



Analysis of the total factor energy efficiency and its influencing factors of the Belt and Road key regions in China

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Abstract

Energy cooperation has been emphasized strongly in the Belt and Road (B&R) initiative. Therefore, the energy efficiency of China has attracted much attention from experts. However, relevant studies are still insufficient. This paper analyzes the total factor energy efficiency (TFEE) and its influencing factors of 17 B&R key regions from 2005 to 2015. We use the ratio of target energy input and actual energy input to calculate the regional TFEE under environmental constraints. The Malmquist index and the Tobit model are applied to investigate the internal and external influences of TFEE. Measurement analysis shows that the TFEE of the B&R key regions has not improved in recent years and it is unbalanced during the study period. Regions in the east area have the highest TFEE; regions in the west area have the second high TFEE; and regions in the north area have the lowest TFEE. Regression analysis shows that for the B&R key regions, technical changes, coal consumption, research and development, and environmental pollution have mainly negative effects on TFEE; pure efficiency changes, scale efficiency changes, economic structure, opening up, and government finance have mainly positive effects on TFEE. Finally, precise policy implications are proposed.

Keywords The Belt and Road · Total factor energy efficiency · Malmquist · Tobit model · Influencing factors

Introduction

Along with the progress of industrialization and urbanization, the situation of energy, economy, and environment of China will be more severe. Although the growth rate of China's energy consumption has been slowed down, China has the world's largest energy consumption and CO₂ emission. In 2017, China accounted 23.2% of the global primary energy consumption and 33.6% of global energy consumption growth (BP 2018). However, such a large amount of energy consumption did not bring the relevant economic growth. In 2017, the growth of the gross domestic production (GDP) of China is 6.9% (NBSC 2018). Compared to the economic growth, the problems of the carbon emission and environmental pollution caused by large amount of energy consumption are much serious. America and Japan consumed 16.5% and

3.4% of the global primary energy consumption in 2017, while they only had the 15.2% and 3.5% of the global CO₂ emission (BP 2018). This means that China lags behind the developed countries in energy input and output. Various reasons may result in these facts, such as the large amount of population, overcapacity, and economic and energy consumption restructuring. How to coordinate the development of economy, energy, and environment is a top priority in the process of the B&R initiative and “New normal economy¹”. Therefore, some major plans and initiatives are proposed by Chinese government to convert the problems of energy, environment, and economy.

The Belt and Road (B&R)² is multilateral cooperation mechanism which was initiated by China in 2015. The B&R initiative regards the energy cooperation among countries and

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¹ The new normal economy is a new economic pattern and economic development model different from the previous one which is guided by GDP. In the new normal economy, the price mechanism is replaced by value mechanism to emphasize the all-round social progress. Besides, the goal of reform and opening up is oriented towards a socialist market economy with sustainable development rather than an unsustainable growth of capitalist market economy (Chen 2015).

² The Belt and Road is the abbreviation of “Silk Road Economic Zone” and “the 21st century Maritime Silk Road”.

regions in Asia, Europe, and Africa as a development goal. It plans to improve the regional energy security, optimize the energy and resources allocation, and promote sustainable energy development. Finally, the growing demand of energy consumption will be satisfied and the economic growth and social progress will be promoted. There are 18 key provinces, autonomous regions, and municipalities³ within the Chinese territory involved in this initiative: Xinjiang, Shaanxi, Gansu, Ningxia, Qinghai, Inner Mongolia, Heilongjiang, Jilin, Liaoning, Guangxi, Yunnan, Shanghai, Fujian, Guangdong, Zhejiang, Hainan, Chongqing, and Tibet.⁴ Each region has its own orientation. For example, Xinjiang was positioned as the core of the “Silk Road Economic Zone.” Fujian was expected to be a key region of the “21st century Maritime Silk Road”.⁵ Unfortunately, there are few studies concerning about the TFEE of the B&R key regions in China. Therefore, paying close attention to the regional energy efficiency of these regions, it will be a solid foundation for B&R initiative implementation. As a result, policymakers can enact more effective regulations for promoting energy efficiency and reducing environmental pollution. According to the geographical location, the B&R key regions can be divided into three areas: the east, north, and west area, as shown in Table 1. This geographical division will be an analysis perspective in this paper. Based on the research objectives of this paper, the major contributions of this paper are as follows: (1) the total factor energy efficiency ratio of B&R key regions is well defined and estimated; (2) three kinds of water pollutions and two kinds of air pollutions are regarded as undesirable outputs and combined into a pollution indicator; (3) the TFEE is analyzed from various perspectives, namely, geographical location, convergence effect, dynamic changes, initiative planning, and influencing factors; (4) 3 internal and 11 external influencing factors are analyzed by Malmquist index and Tobit model; (5) concrete suggestion for improving the TFEE of B&R key regions from different perspectives are proposed in the end.

According to our research goals, this paper is organized as follows. Relative literatures are analyzed in “[Relative literature](#)” section. Then, “[Methodologies](#)” section describes the methodology for this paper. The TFEE of the B&R key regions is measured and analyzed in “[Calculation and analysis](#)” section. The effects of internal and external influences of TFEE are discussed in “[Influencing factors analysis](#)” section. Finally, “[Conclusions and policy implications](#)” section puts forward relevant conclusions and policy implications.

Relative literature

Data envelopment analysis (DEA) models have been increasingly applied in measuring energy efficiency. Researchers chose appropriate DEA models based on their study purposes. Shu et al. (2011) calculated the electricity consumption efficiency of different districts in China with a CCR-DEA⁵ (Charnes et al. 1978). Wang and Ma (2018) analyzed the CO₂ emission efficiency of Jiangsu based on a BCC-DEA (Banker et al. 1984).⁶ Slack-based measure model (SBM model), which can separately deal with the input and output, is widely used to the energy efficiency measurement (Zhang and Choi 2013). Besides, super-efficiency DEA can deal with ranking problem of the decision-making units (DMUs) on the frontier. Chen and Xu (2018) used a super-efficiency directional DEA to measure the energy efficiency of 30 provinces in China based on the environmental constraints. In brief, these researches have revealed the unbalanced and non-improving Chinese regional energy efficiency in recent years. However, the common disadvantage of them is that they had not correctly presented the indicator of TFEE (Li and Li 2018). Most of them have regarded energy input equals to other inputs, thus their result is the total factor productivity rather than total factor energy efficiency. Compared to the above studies, we believe that the ratio of target energy input and actual energy input under environmental performance is more convincing. Hu and Wang (2006) firstly used the CCR-DEA model to construct this real TFEE ratio to measure regional TFEE. Shu et al. (2011), Li and Hu (2012), Lin and Tan (2016), and Li et al. (2018) also applied this ratio to measure real energy efficiency. However, these studies lack of the perspective of international agreement or international organization, especially, the perspective of B&R initiative. Therefore, we applied the CCR-DEA model to obtain the real TFEE with the B&R perspective.

Besides, there are also some literatures about the energy efficiency decomposition and influence factors analysis. The energy efficiency is usually decomposed by the Malmquist index. Lv et al. (2015) analyzed the TFEE of 30 Chinese regions via the Malmquist index. They found that the energy productivity is decreasing in research period. Liu et al. (2015) studied the technical changes, pure technical efficiency changes and scale efficiency changes of the TFEE of western regions in China. Their results reflected that these three internal factors can help to improve the TFEE of western regions. Huang et al. (2017) applied the Malmquist index to find out the driving forces of the China’s energy intensity changes. They concluded that the technological

³ For simplicity, the 18 key provinces, autonomous regions, and municipalities are collectively referred to as “key regions”.

⁴ The national development and reform commission, ministry of foreign affairs and ministry of commerce, The Vision and Action to Promote the Silk Road Economic Belt in the 21st Century Maritime Silk Road. 2015-03-28. <http://finance.people.com.cn/n/2015/0328/c1004-26764666.html>.

⁵ CCR-DEA, input-oriented DEA with constant returns to scale, proposed by Charnes et al. (1978).

⁶ BCC-DEA, input-oriented DEA with variable returns to scale, proposed by Banker et al. (1984).

Table 1 Three areas of B&R key regions

East area (6 regions)		North area (4 regions)	West area (7 regions)	
1 Shanghai	5 Guangxi	7 Inner Mongolia	11 Chongqing	15 Qinghai
2 Zhejiang	6 Hainan	8 Liaoning	12 Yunnan	16 Ningxia
3 Fujian		9 Jilin	13 Shaanxi	17 Xinjiang
4 Guangdong		10 Heilongjiang	14 Gansu	

Tibet is excluded of the analysis for the lack of energy consumption data

progress can decrease the energy intensity in the eastern and central regions. Furthermore, the influence factors of energy efficiency come from various aspects, such as economic development (Chen et al. 2018), industrial structure (Liu and Lin 2018), research and development (R&D) (Wang and Ma 2018), energy price (Guan et al. 2014), coal consumption (Liu et al. 2015), government intervention (Ma et al. 2017), opening up (Wang et al. 2017), production endowment (Wang and Liu 2018), and environmental pollution (Zhang et al. 2017). The regression result of Liu et al. (2015) suggested that the coal consumption has encumbered the TFEE of west regions in China through the Tobit model. By using the Tobit model, Liu and Lin (2018) revealed that the industrial structure has positive effect on energy efficiency. Wang and Ma (2018) found that the R&D does not improve the energy efficiency of Jiangsu province via the Tobit model. These researches offered the reference of the choice of influence factors and regression model in this paper.

Methodologies

After reviewing relative literatures, the CCR-DEA model, the Malmquist index, and the Tobit model are adopted in this paper.

CCR-DEA

DEA is a widely used nonparametric and non-stochastic method that can measure the efficiency of DMUs.⁷ One of the main purposes of this paper is to calculate the real TFEE of the B&R key regions with respect to environmental performance. That is, how to reduce energy input while maintaining the economic output and reducing the undesired output. Therefore, we considered the input-oriented DEA model with constant return to scale (CCR-DEA, Charnes et al. 1978). In this section, the B&R key regions are represented by DMUs. If there are I DMUs, each DMU has input X and output Y . λ is an $I \times 1$ constant vector. θ is a scalar that represents the efficiency of DMUs. The efficiency of the j -th DMU can be solved by Eq. (1) (Farrell 1957). The scope of θ is $[0, 1]$. If $\theta = 1$ means that the j -th DMU is efficient (Coelli et al.

2005). The linear programming of this model is given as follows:

$$\begin{aligned}
 & \min \theta \\
 & s.t. \begin{cases} \sum_{j=1}^N x_{i,j} \lambda_j + s^- = \theta x_{i_0}, i = 1, 2, \dots, K \\ \sum_{j=1}^N y_{h,j} \lambda_j - s^+ = y_{h_0}, h = 1, 2, \dots, M \\ s^- \geq 0, \quad s^+ \geq 0 \\ \lambda_j \geq 0, \quad j = 1, 2, \dots, n-1, n, n+1, \dots, N \end{cases} \quad (1)
 \end{aligned}$$

x and y denote the inputs and outputs, respectively. Each DMU uses K kinds inputs to produce M kinds outputs. s^- is residue vector, and s^+ is the slack vector.

Figure 1 has been drawn to understand the calculation of the ratio of energy efficiency in this paper. E represents energy input. FF' represents the curve of the production frontier. A, B, C, D, A' , and B' are different DMUs. A, B, C , and D are located on the production frontier, which indicates that they are efficient. A' and B' are above the curve, so they consume more input while producing the same unit of output, which means they are inefficient. Moreover, the efficiency of DMU A' and DMU B' is calculated by OA/OA' and OB/OB' , respectively (Farrell 1957). However, A is not optimal for A' ; C has the exact same output as DMU A while it consumes less energy. Therefore, the input loss of DMU A' can be determined by CA' , $CA' = AC + AA'$. Generally, the distance of AA' represents the radial adjustment, which reflects the technology inefficiency. The distance of AC represents the slack adjustment, which reflects the resource allocation inefficiency (Ferrier and Lovell 1990). If there are radial adjustments and slack adjustments,

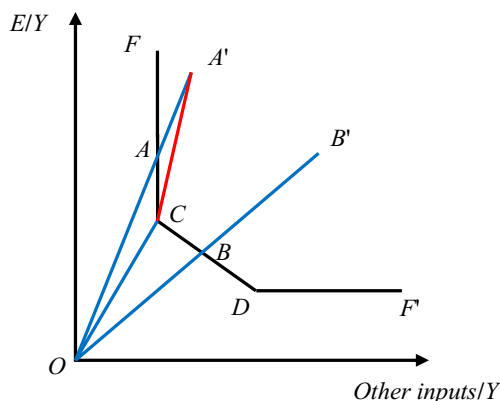


Fig. 1 The input-oriented CCR-DEA model

⁷ Decision-making unit is the object that is evaluated by DEA method.

the TFEE will be lower. According to the above analysis, TFEE can be established as follows (Hu and Wang 2006):

$$TFEE_{i,t} = \frac{\text{Target energy input}_{i,t}}{\text{Actual energy input}_{i,t}} \tag{2}$$

TFEE_{*i, t*} represents the TFEE of the *i* – th region in period *t*. Target energy input represents the optimal energy input. A real TFEE can be reflected by the ratio of the total amount of target energy input devices to the total amount of actual energy input.

According to the theory of CCR-DEA and the TFEE ratio, we believe that the CCR-DEA is more proper for evaluating the real TFEE. The application of CCR-DEA through Software DEAP2.1 can decompose the target energy input easily. However, advanced DEA models and corresponding operational software are too complex to decompose the target energy input. Therefore, we chose CCR-DEA and Software DEAP2.1 as the research method and operation software.

Malmquist index

The Malmquist index was proposed by Malmquist in 1953 and first introduced by Caves et al. (1982a, b). It can reflect the total factor productivity change (TFPCH). An input-oriented distance function is defined as follows: $d(x, y) = \max \{ \theta : (x/\theta, y) \in L \}$. Among the equations, the same meanings are given to *x*, *y*, and θ as in the “CCR-DEA” section, and *F* represents the production set. Suppose the technology of period *t*+1 is a reference technology. According to Färe et al. (1994), the Malmquist productivity index in period *t*+1 can be defined as follows:

$$m^{t+1}(y_{t+1}, y_t, x_{t+1}, x_t) = \left(\frac{d^{t+1}(y_t, x_t)}{d^{t+1}(y_{t+1}, x_{t+1})} \right) \tag{3}$$

Similarly, the input-oriented Malmquist productivity index based on the technology of period *t* can be described as Eq. (4). If DMUS are efficient in period *t* and period *t*+1, the corresponding distance functions are equal to 1. That is, $d^{t+1}(y_{t+1}, x_{t+1}) = 1$ and $d^t(y_t, x_t) = 1$.

$$m^t(y_{t+1}, y_t, x_{t+1}, x_t) = \left(\frac{d^t(y_t, x_t)}{d^t(y_{t+1}, x_{t+1})} \right) \tag{4}$$

Also, Färe et al. (1994) defined the Malmquist productivity index as Eq. (5) based on the geometric averages of the Malmquist productivity index of period *t* and period *t*+1. Thus, the Malmquist productivity index can be rearranged into two parts in Eq. (6): technical changes (Eq. (7)) and efficiency changes (Eq. (8)).

$$m(y_{t+1}, y_t, x_{t+1}, x_t) = [m^{t+1}(y_{t+1}, y_t, x_{t+1}, x_t) \times m^t(y_{t+1}, y_t, x_{t+1}, x_t)]^{1/2} \tag{5}$$

$$m(y_{t+1}, y_t, x_{t+1}, x_t) = \frac{d^{t+1}(y_{t+1}, x_{t+1})}{d^t(y_t, x_t)} \left[\frac{d^t(y_t, x_t)}{d^{t+1}(y_t, x_t)} \times \frac{d^t(y_{t+1}, x_{t+1})}{d^{t+1}(y_{t+1}, x_{t+1})} \right]^{1/2} \tag{6}$$

Technical changes

$$= \left[\frac{d^t(y_t, x_t)}{d^{t+1}(y_t, x_t)} \times \frac{d^t(y_{t+1}, x_{t+1})}{d^{t+1}(y_{t+1}, x_{t+1})} \right]^{1/2} \tag{7}$$

$$\text{Efficiency changes} = \frac{d^{t+1}(y_{t+1}, x_{t+1})}{d^t(y_t, x_t)} \tag{8}$$

Finally, Färe et al. (1994) decomposed the efficiency changes further based on the VRS technology. Pure efficiency changes (Eq. (9)) and scale efficiency changes (Eq. (10)) are divided from efficiency changes by the following mathematical derivation.

$$\text{Pure efficiency changes} = \frac{d_v^{t+1}(y_{t+1}, x_{t+1})}{d_v^t(y_t, x_t)} \tag{9}$$

$$\text{Scale efficiency changes} = \left[\frac{d_v^{t+1}(y_{t+1}, x_{t+1})/d_c^{t+1}(y_{t+1}, x_{t+1})}{d_v^{t+1}(y_t, x_t)/d_c^{t+1}(y_t, x_t)} \times \frac{d_v^t(y_{t+1}, x_{t+1})/d_c^t(y_{t+1}, x_{t+1})}{d_v^t(y_t, x_t)/d_c^t(y_t, x_t)} \right]^{1/2} \tag{10}$$

For simple description, the relationship between technical changes (TECH) and pure efficiency changes (PECH) and scale efficiency changes (SECH) are shown as Eq. (11).

$$m(y_{t+1}, y_t, x_{t+1}, x_t) = \text{TECH} \times \text{PECH} \times \text{SECH} = \text{TFPCH} \tag{11}$$

Tobit Model

Tobit model was proposed by Tobin (1958) for solving the limited or truncated dependent variable regression problem. This model contains two parts. One is a selection equation model which represents the constraint conditions. The other is a continuous variable equation model that satisfies the constraint conditions. Some researchers have been interested in the limited continuous variable equation model when the dependent variable is constrained by some conditions. However, due to the dependent variable constraints, the ignorance of some unmeasurable factors will lead to the selection bias (Zhou and Li 2012).

Due to the TFEE, value in this paper is between 0 and 1, thus the Tobit model is a better option for the regression analysis of TFEE. Ma et al. (2017), Yu (2017), and Chen (2017) applied Tobit model to conduct the regression of TFEE and external influence factors. A traditional Tobit model is as Eq. (12):

$$Y_i^* = x_i\beta + \varepsilon_i, \quad i = 1, 2, \dots, N \quad (12)$$

In Eq. (12), Y_i^* is a latent variable. In our case, we applied a left truncated Tobit model. The dependent variable should satisfy the following constraint:

$$Y_i = \begin{cases} Y_i^*, & \text{if } Y_i^* > 0 \\ C, & \text{if } Y_i^* \leq 0 \end{cases} \quad (13)$$

Due to the TFEE being bigger than 0, the value of dependent variable is defined as $[0, Y_i^*]$. Other values will not be observed so that the loss of calculations can be avoided.

Calculation and analysis

Index selection and data source

Due to the inconsistency of the statistical indicators of pollutants before 2004, the research interval is set as 2005–2015. Our data sources are China Statistical Yearbook (2006–2016), Statistical Yearbook of provinces, autonomous regions and municipalities (2006–2016), China Energy Statistical Yearbook (2006–2016), China Statistical Yearbook of Science and Technology (2006–2016), and China Compendium of Statistics (1949–2009). According to the previous researches, capital stock, labor capital, and energy consumption are regarded as the input indicators. GDP and industrial pollutants represent the economic output and the undesirable outputs, respectively.

- (1) Capital stock. Zhang et al. (2004) pointed out that the earlier the base period, the less calculation error. As a result, the base period is set at 1952. Capital stock can be computed according to Zhang et al. (2004).

$$K_{i,t} = (I_{i,t} - D_{i,t}) / P_{i,t} + K_{i,t-1} \quad (14)$$

In Eq. (14), $I_{i,t}$ is the gross fixed capital formation. $D_{i,t}$ is the depreciation of fixed assets, this variable is referenced from the income approach of GDP.⁸ The depreciation of fixed assets is given by the national accounts from the China Statistic Yearbook. Therefore, compare to a constant depreciation ratio, the $D_{i,t}$ may be more accurate. $P_{i,t}$ is the price index of investment in fixed assets. $K_{i,t-1}$ is the capital stock of the prior

⁸ GDP = compensation of employees + net production tax + depreciation of fixed assets + operating surplus

period (Zhang et al. 2004; Shan 2008). Base-period capital stock was referenced from Shan (2008). After the calculation, the capital stock was transferred into 2005 prices.

- (2) Labor capital. Similar to other researches, the total number of employed persons at year-end was regarded as labor capital.
- (3) Energy input. Similar to other researches, the total energy consumption was taken as energy input.
- (4) Economic output. GDP served as an economic output in this paper. The GDP value was transformed into the 2005 price with a GDP deflator.
- (5) Undesirable output. As byproducts of the productive process, pollutants should also be considered in the TFEE calculation. Therefore, five industrial pollutants had been chosen as undesirable outputs: waste water (WW), chemical oxygen demand (COD), ammonia nitrogen (AN), sulfur dioxide (SO₂), and smoke and dust (SD). Because of the inconsistent dimensions of these five pollutants, the improved entropy method (Yuan et al. 2009) was applied to calculate a comprehensive pollutant index. As the undesirable output, this index should be as small as possible from the environmental protection perspective. Hence, the reciprocal of this index was considered to make the DEA model more meaningful.

The statistical descriptions of the input-output factors are displayed in Table 2. Table 2 shows that there are large gaps of the input-output situations among regions. Zhejiang has the highest but the most fluctuant capital stock. Guangdong has the largest amount of labor force, the highest energy consumption, and the largest GDP. Qinghai has the lowest capital stock, the least labor force, the lowest energy consumption, and the smallest GDP. Xinjiang has the relatively severe industrial pollution. In brief, Zhejiang, Guangdong, Shanghai, Liaoning, and Fujian have the relatively high input-output level. On the contrary, Jilin, Gansu, Hainan, Ningxia, and Qinghai have the relatively low input-output level.

TFEE analysis

The software DEAP 2.1⁹ is used to decompose the target energy input, therefore the TFEE ratio can be calculated. We also calculated the TFEE mean and coefficient of variation (CV)¹⁰ of B&R key regions. The calculation results of the 17 B&R key regions are shown in Table 3.

⁹ DEAP 2.1 is developed by Coelli T. J. in Australia, the University of Queensland. <http://www.uq.edu.au/economics/cepa/deap.php>.

¹⁰ CV is calculated by the ratio of the standard deviation and mean value. The equation is $CV = \frac{\sigma}{\mu}$, σ is the annual standard deviation of an area, μ is the annual mean of an area.

Table 2 The description of input-output factors

Region	Capital		Labor		Energy		GDP		Pollution	
	(100 million RMB in 2005 prices)		(10,000 persons)		(10,000 tons of standard coal equivalence)		(100 million RMB in 2005 prices)		Comprehensive index	
	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD
Inner Mongolia	8424.08	265.40	1228.71	157.55	17205.48	3219.33	9413.21	3661.64	0.1958	0.0023
Liaoning	16157.80	556.02	2318.33	145.18	19493.71	3167.64	15962.20	5031.54	0.1955	0.0025
Jilin	7071.35	191.71	1334.79	77.85	7717.22	1265.76	7786.04	2783.04	0.1936	0.0018
Heilongjiang	9833.35	337.77	1927.47	110.99	10779.40	1489.92	10335.95	3233.35	0.1951	0.0021
Shanghai	23791.84	794.17	1119.68	170.18	10177.82	1244.86	16462.47	4612.60	0.1947	0.0029
Zhejiang	32646.34	1235.12	3537.69	212.81	16390.29	2361.75	24817.54	7472.99	0.1969	0.0024
Fujian	12179.78	345.72	2302.30	295.93	9134.24	2142.08	13813.69	5128.48	0.1962	0.0029
Guangdong	27289.08	812.05	5729.02	398.73	24424.61	3792.78	47263.83	17517.01	0.1951	0.0024
Guangxi	8724.40	246.63	2807.65	63.63	7280.65	1758.62	7580.35	2366.39	0.1930	0.0034
Hainan	3966.15	167.17	454.11	59.54	1376.68	360.07	1871.69	678.37	0.1949	0.0028
Chongqing	9816.99	337.64	1566.49	94.65	7387.48	1450.51	6969.08	2417.94	0.1955	0.0036
Yunnan	9935.89	248.10	2745.27	171.22	8623.01	1571.18	7274.66	2880.18	0.1950	0.0025
Shaanxi	11030.58	317.68	2042.18	33.11	8617.69	1977.79	7750.82	2816.68	0.1943	0.0024
Gansu	4516.37	107.82	1472.22	47.75	6010.33	1118.74	4282.27	1664.53	0.1961	0.0021
Qinghai	2149.37	67.45	306.24	9.14	2964.83	754.47	1034.71	356.83	0.1962	0.0026
Ningxia	2537.52	81.70	330.04	21.44	3850.33	926.29	1261.40	465.45	0.1943	0.0025
Xinjiang	8931.16	334.34	948.44	134.36	9725.64	3530.38	5163.11	1801.94	0.1989	0.0010

There are TFEE gaps among the B&R key regions. (1) Regions on the production frontier are Shanghai, Guangdong, Hainan, and Qinghai. The TFEE of these regions is 1.00 between 2005 and 2015. Corresponding to their high input-output levels, the TFEE of Shanghai and Guangdong is also high. However, Hainan and Qinghai have a higher TFEE basically due to their relatively low energy consumption rather than their input levels. (2) Besides, regions with the medium TFEE are Zhejiang, Fujian, Ningxia, Guangxi, Heilongjiang, Chongqing, Shaanxi, and Jilin; their TFEE mean is between 0.60 and 0.90. Regions with the low TFEE are Yunnan, Liaoning, Xinjiang, Gansu, and Inner Mongolia; their TFEE mean is between 0.30 and 0.60. (3) In addition, some regions have high input-high emission development mode. For example, the capital input, labor input, and energy input of Liaoning are all in the top five among the B&R key regions. However, the TFEE of Liaoning is in the bottom among the B&R key regions. There is large energy waste in the production progresses of Liaoning province. (4) Furthermore, the CV of TFEE can reflect the energy efficiency convergence effect within an area. The CV of north area shows a decreasing trend in 2007–2015. The CV of east area is a stationary series, and it is lower than the CV of north area in 2005–2012. The CV of west area shows an N-shaped tendency, and it is higher than the CV of north and east area. Therefore, the convergence effect in east area was the highest in 2005–2012, the north ranked second in 2007–2012 and ranked first in 2013–2015. The west area has lower TFEE convergence

effect. This means that the internal drive force of the west area is quite weak.

We had drawn a radar chart to demonstrate the dynamic changes of B&R key regions for the year 2005, 2010, and 2015 (Fig. 2). In Fig. 2, Shanghai, Guangdong, Hainan, and Qinghai are the frontier regions in all of these three periods. (1) Besides these regions, the TFEE of some regions had slightly improved. During 2005–2010, the TFEE of Inner Mongolia, Liaoning, Jilin, and Chongqing had increased by 0.031, 0.037, 0.066, and 0.041. The TFEE of Inner Mongolia, Liaoning, Heilongjiang, Fujian, Chongqing, Yunnan, Gansu, and Ningxia had increased by 0.052, 0.019, 0.040, 0.002, 0.146, 0.055, 0.030, and 0.075 between 2010 and 2015. (2) On the contrary, the TFEE of some regions had decreased. The TFEE of Heilongjiang, Zhejiang, Fujian, Guangxi, Yunnan, Shaanxi, Gansu, Ningxia, and Xinjiang had decreased by 0.410, 0.012, 0.020, 0.152, 0.147, 0.078, 0.153, 0.278, and 0.003 during 2005–2010. In addition, the TFEE of Jilin, Zhejiang, Guangxi, Shaanxi, and Xinjiang had decreased by 0.002, 0.008, 0.032, 0.006, and 0.185 between 2010 and 2015. The above analysis reveals that there are large TFEE gaps among the B&R key regions.

To find out the TFEE level of the B&R key regions based on the initiative planning, we calculated the TFEE of nationwide¹¹ and non-B&R key regions (Fig. 3). It is

¹¹ Nationwide includes 30 regions in China except Tibet, Hong Kong, Macao, and Taiwan.

Table 3 The TFEE, TFEE mean, and CV of B&R key regions

Regions		2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Mean
North	Inner Mongolia	0.36	0.35	0.35	0.36	0.37	0.39	0.38	0.40	0.46	0.45	0.44	0.39
	Liaoning	0.47	0.48	0.49	0.50	0.50	0.51	0.50	0.50	0.54	0.53	0.53	0.50
	Jilin	0.56	0.57	0.58	0.60	0.61	0.63	0.62	0.62	0.63	0.63	0.63	0.61
	Heilongjiang	1.00	1.00	0.56	0.57	0.58	0.59	0.60	0.59	0.63	0.64	0.63	0.67
	Mean	0.60	0.60	0.50	0.51	0.52	0.53	0.53	0.53	0.57	0.56	0.56	–
	CV	0.41	0.40	0.18	0.18	0.18	0.17	0.18	0.17	0.13	0.14	0.14	–
East	Shanghai	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Zhejiang	0.89	0.88	0.88	0.87	0.87	0.87	0.86	0.87	0.85	0.87	0.87	0.87
	Fujian	0.86	0.86	0.86	0.84	0.84	0.84	0.84	0.84	0.84	0.84	0.84	0.85
	Guangdong	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Guangxi	0.81	0.79	0.67	0.67	0.67	0.66	0.65	0.63	0.63	0.63	0.63	0.68
	Hainan	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Mean	0.93	0.92	0.90	0.90	0.90	0.90	0.89	0.89	0.89	0.89	0.89	–
	CV	0.08	0.09	0.13	0.13	0.13	0.14	0.14	0.15	0.15	0.15	0.15	–
West	Chongqing	0.57	0.58	0.59	0.60	0.61	0.62	0.63	0.64	0.75	0.75	0.76	0.65
	Yunnan	0.63	0.63	0.47	0.48	0.48	0.48	0.49	0.48	0.51	0.51	0.54	0.52
	Shaanxi	0.69	0.67	0.59	0.60	0.61	0.61	0.62	0.61	0.62	0.61	0.60	0.62
	Gansu	0.56	0.55	0.38	0.39	0.40	0.40	0.42	0.42	0.41	0.41	0.43	0.43
	Qinghai	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Ningxia	1.00	0.68	0.70	1.00	0.73	0.72	0.73	0.79	0.81	0.83	0.80	0.80
	Xinjiang	0.54	0.54	0.56	0.56	0.55	0.54	0.51	0.46	0.41	0.38	0.36	0.49
	Mean	0.71	0.66	0.61	0.66	0.63	0.62	0.63	0.63	0.64	0.64	0.64	–
	CV	0.26	0.22	0.30	0.34	0.29	0.29	0.29	0.31	0.32	0.33	0.32	–

worth noting that the TFEE of regions in China has not improved in recent years whether it belongs to nationwide, B&R key regions, or non-B&R key regions. (1) The tendencies of the nationwide, B&R key regions, and non-B&R key regions were essentially consistent and slightly showed U-shape between 2005 and 2013. (2) The TFEE mean of key regions is higher than 0.70. The TFEE mean of nationwide is lower than 0.70. The non-B&R key regions have a lower TFEE than the B&R key regions and nationwide. This means that compared to the nationwide and non-B&R key regions, B&R key regions have a better TFEE.

As a result, the B&R key regions could lead the way in improving energy efficiency.

Furthermore, to thoroughly analyze the TFEE from the perspective of geographical location, we calculated the TFEE means of the east, north, and west area, respectively. The TFEE means of these three areas are displayed in Fig. 4. (1) The TFEE mean of the east area has basically kept a stable trend at about 0.89. It is much higher than the TFEE means of other two areas. (2) The TFEE mean of the north area shows a U-shaped relationship with time: it had decreased to 0.50 in 2007, and then it rebounded

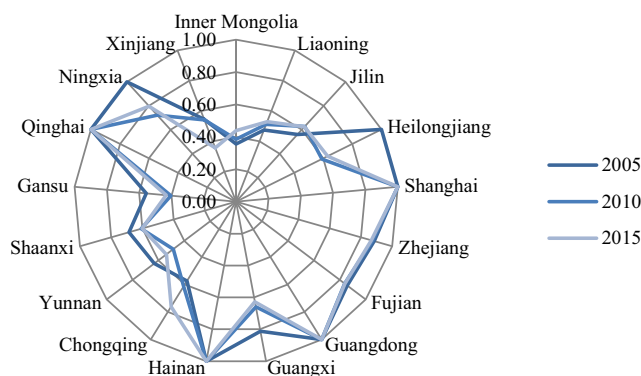


Fig. 2 The TFEE in 2005, 2010, and 2015

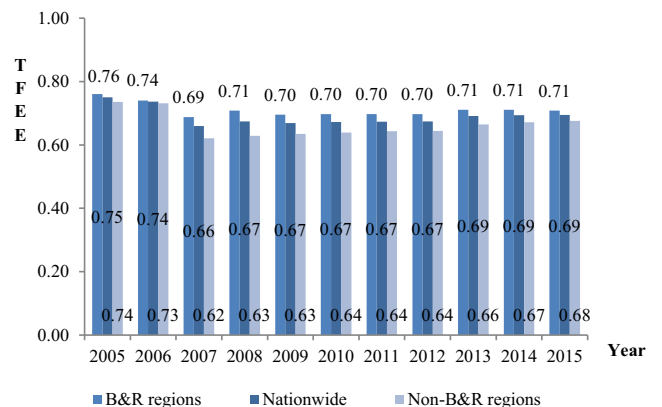


Fig. 3 The TFEE means of the B&R initiative planning division

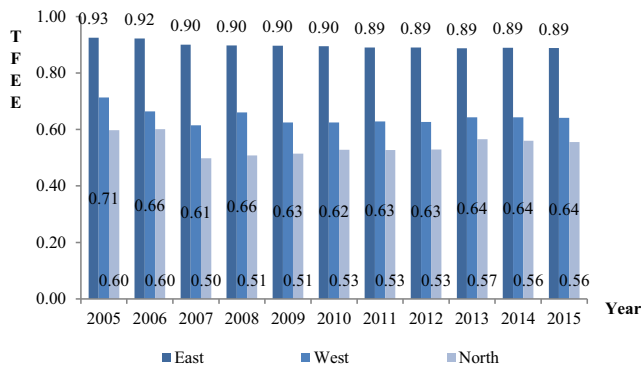


Fig. 4 The TFEE means of three areas

from 2008, finally it basically stabled at 0.56. (3) The TFEE mean of the west area had fluctuated in 2005–2008, and then it kept stable in recent years. Based on the analysis, the U-shaped trend of B&R key regions is mainly contributed by the west and north area. In brief, Fig. 4 visually reveals that the east area ranks first with the highest TFEE, the west area follows, and the north area has the lowest TFEE.

Influencing factors analysis

Internal influencing factors

Decomposition analysis

According to “Malmquist index” section, technical changes (TECH), pure efficiency changes (PECH), scale efficiency changes (SECH), and the total factor productivity changes (TFPCH) can be acquired by choosing the Malmquist model in Software DEAP2.1. The TFPCH represents the Malmquist index which can be decomposed into the product of the TECH, PECH, and SECH. Besides, the TFEE changes (TFEECH) represented the ratio of the current year and the last year is shown in Table 4. Table 4 displays these changes in each time period. (1) The TECH only showed the improvement in periods 2005–2006 and 2006–2007, while there were setbacks in the other 8 periods. (2) Similarly, the PECH only showed the improvement in 4 periods: 2006–2007, 2008–2009, 2010–2011, and 2012–2013. (3) On the contrary, the SECH only had decreased in 2006–2007, 2008–2009, 2010–2011, and 2012–2013. This reveals that the management efficiency has progress in most of the periods. (4) According to Lv et al. (2015), the total factor productivity had not improved in recent years. The TFPCH showed improvement only in 2005–2006 and 2006–2007 while the TFEECH has been improved in 2007–2008, 2009–2010, 2011–2012, and 2012–2013. In addition, the movements of TFEE are inconsistent with the TFP changes. Thus, the incorrect utilization of the concept of TFP will lead to the misunderstanding of TFEE. In

Table 4 The decomposition result of TFEE in B&R key regions

Periods	TECH	PECH	SECH	TFPCH	TFEECH
2005–2006	1.009	0.983	1.011	1.002	0.973
2006–2007	1.006	1.037	0.961	1.002	0.930
2007–2008	0.996	0.957	1.041	0.992	1.030
2008–2009	0.981	1.014	0.984	0.980	0.981
2009–2010	0.992	0.986	1.004	0.983	1.003
2010–2011	0.991	1.039	0.958	0.986	0.999
2011–2012	0.985	0.965	1.040	0.989	1.000
2012–2013	0.975	1.053	0.964	0.989	1.021
2013–2014	0.985	0.976	1.016	0.977	0.999
2014–2015	0.986	0.972	1.034	0.990	0.997
Mean	0.991	0.998	1.001	0.989	0.993

brief, the decomposition result suggests that it is difficult to promote the TFEE by internal factors.

Regression analysis

The above analysis shows that the TFEE may be related with these internal influencing factors (Liu et al. 2015). Therefore, the TECH, PECH, and SECH are regarded as explanatory variables in the following regression model. Thus, the TFEECH was taken as the dependent variable. The unit roots test was run to confirm that every variable is in a stationary series, and the random effect was examined by the Hausman test. Eventually, we established a random effect regression model with the weighted generalized least squares (WGLS) method.¹² As shown in Eq. (15), *i* represents the region, *j* represents the period, ε_{ij} is the random error, β_1 , β_2 , and β_3 are the parameters of the explanatory variables.

$$TFEE_{ch} = C + \beta_1 TECH_{ij} + \beta_2 PECH_{ij} + \beta_3 SECH_{ij} + \varepsilon_{ij} \tag{15}$$

To comprehensively verify the impacts of internal influences, we established five regressions: the nationwide, the B&R key regions, the east, north, and west. All the regressive operations were implemented through Eviews8.0.¹³ Regression results are displayed in Table 5. Unexpectedly, the regression of the north area is insignificant. Thus, the results of the north area are not listed.

According to Table 5, TECH, PECH, and SECH have different effects on the five regressions. (1) PECH and SECH have significant positive effects on the TFEE changes. This result is consistent with Liu et al. (2015). (2) Similar to Huang et al. (2017), TECH shows negative influence in all regressions but has significant negative effects only in the

¹² WGLS represents the weighted generalized least squares method.

¹³ Eviews8.0 is developed by IHS Global INC.

Table 5 Regression results of internal influencing factors

Variables	Coefficients			
	Nationwide	B&R	East	West
C	0.6770***	0.7851***	0.5949***	0.7340***
TECH	-0.2438**	-0.0083	-0.0110	-0.0491
PECH	0.2694**	0.1092***	0.1971***	0.1438*
SECH	0.2868***	0.1134***	0.2183***	0.1673*

***, **, * represent the significance level for 1%, 5%, and 10%

nationwide. The negative effect of technical changes on TFEE changes may cause by the so-called rebound effect. The rebound effect means that the energy consumption rise while an advanced technology is applied, thus leading to a low energy efficiency (Greening et al. 2000). Therefore, it is not feasible to boost energy efficiency by simply improving production techniques.

According to the decomposition and regression analysis of internal influencing factors, we find that the PECH and SECH can promote TFEE from the management side. However, the PECH had decreased in most of the research periods. Despite the SECH had improved in most of the research periods, the effects of PECH and SECH may offset each other. TECH shows no progress in recent years and the possible rebound effect may inhibit the positive influence of technological progress. Therefore, it is difficult to improve the TFEE of the B&R key regions from internal side.

External influencing factors

After examined the influence of internal factors, we tried to find out the effect of external influencing factors. Referenced from some researches, we had considered various external influencing factors, such as economic development, industrial structure, environmental pollution, opening up, research and development, government finance, production endowment, and energy factors. After examining the correlation among variables, 11 explanatory variables from 8 aspects were chosen to construct the regression models. The variables are shown in Fig. 5.

Since TFEE is a limited dependent variable, the Tobit model is adopted to figure the regression. The regression model is constructed as follows:

$$EE_{i,t} = c + \beta_1 ED_{ij} + \beta_2 IS_{ij} + \beta_3 SS_{ij} + \beta_4 TS_{ij} + \beta_5 IP_{ij} + \beta_6 OP_{ij} + \beta_7 RD_{ij} + \beta_8 GI_{ij} + \beta_9 PE_{ij} + \beta_{10} CS_{ij} + \beta_{11} EP_{ij} + \varepsilon_{ij} \quad (16)$$

In Eq. (16), i , t , and ε_{ij} have the same meaning as in “Internal influencing factors” section. This model was also run in Eviews8.0. Again, the WGLS method was applied to reduce heteroscedasticity and sequence correlation. Five

regressions of the nationwide, B&R key regions, the east, north, and west areas had been established. Regression results are presented in Table 6. The coefficients of the variables cannot be compared with each other because of the different sample sizes of the five regressions.

- (1) The impact of economic development. Consistent with expectations, there is a significant positive correlation between economic development and TFEE in nationwide, the east, and west area. The coefficients are 0.1525, 0.0801, and 0.8013. Regions in east area basically have a higher per capita GDP. For example, Shanghai, Zhejiang, and Guangdong have the higher TFEE and per capita GDP than other key regions. This means that the high economic development relative with the high TFEE of the east area. However, the economic development of north area had not improved their TFEE. For example, the per capita GDP of Inner Mongolia ranked third in 2009–2011 and 2013–2015 among B&R key regions, while it had the lowest TFEE in 2005–2013. The relationship of economic development and TFEE is quite complex and it depends on the different situation of regions.
- (2) The impact of industrial structure. First, IS has significant positive influence on the TFEE of key regions and the north area at 1% level. The positive impact in the north area may be related to the large amount of industrial-intensive enterprises. Second, SS has a negative effect in the north area at 1% level with a high coefficient of 7.3880. But it has positive effects in other regressions. The high share of secondary industry in the north area has caused much environmental pollution, thus the TFEE under environmental constraints does not perform well. Third, TS shows positive effects in nationwide, key regions, and the east area with the coefficients of 0.5803, 2.4675, and 0.8038, respectively. The share of tertiary industry in the east area is basically higher than other areas. Therefore, the tertiary industry is benefit to the TFEE of the east area. In brief, the effects of industrial structures vary a lot in different regions.
- (3) The impact of environmental pollution. The industrial pollution reflects both the energy inefficiency and the environmental damage. This variable has significant negative effects in nationwide and key regions with the coefficients of 3.4703 and 4.7071, while it shows insignificant negative effect in other regions. This reveals that some key regions still have the “high emission” development mode. For instance, the SO_2 emission of Inner Mongolia ranked first for 11 consecutive years among key regions. Besides, some regions in west area have severe pollution and low TFEE (Liu et al. 2015).
- (4) The impact of opening up. Import and export activities simply reflect the communication with other countries

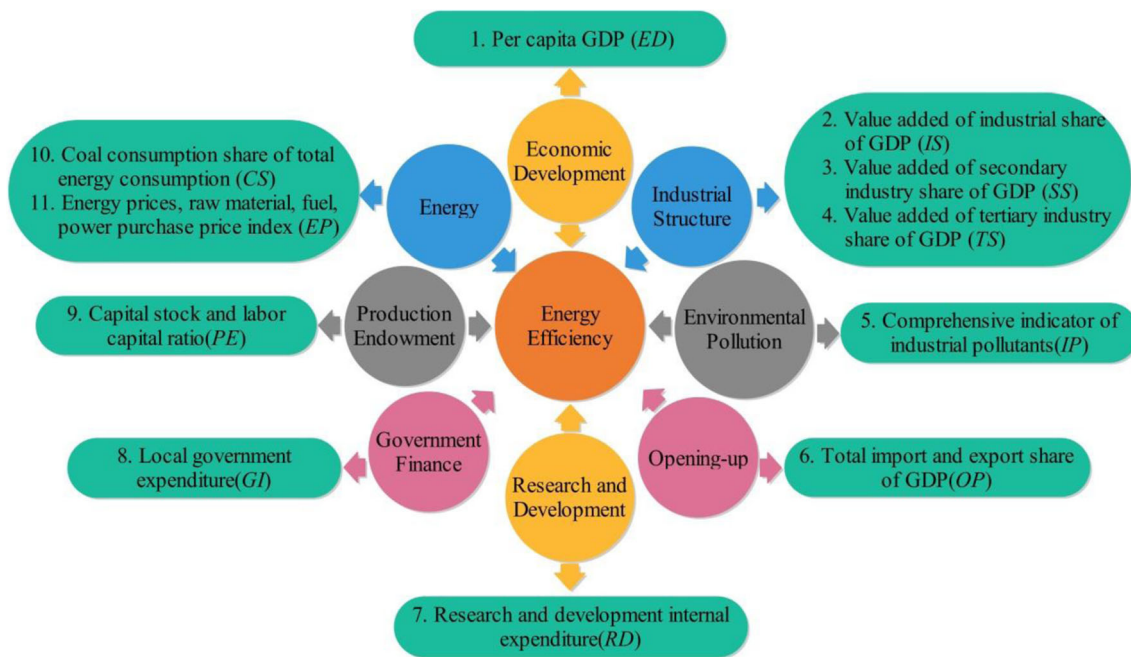


Fig. 5 The external influencing factors

and regions, especially the technology exchange brought by the trade of high-tech products. As expected, *OP* is significantly positive in nationwide, key regions, and the east area at 1% level. Due to the lower import and export volume of the north area, *OP* has a negative effect on the TFEE of the north area. As the gateway of the northeast Asia, the north area is expected to behave better under the implementation of the B&R initiative.

- (5) The impact of research and development. Due to the inconsistent statistical caliber of the indicator “R&D internal expenditure of industrial enterprise,” “regional total R&D internal expenditure” was adopted as an alternative. Similar to Ma et al. (2017), R&D shows significant negative impacts on the TFEE of nationwide, key regions, and the west area. Some regions in east area such as Guangdong, Zhejiang, and Shanghai have a higher R&D internal expenditure than other key regions. Thus, their high TFEE may be related with the research and development. Besides, R&D contains the funds for basic research, applied research, and experimental development,¹⁴ the benefits of the emission reduction and optimization of production deserve more consideration.
- (6) The impact of government finance. We intended to examine the impact of environmental expenditure which is a part of government financial expenditures. However, environmental expenditure did not separate from the government expenditure in several regions before 2007. Therefore, we regarded government financial

expenditure as a substitute. According to the regression result, this variable is significantly positive in key regions, while it shows significant negative effects in the east and west area. Gansu, Yunnan, and Xinjiang have the government finance in the forefront among key regions, while their TFEE is at the bottom. In conclusion, although government expenditure on energy conservation and emission reduction does have positive effects in some regions, the influence degree still needs to be enhanced.

- (7) The impact of production endowment. Similar to the results of Zhang and Wu (2011), significant negative effects are shown in the east area at the 1% level. And in other regressions, this variable shows the insignificant negative effects. Xinjiang, Inner Mongolia, and Jilin have a higher capital-labor ratio while their TFEE is not optimistic among key regions. Besides, the capital-labor ratio of Yunnan and Gansu is lagging behind of other key regions, and their TFEE is also poor in the research period. These results reveal that the unbalanced input proportion will encumber energy efficiency and waste resources. Hence, for sustainable development, it is urgent to distribute the inputs rationally and avoid the unnecessary waste.
- (8) The impact of energy factors. *CS* shows significant negative effects in nationwide, key regions, and the east area. This suggests that the coal consumption of these regions is not optimal. Though their coefficients are insignificant, *CS* also has negative relationships with the TFEE of the north and west area. For instance, regions in the north and west area, such as Inner Mongolia,

¹⁴ National Bureau of Statistics of China. 2013-10-29. http://www.stats.gov.cn/tjsj/zjbs/201310/t20131029_449419.html.

Table 6 Regression results of external influencing factors

Variables	Coefficients				
	Nationwide	B&R	East	North	West
C	1.3900***	− 0.0862	0.7141***	3.8141*	1.9451*
ED	0.1525**	− 0.0180	0.0801***	0.0519	0.8013***
IS	0.1278	1.9241***	0.0513	5.5037***	0.7662
SS	0.4952***	0.3676*	0.3620***	− 7.3880***	1.0864***
TS	0.5803*	2.4675***	0.8038***	− 3.3147	− 0.3495
IP	− 3.4703*	− 4.7071**	− 0.4573	− 1.0377	− 1.7122
OP	0.3656***	0.4896***	0.0962***	− 1.1402***	0.2557
RD	− 0.0576***	− 0.0758***	0.0153**	0.1225	− 0.1930***
GI	0.0950	0.4272***	− 0.4551***	− 0.6455	− 0.6281**
PE	− 0.0574	0.0120	− 0.0987***	− 0.1237	− 0.1865
CS	− 0.3072***	− 0.1680**	− 0.1125*	− 0.1401	− 0.0346
EP	− 0.0873**	− 0.0275	− 0.1008***	− 0.2074	− 0.3541***

***, **, * represent the significance level for 1%, 5%, and 10%

Liaoning, Heilongjiang, and Shaanxi have abundant coal resources. The huge coal consumption may bring the economy growth but also cause serious environmental pollution. Since China has the largest coal consumption and CO₂ emission in the world, the carbon reduction should be emphasized in the future. In addition, further discussion should be drawn on how to adjust the energy consumption structure.

EP shows significant negative effects in nationwide, the east, and west area. Our results are similar to the results of Guan et al. (2014) and Liu et al. (2015): *EP* has a negative impact on TFEE in some regions. Xinjiang, Heilongjiang, and Gansu have higher energy prices, while their TFEE is decreasing. Energy price can be affected by various factors such as the exploitation cost, transportation cost, and the relationship of energy demand and energy supply. In addition, the changes of energy price will ultimately affect the energy consumption structure.

Conclusions and policy implications

Conclusions

This paper bridges the research gap in regional total factor energy efficiency from the perspective of B&R initiative. Regional TFEE in this paper is calculated by the ratio of target energy input to the actual energy input. The TFEE results are analyzed from various perspectives: geographical location, convergence effect, dynamic changes, initiative planning, and the influencing factors. (1) Although the TFEE of B&R key regions is higher than the nationwide and non-B&R key regions, it is unbalanced and had not improved in recent years.

Specifically, the east area has the highest TFEE and remains basically at 0.89, the west area takes the second position with the TFEE of approximately 0.64 and the north area has the lowest TFEE at approximately 0.56. Besides, the convergence effect of the west area is quite weak. Furthermore, there are large TFEE gaps among B&R key regions. (2) The decomposition results show that the technical changes, pure efficiency changes, and total factor productivity changes have retrogress in the most of the research periods. (3) According to the regression analysis of internal factors, pure efficiency changes and scale efficiency changes bring mainly positive effects to the TFEE of B&R key regions. The negative effect of technical changes indicates that there may have the rebound effects. (4) The analysis of the external factors show that industrial structure, opening up, and government finance have significant positive effects on the TFEE of B&R key regions. In addition, coal consumption, research and development, and environmental pollution have significant negative effects on the TFEE of B&R key regions. However, the economic development, energy price, and productive endowment in B&R key regions do not reveal a clear influence direction.

Policy implications

According to the calculation and analysis of TFEE, the energy efficiency improving, and emission reducing of B&R key regions should be regarded as future development goals.

- (1) Compared with other area, the east area has better economic development level and energy efficiency convergence effect. Regions in the east area should optimize their industrial structures to keep their high economic development levels. The expenditure that contributed to the energy-saving and environment protection should be

raised. The capital investments of regions in east area need to be adjusted to optimize the capital-labor ratio and avoid the overinvestment. Besides, some renewable and low-pollution energy resources, such as solar energy, marine energy, and nuclear energy may be the better replacements of coal consumption for east area.

- (2) The TFEE of regions in north area is not optimistic. The decreasing trend of north area may cause by the unbalanced industrial structures. Although the industrial sector is the main force of economic development of north area, it also has brought heavy environmental pollution. Therefore, the industrial structure should be adjusted to emphasis the low-emission industries, such as service sector and trade sector. Also, regions in north area should take advantage of its natural geographical location to export China's excess capacity and absorb advanced production experience through the Silk Road.
- (3) Economic growth and energy efficiency of the west area should be mutually reinforcing. The technology innovation of west area needs to be strengthened to stimulate the economy and TFEE growth. The R&D expenditure and government expenditure of west area have not played the role of energy conservation and emission reduction. Therefore, these expenditures should be well planned and strictly supervised to emphasize the TFEE improving. Besides, the energy consumption structure can be optimized to be more sustainable so that the energy price mechanism improved.
- (4) For the entire B&R key region, the negative effects of industrial pollution cannot be ignored. First, enterprises need to improve the technology of emission reduction. Second, sustainable environmental standards could be enacted by regional governments. Third, the reward and punishment mechanism should be implemented effectively. Fourth, the expenditures for environment protection need to be increased in various forms, for example, tax incentives or financial incentives.

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