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China's Regional Energy Efficiency: Results Based on Three-stage DEA Model

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Abstract: Traditional DEA models ignore the influence of environmental variables and statistical noise which may result in biased efficiency estimates. To solve this problem, three-stage DEA model was proposed and has been widely applied in many areas. This study evaluates China's regional energy efficiency by using three-stage DEA model based on the statistical data of 2010, and discusses the divergence of three different efficiency assessment methods. The empirical results show that the environmental factors indeed influence the regional energy efficiency performance. After the adjustment of environmental variables, the national average technical efficiency by adopting three-stage DEA model decreased significantly than by using traditional DEA model, but the influences to regions are different due to diverse features, some regions were overestimated by using BCC-DEA model, and some regions were underestimated. Three-stage DEA model is able to reflect the true efficiency by eliminating environmental effects compared with other methods.

Key words: Evaluation; Three-stage DEA Model; SFA; Environmental Influence; Regional Energy Efficiency

1 Introduction

With the rapid development of economy, the total energy consumption has grown so fast that China has become the second largest energy consumer and largest CO_2 emitter in the world. The large amount of energy consumption and its continuous growth trends are challenging the energy security, climate change and sustainable development of China. In this context, the Chinese government decisively put forward a legally binding energy efficiency target of decreasing the energy intensity by 20% during the 11th Five Year Plan, and allocated the target to provincial level. By adopting a comprehensive way involving legal, administrative and economic means, the energy efficiency work had achieved remarkable results including a 19.1% drop of energy intensity. However, due to the lack of sufficient theoretical support and experience, most provinces carried out work in the dark or promoted energy efficiency ineffectively, and the local level also faced different difficulties to meet their goals owing to "one-size-fits-all" national policy. Chinese government has proposed a further energy efficiency target of 16% energy intensity decrease during the 12th Five Year Plan in 2011, and it is significant and necessary to assess the provincial energy efficiency scientifically and rationally to provide support for the central and local policy makers.

For macro research, energy efficiency used to be classified as single factor efficiency and total factor efficiency according to the number of input factor. Single factor energy efficiency only considers energy as input, and is often represented by energy intensity which is equal to the ratio of energy consumption with gross domestic product (GDP). However, single factor energy efficiency may have defect, it only reflects the influence of energy on economic output, but ignores the relations between energy and other factors. Any economic production activity is a joint-production process which utilizes energy resources and other non-energy resources (labor and capital) to produce outputs. In 2006, Hu and Wang firstly introduced the concept of total factor energy efficiency, which emphasized the relationships between economic output and multivariate inputs including energy, labor and capital reservation, and calculated China's total factor energy efficiency from 1995 to 2002 using DEA model which first proposed by Charnes et al. (1978). Therefore, total factor efficiency can be more appropriate to reflect the true efficiency than single factor efficiency. In addition, DEA model has recently been widely used to study energy efficiency at the macro-economy level. Wei and Shen (2007), Xu and Liu (2007) analyzed the total factor energy efficiency of Chinese provinces. Honma and Hu(2008) estimated regional total factor energy efficiency in Japan. Moreover, some scholars consider undesirable outputs such as SO_2, CO_2 to evaluate the environmental efficiency. For example, based on a non-radial DEA framework, Zhou et al. (2007) evaluated the energy and environment efficiency of 26 OECD countries from 1995 to 1997.The factors of labor, primary energy consumption, GDP, CO_2, sulphur oxides, nitrogen oxides and carbon monoxide were all included as input or output factors in their study. Zhou et al. (2008) developed several DEA-based environment efficiency evaluation models for the measurement of the carbon emission efficiency of several world regions. Bian and Yang (2010) proposed several DEA models to simultaneously measure resource (energy) and environmental efficiency, and applied their models in the resource and environmental efficiency evaluation problem of 30 Chinese provinces. Wang, Wei, and Zhang (2012) utilized several DEA based models to evaluate the total factor energy and emission performance of China's 30 regions within a joint production framework of considering desirable and undesirable outputs as well as separated energy and non-energy inputs.

However, the traditional DEA models ignore the influence of environmental variables and statistical noise which may result in biased efficiency estimates. To solve this problem, Fried et al. (2002) proposed the three-stage DEA approach which consists of a three-stage analysis: start with a traditional BCC-DEA, continue with a stochastic frontier analysis (SFA) to explain the variations in terms of environment, statistical noise and managerial efficiency, and conclude with traditional BCC-DEA using adjusted data from the second stage to gain the real efficiency. The three-stage DEA approach has been applied in a wide range of industries and shows the superiority for efficiency evaluation. Shang et al. (2008) estimated the commerce and hotel performance in Taiwan by three-stage DEA analysis. Wang and Zhang (2009), Guo, Ni, and Li (2010), Deng, Zhang, and Guo (2011), and Jonchi and Terri (2012) used three-stage DEA model to evaluate the cultural industries efficiency of China in 2004, agricultural production efficiency of China in 2008, ecological efficiency of China in 2008, and the true managerial efficiency of bank branches in Taiwan, respectively. Jiang and Wang (2011) adopted three-stage and super-efficiency DEA model to analyze the cultural industries efficiency among 31 provinces of China in 2008. All the studies found that the efficiency values from a three-stage DEA analysis vary significantly from traditional DEA model. The environmental variables have remarkable effect on efficiency.

In this paper, we will evaluate the energy efficiency of China's 30 regions in 2010 by using a three-stage DEA analysis and compare the results and ranking with another two evaluation methods including single factor energy efficiency and the total factor efficiency by using traditional BCC-DEA model. The rest of the paper is organized as follows: Section 2 introduces the three-stage DEA model, the data and variables. Section 3 analyzes the empirical results. In section 4, the assessment results by using three different methods will be discussed. Section 5 concludes the paper.

2 Methodology

2.1 The three-stage DEA model

To examine the influence of environment and statistical noise on regional total factor energy efficiency, we introduce the three-stage DEA model proposed by Fried et al.(2002). The Fig.1 shows the framework of this model, and the detailed explanations are as follows:

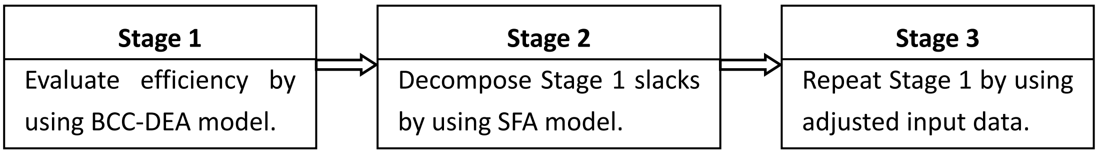

Fig. 1 The framework of three stage DEA model

Stage 1: The Initial DEA Evaluation

In stage 1, the initial DMU performance evaluation is conducted using a conventional oriented DEA model. Technical efficiency and the total input slacks of DMUs will be calculated in relation to the original input and output data.

The traditional DEA model for the *k*th DMU can be written as follows:

$$\text{Min} \quad \theta_k - \varepsilon\left(\sum_{r=1}^{s} s_{rk}^{+} + \sum_{i=1}^{m} s_{ik}^{-}\right)$$

$$\text{St.} \quad \sum_{j=1}^{n} \lambda_j x_{ij} + s_{ik}^{-} = \theta_k x_{ik}, \quad i = 1,2,\ldots m,$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_{rk}^{+} = y_{rk}, \quad r = 1,2,\ldots s, \qquad (1)$$

$$\sum_{j=1}^{n} \lambda_j = 1,$$

$$\lambda_j, s_{rk}^{+}, s_{ik}^{-} \geq 0, \quad j = 1,2,\ldots n, \quad r = 1,2,\ldots s, \quad i = 1,2,\ldots m.$$

where y_{rk} is the *r*th output of the *k*th DMU; x_{ik} is the *i*th input of the *k*th DMU; s_{rk}^{+} is the slack variable of the *r*th output of the *k*th DMU; s_{ik}^{-} is the slack variable of the *i*th input of the *k*th DMU; ε is a minimum positive number indicating that no factor should be neglected; and θ is the relative TE. For the efficient units, their efficiency value θ is 1 and $s_{rk}^{+} = s_{ik}^{-}$=0, which forms the efficient frontier.

Stage 2：Using SFA to Decompose Stage 1 Slacks

The objective of the Stage 2 analysis is to decompose Stage 1 slacks into these three effects: environmental effects, managerial inefficiencies, and statistical noise. We can meet this objective by using SFA model, in which Stage 1 slacks are regressed against observable environmental variables and a composed error term, which both captures and distinguishes the effects of managerial inefficiency and statistical noise. Since our Stage 1 model is input-oriented, we prefer to focus on just the *m* Stage 1 input slacks, and opt for the estimation of *m* separate SFA regressions.

The dependent variables in the Stage 2 SFA model are the Stage 1 total input slacks s_{ik}, i=1，2，…，*m*, k=1，2，…，*n*, where s_{ik} is the Stage 1 slack in the usage of the *i*th input for the *k*th DMU. The independent variables in the Stage 2 SFA regression model are the elements of *p* observable environmental variables z_k=(z_{1k} ，z_{2k} ,…，z_{pk}), k=1, 2, …, *n*. The *m* separate Stage 2 SFA regressions take the general form

$$s_{ik} = f^{i}(z_k;\beta^i) + v_{ik} + \mu_{ik} \qquad (2)$$

where $f^{i}(z_k;\beta^i)$ are deterministic feasible slack frontiers with parameter vectors β^i to be estimated and composed error structure ($v_{ik} + \mu_{ik}$). Consistent with a stochastic cost frontier formulation, it assumes that $v_{ik} \sim N(0,\sigma_{vi}^2)$ reflect statistical noise and that μ_{ik} ≥ 0 reflect managerial inefficiency. If make a distributional assumption on μ_{ik}, such as $\mu_{ik} \sim N^{+}(\mu^i,\sigma_{\mu i}^2)$, and if assume that v_{ik} and μ_{ik} are distributed independently of each other, and of the z_k, each of the *m* regressions may be estimated by maximum likelihood techniques. In each regression the parameters to be estimated are (β^i , μ^i , σ_{vi}^2 , $\sigma_{\mu i}^2$). All parameters are allowed to vary across the M input slack regressions, which allow the environmental variables, statistical noise and managerial inefficiency each to exert different impacts across inputs.

The next step is to adjust DMUs’ inputs for the variable impacts of different operating environments and random statistical noise by utilizing the results of the Stage 2 SFA analysis. The purpose of the adjustment is to make all DMUs face the same environments and luck before repeating the DEA analysis. There are two ways to level the playing field: downward the inputs of these DMUs with unfavorable environments or bad luck; another choice is to upward the inputs of DMUs with advantaged conditions. Like most previous study, we adopt the second approach to avoid the possibility that some extremely disadvantaged producers might have some inputs adjusted so far downward as to become negative.

DMUs’ adjusted inputs are constructed from the results of the Stage 2 SFA regressions by means of

$$\hat{x}_{ik} = x_{ik} + [\max_k\{z_k\hat{\beta}^i\} - z_k\hat{\beta}^i] + [\max_k\{\hat{v}_{ik}\} - \hat{v}_{ik}] \qquad (3)$$

where $\hat{x}_{ik}$ and x_{ik} are adjusted and observed input quantities, respectively. The first bracket is to put all DMUs into a common environment, the least favorable environment observed in the sample. The second one is to put all DMUs into a common state of nature, the unluckiest situation encountered in the sample.

In order to implement equation (3) it is necessary to separate statistical noise from managerial inefficiency in the residuals of the SFA regression model (2) to obtain estimates of ν_{ik} for each DMU. This can be accomplished by using the model (4) proposed by Jondrow et al.(1982).

$$\hat{E}[\nu_{ik} \left| \nu_{ik} + \mu_{ik} \right.] = s_{ik} - z_k \hat{\beta}^i - \hat{E}[\mu_{ik} \left| \nu_{ik} + \mu_{ik} \right.] \qquad (4)$$

where the $\hat{E}[\mu_{ik} \left| \nu_{ik} + \mu_{ik} \right.]$ depends on ($\hat{\beta}^i, \hat{\sigma}^2_{\nu i}, \hat{\sigma}^2_{\mu i}, \hat{\mu}^i$), so do the $\hat{E}[\nu_{ik} \left| \nu_{ik} + \mu_{ik} \right.]$. The elements of $\hat{\beta}^i$ provide estimates of the contributions of each observable environmental variable to slack in usage of the *i*th input, while the parameters ($\mu^i, \sigma^2_{\nu i}, \sigma^2_{\mu i}$) characterize the separate contributions of managerial inefficiency and statistical noise to slack in use of the *i*th input. In particular, as $\gamma = \sigma^2_{\mu i} / (\sigma^2_{\mu i} + \sigma^2_{\nu i})$ approximates to 1, the impact of managerial inefficiency dominates while statistical noise instead when γ is close to 0.

Stage 3: Adjusted DEA

Stage 3 is a repetition of Stage 1, with observed input data x_{ik} replaced with input data x_{ik} which have been adjusted for the impacts of both the observable environmental variables and statistical noise. Thus, the efficiency obtained in the third stage will be more realistic to reflect the managerial efficiency.

2.2 Data and variables

In consideration of reliability, integrity, and time-sensitive of the data, we use the data in 2010 of 30 regions in China. Tibet, Taiwan, Hong Kong and Macau are omitted due to the absence of relevant data. For the DEA model, we choose labor, capital stock as two non-energy inputs and use the provincial total energy consumption as the last input according to production function. Local GDP is utilized as the only output. The data of labor and GDP are from China Statistical Yearbook 2011 and energy consumption data from China Energy Statistical Yearbook 2011. Due to the lack of the official statistics, we estimate the regional capital stock of China by using the methodology and fundamental data proposed by Zhang, Wu, and Zhang(2004).

As for the selection of environment variables, we consider the key influence to regional disparity of energy efficiency which has been widely studied by domestic and international academics. In this paper, we quote the research conclusion of Shi(2011) as a main reference, and choose the related data on energy consumption mix, economic development, industry structure, and geographic condition of 30 regions. Finally, four environmental variables are adopted according to the availability and comparability of data, including local coal consumption, climate condition in major cities, regional per capita GDP, and the local output value of tertiary industry.

3 Empirical Results

3.1 The results of Stage 1

In this stage, we adopt BCC-DEA model and calculate the total factor energy efficiencies of 30 regions by using the software of DEAP 2.1. The detailed results in Table 2 (BCC) shows that Beijing, Shanghai, and Guangdong are lying on the frontier with the average energy efficiency of 1. Without considering the external environment variables and statistical noise, the average energy technical efficiency (TE), the average energy pure technical efficiency (PTE), and the average energy scale efficiency (SE) of all regions are 0.742, 0.822, and 0.908, respectively. In general, it means 25.8% of the input factors resulted in waste. And most regions operated at an increasing return to scale. Therefore, these regions are not operating under the optimal scale.

3.2 The results of Stage 2

The Frontier 4.1 software is used to carry out SFA regressions. Because only two regions have the capital stock slacks, so we ignore the regression process of capital stock. The regression analysis is conducted to find the influence of four environmental variables and statistical noise on input slack variables. Results of the Stage 2 SFA regressions are summarized in Table 1.

Table 1 Stochastic frontier estimation results

	Dependent Variable	
Independent Variable	Energy Input Slack	Labor Input Slack
Constant	8.454***	54.026***
	(5.779)	(48.632)
Coal Consumption	1.018***	-2.076***
	(8.041)	(-5.215)
Average Temperature	-0.996***	0.744
	(-5.87)	(-0.797)
Per Capita GDP	-1.075***	-5.789***
	(-7.598)	(-9.423)
Output of Tertiary Industry	0.423***	3.923***
	(2.632)	(8.29)
σ^2	3.882***	1.718**
	(4.519)	(1.828)
γ	0.9999***	0.9999***
	(1279147)	(28.728)
Log likelihood Function	-9.172	-17.371
LR test of the one-sided error	22.857***	5.667

** , *** indicate the significance level at 5% and 1% respectively. The data in brackets are t statistics.

In Table 1, most parameters of environment variables are at 1% significance level. These results suggest that the environment indeed exert a statistically significant influence on regional energy efficiency. It is necessary to eliminate the environmental effects on regional energy efficiency. The results also explain the contribution of statistical noise to the efficiency. The estimated values of the parameter γ are approaching to 1 for the two inputs. That means the effect of noise plays little role to the variation in slacks in the two inputs. Therefore, we will almost ignore the influence of statistical noise when adjust the input.

The regression coefficients of environmental variables also shed light on the relationship between environmental factors and input slacks. The positive coefficients suggest that the environment is unfavorable to the greater excess in input use. Conversely, the negative coefficients mean that environment is favorable to the lesser excess in input use. Table 1 illustrates that each environmental variables will cause different influences to the input slacks.

According to results, the regression coefficients of coal consumption are positive to energy input slacks, but negative to labor input slacks. It implies that the increase of the proportion of coal will cause the increase of energy input slacks, but can reduce the input slacks of labor. As we all know that the thermal and combustion efficiency of coal is lower than other main fossil energy, such as oil and natural gas. Improving the ratio of coal may decrease the regional energy efficiency. In addition, coal industry belongs to labor-intensive industries. Thereby more coal demand needs more labor. That is why increase the proportion of coal can reduce the input slacks of labor.

On the contrary, the regions with higher average temperature will be prone to reduce the energy input slacks and increase the labor input slacks. For the regions with lower average temperature, especially north of the Yangtze River in China, it needs to supply heating in winter. In general, heating mainly relies on coal-fired boilers. Consequently, more coal will be consumed in the regions with lower average temperature.

In terms of the per capita GDP, all the regression coefficients are negative which suggest that the regions with higher per capita GDP will create more input slacks for energy and labor. We can understand the results by comparing developed countries with developing countries. One of the significant indicators to reflect the developmental level of a country is the per capita energy consumption. In 2009, the per capita energy consumptions of USA, Japan, Germany, France, Canada, and Russia are 10151kilogram coal equivalent (kgce), 5194kgce, 5030kgce, 5556kgce, 13531kgce, 6400kgce, respectively (Wang, 2010). By contrast, the indicators in China and Brazil are 2297kgce and 1684kgce. So, we can find that the regions will consume more energy with the development of economy and the improvement of living standard. Meanwhile, economically advanced regions will attract more human resources. It is easy to realize that just through a basic “trip” to New York, London, Beijing, Hongkong, or any other big cities in the world.

We can also know that it is beneficial to reduce the energy and labor input slacks by optimize the industrial structure. Compared with secondary industry, tertiary industry could create more value with less energy consumption. Many scholars have clarified that it is a rational approach to improve the energy efficiency by promoting the development of tertiary industry, especially in the regions with higher proportion of secondary industry.

Meanwhile, the results can give guidance to improve the regional energy efficiency. The four environmental variables that we adopted are also the key factors to influence the regional energy efficiency, and three of them are able to be adjusted. Therefore, through regression analysis, we find that reduce coal proportion, optimize industrial structure, and reduce energy waste are helpful to improve regional energy efficiency.

3.3 The results of Stage 3

Observed input usage is adjusted for the influence of the environment by inserting the parameter estimates obtained from the Stage 2 regressions into equation (3). In this stage, we recalculate the true managerial efficiency of regions with adjusted inputs by using traditional DEA model. The results can be obtained in Table 2.

Table 2 The results comparison between BCC-DEA and Three-Stage DEA model

Regions	TE		PTE		SE		Returns to Scale	
	BCC	Three Stage	BCC	Three Stage	BCC	Three Stage	BCC	Three Stage
Beijing	1.000	1.000	1.000	1.000	1.000	1.000	—	—
Tianjin	0.954	0.751	1.000	0.801	0.954	0.938	irs	irs
Hebei	0.687	0.687	0.706	0.706	0.974	0.974	irs	irs
Shanxi	0.663	0.646	0.728	0.706	0.911	0.916	irs	irs
Inner Mongolia	0.725	0.587	0.755	0.624	0.959	0.941	irs	irs
Liaoning	0.748	0.748	0.761	0.761	0.983	0.983	irs	irs
Jilin	0.603	0.602	0.645	0.645	0.936	0.933	irs	irs
Heilongjiang	0.717	0.716	0.777	0.777	0.923	0.921	irs	irs
Shanghai	1.000	1.000	1.000	1.000	1.000	1.000	—	—
Jiangsu	0.854	0.855	1.000	1.000	0.854	0.855	drs	drs
Zhejiang	0.860	0.861	0.917	0.918	0.937	0.938	drs	drs
Anhui	0.770	0.770	0.815	0.815	0.945	0.945	irs	irs
Fujian	0.819	0.819	0.831	0.835	0.985	0.981	irs	irs
Jiangxi	0.808	0.808	0.839	0.848	0.962	0.953	irs	irs
Shandong	0.758	0.759	0.804	0.807	0.942	0.942	drs	drs
Henan	0.630	0.630	0.644	0.644	0.979	0.979	irs	irs
Hubei	0.762	0.762	0.792	0.792	0.961	0.961	irs	irs
Hunan	0.774	0.774	0.806	0.806	0.961	0.961	irs	irs
Guangdong	1.000	1.000	1.000	1.000	1.000	1.000	—	—
Guangxi	0.677	0.677	0.706	0.714	0.958	0.947	irs	irs
Hainan	0.789	0.738	1.000	1.000	0.789	0.738	irs	irs
Chongqing	0.658	0.658	0.726	0.726	0.906	0.906	irs	irs
Sichuan	0.709	0.709	0.735	0.735	0.965	0.965	irs	irs
Guizhou	0.669	0.669	0.798	0.798	0.838	0.838	irs	irs
Yunnan	0.596	0.596	0.665	0.665	0.897	0.897	irs	irs
Shaanxi	0.645	0.645	0.684	0.683	0.942	0.944	irs	irs
Gansu	0.692	0.692	0.844	0.844	0.821	0.821	irs	irs
Qinghai	0.535	0.514	1.000	1.000	0.535	0.514	irs	irs
Ningxia	0.540	0.492	0.932	0.818	0.579	0.601	irs	irs
Sinkiang	0.630	0.614	0.738	0.724	0.854	0.848	irs	irs
Mean	0.742	0.726	0.822	0.806	0.908	0.905		

Compared with the results of the BCC-DEA model, Table 2 shows that, after the removal of environmental influence, the mean score of TE, PTE, and SE dropped from 0.742, 0.822, and 0.908 to 0.726, 0.806, and 0.905, respectively, and the pure technical efficiency declined obviously. This decrease suggests that the mean efficiency value was overestimated due to environmental influence by using BCC-DEA model.

At the local level, the results of 30 regions are complicated after eliminating the environmental impact. The influences to regions are different due to diverse features. It shows that some regions were overestimated by using BCC-DEA model, some regions were underestimated, while some regions had rarely changes. For example, the pure technical efficiency of Tianjin, Shanxi, Inner Mongolia, Ningxia, Sinkiang, and Shaanxi decreased while Jiangxi, Guangxi, Fujian, Zhejiang, and Shandong increased. It means that the environmental variables play a significant role to the pure technical efficiency in these regions. And we also know that the pure technical efficiency of major coal production regions in China was overestimated by using BCC-DEA model. The situation of scale efficiency is similar to pure technical efficiency. Tianjin, Inner Mongolia, Jilin, Heilongjiang, Fujian, Jiangxi, Guangxi, Hainan, Qinghai, and Sinkiang were overestimated in the first stage, contrarily, Shanxi, Jiangsu, Zhejiang, Shaanxi, and Ningxia were underestimated. In terms of technical efficiency, Tianjin, Shanxi, Inner Mongolia, Jilin, Heilongjiang, Hainan, Qinghai, Ningxia, and Sinkiang dropped which suggests these regions were overestimated by using BCC-DEA model while Jiangsu, Zhejiang, Shandong were underestimated.

To be concerned, some regions are hardly influenced by environment. For instance, Beijing, Shanghai, and Guangdong are always lying on the frontier, reflect DEA-effective. The analysis results of Hebei, Liaoning, Hubei, Sichuan, and etc also keep higher consistency between BCC-DEA and three-stage DEA model. It may have two reasons. The first one is that the changes of score may be too small. The second reason is that the evaluation results by using DEA model are relative index which depend on all DMUs. In term of the return to scale, there is no change after adjustment. Most regions showed increasing returns to scale, it suggests that these regions did not operate under the optimal scale resulted in the waste of production factors.

4 The comparison of the three evaluation results

The evaluation of regional energy efficiency is significant and valuable for the policy makers. The true and realistic assessment is helpful to formulate feasible, effective, and targeted policies. Energy intensity is widely used in the world to evaluate the energy efficiency. The energy efficiency targets of 11th Five Year Plan and 12th Five Year Plan set in China are also based on the energy intensity. In this study, we will compare and analyze the results especially the rank of regions by using three different methods including energy intensity, BCC-DEA, and three-stage DEA model. The detailed ranking results are shown in Fig. 2, Fig. 3, and Fig. 4 separately.

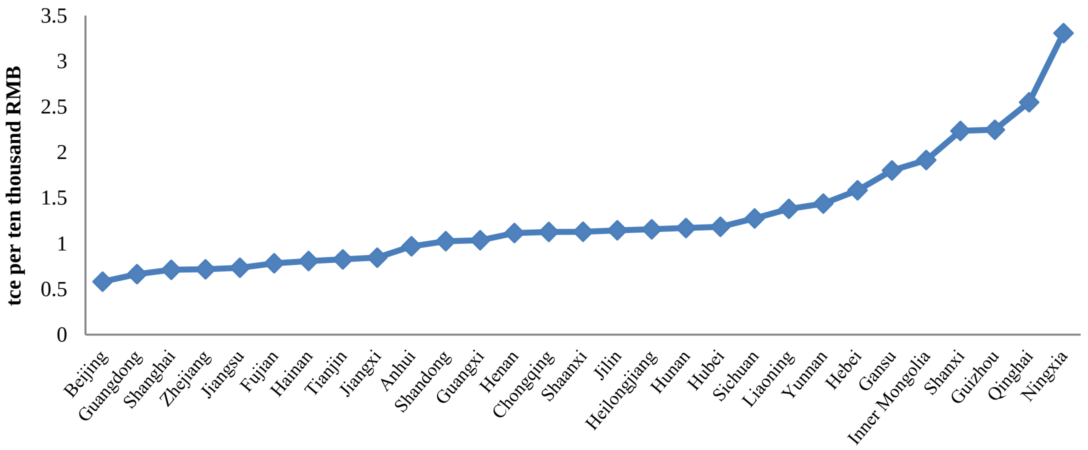

Fig. 2 The energy efficiency rank of China's 29 regions by using energy intensity

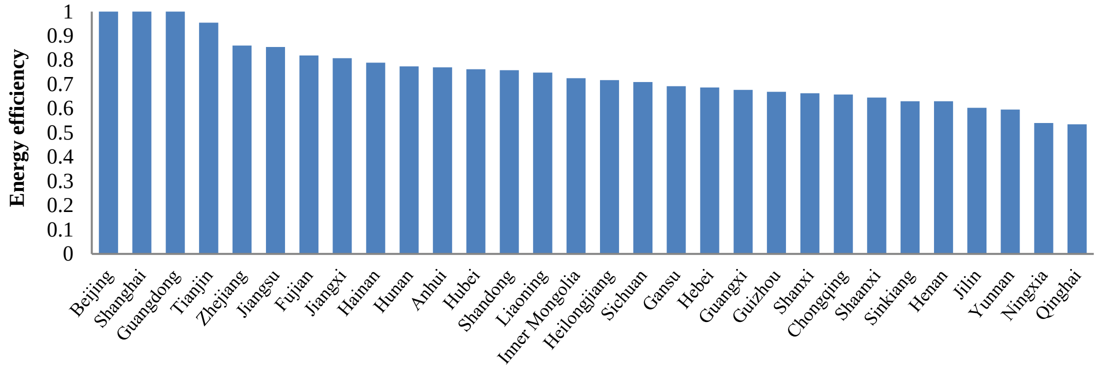

Fig. 3 The energy efficiency rank of China's 30 regions by using BCC-DEA model

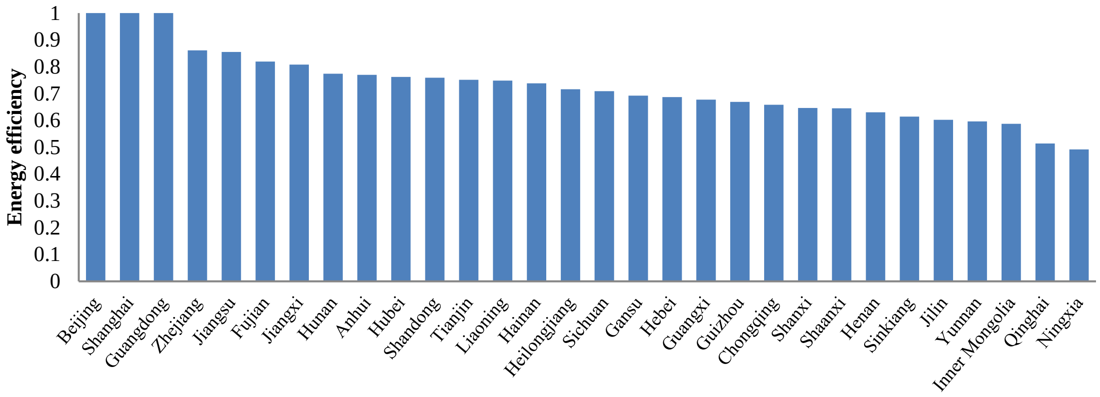

Fig. 4 The energy efficiency rank of China's 30 regions by using three-stage DEA model

As one of single factor efficiencies, energy intensity only reflects the influence of energy on economic output, and ignores the relations between energy and other factors. Therefore, the evaluation by using energy intensity will have flaws. Just take Jilin as an example, its energy efficiency is better than Liaoning Province according to the energy intensity with ranking of 14 in 29 regions shown in Fig. 2. However, the result is totally different from total factor efficiency. The energy efficiency of Jilin drops dramatically from 14 to 27 and 26 by using BCC-DEA and three-stage DEA respectively. By contrast, the assessment rank of Liaoning promotes by total factor energy efficiency. As far as we know, the economic level, technical level, and the proportion of tertiary industry in Liaoning are all higher than that in Jilin. It is difficult to define that the energy efficiency of Jilin is better than Liaoning subjectively. The evaluation results by total factor efficiency also support the above opinion. Hence, total factor energy efficiency is superior to reflect the true efficiency level.

Again, compared BCC-DEA with three-stage DEA, there are also some changes of efficiency values. However, the ranks of regions by using these two methods keep a higher consistency besides Inner Mongolia and Tianjin. It suggests that BCC-DEA is a reasonable way to evaluate regional energy efficiency, but three-stage DEA is more favorable to determine the influence of environmental factors or statistical noise and can also find out some special regions with higher impact.

The assessment results are different from three different methods. However, part of the conclusion is consistent. Especially, Beijing, Guangdong, and Shanghai are always with the better energy efficiency, but Qinghai and Ningxia keep the lowest level. In general, as a simple indicator, energy intensity is helpful to reflect the basic situation such as the gap between best and worst. Since the total factor efficiency considers the influence and substitutability of each input factors, it is useful to tap the energy efficiency potentials to regions. The results also suggest that three-stage DEA model is a valuable method to reflect the realistic energy technical efficiency. In a word, three approaches can be adopted for different purpose. Nonetheless, the three-stage DEA model is most effective to reflect the real level of regional energy efficiency.

5 Conclusions

The traditional DEA models ignore the influences of environmental variables and statistical noise which may result in biased efficiency estimates. In this paper, we use three-stage DEA model to measure the true energy efficiency of China's 30 regions in 2010. The first stage is a traditional DEA model with three inputs of labor, capital stock, and energy, and with one output of local GDP. The second stage is to explain the effects caused by external environment and statistical noise through SFA regressions. The third stage is another BCC-DEA model, but this model is based on original output and adjusted inputs. Additionally, we compare and analyze the evaluation results by using three different evaluation ways. The main findings are as follows:

(1) The environmental variables indeed influence the regional energy efficiency performance. In this study, we take four environmental variables to implement SFA regressions, the results shows that most parameters of environment variables are at 1% significance level. Through regression analysis, we also find that reduce coal proportion, optimize industrial structure, and reduce energy waste are reasonable to improve regional energy efficiency.

(2) The mean technical efficiency by using three-stage DEA decreased than by using BCC-DEA model. This finding suggests that the overall national efficiency may be overestimated due to the impact of environmental factors. But at the local level, some regions were overestimated by using BCC-DEA model, some regions were underestimated, while some regions had rarely changes.

(3) The efficiency values from a three-stage DEA analysis vary from a traditional DEA model, especially to some regions which are influenced significantly by external environment. It suggests that three-stage DEA model is effective to reflect the true efficiency by eliminating environmental impact.

(4) In the regional energy efficiency assessment, we gain different results and regional rankings through three different approaches. Nevertheless, three methods can make sense for different purposes. Energy intensity is helpful to realize the differences of regional energy efficiency. Traditional DEA models could reflect the substitutability of factors. Regarding to three-stage DEA model, it is better to find out the true energy efficiency after eliminating the environmental influence. Therefore, three-stage DEA model is more favorable for policy makers to formulate targeted, feasible, and efficient policies.

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