional distance function · Data envelopment analysis · Environmental constraint · Total factor energy efficiency · Malmquist-Luenberger productivity index · Generalized least squares method

Introduction

Problem statement

China has implemented many effective energy development strategies in recent years, such as the "One Belt, One Road" strategy, which plays a powerful role in optimizing and promoting energy structure. These strategies have provided China with low-cost access to energy and high environmental efficiency and have effectively enhanced China's status in

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global energy governance. Compared to 2015, in 2016 coal consumption in China fell by 1.6% and coal production fell by 7.9%, which is the largest annual decline since records began in 1981. Also in 2016, China's carbon dioxide (CO_2) emissions fell for the second consecutive year, with a decline of 0.7% compared to 2015 levels. Nonetheless, China's energy consumption in 2016 still accounted for 23% of global primary energy consumption (BP 2017).

According to the Global Energy Architecture Performance Index Report (2017), among the 127 countries for which global energy data was available, the energy architecture performance index (EAPI) score of China in 2017 was only 0.53 (against a global mean of 0.8), which resulted in the country being ranked at 95. China lags behind other global superpowers, with high levels of energy intensity (ranked 107) and high CO_2 emissions from electricity production (ranked 102) impacting on its comparative performance. The rapid economic development in China has resulted in a large

demand for energy, and the economic model of "high energy consumption, low output" has been a constraint on the country's economic development. Therefore, it is a priority for countries such as China to improve their energy efficiency and realize a resource-intensive economy.

Given the current levels of energy consumption and the associated environmental pollution, it was clearly proposed in the "enhanced action on climate change-China National Autonomous contribution" policy that peak CO_2 emissions will be reached by 2030, but that the peak should occur as early as possible. Compared with 2005, CO_2 emissions per GDP in 2030 are predicted to fall by 60–65%, and the proportion of non-fossil fuels in primary energy consumption will be around 20%. The efficient use of clean energy and rational distribution of energy production is an important strategic objective of the "thirteenth Five Year Plan". The amount of energy produced and consumed in China is the largest in the world; however, there are a several issues within the energy supply and usage patterns, such as an irrational energy structure, energy inefficiency, little use of renewable energy, and low levels of safe energy use. The characteristics of energy efficiency vary among the provinces in China, which is largely due to the imbalances in regional economic development and regional energy endowment, the process of industrialization, and the industrial structure (Li et al. 2014).

Literature review

In recent years, data envelopment analysis (DEA) has been the mainstream method used to determine energy efficiency. Hu and Wang (2006) first applied the DEA model to measure the energy efficiency of China from the perspective of multiple-input factors, followed by a series of similar studies (Wang and Zhou 2008; Honmas and Hu 2008; Ma et al. 2011; Wu et al. 2012; Shen and Cheng 2015). However, factors of production constraint rather than environmental constraint were considered, and therefore the undesirable outputs (e.g., pollution) of energy consumption were not considered. This would distort the evaluation of changes in social welfare and economic performance generated by energy usage. Pollution derived from inefficient production technology and the costs of reducing pollutant emissions determine environmental efficiency. Hence, previous studies have measured total factor productivity (TFP) by introducing environmental factors and selecting pollutants as undesirable outputs in the DEA model (Goto et al. 2014; Wang et al. 2014; Suzuki and Nijkamp 2016). Traditional DEA models cannot effectively deal with undesirable outputs, and many previous studies have considered environmental efficiency by means of various modified DEA models. In recent years, the directional distance function (DDF) has been widely used for estimating both energy and environmental efficiency, because it can expand output and reduce input (Halkos and Trezemes 2012; Ramli et al. 2013; Diabat et al. 2015; Lee et al. 2017; Halkos and Managi 2017).

Researchers in both China and overseas have considered how to improve China's energy efficiency and energy conservation. Measurement methods and factors influencing energy efficiency at national and provincial levels have been investigated, and a series of valuable conclusions and policy recommendations have been obtained. Most studies have focused on capital, employees, energy consumption, and investment indicators to measure provincial energy efficiency under environmental constraints (Guo et al. 2015; Chen et al. 2015; Sueyoshi and Yuan 2015). Based on the slacks-based measure (SBM), He et al. (2016) found that the excessive emission of an undesirable output (sulfur dioxide, SO_2) and redundant resources were the main causes of the low energy efficiency in terms of outputs to the atmospheric environment. Tian et al. (2017) used the DDF approach to estimate the energy–carbon performance of the Chinese transportation sector. These models can be used for a static comparison at the same point, but cannot be used for a dynamic analysis of energy efficiency in different provinces; therefore, the Malmquist-Luenberger productivity index (MLPI) (Munisamy and Arabi 2015; Emrouznejad and Yang 2016; Du et al. 2017; Arabi et al. 2017) and the window DEA model (Halkos and Tzereme 2009; Wang et al. 2013) have been proposed as solutions to analyze the variation of energy efficiency over time. Based on an innovation-driven model, Huang and Shi (2015) and Wang et al. (2016) compared the utilization efficiency of innovation elements with that of traditional elements by introducing research and development (R&D) factors. When considering the maximization of economic capacity, SO_2, CO_2, and nitrogen oxides (NO_x) are used as the basic indicators of undesirable outputs to measure energy efficiency. Table 1 summarizes the previous application of different DEA models in terms of the industries under environmental constraints and their input and output indicators as production factors.

Considering the high energy consumption in provinces and administrative departments, DEA models have been used to investigate energy efficiency across provinces and industries under environmental constraints, including the environmental efficiency of industrial sectors, which accounts for about 70% of the total energy consumption (Meng et al. 2013; Chen et al. 2014; Wang et al. 2016), and the utilization efficiency of industrial water resources and efficiency of wastewater disposal (Mai et al. 2014; Shen and Cheng 2015). Chang et al. (2013) measured the total energy efficiency of the transport sector, which produced 22% of global CO_2 emissions, as well as the electricity generation efficiency of coal-fired power plants, which account for almost half (41%) of the world's CO_2 emissions (Du et al. 2016).

It is very important to analyze the factors that influence total energy efficiency because they will enable the relation

Table 1　Previous studies in which a data envelopment analysis (DEA) model was applied in an environmental assessment

Author	Method type	Area	Input	Desirable output	Undesirable output
Chang Young-Tae 2013	Slacks-based measure (SBM)	Transportation	Capital, labor, energy	Value-added	CO_2
Wang and Feng 2013	DEA window	Nation	Capital, labor, energy	GDP	SO_2, CO_2
Mika Goto, Toshiyuki Sueyochi 2014	DEA	Industry	Capital, labor, energy	GDP	SO_2, Carbon, NO_x, dust
George Vlontzos 2014	A non-radial DEA	EU agriculture	Capital, labor, energy consumption	Agricultural added value	CO_2, gross nutrient balance
Guo et al. 2015	SBM	Nation	Capital, labor, energy	GDP	Composite index
Sueyochi and Yuan 2015	DEA	Nation	Population, environmental investment, electricity, consumption expenditure,	GRP	$PM_{2.5}$, PM_{10}, SO_2, NO_2
Huang and Shi 2015	SBM-Tobit	Nation	Capital, labor, energy, R&D	GDP	SO_2, COD
Yang et al. 2015	Super-efficiency-DEA	Nation	Capital, labor, resource, environment	GDP	SO_2, CO_2
Wang et al. 2014	DEA	Industry	Capital, labor, energy, R&D	Industrial added value	CO_2
Michiyuki Yagi and Shunsuke Managi 2015	Directional distance function (DDF)-DEA	Firm	Capital, labor, energy of electricity, Paper, water	Gross profit	SO_x, NO_X
Yu et al. 2016	Malmquist	Industry	Water consumption	Total industrial output value	Wastewater emissions, COD, ammonia nitrogen (AN)
Munisamy and Arabi 2015	Malmquist	Power plant	Effective capacity, fuel consumption	Generated energy	SO_2, NO_x, CO_X
Wang et al. 2016	DEA, truncated	Industry	Capital, labor energy, R&D	Industrial added value	CO_2
He et al. 2016	SBM-Tobit	Region	Capital, labor, energy	GDP	SO_2
Suzuki and Nijkamp 2016	DEA	Country	Population, energy	GDP	CO_2
Du et al. 2016	A parametric meta-efficiency frontier	Power plant	Capital, labor, energy	Electricity output	CO_2
Halkos and Managi, 2017	DDF-DEA	Country	total employment, capital	Real GDP	CO_2

among economic development, energy consumption, and environmental pollution to be investigated. There is a need to embrace sustainable development, in order to achieve economic development, improve energy efficiency, and reduce pollution intensity. Yuan et al. (2009) argued that industrial structure, property rights, energy consumption, and resource variables have a significant negative influence on the TFEE and a weak positive correlation with energy price. Zhang and Wu (2011) reported that the accumulative growth rate of technical efficiency, GDP per capita (PG), volume of exhaust emissions per GDP, the degree of technical progress, foreign direct investment (FDI), and energy consumption per capita had a variable influence on energy efficiency, while the growth rate of technical efficiency and technical advances, PG, extent of industrial production, and the volume of exhaust emissions per GDP affected the growth rate of energy efficiency. Li et al. (2013) used a two-step DEA model to evaluate the TFEE and reported that industrial structure was the most influential factor. Guo et al. (2015) considered that factors of R&D investment and the degree of openness in a country's trade were positively correlated with energy efficiency, compared to the negative impact of industrial structure and system variables. From the perspective of industry, Wang et al. (2016) reported that the industrial structure, energy structure, technological innovation, and market competition had significant impacts on efficiency, which would be suppressed by the increasing proportion of coal used in energy generation, and be promoted by R&D. For Tianjin, He et al. (2016) found that trade had a significant positive impact on the atmospheric total energy efficiency, while the factors of PG and industry structure was not significant.

There are several consistent features within the past literature. First, the assessment of environmental constraints in most studies has focused on either industries and departments or has only been measured by referring to cross-sectional data for China. Second, most investigators have considered a diverse range of undesirable outputs when estimating total energy efficiency. Third, various DEA methods have been introduced to calculate the energy efficiency, but they have been applied without considering the limitations of DEA when applied to undesirable outputs. This study continued the analytical framework of Yuan et al. (2009) and Zhang and Wu (2011), but also introduced pollution emissions as an undesirable output into the production process alongside the desirable outputs. In this paper, it is more important than to explore the conversion of energy efficiency with the aspects of space and time; and to identify the differentiations of undesirable output within the whole national and regional comparison each other. Meanwhile, the design and selection of multiple decision-making units are considering and lying on the production frontier, all at once; they will result in the consistency of effective recognition. The merit of multi decision-making units

is enough to gain further validity and consistency in the study issues of energy efficiency; hence SEDDF-DEA will be adopted in the paper. In this research, the researcher discusses a multi-methodology of a systems approach in designing an input-output structure, which not only identifies the MLPI of SEDDF-DEA in energy efficiency, but also develops the means of regression model in value added outputs. First, based on SEDDF, an input-oriented DEA model with constant returns to scale (CRS) was applied to measure TFEE under environmental constraints during the period of 2000–2014. Second, the study adopted the MLPI combined with an undesirable output model to evaluate the growth rate of environmental efficiency and its decomposition into changes in technical efficiency and technology. Finally, a generalized least squares (GLS) model was used to inspect the factors of TFEE to provide a scientific basis for policy formulation regarding regional energy conservation.

The remainder of the paper is organized as follows: "Methods" presents the methodology of the SEDDF-DEA and explains how the MLPI was constructed. In "Data", the variables and data are described. "Discussion" presents an analysis of the results of empirical research. "Quantitative analysis of the factors affecting TFEE" tests the factors that influenced the TFEE, and the final section is a conclusion.

Methods

The study used a model that was a modification of those used in Yuan et al. (2009), Zhang and Wu (2011), and Wang et al. (2014).

TFEE

In the study, each province was considered to be a DMU, which enabled an efficiency frontier to be built. Due to the minimization of related inputs, a CRS-DEA model was applied to measure the TFEE across provinces in 2001–2016. A traditional DEA model may have resulted in multiple-DMUs simultaneously lying on the efficiency frontier, which would be difficult to evaluate and compare; thus, we adopted super-efficiency DEA (Andersen and Petersen 1993) to overcome this dilemma. According to the DDF model proposed by Färe et al. (2007), we first needed to determine the environmental technology that produces the maximum desirable outputs by consuming a set of inputs. Then we calculated the distance function, i.e., the distance that the various DMUs move up to the efficiency frontier.

Assuming that x represents the input vector $x \in R_+^N$, y represents the desirable output vector $y \in R_+^M$, and b represents the undesirable output vector $b \in R_+^J$, the technical set of the DMU can be expressed as $P(x) = \{(y, b): x \text{ can produce } (y, b)\}$.

Given that $g = (g_y, g_b)(g > 0)$ represents the directional vector, the DDF can be defined as:

$$\overrightarrow{D_0}\left(x, y, b; g_y, g_b\right)$$
$$= \max\left\{\beta : \left(y + \beta g_y, b - \beta g_b\right) \in P(x)\right\}(\beta \geq 0) \quad (1)$$

In the production set $P(x)$, y and b were increased and decreased separately in the directional output distance function along with g, until $P(x)$ at the critical point $(b - \beta^* g_b, y + \beta^* g_y)$. Then $\left(\beta^* = \overrightarrow{D_0}(x, y, b; g)\right)$, as shown in Fig. 1.

The purpose of the study was to expand the desirable outputs and reduce the undesirable outputs, and therefore desirable outputs were increased by 1:1 and undesirable outputs were decreased by 1:1. We referred to the way Chung et al. (1997) processed the undesirable outputs, in which the direction vector was set to $g = (y^t, b^t)(g > 0)$. The essential feature of a super-efficiency DDF model is the addition of a restriction of $i \neq j$.

$$\overrightarrow{D_0}\left(x_i^t, y_r^t, b_k^t; g_{r,y}^t, g_{k,b}^t\right) = \max\left\{\beta : \left(y_i^t + \beta g_{r,y}^t, b - \beta g_{k,b}^t\right) \in P(x_i^t)\right\}$$
$$s.t. \begin{cases} \sum_{i=1, i \neq j}^{n} \lambda_i x_{ij}^t \leq x_{jk}^t \\ \sum_{i=1, i \neq j}^{n} \lambda_i y_{rj}^t \leq \left(y_{rj}^t + \beta g_{yr}^t\right) \\ \sum_{i=1, i \neq j}^{n} \lambda_i b_{ik}^t \geq \left(b_{kj}^t - \beta g_{bk}^t\right) \\ \sum_{i=1, i \neq j}^{n} \lambda_i \leq 1, \beta \geq 0, \lambda_i \geq 0, \\ i = 1, 2 \ldots, n; j = 1, 2 \ldots, m; r = 1, 2 \ldots, n; k = 1, 2 \ldots, q; (i \neq j) \end{cases}$$
$$(2)$$

Malmquist-Luenberger productivity index

Combining DDF model with Malmquist model, Chung et al. (1997) formulated MLPI to estimate the change rate of total energy efficiency (ML_t^{t+1}), and further decomposed into
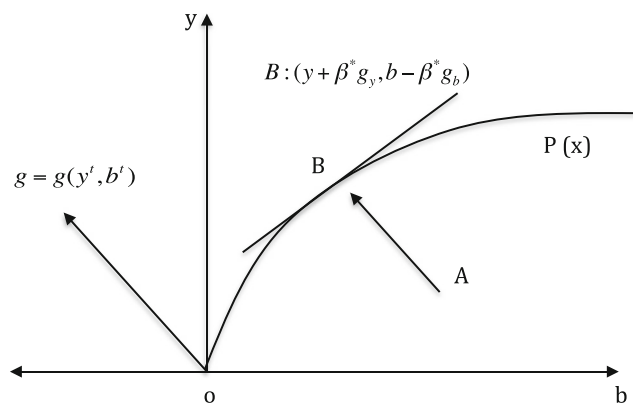

Fig. 1 Environmental directional distance function

technical efficiency change (EC_t^{t+1}) and technology change (TC_t^{t+1}). Measuring of TFEE was a type of static analysis, while Malmquist-Luenberger productivity index (MLPI) was a method of dynamic analysis, assessing relative position change of each province and the production boundary (technical efficiency change) and the movement of the production boundary (technology change) (Wang et al. 2010). So, EC_t^{t+1} evaluated the extent of production efficiency frontier from t to $t + 1$, and TC_t^{t+1} evaluated the moving extent of technical border form t to $t + 1$. Hence, if EC > 1, then there is an increase in the technical efficiency of converting inputs to outputs; if TC > 1, then there is prove of technological progress; and vice versa. We refer to the method of Chung et al. (1997) of combing DDF of undesirable output with adjacent cross-efficiency frontier reference Malmquist model, employ DEA to measure total energy efficiency, and further resolute the MLPI into technical efficiency change index and technology change index.

Data

In the paper, 30 provinces of China are taken as the basic research units in 2001–2016 (considering data compilation, Tibet, Taiwan, Hong Kong, and Macao are not included within the scope of the analysis). The study employs a geographical divide of eastern–central–western and northeast provinces, which is based on the social and economic growth status according to the National Bureau of Statistics of China. Many studies adopt such divide, such as Yuan et al. (2009), Tu and Liu (2011), and Wang et al. (2016). Specifically, eastern province covers ten provinces, including Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. Central province contains nine provinces, including Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan. Western province consists of 12 provinces, including Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Xizang, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. And Liaoning, Jilin, and Heilongjiang comprise the northeast region. On the comparison of the nation and four economic provinces, the paper tests the factors affecting TFEE.

To apply the theoretical model described above, we used panel data for the period from 2001 to 2016. In terms of input and output vectors, there were three types of production input: capital, labor, and energy. GDP was referred to as a desirable output and pollutant emissions were undesirable outputs.

(1) Capital. According to the method for estimating the capital stock proposed by Shan (2008), we deflated the monetary indicators to a constant price in 2000 and took a 9.6% depreciation rate into account.

Table 2 Descriptive statistics for sample input and output variables (from 2001 to 2016)

Variables	Capital (1 billion CNY)	Labor (million workers)	Energy consumption (million coal equivalent)	GDP (1 billion CNY)	CO_2 emission (million tons)	SO_2 emission (million tons)
Max	11,722.19	67.26	387.23	6349.01	904.55	2.00
Min	74.52	2.28	5.20	29.27	11.52	0.02
Mean	2233.28	25.15	105.86	1071.39	227.26	0.70
Std.	2224.20	16.77	71.49	1078.38	163.37	0.44

The panel data is a time series for 30 provinces of China over 15 years, with a total of 480 samples. The data were obtained in accordance with the corresponding year's "China Statistical Yearbook," "China Energy Statistical Yearbook," and the statistical yearbook of each province

Capital was calculated as follows:

$$K_{i,t} = I_{i,t} + (1-\varphi_{i,t})K_{i,t-1} \tag{3}$$

The variable $K_{i,t}$ represents the capital of province i and year t; $I_{i,t}$ represents the investment in the ith province and tth year; and $\varphi_{i,t}$ represents the depreciation rate in the ith province and tth year.

(2) Labor. When measuring the input of labor, quality and time are important factors. Because of the availability of data, we continued the method used in most studies, where the number of current employees is used as the indicator of labor in each province.

(3) Energy. As a result of the different types of energy consumption in different provinces, energy input was measured as the four major primary energy sources of coal, coke, oil, and natural gas. The data was obtained from energy balance tables across provinces in the National Bureau of Statistics of China. The four types of energy were converted into coal equivalent and summed.

(4) Desirable output. The annual GDP of each province was presented as a desirable output. The figure used was the actual GDP calculated in constant prices for 2000. The original data were obtained from the National Bureau of Statistics of China (2001–2016).

(5) Undesirable output. This study focused on the impact of energy consumption on the environment. Since 2000, fossil fuel energy generation has accounted for more than 90% of Chinese energy consumption, with CO_2 and SO_2 being the main gaseous pollutants emitted from fossil fuel consumption. Based on the research focus and the availability of data, we used CO_2 and SO_2 emissions as the energy constraint indicators. Data for SO_2 emissions were obtained from the "China statistical Yearbook", while data for CO_2 emissions could not be obtained directly. We applied the method used to calculate CO_2 emissions in the "IPCC National Greenhouse Gas Emission Inventory Guidebook 2006".[1] Based on the energy consumption of three major

consumers of coal, oil, and natural gas, we estimated the CO_2 emissions during 2001–2016 using the low calorific value, the proportion of carbon oxides in emissions, and the carbon emission coefficients of each fossil fuel. The low calorific value was obtained from the National Bureau of Statistics of China (2006), and the carbon content and the rate of oxidation was obtained from the IPCC (2006). The characteristics of the data for inputs and outputs are shown in Table 2.

Discussion

We calculated the total energy efficiency of 30 provinces that were divided into four economic regions of China from 2001 to 2016, and the results are presented in Table 3. The following results were obtained. (1) The TFEE score for Beijing in 2016 was 1.75, which was the highest score obtained in the study. Guangdong was the second highest with a TFEE score of 1.17 in 2016. (2) After 2011, the TFEE scores for Beijing, Tianjin, and Shanghai were similar and were all over 0.9. The scores for some other provinces, including Liaoning, Jilin, Jiangsu, Zhejiang, Guangdong, and Inner-Mongolia, were also similar and were all over 0.8. (3) The TFEE scores of Liaoning, Jilin, Zhejiang, Guangdong, Guangxi, and Inner Mongolia displayed a U-shaped trend, with the scores in the remaining provinces generally increasing from 0.5 to 0.75. (4) The mean TFEE score of the nation displayed an upward trend after 2002, apart from a slight decline in 2009.

Figure 2 shows the mean TFEE scores of 30 provinces from 2001 to 2016. The mean TFEE score of Beijing and Shanghai were higher than the values for the other provinces, with scores over 0.85. The TFEE score of Gansu was the lowest of all provinces, with a mean score of 0.57. The mean TFEE scores of 11 provinces (Liaoning, Jilin, Heilongjiang, Hebei, Jiangsu, Zhejiang, Guangdong, Shanxi, Inner Mongolia, Ningxia, and Xinjiang) were between 0.7 and 0.8, while the scores of the remaining provinces were below 0.6.

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[1] IPCC guidelines for national greenhouse gas inventories. 2006. IGS, Japan: the National Greenhouse Gas Inventories Programmer.

Table 3 TFEE scores for 30 provinces in China (from 2001 to 2016)

| Province	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Liaoning	0.96	0.84	0.71	0.67	0.68	0.7	0.71	0.74	0.75	0.78	0.81	0.82	0.82	0.82	0.84	0.85
Jilin	0.72	0.65	0.63	0.64	0.65	0.66	0.68	0.71	0.72	0.75	0.77	0.78	0.78	0.79	0.78	0.79
Heilongjiang	0.63	0.63	0.65	0.66	0.66	0.67	0.68	0.69	0.7	0.72	0.74	0.74	0.74	0.74	0.75	0.75
Beijing	0.75	0.76	0.77	0.76	0.77	0.78	0.82	0.84	0.86	0.89	0.89	0.91	0.93	0.95	0.97	1.75
Tianjin	0.7	0.71	0.73	0.74	0.76	0.77	0.78	0.82	0.84	0.87	0.91	0.91	0.93	0.95	0.95	0.77
Hebei	0.61	0.62	0.64	0.65	0.66	0.67	0.69	0.7	0.71	0.72	0.74	0.74	0.74	0.75	0.75	0.75
Shanghai	0.79	0.8	0.8	0.82	0.84	0.85	0.86	0.89	0.9	0.93	0.96	0.95	0.91	0.93	0.95	0.71
Jiangsu	0.57	0.58	0.61	0.63	0.67	0.68	0.71	0.73	0.75	0.78	0.82	0.82	0.84	0.86	0.88	0.91
Zhejiang	1.16	0.89	0.8	0.66	0.67	0.69	0.7	0.72	0.73	0.75	0.78	0.78	0.79	0.81	0.82	0.8
Fujian	0.56	0.58	0.6	0.61	0.64	0.65	0.67	0.69	0.7	0.73	0.74	0.74	0.76	0.77	0.77	0.79
Shandong	0.5	0.52	0.53	0.56	0.63	0.64	0.66	0.68	0.69	0.71	0.74	0.74	0.76	0.77	0.78	0.75
Guangdong	0.72	0.69	0.7	0.66	0.65	0.67	0.71	0.94	0.72	0.75	0.81	0.77	0.79	0.8	0.82	1.17
Hainan	0.59	0.6	0.61	0.62	0.63	0.64	0.66	0.63	0.64	0.66	0.69	0.69	0.69	0.7	0.71	0.72
Shanxi	0.65	0.66	0.66	0.67	0.68	0.68	0.7	0.72	0.72	0.74	0.76	0.75	0.75	0.75	0.75	0.78
Anhui	0.46	0.48	0.49	0.5	0.52	0.53	0.55	0.57	0.58	0.6	0.63	0.63	0.64	0.65	0.66	0.67
Jiangxi	0.6	0.47	0.5	0.52	0.54	0.55	0.57	0.59	0.6	0.63	0.65	0.66	0.67	0.69	0.7	0.8
Henan	0.48	0.5	0.53	0.56	0.58	0.6	0.62	0.63	0.64	0.66	0.67	0.67	0.67	0.68	0.68	0.69
Hubei	0.51	0.53	0.55	0.58	0.59	0.61	0.63	0.64	0.66	0.68	0.71	0.77	0.72	0.74	0.75	0.77
Hunan	0.51	0.52	0.54	0.56	0.57	0.58	0.6	0.63	0.64	0.67	0.69	0.69	0.7	0.71	0.73	0.74
Inner-Mongolia	1.08	0.69	0.69	0.69	0.71	0.72	0.75	0.79	0.8	0.83	0.86	0.85	0.85	0.84	0.85	0.79
Guangxi	0.7	0.6	0.47	0.49	0.51	0.53	0.55	0.58	0.59	0.61	0.64	0.66	0.67	0.68	0.69	0.7
Chongqing	0.5	0.53	0.56	0.57	0.59	0.6	0.63	0.65	0.66	0.69	0.72	0.72	0.74	0.76	0.77	0.71
Sichuan	0.45	0.47	0.49	0.52	0.54	0.56	0.58	0.6	0.62	0.64	0.67	0.67	0.69	0.69	0.7	0.98
Guizhou	0.52	0.52	0.54	0.55	0.58	0.59	0.6	0.61	0.62	0.64	0.66	0.67	0.68	0.69	0.7	0.71
Yunnan	0.49	0.51	0.52	0.55	0.56	0.58	0.59	0.6	0.61	0.62	0.64	0.65	0.65	0.66	0.67	0.84
Shanxi	0.51	0.52	0.54	0.57	0.59	0.61	0.63	0.66	0.67	0.69	0.72	0.73	0.75	0.77	0.77	0.99
Gansu	0.53	0.53	0.54	0.56	0.59	0.6	0.61	0.62	0.62	0.64	0.66	0.67	0.68	0.68	0.68	0.69
Qinghai	0.59	0.6	0.61	0.63	0.65	0.66	0.67	0.69	0.7	0.71	0.74	0.74	0.75	0.76	0.77	0.8
Ningxia	0.64	0.64	0.65	0.66	0.67	0.67	0.69	0.71	0.71	0.73	0.76	0.76	0.77	0.77	0.78	0.78
Xinjiang	0.65	0.66	0.67	0.68	0.68	0.69	0.7	0.72	0.72	0.75	0.77	0.77	0.77	0.78	0.77	0.67
Mean	0.63	0.61	0.61	0.62	0.64	0.65	0.67	0.69	0.7	0.72	0.74	0.75	0.75	0.77	0.77	0.79

Figure 3 shows the results of the mean TFEE scores of the four regions of China. In this figure, it can be seen that (1) compared to the central and western regions, the TFEE scores in the eastern region, except for Fujian, were evenly distributed around 0.66–0.85, (2) the provinces in the western region, except Inner Mongolia, had similar scores, and (3) Liaoning had the highest TFEE score in the northeast region, and Shanxi had the highest TFEE score in the central region.

Table 4 shows the results of the MLPI for 30 provinces during three periods. (1) In half of the 30 provinces, there was low productivity, with the MLPI score being less than 1 during 2001–2005, while the MLPI scores in these provinces were all above 1 during 2005–2010 and 2010–2015. After 2005, almost all the provinces had

high MLPI scores apart from Guangxi and Henan. (2) The mean MLPI score for the whole nation increased by 23.15% during 2005–2010 but had reduced back to 1.13 during 2010–2015, which was mainly due to TC (with an increase of 25.39% and a decline of 8.24%). In contrast, the score for EC displayed a trend to decline and then to rise.

The mean MLPI and its decomposition in the four regions of China during different periods, and a comparison of the results are presented in Fig. 4. The fluctuating trends of MLPI and its decompositions were generally similar between the whole nation and the different regions during the study periods. The productivity in the western region was higher than in other regions during 2005–2010, which was mainly due to changes in technical efficiency. The

Fig. 2 The mean total factor energy efficiency (TFEE) score for 30 provinces
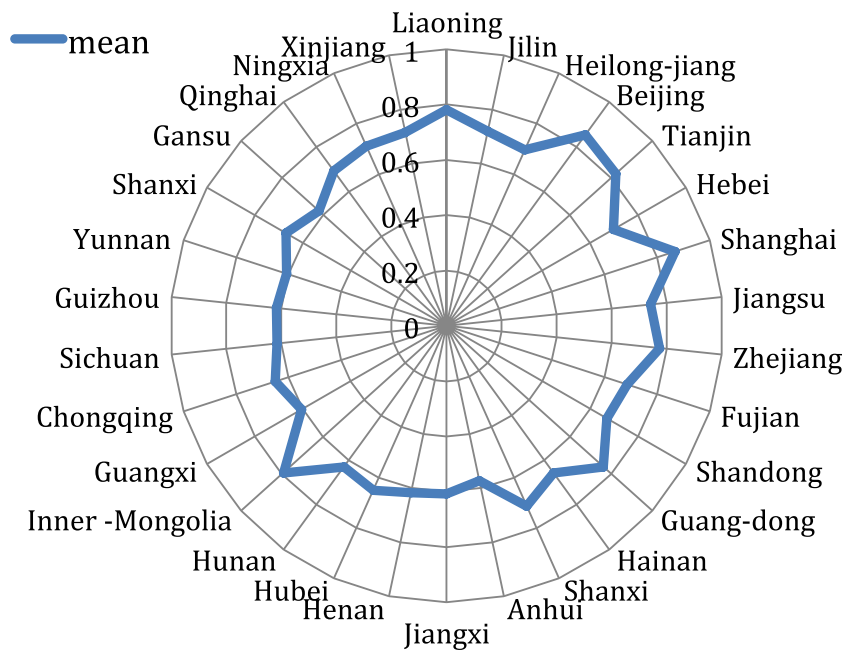
productivity in the northeast region had the lowest score due to the decline in technical efficiency. Technological change led to analogous changes in productivity in both the eastern region and the whole nation.
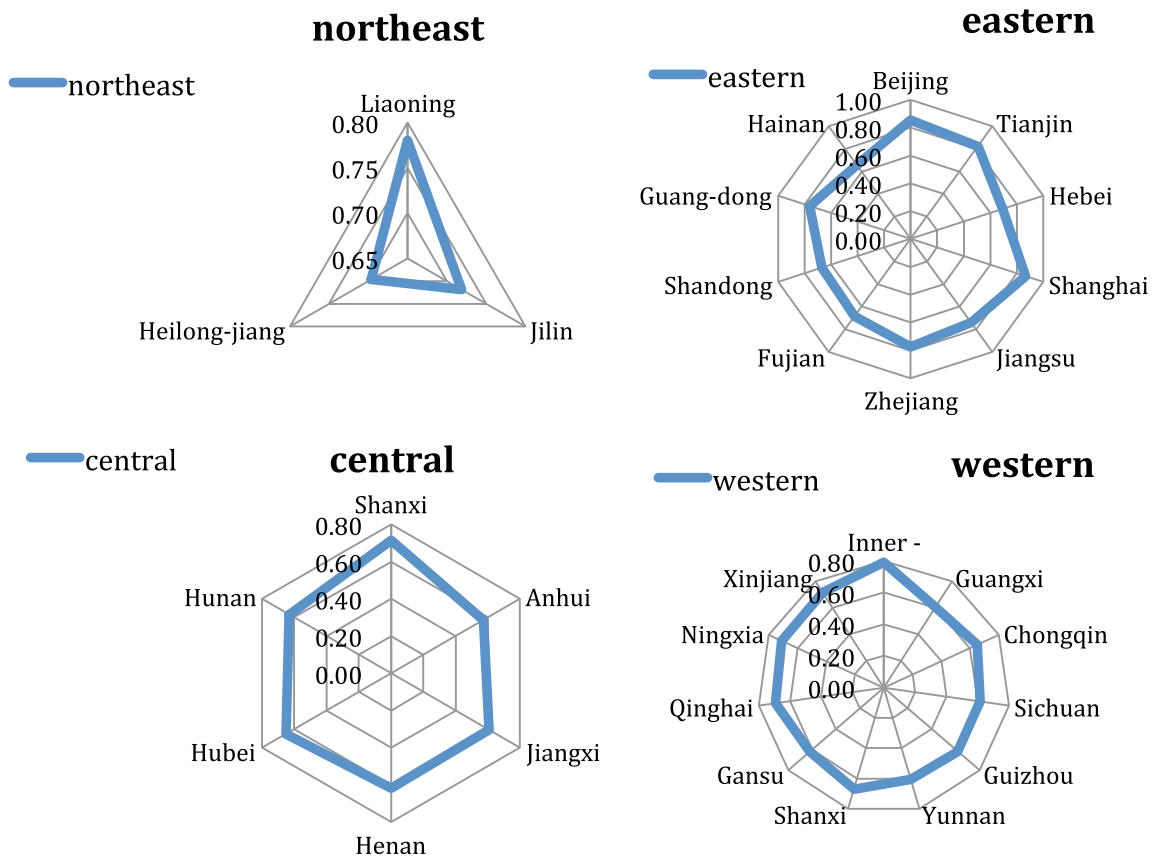
Fig. 3 Comparison of the mean total factor energy efficiency (TFEE) score in China's four regions

Table 4 Malmquist-Luenberger productivity index (MLPI) scores and their decomposition in different periods

Region	Province	2001–2005			2005–2010			2010–2016		
		M-L	EC	TC	M-L	EC	TC	M-L	EC	TC
Northeast	Liaoning	0.7441	0.8659	0.8594	1.1264	0.9250	1.2177	1.0422	0.9928	1.0498
	Jilin	0.7920	0.9293	0.8523	1.1596	0.9852	1.1771	1.0887	1.0250	1.0622
	Heilongjiang	0.9417	0.9944	0.9470	1.0527	0.8704	1.2094	1.0670	1.0171	1.0491
Eastern	Beijing	1.0591	1.0000	1.0591	1.1201	1.0000	1.1201	1.0641	1.0000	1.0641
	Tianjin	1.1742	1.1009	1.0665	1.1057	0.9601	1.1516	1.1024	1.0526	1.0473
	Hebei	1.1066	1.1014	1.0048	1.1246	0.9380	1.1990	1.0615	1.0108	1.0501
	Shanghai	1.1529	1.0000	1.1529	1.0681	1.0000	1.0681	1.0335	0.9927	1.0411
	Jiangsu	1.1579	1.0912	1.0611	1.2252	1.0053	1.2186	1.1803	1.0709	1.1021
	Zhejiang	0.8030	0.9406	0.8537	1.1329	0.9846	1.1505	1.1059	0.8989	1.2303
	Fujian	0.8189	0.7770	1.0539	1.2481	0.9770	1.2774	1.2103	1.0360	1.1682
	Shandong	1.0545	1.0219	1.0319	1.3770	0.9751	1.4122	1.1435	1.0673	1.0714
	Guangdong	0.9098	1.0000	0.9098	1.0407	1.0000	1.0407	1.0899	1.0000	1.0899
	Hainan	0.9499	1.0000	0.9499	1.0598	0.6801	1.5583	1.2818	1.0385	1.2343
The Central	Shanxi	1.0004	1.0943	0.9142	1.0814	0.9226	1.1721	1.0385	0.9963	1.0424
	Anhui	0.7862	0.9957	0.7896	1.1796	0.8987	1.3126	1.2013	0.9976	1.2042
	Jiangxi	0.6931	0.8155	0.8500	1.1465	0.9564	1.1987	1.2737	1.0594	1.2022
	Henan	0.9008	1.1329	0.7951	0.8569	0.7732	1.1083	1.1068	1.0497	1.0545
	Hubei	1.2023	1.1588	1.0376	1.4312	1.1254	1.2717	1.1907	1.1035	1.0791
	Hunan	0.9512	1.2632	0.7531	1.2099	1.0204	1.1856	0.8849	0.7867	1.1248
Western	Inner-Mongolia	0.6978	0.8255	0.8453	1.2081	1.0431	1.1582	1.0370	0.9824	1.0557
	Guangxi	0.7054	0.9080	0.7770	0.8618	0.7312	1.1787	1.2199	1.1442	1.0662
	Chongqing	0.8502	0.9487	0.8962	1.3508	1.0670	1.2660	1.2591	1.1286	1.1157
	Sichuan	0.8778	0.9965	0.8809	1.2521	1.0949	1.1435	1.1954	1.0327	1.1575
	Guizhou	0.9715	1.1230	0.8652	1.2997	1.1455	1.1346	1.1896	1.1407	1.0429
	Yunnan	0.6931	0.7967	0.8700	1.1093	0.9961	1.1137	1.1582	1.1086	1.0448
	Shanxi	1.0758	1.1366	0.9465	1.2804	1.0794	1.1862	1.1717	1.1099	1.0557
	Gansu	1.0203	1.1787	0.8656	1.2023	1.0328	1.1641	1.1339	1.0892	1.0411
	Qinghai	1.2148	1.1810	1.0286	1.1939	1.1286	1.0579	1.1194	1.0802	1.0363
	Ningxia	1.0486	1.0228	1.0252	1.2112	1.1405	1.0620	1.0978	1.0569	1.0388
	Xinjiang	0.9649	0.9322	1.0351	1.1603	1.0750	1.0793	1.0455	1.0052	1.0402
Nation	Mean	0.9440	1.0111	0.9326	1.1625	0.9844	1.1865	1.1265	1.0358	1.0887

Quantitative analysis of the factors affecting TFEE

The results presented above demonstrate the variation of total energy efficiency in each province. The factors affecting TFEE were then investigated to clarify the internal mechanisms of economic development, environmental pollution, and energy consumption.

Variable description and modeling

Most researchers have applied the structure decomposition method to analyze the effects of economic structure and technical progress on total energy efficiency. Yuan et al. (2009) emphasized the impact of economic structure (comprising industrial structure and industrial internal structure) on energy efficiency. Zhang and Wu (2011) focused on the factors affecting the efficiency of CO_2 emission reduction in China and found that after economic development and industrial structure, energy structure and CO_2 emission intensity were of most importance. Wang and Ji (2014) considered a more comprehensive range of factors, including government, markets, technology, and development, although they neglected the impact of undesirable outputs. Huang and Shi (2015) and Ma et al. (2017) reported that the technical level was the essential factor for determining energy efficiency.
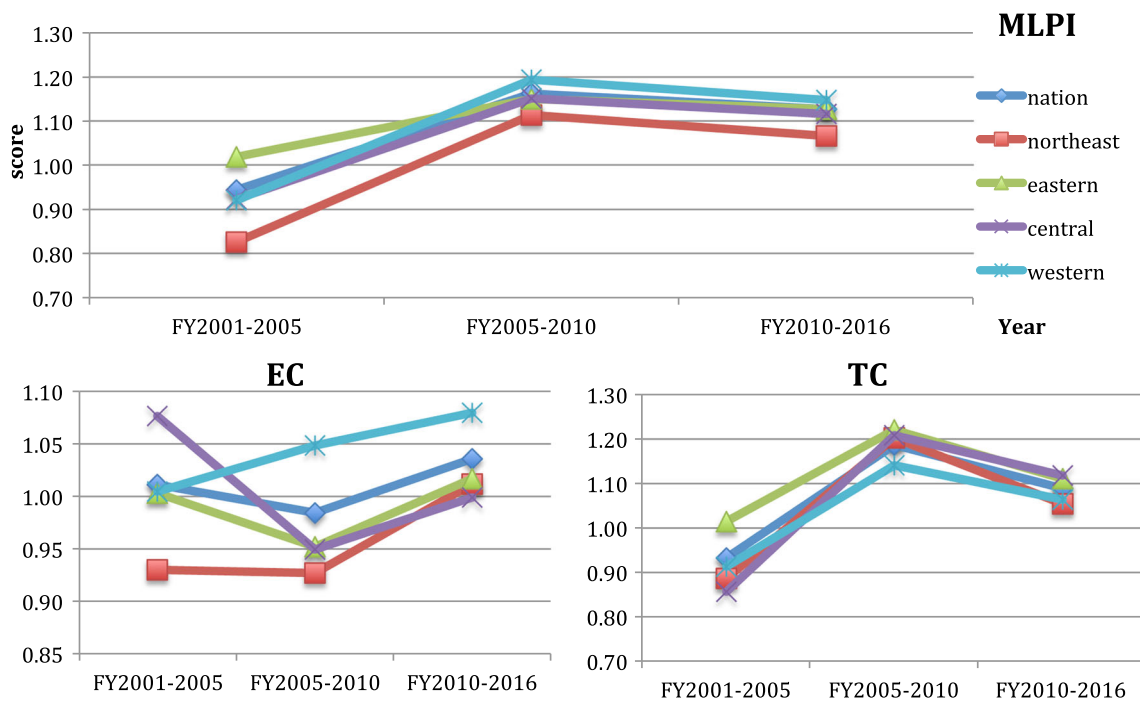
Fig. 4 A comparison of Malmquist-Luenberger productivity index (MLPI) scores and their decomposition among different regions in different periods

Methods based on economic structure can account for the perspectives of micro industries, but factors of energy consumption itself and factors associated with pollution are not considered.

Hence factors influencing TFEE can be divided into economic factors, technology factors, government factors, and energy factors. These factors and variables are described in Table 5.

Table 5 The description of factors and variables

Factors	Name of variables	Definition of variables	Average of variables
Economic factors	Logarithm of GDP per capita (Ln (PG))	Logarithm of the ratio of GDP to population (thousand Yuan per capita). Economic development and energy efficiency are highly relevant; level of economic activity differs in each province.	2.96
	(Ln ^{2}(PG))	Logarithm of the ratio of GDP to population (thousand Yuan per capita).	9.30
	Secondary industry share (IS)	The share of secondary industry in GDP (%).	46.54
	Capital-labor ratio (CL)	The ratio of capital to labor (¥10,000 per capita). Capital, labor, and energy are basic factors of production; production endowment of provinces also determines the discrepancy in energy efficiency.	9.76
Technology factors	R&D expenditure input intensity (RD)	The share of research and development (R&D) in GDP (%). The scale and intensity of R&D activities reflect the scientific and technological strength and core competitiveness.	1.30
	Foreign direct investment share (FDI)	The share of FDI in GDP (%). FDI reflects the external technology absorbed and introduced in provinces to analyze the impact of technological progress on energy efficiency.	29.09
Government factor	Investment share of environmental protection (IEP)	The share of investment in environmental protection in GDP (%). IEP reflects the influence of government on economic society.	0.94
Energy factors	Energy consumption per capita (PE)	The ratio of energy consumption to population (10,000 tons per capita). Energy here is consistent with the foresaid, mainly refers to primary energy.	2.57
	Proportion of coal consumption (CE)	The proportion of coal consumption in total energy consumption (%).	67.03
	Energy endowment ratio (EER)	The ratio of energy production to consumption, representing the resource endowment of provinces.	0.84

Based on the variables described, we constructed the regression equation as follows:

$$EE_{i,t} = c + \beta_1 Ln(PG_{i,t}) + \beta_2 Ln^2(PG_{i,t}) + \beta_3 IS_{i,t} + \beta_4 CL_{i,t} + \beta_5 RD_{i,t} + \beta_6 FDI_{i,t} + \beta_7 IEP_{i,t} + \beta_8 CE_{i,t} + \beta_9 EER_{i,t} + \varepsilon_{i,t} \quad (4)$$

The value of c is a constant; the subscripts i and t represent the year and province, respectively; $EE_{i,t}$ represents the total energy efficiency of different provinces over time; β_i is an estimated parameter; $\varepsilon_{i,t}$ is a random error term, obeying a normal distribution. To reduce the impact of hetero-scedasticity and serial correlation in the error term, a feasible GLS model was applied for parameter estimation. According to the Hausman test results of a regression for the nation, the value of P was much less than 0.05, and we therefore adopted the fixed effects model to achieve the regression results. Considering that the random effects estimation required more cross sections than coefs for determining between estimators when estimating the RE innovation variance, we performed a likelihood ratio test for the estimation of fixed effects in the northeast and central regions.

Regression analysis

The regression results of the influential factors for the nation and four economic provinces are presented in Table 6.

The value of the F-statistic in each regression indicated that the dependent variable could be explained better by the independent variables.

(1) Economic factors. The relations between PG and TFEE were linear, U-type, or an inverted U-type. This result is contrary to that of most previous studies, but is consistent

with the conclusion of Yao et al. (2015). The national TFEE and economic growth had an inverted U-shaped relation and did not reach the inflection point. With rapid economic development and a higher PG, the relation between economic growth and energy efficiency was U-shaped. In contrast, PG in the central and western regions was relatively lower and the relation was linear.

The IS factor had a negative influence on the TFEE. This was consistent with the findings of most previous studies (Wang et al. 2010; Wang and Ji 2014; Ma et al. 2017). There are many energy-intensive industries within the secondary industry category. As an old industrial base, the northeast has a relatively low level of industrialization, and most of the investment made in the region has been inefficient. There is a need for a transformation of the economic base and for structural reforms in the region. The CL factor had a significant negative influence on the TFEE score in the western region. This suggests that the unbalanced allocation of basic production factors has hindered the TFEE of the western region.

(2) Technology factors and government factor. The RD factor and the TFEE score of the nation and eastern region were positively correlated, while RD had a negative influence on the TFEE score of the northeast region. This indicates that an increase in the intensity of R&D can provide strong financial support for further R&D activities, strengthening the potential for regional innovation and promoting economic development. With a relatively mature market economy and technical level, the TFEE score of the eastern region indicated that it is performing efficiently. In contrast, the TFEE score of the central and western regions indicated inefficiency due to the low

Table 6 Results of a regression exercise with efficiency score as the dependent variable

Regressor	Nation	Northeast	Eastern	Central	Western
C	0.406743***	0.575023**	0.527070***	0.494037***	0.596774
Ln (PG)	0.103295***	0.440799*	−0.107662	0.000229	0.031229
Ln^2 (PG)	−0.001423	−0.059080	0.039735	0.028586***	0.018917*
IS	−0.018340	−0.166721*	−0.021909	−0.038460	−0.098308
CL	−0.000866	−0.000843	0.001037	−0.002649	−0.003028***
RD	0.040695***	−0.170677***	0.050301***	−0.038068*	−0.030119
FDI	−0.014369	−0.008580	−0.015781	−0.057506**	0.034426
IEP	−0.913413**	−3.408286***	−1.064852	0.003034	−0.448282
CE	−0.074669**	−0.458771**	0.005722	0.053270*	−0.089221
EER	0.019974**	0.026163	−0.074368**	−0.028800***	−0.001439
R-squared	0.890092	0.910588	0.832864	0.958454	0.785993
F-statistic	101.69815	120.55242	39.03476	133.4740	30.15519
Hausman Test	43.236694	–	54.370823	–	39.257546
Likelihood ratio		13.838121	–	14.268677	–

***, **, * indicate that the coefficient of variables was significant at the 1, 5, and 10% level, respectively

technical levels and lack of a basic independent research capability. This result was similar to that of Huang and Shi (2015). The FDI factor and the TFEE score were negatively correlated, except in the western region, which was inconsistent with the results of Wang and Ji (2014). The economists Crossman and Kruger (1995) reported that the liberalization of trade and investment would inevitably expand market and economic activities and would unavoidably lead to more resource consumption and environmental pollution. FDI brings urgently needed development capital, production technology, and management experience, but industrial pollution then follows. The IEP factor had a significant negative effect on the TFEE of both the nation and the northeast region. The probable reason for this was the defective market mechanism, which resulted in a low conversion rate in investment in environmental protection.

(3) Energy factors. The influence of the CE factor was generally negative. The greater the proportion of coal used for energy generation, the lower the TFEE score. Coal is a typical low-efficiency energy source with a low utilization rate, and its use therefore represents a serious waste of resources. Large amounts of greenhouse gases are produced during coal combustion, which has a negative influence on the ecological environment. Wei and Shen (2007) used the proportion of net electricity generated by various sources as the energy structure and obtained the opposite conclusion; thus, we confirmed their conclusions from the opposite perspective. The EER factor had a positive influence on the national TFEE, while the EER factor and TFEE score of the central region had a negative correlation. The regions with a relatively high energy-self-sufficiency rate had a lower TFEE score, which was in accordance with the actual situation observed during China's economic development and also concurred with the conclusion of Yuan et al. (2009). The central region has rich reserves of coal, most of which have been exported to other regions. Therefore, the high energy-self-sufficiency rate was responsible for the low energy efficiency.

Conclusions

Considering the undesirable output, based on a super-efficiency DDF, we used an input-oriented CRS-DEA model to estimate the provincial TFEE for the period of 2001–2016. Then we measured the MLPI and its decomposition (EC and TC) for the whole nation and four economic regions during the study period. Finally, a generalized least square (GLS) model was applied to determine the factors influencing TFEE. We obtained the following conclusions.

(1) The mean TFEE score of the nation displayed an upward trend after 2002, apart from a slight decline in 2009. Compared with the central and western regions, the TFEE scores in the eastern region were evenly distributed in 0.66–0.85, except for Fujian. With the exception of Inner Mongolia, the provinces in the western region had similar efficiencies. Liaoning had the highest TFEE score in the northeast region and Shanxi had the highest score in the central region.

(2) The mean MLPI score for the whole nation increased by 23.15% during 2005–2010 but fell back to 1.13 during 2010–2015, with the largest contribution from TC. In contrast, the EC score initially declined and then rose. The productivity in the western region was higher than in other regions during 2005–2010, which was mainly due to changes in technical efficiency. The productivity was lowest in the northeast region due to the decline in technical efficiency. Technological changes led to analogous productivity changes in both the eastern region and the whole nation.

(3) The regression results showed that, the dependent variable could be explained by independent variables for the whole nation and the four regions. The relations between PG and TFEE were linear, U-type, or inverted U-type. The IS and CL factors both had negative influences. The influence of RD on TFEE for the nation and eastern region were clearly positive, whereas the effect was negative in the northeast. The IEP and CE factors were negatively correlated with TFEE for the nation and northeast region, while EER had a significant negative impact in the eastern and central regions.

From these conclusions, the following policy implications can be offered.

(1) It is evident that technological progress has reduced pollutant emissions and played a more significant role in the improvement of TFEE than technical efficiency. This suggests that the implementation of environmental technology is approaching its optimal level; hence, the intensification of energy usage should be possible. In contrast, there is much potential for environmental efficiency to be improved. Currently, the best way to enhance TFEE would be to rapidly improve the inefficient production capacity and to develop clean and renewable energy.

(2) Compared to developed countries, the PG of China was relatively low, with the level of economic development varying among the regions. Considering the environmental constraints, the relation between energy efficiency and economic growth should be addressed according to the actual conditions. In the

eastern region, where the PG was higher, there is a need to rationally control the scale of energy inputs and to promote intensive economic growth through energy conservation and a resetting of the factors influencing energy efficiency. In the central and western regions, where economic conditions are less well developed, it is necessary to speed up the transformation of economic growth, readjust the industrial structure, raise the rate of energy and resource use, and increase economic efficiency. There is a need to focus on the energy efficiency of heavy industry, while optimizing and upgrading the industrial structure. This is considered the most effective strategy for realizing high TFEE scores and accelerating the adjustment of secondary industry to tertiary industry.

(3) Technical innovation and R&D in energy conservation should be further strengthened. The eastern region should take advantage of its location and accumulation of technology to introduce advanced green technology, and then improve the technical market environment. Through industrial transfer and cooperative energy projects, the transfer of advanced technologies to the central and western regions could be promoted, which would enable them to enhance their energy efficiency. Foreign investment policy and environmental policy should be formulated and adjusted to coordinate the conflicts among foreign investment, environmental pollution, and economic growth.

(4) The northeast province used to be an industrial base. It has a relatively lower level of industrialization and a smaller industrial economy than the other provinces. Hence, the primary task for the northeast is to speed up its economic transformation and upgrade traditional industries. The structure of the economy and energy generation could also be adjusted through the implementation of internal institutional innovation.

The central and western regions have a large energy endowment, but their energy efficiency is fairly low. The central region is dominated by traditional industries, with high-energy consumption, high levels of pollution, and a lack of technical resources. There is a need to optimize the industrial structure, designate cleaner production standards, and transform the economy to embrace green production in the central region. In the western and central regions, there is a need to undertake technological and industrial transfer and to prevent the excessive and inefficient exploitation of resources. In the western region there is a need to increase foreign exchange and create a favorable investment environment to promote economic development.

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