

Rank reversal issues in DEA models for China's regional energy efficiency assessment

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Received: 30 January 2018 / Accepted: 17 September 2018 / Published online: 2 October 2018
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Abstract Energy efficiency (EE) is an important strategy for China to save energy and reduce energy-related emissions. With significant regional diversities in China, it is important to conduct the EE assessment at the regional level. Usually, the regional EE assessment is applied to 30 regions in Mainland China using the data envelopment analysis (DEA) technique. With the “Belt and Road” strategy initiated by the Chinese government, it is reasonable and necessary to take Hong Kong, Macao, and Taiwan into consideration. However, such data expansion for China's regional EE assessment using DEA can reverse the relative rankings of some decision-making units, which is called the “rank reversal” phenomenon. In this paper, we illustrate in theory that rank reversal occurs in general DEA models, and apply the most popular five DEA models to assess China's regional energy efficiency from 2000 to 2014. The empirical study shows that the 30 regions in Mainland China have the least rank reversal when Tone's slack-based model (SBMT) is adopted. The main cause of ranking reversal is the addition of decision-making

units lying on production frontier. Better understanding of the rank reversal phenomenon is critical for the energy efficiency assessment using DEA to inform the policy makings.

Keywords Rank reversal · Data envelopment analysis · Energy efficiency · China

Introduction

In the past three decades, China's economy has grown aggressively. The rapid economic development causes substantially increase of its energy consumption. Though nowadays China's economy steps into a “new normal,” which means it is growing in a relatively balanced manner, the energy consumption still maintains a high level. According to the latest *Key World Energy Statistics* (IEA 2017), China's total final energy consumption reached 1914 Mtoe in 2015, accounting for 20.4% of the world's total final energy consumption (see Fig. 1).

Energy efficiency is regarded as the world's “first energy” in emission reduction and energy security improvement (IEA 2014). In order to combat the energy crisis and air pollution caused by excess energy consumption, China's government makes great efforts in improving its energy efficiency. With large regional disparities, it is necessary and meaningful to measure its energy efficiency from regional perspectives in China. In previous studies, Hong Kong, Macao, and Taiwan are usually excluded due to data availability. However, along with the “Belt and Road” strategy initiated by the

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Chinese government in 2014, Hong Kong, Macao, and Taiwan are having more economic connections with Mainland China, and data is getting complete gradually. Therefore, it is important and useful to include Hong Kong, Macao, and Taiwan when assessing China's regional energy efficiency.

The measurement of energy efficiency is often in the form of an aggregated energy efficiency index. Among the existing approaches to develop energy efficiency index, data envelopment analysis (DEA) models have been widely used as shown in the review by Zhou et al. (2008) and Meng et al. (2016).¹ DEA developed by Charnes et al. (1978) is a well-established methodology for evaluating the relative efficiency of a set of comparable entities often called decision-making units (DMUs) with multiple inputs/outputs (Meng et al. 2013). Energy efficiency values can be obtained by solving above DEA models.

Based on the energy efficiency values and ranking information of DMUs obtained by DEA models, a lot of policy recommendations in energy efficiency improvement are provided. Considering the efficiency values of a certain DMU in different DMU sets are not comparable, which results from the relativity of DEA efficiency values, rankings of DMUs will provide more information sometimes. In fact, the most widely use of the ranks is to find the benchmarks. In our study, benchmark provinces and other provinces have different energy development paths, and affect the improvement of energy efficiency across the country. It is noticed that no matter what type of DEA model is adopted, there is a possible change of regional rankings in Mainland China after adding Hong Kong, Macao, and Taiwan. This phenomenon is called "rank reversal," which will be discussed in this paper due to its effect on the stability and rationality of policy recommendation.

This paper focuses on rank reversal phenomenon in China's regional energy efficiency measurement, and contributes to the literature in the following aspects: (1) explore China's energy efficiency from the regional perspective, including Hong Kong, Macao, and Taiwan; (2) illustrate the rank reversal phenomenon of DEA

models in theory; (3) investigate the degree of rank reversal in five different and widely used DEA models for energy efficiency assessment in China; and (4) analyze the impact of rank reversal in policy making.

The remaining parts are organized as follows: "Literature review" section reviews previous studies. "Models and rank reversal issue" section introduces five different DEA models for energy efficiency assessment and proposes the rank reversal index. "China's regional energy efficiency analysis" section applies the proposed approaches to model the regional energy efficiency in China using different datasets from 2000 to 2014. In "Energy efficiency rank reversal" section, we show the impacts of rank reversal on regional energy efficiency assessment and study the degree of rank reversal in different DEA models. The final section concludes this paper.

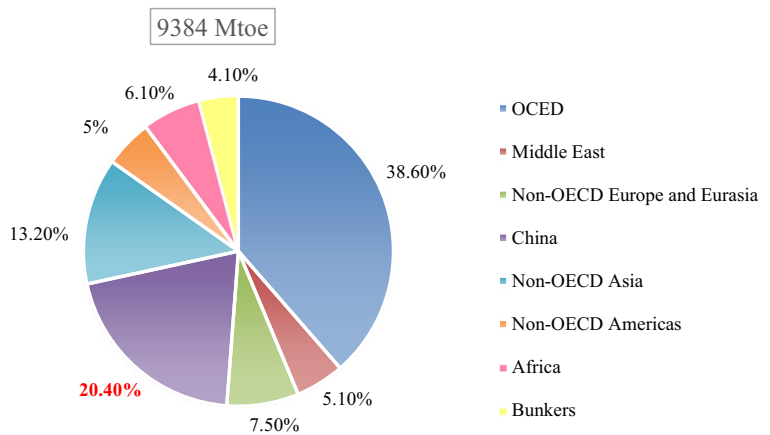
Literature review

Among the existing approaches to develop energy efficiency index, DEA has been widely used due to its practicability (Huang et al. 1995; Zhou et al. 2008). Since the early 1980s, it has been widely investigated and gain popularity in many application areas, especially the energy efficiency measures. Following the literature survey by Zhou et al. (2008) on issues relating to DEA for energy and environment analysis, a systematic review of studies on China's regional energy and carbon emission efficiency (EE&CE) assessments using different DEA models is reported in Meng et al. (2016). It is found that five DEA-type models have been widely used in China's regional EE&EC assessment, i.e., radial model, modified radial model (M-Radial), Tone's slack-based model (SBMT), range adjusted model (RAM), and directional distance function model (DDF).

Among these five DEA models, radial model is probably the most widely used model for measuring energy efficiency. It adjusts inputs and outputs proportionally. The most famous Radial models are the CCR model (Charnes et al. 1978) and BCC model (Banker et al. 1984). Following their seminal work, many studies apply the radial model to estimate China's regional energy efficiency, for example, Wei et al. (2007), Shi et al. (2010), Xue et al. (2014), and Al-Refaie et al. (2016). While M-Radial model attempts to measure energy efficiency by constructing an index which

¹ Besides the DEA models, the decomposition techniques can also be applied to measure the relative energy efficiency. Recently, Ang et al. (2015) and Su and Ang (2016) have extended the traditional temporal decomposition techniques to the so-called spatial decomposition techniques in index decomposition analysis (IDA) and structural decomposition analysis (SDA), respectively.

Fig. 1 Shares of world total final energy consumption by region, 2015



utilizes radial indicators and slacks together. Hu and Wang (2006) firstly develop an index called total factor energy efficiency by using M-Radial model. It has been widely adopted, such as Wang et al. (2012), Zhou et al. (2014), Pan et al. (2015), and Fernández et al. (2018).

SBMT (Tone 2001) and RAM (Cooper et al. 1999) models both belong to slack-based measure which constructs energy efficiency index with slacks of all the inputs and outputs. DDF model (Chung et al. 1997)

allows adjusting the inputs and desirable/undesirable outputs at different rates on the basis of different direction vectors for input-output variables. SBMT, RAM, and DDF models, known collectively as non-radial models, have become increasingly popular in recent years due to their relatively strong discriminating power and capability to expand desirable outputs and reduce undesirable outputs simultaneously. For instance, Choi et al. (2012), Wang et al. (2013), Hu et al. (2017), Zaim

Table 1 DEA models for energy efficiency measurement

Models	Energy efficiency index
Radial	$EE_1 = \beta^*$
	$\begin{aligned} & \text{Min } \beta \\ & \text{s.t. } \sum_{k=1}^K \lambda_k x_{nk} \leq x_{n0} \quad (n = 1, \dots, N) \\ & \quad \sum_{k=1}^K \lambda_k e_{mk} \leq \beta e_{m0} \quad (m = 1, \dots, M) \\ & \quad \sum_{k=1}^K \lambda_k y_{ik} \geq y_{i0} \quad (i = 1, \dots, I) \\ & \quad \sum_{k=1}^K \lambda_k b_{jk} = b_{j0} \quad (j = 1, \dots, J) \\ & \quad \lambda_k \geq 0 \quad (k = 1, \dots, K) \end{aligned}$
Modified radial (M-Radial)	$EE_2 = \sum_{m=1}^M \varpi_m \frac{\beta^* e_{m0} - s_m^-}{e_{m0}}$
	$\begin{aligned} & \text{Min } [\beta - \varepsilon (e^T s_n^- + e^T s_m^- + e^T s_i^+)] \\ & \text{s.t. } \sum_{k=1}^K \lambda_k x_{nk} + s_n^- = \beta x_{n0} \quad (n = 1, \dots, N) \\ & \quad \sum_{k=1}^K \lambda_k e_{mk} + s_m^- = \beta e_{m0} \quad (m = 1, \dots, M) \\ & \quad \sum_{k=1}^K \lambda_k y_{ik} - s_i^+ = y_{i0} \quad (i = 1, \dots, I) \\ & \quad \sum_{k=1}^K \lambda_k b_{jk} = b_{j0} \quad (j = 1, \dots, J) \\ & \quad \lambda_k \geq 0; s_n^-, s_m^-, s_i^+ \geq 0 \quad (k = 1, \dots, K) \end{aligned}$

Table 1 (continued)

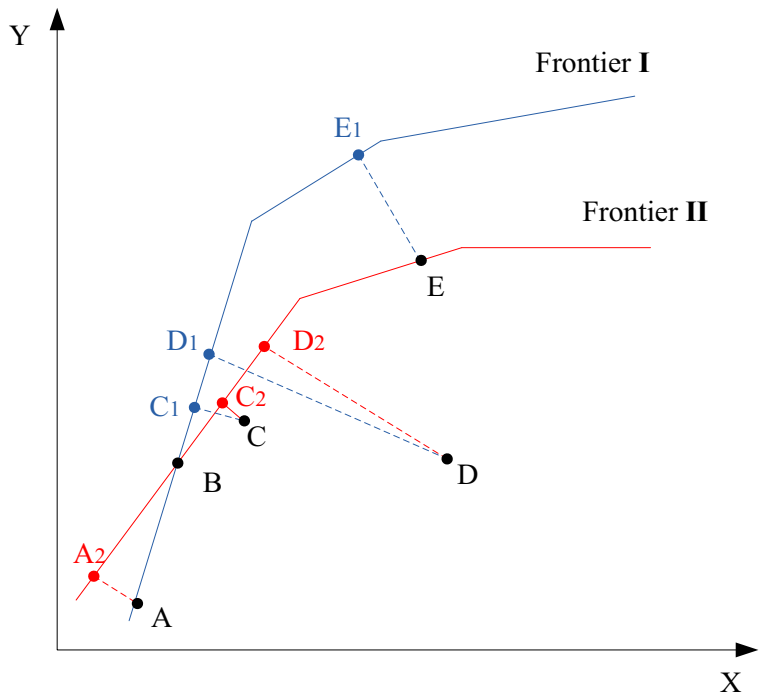
Models	Energy efficiency index
<p>Tone’s slack-based measure (SBMT)</p> $\text{Min } \frac{1 - \frac{1}{N+M} \left(\sum_{n=1}^N s_n^- / x_{n0} + \sum_{m=1}^M s_m^- / x_{m0} \right)}{1 + \frac{1}{I+J} \left(\sum_{i=1}^I s_i^+ / y_{i0} + \sum_{j=1}^J s_j^+ / b_{j0} \right)}$ <p>s.t.</p> $\sum_{k=1}^K \lambda_k x_{nk} + s_n^- = x_{n0} \quad (n = 1, \dots, N)$ $\sum_{k=1}^K \lambda_k e_{mk} + s_m^- = e_{m0} \quad (m = 1, \dots, M)$ $\sum_{k=1}^K \lambda_k y_{ik} - s_i^+ = y_{i0} \quad (i = 1, \dots, I)$ $\sum_{k=1}^K \lambda_k b_{jk} + s_j^- = b_{j0} \quad (j = 1, \dots, J)$ $\lambda_k \geq 0; s_n^-, s_m^-, s_i^+, s_j^- \geq 0 \quad (k = 1, \dots, K)$	$EE_3 = \sum_{m=1}^M \varpi_m \frac{e_{m0} - s_m^-}{e_{m0}}$
<p>Directional distance function (DDF)</p> $\vec{D}(x, e, y, b; g) = \text{Max } \omega_x \beta_x + \omega_e \beta_e + \omega_y \beta_y + \omega_b \beta_b$ <p>s.t.</p> $\sum_{k=1}^K \lambda_k x_{nk} \leq x_{n0} - \beta_x g_x \quad (n = 1, \dots, N)$ $\sum_{k=1}^K \lambda_k e_{mk} \leq e_{m0} - \beta_e g_e \quad (m = 1, \dots, M)$ $\sum_{k=1}^K \lambda_k y_{ik} \geq y_{i0} + \beta_y g_y \quad (i = 1, \dots, I)$ $\sum_{k=1}^K \lambda_k b_{jk} = b_{j0} - \beta_b g_b \quad (j = 1, \dots, J)$ $\lambda_k \geq 0 \quad (k = 1, \dots, K)$	$EE_4 = \frac{\sum_{m=1}^M (e_{m0} - \beta_e g_e)}{\sum_{m=1}^M e_{m0}}$
<p>Range adjusted model (RAM)</p> $\text{Max } \sum_{n=1}^N R_n s_n^- + \sum_{m=1}^M R_m s_m^- + \sum_{i=1}^I R_i s_i^+ + \sum_{j=1}^J R_j s_j^-$ <p>s.t.</p> $\sum_{k=1}^K \lambda_k x_{nk} + s_n^- = x_{n0} \quad (n = 1, \dots, N)$ $\sum_{k=1}^K \lambda_k e_{mk} + s_m^- = e_{m0} \quad (m = 1, \dots, M)$ $\sum_{k=1}^K \lambda_k y_{ik} - s_i^+ = y_{i0} \quad (i = 1, \dots, I)$ $\sum_{k=1}^K \lambda_k b_{jk} + s_j^- = b_{j0} \quad (j = 1, \dots, J)$ $\lambda_k \geq 0; s_n^-, s_m^-, s_i^+, s_j^- \geq 0 \quad (k = 1, \dots, K)$	$EE_5 = 1 - \sum_{m=1}^M R_m s_m^-$

and Gazel (2018), Khoshroo et al. (2018), Iftikhar et al. (2018), Zhang and Chen (2018), and so on.

Based on the energy efficiency values and rankings of different regions obtained from various DEA models, a lot of policy recommendations for China’s energy efficiency improvement are provided. If we focus on the ranking, it is noticed that no matter what type of DEA model is adopted, there is a possible change of regional rankings in Mainland China after adding Hong Kong, Macao, and Taiwan. This phenomenon is called

rank reversal, which is firstly observed in multiple criteria decision-making (MCDM) approach by Belton and Gear (1983). It is found that rank reversal can also occur in DEA ranking models. Green et al. (1996) firstly notice that the relative rankings of two DMUs can be reversed when a DMU is added in the DEA cross-efficiency evaluation method. Recently, Wang and Luo (2009) and Soltanifar and Shahghobadi (2014) also study the rank reversal in DEA ranking approaches. Moreover, different DEA models may have the

Fig. 2 Illustration of rank reversal in DEA



varying degree of rank reversal. This is an area deserving further investigation.

Models and rank reversal issue

DEA models for energy efficiency assessment

Following the neoclassical production framework, we consider a production process which use non-energy inputs (x) and energy inputs (e) to product desirable outputs (y) and undesirable outputs (b) jointly. The reference technology T can be described as follows:

$$T = \{(x, e, y, b) : (x, e) \text{ can produce } (y, b)\},$$

where T is a closed and bounded set. In the traditional framework of reference technology, the inputs and desirable outputs are all strongly disposable, i.e., if $(x, e, y) \in T$ and $(x', e') \geq (x, e)$ (or $y' \leq y$), then $(x', e', y) \in T$ (or $(x, e, y') \in T$).

As for the disposability of undesirable output, one way is to treat undesirable output as input and utilize the traditional model (Seiford & Zhu, 2002). In this case, suppose that there are K DMUs (refer to regions in this study), we can describe the reference technology under strong disposability on undesirable output (T -SD) as:

Table 2 Summary statistics of inputs/outputs for China’s regional dataset, 2000–2014

Variables		Unit	Max	Min	Mean	Std.
Inputs	Capital stock	Billion constant 2011 USD	8291.03	21.01	1101.48	1163.11
	Labor force	Ten thousand peoples	6459.37	21.66	2356.49	1731.12
Desirable outputs	Total final energy consumption	Mtoe	161.94	0.31	41.94	29.62
Undesirable outputs	GDP	Billion constant 2011 USD	1150.42	14.14	325.15	234.18
	CO ₂ emissions	Million tonnes	789.06	1.18	194.31	147.66

$$T\text{-}SD = \left\{ (x, e, y, b) : \sum_{k=1}^K \lambda_k x_{nk} \leq x_n; \sum_{k=1}^K \lambda_k e_{mk} \leq e_m; \sum_{k=1}^K \lambda_k y_{ik} \geq y_i; \sum_{k=1}^K \lambda_k b_{jk} \leq b_j; \lambda_k \geq 0 (k = 1, \dots, K). \right\} \quad (1)$$

Another way to involve undesirable output into the reference technology is to satisfy the following assumptions suggested by Färe et al. (1989):

- (i) Weak disposability on undesirable outputs, i.e., if $(x, e, y, b) \in T$ and $0 \leq \theta \leq 1$, then $(x, e, \theta y, \theta b) \in T$.
- (ii) Desirable and undesirable outputs are null-joint, i.e., if $(x, e, y, b) \in T$ and $b = 0$, then $y = 0$.

$$T\text{-}WD = \left\{ (x, e, y, b) : \sum_{k=1}^K \lambda_k x_{nk} \leq x_n; \sum_{k=1}^K \lambda_k e_{mk} \leq e_m; \sum_{k=1}^K \lambda_k y_{ik} \geq y_i; \sum_{k=1}^K \lambda_k b_{jk} = b_j; \lambda_k \geq 0 (k = 1, \dots, K). \right\} \quad (2)$$

Based on the production framework under strong and weak disposability, previous studies have developed many alternative nonparametric models for energy efficiency measurement. Table 1 summarizes the most popular five DEA models applied in this field, namely the Radial, M-Radial model, SBMT model, DDF model, and RAM.

Rank reversal in DEA models

In this section, we intend to discuss the occurrence of rank reversal without change in the production possibility set. Figure 2 illustrates how this phenomenon occurs in theory, considering a production process that transforms only one input X to one output Y. According to the production theory, efficiency can be defined by the distance between each DMU and its production frontier. The DMUs that lie on the production frontier are called efficient DMUs with efficiency values equal to unit. DMUs that lie under the production frontier are deemed to be relatively inefficient. And the DMUs which are near to production frontier have higher efficiency values than others.

Assume that A, B, C, D, and E are five DMUs in group I who perform under production frontier I. Thus, the rank of efficiency for five DMUs is $A = B = 1 > C > E > D$. When some DMUs in group I are added, the production frontier of the remaining DMUs changes to frontier II. In this case, the rank of efficiency for five DMUs is $B = E = 1 > C > A > D$. Obviously, the phenomenon called rank reversal occurs. More specifically, for instance, E has lower efficiency than C under frontier I. However, under frontier II, the efficiency of E is equal

The first property means that the proportional reduction in desirable and undesirable outputs is possible, and the second implies that the only way to remove all the undesirable outputs is to cease the production process. According to above assumptions, the reference technology under weak disposability on undesirable output *T*-WD can be characterized as:

to unit and higher than C. Different from E, A is efficient DMU which lies on frontier I, and the changing of frontier makes its efficiency even lower than C under frontier II. There are some other DMUs (like B) which always lie on production frontier in both cases. Based on above analysis, generally speaking, the increase of DMUs is likely to result in rank reversal to some DMUs by affecting the production frontier.

In order to investigate the rank reversal phenomenon in various DEA models, we define the difference between the rank of DMU_k in group I and group II as rank reversal index (RRI), i.e.,

$$RRI_k = R_k(\text{I}) - R_k(\text{II}) \quad (3)$$

where k represents the k th DMU; $R_k(\text{I})$ and $R_k(\text{II})$ are the ranks of the k th DMU in group I and group II, respectively. The larger $|RRI_k|$ means the greater difference of rank for DMU_k between group I and group II, and vice versa.

China's regional energy efficiency analysis

In this section, we apply five different DEA models discussed in “Models and rank reversal issue” section to measure China's regional energy efficiency. Along with the rapid development of the cross-strait trade scale and economic integration, putting Mainland China, Hong Kong, Macao, and Taiwan together when studying China's regional energy efficiency issues becomes possible. It can help constructing a production frontier matching reality more. As mentioned above, previous

Table 3 EE of China's regions in groups I/II with different DEA models, 2014

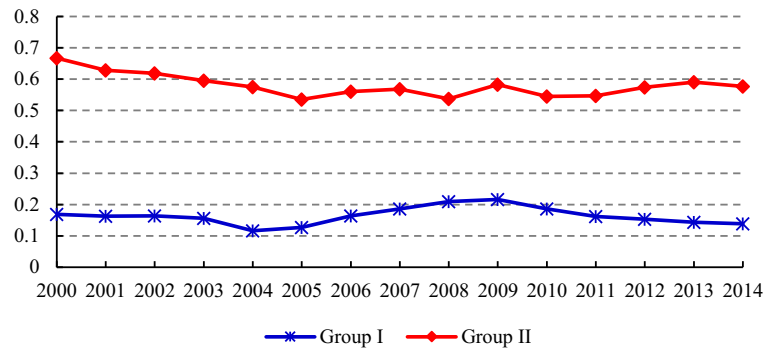
Energy efficiency	Radial		M-Radial		SBMT		DDF		RAM	
	I	II	I	II	I	II	I	II	I	II
Hong Kong SAR	1.000	–	1.000	–	0.347	–	0.746	–	0.997	–
Macao SAR	1.000	–	1.000	–	1.000	–	1.000	–	1.000	–
Taiwan	0.717	–	0.752	–	0.062	–	0.230	–	0.935	–
Anhui	0.960	0.993	0.969	0.994	0.084	0.657	0.135	0.693	0.941	0.974
Beijing	0.772	1.000	0.795	1.000	0.191	1.000	0.537	1.000	0.983	1.000
Chongqing	0.727	0.766	0.784	0.801	0.070	0.547	0.111	0.554	0.953	0.974
Fujian	0.904	0.912	0.908	0.916	0.060	0.466	0.148	1.000	0.947	0.964
Gansu	0.893	0.903	0.915	0.919	0.058	0.452	0.091	0.808	0.959	0.973
Guangdong	0.959	0.962	0.961	0.965	0.065	0.505	0.240	1.000	0.892	0.924
Guangxi	0.955	1.000	0.965	1.000	0.096	0.750	0.150	0.770	0.954	0.985
Guizhou	0.913	0.913	0.915	0.915	0.058	0.454	0.076	0.476	0.948	0.966
Hainan	0.610	0.636	0.681	0.684	0.058	0.456	0.096	0.472	0.987	0.991
Hebei	1.000	1.000	1.000	1.000	0.048	0.374	0.109	0.764	0.837	0.876
Heilongjiang	0.923	1.000	0.925	1.000	0.128	1.000	0.131	1.000	0.944	1.000
Henan	0.892	0.902	0.898	0.909	0.073	0.573	0.234	1.000	0.909	0.945
Hubei	0.890	0.923	0.898	0.934	0.082	0.638	0.155	0.640	0.921	0.963
Hunan	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Inner Mongolia	0.957	0.957	0.961	0.961	0.033	0.252	0.206	0.633	0.924	0.923
Jiangsu	1.000	1.000	1.000	1.000	0.070	0.536	0.300	1.000	0.890	0.922
Jiangxi	0.971	1.000	0.974	1.000	0.106	0.831	0.240	0.824	0.964	0.991
Jilin	0.760	0.811	0.779	0.832	0.080	0.614	0.192	0.556	0.956	0.977
Liaoning	0.908	0.976	0.927	0.980	0.083	0.643	0.123	0.647	0.884	0.949
Ningxia	1.000	1.000	1.000	1.000	0.039	0.302	0.076	0.497	0.976	0.981
Qinghai	0.964	0.992	0.967	0.993	0.056	0.434	0.144	0.762	0.983	0.988
Shaanxi	0.773	0.802	0.801	0.830	0.068	0.527	0.128	0.522	0.939	0.964
Shandong	0.883	0.891	0.889	0.899	0.059	0.457	0.138	1.000	0.827	0.882
Shanghai	0.876	1.000	0.895	1.000	0.130	1.000	0.193	1.000	0.946	1.000
Shanxi	0.923	0.932	0.935	0.944	0.049	0.385	0.092	0.647	0.913	0.936
Sichuan	0.773	0.774	0.775	0.775	0.068	0.534	0.070	0.566	0.878	0.934
Tianjin	0.799	0.862	0.818	0.884	0.076	0.586	0.240	0.445	0.964	0.979
Xinjiang	0.792	0.793	0.807	0.808	0.034	0.264	0.069	0.471	0.923	0.934
Yunnan	0.889	0.906	0.914	0.920	0.068	0.531	0.099	0.559	0.942	0.967
Zhejiang	0.974	0.983	0.975	0.984	0.069	0.538	0.191	1.000	0.923	0.952
Average of 30 regions	0.888	0.920	0.901	0.928	0.105	0.577	0.190	0.744	0.933	0.960

studies usually adopt 30 provinces in Mainland China as DMU set, and in this case, some provinces like Beijing stay in first place for a long time. So no policy suggestions can be made for Beijing's energy efficiency improvement, which is not helpful to the overall improvement of energy efficiency level of China. Inclusion of Hong Kong, Macao, and Taiwan into the DMU set may

provide new benchmarks to these provinces and provide different policy recommendations.

To compare the efficiency results in different DMU sets, China's regional data from 2000 to 2014 are adopted to construct the comparison groups I and II. Group I includes Hong Kong, Macao, Taiwan, and 30 regions in Mainland China, while group II only

Fig. 3 Regional average energy efficiency values in China, 2000–2014



includes 30 regions in Mainland China as most previous studies did.

Data source

As for inputs, we take labor force and capital stock as non-energy inputs and total final energy consumption (TFEC) as the only energy input. For outputs, we choose gross domestic product (GDP) and CO₂ emissions as desirable and undesirable outputs, respectively. The data on TFEC and CO₂ emissions are collected from IEA,

the data on labor force and GDP using PPP come from Word Bank, and the data on capital stock using PPP are from the Penn World Table (Version 9.0). Particularly, the data on labor force and capital stock of Taiwan are obtained from Chinese Taiwan Statistics; the data on CO₂ emissions and TFEC of Macao come from Word Bank and China Energy Statistical Yearbook. The data of 30 regions in Mainland China are calculated according to their ratio of China's total amount on the basis of data published by IEA or World Bank. Table 2 presents the summary statistics of all inputs/outputs in this study.

Fig. 4 Average energy efficiency values in China's nine economic regions, 2000–2014

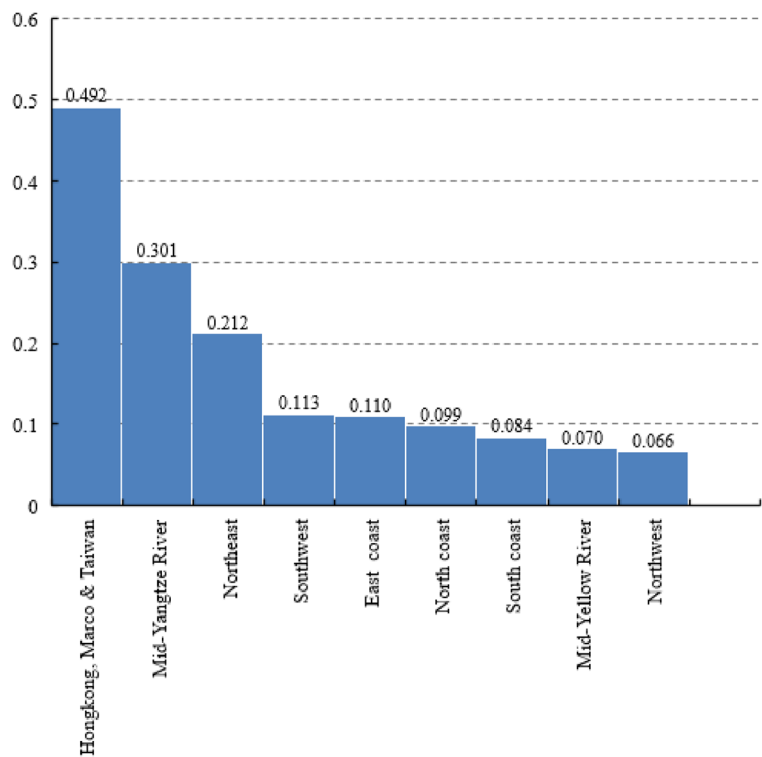


Table 4 Rankings of 30 regions in Mainland China in groups I/II, 2014

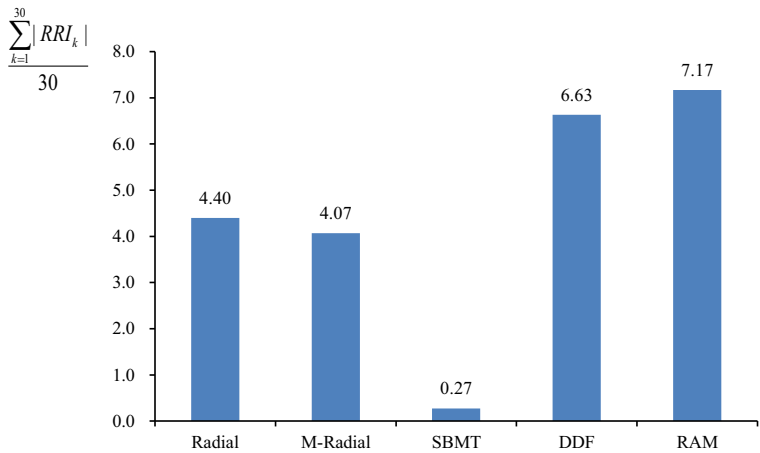
Ranking	Radial			M-Radial			SBM-T			DDF			RAM		
	I	II	RRI	I	II	RRI	I	II	RRI	I	II	RRI	I	II	RRI
Anhui	8	10	-2	7	10	-3	7	7	0	17	16	1	17	12	5
Beijing	27	1	26	26	1	25	2	1	1	2	1	1	4	1	3
Chongqing	29	29	0	27	28	-1	13	13	0	21	24	-3	11	18	-7
Fujian	16	19	-3	18	20	-2	20	20	0	14	1	13	13	1	12
Gansu	17	21	-4	16	19	-3	24	24	0	26	12	14	8	17	-9
Guangdong	9	14	-5	10	14	-4	19	19	0	6	1	5	25	1	24
Guangxi	11	1	10	9	1	8	6	6	0	13	13	0	10	14	-4
Guizhou	14	18	-4	15	21	-6	23	23	0	27	27	0	12	20	-8
Hainan	30	30	0	30	30	0	22	22	0	24	28	-4	2	13	-11
Hebei	1	1	0	1	1	0	27	27	0	22	14	8	29	30	-1
Heilongjiang	13	1	12	14	1	13	4	1	3	18	1	17	15	24	-9
Henan	18	22	-4	20	22	-2	12	12	0	7	1	6	24	1	23
Hubei	19	17	2	19	17	2	9	9	0	12	19	-7	22	25	-3
Hunan	1	1	0	1	1	0	1	1	0	1	1	0	1	1	0
Inner Mongolia	10	15	-5	11	15	-4	30	30	0	8	20	-12	19	22	-3
Jiangsu	1	1	0	1	1	0	14	15	-1	3	1	2	26	1	25
Jiangxi	6	1	5	6	1	5	5	5	0	5	11	-6	6	11	-5
Jilin	28	25	3	28	25	3	10	10	0	10	23	-13	9	15	-6
Liaoning	15	13	2	13	13	0	8	8	0	20	18	2	27	29	-2
Ningxia	1	1	0	1	1	0	28	28	0	28	26	2	5	23	-18
Qinghai	7	11	-4	8	11	-3	25	25	0	15	15	0	3	16	-13
Shaanxi	26	26	0	25	26	-1	18	18	0	19	25	-6	18	19	-1
Shandong	21	23	-2	22	23	-1	21	21	0	16	1	15	30	28	2
Shanghai	22	1	21	21	1	20	3	1	2	9	1	8	14	1	13
Shanxi	12	16	-4	12	16	-4	26	26	0	25	17	8	23	27	-4
Sichuan	25	28	-3	29	29	0	16	16	0	29	21	8	28	21	7
Tianjin	23	24	-1	23	24	-1	11	11	0	4	30	-26	7	1	6
Xinjiang	24	27	-3	24	27	-3	29	29	0	30	29	1	21	26	-5
Yunnan	20	20	0	17	18	-1	17	17	0	23	22	1	16	1	15
Zhejiang	5	12	-7	5	12	-7	15	14	1	11	1	10	20	1	19

Energy efficiency results

Firstly, energy efficiency (EE) values of all regions in groups I and II using different DEA models in 2014 are shown in Table 3. From the perspective of models, it is found that EE values obtained from SBMT and DDF models are lower than those calculated by Radial, M-Radial, and RAM models. Besides, SBMT model has higher discrimination power since there are less efficient DMUs in this case. So we further explore China’s regional energy efficiency from 2000 to 2014 by applying SBMT model.

Figure 3 shows the change of energy efficiency over time in group I and group II, respectively. We find that the regional average EE values in group II are larger than those in group I during the observation period. It indicates that the addition of Hong Kong, Macao, and Taiwan leads to the shift of production frontier, and the regions in Mainland China in group I are farther away from the frontier than group II. In other words, although the energy efficiency of Mainland China seems barely satisfactory, it can be improved greatly compared with Hong Kong and Macao. Focusing on the variation of EE, it is found that the variation trend of group I and group II is basically the same. China’s energy efficiency

Fig. 5 Average |RRI| values of 30 regions in Mainland China by different DEA models, 2014



decreased during the 10th Five Years Plan phase (2001–2005), and then increased from the beginning of the 11th Five Years Plan (2006) until to 2009. Difference appears after the year 2011. It can be interpreted that energy efficiency of Mainland China was going up in 2012 and 2013, but that of Hong Kong and Macao increased more. It suggests China’s government can make more effort to improve its regional energy efficiency in Mainland China to catching up Hong Kong and Macao.

Shifting our interest to the regional differences, we divide the whole studying area into nine regions: Hong Kong, Macao, and Taiwan, northeast region, north coast region, east coast region, south coast region, Mid-Yellow River region, Mid-Yangtze River region, southwest region, and northwest region. Figure 4 presents the average EE values from 2000 to 2014 in nine regions mentioned above. It shows that energy efficiencies of Hong Kong, Macao, and Taiwan are much higher than

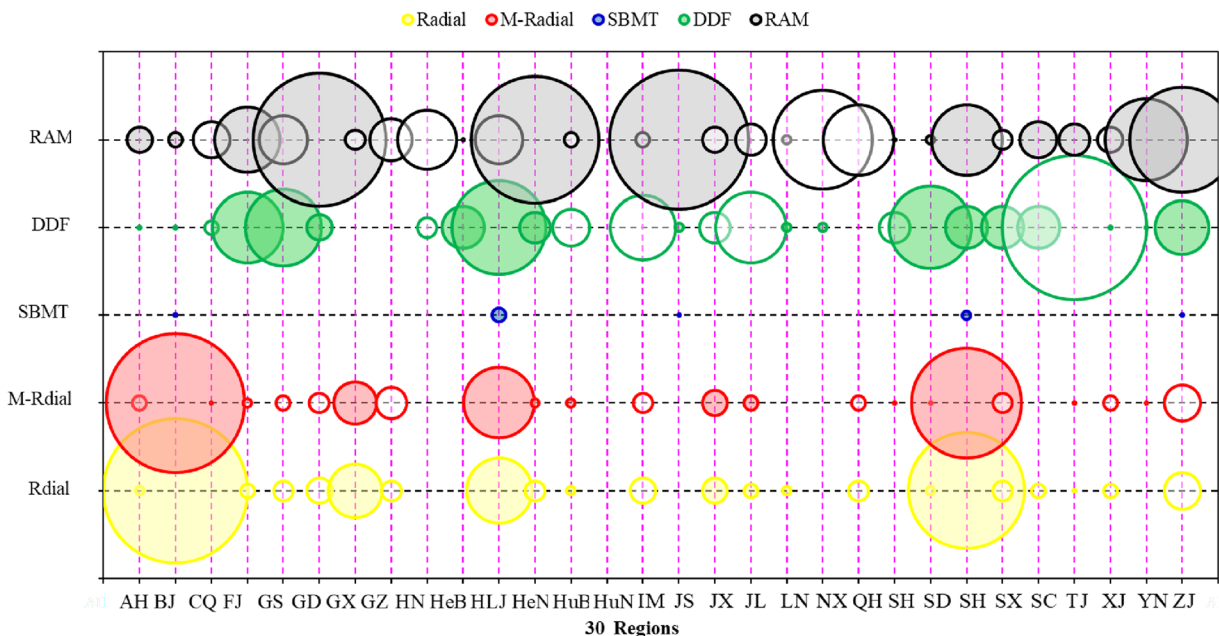


Fig. 6 Bubble chart for RRI values of 30 regions in Mainland China by different DEA models, 2014. Note: AH (Anhui), BJ (Beijing), CQ (Chongqing), FJ (Fujian), GS (Gansu), GD (Guandong), GX (Guangxi), GZ (Guizhou), HN (Hainan), HeB (Hebei), HLJ (Heilongjiang), HeN (Henan),

HuB (Hubei), HuN (Nunan), IM (Inner Mongolia), JS (Jiangsu), JX (Jiangxi), JL (Jilin), LN (Liaoning), NX (Ningxia), QH (Qinghai), SaX (Shaanxi), SD (Shandong), SH (Shanghai), SX (Shanxi), SC (Sichuan), TJ (Tianjin), XJ (Xinjiang), and ZJ (Zhejiang)

Table 5 RRI values of 30 regions in Mainland China by SBMT model, 2000–2014

RRI	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Anhui	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0
Beijing	2	2	1	1	2	0	-1	2	4	5	3	2	2	1	1
Chongqing	0	0	0	-1	0	0	0	0	0	1	0	0	0	-1	0
Fujian	1	-1	0	0	0	0	0	0	0	1	0	0	0	0	0
Gansu	0	0	0	0	0	0	0	0	0	0	0	0	0	-1	0
Guangdong	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Guangxi	1	0	-1	0	0	-1	0	0	-2	-1	1	1	0	0	0
Guizhou	0	0	0	0	0	0	0	0	0	-2	0	0	0	0	0
Hainan	1	0	0	0	0	-2	0	0	1	1	0	0	0	-1	0
Hebei	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Heilongjiang	2	1	1	1	0	0	1	0	0	0	0	1	1	2	3
Henan	1	0	-1	0	0	0	0	0	0	0	0	0	-1	0	0
Hubei	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hunan	0	0	0	0	1	7	0	0	0	0	0	0	0	0	0
Inner Mongolia	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Jiangsu	1	0	0	0	0	0	0	0	0	0	0	1	1	0	-1
Jiangxi	3	-1	-1	-1	-2	-3	-1	0	3	3	0	-1	0	0	0
Jilin	1	0	0	0	0	0	0	0	0	1	0	1	0	0	0
Liaoning	1	-1	0	0	-1	0	0	0	1	1	1	0	0	0	0
Ningxia	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Qinghai	1	0	0	0	0	0	0	0	0	1	0	0	0	3	0
Shaanxi	0	0	-1	0	0	0	0	0	1	1	0	0	0	0	0
Shandong	1	0	0	0	0	0	0	0	0	0	0	0	0	-1	0
Shanghai	4	3	3	2	3	2	4	3	5	6	5	4	3	3	2
Shanxi	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sichuan	1	-1	0	0	-1	-1	0	0	-5	-5	-7	-7	0	0	0
Tianjin	1	1	2	1	2	1	0	0	2	2	1	2	0	1	0
Xinjiang	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Yunnan	1	0	0	0	-1	0	0	0	-6	-12	0	0	0	0	0
Zhejiang	-18	0	0	0	0	0	0	0	0	1	0	1	0	0	1

those of other regions. In Mainland China, Mid-Yangtze River region performs the best while the northwest and Mid-Yellow River region are the worst. The northwest region includes Gansu, Qinghai, Ningxia, and Xinjiang; their discrepancy in the level of economic and technology development may be the main reasons of low energy efficiency. The Mid-Yellow River region includes Shanxi, Shanxi, Henan, and Inner Mongolia, and their developments all depend on the coal industry. It implies that China can pay more attention to northwest and Mid-Yellow River region to improve the regional energy efficiency throughout the country.

Energy efficiency rank reversal

In this section, we demonstrate the phenomenon of rank reversal in DEA and further investigate the degree of rank reversal on five DEA models discussed in “[Models and rank reversal issue](#)” section. We first analyze rank reversal phenomenon in the year of 2014 in detail as it is the most recent year with complete data. After that, we choose a 15-year period (2000–2014) to get more information.

We sort 30 regions in Mainland China according to their EE values in group I and group II, respectively, where the region with the largest EE value ranks first.

Table 4 shows their ranking and RRI values calculated using Eq. (3). The ranks of most regions change after adding Hong Kong, Macao, and Taiwan. Beijing has the highest $|RRI|$ value by using Radial and M-Radial models, respectively. For DDF and RAM models, Tianjin and Jiangsu have the highest $|RRI|$ value, respectively.

On the other hand, the highest $|RRI|$ value for SBMT model is 3, which is much smaller than those for other DEA models. It indicates that addition of DMUs in SBMT model has less impact on the ranks of DMUs than in other DEA models. We also find that there are 25 regions with RRI values equal to 0 in SBMT model. It denotes that rank reversal does not occur in these regions after adding these three DMUs (Hong Kong, Macao, and Taiwan). Different from SBMT model, RAM model only have two regions whose RRI values equal to 0.

In order to investigate the degree of rank reversal in different models, Figs. 5 and 6 present the average $|RRI|$ values of 30 regions in Mainland China by different types of models. From Fig. 5, SBMT model has the least rank reversal, followed by M-Radial and Radial model. The ranks of 30 regions in RAM model change most after adding Hong Kong, Macao, and Taiwan. Thus, we suggest using the SBMT model to get more stable policy recommendations on energy efficiency improvement.

Bubble charts for RRI values of 30 regions by DEA models are shown in Fig. 6 to illustrate the phenomenon of rank reversal visually. The size of bubbles represents $|RRI|$ value—larger bubbles imply larger $|RRI|$ values. Bubbles in color denote positive RRI values and those in white denote negative RRI values.

Firstly, from the viewpoint of horizontal axis, it is apparent that $|RRI|$ values in RAM model and DDF model are larger than those in other DEA models as a whole. It implies that the ranks of 30 regions change most in RAM model and DDF model. SBMT is proved to show the least rank reversal according to its smaller $|RRI|$ values for all the 30 regions. As for Radial model and M-Radial model, significant differences for ranks between groups I and II are mainly observed in four regions, i.e., Beijing, Guangxi, Heilongjiang, and Shanghai.

Secondly, from the viewpoint of vertical axis, we observe that some regions always have positive changes by applying five DEA models, such as Heilongjiang and Shanghai. On the contrary, some regions always present negative changes in any types of DEA models, for example, Guizhou, Inner Mongolia, Qinghai, and Xinjiang.

To verify the stability of SBMT model on rank reversal, we show the regional RRI values of SBMT

model from 2000 to 2014 in Table 5. We find that the degree of rank reversal has been small during the 15 years period excluding Zhejiang in 2000 and Yunnan in 2009. Even though, rank reversal occurs in some regions. Take Beijing as an example, its RRI values of 2007 to 2014 are all positive, which means that the rankings of Beijing decline after adding Hong Kong, Macao, and Taiwan. It implies that Beijing has more energy efficiency improvement potential when including Hong Kong, Macao, and Taiwan into the DMUs.

Discussions and conclusion

Along with the Belt and Road strategy initiated by the Chinese government, taking Hong Kong, Macao, and Taiwan into consideration is reasonable and necessary when exploring China's regional energy efficiency. However, it is noticed that no matter what type of DEA model is adopted, there is a possible change of regional rankings in Mainland China after adding Hong Kong, Macao, and Taiwan. This phenomenon is called rank reversal which means the relative rankings of two DMUs can be reversed when one or more units are added. This paper focuses on the rank reversal in China's regional energy efficiency ranking after adding Hong Kong, Macao and Taiwan into the DMUs set.

Based on the principle of rank reversal in DEA in theory illustrated in this paper, rank reversal in DEA is caused by the change of the position for production frontier when some DMUs are added. The most popular five DEA models in efficiency measurement, including Radial model, M-Radial model, SBMT model, DDF model, and RAM model, are applied to assess China's regional (30 regions and Hong Kong, Macao, and Taiwan) energy efficiency. The degrees of rank reversal in five different DEA models are investigated using China's regional data. Among these models, SBMT model shows the least rank reversal when measuring energy efficiency for 30 regions in Mainland China.

According to our study, rank reversal is an important factor to be considered for energy efficiency evaluation using DEA models. The policy suggestions based on the ranking of DMUs are subject to their pre-defined production frontier. When some regions without data before (or are excluded for some other reasons) are added, policy suggestions may change due to rank reversal. Taking Beijing as an example, according to the results obtained from Radial model, Beijing's EE ranking drops

from no. 1 to no. 27 among the 30 regions in Mainland China after taking Hong Kong, Macao, and Taiwan into consideration in year 2014. Obviously, rank reversal can result in different policy implications for Beijing's future energy development.

The influence of rank reversal on policy makings can be further expanded from China's regional study to other countries and regions' study. For instance, EU as an important economy which is worth studying, its members have changed over time. The policy implications proposed based on DEA model which has less rank reversal will be more robust. Besides, the regions in China can be further compared with some other developing countries along the Belt and Road initiative, such as the Southeast Asian Countries.

Rank reversal which reflects the robustness of a DEA model should be gained more attention in the future studies. Besides energy efficiency assessment, rank reversal issues can also happen in other efficiency assessment using DEA, such as the CO₂ emission and pollution efficiency. This is an important aspect that should be considered when selecting DEA models for efficiency assessment. Theoretically, the ideal DEA ranking model shall not change the ranks of other DMUs after the addition or removal of one or more DMUs. The development of such DEA model with rank preservation would be a meaningful topic for future research.

Acknowledgements The authors thank the financial supports from the National Natural Science Foundation of China (Nos. 71704080, 71774087, and 71573186), the Fundamental Research Funds for the Central University (No. 30917013101), and the Research Foundation of Nanjing University of Science and Technology for the Young Scholars (Grant No. JGQN1703).

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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