Total Factor Energy Efficiency Measurement in the Provinces of China Along the ‘Belt and Road’

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This work was supported in part by the Natural Science Foundation of China under Grant 71803106, and in part by the Shanxi Provincial Higher Education Humanities and Social Sciences Project under Grant 201801026.

ABSTRACT Energy is an important element of a regional economic development strategy. According to the China Energy Statistical Yearbook and the China Statistical Yearbook, the proportion of energy efficiency in the provinces along the Belt and Road (B&R) in China is not proportional to the contribution rate of their GDPs. To achieve high quality economic growth, it is necessary to improve the energy efficiency of the provinces along the B&R in China. The objective of this study is to conduct a total factor energy efficiency (TFEE) analysis of the provinces along the B&R in China. In this paper, data envelopment analysis (DEA) method is incorporated under static dimensions, and under dynamic dimensions, the Malmquist index is introduced to evaluate the TFEE of these provinces from 2006 to 2015. The empirical results show that the TFEE in the provinces in China along the B&R increased yearly from 2006 to 2015. The empirical results also indicate that there are huge differences in energy efficiency between different provinces but that the energy efficiency gap in different provinces has been gradually narrowed. From a regional perspective, the TFEE in the eastern region of China achieved the highest value, followed by the western region and the northeast region. Importantly, the empirical results reveal that there are different factors restricting the TFEE in the three regions; the eastern region is restricted by technical efficiency issues, and the northeast and western regions are restricted by issues relating to technological progress.

INDEX TERMS The belt and road, total factor energy efficiency, DEA, malmquist index.

I. INTRODUCTION
In terms of energy consumption, Asia is the leading regional consumer of oil, coal, renewable power and hydroelectricity, especially dominating global coal consumption, accounting for nearly three quarters of global consumption (74.5%).1 Asia’s share of the coal consumption has grown steadily since 1965 when it made up only 17% of the coal consumption. It reached the 50% mark in 2001. At this time, China is the leading country of coal consumption in the Asia-Pacific region. As shown in Fig. 1, coal has been in a relatively stable position in the energy consumption structure. From 2000 to 2010, due to the development of resource-intensive industries, coal consumption continued to grow; after 2010, because of China’s efforts in energy transformation, the growth rate of coal is relatively slow, while the growth of oil, natural gas, hydroelectricity and renewable energy is accelerating. Due to the rapid economic development, China’s coal has experienced rapid development in a certain stage. Fig. 2 indicates that from 2000 to 2010, the production of the coal has grown sharply. At the same time, China’s share of world coal production and

FIGURE 1. China’s energy consumption structures from 1995 to 2020. Data sources: Bp world energy statistics yearbook.

The associate editor coordinating the review of this manuscript and approving it for publication was Oussama Habachi.
1 Data sources: Bp World Energy Statistics Yearbook (67th edition, 2018).
consumption increased 30% to nearly 50%. However, this significant change is caused by an energy-intensive mode. In addition, because energy in China continues to be dominated by coal, the enormous amount of energy consumption by the coal has triggered a series of environment problems, such as severe air pollution. Therefore, to achieve cleaner production and sustainable development, China has adopted a series of governance policies to control pollution and evaluated the effectiveness of the policies to improve energy efficiency [1]–[3].

As one of the elements of a regional economic development strategy, energy utilization will affect the regional economic competitive advantage to a large extent [4]. The successful high-quality development of China’s economy will improve its total factor productivity [5]. Since the implementation of the B&R initiative, China’s primary energy demand will grow at an annual rate of 2.4% from 2015 to 2020. In 2014, China imported 87.5% and 88.2% of oil and natural gas from overseas came from major regions and countries along the B&R route. In addition, the total energy consumption of the provinces in China along the B&R has increased from 1,985,750 tons of standard coal in 2013 to 2,137,860 tons of standard coal in 2016, representing an increase in the energy consumption ratio of the provinces along the B&R from 50.30% to 52.77%. However, the regional GDP of the provinces in China along the B&R has risen from 296.103 billion RMB in 2013 to 352.524 billion RMB in 2016, the regional GDP’s proportion of the total GDP fell from 51.26% to 47.37%. This data shows that the contribution of these Chinese provinces to China’s energy consumption ratio and GDP ratio are asymmetric and that their energy utilization efficiency is not high overall.

Therefore, strengthening energy cooperation and improving energy efficiency is an important issue of the B&R initiative. Given the issue of the contribution of different inputs to the economy and feasibility of energy efficiency measurement methods, this paper has adopted an input-oriented DEA-BCC model [6] to analyze provincial panel data from 2006-2015 and to measure the total factor energy efficiency (TFEE) of the provinces in China along the B&R; in addition, the Malmquist index has been used to study the dynamic changes of TFEE in provinces in China along the B&R. Different from past studies, this study uses capital stock, labor input, energy consumption, and environmental costs as input indicators and uses the GDP as a single output indicator. The environmental costs have been highlighted and divided into three parts: sulfur dioxide emissions, chemical oxygen demand emissions, and dust emissions. According to the “Vision and Action of Promoting the Silk Road Economic Belt and the 21st Century Maritime Silk Road” (Vision and Action) [7], the B&R initiative mainly involves 18 key provinces, municipalities and autonomous regions in China: Xinjiang, Fujian, Shaanxi, Ningxia, Gansu, Qinghai, Inner Mongolia, Heilongjiang, Jilin, Liaoning, Guangxi, Chongqing, Yunnan, Shanghai, Zhejiang, Guangdong and Hainan and Tibet. Due to the limitation of data availability, Tibet has been removed from the 18 provinces along the B&R. Therefore, we focus on the remaining 17 provinces (shown as the blue parts in Fig. 3.).

The reminder of this paper is organized as follows. Section II will present a literature review. Section III will introduce the methodology adopted. Section IV will illustrate the selected input and output indicators and data processing. In addition, we will present estimation results and discussion in Section V followed by conclusions and policy implications in Section VI.

II. LITERATURE REVIEW

In the past several years, energy efficiency has been the focus of several studies. Energy efficiency refers to the ability to produce the same amount of service or useful output with less energy [8]. This paper mainly sorted out TFEE related literatures from three aspects: research method, research area and regions, evaluation indicators.

Data sources: World and China Energy Outlook Report (2019).
1 Data sources: China Customs Statistical Yearbook (2015) and BP’s World Energy Statistical Yearbook.
2 Data sources: China Energy Statistical Yearbook (2014,2017).
3 Data sources: China Statistical Yearbook (2014,2017).
and research indicators. Firstly, the literatures ranged from single factor energy efficiency study to total factor energy efficiency study, and the research methods have been constantly updated and improved. Secondly, in recent years, many scholars use DEA and its derivative methods to study different fields and regions, while the study on B&R region is relatively rare, which is also the first contribution of this paper. Finally, in the construction of TFEE evaluation index system, this paper focuses on the analysis of environmental indicators, which is the second contribution. After reviewing and sorting out relevant literatures, we determined the research focus and content of this paper. That is, taking capital, labor, energy and environmental costs as input indicators and GDP as output indicators, we measured the energy efficiency of 17 provinces along B&R and analyzed the measurement results.

Since 1996, there have been an increasing number of research studies that have used different factors and indices to measure energy efficiency in different industries and regions [9]–[11]. The traditional research method to estimate energy efficiency is single-factor energy efficiency, measured by the ratio of energy consumption to gross domestic product (GDP) [8]. The ratio only focuses on energy input instead of other factors involved in the process of energy utilization. As a result, it cannot truly reflect the interaction of other input factors in the energy utilization process and the changes in economic structure, which may exaggerate energy efficiency. Therefore, Hu and Wang [12] first put forward a total factor energy efficiency index (TFEE) based on the DEA-CCR model, which a traditional data envelopment analysis (DEA) model is proposed by Charnes, Cooper, and Rhodes (CCR) [13]. They used the DEA-CCR model to integrate the interplay of other inputs and energy inputs to measure energy efficiency in various regions of China [13]. TFEE is a relative efficiency index for energy use, referring to the ratio of the target energy input divided by the actual energy input, effectively correcting the disadvantages of traditional single-factor energy efficiency indicators. According to the best production practice, it can be defined as the ratio of the target energy input and the actual input required for a certain output, under the premise that other elements other than energy input remain unchanged. So far, there are two methods for measuring TFEE, one is a parameter-based stochastic frontier analysis (SFA) method, and the other is a non-parametric DEA method. When measuring efficiency, SFA method assumes the form of an equation, which may make the production frontier subjective. When input and output have a certain functional relationship, the frontier surface estimation can use SFA method. When the function form is determined, the econometric method needs to be further used to determine the function parameters, which makes SFA require more calculation than DEA. However, the DEA method is simple to calculate numerically, and the DEA method can still be applied when the algebraic relationship between input and output is unknown. Therefore, measuring TFEE with DEA has become the mainstream method for global research on energy efficiency in the past few years.

In this paper, we use the DEA model to measure the TFEE of the provinces in China along the B&R, selecting four aspects, namely, capital, labor, energy consumption and environment costs, as input indicators.

Many scholars have studied energy efficiency in different fields and regions with DEA and DEA derivative methods [14]. Some scholars have focused on the energy efficiency of one industry. Ernst et al. [15] measured the energy intensity of the steel industry in seven countries, including China, in 1980-1991. Some scholars were also concerned about the energy efficiency of the iron [16] and steel industry [17], [18]. Energy efficiency evaluation has also been examined in other industries, including cement [19], electricity [20], [21], and construction [22]. While other scholars made an assessment of the energy efficiency of multiple different industries, Li and Zhou [23] used non-parametric DEA methods to evaluate the energy efficiency of 35 industrial sectors, including coal, petroleum, metallurgical and other industries. Using the DEA, Azadeh et al. [24] assessed the TFEE of energy-intensive manufacturing, including paper, petroleum refining and cement manufacturing. At the same time, other scholars focused on the energy efficiency of different regions. Wu et al. [25] utilized the DEA-CCR method to build an energy efficiency measurement model and analyzed the energy efficiency differences in various parts of China. Zhang et al. [26] used the TFEE method to empirically analyze the factors of regional differences in China and confirmed the feasibility and effectiveness of the TFEE method for China’s energy efficiency problems. Scholars for China’s energy efficiency measurement also include Wu and Wen [25], Li [27], Wang and Feng [28]. In addition, there are some scholars studied the energy efficiency of the environment. Yu et al. [29] used slacks-based measure (SBM)⁷ to analyze the efficiency levels of 16 provinces’ pulp

⁷Different from the traditional DEA model, the SBM model put the slacks of input and output directly into the objective function, which can measure the inefficiency of a decision-making unit (DMU) caused by the slack with comparing with the optimal production frontier.
and paper industries in China. To uncover the underlying causes of Eco-efficiency performance, Malmquist Luenberger index was calculated to discover the drivers of productivity growth of pulp and paper industries. Wu et al. [30] used DEA-based model to measure the environmental efficiency of 38 different industrial sectors in China that use different environment resources to produce various outputs. They also give a five-year analysis to describe the environmental performance of China’s industries and analyze the environmental performance of China’s industry from a new aspect of industrial sectors. An et al. [31] applied an optimized undesirable-SBM approach and Malmquist index to analyze the energy and environmental efficiency and total factor productivity of 15 trunk streams and tributaries along the Xiangjiang River basin cities during 2008-2014, taking the water quality of the upstream and downstream of cities as the environmental indicator.

When constructing an energy efficiency evaluation index system of the provinces in China along the B&R, we focus on the indicators for measuring environmental costs. Most scholars, such as Wang et al. [32], Xu et al. [33], Guan et al. [34], Zhang [35], have used the estimated carbon dioxide levels to measure environmental costs. To measure environmental costs, other scholars have committed to use carbon footprints to analyze the driving factors of pollution emissions. From the households’ perspective, the dominant factor increasing the carbon footprint was the amount of household expenditures [36]. Peters [37] held the opinion that cities and regions could use carbon footprints to implement local policies that helped meet overarching national objectives. Measuring the carbon footprint from the production of three hexacopter components during the product’s design, manufacture and transportation, Raoufi et al. [38] considered this footprint as an indicator of environmental impact. After 2015, some scholars, such as Jiang et al. [39], whose method has been supported by many scholars and widely used since 2015, used sulfur dioxide instead of carbon dioxide to measure environmental costs.

According to previous studies, we find that research on energy efficiency measures has been mainly concerned with different industries or with various parts of China, and there is a relative lack of quantitative research on energy efficiency in certain regions of China, such as the B&R area. In conducting research on the energy problem of the B&R, however, other scholars have explored the ideas [40], [41], models [42] and challenges [43] of energy cooperation between China and the countries along the B&R. The research conducted on the energy problems of the B&R has been more concerned with how to strengthen energy cooperation, and few scholars have measured the energy efficiency of provinces in China along the B&R [44]. Since the implementation, in provinces in China along the B&R, the impact of energy cooperation on energy efficiency has not been determined. As a result, this paper focuses on the TFEE in provinces in China along the B&R and conducts an in-depth analysis of the factors influencing the improvement of the TFEE in those provinces; this is the first important contribution.

Another contribution in this paper is the innovation of indicators. Note that as former scholars describe the estimated carbon dioxide emissions and carbon footprints as input indicators in the TFEE research system, the estimated efficiency values may be biased. In this paper, we use sulfur dioxide emissions, chemical oxygen demand emissions and dust emissions as indicators measuring environmental costs. These indicators have stronger reliability than the estimated carbon dioxide indicator. Therefore, the second major contribution of this paper is to measure environmental costs with the three environmental pollution indicators, which are China’s main environmental control targets.

III. METHODS AND MODELS

In this paper, under a static level, the non-parametric analysis of DEA proposed by Charnes et al. [13] is employed to study the TFEE of the 17 provinces. DEA is a statistical method for evaluating the relative efficiency of input and output of multiple Decision-Making Units (DMUs) of the same type. The variety of indicators and data dimensions is out of consideration. Taking advantages of simplifying algorithms, reducing errors, etc., the TFEE of each province along the B&R as a DMU has been measured and compared.

A. RESEARCH METHOD TO STATIC OF TFEE

The input-oriented DEA-BCC model has been selected to optimize the energy input. In 1984, Banker, Charnes and Cooper established convexity properties for possible sets of production and introduced Shepherd distance function to decompose technical efficiency (TE) into pure technical efficiency (PTE) and scale efficiency (SE), thereby establishing the following variable model of scale reward.

Assume that there are n decision-making units (DMUs), each of which has p inputs and q outputs, which are represented by different economic indicators. Thus, the muti-indicator input and muti-index output evaluation system composed of n DMUs can be represented by the following figure:

Where, $X_{ik}$ represents the input amount of the i-th input indicator of the k-th decision unit, $X_{ik} > 0$; $V_i$ represents the weight coefficient of the k-th input indicator, $V_i \geq 0$; $Y_{jk}$ represents the output of the j-th output indicator of the k-th decision unit, $Y_{jk} > 0$; $U_j$ represents the weight coefficient of the k-th output indicator, $U_j \geq 0$. The input data for each DMU is $x_k = (x_{1k}, x_{2k}, \ldots, x_{pk})^T$, $k = 1, 2, \ldots, n$, the output data for each DMU is $y_k = (y_{1k}, y_{2k}, \ldots, y_{qk})^T$, $k = 1, 2, \ldots, n$. The specific formula is shown as follow:

$$\max \gamma = V_{BCC}$$

s.t. $\sum_{k=1}^{n} x_k \lambda_k \leq x_0$
\[ Y \geq \gamma y_0 \]
\[ \sum_{k=1}^{n} \lambda_k = 1 \]
\[ \lambda_k \geq 0, \quad k = 1, 2, \ldots, n \] (1)

\( \gamma \) is the effective value of the DMU. If \( \gamma \) is equal to 1, the DMU is effective at the production frontier; if \( 0 < \gamma < 1 \), the DMU is not at the production frontier, and the input and output are invalid.

In the DEA-BCC model, TFEE is represented by technical efficiency (TE), which measures the resource allocation capabilities of the DMUs. TE is the product of pure technical efficiency (PTE) multiplied by scale efficiency (SE). PTE measures the business production efficiency affected by management and technology factors. If PTE equals 1, it indicates that at the current technological level, the resource utilization is efficient. SE, under certain conditions of the enterprise system and management capabilities, measures the gap between current input size and the optimal input size, reflecting that the production efficiency will be affected by the size of the company. If SE equals 1, it indicates that at the current production level, the resource utilization is efficient. The decomposition of TE can further explore whether TFEE is affected by corporate management and technical factors or by scale factors. The values of TE, PTE, and SE are all between 0 and 1.

### B. RESEARCH METHOD TO DYNAMIC CHANGES OF TFEE

To measure the dynamic changes of TFEE of the 17 provinces, Malmquist index and DEA model can be combined to build DEA-Malmquist model. The Malmquist index was put forward by Caves et al. [45] and further developed by Färe et al. [46]. According to the method of Färe et al. [47], each province is regarded as a DMU, the frontier of energy efficiency in different periods is constructed, and the TFEE in the 17 provinces with the frontier are compared, so as to measure the changes of TE and technological progress (TP) in different provinces. Malmquist index is constructed as follows:

\[
M(x_{zt}^{t+1}, y_{zt}^{t+1}, x_{zt}^{t}, y_{zt}^{t}) = TFEE = TE \times TP = PTE \times SE \times TP
\] (2)

\[
M(x_{zt}^{t+1}, y_{zt}^{t+1}, x_{zt}^{t}, y_{zt}^{t}) = \left[ \frac{D_{zt}^{t+1}(x_{zt}^{t+1}, y_{zt}^{t+1})}{D_{zt}^{t}(x_{zt}^{t}, y_{zt}^{t})} \right]^{1/2}
\] (3)

\[
D_{zt}^{t+1}(x_{zt}^{t+1}, y_{zt}^{t+1}) \times \frac{D_{zt}^{t+1}(x_{zt}^{t+1}, y_{zt}^{t+1})}{D_{zt}^{t}(x_{zt}^{t}, y_{zt}^{t})}
\] (4)

TFEE indicates the total factor energy efficiency.

\[ TE = \frac{D_{zt}^{t+1}(x_{zt}^{t+1}, y_{zt}^{t+1})}{D_{zt}^{t}(x_{zt}^{t}, y_{zt}^{t})}, \quad PTE = \frac{D_{zt}^{t}(x_{zt}^{t}, y_{zt}^{t})}{D_{zt}^{t+1}(x_{zt}^{t+1}, y_{zt}^{t+1})}, \quad SE = \frac{D_{zt}^{t+1}(x_{zt}^{t+1}, y_{zt}^{t+1})}{D_{zt}^{t}(x_{zt}^{t}, y_{zt}^{t})} \]

\[ TP = \left[ \frac{D_{zt}^{t}(x_{zt}^{t}, y_{zt}^{t})}{D_{zt}^{t+1}(x_{zt}^{t+1}, y_{zt}^{t+1})} \times \frac{D_{zt}^{t}(x_{zt}^{t}, y_{zt}^{t})}{D_{zt}^{t+1}(x_{zt}^{t+1}, y_{zt}^{t+1})} \right]^{1/2} \]

IV. THE INPUT AND OUTPUT INDICATORS SELECTED AND THE DATA PROCESSING

A. THE INPUT AND OUTPUT INDICATORS SELECTED

Using the proposed model, in order to evaluate the TFEE of each DMU (provinces in China), on one hand, we have to build up an input and output indicator system of the 17 provinces; on the other hand, in compliance with the principle of the DEA theory that the number of DMUs should be no less than three times the total numbers of input and output indicators, there are 17 DMUs in this paper. Since we conduct the TFEE measurement of 17 DMUs in China, for the measurement, we use four inputs and one output, as indicated below.

**The input indicators are as follows:**

- X1, denoting real capital stocks (CS) [48]–[50];
- X2, denoting the total number of employees every year (TNE);
- X3, denoting the total energy consumption (TEC);
- X4, denoting the total environmental pollution (TEP) [51], [52].

**The output indicator** \( Y \), denotes the real gross domestic product in the provinces (GDP).

Specifically, CS represents the financial capital investment, TNE represents the human capital investment, TEC denotes the energy input, and TEP denotes ‘bad’ output or undesirable output. In the existing literature, there are many methods for dealing with undesirable outputs, such as data conversion processing method [53], [54], pollutant input processing method [55], [56], directional distance function method [58]–[60], etc. Each method has its own advantages and disadvantages. This paper argues that environmental pollution is an inevitable ‘bad’ output that is produced by DMUs in order to obtain “good” output, that is,
force majeure of environmental costs. Therefore, following Honma and Hu [57], Chung et al. [58], Fare et al. [59], we alternatively consider TEP an environmental cost and set it as an input indicator. GDP expresses the 'good' output, i.e., the economic output. According to the summary of previous literatures, we chose capital input, labor input, energy input and environmental costs for the input indicators, and took capital stock, employed population, energy consumption and pollutant emissions as quantitative indicators respectively. Meanwhile, output index was the GDP representing economic development. So how do these input indicators affect output indicator? We speculate on one of these possibilities, as shown in Fig. 5.

In macroeconomics, the accounting methods for GDP mainly include expenditure method, income method and production method. This paper mainly analyzes the mechanism of total factor energy efficiency by expenditure method. Accounting for GDP by expenditure method is the sum of the expenditures of the four departments of enterprise investment, household consumption, government purchase and net export in a certain period of time. We speculate that the four input indicators indirectly affect GDP by affecting four departments of expenditure accounting. The capital stock can reflect the capital storage and investment of the company in a certain period of time. The increase in employment will increase national income, which in turn will increase personal income and disposable income, leading to an increase in household consumption. There is a positive correlation between employment and GDP. Higher energy consumption means more investment by businesses and government purchases, while energy extraction also affects net exports. The generation of environmental pollutants is accompanied by all aspects of economic and social. In a certain period of time, environmental costs are positively correlated with GDP, and GDP growth has led to an increase in environmental pollution. However, when GDP reaches a certain value, environmental pollution becomes an important factor restricting economic development. The faster the economic development, the higher the environmental cost. In recent years, China has advocated “green GDP” and believes that GDP should be the result of economic activities after considering the influence of natural factors and environmental factors, and actually represents the net positive effect of national economic growth. Since the impact of input indicators on GDP is uncertain, the DEA model is suitable for the determination of TFEE without considering the “internal” influence.

B. DATA PROCESSING

In this paper, the corresponding data (2006-2015) mainly sourced from the China Statistical Yearbook, the China Energy Statistical Yearbook and the China Environmental Statistics Yearbook. In the DEA model, the constructed input-output indicators need to satisfy the principle of “isotropic”, that is, the increase of input indicators will inevitably bring about an increase in output indicators. To this end, Pearson correlation coefficient analysis is performed in the above index system. The specific formula is as follows:

$$r = \frac{1}{n-1} \sum_{i=1}^{n} \frac{X_i - \bar{X}}{S_X} \left( \frac{Y_i - \bar{Y}}{S_Y} \right)$$

(5)

where, r is the correlation coefficient between samples, n is the sample size, and $X_i$, $Y_i$ and $\bar{X}$, $\bar{Y}$ are the observed values and mean values of the two variables, respectively. $S_X$ and $S_Y$ represent the variance of the two variables. $r$ describes the degree of linear correlation between two variables. The value of $r$ is between $-1$ and $+1$. If $r > 0$, it means that the two variables are positively correlated; if $r < 0$, it means that the two variables are negatively correlated.

The analysis results show that the positive correlation between CS, TNE, TEC, TEP and GDP are 0.960, 0.931, 0.895 and 0.571, respectively, at the 5% significance level. As a result, the input-output index system conforms to the principle of “isotropic”. The specific results are shown in Table 1 below.

V. RESULTS AND DISCUSSIONS

Under static and dynamic dimensions, the TFEE of the 17 provinces in China along the B&R from 2006 to 2015 are evaluated by the DEA-BCC model and the DEA-Malmquist...
Y. Xue et al.: Total Factor Energy Efficiency Measurement in the Provinces of China Along the 'Belt and Road'

TABLE 1. Pearson correlation analysis between input variables and output variables.

| Input | CS   | TNE  | TECT | TEP  |
|-------|------|------|------|------|
| Real  | 0.960** | 0.931** | 0.895** | 0.571** |
| GDP   | (0.000) | (0.000) | (0.000) | (0.000) |

A. TFEE ANALYSIS BASED ON DEA-BCC MODEL

Note that the higher the TFEE is, the more efficient the province. From Fig. 6, the following conclusions can be drawn. As a whole, the TFEE, PTE and SE of the 17 provinces continued to grow from 2006 to 2015. The average TFEE rose from 0.737 in 2006 to 0.872 in 2015, the average PTE increased from 0.842 in 2006 to 0.916 in 2015, and the average SE went up from 0.879 in 2006 to 0.952 in 2015; thus, the three efficiency indexes, namely, TFEE, PTE and SE, increased by 18.3%, 8.8%, and 8.3%, respectively. Additionally, it can be concluded that the average SE is close to the optimal level and that there is still room left for improvement in TFEE and PTE. Therefore, to improve energy efficiency, more actions need to be taken by various entities.

As shown in Fig. 7, according to the 10-year average TFEE ranking, the top five provinces in China along the B&R are Shanghai, Guangdong, Zhejiang, Inner Mongolia and Fujian. The TFEE of the first two provinces during the inspection period was always 1, and the TFEE of the last three provinces reached 1 over many years. The last five provinces are Ningxia, Yunnan, Qinghai, Xinjiang, and Gansu. Across many years, the energy efficiency of the five provinces did not exceed 0.65. It can be seen that there are obvious regional differences in TFEE in China. The provinces with the highest TFEE are mainly located in the eastern region, while the lower ranked provinces are mostly located in the western region.

The TFEE in different provinces differs significantly, but the gap of energy efficiency between provinces is gradually being narrowed, which is summarized in Fig. 8. Taking 0.667 as a cut-off point, the TFEE in different provinces is divided into “improved” and “optimized”...
types. The TFEE value below 0.667 is an “improved” type, that is, the TFEE performance of these provinces is not good. The TFEE value between 0.667 and 1 is an “optimized” type. In 2006, the TFEE was lower than 0.667 in six provinces including Xinjiang, Shaanxi, Ningxia, Gansu, Qinghai and Jilin, of which Ningxia had the lowest TFEE, with a value of only 0.451. In 2015, only the TFEE in Gansu was lower than 0.667, with a value of only 0.584, while the remaining provinces were all “optimized”. The TFEE in Xinjiang, Shaanxi, Ningxia and Qinghai increased significantly by 11.6%, 27.1%, 66.5% and 50.8%, respectively. Additionally, the provinces that have reached the frontier of TFEE have increased, and include Zhejiang, Inner Mongolia, and Jilin. The difference between Gansu’s TFEE and that of the provinces with optimal production frontiers is 0.416, representing a decrease of 24.2%, which indicates that the energy gap between the provinces is gradually narrowing.

Taking into account the differences in the level of economic development in different provinces in China along the B&R, the differences in the TFEE among different regions are explored. According to the latest four major economic regions in China, the 17 provinces are divided into three regions: the eastern region, the western region, and the northeast region. The eastern region consists of Fujian, Shanghai, Zhejiang, Guangdong and Hainan; Xinjiang, Shaanxi, Ningxia, Gansu, Qinghai, Inner Mongolia, Guangxi, Chongqing and Yunnan belong to the western region. The northeast region is composed of Heilongjiang, Jilin and Liaoning. The changes of TFEE and its decomposition in each region are shown Fig. 8.

(1) From the perspective of the three regions, the development of TFEE is significantly uneven. In Fig. 9(a), consistent with the findings in most of the studies on TFEE in China, the average TFEE in the eastern region, 0.948, is larger than that in the northeast region and the western region, which are 0.793 and 0.696, respectively.

(2) The results in Fig. 9(b) highlight that the PTE values of energy utilization in the three regions are 0.977, 0.822 and 0.826, which implies an upward trend in energy utilization from the western to the eastern region, reflecting the huge differences between the three regions in terms of economic development potential, science and technology levels, and innovation ability. In addition, since 2012, the PTE of the northeast region has increased significantly, exceeding that of the western region. Even in 2015, compared to that of the western region, the PTE of the northeast region increased by 8.5%.

(3) As depicted in Fig. 9(c), the average values of SE of the eastern, western and northeast regions are 0.971, 0.856 and 0.959, respectively, and the average SE of the B&R is 0.929. This indicates that the SE in the eastern region is the highest, followed by the northeast region, the B&R, and the western region. The SE in the three regions is at a relatively high level, overall, with the northeast region and the eastern region being close to each other due to the large-scale

Footnote 9: The provinces in China along the B&R exclude the six provinces in the central provinces, namely, Shanxi, Henan, Hunan, Hubei, Jiangxi and Anhui.
development of heavy industries, coal, oil, and natural gas in the northeast region. In addition, in the northeast region, as the SE is significantly higher than the PTE, it is essential to maintain energy input levels and to rely on TP to improve the TFEE. The energy use in the western region is still exhibiting an increasing level of returns; however, there is currently a problem of energy input insufficiency. Hence, it is necessary to optimize energy input and then increase the TFEE.

### B. TFEE ANALYSIS AND ITS DECOMPOSITION BASED ON THE DEA-MALMQUIST INDEX

With the DEA-Malmquist index model, the TFEE from 2006 to 2015 of the 17 provinces is decomposed according to the annual and provincial standards. Based on this, the energy efficiency trends of these provinces are deeply analyzed. The specific results are shown in Table 2 and Table 3.

Table 2 shows that from 2006 to 2015, the average TFEE change index of the 17 provinces is 1.040, with an average annual growth rate of 4.0%. Overall, the energy utilization rate is increasing. The average value of TE changes is 1.021, with an average annual growth rate of 2.1%, which fully demonstrates that the production technologies and management methods of the 17 provinces have been continuously innovated, resources have been more rationally allocated, and more output has been achieved with the same energy. The TE is decomposed into PTE and SE. The values of these two indicators are greater than 1 in most years. The mean value of the PTE change is 1.010, reflecting an average annual growth rate of 1.0%, and the average value of the SE change is 1.013, reflecting an average annual growth rate of 1.3%. The rate of increase in SE is greater than the rate of increase in PTE. The average TP change index is 1.019, and the average annual TP is 1.9%, indicating that during the research period, the technology production frontier is moving forward. The reason may be due to the strengthening of R&D, the introduction of advanced technologies, and the increase in investments in research funding in the provinces. In addition, the promotion and diffusion of technology in the developed eastern provinces also contributed to TP.

From the trend of TFEE and its decomposition value, it can be determined that the trend of TFEE, TE and TP exhibits an increasing tendency and that the annual growth rate of TE is slightly higher than the annual growth of TP, explaining the importance of TE and TP for improving the TFEE. In particular, TP plays a crucial role in promoting the improvement of the TFEE. In addition, the lack of certain aspects of PTE and SE has restricted the TE. In particular, there are obvious factors restricting the PTE in the provinces in China along the B&R.

For the period 2006–2015, TABLE 3 illustrates the DEA-Malmquist index and its decomposition for the changes
in the TFEE of the 17 provinces. The average TFEE is 1.036, reaching the frontier of efficiency, and the average annual growth rate of energy efficiency is 3.6%, which indicates that energy efficiency is increasing yearly. The TFEE in the following provinces all exceed 1: Shaanxi (1.040), Ningxia (1.061), Qinghai (1.047), Inner Mongolia (1.075), Guangxi (1.026), Chongqing (1.020), Jilin (1.074), Liaoning (1.078), Fujian (1.061), Shanghai (1.089), Zhejiang (1.086), Guangdong (1.011) and Hainan (1.062); for these provinces, the annual average increases in energy efficiency are 4.0%, 6.1%, 4.7%, 7.5%, 2.6%, 2.0%, 7.4%, 7.8%, 6.1%, 8.9%, 8.6%, 1.1% and 6.2%, respectively. Among them, Shaanxi, Ningxia, Qinghai, Inner Mongolia, Jilin, Liaoning, Fujian, Shanghai, Zhejiang and Hainan have TFEE growth rates that are higher than the average TFEE growth rate of the B&R. For comparison with the TFEE analysis based on the DEA-BCC model, incorporating the Malmquist index, a dynamic analysis of the TFEE of the 17 provinces can be conducted. From the perspective of the provinces, the TFEE values in Xinjiang (0.966), Gansu (0.962), Yunnan (0.992), and Heilongjiang (0.948) are less than 1, with average annual energy efficiency increases of −3.4%, −3.8%, −0.08% and −0.52%, respectively. While the four provinces are located in the western region and northeast region, the main reason for the negative growth is the decline in the rate of TP.

The Malmquist index of each province is decomposed. From the perspective of TP, the change index of TP in most provinces is greater than 1, indicating that the frontiers of technological production are moving forward and that TP has promoted significant improvements in energy efficiency. Only the TP change index of Xinjiang (17), Gansu (15), Yunnan (14) and Heilongjiang (16) is less than 1, resulting in the lower ranking of the TFEE of 15, 16, 14 and 17, respectively. Due to changes resulting in lower TP, even Yunnan (8) and Xinjiang (9), which have moderate TE rankings, are unable to improve their lower energy efficiency rankings. From the perspective of TE, the TE change index of Shanghai and Guangdong is 1, indicating that there is no significant change in TE over the past 10 years; in Gansu and Heilongjiang, the TE change index is less than 1, the TE shows a downward trend, and the decline in TE has been caused by the decline in PTE. The TE of the remaining provinces shows an upward trend to a different degree, which is the result of the combination of PTE and SE.

At the same time, Table 3 shows the trend of the TFEE in each province is roughly similar to the trend of TP.

(1) Inner Mongolia, Shanghai, Zhejiang, Liaoning and Jilin are ranked in the top five provinces. Their TE changes and TP changes have exceeded the average level. Although the ranking of their TE change is not dominant, their TFEE ranks are high due to the large degree of TP. For Inner Mongolia, the added value of its secondary industry has accounted for a gradual increase in a proportion of the GDP, and energy efficiency has increased as the proportion of the secondary industry has increased. Since Inner Mongolia is a resource-based province that relies on coal development, its secondary industry has made tremendous contributions to economic development. Ma et al. [61], using the Tobit regression model, estimated the industrial structure of the northeast region and concluded that the tertiary industry in Liaoning and Jilin had a significant impact on the TFEE, indicating that the proportion of the tertiary industry increased yearly. The gap between its proportion and the proportion of the secondary industry is gradually narrowing, and the TP and TE brought by the growth of the tertiary industry are increasingly making up for the energy consumption of the secondary industry.

(2) Guangdong, Yunnan, Xinjiang, Gansu and Heilongjiang are ranked in the bottom five provinces. It can be seen that their rankings of TE changes and TP changes are relatively backward, indicating that the improvement in TFEE has been affected by TE and TP. Among these five provinces, since the reform and opening, the economy of Guangdong has continued to grow rapidly, and the demand for energy consumption has been increasing. However, compared with Shanghai and Zhejiang, the five provinces’ lower TE and TP has resulted in lagging energy efficiency, and the backward energy efficiency has further exacerbated the energy consumption. Second, in Heilongjiang, which is located in the northeast region, due to the deficiency of public finance funding of technology costs and less scientific research cooperation with neighboring universities, the investment in various scientific research projects has not been enough, leading to the lack of TP.

(3) The provinces ranked in positions 6–12 are Hainan, Fujian, Ningxia, Qinghai, Shaanxi, Guangxi and Chongqing. Ningxia and Qinghai have increased the development and utilization of clean energy. Ningxia encourages traditional industries to use advanced technology to carry out energy-saving technological transformation, and vigorously promote clean heating and to accelerate the promotion of energy-saving products and equipment. Qinghai relies on the advantages of solar energy resources, increases investments in science and technology research, and actively strives to overcome the problems in the field of clean energy. However, due to the backward TP, the technological improvements have been relatively small, which has greatly limited the improvement of the TFEE. The energy efficiency in Shaanxi, Guangxi, and Chongqing showed a downward trend in 2006 and has rebounded since approximately 2009, but its levels have been lower than those in the other provinces in the eastern region. The low level of energy efficiency is mainly related to the low growth rate of TP. Therefore, TP is a key factor affecting the change of TFEE in the western region.
the northeast region has been mainly affected by TP, and the space for improving the energy efficiency of Heilongjiang is attributable to the limitations of TE and TP. The TFEE in the eastern region has maintained a high level of growth: the substantial increase in TE and TP has been due to the convenience of geographical location, the innovation of science and technology, and the superiority of policy conditions.

C. DISCUSSION

In summary, the TFEE changes of the provinces in China along the B&R from 2006 to 2015 demonstrate that the TFEE in some provinces has been improved, while it has remained constant or deterioration in others. Meanwhile, the development of the TFEE in the three regions is significantly uneven. The two phenomena can be analyzed as below.

First, we focus on the phenomenon that the TFEE in some provinces has been improved, while it has remained constant or deterioration in others. Improved provinces include Xinjiang, Shaanxi, Ningxia, Qinghai, Inner Mongolia, Guangxi, Yunnan, Chongqing, Jilin, Liaoning, Zhejiang, Hainan and Fujian. Remain constant provinces are Shanghai and Guangdong. Deterioration provinces are Gansu and Heilongjiang. In 2012, large smog weather occurred in China, the Chinese government decided to strengthen the treatment of environmental pollution, imposed tougher penalties on high-energy and high-pollution enterprises, and forced provinces to rely on TP to improve energy efficiency and reduce pollutant emissions. As a result, the natural environment in most regions of China has been significantly improved. In all improved provinces, only Jilin reached the optimal production frontier in 2015. In order to improve the quality of economic development and energy efficiency, the local government promotes the continuous transformation of traditional industries, cultivates emerging industries, such as bio-pharmaceuticals, new materials, big data, and orbital equipment manufacturing. Shanghai and Guangdong have achieved the optimal TFEE with a high degree of openness, an abundant talent pool and a good economic foundation, there is convenient transportation and comprehensive infrastructure in Shanghai and Guangdong, many people choose subways and electric buses as their primary travel tools. Besides, Gansu and Heilongjiang with deteriorate TFEE may be relate to poor local economic base.

Second, we focus on the phenomenon that the development of TFEE in three regions is significantly uneven. The differences in TFEE across the three regions may be relevant to the economic strength of the region. In general, the economic strength of the eastern region is stronger than that of the northeast region, followed by the western region. The stronger the economic strength is, the higher the level of production technology and the higher the energy use efficiency. Additionally, during the sample period, the TFEE in the three regions showed a fluctuating upward trend, and the level of energy utilization increased yearly. The fluctuations mainly occurred in 2008 and 2013. In 2008, the global financial crisis broke out, which caused a relatively large impact on the economy of China. Due to the global financial crisis, Chinese economy experienced a slowdown in growth coupled with rising costs and declining benefits. Since the western region and the northeast region, unlike the eastern region, are located in remote inland areas with poor economic base and weak risk resistance, the impact of the financial crisis in these regions has been relatively large. At the same time, the Chinese government has implemented the “four trillion plans” to accelerate the utilization of production capacity. Therefore, the three regions show a fast growth trend after 2008. In 2013, the most sever haze events in the past 52 years broke out in China, especially in the northeast region. Many cities had very low visibility, causing flights to be suspended and schools to be stop. The Chinese government has introduced a series of measures to control haze to improve the ecological environment. Simultaneously, many high-pollution and energy-intensive factories in the three regions were closed, of which most in the northeast region. As a result, TFEE in the three regions fast increased after 2013.

Furthermore, the eastern region relies on excellent regional conditions, titled state policies, high technological levels, and R&D capabilities, which lay a foundation for the efficient use of energy. Since the reform and opening-up policy, China has been implementing a strategy of regional unbalanced development for a long period of time, which has led the eastern region to be the first to become prosperous. As a result, the level of technology, R&D capabilities and the allocation of resource elements in the eastern region have been stronger than that in the western region. In the western region, the backward technological level has kept the energy use at a low level over the long run.

VI. CONCLUSIONS AND SUGGESTIONS

In recent years, a large amount of research has focused on the environmental cost of estimated carbon dioxide emissions as an undesired output, using DEA or DEA derivative methods to measure the TFEE of different fields and regions, which has been mainly concerned with different industries or with various parts of China. This would cause deviations during the measurement of the energy efficiency. Therefore, this paper uses sulfur dioxide emissions, chemical oxygen demand emissions and dust emissions instead of carbon dioxide as input indicators to study the TFEE of the 17 provinces along the B&R in China between the years 2006 to 2015. Specifically, in this paper, for poorly performing provinces along the B&R, we aim to put forward some suggestions that may help them to achieve high-quality economic growth. First, under static and dynamic dimensions, the DEA-BCC model and the DEA-Malmquist index were selected to measure the TFEE of the 17 provinces. Then, four input indicators and one output indicator were set up to construct an energy efficiency evaluation index system. Note that in our model, a carbon dioxide indicator is replaced by sulfur dioxide emissions, chemical oxygen demand emissions and dust emissions. This is a novel approach for measuring environment costs. Further, the panel data from the year
2006–2015 were used to measure the TFEE of the research areas. Through this analysis, the following conclusions are drawn. As a whole, the TFEE of the research areas rose from 0.737 in 2006 to 0.872 in 2015, increasing by 18.7%, but there is still room for improvement. From the perspective of different provinces, between 2006 and 2015, the number of “improved” provinces decreased, while the number of “optimized” provinces increased, which indicated that the energy efficiency gap in different provinces was narrowing. In terms of the three regions, the TFEE in the eastern region, 0.948, is larger than those in the northeast and western regions, which are 0.793 and 0.696, respectively. Technological progress is a key factor affecting the change in TFEE in the western and northeast region, while the eastern region needs to improve technical efficiency. By calculating and analyzing the difference in TFEE between the eastern, the western, and the northeastern of China, we can conclude that there exists great room for progress in improving energy efficiency and promoting energy conservation and emission reduction in the future.

According to the above discussions and conclusions, a number of policy implications can be proposed to improve the TFEE of these major study areas. Firstly, the increasing trend observed in China’s TFEE implies that the energy conservation and emission reduction policies implemented have reached the expected level. However, government should adopt more stringent measures for the energy conservation and environmental regulatory, which will help improve energy efficiency and environmental performance. Secondly, at the regions level, the eastern region should continue to give play to geographical advantage and economic superiority to introduce advanced production technology and management experience, which are of crucial importance in improving the overall technology level of energy conservation and emission reduction in China. Compared to the eastern region, it is evident that the way to accelerate energy efficiency in the western and northeastern regions of China is to improve TP. Therefore, these regions should devise energy policies to ensure the achievement of technology introduction and efficiency targets. The western region that have weak capital but rich resources can establish financial special funds for research funding to realize the effective utilization of resources. In the northeastern regions, the areas that have a certain industrial scale can further strengthen the implementation of energy conservation and emission reduction policies and guide cooperation through actions, such as promoting the integration of production, teaching and research in a variety of approaches. Finally, considering the significant differences between different regions, exchanges and cooperation between Chinese regions should be expanded. In the field of energy conservation and emission reduction, knowledge transfer of relevant advanced technologies and management experience should be realized, and coastal developed areas should be compensated to inland backward areas to make up for and balance the energy efficiency gap between different regions. For example, to improve energy efficiency, the eastern provinces should formulate industrial transfer policies and strengthen the connection with two other regions. The empirical analysis gives us a clue about the importance of progress in TE in achieving effective energy utilization goals. To achieve regional energy cooperation, the areas with advanced technology need to reconsider the transfer of their mature and well-established industries to the areas with poor technology.

In summary, this paper primarily concentrates on how to accurately measure and decompose the TFEE of provinces in China along the B&R, although it may not fully consider how to address the factors affecting TFEE, an examination that may represent a future research opportunity.

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