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Allocation of Regional Emission Permits in China: Based on the Technology of Energy Conservation and Emission Reduction

Lei Li[1,2] and Xiaohong Liu[3]

Abstract

As a large developing country experiencing rapid economic growth, China is facing the dual pressures and challenges of insufficient resources and protecting the ecological environment. However, China is a vast territory, and the spread of regional economic development is extremely uneven. Therefore, the responsibility for emission reductions undertaken by each region cannot be allocated equally. In response to this problem, this study proposes an emission permit allocation model that is built from the perspective of efficiency and energy conservation and emission reduction (ECER) technology. Compared with other models, the model proposed in this study has two innovations. First, the model allows central decision makers to adjust the emission reduction index under various conditions and for various reasons. This further allows the total emissions reduction amounts to be adjusted. Second, the proposed model could also allocate emission permits from the perspective of ECER technology. An empirical study on the allocation of SO_2 emission permits at provincial level in China shows the following: (a) The overall ECER level in China is low, and there are significant differences in ECER efficiency in different regions. (b) Significant differences in ECER technologies exist in different regions of China. In particular, the ECER technology standards in China's northeast region are far below the national average. (c) Each province's emission reduction targets should be reasonably set, based on actual production conditions. If excessive emission reduction targets are set, it becomes unreasonably difficult to complete the emission reduction task.

Keywords

emission permits, energy saving and emission reduction, technology gap, efficiency, metafrontier

Introduction

With the ongoing development of China's economy, environmental issues have become increasingly prominent (Li, 2019; Song, Peng, Wang, & Dong, 2018a). Since the 2009 Global Climate Conference in Copenhagen, the issues related to energy conservation and emission reduction (ECER) have caused widespread concern around the world. As the largest developing country and the largest emitter of greenhouse gases, China is facing enormous pressure from other countries (Song, Zheng, & Wang, 2017). In addition, the continuous smoggy weather has seriously affected the daily life of the Chinese people; their demands to improve the environment are becoming increasingly intense (Wang, Su, Sun, Zhou, & Zhou, 2015). In response to these increasingly serious environmental problems, the Chinese government has proposed a series of environmental policies and measures, of which the emissions trading system (ETS) has proven to be the most effective (Sun & Li, 2018a; Song, Zhang, & Qiu, 2015b). The ETS mainly consists of two stages. In the first stage, emission permits are allocated to each production unit free of charge. In the second stage, if a production unit's permits are insufficient to cover their emissions, that unit can purchase additional permits from production units

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with surplus emissions covered by their permits. It is clear that the most important issue with the ETS is how to rationally and effectively allocate emission permits among production units. The allocation of emission permits (AEPs) scheme deals with this issue (Sun, Wu, Liang, Zhong, & Huang, 2014).

The amount of emission permits issued will directly affect a production unit's production plan (Böhringer & Lange, 2005). If too few emission permits are allocated, the production unit will have to purchase additional permits, which increases the production unit's costs (Ono, 2002). In addition, any unreasonable or unfair AEP scheme may also disrupt the emission permits trading market, thereby affecting the implementation of the ETS. Therefore, how to effectively allocate emission rights has increasingly attracted the attention of scholars and government environmental protection departments.

The study of how to solve the AEP problem mainly considers two different methods, namely auction and free allocation methods (Sun, Fu, Ji, & Zhong, 2017a). The results obtained by these two different methods are controversial and contradictory. From the perspective of economic utility, the auctioning of emission permits is an effective AEP method. However, this method is rarely used in practice. The main reason for not using the auction method is the complexity and difficulty involved in designing a viable auction mechanism. In addition, auction costs are borne by both buyers and sellers; this has led to increasing opposition from emissions permit traders (Cramton & Kerr, 2002).

Given the disadvantages of the auctioning of emission permits, the free AEP method is very popular with production units or organizations, especially in developing countries. The free AEP method mainly includes grandfathering (Åhman, Burtraw, Kruger, & Zetterberg, 2007), output-based allocation (Neuhoff, Martinez, & Sato, 2006), and data envelopment analysis (DEA) methods (Zhang, Wang, & Tan, 2015). Of these three, the DEA method is gradually favored by scholars (Miao, Geng, & Sheng, 2016).

Originally introduced by Charnes, Cooper, and Rhodes (1978), DEA has been widely used in the field of environmental efficiency assessment (Song, Peng, Wang, & Zhao, 2018b; Song, Wang, & Cen, 2015a). It has also been demonstrated that DEA is a method by which efficiency-based allocation issues can be resolved fairly. Currently, the DEA method is increasingly being used to study AEP issues. Lozano, Villa, and Brännlund (2009) proposed a three-stage DEA allocation model from the perspective of centralization. The three objective functions are considered in the model, and the decision maker can set the priority level for each objective function, according to the actual situation. Wei, Ni, and Du (2012) used the slack-based measures model and the abatement capacity index to estimate the CO_2 emission reduction potential and marginal abatement costs of 29 provinces in China, during the period 1995–2007. The empirical results show that a large gap exists between China's eastern, central, and western regions in terms of emission reduction potential and marginal abatement costs. The eastern region has the lowest emission reduction potential and the highest marginal abatement cost, while the western region has the largest emission reduction potential and the lowest marginal abatement cost. Wang, Zhang, Wei, and Yu (2013a) used the zero-sum DEA model to study the issue of the AEPs at the provincial level in China. The empirical results show that different Chinese provinces should bear different responsibilities in terms of reducing emission intensity, reducing energy intensity, and increasing the proportion of nonfossil fuels being used.

Based on ecoefficiency and emission levels, Wu, Du, Liang, and Zhou (2013) proposed a bargaining game DEA model to address the AEP issue. The model can optimally allocate emission permits from the perspective of the maximization of overall efficiency. The empirical results show that the bargaining game DEA model rewards the best operated production units while punishing the poorly operated production units. Sun et al. (2014) proposed two different DEA–AEP models from the perspectives of centralization and decentralization, and then applied the two models to the AEPs for papermaking enterprises. The empirical results show that the centralization model has better allocation performance than the decentralization model. The centralization model not only maximizes the overall efficiency of all enterprises but also increases the efficiency of individual enterprises. To encourage each unit to accept the AEP results of the centralized DEA model, Feng, Chu, Ding, Bi, and Liang (2015) introduced a compensation mechanism into the centralized DEA model. The empirical results show that the centralized DEA model that considers a compensation mechanism can take into account the interests of the overall industry and the individual enterprise in the process of the AEPs. Considering the limitations of the total emission permit, Wu, Zhu, Chu, An, and Liang (2016) introduced the concept of satisfaction into DEA, proposing a max-min satisfaction DEA emission permits allocation model. The author further determined the production or trading emission permits for each production unit. To ensure that the AEP results satisfy the Pareto optimality, Ji, Li, and Wang (2017a) proposed three different AEP models: nonrestricted, uniform-restricted, and heterogeneous-restricted AEP models. The study theoretically proves that the results of these three models are Pareto optimal. Empirical studies of coal-fired power plants in China have shown that heterogeneous-restricted AEP models achieve higher levels of performance than the other two models. Therefore, the authors suggest that China's coal-fired power industry should adopt a heterogeneous-restricted AEP model in the actual allocation of SO_2 emission permits. To further improve the reliability of DEA frontier estimation under big data scenarios, Ji, Sun, Wang, and Yuan (2017b) presented a big data-based DEA frontier and possible production set. The study also proposed a new big data set-based DEA model for resolving AEP issues. The empirical results show that the proposed DEA–AEP model can help the central decision maker to formulate the optimal initial allocation of permits. The proposed model also offers higher degrees of stability and reliability in big data situations.

The literature discussed earlier indicates that the existing research that uses DEA to explore AEP has attracted the attention of some scholars. However, most of these studies aim to allocate emission permits from the perspective of efficiency maximization. Few studies to date have considered allocating emission permits from the perspective of ECER technology. In response to this problem, this study will propose a DEA–AEP model based on ECER technology. The theoretical contributions of this study mainly lie in the following three aspects. First, this study uses DEA and metafrontier technology to obtain the technology deficiency (TD) of each production unit. Then, the weight of each production unit is calculated, based on the TD results. Therefore, the weight can effectively reflect the technical level of the production unit. In other words, a large weight indicates that the production unit has a high level of technology. Second, the weights are incorporated into the DEA method to propose the ECER-based DEA–AEP model. Compared with the models of Sun et al. (2014) and Sun et al. (2017a), the AEP model of this study not only considers the efficiency of the production unit but also considers its technical level. Third, the proposed model in this study also considers a total emission reduction adjustment index. Through this index, policy makers can adjust the total amount of emission reductions required according to actual condition.

In addition to the theoretical contributions, this study has also obtained some valuable research results. First, the overall ECER level in China is low, and the ECER efficiency varies greatly among China's different regions. Second, when using different reference objects, the energy saving and emission reduction performance in China's provinces changes significantly, especially in northeast China. Third, there are significant differences in terms of ECER technologies in the different regions of China. Generally, the ECER technologies in China's eastern region are the best, while the ECER technologies in the northeast are the worst. Fourth, the province's emission reduction adjustment index will affect the emission reduction levels of the province and the country. Therefore, the province's emission reduction targets should be reasonably set and should be based on actual production conditions. If excessive emission reduction targets are set, completing the emission reduction task becomes unreasonably difficult.

This study is organized as follows: The Methods section proposes the ECER technology-based AEP method, followed by an empirical analysis in the Results and Discussion sections. The Implications for Conservation section concludes the study with implications.

Methods

Group Frontier and Metafrontier

This study mainly discussed ECER performance and AEP issues of all China's regions (CRs), and the relationship between CRs is shown in Figure 1. Due to the heterogeneity in the production technologies of different CRs, all CRs can be divided into different groups. Each individual group engenders a production frontier, namely, the group frontier. Then, a common production frontier is obtained by enveloping all of the production frontiers of different groups, namely, the metafrontier.

Referring to the description of a metafrontier by Battese and Rao (2002) and O'Donnell, Rao, and Battese (2008), we assume that there are N CRs and divide them into $H(H \geq 1)$ separate and different groups. The CR number in the h^{th} group is $N^h(h = 1, \ldots, H)$, and $\sum_{h=1}^{H} N^h = N$. In this study, we consider that technology heterogeneity of ECER exists between groups. Each CR produces T different desirable outputs $(DY_{tj}, t = 1, 2, \ldots, T)$ and F different undesirable outputs $(b_{fj}, f = 1, 2, \ldots, F)$, using Q different non-energy inputs $(NI_{qj}, q = 1, 2, \ldots, Q)$ and K different energy inputs $(N_{kj}, k = 1, 2, \ldots, K)$.

The production frontier of the h^{th} group is represented as T^h, which is called the group frontier. The production frontier of all CRs is represented by T, which is called the metafrontier. In addition, T^h and T have the following characteristics: (a) For any h,

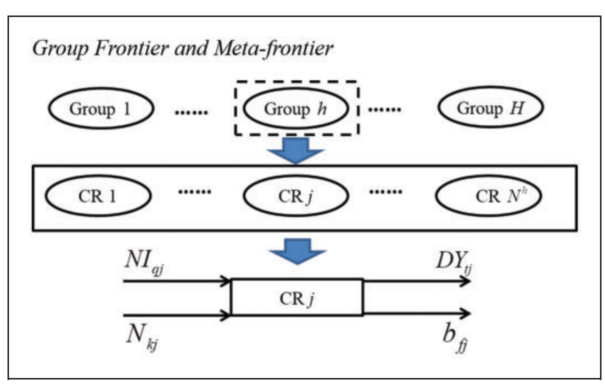

Figure 1. The relationship between CRs. CRs = China's regions.

if $(NI, N, DY, b) \in T^h$, then $(NI, N, DY, b) \in T$; (b) $T = \left\{T^1 \cup T^2 \cdots \cup T^H\right\}$.

The ECER Efficiency

Based on the forms of the group frontier and metafrontier, this section uses the directional distance function method to explain ECER efficiency from the aspects of input and output. Accordingly, we can use the DEA linear programming proposed by Wang, Zhou, and Zhou (2012); Wang, Zhao, Zhou, and Zhou (2013b); Wang et al. (2015), to obtain the inefficiency of each CR under the group frontier and metafrontier. The programming is as shown in Equations 1 and 2, as follows:

$$\begin{aligned}
&\max \beta_o^h\\
&s.t. \sum_{j=1}^{N^h} \lambda_j^h NI_{qj} \le NI_{qo}, && q = 1,\ldots,Q\\
&\sum_{j=1}^{N^h} \lambda_j^h N_{kj} \le \left(1-\beta_o^g\right) N_{ko} && k = 1,\ldots,K\\
&\sum_{j=1}^{N^h} \lambda_j^h DY_{tj} \ge DY_{to} && t = 1,\ldots,T\\
&\sum_{j=1}^{N^h} \lambda_j^h b_{fj} \le \left(1-\beta_o^g\right) b_{fo} && f = 1,\ldots,F\\
&\sum_{j=1}^{N^h} \lambda_j^h = 1,\\
&\lambda_j^h \ge 0.
\end{aligned} \tag{1}$$

$$\begin{aligned}
&\max \beta_o^m\\
&s.t. \sum_{h=1}^{H}\sum_{j=1}^{N^h} \lambda_j^h NI_{qj} \le NI_{qo}, && q = 1,\ldots,Q\\
&\sum_{h=1}^{H}\sum_{j=1}^{N^h} \lambda_j^h N_{kj} \le \left(1-\beta_o^m\right) N_{ko}, && k = 1,\ldots,K\\
&\sum_{h=1}^{H}\sum_{j=1}^{N^h} \lambda_j^h DY_{tj} \ge DY_{to}, && t = 1,\ldots,T\\
&\sum_{h=1}^{H}\sum_{j=1}^{N^h} \lambda_j^h b_{fj} \le \left(1-\beta_o^m\right) b_{fo}, && f = 1,\ldots,F\\
&\sum_{h=1}^{H}\sum_{j=1}^{N^h} \lambda_j^h = 1,\\
&\lambda_j^h \ge 0.
\end{aligned} \tag{2}$$

In Equations 1 and 2, λ_j^h is the weight of the evaluated CR_o; β_o^h is the ratio of increase in the desirable output, as well as the ratio of decrease in the undesirable output under the group frontier; β_o^m is the ratio of increase in the desirable output and is also the ratio of decrease in the undesirable output under the metafrontier.

After the β_o^h and β_o^m are obtained, the ECER efficiency of CR_o under the group frontier is expressed as

$$E_o^h = 1 - \beta_o^h \tag{3}$$

and the ECER efficiency of CR_o under the metafrontier is expressed as

$$E_o^m = 1 - \beta_o^m \tag{4}$$

ECER Technology Gap and Weights

From Equations 3 and 4, it is noted that the closer E_o^h and E_o^m are to 1, the higher the ECER efficiency of the CR_o will be. On the contrary, the closer E_o^h and E_o^m are to 0, the lower the ECER efficiency of the CR_o will be.

To quantitatively characterize the heterogeneity degree of the ECER technology, the ECER-technology gap (*ECER-TG*) of CR_o in the h^{th} group based on the efficiency difference between the group frontier and metafrontier is applied, as shown in Equation 5.

$$ECER - TG_o = \frac{E_o^m}{E_o^h} = \frac{1-\beta_o^m}{1-\beta_o^h} \tag{5}$$

The E_o^m is the ECER efficiency in the metafrontier, and the E_o^h is the ECER efficiency in the group frontier. The group frontier is a subset of the metafrontier, which means $E_o^m \le E_o^h$. Therefore, the closer the E_o^m and $ECER - TG_o$ are to 1, the higher the ECER technology of CR_o will be. On the contrary, the closer the E_o^m and $ECER - TG_o$ are to 0, the lower the ECER technology of CR_o will be.

According to Chiu, Liou, Wu, and Fang (2012) and Sun, Li, and Wang (2018b), the efficiency deficiency of a CR can be further broken down into TD and nontechnology deficiency (N-TD), as shown in Equations 6 to 8.

$$ED_o = TD_o + N\text{–}TD_o = \beta_o^m \tag{6}$$

$$TD_o = \beta_o^m - \beta_o^h \tag{7}$$

$$N\text{–}TD_o = 1 - E_o^h = \beta_o^h \tag{8}$$

Figure 2 shows three short curves (representing three group frontiers) and a long curve (representing the metafrontier). The projection of A on the group frontier is

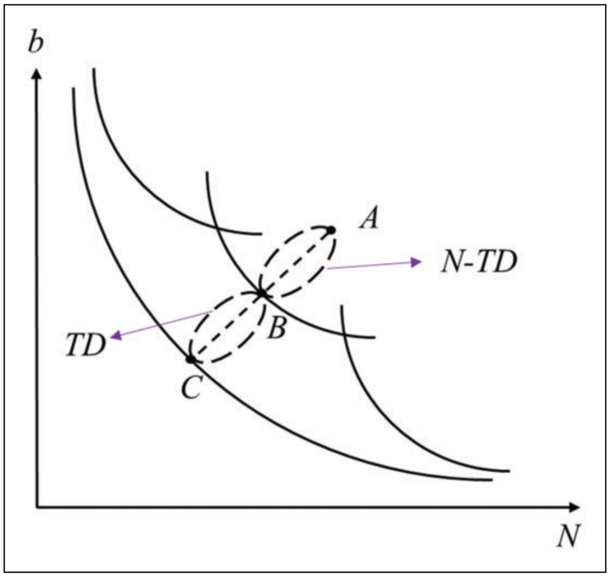

Figure 2. Decomposition of ECER inefficiency. N-TD = nontechnology deficiency; TD = technology deficiency.

point B, and the projection on the metafrontier is point C; BC is A's TD, and AB is A's N-TD.

Figure 2 shows that the smaller the TD is, the smaller the technology improvement potential of A will be. Therefore, the TD can also reflect the ECER technology level of A to a certain extent. Based on the TD value, this study defines the weight of the ECER technology level of each CR, as shown in Equation 9.

$$W_o = 1 - \frac{TD_o}{\sum_{j=1}^{N} TD_j} \tag{9}$$

Equation (9) shows that the smaller the TD_o of the CR_o is, the larger the ECER technology weight W_o of CR_o will be.

AEP Based on ECER Technology Level

Many scholars have proposed a large number of models that deal with the initial AEPs. However, this section will discuss the reallocation of emission permits. Specifically, to further protect the environment and to control pollution emissions, the government's environmental protection department decided to cut a portion of the total number of emission permits being issued. How each CR should share the emission reduction task will be discussed in this section. Compared with other models, the DEA–AEP model proposed in this study has two main innovations. First, the model used in this study considers the ECER technology of each CR when assigning emission reduction tasks (e.g., ECER weights). Second, this study's model introduces a total emission reduction adjustment index. Through this index, policy makers can adjust the total amount of emission reductions required. The AEP model based on ECER technology level is proposed as follows:

$$\begin{aligned}
&\min \sum_{f=1}^{F}\sum_{j=1}^{N} W_j(w_f \bar{b}_{fj}) \\
&s.t. \frac{\sum_{t=1}^{T} u_t DY_{tj}}{\sum_{q=1}^{Q} v_q NI_{qj} + \sum_{k=1}^{K} \rho_k N_{kj} + \sum_{f=1}^{F} w_f (b_{fj} - \bar{b}_{fj})} \\
&\quad \geq \alpha_j, j = 1, \ldots, N, \\
&\quad \frac{\sum_{t=1}^{T} u_t DY_{tj}}{\sum_{q=1}^{Q} v_q NI_{qj} + \sum_{k=1}^{K} \rho_k N_{kj} + \sum_{f=1}^{F} w_f (b_{fj} - \bar{b}_{fj})} \\
&\quad \leq 1, \quad j = 1, \ldots, N, \\
&\quad b_{fj} - \bar{b}_{fj} \geq 0, \quad f = 1, \ldots, F, \quad j = 1, \ldots, N, \\
&\quad v_q, \rho_k, w_f, u_t, \bar{b}_{fj} \geq 0
\end{aligned} \tag{10}$$

In Model (10), α_j is a parameter, which can be determined by the decision maker. The first constraint shows that, when allocating emission reduction tasks, the efficiency of each CR_j cannot be lower than α_j. If the degree of efficiency α_j is larger, the CR_j's emission reduction task will be larger, and the total emission reduction of all CRs will be larger. The objective function of the model shows that the better the ECER technology of the CR_j is, the larger the weight will be, and the lesser will be the emission reduction task that is allocated. Model (4) is nonlinear. Let $\hat{b}_{fj} = w_f \bar{b}_{fj}$, and then Model (10) can be transformed into Model (11) expressed as

$$\begin{aligned}
&\min \sum_{f=1}^{F}\sum_{j=1}^{N} W_j \hat{b}_{fj} \\
&s.t. \alpha_j \sum_{q=1}^{Q} v_q NI_{qj} + \alpha_j \sum_{k=1}^{K} \rho_k N_{kj} + \alpha_j \sum_{f=1}^{F} w_f b_{fj} \\
&\quad - \alpha_j \sum_{f=1}^{F} \hat{b}_{fj} - \sum_{t=1}^{T} u_t DY_{tj} \leq 0, \quad j = 1, \ldots, N, \\
&\quad \sum_{q=1}^{Q} v_q NI_{qj} + \sum_{k=1}^{K} \rho_k N_{kj} + \sum_{f=1}^{F} w_f b_{fj} - \sum_{f=1}^{F} \hat{b}_{fj} \\
&\quad - \sum_{t=1}^{T} u_t DY_{tj} \geq 0, \quad j = 1, \ldots, N, \\
&\quad \sum_{q=1}^{Q} v_q NI_{qj} + \sum_{k=1}^{K} \rho_k N_{kj} + \sum_{f=1}^{F} w_f b_{fj} \\
&\quad - \sum_{f=1}^{F} \hat{b}_{fj} \geq C, \quad j = 1, \ldots, N, \\
&\quad w_f b_{fj} - \hat{b}_{fj} \geq 0, \quad f = 1, \ldots, F, \quad j = 1, \ldots, N, \\
&\quad v_q, \rho_k, w_f, u_t, \hat{b}_{fj} \geq 0
\end{aligned} \tag{11}$$

In Model (11), the third constraint is to ensure that the model obtains the nonzero solutions. By solving Model (11), the optimal solution of Model (11) is represented as $(v_q^*, \rho_k^*, w_f^*, u_t^*, \hat{b}_{fj}^*)$. Then, the emission reduction task for each CR is $\bar{b}_{fj}^* = \frac{\hat{b}_{fj}^*}{w_f^*}(j = 1, \cdots, N;\ f = 1, \cdots, F)$. Under the constraint of α_j, the total emission reduction amount for all CRs is $B_f = \sum_{j=1}^{J} \bar{b}_{fj}^*(f = 1, \cdots F)$.

Sampling and Data Collection

This section further validates the approach presented in this study by presenting data on ECERs from China's 30 provinces. Due to the lack of data, Tibet is not included in these provinces. Based on the study of Sun et al. (2018b) and Sun, Wang, and Li (2018c), the inputs in each province include fixed assets, labor, and coal consumption. Labor and fixed assets are usually treated as nonenergy input variables (Wang et al., 2015). Economic development is the most important output for a province (Hu & Wang, 2006). Thereby, the gross domestic product is considered as desirable output. According to the study of Sun et al. (2018b), SO_2 is regarded as the undesirable output in this study. All data come from the China National Statistical Yearbooks (Sheng, 2014, 2015, 2016; Xing & Ye, 2017). Table 1 shows the descriptive statistical variables.

Table 1 shows that the economic development and SO_2 emissions vary greatly in different regions of China. In 2017, for example, the maximum gross domestic product is 31.43 times its minimum, and the maximum SO_2 is 66.74 times its minimum. These data show that there are huge differences in economic development and pollution emissions between regions in China. These factors need to be fully considered in the calculation of EREC performance and AEP.

Considering the technical heterogeneity between different regions, this study divides 30 Chinese provinces into 4 groups, according to their geographical distribution and economic development characteristics (Sun et al., 2018b, 2018c), for example, Eastern China, Northeast China, Central China, and Western China. The specific grouping results are shown in Table 2.

Results

We used Equations 1 and 2 to calculate the ECER efficiency of each province for 4 years, using the metafrontier and group frontier as references. Table 3 shows the descriptive statistical results. It is noted that the ECER efficiency of China's provinces is not high. Specifically, when comparing all regions in the metafrontier, the efficiency of each region is less than 1, and the overall average efficiency is 0.3768. This indicates that China has not achieved a win-win situation with regard to environmental protection and energy saving; the country still has the

Table 1. Statistical Description of Input–Output Variables for 4 Years.

Year	Statistics	Fixed assets (10^8 RMB)	Labor (10^4)	Coal consumption (10^4 ton)	GDP (10^8 RMB)	SO_2 (10^4 ton)
2014	Maximum	36,789.07	1,966.98	37,683.44	62,474.79	164.50
	Minimum	2,361.09	64.19	1,008.78	2,122.06	3.24
	M	14,658.76	602.58	14,407.12	21,117.66	68.12
	Mdn	12,378.96	486.56	11,922.64	16,560.98	59.64
	Std.	8,953.17	425.57	10,339.07	15,541.94	40.21
2015	Maximum	42,495.55	1,973.28	39,561.73	67,809.85	159.02
	Minimum	2,861.23	63.19	1,018.30	2,303.32	3.26
	M	16,822.77	608.17	14,391.30	22,780.95	65.80
	Mdn	14,461.24	490.89	11,466.61	17,730.07	57.97
	Std.	10,330.56	434.09	10,576.55	16,810.32	38.53
2016	Maximum	48,312.44	1,948.04	40,926.94	72,812.55	152.57
	Minimum	3,210.63	62.71	1,071.92	2,417.05	3.23
	M	18,505.06	600.97	14,182.61	24,058.05	61.95
	Mdn	15,290.51	496.17	11,454.09	17,926.69	56.10
	Std.	11,588.41	426.46	10,753.06	18,046.47	36.33
2017	Maximum	53,322.94	1,957.57	40,939.20	80,854.91	113.45
	Minimum	3,528.05	63.09	847.62	2,572.49	1.70
	M	19,983.05	595.22	14,164.73	25,963.95	36.74
	Mdn	16,083.75	491.43	11,564.71	18,949.30	30.32
	Std.	13,055.54	423.18	10,727.34	19,937.99	24.65

Note. GDP = gross domestic product; RMB = Renminbi; Std. = standard deviation.

potential to reduce SO_2 emissions and coal consumption. On the other hand, there are significant differences in the levels of efficiency of China's four regions. The efficiency in Eastern China is relatively high, at 0.6425. The efficiency levels in Central China and Western China are not high, at 0.2339 and 0.2695, respectively. The efficiency in Northeast China is relatively low, at 0.1699. Comparing the ECER efficiencies of the metafrontier and group frontier, the efficiency values of each region are different; in each case, the metafrontier efficiency is lower than the group frontier efficiency. Specifically, in the group frontier, the ECER efficiency values of Northeast China and Central China show clear signs of improvement.

We further test the significance of the differences in ECER performance with respect to the metafrontier and group frontier. We applied the nonparametric Mann–Whitney statistical method to conduct the test, and the results are shown in Table 4. As can be seen, for Northeast China, Central China, and Western China, the null hypothesis of the same center position of the efficiency distribution was rejected at the 1% significance level. In other words, different reference frontiers lead to significant differences in the level of ECER efficiency. However, the test results for Eastern China show different results, with a p value of 1. This means that Eastern China does not have significant differences, in terms of ECER efficiency levels, when the two frontiers are used. The contribution of these findings is that the choice of the comparison object (group frontier or metafrontier) is different, and the efficiency results of the region may therefore also have a greater difference.

Table 2. Regional Grouping Results.

Region	Regional grouping results
Eastern China	Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Shandong, Hainan, Fujian, and Guangdong
Northeast China	Liaoning, Jilin, and Heilongjiang
Central China	Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan
Western China	Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang

Table 3. Statistical Description of Environmental Efficiency for 4 Years.

	Metafrontier		Group frontier	
Region	*M* for 4 years	*SD*	*M* for 4 years	*SD*
Eastern China	0.6425	0.3032	0.6425	0.3032
Northeast China	0.1699	0.0778	0.9462	0.0767
Central China	0.2339	0.1940	0.8983	0.1612
Western China	0.2695	0.2907	0.6669	0.3062
M	0.3768	0.3239	0.7330	0.2899

Discussion

Technology Gaps of ECER Efficiency

To measure the degree of heterogeneity between the ECER technology levels of different regions, we first used Equation 5 to calculate the ECER-TG score of each province's ECER efficiency. The nonparametric Kruskal–Wallis method was then used to test the technology gaps under multiple independent sample conditions. The test results are shown in Table 5. It is found that the p value is .000 at the 1% significance level, so the null hypothesis is rejected. In other words, the technical levels of the four groups have statistically significance differences.

Figure 3 presents the boxplot of the ECER-TG in each region. The results show that the technology gaps across the four regions have significant differences.

Table 5. Kruskal–Wallis Test Results for the ECER-TG of All Provinces for 4 Years.

Null hypothesis	Kruskal–Wallis *H* statistics value	*p*
The center positions of the four technology gap distributions for all four regions are the same.	79.190	0.000

Note. ECER-TG = energy conservation and emission reduction-technology gap.

Table 4. Mann–Whitney Test Results for Environmental Efficiency Performance.

Region	Null hypothesis	*U* statistic value	z statistic value	*p*
Eastern China	The center positions of the two efficiency distributions are the same	760.500	0.000	1.000
Northeast China		0.000	–4.189	0.000
Central China		8.000	–5.819	0.000
Western China		284.500	–5.738	0.000

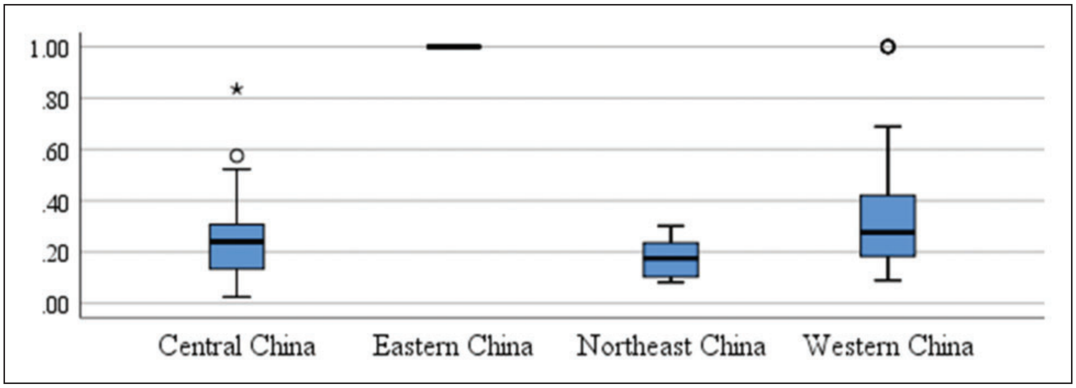

Figure 3. Boxplot of each region's ECER-TG for 4 years.

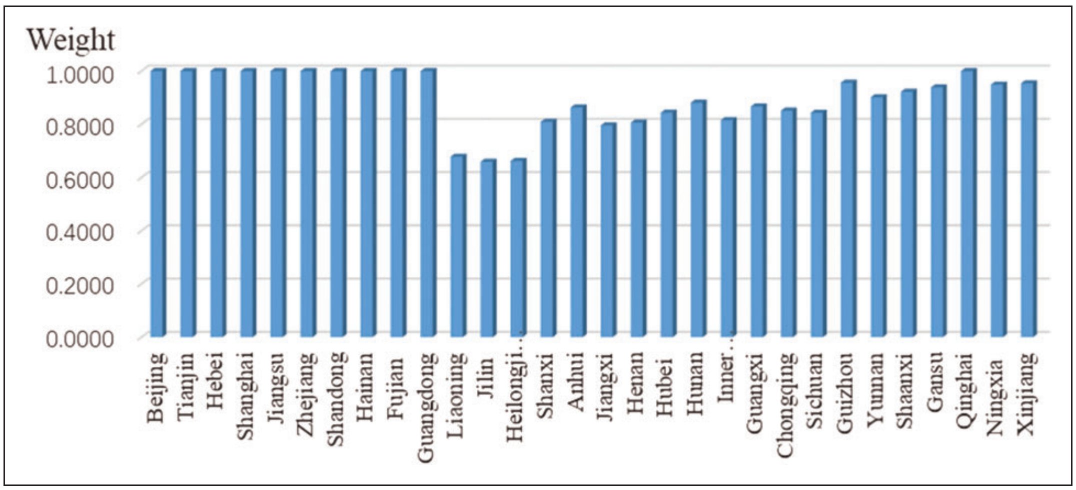

Figure 4. The weight of each province based on ECER technology.

Eastern China's technology gap is close to 1, coming near to the optimal level of the national ECER technology. Some reasons can explain this phenomenon. For example, China's eastern region is located on the coast. This region has a better industrial base and has experienced rapid economic growth over the past few decades. At present, the eastern region is accelerating the upgrading of its industrial structure and actively developing high-tech industries and advanced manufacturing industries. Therefore, having a more developed economy and industry is also providing the eastern China region with more efficient energy saving and emission reduction technologies.

Figure 3 shows that Northeast China has the lowest technical gap. In addition, Table 2 shows that the metafrontier efficiency of Northeast China is also the lowest. These results show that the ECER technologies in Northeast China are of the lowest standard. The northeast region is one of China's traditional industrial bases, and its economic development relies heavily on industries such as steel and coal (Zhou, Wang, Su, Zhou, & Yao, 2016). However, the state of the economy of Northeast China has fallen sharply in the past decade, and the regional industries have shown a negative growth trend (Sun, Yuan, Yang, Ji, & Wu, 2017b). Therefore, the factors upon which industries rely heavily (e.g., high energy consumption and high emissions), combined with deteriorating economic development, have had a negative impact on the development of EREC technology in Northeast China.

AEP Based on ECER Technologies

According to the proposed Equation 7, we can obtain the TD results of each province for 4 years. Then, according to the average TD values of each province for 4 years and the Equation 9, the weight of each province based on ECER technology can be provided, as shown in Figure 4. Figure 4 shows that the weights of the eastern region are the largest, followed by the

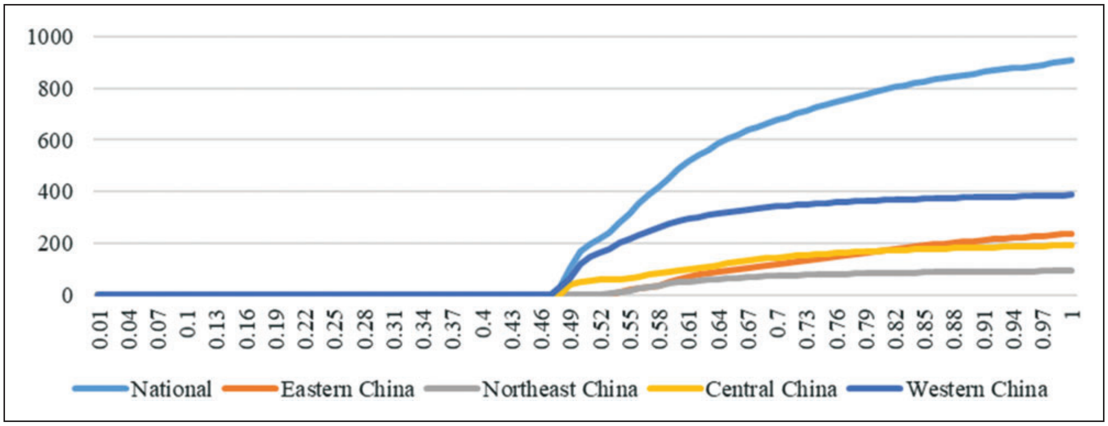

Figure 5. Reduction of SO_2 emission permits.

weights of the central and western regions; the weights of the northeast region are the smallest. These weight results are consistent with the results of the ECER technologies obtained in the Technology Gaps of ECER Efficiency section.

Figure 5 shows the relationship between the emission reduction adjustment index and the total amount of emission reductions of all regions, using the 2017 data of each province. This section considers that the central decision makers apply the same requirements to each province's emission reduction adjustment index. That is, the emission reduction adjustment index of each province is assumed to be equal in this section and gradually increases from 0 to 1. From Figure 5, it is found that when the index is below 0.47, the total amount of emissions reduction is zero. In other words, each province does not need to reduce its SO_2 emission levels. When the index is greater than 0.47, the total amount of emissions reduction shows a positive correlation with the index. When the index is 1, the total amount of emissions reduction required is 906.72 (10^4 ton). This figure would account for 82.26% of the actual SO_2 emissions in China in 2017. This emission reduction requirement is clearly unachievable. In fact, the Chinese government has formulated SO_2 emission reduction tasks based on a step-by-step strategy. In other words, the ratio of total SO_2 reductions in the current period to total SO_2 emissions in the previous period does not exceed one ratio (e.g., 10%). In 2017, China's SO_2 emissions decreased by 8.0% compared with the total SO_2 emissions in 2016.

The earlier results provide two valuable research findings. First, each province's emission reduction adjustment index will affect the amount of each province's emissions reductions, as well as the total amount of national emissions reductions. Second, each province's emission reduction index should be set at a reasonable level, according to actual production conditions. If an excessive emission reduction index is set, the emission reduction task is unrealistic and too difficult to complete.

Implications for Conservation

This study investigates the AEP problems found in a group of regions that aim to control their total emission levels. The DEA approach is adopted to model this practical issue and provide an optimal scheme for decision makers. The DEA and metafrontier methods are first used to determine the ECER performance of each region. Then, based on the group frontier and the metafrontier, the ECER technology level of each area is obtained. Third, through the weight obtained by ECER technology, this study proposes the DEA–AEP model, considering each region's ECER technology. The empirical study on SO_2 in China is also conducted to verify the model.

The main theoretical contributions of this study are as follows: First, the DEA and metafrontier methods are used to obtain the ECER TD for each CR. Then, the ECER weights of each CR are defined by the ECER TD. Therefore, the ECER weights proposed in this study can, to a certain extent, reflect the ECER technology level. Second, this study proposes an improved DEA–AEP model. Compared with other AEP models, the model in this study not only considers the efficiency of the CR in the process of allocating emission permits but also considers the CR's ECER technology level.

In addition to the theoretical contributions, this study has also obtained some valuable research findings. First, the overall ECER level in China is low, and the level of ECER efficiency varies greatly between China's different regions. Second, the ECER performance of China's provinces has changed significantly, if a different frontier is used. Third, Eastern China has the best ECER technology, while the ECER technology in Northeastern China is the worst. Fourth, the emission reduction targets of a province should be set reasonably and according to the actual production conditions. If emission reduction targets are set too high, it will be difficult for the province to complete the emission reduction task.

Based on these results, this study suggests the following implications for environmental conservation. First, the results of metafrontier efficiency show that the environmental efficiency of Northeast China is lower than that of other regions. The industrial structure of Northeast China is mainly the second industry, and the proportion of industry is large. Northeast area is China's heavy industry base, mainly including metallurgy, energy, chemical, and other industries. These industries have the problems of high energy consumption and high pollution. Therefore, the excessive dependence on industry makes the industrial structure of Northeast China unreasonable and the environmental improvement difficult to achieve. Therefore, Northeast China should gradually eliminate the dependence on the industries with high energy consumption and high emission industries and adjust the industrial structure. For example, the traditional industries need to be reformed in pollution control technology. In addition, the northeast region should realize the transformation from low-level industry to high-level industry under the circumstances of China's economic structural transition.

Second, Eastern China, especially in the eastern coastal areas, has always been the leader of China's economic development. The economy and industrialization of the eastern region are ahead of other regions, making the production technology in the eastern region higher than other regions. To achieve the overall improvement of China's ECER, it is necessary to transfer technology from the eastern region to other regions, especially the transfer of green production technology, promoting the growth of green economy growth efficiency in other regions.

Third, the results show that a slight change in emission reduction index will lead to a large change in total emission reduction. Therefore, the setting of emission reduction targets is particularly important. If the target is set too low, the effect of emission reduction on environmental improvement is limited. If the target is set too high, the emission reduction task will be difficult to achieve. In addition, China has a vast territory and great differences in resource endowments among regions. Therefore, different regions cannot adopt uniform emission reduction target setting rules. The region should fully consider the local industrial structure and economic development and formulate appropriate emission reduction targets according to local conditions.

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