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Evaluation and Dynamic Evolution of the Total Factor Environmental Efficiency in China's Mining Industry

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Abstract: The mining industry plays an extremely important strategic role in China's economic and social development. In the new era of pursuing circular/green/efficient development, the evaluation of the total factor environmental efficiency (TFEE) of China's mining industry is essential for alleviating resource waste and environmental pollution. The Epsilon-Based Measure (EBM) model effectively solves the shortcomings of radial and non-radial DEA models. In addition, the Malmquist–Luenberger (ML) index can measure the dynamic change of efficiency value. Combining the EBM model and the ML productivity index, this paper evaluates the TFEE from the static and dynamic perspective in China's 31 provincial mining industries over the period 2007–2016. The Theil index is employed to reveal the root of the overall provincial TFEE gap (OGTFEE) in China's mining industry. The results show that the average total factor static environmental efficiency (TFSEE) of China's provincial mining industry exhibits a low score of 0.6589 and with significant spatio-temporal differences. The provincial TFEE gap within four major areas (WGTFEE), especially that in east and west areas, is the main cause of the OGTFEE in China's mining industry. Technical change contributes more to the TFEE decline in China's mining industry. There are differences in improving the TFEE among China's 31 provincial mining industries, and corresponding countermeasures can be formulated accordingly. This study provides theoretical and practical basis for the clean and green development of China's mining industry.

Keywords: mining industry; environmental efficiency; spatio-temporal differences; EBM model; ML productivity index

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1. Introduction

Minerals and metals are fundamental raw materials for contemporary society, as they are core supplies for supporting the life of humankind. According to Hartman and Mutmansky (2002), the industrial mining cycle consists of a broad macro process with five long-term stages, each with a strong impact on the environment [1]. Mining has recently garnered increased attention due to its vast environmental impacts [2–5].

With China's reform and opening up, the mining industry has always played a strong supporting role in the rapid development of economy and society, and the acceleration of industrialization and urbanization. The mining industry has always been an important engine to promote China's economic development, and its position in the national economy is self-evident [6,7]. Meanwhile, a series of resource and environmental problems have become increasingly prominent, such as high energy consumption, low resource utilization rate, serious land resource waste and the weak recovery ability of the mine environment, all which restrict the sustainable development of the mining industry [8–10], and are contrary to the goal of developing green recycling mining industry and improving the area of land restored and reused. In order to control environmental pollution in the mining industry, the Chinese government has issued many policy documents, including saving energy consumption, reducing pollution and emission, and strengthening monitoring and evaluation [11,12]. How to improve the environmental problems of China's mining industry has attracted the attention of scholars in recent years [13–17].

The evaluation of environmental efficiency has become one of the main focuses, which can not only help the government and enterprises understand the current environmental situation of China's mining industry, but also provide a reference for them to better formulate and implement environmental policies accordingly. The Data Envelopment Analysis (DEA) method is a typical method for measuring the TFEE, which is widely used in TFEE evaluation of the China's mining industry because it does not need to set parameters and can effectively solve the diversification of input and output indicators. Liu and Meng (2018) introduced environmental pollutants such as waste water discharge and waste gas emissions into the energy efficiency evaluation framework system, and discussed the energy and environmental efficiency of 20 mining cities in Central and Eastern China based on the DEA model [18]. Zhu et al., (2018) used the global DEA method to analyze the green total factor productivity of China's mining industry over the period 1991 to 2014, and found that some sub-industries among China's mining industry have significant differences, and technological progress has been the contributor of the green total factor productivity growth in China's mining industry [19]. Wu et al., (2019) employed DEA to study the energy and environmental efficiency of China's mining industry, and concluded that the efficiency exhibits a low score [20]. In addition, Xiao et al., (2018) and Zhou et al., (2013) applied a Slacks-Based Measure (SBM) model to calculate the environmental efficiency of China's mining industry [21,22].

As mentioned above, a lot of efforts have been put forward to study the environmental efficiency of China's mining industry by employing traditional radial DEA models or non-radial DEA models. However, both radial and non-radial DEA models have their own shortcomings [23–25]. Therefore, Tone and Tsuchui (2010) [26] put forward an Epsilon-Based Measure model, which effectively solved the shortcomings of radial and non-radial DEA models, and has been widely used in environmental efficiency evaluation in recent years [27–30]. On the basis of the above research, the cumulative area of land occupied or destroyed by mining is taken as an undesirable output and an environmental efficiency evaluation model is established in this paper to estimate the TFSEE based on the EBM model for China's provincial mining industry. The EBM model can only measure the TFSEE for decision-making units (DMUs), but cannot provide dynamic evolution information about efficiency score change, nor does it obtain the driving factors of efficiency score change. Furthermore, the ML productivity index is used to calculate the total factor dynamic environmental efficiency (TFDEE) of China's provincial mining industry [31–34], and the key driving factors for improving the TFEE of China's mining industry are obtained through productivity index decomposition, which provides a reference for improving environmental efficiency.

The contributions of this paper are as follows: (1) The EBM model incorporating both radial and non-radial advantages is structured under the total factor framework, which provides a new method for evaluating the TFEE of China's provincial mining industry. Such work has not been found in the existing research. (2) This paper analyzes the potential of input-saving and undesirable output reduction, which will help scholars and the Chinese government to clarify the gains and losses in the process of mineral resources development in China, thereby providing quantitative guidance for improving the environmental efficiency of mining industry. (3) The Theil index method is employed to explore the formation mechanism of the OGTFEE in China's mining industry, which will help the government to adjust its policies according to local conditions. (4) Based on the ML productivity index, this paper investigates the TFDEE of China's provincial mining industry, and clarifies the effects of efficiency change (EC) index and technical change (TC) index on environmental efficiency, which not only helps scholars to understand the evolution trend of the environmental efficiency in China's mining industry, but also helps relevant governments to determine the priorities of the environmental management for China's mining industry in the future.

The remainder of this paper is organized as follows. Section 2 presents the research methods used in this study in detail. Section 3 introduces the variable selection and data sources. Section 4 provides the results and discussion. Conclusions will be drawn and corresponding policy implications proposed in Section 5.

2. Research Methods

The overall research methodology is presented in Figure 1. The research framework is comprised of four steps: step 1 focused on research questions and literature reviews; step 2 focused on the analytical structure; step 3 focused on results and analysis; and step 4 presented a macro-policy perspective based on this study.

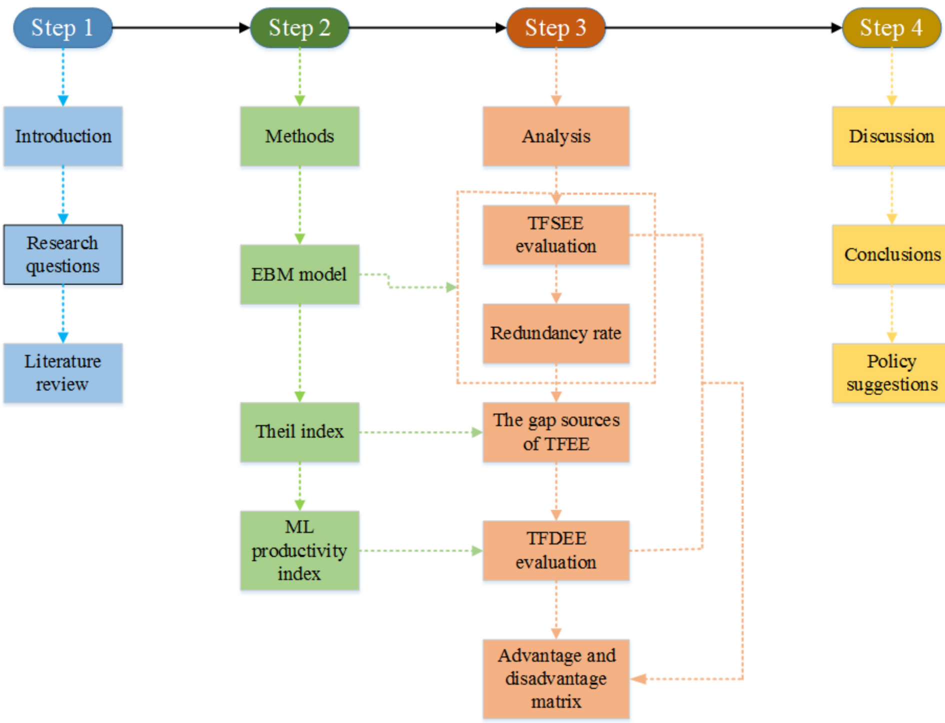

Figure 1. Research framework for this study.

2.1. *Epsilon-Based Measure Model*

The traditional DEA model is characterized with radial and oriented measurement, and it ignores the slack variables [27,35]. Avkiran and Rowlands (2008) [36] considered that although the non-radial and non-oriented SBM model can avoid the shortcomings, the traditional radial and oriented DEA model may overestimate the regional environmental efficiency. However, resources, energy consumption (input variables) and pollutant emission are "inseparable", and their relationship is radial and changes based on the ratio of α ($0 < \alpha < 1$) in the presence of undesirable output variables. However, there is a "separable" and non-radial relationship between other input variables and output variables [37]. However, neither the traditional DEA model nor SBM model can address the situation where the input and output variables are both characterized with radial and non-radial evaluation characteristics. In view of this, a hybrid model which takes into account both radial and non-radial distance functions was put forward by Tone and Tsutsui in 2010 [26]. Because ε parameter is employed in the model, it is named EBM model by Tone. The EBM model can make up for the defect of original DEA model and SBM model to a certain extent, and is widely applied in the field of environmental efficiency evaluation. Therefore, in this paper, the EBM model is introduced to calculate the TFEE of China's provincial mining industry in order to obtain the efficiency score closer to the actual score through the EBM model, thus we can improve the accuracy and reliability of the data, and provide a more reliable basis for the research results.

In this paper, an input-oriented EBM model under constant returns to scale (EBM-I-C) is established as shown in Formula (1):

$$
\begin{gathered}
\gamma^* = \min\theta - \varepsilon_x \sum_{i=1}^{m} \frac{w_i{}^- s_i{}^-}{x_{ik}} \\
\text{Subject to}: \sum_{j=1}^{n} x_{ij}\lambda_j + s_i{}^- = \theta x_{ik}, i = 1, \cdots, m \\
\sum_{j=1}^{n} y_{rj}\lambda_j \geq y_{ik}, r = 1, \cdots, s \\
\lambda_j \geq 0, s_i{}^- \geq 0
\end{gathered}
\tag{1}
$$

where γ^* represents the best efficiency score of EBM model, and it is satisfied with $0 \leq \gamma^* \leq 1$; x_{ik} and y_{ik} denote the ith input variable and the ith output variable of the DMU_k, respectively; Subscript k indicates the DMU being evaluated; m and s represent the input and output quantity, respectively; λ is linear combination coefficient of the DMU; θ is planning parameter of the radial part; s_i^- indicates the slacks of the ith input variable; w_i^- indicates the relative importance of each input variable, satisfying the condition $\sum_{i=1}^{m} w_i^- = 1(w_i^- \geq 0)$; ε_x is a key parameter connecting radial and non-radial slacks conditions, and satisfies the condition $0 \leq \varepsilon_x \leq 1$,which indicates the importance of non-radial part in efficiency calculation. It can be found that the EBM model will be simplified to the radial model when $\varepsilon_x = 0$, and it will be the SBM model when $\varepsilon_x = 1$.

As this paper involves the treatment of undesirable output, we extend the EBM-I-C model of Formula (1) to a non-oriented EBM model based on undesirable output. As expressed in the following Formula (2):

$$
\begin{gathered}
\gamma^* = \min \frac{\theta - \varepsilon_x \sum_{i=1}^{m} \frac{w_i{}^- s_i{}^-}{x_{ik}}}{\varphi + \varepsilon_y \sum_{r=1}^{s} \frac{w_r{}^+ s_r{}^+}{y_{rk}} + \varepsilon_b \sum_{p=1}^{q} \frac{w_p{}^{b-} s_p{}^{b-}}{b_{pk}}} \\
\text{subject to}: \sum_{j=1}^{n} x_{ij}\lambda_j + s_i{}^- = \theta x_{ik}, i = 1, \cdots, m \\
\sum_{j=1}^{n} y_{rj}\lambda_j - s_r{}^+ = \varphi y_{rk}, r = 1, \cdots, s \\
\sum_{p=1}^{n} b_{ij}\lambda_j + s_p{}^{b-} = \varphi b_{ik}, p = 1, \cdots, q \\
\lambda_j \geq 0, s_i{}^-, s_r{}^+, s_p{}^{b-} \geq 0
\end{gathered}
\tag{2}
$$

In Formula (2), b_{tk} stands for the tth undesirable output of the DMU_k; s_r^+ and s_p^{b-} denote the slacks of the rth desirable output and the pth undesirable output, respectively; w_r^+ and w_p^{b-} respectively represent the weights of the rth desirable output and the pth undesirable output, respectively.

2.2. Theil Index

On the basis of measuring the TFEE of China's 31 provincial mining industries, in this paper, the Theil index decomposition method is further applied to measure the OGTFEE in China's mining industry and we decompose it into two components, namely the TFEE gap between four major areas (BGTFEE) in China's mining industry and the WGTFEE in China's mining industry. Thus, the roots of the provincial TFEE gap in China's mining industry can be obtained. In order to reveal the root causes of the provincial TFEE gap in China's mining industry, this paper divides China's 31 provincial mining industries into four major areas according to geographical location, namely the east area, the northeast area, the central area and the west area, which will be further discussed in the following section. The Theil index value ranges from 0 to 1, and the smaller the value, the smaller the provincial gap. On the contrary, it shows that the provincial gap is bigger. Based on the research of Theil (1967), Bourguignon (1979), Cowell (1980), Shorrocks (1980) and Yang and Liu (2012) [38–42], the calculation formula of the Theil index and its structural decomposition of the TFEE in China's mining industry are established as follows:

$$OGTFEE = \sum_{i=1}^{31} (e_i/\bar{e}) \ln(e_i/\bar{e})/31 \tag{3}$$

$$MGTFEE_P = \sum_{i=1}^{n_p} (e_{pi}/\bar{e}_p) \ln(e_{pi}/\bar{e}_p)/n_p \tag{4}$$

$$WGTFEE = \sum_{p=1}^{4} (n_p\bar{e}_p/\bar{e})MGTFEE_P/31 \tag{5}$$

$$BGTFEE = \sum_{p=1}^{4} n_p(\bar{e}_p/\bar{e}) \ln(e_p/\bar{e})/31 \tag{6}$$

$$OGTFEE = WGTFEE + BGTFEE \tag{7}$$

where $n_p(p = 1,2,3,4)$ denotes the number of provinces in the east, northeast, central and west area in China. $e_i(i = 1,2,\cdots,31)$ represents the TFEE of each province in China's mining industry. $\bar{e}$ denotes the average TFEE score of China's 31 provincial mining industries. $\bar{e}_p(p = 1,2,3,4)$ denotes the average TFEE score of the mining industry in each major area, respectively. $e_{pi}(p = 1,2,3,4; i = 1,\cdots,n_p)$ represents the TFEE of the mining industry for each province in China's four major areas. $MGTFEE_p(p = 1,2,3,4)$ represents the Theil index of the provincial TFEE gap of the mining industry in the four major areas.

Here, between-group contribution rate and within-group contribution rate are used to represent the influence of the BGTFEE and WGTFEE on the OGTFEE in China's mining industry, respectively. The between-group contribution rate is defined as the ratio of the BGTFEE to the OGTFEE in China's mining industry; the within-group contribution rate is formulated as the ratio of the WGTFEE to the OGTFEE in China's mining industry. In addition, the contribution rate of each sub-group is defined as shown in Formulas (8)–(11). C_1,C_2,C_3,C_4 denote the contribution rates made by the east, northeast, central and west areas to the WGTFEE, respectively.

$$C_1 = \left(\sum_{n=1}^{10} e_{1n} / \sum_{i=1}^{31} e_i \right) \times (MGTFEE_1/OGTFEE) \tag{8}$$

$$C_2 = \left(\sum_{n=1}^{3} e_{2n} / \sum_{i=1}^{31} e_i \right) \times (MGTFEE_2/OGTFEE) \tag{9}$$

$$C_3 = \left(\sum_{n=1}^{6} e_{3n} / \sum_{i=1}^{31} e_i \right) \times (MGTFEE_3/OGTFEE) \tag{10}$$

$$C_4 = \left(\sum_{n=1}^{12} e_{4n} / \sum_{i=1}^{31} e_i \right) \times (MGTFEE_4/OGTFEE) \tag{11}$$

2.3. Malmquist–Luenberger Productivity Index

The EBM model introduced above is aimed at the production technology at a certain time. The production process is generally long-term and continuous, and in this process, the level of production technology is constantly changing. When the data of DMU are panel data, we can analyze the productivity changes and the effects of efficiency change and technical change on the productivity changes, which is the Malmquist Total Factor Productivity (TFP) index analysis. The Malmquist productivity index was put forward by

Malmquist (1953) [43]. Fare et al., (1992) [44] employed the DEA model to calculate the Malmquist index for the first time, and decomposed the Malmquist index into efficiency change and production technological change to reflect the change of production frontier. Chung et al., (1997) [31] applied the directional distance function (DDF) incorporating undesirable output to the Malmquist index, and the obtained productivity index was named the Malmquist–Luenberger productivity index.

The Malmquist–Luenberger productivity index is defined according to directional distance function. ML needs to define directional distance functions of two adjacent different periods:

$$\vec{D}_0^{t+1}(x^t, y^t, b^t; g) = \sup\{\beta : (y^t, b^t)\} + \beta g \in p^{t+1}(x^t)\Big\} \tag{12}$$

Each Chinese province is taken as a DMU, then following the ML index method, the TFDEE in the mining industry of province $p0$ between t and $t + 1$ is defined as follows:

$$TFDEE_t^{t+1} = \sqrt{\frac{1+\vec{D}_0^{t+1}\left(x_{p0}^t, y_{p0}^t, b_{p0}^t; y_{p0}^t, -b_{p0}^t\right)}{1+\vec{D}_0^{t+1}\left(x_{p0}^{t+1}, y_{p0}^{t+1}, b_{p0}^{t+1}; y_{p0}^{t+1}, -b_{p0}^{t+1}\right)}} \times \sqrt{\frac{1+\vec{D}_0^{t}\left(x_{p0}^t, y_{p0}^t, b_{p0}^t; y_{p0}^t, -b_{p0}^t\right)}{1+\vec{D}_0^{t}\left(x_{p0}^{t+1}, y_{p0}^{t+1}, b_{p0}^{t+1}; y_{p0}^{t+1}, -b_{p0}^{t+1}\right)}} \tag{13}$$

Then, TFDEE is further decomposed into the product of EC index and TC index to dig out the causes of productivity change. The functional expression is as follows:

$$TFDEE_t^{t+1} = EC_t^{t+1} \times TC_t^{t+1} \tag{14}$$

$$EC_t^{t+1} = \frac{1+\vec{D}_0^{t}\left(x_{p0}^t, y_{p0}^t, b_{p0}^t; y_{p0}^t, -b_{p0}^t\right)}{1+\vec{D}_0^{t+1}\left(x_{p0}^{t+1}, y_{p0}^{t+1}, b_{p0}^{t+1}; y_{p0}^{t+1}, -b_{p0}^{t+1}\right)} \tag{15}$$

$$TC_t^{t+1} = \sqrt{\frac{1+\vec{D}_0^{t+1}\left(x_{p0}^t, y_{p0}^t, b_{p0}^t; y_{p0}^t, -b_{p0}^t\right)}{1+\vec{D}_0^{t}\left(x_{p0}^{t}, y_{p0}^{t}, b_{p0}^{t}; y_{p0}^{t}, -b_{p0}^{t}\right)}} \times \sqrt{\frac{1+\vec{D}_0^{t+1}\left(x_{p0}^t, y_{p0}^t, b_{p0}^t; y_{p0}^t, -b_{p0}^t\right)}{1+\vec{D}_0^{t}\left(x_{p0}^{t+1}, y_{p0}^{t+1}, b_{p0}^{t+1}; y_{p0}^{t+1}, -b_{p0}^{t+1}\right)}} \tag{16}$$

where $TFDEE_t^{t+1}$ measures the dynamic change of the environmental efficiency in China's mining industry from period t to $t + 1$, and $TFDEE_t^{t+1} > 1$ indicates environmental efficiency improvement, representing that resource development gets more desirable outputs and less environmental pollutions. EC is the efficiency change index and EC_t^{t+1} measures the change of technical efficiency production possibility frontier during the period t to $t + 1$; When it satisfies the condition $EC_t^{t+1} = 1$, indicating that efficiency change has no contribution to the TFDEE growth; $EC_t^{t+1} > 1$ represents that EC index rises and has positive effect on TFDEE; $EC_t^{t+1} < 1$ represents that EC index decreases and has side influence on TFDEE. TC is the technical change index and TC_t^{t+1} evaluates the production technology change from period t to $t + 1$, and $TC_t^{t+1} > 1$ indicates the technological progress and acts positively on TFDEE and vice versa.

3. Variable Selection and Data Sources

3.1. Input and Output Variables

Based on the relevant literature and considering the characteristics of China's mining industry [45–47], the input variables of this paper include labor input, capital input and land use input. The average annual number of employees in China's mining industry is taken as the labor input, the approved registered area by the mining license is used to represent land use input, and the capital stock is selected as the capital investment variables. The capital stock is usually estimated using the perpetual inventory method [48]. Since the data of the initial capital stock and capital depreciation rate of China's mining industry are difficult to obtain, this paper refers to the research of Gao et al., (2018) [49], taking the net fixed asset value of the mining industry in 2006 (constant price of the year) as the initial capital stock, and the net added value of fixed assets in the next two years as new fixed assets; then, we convert the value into 2007 constant prices according to the price index of investment in fixed assets.

$$K_{it} = K_{it_0} + \sum_{t_0+1}^{t} \Delta K_{it} \quad (17)$$

The industrial sales output value of the mining industry is introduced as desirable output, and is converted into 2007 constant prices using the producer price index of industrial products by industry. Cumulative area of land occupied or destroyed by mining is taken as undesirable output to reflect the damage to the land environment during the process of resource exploitation and utilization. The data of the labor input, capital input and industrial sales output value are obtained from the China Industrial Statistical Yearbook (2008–2017). The data of the approved registered area by the mining license and the cumulative area of land occupied or destroyed by mining are taken from the China Land and Resources Statistical Yearbook (2008–2017). The data of the price index of investment in fixed assets and the producer price index of industrial products by industry are obtained from the National Bureau of Statistics. Table 1 provides the statistical information for each of the indicators.

Table 1. Descriptive statistical information of input and output variables (2007–2016).

Variables	Unit	Max	Min	Mean	Std. Dev
Labor input	10^4 people	108.42	0.02	24.19	24.25
Capital input	Billion RMB	4407.66	1.01	733.53	838.00
Land use input	Km^2	22,068.25	11.85	2471.90	2566.67
Desirable output	Billion RMB	5742.66	6.18	1149.83	1188.97
Undesirable output	Km^2	50,182,243.00	0.01	239,621.73	2,850,731.51

3.2. Region Description

Considering that city-level data and enterprise-level micro-data are incomplete and the statistical criteria of them are often different, 31 provinces (including autonomous regions and municipalities) in China are selected as the research objects of this paper. This article refers to relevant research and takes the characteristics of the resource endowment in various regions of China's mining industry into account [50,51]. Thus, 31 DMUs are divided into four groups according to the geographical location. The east area includes Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Shandong, Guangdong, Hainan and Fujian. The northeast area includes Liaoning, Jilin and Heilongjiang. The central area includes Shanxi, Anhui, Jiangxi, Henan, Hubei and Hunan. The west area includes Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang. The east area is the most developed area in China, and its mineral resources are relatively poor. The northeast area includes the main old industrial bases in China, with an early history of resource development. The central area is rich in mineral resources, with moderate geographical location and good resource exploitation conditions. The west area has large mineral resources reserves and a fragile ecological environment, so it is necessary to strengthen the coordination between resource development and ecological environment protection. Since the Ministry of Land and Resources of the People's Republic of China implemented a new mineral resource planning database from 2007 and the data on the number of employees in mining industry by province have only been updated to 2016 at the time of writing, this study period is set from 2007 to 2016.

4. Results and Discussion

4.1. Analysis of TFSEE in China's Mining Industry

According to Formula (2), the TFSEEs of China's 31 provincial mining industries and its four major areas in the east, central, west and northeast during the period 2007 to 2016 are evaluated, and the results are presented in Table 2. The TFSEE score in China's mining industry is relatively low with the average score of 0.6589 during 2007–2016, and there is about 35% room for improvement from the production frontier, indicating that there exists great potential for energy conservation and pollution reduction. The table reveals that the average TFSEE scores of the mining industry in the east, northeast, central and west areas are 0.7860, 0.5965, 0.6718 and 0.5620, respectively. The average score in the east area is obviously higher than that in other areas, and that in west area shows the lowest. We must realize that the DEA method employed in this paper is a "relative efficiency" evaluation method. Although the efficiency evaluation results can accurately reflect the relative level of the environmental efficiency for the mining industry in China's 31 provinces, the efficiency scores are closely related to the research samples and the selected variables. Once the research samples and the selected variables change, the efficiency measurement results may change accordingly. Therefore, the higher TFSEE for the mining industry of the provinces in eastern China is only relative to 31 provinces in China. Once it exceeds this range, for example, if Western developed countries or regions with higher environmental efficiency in the mining industry are added to the evaluated samples, the efficiency score in eastern China will obviously decrease.

Table 2. The TFSEE in the mining industry of China's 31 provinces and its four major areas.

Province	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Mean
Beijing	1.0000	0.6877	1.0000	0.7928	0.7913	1.0000	0.8106	0.4430	0.3838	0.4743	0.7383
Tianjin	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Hebei	0.7135	0.6953	0.5014	0.7914	1.0000	0.9163	0.9144	0.7971	0.7773	0.8075	0.7914
Shanxi	0.9308	0.7557	0.4115	0.5441	0.6190	0.6972	0.6377	0.1769	0.5550	0.6478	0.5976
Inner Mongolia	0.6341	0.3235	0.4908	0.5483	0.7742	0.7735	0.6575	0.4720	0.8580	1.0000	0.6532
Liaoning	0.5984	0.3625	0.4809	0.6463	0.8416	0.8720	0.8653	1.0000	0.6988	0.5256	0.6891
Jilin	0.5663	0.4698	0.4522	0.5493	0.5316	0.5818	0.5576	0.6308	0.6361	0.7323	0.5708
Heilongjiang	0.8395	0.6172	0.4161	0.4774	0.5045	0.5038	0.4844	0.5226	0.4611	0.4682	0.5295
Shanghai	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Jiangsu	0.5706	0.4964	0.4107	0.5136	0.5413	0.5755	0.5422	0.4351	0.6458	0.7122	0.5443
Zhejiang	0.8521	0.4506	0.5582	0.7363	0.8398	1.0000	1.0000	0.4557	1.0000	1.0000	0.7893
Anhui	0.5297	0.3765	0.4271	0.5541	0.6074	0.5463	0.5261	0.4522	0.6017	0.6516	0.5273
Fujian	0.8725	0.5660	0.5795	1.0000	1.0000	1.0000	1.0000	0.6479	1.0000	1.0000	0.8666
Jiangxi	0.5801	0.5661	0.4537	0.6166	0.7519	0.7874	0.7604	0.6748	0.7505	0.8483	0.6790
Shandong	1.0000	0.5888	0.5757	0.7138	0.7137	1.0000	0.6964	0.5559	0.8164	1.0000	0.7661
Henan	1.0000	0.6653	0.5212	0.6938	0.7491	0.7923	0.8116	0.5373	0.7872	0.7699	0.7328
Hubei	0.9374	0.4099	0.4123	0.5333	0.6942	0.8457	0.8765	0.5303	0.9118	0.9651	0.7116
Hunan	0.6794	0.4520	0.5117	0.6548	1.0000	1.0000	1.0000	0.5279	1.0000	1.0000	0.7826
Guangdong	1.0000	0.6972	0.7172	1.0000	0.7264	1.0000	1.0000	1.0000	0.8608	1.0000	0.9002
Guangxi	0.6742	0.4234	0.5008	0.5982	0.8244	1.0000	1.0000	1.0000	1.0000	1.0000	0.8021
Hainan	0.5145	0.5841	0.2843	0.4057	0.4886	0.5062	0.4787	0.4644	0.4348	0.4813	0.4643
Chongqing	0.9688	1.0000	0.4001	0.5396	0.5605	0.6392	0.5151	0.1540	0.4980	0.5199	0.5795
Sichuan	0.8950	0.4739	0.5060	0.6842	0.9044	0.9157	0.8442	0.6714	1.0000	1.0000	0.7895
Guizhou	0.5987	0.2837	0.2879	0.5224	0.6376	0.7078	0.8021	0.1784	0.9289	1.0000	0.5948
Yunnan	0.6983	0.3306	0.3100	0.4640	0.5479	0.5418	0.5999	0.4523	0.5657	0.6189	0.5130
Tibet	0.4632	0.1515	0.1370	0.2328	0.3477	0.4058	0.3768	0.3830	0.4061	0.4992	0.3403
Shaanxi	0.7078	0.5129	0.5101	0.5993	0.5252	0.5379	0.6626	0.4951	0.5649	0.7881	0.5904
Gansu	0.5318	0.3735	0.3460	0.4352	0.5029	0.5014	0.5091	0.5001	0.5527	0.6778	0.4930
Qinghai	0.5013	0.2491	0.1996	0.3727	0.4678	0.4829	0.4999	0.4448	0.4548	0.4879	0.4161
Ningxia	0.5555	0.4636	0.4407	0.4894	0.4953	0.4807	0.4930	0.0890	0.5269	0.6512	0.4685
Xinjiang	0.6493	0.4550	0.4230	0.4984	0.5085	0.5027	0.4819	0.5095	0.4674	0.5401	0.5036
East area	0.8523	0.6766	0.6627	0.7954	0.8101	0.8998	0.8442	0.6799	0.7919	0.8475	0.7860
Northeast area	0.6681	0.4832	0.4497	0.5576	0.6259	0.6525	0.6358	0.7178	0.5987	0.5754	0.5965
Central area	0.7762	0.5376	0.4563	0.5994	0.7369	0.7781	0.7687	0.4832	0.7677	0.8138	0.6718
West area	0.6565	0.4201	0.3793	0.4987	0.5914	0.6241	0.6202	0.4458	0.6520	0.7319	0.5620
Overall China	0.7440	0.5317	0.4924	0.6196	0.6934	0.7456	0.7227	0.5549	0.7143	0.7699	0.6589

From the 31 provinces, as displayed in Table 2, Tianjin and Shanghai are located at the production frontier with the average score of 1 during 2007–2016, indicating that these two provinces have effectively realized ecological and environmental protection in the process of resource exploitation, representing the highest level of the environmental governance in China's mining industry. Beijing, Hebei, Zhejiang, Fujian, Shandong and Guangdong also show relatively high TFSEE score of the mining industry among 31 provinces. Tibet, Gansu, Qinghai and Ningxia exhibit relatively low TFSEE score of the mining industry, and these provinces are located in the west area with an underdeveloped economy. The east area has always been the area with the strongest economic strength, the most advanced production technology and the highest environmental governance level, so it has exhibited the highest TFSEE of the mining industry. The northeast area is an important industrial base in China, with abundant mineral resources and good location conditions. The energy and mineral resources in northeast area have laid a solid foundation for China's industrialization process. In recent years, "The 13th Five-Year Plan for Northeast Revitalization" has promoted the transformation of mining industry in northeast area. The central area is an important energy base in China due to its large amount of mineral resources and high concentration of resources. However, resource exploitation mode in central China is relatively extensive, and the long-term resource-based economic development mode makes it difficult to realize a rapid mode of transformation, and the pressure on mine environmental protection is enormous. The west area is sparsely populated with the fragile ecological environment. In recent years, the western development strategy has stimulated the acceleration of industrial development in the west area, which strengthens mineral resources development, and the environmental quality of mines has been deteriorating. From the time perspective, from 2007 to 2016, the overall TFSEE of China's mining industry increased from 0.7440 in 2007 to 0.7699 in 2016, but the efficiency value fluctuates greatly and ranges from 0.49 to 0.77. The TFSEE scores of the mining industry in the central and west areas also show a trend similar to that of the overall China, with the central area rising from 0.7762 in 2007 to 0.8138 in 2016 and the west area rising from 0.6565 to 0.7319. The TFSEE values of the mining industry in the east and northeast areas share the opposite trend characteristics to that of China overall, with the east area decreasing from 0.8523 to 0.8475 and the northeast area decreasing from 0.6681 to 0.5754. This shows that the contradiction between China's mining industry development and environmental protection has not been effectively solved, and it still faces challenges to realize the development coordination and sustainability of mining industry and environment.

4.2. The Potential of Input-Saving and Undesirable Output Reduction

4.2.1. Overall Analysis

The DEA method provides quantitative guidance for provinces with DEA inefficiency to reduce production input and negative environmental impact while satisfying the condition that economic output is constant [52,53]. The following figures show the reduction potential of input and "bad" output variables from the perspective of overall China, its four areas and its 31 provinces, which can provide a targeted direction for improving the environmental efficiency of China's mining industry. It can be seen from Figure 2 that, on the whole, the redundancy of the average annual number of employees (P) is an important reason for the environmental inefficiency of China's mining industry, with an average redundancy rate of 33.66%, indicating that more than 33% of human capital input elements have not been effectively utilized. During 2007 to 2014, China's mining industry developed rapidly with high investment, resulting in a large number of redundant labor forces. In 2015, with the serious overcapacity, the mineral products price showed a downward trend, and the mineral products market changed from "seller's market" to "buyer's market"; the country began to implement supply-side structural reform along with some measures such as reducing staff input and increasing efficiency. The average redundancy rates of land resource input (L) and undesirable output (D) are 16.44% and 16.30% respectively, and the average redundancy rate of capital input (C) is 0.42%. A large amount of resource input and serious land destruction and pollution not only result in the surface environment destruction, but also cause the environmental efficiency reduction of the mining industry, which reflects China's mining economic growth mode at the expense of resources and environment. From a dynamic point of view, although the redundancy rates of inputs and undesirable outputs in China's mining industry show a decreasing trend over time, they show great fluctuations, which is consistent with the conclusion given above that the environmental efficiency of mining industry increases slightly and the efficiency score fluctuates greatly and has been ranging from 0.49 to 0.77. In the process of pursuing the sustainable growth of the mining economy, more attention should be paid to the environmental efficiency by relevant departments, effective measures should be implemented, and mining environmental governance and restoration should be promoted, as only in these ways can the coordinated development between mining industry and environment be achieved.

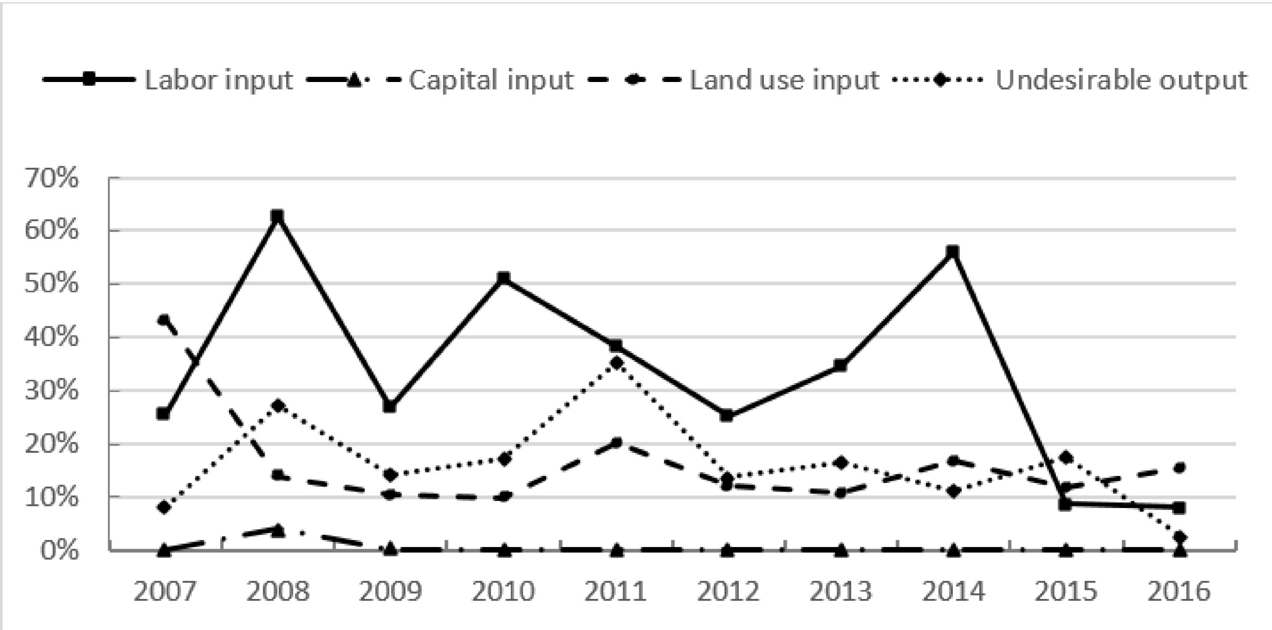

Figure 2. Changes of redundancy rate of the input and output variables in China's mining industry.

4.2.2. Provincial Analysis

The average redundancy rates of labor input, capital input, land input and undesirable output in China's mining industry by province over the sample period are shown in Figure 3. It is found that there are significant differences in input-saving and undesirable output reduction potential of China's provincial mining industry. Specifically, the average redundancy rates of the four variables in Tianjin and Shanghai are 0.00%, which indicates that these two have higher environmental efficiency in the mining industry and are in the forefront of the whole country. The average redundancy rates of labor input in Sichuan, Anhui, Guizhou, Shanxi, Jiangsu and Henan are more than 50.00%, meaning that there is a serious phenomenon of excessive labor input in these provinces' mining industry. On the whole, the capital input of China's mining industry is reasonable, and the redundancy rate of capital input in most provinces reaches 0.00%, but the investment funds of mining industry in Shandong, Henan and Qinghai provinces are still not effectively utilized. The average redundancy rates of land use input in Tibet, Qinghai, Guizhou and Yunnan are over 45.00%, implying that there are a lot of mine land redundancies in these provinces. In addition, these provinces have low land use values and large room for land utilization rate improvement. The average redundancy rates of undesirable output in Jiangxi, Inner Mongolia, Henan, Guangdong, Guangxi, Liaoning and Beijing are more than 30.00%, which shows that these provinces have serious problems of accumulated occupied or damaged land by mining.

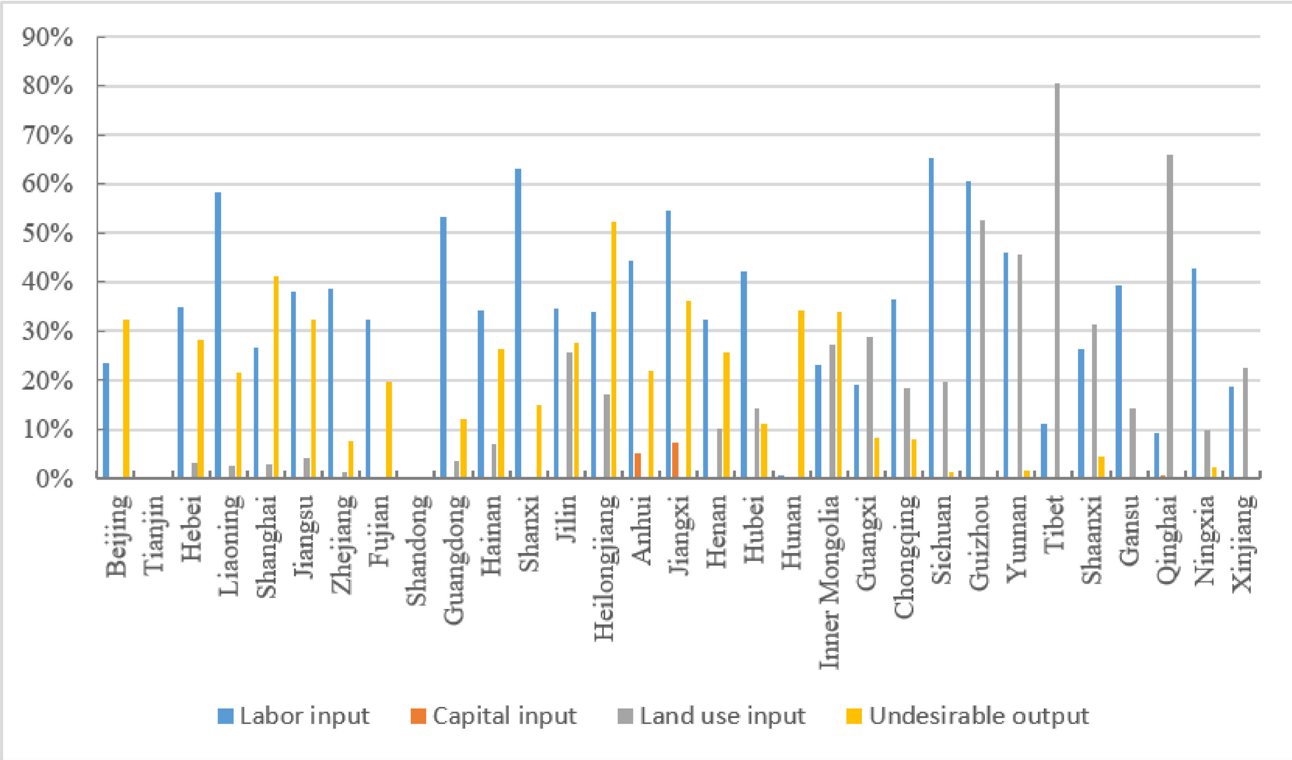

Figure 3. Average redundancy rate of input and output variables in China's 31 provincial mining industries from 2007 to 2016.

4.2.3. Regional Analysis

The four areas, eastern China, northeastern China, central China and western China, share some similarities with the ranking of average redundancy rate of selected variables, but the scores of redundancy rate are quite different. The average redundancy rate of labor input in the east area is 24.45%, which is the lowest among the four areas. The average redundancy rates of cumulative area of land occupied or destroyed, land use input and capital input in the east area are 19.08%, 6.87% and 0.50%, respectively. Due to its superior geographical location, suitable living environment and developed economic level, eastern China has attracted more human capital. However, during the development of the mining industry, the oversupply of human resources has hindered the economic growth efficiency of the mining industry. Compared with the other three areas, the average redundancy rates of capital input and land use input in northeast China show the lowest value, which are only 0.00% and 1.82%, respectively, reflecting that the use of capital and land resources are at a relatively optimal level. The average redundancy rates of labor input and cumulative area of land occupied or destroyed in the central area are the highest in the four areas, reaching 47.39% and 26.97%, respectively, which may be due to the loss of high-quality labor. Usually, highly skilled or highly educated talents are highly mobile. Attracted by the high labor remuneration in eastern China, the high-quality labor force in the central area tends to transfer and gather to the east area, resulting in the lack of high-quality labor force in the central area. Western China exhibits the highest average redundancy rate of land input (32.61%). In view of the geographical disadvantage and resource endowment advantage, in order to promote regional economic development, the western regional government tends to extensively exploit mining resources, resulting in insufficient land use efficiency, which is not conducive to the development of mining industry. Compared with the other three areas, the average redundancy rate of accumulated land damage in the western area is not high, reaching 7.73%. In addition, the average redundancy rate of capital input in the west area is 0.05%, which indicates that western China is likely to use a large amount of funds for land environmental restoration, which not only realizes the transformation of capital investment value, but also improves the quality of mining land.

4.3. The Sources of Provincial Gap of TFEE in China's Mining Industry

According to Formulas (3)–(11), the OGTFEE, BGTFEE and WGTFEE in China's mining industry are obtained based on the Theil index. By measuring the contribution rates of BGTFEE and WGTFEE in OGTFEE, this paper investigates the formation sources of provincial gap in the TFEE in China's mining industry. The calculation and decomposition results of the Theil index are shown in Table 3. It can be found from Table 3 that the Theil index of the TFEE in China's mining industry shows an increasing trend, from 0.0309 in 2007 to 0.0363 in 2016, indicating that the provincial gap among 31 provinces is widening. It also can be inferred from Table 3 that the BGTFEE of the mining industry is gradually narrowing, and the WGTFEE of the mining industry exhibits an expanding trend, suggesting that China has achieved certain results in strengthening the coordinated development strategy of provincial mining industry and promoting industrial gradient transfer in recent years. On the basis of index decomposition results, the average contribution rates of the BGTFEE and the WGTFEE are 26.35% and 73.65%, respectively, and the contribution rate of the WGTFEE is always much higher than that of the BGTFEE during the study period, which shows that the WGTFEE is the main factor affecting the overall provincial TFEE gap in China's mining industry. In line with the average score of the WGTFEE, the provincial gap in the west area presents the largest score, with the highest contribution rate locating at 32.57%, followed by the east area (28.52%), and the provincial gaps in the northeast and central areas display relatively small scores, with contribution rates of 3.99% and 8.57%, respectively. From the decomposition results of the Theil index, it can be inferred that narrowing WGTFEE, especially that in the east and west areas, should be the key to improving the environmental efficiency of China's mining industry in the future.

Table 3. The Theil index and its decomposition of TFEE in China's mining industry.

Year	OGTFEE	BGTFEE		WGTFEE		East Area	Northeast Area	Central Area	West Area
		Value	Contribution Rate	Value	Contribution Rate	Contribution Rate	Contribution Rate	Contribution Rate	Contribution Rate
2007	0.0309	0.0068	21.89%	0.0241	78.11%	28.62%	4.53%	19.28%	25.68%
2008	0.0737	0.0206	28.03%	0.0530	71.97%	18.67%	2.78%	8.63%	41.90%
2009	0.0772	0.0294	38.08%	0.0478	61.92%	39.01%	0.20%	1.11%	21.60%
2010	0.0451	0.0204	45.25%	0.0247	54.75%	32.04%	1.48%	2.07%	19.15%
2011	0.0365	0.0096	26.28%	0.0269	73.72%	27.91%	6.83%	8.39%	30.59%
2012	0.0402	0.0129	32.03%	0.0273	67.97%	22.31%	6.00%	8.07%	31.59%
2013	0.0398	0.0095	23.94%	0.0303	76.06%	27.02%	6.94%	10.67%	31.44%
2014	0.1035	0.0212	20.44%	0.0824	79.56%	22.33%	4.73%	9.58%	42.92%
2015	0.0449	0.0052	11.64%	0.0397	88.36%	34.73%	2.64%	9.79%	41.20%
2016	0.0363	0.0058	15.88%	0.0305	84.12%	32.54%	3.76%	8.15%	39.68%
Mean	0.0528	0.0141	26.35%	0.0387	73.65%	28.52%	3.99%	8.57%	32.57%

4.4. Analysis of TFDEE in China's Mining Industry

In order to further investigate the dynamic evolution features and driving factors of the TFEE in China's provincial mining industry, this paper employs the Malmquist–Luenberger productivity index based on Formulas (12)–(16) to calculate the TFDEE of the mining industry, and then decomposes it into EC index and TC index. The specific results are revealed in Figures 4 and 5.

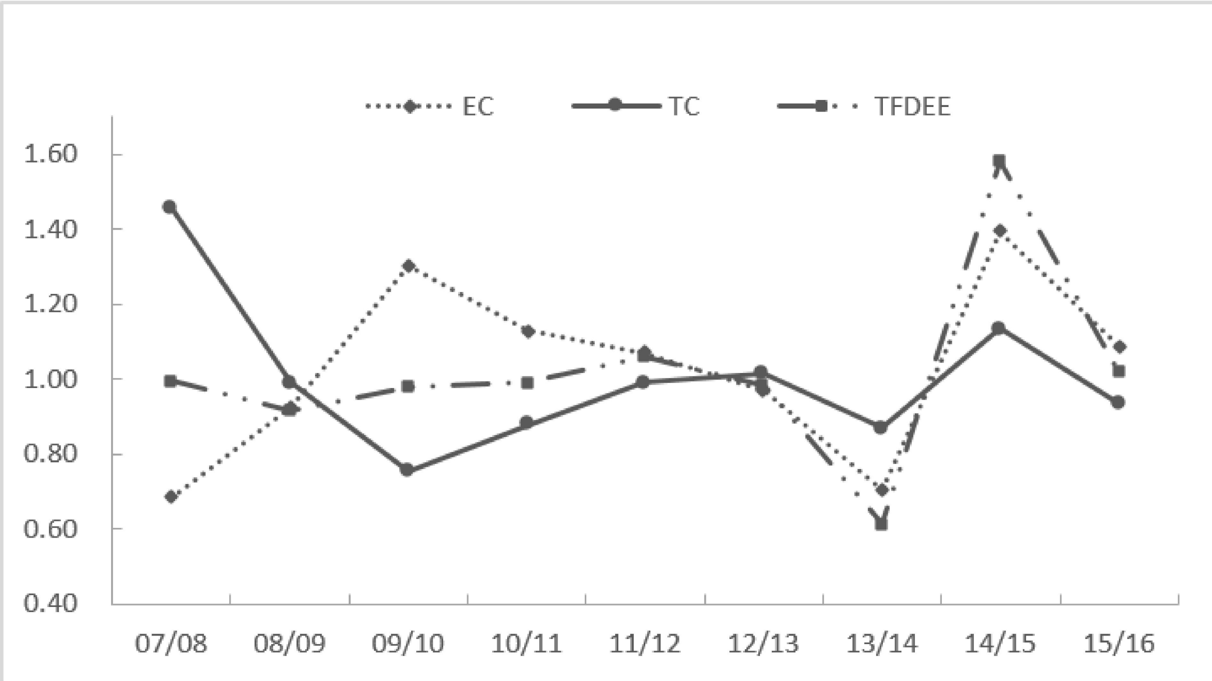

Figure 4. Change trend of TFDEE and its decomposition index in China's mining industry.

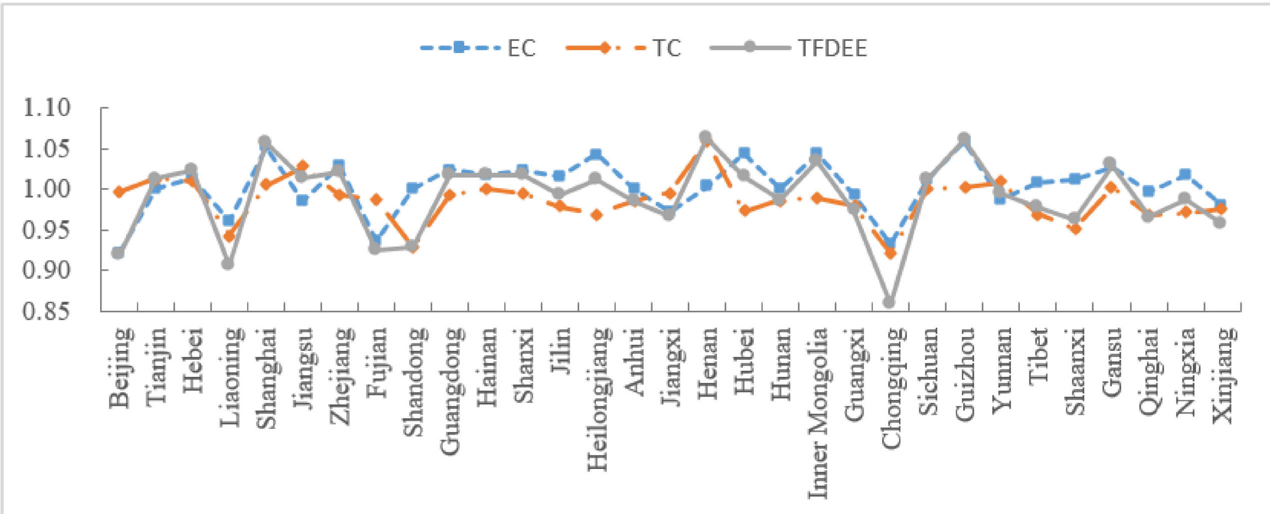

Figure 5. Average score of TFDEE and its decomposition index in China's 31 provincial mining industries during 2007–2016.

4.4.1. Overall Analysis

As shown in Figure 4, the average TFDEE of China's 31 provincial mining industries is 0.989 over the research period, with an average annual decline of 1.1%, indicating that the relationship between mining development and environmental protection in China tends to deteriorate and the situation is not optimistic. According to the index decomposition results, the average EC score is 1.003, with an average annual increase of 0.3%, and the average TC score is 0.986, with an average annual decrease of 1.4%, which means that the technical progress is the biggest obstacle of China's overall TFDEE improvement in the mining industry, while technical efficiency has been the key driving factor in promoting efficiency growth. What needs to be explained here is that the negative growth rate of technical progress is not the speed retrogression of production technology and environmental governance technology, but the slowdown of production technology and environmental governance technology. The reason is that China tends to improve the resource allocation efficiency and reform the environmental management mode and promote advanced environmental protection concepts in the process of mineral resources development and environmental governance, while ignoring the technological progress of production and environmental governance, as well as the renovation and upgrading of mining equipment and technology, thus restricting the improvement of the TFDEE in China's mining industry.

From a dynamic perspective, as shown in Figure 4, the TFDEE of China's mining industry has been in a declining state from 2007 to 2011, and it turns into an increasing state from 2011 to 2012, then it presents a downward trend from 2012 to 2014, and finally with an upward state from 2014 to 2016. EC index maintains a negative growth state from 2007 to 2009, and maintains an upward trend from 2009 to 2012, then it shows a downward trend from 2012 to 2014, and finally it maintains a positive growth from 2014 to 2016. On the contrary, the TC index shows a continuous downward trend from 2008 to 2012, and then it goes up and down around 1. To sum up, in order to optimize the TFEE growth of China's mining industry and realize the harmonious development of economy and environment, the technical progress growth improvement should always be the key point, and it is of great importance to driving the TC and EC to jointly promote the TFDEE improvement of mining industry.

4.4.2. Provincial Analysis

It can be seen from Figure 5 that during 2007–2016, the average TFDEEs of mining industry in Tianjin, Hebei, Inner Mongolia, Liaoning, Jilin, Jiangsu, Zhejiang, Anhui, Jiangxi, Hubei, Hunan, Guangxi, Sichuan, Guizhou and Gansu are more than 1, while that in China's other 16 provinces are less than 1. The average TFDEE of mining industry in Hubei exhibits the highest growth rate of 6.19%, followed by Guizhou (6.06%), and that in Chongqing shows the lowest growth rate of −14.11%. For provinces with the average TFDEE more than 1, the EC and TC scores of Tianjin, Hebei, Inner Mongolia, Hubei, Guizhou and Gansu are more than 1, which means that the resources development and technical progress of these provinces have strong synchronization, and they not only rely on the input of resources, but also pay attention to the driving role of technology in the industrial process. However, the other 9 provinces with the average TFDEE more than 1 are driven by one way, either TC index or EC index. For the provinces with the average TFDEE less than 1, Beijing, Shanxi, Heilongjiang, Henan, Hainan, Chongqing, Qinghai and Xinjiang all show the synchronicity of EC index and TC index less than 1, which indicates that the mining industry in these provinces not only plays an intrinsic role in promoting technology, but also fails to realize the effective utilization of resources on the supply side. The technology research and development and technology introduction in these provinces need to be further improved, and optimization of mining resource structure and technical reform should be given full attention. Only in this way can the supply-side reform of these provinces' mining industry be effectively realized and the overall efficiency level improved. The TC is the contributor to the TFDEE deterioration in Shanghai, Fujian, Shandong, Guangdong, Tibet, Shaanxi and Ningxia, indicating that these provinces has been focused on improving management measures of the mining industry and improving production management level, and the production technology innovation has been ignored. By contrast, EC is the obstacle of the TFDEE improvement in Yunnan.

4.4.3. Regional Analysis

In the four areas, the TFDEEs of the mining industry in eastern, northeast, central and western China without exception show a downward trend, and the average scores of them are 98.5%, 98.7%, 99.7% and 99.2%, respectively. The east area shows the fastest decline rate, followed by the northeast area, and the central area exhibits the slowest decline rate. In the light of the ML productivity index decomposition results, there are different reasons for the decline of the TFDEE in the four areas' mining industry. During the study period, the EC index and the TC index in the east area both show a declining trend, with average annual decline scores of 0.1% and 1.3% respectively, which together hinder the TFDEE improvement of eastern China's mining industry. The average values of EC and TC in northeast China are 0.984 and 1.003, respectively. The blocking effect of EC is greater than the promoting effect of TC, so the TFDEE of mining industry in northeast China exhibits a download trend. TC is greater than 1 and EC is less than 1 in the central and west areas. The decomposition results of TFDEE fully indicate that China's mining industry still has not got rid of the traditional "three highs" development mode, and it has a long way to go to realize the green transformation. In addition, compared with the other three areas, the performance of the TFDEE, EC and TC in the east area are relatively poor among the four major areas, and the coordination degree between mining development and environmental protection in the east area exhibits the lowest score, implying that eastern China should be the key concern area in term of the restoration and management of mining environment and the realization of sustainable economic and social development in China in the future.

4.5. The Advantages and Disadvantages for Improving TFEE in China's 31 Provincial Mining Industries

The evaluation results of TFSEE and TFDEE for the mining industry in China's 31 provinces are given above. This part further reveals the advantages and disadvantages of each province in improving the environmental efficiency for the mining industry, and provides strategic guidance for the development of mining environmental governance in the future. First, based on China's provincial average TFSEE and TFDEE in the mining industry, this part constructs a "TFSEE–TFDEE" matrix. Then, China's 31 provinces can be classed into four phalanxes with different characteristics: provinces in the first phalanx present a higher TFSEE and better TFDEE, indicating that these provinces have advantage of high environmental efficiency and fast efficiency growth rate; provinces in the second phalanx, with a higher TFSEE but a lower TFDEE; provinces in the third phalanx present a slower TESEE and a higher TFDEE, which shows that these provinces are expected to challenge efficient provinces through rapid growth in the future; provinces in the fourth phalanx present a slower TFSEE and a lower TFDEE, which are the provinces with the worst performance among 31 China's provincial mining industries. The calculation and classification results are shown in Figure 6.

As can be seen in Figure 6, the horizontal axis describes the TFSEE and the vertical axis describes the TFDEE for mining industry. With the average score of the two as the boundary, the coordinate plane can be divided into four parts, which respectively correspond with the four phalanxes of efficiency characteristics. Through comparison, it is found that there are 10 provinces in the first phalanx, Jiangxi, Liaoning, Zhejiang, Hubei, Hunan, Tianjin, Fujian, Sichuan, Hebei and Guangxi, which have dual advantages of the high environmental efficiency and rapid efficiency growth rate, and are the "benchmark" and leaders in terms of environmental protection for China's mining industry. Shandong, Guangdong, Henan, Beijing and Shanghai are in the second phalanx. The static efficiency is higher than the average value but the dynamic efficiency is slower than the average value. The advantage lies in the high environmental efficiency, while the disadvantage is the low efficiency growth rate. The environmental efficiency in these provinces may be surpassed by other provinces in the future. It also can be found in Figure 5 that Yunnan, Anhui, Jiangsu, Gansu, Jilin, Guizhou and Inner Mongolia are located in the third phalanx, with the lower static environmental efficiency and the higher productivity of the mining industry, which have a great growth potential of environmental efficiency for the mining industry in the future. Relative to the provinces' average value, nine provinces are in the fourth phalanx, whose environmental efficiency and environmental productivity are both lower than the average score, indicating those provinces have relatively lower environmental inefficiency of the mining industry and have a lower dynamic efficiency growth rate. These provinces include Tibet, Ningxia, Qinghai, Hainan, Xinjiang, Shanxi, Heilongjiang, Shaanxi and Chongqing, which are the provinces with the most severe situation in terms of environmental governance and control in China's mining industry.

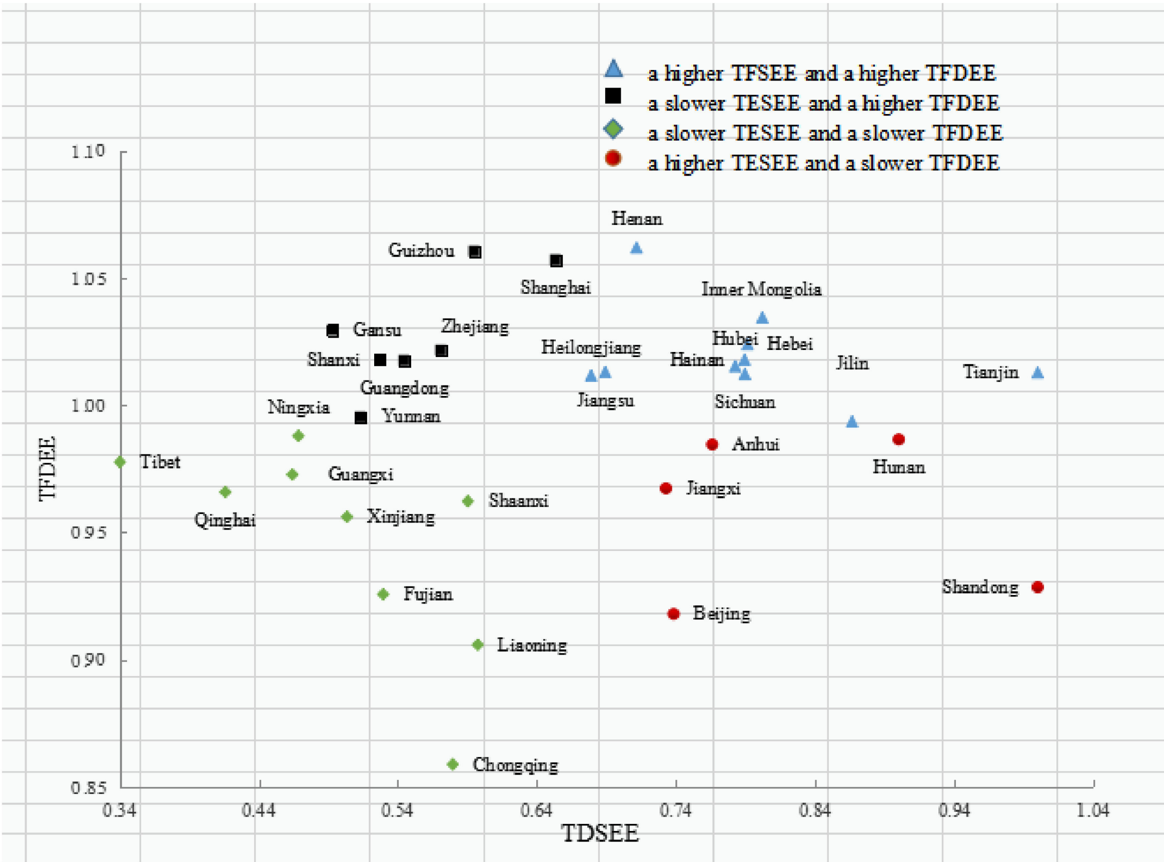

Figure 6. The advantages and disadvantages for improving environmental efficiency in China's 31 provincial mining industries.

5. Conclusions and Policy Recommendations

5.1. Conclusions

In this study, the EBM model and ML productivity index are used to investigate the spatio-temporal heterogeneity and driving factors of environmental efficiency in China's 31 provincial mining industries during the period 2007–2016. Then, the Theil index is employed to reveal the causes of regional differences in environmental efficiency of China's mining industry, and the advantages and disadvantages for improving environmental efficiency of 31 provinces are analyzed by constructing a "TFSEE-TFDEE" matrix in the mining industry. The study finds that: (1) During 2007–2016, the average TFSEE of China's 31 provincial mining industry is 0.6589, and there is about 35% room for improvement from the production frontier. The TFSEE in the east area is higher than that in the other three areas. The labor input, land use input and undesirable output have higher redundancy rate. (2) WGTFEE, especially in the east and west areas, is the main source of the regional gap in environmental efficiency in China's mining industry. (3) During the research period, the TFDEE of China's mining industry shows a downward trend, and TC has been the biggest obstacle. (4) Among China's 31 provinces, there are differences in the advantages and disadvantages for improving the environmental efficiency of mining industry in different provinces, and corresponding countermeasures can be formulated accordingly.

5.2. Policy Recommendations

According to the above research results, some policy suggestions are put forward to improve the environmental efficiency of China's mining industry: (1) The environmental efficiency of China's mining industry exhibits a low score and shows a downward trend, which means that the current policies on resource development and environmental protection of the mining industry are ineffective. Therefore, the government should implement the existing policies and establish a feedback mechanism in time. It is necessary to formulate stricter measures for resource use and environmental supervision, promote the transformation of mining development mode, reduce the waste of input resources such as labor, capital and mine land, and improve environmental efficiency.

(2) In view of the fact that there are regional differences in the environmental efficiency of China's mining industry, exchanges between and within areas should be strengthened in the fields of production technology and environmental protection, and the overall progress in the mining industry will be realized through complementary technological advantages and management optimization learning. On the one hand, the east area should play an exemplary role and make full use of superior geographical conditions, advanced technology and other resources to promote the construction process of green mines in China. On the other hand, it should support the development of mining technology and the improvement of environmental management in other areas of China.In order to promote the overall environmental efficiency improvement in China's mining industry, it is necessary to change the current unreasonable mode of over-reliance on technical efficiency as soon as possible, funds for technology research and development should be increased, the use scale of green mining technology and environmental treatment technology capital can be expanded, and the synergistic effect of technical efficiency and technological progress will be obtained.

(3) In addition, Chinese government should fully take the advantages and disadvantages of regional development reality and the environmental efficiency improvement in the mining industry into consideration when formulating policies, and establish environmental protection policies on local conditions accordingly, and adopt the strategy of individual support and key breakthrough to give full play to the guiding and stimulating role of policies. The governments of Tianjin, Shanghai, Beijing and Hebei province can strengthen exchanges with other provinces to help them improve the quality development of the local mining industry.

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