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Working Paper 100
http://ceep.bit.edu.cn/english/publications/wp/index.htm

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January 2017

This paper can be cited as: *Wang K, Zhang J, Wei Y-M. 2017. Operational and environmental performance in China's thermal power industry: Taking an effectiveness measure as complement to an efficiency measure. CEEP-BIT Working Paper.*

We gratefully acknowledge the financial support from the National Natural Science Foundation of China (Grant Nos. 71471018 and 71521002), the Social Science Foundation of Beijing (Grant No. 16JDGLB013), the National Key R&D Program (Grant No. 2016YFA0602603), and the Joint Development Program of Beijing Municipal Commission of Education. The views expressed in this paper are solely authors' own and do not necessarily reflect the views of the supporting agencies and Beijing Institute of Technology. The authors alone are responsible for any remaining deficiencies.

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Operational and environmental performance in China's thermal power industry: Taking an effectiveness measure as complement to an efficiency measure

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Abstract: The trend toward a more fiercely competitive and strictly environmentally regulated electricity market in several countries, including China has led to efforts by both industry and government to develop advanced performance evaluation models that adapt to new evaluation requirements. Traditional operational and environmental efficiency measures do not fully consider the influence of market competition and environmental regulations and, thus, are not sufficient for the thermal power industry to evaluate its operational performance with respect to specific marketing goals (operational effectiveness) and its environmental performance with respect to specific emissions reduction targets (environmental effectiveness). As a complement to an operational efficiency measure, an operational effectiveness measure not only reflects the capacity of an electricity production system to increase its electricity generation through the improvement of operational efficiency, but it also reflects the system's capability to adjust its electricity generation activities to match electricity demand. In addition, as a complement to an environmental efficiency measure, an environmental effectiveness measure not only reflects the capacity of an electricity production system to decrease its pollutant emissions through the improvement of environmental efficiency, but it also reflects the system's capability to adjust its emissions abatement activities to fulfill environmental regulations. Furthermore, an environmental effectiveness measure helps the government regulator to verify the rationality of its emissions reduction targets assigned to the thermal power industry. Several newly developed effectiveness measurements based on data envelopment analysis (DEA) were utilized in this study to evaluate the operational and environmental performance of the thermal power industry in China during 2006-2013. Both efficiency and effectiveness were evaluated from the three perspectives of operational, environmental, and joint adjustments to each electricity production system. The operational and environmental performance changes over time were also captured through an effectiveness measure based on the global Malmquist productivity index. Our empirical results indicated that the performance of China's thermal power industry experienced significant progress during the study period and that policies

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regarding the development and regulation of the thermal power industry yielded the expected effects. However, the emissions reduction targets assigned to China's thermal power industry are loose and conservative.

Keywords: Efficiency; Environmental effectiveness; Joint performance; Operational effectiveness

1 Introduction

The thermal power industry remains a major source of China's greenhouse gas emissions and air pollution. In 2013, total carbon dioxide emissions in China were 9.77 billion tons, and the thermal power industry was responsible for 38% of this total. In order to control emissions, China's government formulated energy conservation and emissions reduction targets in the last two decades, such as the Shutting Down of Small Thermal Power Units Action (Wang et al., 2016a). In addition, in the 11th Five Year Plan (FYP) and the 12th FYP periods (2006-2010 and 2011-2015), China's government listed specific energy conservation and emissions reduction targets for the thermal power industry. However, because of resource endowment, the growing demand for electricity, and the time required to structurally adjust the electricity industry, it is not realistic to change the situation that thermal power is the dominant component in China's electricity mix in the short term. China's thermal power industry needs, on the one hand, to reduce pollutant emissions for environmental protection and, on the other hand, to improve production efficiency to meet the market demand. Therefore, improving both operational performance and environmental performance is considered the core for the sustainable development of China's thermal power industry.

Frontier analysis is a widely used method to evaluate productive efficiency in the electric power industry. Nonparametric linear programming-based data envelopment analysis (DEA) helps analysts to estimate the production function without a functional form assumption and to identify a productive efficiency frontier by defining efficiency as a ratio of a weighted sum of multiple outputs to a weighted sum of multiple inputs. In the case where both industries have the same levels of input resources, a thermal power industry is considered efficient if it generates at least as much electricity as another observed thermal power industry.

Several previous studies use DEA to evaluate the operational efficiency of an electric power industry. For example, Sueyoshi and Goto (2001) employ a slack-adjusted DEA to evaluate the operational efficiency of the electric power generating companies in Japan from 1984 to 1993. They claim that their DEA results imply that integrating generation and transmission may not enhance efficiency. Chen (2002) measures the efficiency of 22 distribution districts of the Taiwan Power Company and finds that the first task of inefficient distribution districts is to determine the critical targets that can be used as benchmarks for guiding further improvement. Ma and Zhao (2015) evaluate the operational efficiency of hundreds of power plants in China from 1997 to 2010 based on DEA and SFA methods. They find that a large proportion of the overall efficiency improvement occurred in the last decade but that this improvement is not likely to continue. Some studies extend the DEA models to include undesirable outputs, and in addition, evaluate environmental efficiencies. For example, Welch et al. (2009) give a performance analysis of power generation companies in the U.S. from 2002 to 2005. Their results show that both fuel costs and carbon pollution can be reduced simultaneously, given the current technology, by increasing the technical efficiency of inefficient plants to a level closer to that of their more efficient peers. Sueyoshi et al. (2010) use the DEA method to evaluate the performance of coal-fired power plants under the U.S. Clean Air Act (CAA). They find that the CAA became increasingly effective in terms of operational and unified efficiency measures. Yang and Pollitt (2009) evaluate two data sets of China's coal-fired power plants, one containing 221 plants and one containing 582 plants, in 2002 using a traditional DEA model and several uncontrollable variable-adjusting DEA models. Their results confirm the hypothesis that at least some power plants with relatively low efficiency scores in the traditional model achieve these results partly due to their relatively unfavorable operating environments. Bi et al. (2014) estimate the total factor energy efficiency of China's thermal power generation system in each provincial region from 2007 to 2009 with DEA models. They find that environmental efficiency plays a significant role in the energy performance of China's thermal generation sector. There also have been many studies using DEA to evaluate the energy and environmental efficiency and the production performance of the electric power industry (e.g., Chitkara, 1999; Pahwa et al., 2003; Azadeh et al., 2008; Feroz et al., 2009; Picazo-Tadeo et al., 2011; Chen et al., 2012; Shrivastava et al., 2012; Wang et al., 2012; Macpherson et al., 2013; Mou, 2014; Ignatius et al., 2016; Wang et al., 2016b, 2016c; Wang and Wei, 2016).

In recent years, fierce market competition as well as strict environmental regulation both in China and abroad have led to the development of a performance evaluation method that applies to both market and environmental performance. However, the above studies only consider typical efficiency evaluations and do not fully consider the influence of market competition (when desirable outputs need to be sold and not just produced) and environmental regulation (when undesirable outputs are regulated). Thus, efficiency estimation alone is not enough to evaluate the operational and environmental performance of an industry relative to specific targets such as sales and emissions control. In this study, performance estimation that takes these specific targets into account is defined as effectiveness. Therefore, the measurement of operational performance can be divided into two parts: operational efficiency (which is evaluated to improve the ability of production) and operational effectiveness (which is evaluated to improve the ability of market competition). When the operational performance of the thermal power industry is measured, electricity production is commonly considered to be the desirable output. However, electricity should be consumed when it is produced because it cannot usually be stored; otherwise, the inputs for thermal power production are wasted. The amount of electricity consumed is defined as the demand limit. In our study, the concept of the demand limit is neither the lower limit nor the upper limit of electricity demand but is used to capture the gap between electricity generation and electricity consumption in a region, which reveals the effort of a region to match its electricity generation to the local electricity demand. Excess production, which means that more electricity is generated than the local electricity demand, will imply that some electricity cannot be sold or consumed, and the associated inputs are wasted. On the other hand, insufficient production, which means that less electricity is generated than the local demand, will imply that local electricity generation cannot meet local demand and will interrupt normal economic activity. Thus, from the perspective of the thermal power industry, a measure of operational performance should include not only the capacity to generate more electricity given the same inputs (operational efficiency) but also the capacity to meet electricity demand (operational effectiveness).

Similarly, the measurement of environmental performance should also include two components: environmental efficiency, which is evaluated to improve abatement ability, and environmental effectiveness, which is evaluated to improve the rationality of environmental regulations. It is generally known that when thermal power is generated, pollutant emissions are generated at the same time. In order to protect the environment, the government could assign an emissions limit to the thermal power industry, and, in this case, both the capacity of the thermal power industry to decrease the amount of emissions and the rationality of the emissions limit assigned by the regulator should be evaluated. If the emissions reduction technology of a thermal power industry is advanced (high efficiency) but its emissions are still above the emissions limit assigned by the regulator (low effectiveness), the emissions limit assigned to the thermal power industry is considered to be tight. On the contrary, if the emissions reduction technology of a thermal power industry is backward (low efficiency) but its emissions are still less than emissions limit assigned by the regulator (high effectiveness), we assume a loose limit is assigned to the thermal power industry. Therefore, from the perspective of the government regulator, a measure of environmental performance should include not only the capacity of the thermal power industry to decrease the amount of emissions (environmental efficiency) but also the rationality of the emissions limit assigned to the thermal power industry (environmental effectiveness).

Few studies have contributed to measure effectiveness with respect to market competition. For example, Fielding et al. (1985) consider the influence of a sales limit and give an evaluation of the transportation system in terms of the production and consumption processes. In addition, Yu and Lin (2008) measure the effectiveness of 20 selected railway stations in 2002 under the influence of the consumption process. Lee and Johnson (2015) evaluate the profit effectiveness of 13 U.S. airlines taking the sales effect into account. Golany et al. (1993) consider the goal of the evaluation and argue that effectiveness measures should characterize an organization's performance when trying to reach specific goals or objectives.

To achieve sustainable development, the thermal power industry should focus not only on improving its operational performance but also on increasing its environmental performance. Thus, from the perspective of the thermal power industry, the joint performance of operation and abatement should be evaluated. The joint performance evaluation not only measures the capacity of the thermal power industry to optimize its electricity production and emissions reduction, but it also measures the industry's capacity to meet the electricity demand and emissions control targets. Therefore, the joint performance evaluation includes two parts: joint efficiency and joint effectiveness. To the best of our knowledge, few studies have evaluated effectiveness with regard to both market competition (demand) for the desirable outputs and environmental regulation (emissions control) of the undesirable outputs. Lee (2015) provides a model to evaluate the electricity generation performance of 50 U.S. states with power plants operating in 2010 under the influence of demand and emissions limits, and Wang et al. (2016c) provide an effectiveness estimation of China's regional thermal power industry considering the electricity sales effect. However, these studies did not separately estimate the operational effectiveness with respect to the demand limit and the environmental effectiveness with respect to the emissions limit, and, thus, the estimation results were somewhat lacking specific policy implications on the design of emissions control regulations. The measure of operational effectiveness with respect to the demand limit helps a thermal power industry to improve its capacity for adjusting electricity generation to meet the demand, and the measure of environmental effectiveness with respect to the emissions limit helps the government to improve the rationality of the emissions limit assigned to the thermal power industry. Furthermore, joint effectiveness helps the thermal power industry to improve its capacity for adjusting both its production and abatement activities so as to appropriately meet both the electricity demand and the emissions control target. However, to the best of our knowledge, measures of the environmental effectiveness of China's thermal power industry are very limited. Motivated by these research gaps, in this study, we not only provide a traditional efficiency measure of China's thermal power industry, but we also evaluate i) the operational effectiveness considering the electricity demand limit, ii) the environmental effectiveness regarding the pollutant emissions limit, and iii) the joint effectiveness identifying the capacity to both meet electricity demand and fulfill the emissions control target of China's thermal power industry.

The remainder of this paper is organized as follows. Section 2 introduces the models of operational and environmental efficiency and the effectiveness measures for the thermal power industry. Section 3 quantifies the strategic evolution of the performance of the thermal power industry using the global Malmquist productivity index. Section 4 provides an empirical study of China's thermal power industry. Section 5 concludes this paper.

2 Efficiency and effectiveness measurements

In this section, we put forward three groups of measurements from three perspectives: operational efficiency and effectiveness, environmental efficiency and effectiveness, and joint efficiency and effectiveness.

2.1 Operational efficiency and operational effectiveness measurements

Considering a multiple-input and multiple-output thermal power production process, let $x \in R_+^I$ denote a vector of input variables, $y \in R_+^J$ denote a vector of desirable output variables, and $b \in R_+^Q$ denote a vector of undesirable output variables. We define the production possibility set T as $T =$

$\{(x, y, b) \in R_+^{I+J+Q}: x$ can produce $(y, b)\}$. Let I = {1,2,...,I} be the set of input indices, j = {1,2,...,J} be the set of desirable output indices, q={1,2,...,Q} be the set of undesirable output indices, k = {1,2,...,K} be the set of decision making unit (DMU) indices, and t = {1,2,...,T} be the set of year indices. Index r represents a specific DMU and is an alias of index k. x_{ikt} is the ith input of the kth DMU in year t, y_{ikt} is the jth desirable output of the kth DMU in year t, and b_{qkt} is the qth undesirable output of the kth DMU in year t. We use the directional distance function (DDF) to expand the desirable outputs for efficiency estimation. Let g_j^y be the nonnegative directional vector associated with the jth desirable output. Previous studies have pointed out that the choice of the direction vectors in the DDF impacts the estimation results (Färe et al., 2013; Benjamin et al., 2014; Wang et al., 2016). In many studies, the direction vectors are predetermined with a fixed value, such as 0, +1, or -1, or with observed input and output values. However, these measures are considered somewhat arbitrary and less economically or politically meaningful in efficiency evaluation. Since choosing the optimal direction vectors in the DDF is an unsolved issue, in this study, we follow the method proposed by Färe et al. (2013) and Benjamin et al. (2014) to generate an endogenous direction based on an exogenous normalization constraint. Model (1) is put forward as an operational efficiency measure:

$$
\begin{aligned}
&\max_{\lambda_k, \mu_k, \theta^o, g_j^y} \quad \theta^o \\
&s.t. \quad \sum_{k=1}^{K} (\lambda_k + \mu_k) x_{ikt} \le x_{irt}, \quad i = 1,2,\cdots, I \\
&\qquad \sum_{k=1}^{K} \lambda_k y_{jkt} \ge y_{jrt} + \theta^o g_j^y, \quad j = 1,2,\cdots, J \\
&\qquad \sum_{k=1}^{K} \lambda_k b_{qkt} \le b_{qrt}, \quad q = 1,2,\cdots, Q \\
&\qquad \sum_{k=1}^{K} (\lambda_k + \mu_k) = 1 \\
&\qquad \sum_{j=1}^{J} g_j^y = 1, \quad j = 1,2,\cdots, J \\
&\qquad \lambda_k, \mu_k, g_j^y \ge 0
\end{aligned}
$$

(1)

where the decision variable λ_k is the intensity weight multiplier of the convex combination of the kth DMU, μ_k is the decision variable for the weak disposability of Podinovski's technology (Kuosmanen 2005; Kuosmanen and Podinovski, 2009), g_j^y is an endogenous directional vector, and θ^o is the optimal solution that reveals the inefficiency. If θ^o = 0, the associated DMU is efficient; otherwise, it is inefficient. Note that θ^o does not intuitively reflect efficiency (since the efficiency values are usually defined over [0,1]). Thus, we calculate the operational efficiency D_{jt}^o of the jth desirable output of the rth DMU in year t as in Equation (2):

$$
D_{jt}^o(x_t, y_t, b_t) = \frac{y_{jrt}}{y_{jrt} + \theta^o g_j^y}
$$

(2)

If $D_{jt}^o = 1$, the associated DMU is operationally efficient; otherwise, it is operationally inefficient.

Note that Model (1) is a nonlinear programming model that can be further transformed into a linear programming model, as in Model (3), by defining the direction vector $g_j^y = \theta_{y_j} \Big/ \sum_{j=1}^{J} \theta_{y_j}$, which satisfies $\sum_{j=1}^{J} g_j^y = 1$ (Färe et al., 2013; Lee 2015).

$$\begin{aligned}
&\max_{\lambda_k,\mu_k,\theta_{y_j}} \sum_{j=1}^{J} \theta_{y_j} \\
&s.t.\ \sum_{k=1}^{K} (\lambda_k + \mu_k) x_{ikt} \le x_{irt},\quad i = 1,2,\cdots,I \\
&\quad \sum_{k=1}^{K} \lambda_k y_{jkt} \ge y_{jrt} + \theta_{y_j},\quad j = 1,2,\cdots,J \\
&\quad \sum_{k=1}^{K} \lambda_k b_{qkt} \le b_{qrt},\quad q = 1,2,\cdots,Q \\
&\quad \sum_{k=1}^{K} (\lambda_k + \mu_k) = 1 \\
&\quad \lambda_k, \mu_k \ge 0
\end{aligned}$$

(3)

Next, we define operational effectiveness by considering electricity demand with Model (4):

$$\begin{aligned}
&\max_{\lambda_k,\mu_k,\theta^{oE},g_j^y} \theta^{oE} \\
&s.t.\ \sum_{k=1}^{K} (\lambda_k + \mu_k) x_{ikt} \le x_{irt},\quad i = 1,2,\cdots,I \\
&\quad \sum_{k=1}^{K} \lambda_k y_{jkt} \ge y_{jrt}^{P} + \theta^{oE} g_j^y,\quad j = 1,2,\cdots,J \\
&\quad d_{jrt} \ge y_{jrt}^{P} + \theta^{oE} g_j^y,\quad j = 1,2,\cdots,J \\
&\quad \sum_{k=1}^{K} \lambda_k b_{qkt} \le b_{qrt},\quad q = 1,2,\cdots,Q \\
&\quad \sum_{k=1}^{K} (\lambda_k + \mu_k) = 1 \\
&\quad \sum_{j=1}^{J} g_j^y = 1,\quad j = 1,2,\cdots,J \\
&\quad \lambda_k, \mu_k, g_j^y \ge 0
\end{aligned}$$

(4)

In Model (4), we define $y^P \in R_+^J$ as the penalized desirable outputs to quantify the gap between the desirable output level and the demand level. Producing less electricity than the demand will lead to an electricity shortage cost derived from the cost of purchasing electricity from other plants, whereas producing more electricity than the demand will lead to wasted resources of coal and other materials. We develop the following generalized effectiveness measure. Let d_{jkt} represent the demand limit of the jth desirable output of the kth thermal power industry in the tth year, which is further used to calculate the penalized output y_{jkt}^P. If $y_{jkt} < d_{jkt}$, then the opportunity to sell $d_{jkt} - y_{jkt}$ units of electricity is lost, and we set $y_{jkt}^P = y_{jkt} - \alpha_{jkt}\,(d_{jkt} - y_{jkt}) \ge 0$. If $y_{jkt} > d_{jkt}$, then $y_{jkt} - d_{jkt}$ units of electricity inventory or abandon are generated, and we set $y_{jkt}^P = d_{jkt} - \beta_{jkt}\,(y_{jkt} - d_{jkt}) \ge 0$. When calculating y_{jkt}^P, we use the penalty parameters $\alpha_{jkt} \ge 0$ and $\beta_{jkt} \ge 0$ to control the tradeoff effects of electricity shortages and waste resources on the effectiveness measurements.

As in Equation (2), we calculate the operational effectiveness D_{jt}^{oE} in Equation (5):

$$D_{jt}^{oE}(x_t, y_t, b_t) = \frac{y_{jrt}^{P}}{y_{jrt}^{P} + \theta^{oE} g_j^{y}}$$

(5)

The difference between Model (1) and Model (4) is the utilization of desirable output (electricity generation). In Model (4), we use the penalized output to take into account the influence of the demand limit. In Equation (5), if D_{jt}^{oE} equals 1, the associated DMU is operationally effective. Otherwise, it is operationally ineffective.

Figure 1 illustrates a two-dimensional strategic position (SP) between operational efficiency D_{jt}^{o} and operational effectiveness D_{jt}^{oE}. We use the mean values of the operational efficiency scores and the operational effectiveness scores of all DMUs to indicate low and high categories. (i) If the operational efficiency and operational effectiveness scores are both low, it implies that the thermal power industry performs badly both in electricity production and in meeting the local electricity demand, and, thus, further improving the technical efficiency and developing the electricity sales market are both necessary for this thermal power industry. We label such thermal power industries as Laggard (Lag). (ii) If the operational efficiency score is high but the operational effectiveness score is low, it shows that the thermal power industry focuses on electricity generation but ignores the need to match its electricity generation to the local electricity demand. In this case, the thermal power industry should not only focus on operational productivity improvement but also pay more attention to balancing its electricity supply and demand. We label such thermal power industries as Production Focus (PF). (iii) If the operational efficiency score is low but the operational effectiveness score is high, it means that the electricity generation of the thermal power industry matches the local electricity demand, but the electricity generation is technically inefficient. This type of thermal power industry should improve its generating technology and use its inputs more efficiently. We label such thermal power industries as Demand Focus (DF). (iv) If the operational efficiency and operational effectiveness scores are both high, the thermal power industry performs well both in electricity generation and in matching its electricity generation to the local demand, and, thus, we label such thermal power industries as Leader (L). The arrows in Figure 1 indicate the suggested paths for operational performance improvement.

[Insert Figure 1 here]

2.2 Environmental efficiency and environmental effectiveness measurements

The traditional production possibility set and related DEA models for efficiency evaluation assume that the desirable outputs are freely disposable, but this property cannot be directly applied to undesirable outputs. Intuitively, we can reduce the level of the undesirable output, which in turn will result in a proportionate reduction of the desirable outputs. In other words, the strong disposability assumption in efficiency evaluation ignores the possibility of decreasing undesirable outputs by reducing the activity level, i.e., a proportional contraction of desirable outputs and undesirable outputs is feasible simultaneously. We call this property weak disposability (Färe and Grosskopf, 2003; Kuosmanen, 2005). Strong disposability of inputs and desirable outputs means that given $(x, y, b) \in T$, if $x' \geq x$ and $0 \leq y \leq y'$, then $(x', y', b) \in T$, and weak disposability of desirable outputs and undesirable outputs means that given $(x, y, b) \in T$, if $0 \leq \rho \leq 1$, then $(x, \rho y, \rho b) \in T$. The weak disposability of desirable and undesirable outputs is commonly assumed when taking undesirable outputs into the production process. To address the issue, we use the weak disposability of Podinovski's convex technology, which follows the convexity axiom and builds the minimal weakly disposable technology by assuming strong disposability of inputs and desirable outputs. Podinovski's technology assumes strong disposability of all inputs and all outputs, whereas Kuosmanen's technology excludes bad outputs from this assumption (Kuosmanen and Podinovski 2009). Similar to Lee (2015), since this study penalizes bad outputs that violate the emissions limit, one should notice that these penalized bad outputs may be outside of the production possibility set without the strong disposability of bad outputs.

Let g_q^b be the nonnegative directional vector associated with the qth undesirable output. Model (6) calculates the environmental efficiency:

$$\begin{aligned}
&\max_{\lambda_k, \mu_k, \theta^e, g_q^b} \ \theta^e \\
&s.t. \ \sum_{k=1}^{K} (\lambda_k + \mu_k) x_{ikt} \leq x_{irt}, \quad i = 1, 2, \cdots, I \\
&\quad \sum_{k=1}^{K} \lambda_k y_{jkt} \geq y_{jrt}, \quad j = 1, 2, \cdots, J \\
&\quad \sum_{k=1}^{K} \lambda_k b_{qkt} \leq b_{qrt} - \theta^e g_q^b, \quad q = 1, 2, \cdots, Q \\
&\quad \sum_{k=1}^{K} (\lambda_k + \mu_k) = 1 \\
&\quad \sum_{q=1}^{Q} g_q^b = 1, \quad q = 1, 2, \cdots, Q \\
&\quad \lambda_k, \mu_k, g_q^b \geq 0
\end{aligned}$$

(6)

The variables and parameters in Model (6) have the same meanings as in Model (1). Similarly, the optimal solution θ^e of Model (6) only reflects the environmental inefficiency. Thus, the environmental efficiency D_{qt}^e is calculated as in Equation (7):

$$D_{qt}^e(x_t, y_t, b_t) = \frac{b_{qrt} - \theta^e g_q^b}{b_{qrt}}$$

(7)

Next, we define the environmental effectiveness by considering the emissions limit through Model (8):

$$\max_{\lambda_k,\mu_k,\theta^{eE},g_q^b} \theta^{eE}$$

$$\begin{aligned} s.t.\ & \sum_{k=1}^{K}(\lambda_k+\mu_k)x_{ikt} \le x_{irt},\ \ i=1,2,\cdots,I \\ & \sum_{k=1}^{K}\lambda_k y_{jkt} \ge y_{jrt},\ \ j=1,2,\cdots,J \\ & \sum_{k=1}^{K}\lambda_k b_{qkt} \le b_{qrt}^{P} - \theta^{e} g_q^b,\ \ q=1,2,\cdots,Q \\ & \sum_{k=1}^{K}(\lambda_k+\mu_k)=1 \\ & \sum_{q=1}^{Q} g_q^b = 1,\ \ q=1,2,\cdots,Q \\ & \lambda_k, \mu_k, g_q^b \ge 0 \end{aligned}$$

(8)

In Model (8), we define $b^P \in R_+^Q$ as the penalized or benefited undesirable outputs to quantify the excess or insufficient emissions with respect to the emissions limit. Let l_{qkt} represent the emissions limit of the qth undesirable output of the kth thermal power industry in the tth year, and calculate the penalized or benefited output b_{qkt}^P. If $b_{qkt} > l_{qkt}$, then $b_{qkt} - l_{qkt}$ units of excess undesirable outputs are penalized, and we set $b_{qkt}^P = b_{qkt} + \gamma_{qkt}(b_{qkt} - l_{qkt}) \ge 0$, where $\gamma_{qkt} \ge 0$ is the penalty parameter. On the contrary, if $b_{qkt} < l_{qkt}$, then $l_{qkt} - b_{qkt}$ units of emissions allowances are saved and can be sold if there is a carbon trading market. In such a circumstance, although excess emissions reduction will lead to a decrease in electricity generation, the power industry can benefit from emissions allowance trading, and the entire society will benefit from the emissions reduction. Thus, we set $b_{qkt}^P = b_{qkt} - \delta_{qkt}(l_{qkt} - b_{qkt}) \ge 0$, and $\delta_{qkt} \ge 0$ is the benefit parameter. θ^{eE} is the optimal solution to Model (8). It measures the environmental ineffectiveness and can be utilized to calculate the environmental effectiveness D_{qt}^{eE}, as in Equation (9):

$$D_{qt}^{eE}(x_t, y_t, b_t) = \frac{b_{qrt}^P - \theta^{eE} g_q^b}{b_{qrt}^P}$$

(9)

Similar to the definition of the strategic position of the operational performance, Figure 2 illustrates a two-dimensional strategic position between environmental efficiency D_{qt}^{e} and environmental effectiveness D_{qt}^{eE}. We use the mean values of the environmental efficiency scores and environmental effectiveness scores of all DMUs to indicate low and high categories. (i) If the environmental efficiency and environmental effectiveness scores are both low, it shows that the emissions of the thermal power industry are higher than those of other thermal power industries that consume the same amount of input resources because of technical inefficiency in emissions reduction. In addition, considering the emissions limit, this thermal power industry does not match its emissions reduction effort to its emissions reduction target. We label such thermal power industries as Laggard (Lag). (ii) If the environmental efficiency score is high but the environmental effectiveness score is low, it indicates that there is a tight emissions limit for the thermal power industry. The high environmental efficiency shows that the power industry is technically efficient in emissions reduction, but its emissions reduction burden is overweight, which results in low environmental effectiveness. In this case, the emissions reduction target assigned by the government should be loosened. We label such power industries as Tight Limit (TL). (iii) If the environmental efficiency score is low but the environmental effectiveness score is high, it indicates that there is a loose emissions limit for the power industry. The low environmental efficiency reflects that the power industry is technically inefficient in emissions reduction, and its emissions limit is loose, which results in high environmental effectiveness. In this case, the emissions reduction target assigned by the government should be tightened. We label such thermal power industries as Loose Limit (LL). (iv) If both the environmental efficiency and the environmental effectiveness scores are high, the power industry performs well in emissions reductions and matches its emissions reduction effort to the government-assigned emissions reduction target. We label such thermal power industries as Leader (L). The arrows in Figure 2 indicate the suggested paths for environmental performance improvement.

[Insert Figure 2 here]

2.3 Joint efficiency and joint effectiveness measurements

Up to now, we separately provided measures of operational performance in Models (1) and (4) and measures of environmental performance in Models (6) and (8), respectively. However, the power industry should not just focus on how to increase its operational performance while ignoring efforts to improve its environmental performance or, on the contrary, only focus on improving its environmental performance without pay attention to increasing its operational performance. The trend toward a more fiercely competitive and strictly environmentally regulated electricity market requires the efforts of the power industry to simultaneously improve both its operational and its environmental performance. In this section, we define this combined operational and environmental performance as the joint performance, which includes both joint efficiency and joint effectiveness. Next, we put forward Model (10) for calculating the joint efficiency:

$$
\begin{aligned}
&\max_{\lambda_k,\mu_k,\theta^{oe},g_j^y,g_q^b} \quad \theta^{oe} \\
&s.t.\ \ \sum\nolimits_{k=1}^{K}(\lambda_k+\mu_k)x_{ikt} \le x_{irt},\ \ i=1,2,\cdots,I \\
&\qquad \sum\nolimits_{k=1}^{K}\lambda_k y_{jkt} \ge y_{jrt}+\theta^{oe}g_j^y,\ \ j=1,2,\cdots,J \\
&\qquad \sum\nolimits_{k=1}^{K}\lambda_k b_{qkt} \le b_{qrt}-\theta^{oe}g_q^b,\ \ q=1,2,\cdots,Q \\
&\qquad \sum\nolimits_{k=1}^{K}(\lambda_k+\mu_k)=1 \\
&\qquad \sum\nolimits_{j=1}^{J}g_j^y+\sum\nolimits_{q=1}^{Q}g_q^b=1 \\
&\qquad \lambda_k,\mu_k,g_j^y,g_q^b \ge 0
\end{aligned}
$$

(10)

Taking into account the demand limit and the emissions limit, Model (11) calculates the joint effectiveness:

$$\max_{\lambda_k,\mu_k,\theta^{oeE},g_j^y,g_q^b} \theta^{oeE}$$
$$\begin{aligned}
s.t.\ & \sum_{k=1}^{K}(\lambda_k+\mu_k)x_{ikt} \le x_{irt},\ \ i=1,2,\cdots,I \\
& \sum_{k=1}^{K}\lambda_k y_{jkt} \ge y_{jrt}^P+\theta^{oeE}g_j^y,\ \ j=1,2,\cdots,J \\
& d_{jrt} \ge y^P{}_{jrt}+\theta^{oeE}g_j^y,\ \ j=1,2,\cdots,J \\
& \sum_{k=1}^{K}\lambda_k b_{qkt} \le b_{qrt}^P-\theta^{oeE}g_q^b,\ \ q=1,2,\cdots,Q \\
& \sum_{k=1}^{K}(\lambda_k+\mu_k)=1 \\
& \sum_{j=1}^{J}g_j^y+\sum_{q=1}^{Q}g_q^b=1 \\
& \lambda_k,\mu_k,g_j^y,g_q^b \ge 0
\end{aligned}$$

(11)

Similar to the calculations of operational and environmental efficiency and effectiveness, we put forward D_t^{oe} and D_t^{oeE} to evaluate the joint efficiency and joint effectiveness in Equations (12) and (13):

$$D_t^{oe}(x_t,y_t,b_t)=\omega_1\frac{y_{jrt}}{y_{jrt}+\theta^{oe}g_j^y}+\omega_2\frac{b_{qrt}-\theta^{oe}g_q^b}{b_{qrt}}$$

(12)

$$D_t^{oeE}(x_t,y_t,b_t)=\omega_1\frac{y^P{}_{jrt}}{y^P{}_{jrt}+\theta^{oeE}g_j^y}+\omega_2\frac{b^P{}_{qrt}-\theta^{oeE}g_q^b}{b^P{}_{qrt}}$$

(13)

in which θ^{oe} and θ^{oeE} reflect the joint inefficiency and the joint ineffectiveness, respectively. ω_1 and ω_2 represent the importance of operational performance and environmental performance, respectively, in evaluating the joint performance.

The four strategic positions based on the joint performance can be correspondingly derived. Figure 3 illustrates a two-dimensional strategic position between joint efficiency and joint effectiveness. We use the mean values of the joint efficiency scores and the joint effectiveness scores of all DMUs to indicate a low and a high category. (i) If the joint efficiency and joint effectiveness scores are both low, it reflects that the thermal power industry has the potential to improve both its operational and its environmental performance. Specifically, the thermal power industry needs to improve its technical efficiency both in electricity generation and emissions reduction. In addition, the power industry should pay more attention to matching its electricity generation to its electricity demand or should enlarge its market share so as to improve its operational effectiveness, and it should pay more attention to matching its emissions reduction effort to its emissions limit. We label such thermal power industries as Laggard (Lag) in joint performance. (ii) If the joint efficiency score is high but the joint effectiveness score is low, it reflects that the thermal power industry leads in using its input resources for electricity generation, but it may waste resources by generating more electricity than local demand, and it ignores the realization of the emissions reduction target. We label such power industries as Production Focus (PF) in joint performance. (iii) If the joint efficiency score is low but the joint effectiveness score is high, it reflects that the power industry pays more attention to matching its emissions reduction target but fails to efficiently generate electricity and reduce emissions. We label such thermal power industries as Environment Focus (EF) in joint performance. (iv) If both the joint efficiency and the joint effectiveness scores are high, it indicates that the power industry performs well in electricity generation and emissions reduction as well as in developing new markets and realizing the emissions reduction target. We label such thermal power industries as Leader (L) in joint performance. The arrows in Figure 3 indicate the suggested paths for joint performance improvement.

[Insert Figure 3 here]

In the electric power industry, if a capacity surplus happens, it will cause wasted input resources or inventory holding costs. However, a capacity shortage in the electric power industry will result in negative effects on normal life or economic activity. It is generally known that a capacity shortage will lead to more serious consequences. Thus, following Lee (2015) and Wang et al. (2016c), we set α_{jkt} = 1 and β_{jkt} = 0.01. In terms of emissions control, any amount of emissions less than emissions limit is meaningful and should be encouraged; however, we cannot take any action to encourage an increase in the amount of emissions. Therefore, we set the benefit parameter $\delta_{qkt} = 0$. On the contrary, too many emissions should be penalized seriously. Thus, we set γ_{qkt} = 0.01, according to Lee (2015). As mentioned above, ω_1 and ω_2 represent the importance of the operational performance and the environmental performance in joint performance evaluation, and, in this study, we set $\omega_1 = \omega_2$ = 0.5, indicating that improving the operational performance and improving the environmental performance are equally important to improving the joint performance. The parameters α_{jkt}, β_{jkt}, γ_{qkt}, δ_{qkt}, ω_1, and ω_2 can be flexibly adjusted according to the preference of the policy maker. For instance, if improving the environmental performance is preferred, we can increase the values on γ_{qkt} and ω_2.

To summarize this section, we provide Figure 4 to illustrate the relationship between the proposed three performance measurements based on a specific case with one input, one desirable output, and one undesirable output for the convenience of illustration.

[Insert Figure 4 here]

The three-dimensional coordinate image in Figure 4 is interpreted as follows: the x-axis represents the input, the y-axis represents the desirable output, and the b-axis represents the undesirable output. Point F represents a thermal power industry sector. The plane denoted by line D_0D_1 and line D_0D_2 indicates the electricity demand limit, and the plane denoted by line L_0L_1 and line L_0L_2 indicates the pollutant emissions limit.

First, we consider that point A is the projection of point F in the x-y plane and on the line A^PA^e, where the input x and the undesirable output b of A are constant, and, thus, the operational efficiency and operational effectiveness are measured through the adjustment of the desirable output y for point F. In a traditional output-oriented DEA model, the curve $0a_1a_2$ represents the production frontier. The point on the curve $0a_1a_2$ indicates the largest amount of electricity generation given the current consumption of input resources and emissions of pollutants, and, therefore, point A^e on curve $0a_1a_2$ can be considered as a reference point for point A. The distance between A and A^e along the dashed line AA^e indicates the operational inefficiency, which also reflects the improvement potential of the operational efficiency of point F.

When taking into account the influence of the electricity demand limit, we obtain a new, truncated production frontier represented by curve $0a_1a_3$, which indicates that a power industry sector on curve $0a_1a_3$ makes the best use of input resources and meets the electricity demand. In order to include the influence of electricity demand in the estimation so as to get more realistic evaluation results, the power industry sector A is first penalized to A^P (since the electricity production of A is beyond the electricity demand D_0D_1 and the surplus electricity A^EA is wasted), and, thus, A^E on truncated frontier $0a_1a_3$ will be the new reference point of A^P, and the distance between A^P and A^E along the dashed line A^PA^E indicates the operational ineffectiveness of power industry sector F.

Second, we consider that point B is the projection of point F in the x-b plane and on the line B^PB^E, where the input x and the desirable output y of B are constant, and, thus, the environmental efficiency and environmental effectiveness are measured through the adjustment of the undesirable output b. In the environmental technology, the curve $0b_1b_2$ indicates the environmental efficiency frontier, and the point on that curve indicates the best practice for pollutant emissions given the current levels of electricity generation and input resource consumption. Therefore, the point B^e on curve $0b_1b_2$ can be seen as the reference point for point B. The distance between B and B^e along the dashed line BB^e indicates the environmental inefficiency, which also reflects the reduction potential of pollutant emissions that the power industry sector F could achieve.

Similarly, when we take the influence of the emissions limit into consideration, we get a new truncated environmental effectiveness frontier represented by curve $0b_1b_3$, indicating that a power industry sector on this curve uses the best practice in pollutant emissions and strictly meets the emissions limit. Considering the influence of the emissions limit in the estimation, the power industry sector B is first penalized to B^P (since the pollutant emissions of B exceed the emissions limit L_0L_1 and the extra emissions B^EB should be reduced), and, thus, B^E on truncated frontier $0b_1b_3$ will be the new reference point for B^P. Then, the distance between B^P and B^E along the dashed line B^PB^E can be defined as the environmental ineffectiveness of power industry sector F.

Finally, we come to point C, which is the projection of point F in the y-b plane, where the input x is constant and the joint efficiency and joint effectiveness are measured through the adjustments of desirable output y and undesirable output b. Note that C^e is the reference point for point C on the joint efficiency frontier (represented by curve $0c_1c_2$), which indicates the best practice in both electricity production and pollutant emissions. Thus, the distance between C and C^e along the dashed line CC^e measures the joint inefficiency, which also reflects the potential improvement in electricity production and the potential abatement of pollutant emissions at point F.

Then, we simultaneously consider the influence of the electricity demand and the emissions limit. In this case, we get a new truncated effectiveness frontier, $0c_1C^EL_0$. A power industry sector that is located on this frontier is considered to have the best practice in generating electricity with a high operational efficiency and in appropriately fulfilling the electricity demand as well as in emitting pollutants with a high environmental efficiency and appropriately meeting the emissions regulation. In other words, this jointly effective power industry sector not only makes the best use of input resources in electricity generation and the associated emissions reduction but also is successful in electricity market development to fulfill the electricity demand and in pollutant emissions control for meeting the environmental regulation. In this condition, when measuring the joint effectiveness of the power industry sector, point C is first penalized to C^P (since the electricity production of C is beyond the electricity demand D_0D_2 and the pollutant emissions of C exceed the emissions limit L_0L_2) and, then, a new reference point C^E on the joint production frontier $0c_1C^EL_0$ is utilized as a benchmark for the joint effectiveness measure of C. Consequently, the distance between C^P and C^E along the dashed line C^PC^E denotes the joint ineffectiveness of power industry sector F.

3 Performance change measurements

As time goes on, the emergence of new technology and changes in efficiency will lead to new paradigms of competition. Technology development, sales diversity, and efficiency improvement will shock an industry and push the power industry to enhance its core competence. In this section, we put forward three measurements based on the global Malmquist productivity index to identify the changes in the operational and environmental performances of China's thermal power industry over the years.

Färe et al. (1992, 1994) describes the Malmquist productivity index at period t+1 relative to period t, quantifying productivity changes from period t to t+1, by defining the components change in efficiency and the change in technology. Pastor and Lovell (2005) extend the Malmquist productivity index to the global Malmquist productivity index, which does not have the infeasibility problem and is continuous and multipliable.

Here, a decomposition of the global Malmquist productivity index is used to measure productivity evolution (i.e., change in effectiveness) and technology evolution (i.e., change in technology) (Lee and

Johnson, 2014 and 2015; Wang et al., 2016a). By utilizing a global Malmquist productivity index, we first define a global Malmquist productivity index OM_t^{t+1} to capture the operational productivity change from period t to *t*+1, as in Equation (14). OM_t^{t+1} > 1, = 1, or < 1 indicates an operational productivity improvement, no change, or a reduction, respectively. OM_t^{t+1} can be decomposed into the change in operational effectiveness (CIE^o) and the change in operational technology (CIT^o), as shown in Equation (14). Similarly, CIE^o > 1, = 1, or < 1 indicates an operational effectiveness improvement, no change, or a reduction, respectively, and CIT^o > 1, = 1, or < 1 indicates operational technology progress, no change, or a regression, respectively.

$$OM_t^{t+1} = [\frac{D_{t+1}^{oE}(x_{t+1}, y_{t+1}, b_{t+1})}{D_G^{oE}(x_t, y_t, b_t)} \times \frac{D_G^{oE}(x_{t+1}, y_{t+1}, b_{t+1})}{D_t^{oE}(x_t, y_t, b_t)}]^{\frac{1}{2}}$$
$$= \frac{D_{t+1}^{oE}(x_{t+1}, y_{t+1}, b_{t+1})}{D_t^{oE}(x_t, y_t, b_t)} \times [\frac{D_t^{oE}(x_t, y_t, b_t)}{D_{t+1}^{oE}(x_{t+1}, y_{t+1}, b_{t+1})} \times \frac{D_G^{oE}(x_{t+1}, y_{t+1}, b_{t+1})}{D_G^{oE}(x_t, y_t, b_t)}]^{\frac{1}{2}} = CIE^o \times CIT^o$$

(14)

$D_G^{oE}(x_t, y_t, b_t)$ and $D_G^{oE}(x_{t+1}, y_{t+1}, b_{t+1})$ are the cross-period effectiveness scores of an observation in periods *t* and *t*+1 relative to the reference technology in all periods.

Second, we define the global Malmquist productivity index EM_t^{t+1} to capture the environmental productivity change from period *t* to *t*+1, as in Equation (15). EM_t^{t+1} > 1, = 1, or < 1 indicates an environmental productivity improvement, no change, or a reduction, respectively. EM_t^{t+1} can be decomposed into the change in environmental effectiveness (CIE^e) and the change in environmental technology (CIT^e), as shown in Equation (14). Similarly, CIE^e > 1, = 1, or < 1 indicates an environmental effectiveness improvement, no change, or a reduction, respectively, and CIT^e > 1, = 1, or < 1 indicates environmental technology progress, no change, or a regression, respectively.

$$EM_t^{t+1} = [\frac{D_{t+1}^{eE}(x_{t+1}, y_{t+1}, b_{t+1})}{D_G^{eE}(x_t, y_t, b_t)} \times \frac{D_G^{eE}(x_{t+1}, y_{t+1}, b_{t+1})}{D_t^{eE}(x_t, y_t, b_t)}]^{\frac{1}{2}}$$
$$= \frac{D_{t+1}^{eE}(x_{t+1}, y_{t+1}, b_{t+1})}{D_t^{eE}(x_t, y_t, b_t)} \times [\frac{D_t^{eE}(x_t, y_t, b_t)}{D_{t+1}^{eE}(x_{t+1}, y_{t+1}, b_{t+1})} \times \frac{D_G^{eE}(x_{t+1}, y_{t+1}, b_{t+1})}{D_G^{eE}(x_t, y_t, b_t)}]^{\frac{1}{2}} = CIE^e \times CIT^e$$

(15)

Third, we define the global Malmquist productivity index OEM_t^{t+1} to capture the joint productivity change from period *t* to *t*+1, as in Equation (16). OEM_t^{t+1} > 1, = 1, or < 1 indicates a joint productivity improvement, no change, or a reduction, respectively. OEM_t^{t+1} can be decomposed into the change in joint effectiveness (CIE^{oe}) and the change in joint technology (CIT^{oe}), as shown in Equation (16). Similarly, CIE^{oe} > 1, = 1, or < 1 indicates a joint effectiveness improvement, no change, or a reduction, respectively; CIT^{oe} > 1, = 1, or < 1 indicates a joint technology progress, no change, or a regression, respectively.

$$OEM_t^{t+1} = [\frac{D_{t+1}^{oeE}(x_{t+1}, y_{t+1}, b_{t+1})}{D_G^{oeE}(x_t, y_t, b_t)} \times \frac{D_G^{oeE}(x_{t+1}, y_{t+1}, b_{t+1})}{D_t^{oeE}(x_t, y_t, b_t)}]^{\frac{1}{2}}$$

$$= \frac{D_{t+1}^{oeE}(x_{t+1}, y_{t+1}, b_{t+1})}{D_t^{oeE}(x_t, y_t, b_t)} \times [\frac{D_t^{oeE}(x_t, y_t, b_t)}{D_{t+1}^{oeE}(x_{t+1}, y_{t+1}, b_{t+1})} \times \frac{D_G^{oeE}(x_{t+1}, y_{t+1}, b_{t+1})}{D_G^{oeE}(x_t, y_t, b_t)}]^{\frac{1}{2}} = CIE^{oe} \times CIT^{oe}$$

(16)

4 Empirical study of China’s thermal power industry

In this section, we conduct an empirical case study to estimate the operational and environmental efficiency and effectiveness of China’s thermal power industry at the provincial level from 2006 to 2013, which covers the 11th FYP period (2006-2010) and the first three years of the 12th FYP period (2011-2013).

4.1 Data Set

The data set is the provincial level annual data set that covers China’s 30 provinces from 2006 to 2013, which covers the entire 11th FYP period and the first three years of the 12th FYP period (the latest two years’ data are temporarily unavailable). For convenience of expression and comparison, we refer to the “12th FYP period” instead of the “first three years of the 12th FYP period” to represent the period from 2011 to 2013. There are three inputs, two desirable outputs, and two undesirable outputs in this study. The three inputs are (i) the nameplate capacity of thermal power, measured in megawatts (MW), (ii) the annual amount of coal consumption, measured in tons of coal equivalent (tce), and (iii) the annual average amount of staff in the thermal power industry, measured in people. Since the electricity generated in some of China’s provinces cannot meet those provinces’ electricity demands, there exists a comparatively large amount of interprovincial electricity reallocation in China. We utilize two desirable outputs to identify such electricity reallocation: (i) the annual amount of electricity generated in each province, measured in megawatt-hours (MWh), is utilized for performance evaluation before reallocation, and (ii) the annual electricity supply of each province, also measured in MWh, is used for performance evaluation after reallocation. The two undesirable outputs are the annual amounts of CO_2 and SO_2 emissions, measured in tons. We use the retail sale of electricity, measured in MWh, in each province as the electricity demand limit, and the emissions reduction targets of CO_2 and SO_2 as the emissions limits, which are calculated based on China’s energy conservation and emissions reduction plans in the 11th and 12th FYP periods. Specifically, the SO_2 emissions reduction target in the 11th FYP period is 29.50% (reducing from 13.50 million tons per year to 9.57 million tons per year), and the reduction target in the 12th FYP period is 16.32% (reducing from 9.56 million tons per year to 8.00 million tons per year). Neither a total emissions reduction target nor carbon intensity reduction targets are assigned to China's power industry during the 11th and 12th FYP periods. Thus, we use the reduction target of the coal consumption rate of electricity generation to calculate the CO_2 emissions limit. In the 11th and 12th FYP periods, the coal consumption rate of electricity generation should reduce by 4.05% (from 370 gce/kWh to 355 gce/kWh) and by 2.4% (from 333 gce/kWh to 325 gce/kWh), respectively. We let CEL_{kt}, C_{kt}, CR_{kt}, E_{kt}, and TCR_{kt} represent the CO_2 emissions limit, CO_2 emissions, the coal consumption rate of electricity generation, electricity generation, and the reduction target of the coal consumption rate of electricity generation, respectively, for the kth province in year t. Then, the CO_2 emissions limit of the kth province in year t is calculated as in Equation (17):

$$CEL_{kt} = (C_{kt} / CR_{kt}) \cdot E_{kt} \cdot TCR_{kt}$$

(17)

In addition to the SO_2 and CO_2 emissions reduction targets, a dust emissions reduction target was also proposed in China's energy conservation and emissions reduction plans for the 11th FYP period. Dust emissions were targeted to decrease by 55.6% (from 3.60 million tons per year to 1.60 million tons per year). In addition, in China's energy conservation and emissions reduction plans for the 12th FYP period, a 28.9% reduction target for NO_x emissions was proposed (from 10.55 million tons per year to 7.50 million tons per year). However, since the reduction targets for these two pollutant emissions cannot be compared between the 11th and 12th FYP periods, they are not analyzed in this study.

4.2 Operational Performance

Table 1 lists the operational performances of the thermal power industry sectors of China's 30 provinces during the 11th and 12th FYP periods.

[Insert Table 1 here]

During the 11th and 12th FYP periods, the annual gap between electricity generation and local electricity demand in Hebei decreased from 16.47 million MWh to 3.2 million MWh, indicating that compared to the 11th FYP period, Hebei generated more electricity to match its demand during the 12th FYP period. The decrease in the gap between electricity generation and local electricity demand results in an improvement in operational effectiveness, and this improvement in operational effectiveness moved Hebei from Production Focus to Leader. Similar progress in operational effectiveness also occurred in Tianjin, which switched from Production Focus to Leader.

Table 1 also shows that another seven provinces, e.g., Anhui, Henan, Guangxi, and Yunnan, shifted from Demand Focus to Leader, which indicates that these provinces made progress in simultaneously improving their operational efficiencies while maintaining their high operational efficiencies of electricity production. For instance, the operational effectiveness of Henan increased from 0.9979 in the 11th FYP period to 0.9983 in the 12th FYP period, and during the same period, its operational efficiency increased from 0.8731 to 0.9896.

Since the beginning of the 12th FYP period, China has proposed a national integrated power industry development plan, which was not proposed or implemented before or during the 11th FYP period. According to this plan, the further distribution of China's energy supply would be in the form of "five bases plus two belts," indicating five energy bases and two energy belts. The five energy bases are Xinjiang, Shanxi, Southwest, Eastern Inner Mongolia, and Ordos Basin (including Shaanxi, Ningxia, and Gansu), and the two energy belts are the Eastern Nuclear belt and the South China Sea deep-sea oil and gas belt. As energy bases, these provinces were encouraged to increase their electricity generation to support electricity consumption in other provinces. Given this circumstance, it would be acceptable for these provinces located in energy bases to reduce their operational effectiveness scores in the 12th FYP period. From Table 1, it can be seen that the operational effectiveness scores of Shanxi, Inner Mongolia, Shaanxi, Ningxia, and Gansu all experienced slight decreases, which reveals that although the operational performances of these energy base provinces regressed, they are in line with the energy resource endowments of these provinces and are in accordance with China's national integrated power industry development plan.

Figure 5 additionally illustrates the strategic positions and their changes during the 11th and 12th FYP periods for China's 30 provincial power industry sectors. The size of a bubble indicates the amount of electricity generation in the corresponding province. It can be seen that during the 11th FYP period, there were 11 provinces in the Leader quadrant, with Shandong, Shanxi, and Jiangsu in the leading positions, since they all have relatively higher operational efficiency and effectiveness scores and they generate comparatively more electricity than other provinces. Thus, these provinces were the major contributors to improving the operational performance of China's thermal power industry during the 11th FYP period. Similarly, it can be seen that there were 14 provinces in the Leader quadrant during the 12th FYP period, with Jiangsu, Guizhou, Zhejiang, and Henan as the major contributors for the same reason.

[Insert Figure 5 here]

In order to evaluate the effect of China's interprovincial electricity transition and reallocation, we further estimate the operational performance of the thermal power industry sectors before and after the interregional electricity reallocation. Table 2 reports the average operational efficiency and operational effectiveness before and after the reallocation.

[Insert Table 2 here]

In the 11th and 12th FYP periods, China gradually executed the West-East electricity transmission project, under which large amounts of electricity generated in provinces in western China (e.g., Guizhou, Yunnan, Guangxi, Sichuan, Gansu, Inner Mongolia, and Shanxi), which are rich in fossil fuel resources, were transferred to provinces in eastern China (e.g., Guangdong, Shanghai, Jiangsu, Zhejiang, Beijing, and Tianjin), which had heavy demand for electricity consumption. China's interprovincial electricity reallocation is in line with this policy.

From Table 2, we find that Shanghai, Qinghai, and Guangdong shifted from PF (before reallocation) to L (after reallocation) due to their improvements in operational effectiveness, which were driven by decreases in the gaps between their electricity production and consumption. Before reallocation, the operational effectiveness scores of Shanghai, Qinghai, and Guangdong were 0.8800, 0.9314, and 0.9225, respectively, whereas after reallocation, their scores increased to 0.9994, 0.9996, and 0.9994, respectively. Specifically, the electricity generated locally in Shanghai does not meet its electricity demand, and Shanghai annually consumes on average 10.2 million MWh of power that is generated in and transferred from other provinces, such as Jiangsu, Hubei, and Sichuan. Similarly, the electricity generated locally in Guangdong does not meet its electricity demand, and Guangdong annually consumes on average 21.6 million MWh of power that is generated in and transferred from other provinces, such as Guizhou, Yunnan, Hubei, and Hunan. On the contrary, Qinghai generated more electricity than its local demand and supported the electricity consumption of many other provinces. Qinghai is evaluated as Production Focus if the effect of this electricity reallocation is not taken into account (before reallocation), but it is categorized as a Leader when this effect is considered (after reallocation). Hence, taking the influence of electricity reallocation into account can help to provide a more reasonable and objective performance evaluation for provinces that have large amounts of electricity imports (e.g., Shanghai and Guangdong) or exports (e.g., Qinghai). In addition, the average operational effectiveness of the thermal power industry sectors of China's 30 provinces increased from 0.9657 to 0.9994 after electricity reallocation, and no province experienced an effectiveness reduction after electricity reallocation. This result implies that China's electricity reallocation is overall effective.

Next, we come to the results of operational effectiveness changes denoted by the global Malmquist productivity index OM and its decompositions CIE^o and CIT^o. In the 11th FYP period, the average OM, CIE^o, and CIT^o of China's 30 provincial thermal power industry sectors were 0.9982, 0.9981, and 1.0001, respectively, whereas in the 12th FYP period, they were 1.0054, 1.0048, and 1.0006, respectively. This result shows that in the 12th FYP period, the operational performance of China's thermal power industry improved more quickly than in the 11th FYP period, and this operational effectiveness increase is the major driving force for improving the operational performance during the 12th FYP period. As shown in Figure 6, in the 11th FYP period, the operational performance improvements of the thermal power industries in Chongqing, Beijing, and Guangxi were the highest, and in the 12th FYP period, those of Hebei, Liaoning, and Tianjin were the highest.

[Insert Figure 6 here]

4.3 Environmental performance

Since two undesirable outputs from the thermal power industry, CO_2 and SO_2, are included in the evaluation in this study, the environmental performance of the thermal power industry can be divided into two components: the CO_2 emissions reduction performance and the SO_2 emissions reduction performance.

4.3.1 CO_2 Emissions Reduction Performance

Figure 7 shows the strategic positions of China's 30 provincial thermal power industries with respect to their CO_2 emissions reduction performances, in which the size of a bubble indicates the amount of CO_2 emissions from the corresponding provincial thermal power industry sector. During the 11th FYP period, according to the reduction target of coal consumption rate of electricity generation assigned to each province, the average annual CO_2 emissions limit was 3.67 billion tons, whereas the observed average annual amount of CO_2 emissions was 3.19 billion tons. In addition, during the 12th FYP period, the average annual CO_2 emissions limit was 4.74 billion tons, whereas the observed average annual amount of CO_2 emissions was 3.75 billion tons. It is clear that the CO_2 emissions reduction target for China's thermal power industry is not very strict. This phenomenon can also be observed in Figure 7, in which the environmental efficiency and environmental effectiveness scores are positively related with a relatively high correlation. This finding indicates that most of China's provincial thermal power industry sectors can match their CO_2 emissions reduction efforts with their CO_2 emissions reduction targets appropriately. However, this finding also indicates that the CO_2 emissions reduction targets assigned to China's thermal power industry are loose and conservative and that the central government may need to increase the burden of CO_2 emissions control on this industry in the 13th FYP period.

Figure 7 additionally illustrates that the environmental efficiency and environmental effectiveness of the power industries of Zhejiang and Jiangsu are comparatively higher and their CO_2 emissions are greater than those of other provinces, whereas, on the contrary, these scores for the power industries of Inner Mongolia and Henan are comparatively lower, and their CO_2 emissions are greater than those of other provinces. This result means that the power industry sectors of Zhejiang and Jiangsu are major contributors and the power industry sectors of Inner Mongolia and Henan are major obstructions to improving the CO_2 environmental performance of China's thermal power industry.

[Insert Figure 7 here]

In terms of the CO_2 emissions reduction performance, during the 11th FYP period, the average *EM*, CIE^e, and CIT^e of China's 30 provincial thermal power industry sectors were 1.0256, 1.0168, and 1.0115, respectively, and during the 12th FYP period, the average *EM*, CIE^e, and CIT^e were 1.0322, 1.0265, and 1.0060, respectively. This result indicates that environmental performance improved more in the 12th FYP period than in the 11th FYP period, and the improvement in environmental effectiveness is the major driving force for this improvement over our entire study period. However, the environmental technology of China's thermal power industry improved less during the 12th FYP period than during the 11th FYP period. Figure 8 illustrates the average *EM*, CIE^e, and CIT^e for each provincial thermal power industry. It can be seen that during the 11th FYP period, CO_2 emissions reduction performances improved the most for the thermal power industries of Beijing, Chongqing, and Yunnan, and during the 12th FYP period, these performances improved the most in Inner Mongolia, Heilongjiang, and Henan.

[Insert Figure 8 here]

4.3.2 SO_2 Emissions Reduction Performance

A similar explanation can be derived for the SO_2 emissions reduction performance. During the 11th FYP period, China's thermal power industry had a national SO_2 emissions reduction target of 9.571 million tons, which was completed one year earlier, at the end of 2009. In addition, during the 12th FYP period, the annual SO_2 emissions limit of China's thermal power industry was 8.87 million tons, whereas the observed annual amount of SO_2 emissions of China's thermal power industry was just 7.54 billion tons. This result shows that the SO_2 emissions reduction targets assigned to China's thermal power industry were also loose. Figure 9 shows that the environmental efficiency and effectiveness scores were highly and positively correlated, indicating that the SO_2 emissions reduction efforts and the SO_2 emissions reduction targets of most provincial thermal power industry sectors were appropriately matched, and thus the SO_2 emissions reduction target assigned to China's thermal power industry was conservative. Figure 9 further indicates that the thermal power industry sectors of Jiangsu and Guangdong were the major contributors to improving the SO_2 environmental performance of China's thermal power industry since they both had relatively higher environmental efficiency and effectiveness scores and comparatively greater amounts of SO_2 emissions. For a similar reason, Chongqing and Shaanxi are considered the major obstructions to improving this environmental performance.

[Insert Figure 9 here]

With respective to the SO_2 emissions reduction performance, the average *EM*, CIE^e, and CIT^e of China's 30 provincial thermal power industry sectors were 1.0650, 0.9708, and 1.0935 during the 11th FYP period, and were 1.0816, 0.9800, and 1.1041 during the 12th FYP period, respectively. This result indicates that the improvement in environmental technology played a positive role in increasing the SO_2 environmental performance, whereas the reduction in environmental effectiveness slowed this increase in China's thermal power industry. Figure 10 additionally illustrates that the environmental performance improvements in the thermal power industries of Beijing, Shanghai, and Zhejiang were the most clear in the 11th FYP period, and the improvements of Shanxi, Shaanxi, and Ningxia were the most significant in the 12th FYP period.

[Insert Figure 10 here]

4.3 Joint Performance

The joint performance is considered a combination of both the operational and the environmental performance and provides a comprehensive performance evaluation of the thermal power industry by taking into account the efforts both toward achieving specific marketing goals and toward matching appropriate emissions reduction targets.

Figure 11 illustrates the geographic distribution of the joint performances. First, it can be seen that the thermal power industries of Yunnan and Hebei shifted from Environment Focus (in the 11th FYP period) to Leader (in the 12th FYP period), indicating that these provinces made good progress in improving their joint efficiency by increasing their technical efficiency both in energy consumption for electricity generation and in related CO_2 and SO_2 emissions control. Second, Guizhou and Shanxi shifted from Production Focus to Laggard during the same period, indicating that the joint effectiveness of the thermal power industries in these provinces decreased. However, this decrease is reasonable since according to China's West-East electricity transmission project, provinces in western China, such as Guizhou and Shanxi, were encouraged to enhance their electricity generation capacities so as to increase their electricity generation and exports to provinces in eastern China, such as Guangdong and Zhejiang, to meet their electricity demands. In addition, during the 11th FYP period, 17.71% of the electricity produced by Gansu was exported and consumed by other provinces, but this percentage increased to 31.05% during the 12th FYP. The increase in the gap between electricity generation and local electricity demand resulted in a decrease in the joint effectiveness of Gansu's thermal power industry and drove Gansu's transition from Leader to Laggard. However, this transition is acceptable since it is in line with China's national integrated power industry development plan, in which Gansu is constructed as one of the energy bases in China and is expected to increase its electricity generation to support the electricity consumption of northern China regions like Hebei, Shandong, Beijing, and Tianjin. The above findings reveal that, in general, China's interprovincial electricity reallocation during the 12th FYP period is in line with its national energy planning policy.

[Insert Figure 11 here]

Figure 12 illustrates the joint productivity change and its components, joint effectiveness change and joint technology change, for China's 30 provincial thermal power industry sectors during the study period. The horizontal and vertical axes indicate the average CIE^{oe} and CIT^{oe}, respectively, and the size of the bubble indicates the *OEM*. It can be seen that most of the bubbles representing the 11th FYP period are concentrated in the lower right of the figure, whereas most of the bubbles representing the 12th FYP period are symmetrically located in the upper half of the figure. This implies that during the 11th FYP period, the increase in joint effectiveness was the major driving force for improving the joint productivity of China's thermal power industry, whereas during the 12th FYP period, increases in both joint effectiveness and joint technology equally contributed to the improvement of the joint productivity.

[Insert Figure 12 here]

5 Conclusion

As a complement to the operational efficiency measure, the operational effectiveness measure helps to identify the capacity of an electricity production system to adjust its electricity generation activities to match the electricity demand. In addition, as a complement to environmental efficiency measure, the environmental effectiveness measure helps to identify the capacity of an electricity production system to adjust its emissions abatement activities to fulfill environmental regulations. Furthermore, the environmental effectiveness measure helps the government regulator to verify the rationality of its emissions reduction targets assigned to the thermal power industry.

Several newly developed DEA-based effectiveness measurements were utilized in this study to evaluate the operational and environmental performance of the thermal power industry in China's 30 provincial regions during 2006-2013. Both efficiency and effectiveness were evaluated from the three perspectives of operational, environmental, and joint adjustments to each regional electricity production system. The operational and environmental performance changes over time were also captured in this study through an effectiveness measure based on the global Malmquist productivity index.

The estimation results of the empirical study draw several conclusions. (i) Effectiveness measures are different from efficiency measures, and a strong performance in electricity generation guarantees a strong performance neither in matching electricity generation to electricity demand nor in fulfilling emissions control targets. (ii) According the estimates of operational productivity change, environmental productivity change, and joint productivity change during the study period, China's thermal power industry experienced significant progress during the 12^{th} FYP period. (iii) In general, the CO_2 and SO_2 emissions reduction targets assigned to China's thermal power industry are loose. (iv) Specifically, Shandong, Shanxi, and Jiangsu were the major contributors to improving the operational performance of China's thermal power industry during the 11^{th} FYP period, whereas Jiangsu, Guizhou, and Zhejiang were the major contributors to improving the operational performance during the 12^{th} FYP period. (v) The power industry sectors of Zhejiang and Jiangsu were the major contributors to improving the CO_2 environmental performance, and those of Jiangsu and Guangdong were the major contributors to improving the SO_2 environmental performance of China's thermal power industry. (vi) The construction of "five energy bases" proposed in China's national integrated power industry development plan gradually yielded the expected positive effect, and the West-East electricity transmission project for interprovincial electricity reallocation was overall effective in China.

Acknowledgement

We gratefully acknowledge the financial support from the National Natural Science Foundation of China (Grant Nos. 71471018 and 71521002), the Social Science Foundation of Beijing (Grant No. 16JDGLB013), the National Key R&D Program (Grant No. 2016YFA0602603), and the Joint Development Program of Beijing Municipal Commission of Education.

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Tables and Figures

Table 1 Operational performance

Province/ Abbreviation	11th FYP period					12th FYP period				
	Efficiency		Effectiveness		SP	Efficiency		Effectiveness		SP
	Score	Rank	Score	Rank		Score	Rank	Score	Rank	
Beijing/ BJ	0.9630	14	0.4904	30	PF	1.0000	1	0.5000	30	PF
Tianjin/ TJ	0.9815	10	0.9153	26	PF	0.9447	15	0.9992	1	L
Hebei/ HB	0.9409	17	0.8777	28	PF	0.9232	19	0.9898	25	L
Shanxi/ SX	0.9656	13	0.9952	20	L	0.8018	27	0.9949	22	DF
Inner Mongolia/ IM	0.8681	26	0.9952	19	DF	0.7612	28	0.9937	23	DF
Liaoning/ LN	0.9021	19	0.9806	23	DF	0.6301	30	0.9927	24	DF
Jilin/ JL	0.7089	30	0.9974	13	DF	0.7531	29	0.9964	15	DF
Heilongjiang/ HLJ	0.8161	28	0.9968	15	DF	1.0000	1	0.9969	13	L
Shanghai/ SH	1.0000	1	0.8750	29	PF	1.0000	1	0.8885	29	PF
Jiangsu/ JS	1.0000	1	0.9987	2	L	1.0000	1	0.9986	5	L
Zhejiang/ ZJ	0.9962	8	0.9993	1	L	0.9927	13	0.9991	2	L
Anhui/ AH	0.9020	20	0.9963	18	DF	1.0000	1	0.9954	20	L
Fujian/ FJ	0.9994	7	0.9977	11	L	0.8453	25	0.9976	8	DF
Jiangxi/ JX	0.7926	29	0.9982	5	DF	0.8693	23	0.9987	4	DF
Shandong/ SD	0.9757	11	0.9973	14	L	0.8880	21	0.9990	3	DF
Henan/ HN	0.8731	25	0.9979	8	DF	0.9896	14	0.9983	6	L
Hubei/ HuB	1.0000	1	0.9949	21	L	0.9374	17	0.9951	21	L
Hunan/ HuN	0.8652	27	0.9980	6	DF	1.0000	1	0.9971	10	L
Guangdong/ GD	1.0000	1	0.9108	27	PF	0.9059	20	0.9422	27	Lag
Guangxi/ GX	0.8918	21	0.9887	22	DF	1.0000	1	0.9979	7	L
Hainan/ HaN	1.0000	1	0.9978	10	L	0.9435	16	0.9971	11	L
Chongqing/ CQ	0.8839	23	0.9526	24	Lag	1.0000	1	0.9706	26	PF
Sichuan/ SC	0.9589	15	0.9978	9	L	0.8734	22	0.9964	16	DF
Guizhou/ GZ	0.9755	12	0.9979	7	L	1.0000	1	0.9974	9	L
Yunnan/ YN	0.8813	24	0.9982	4	DF	0.9366	18	0.9971	12	L
Shaanxi/ SaX	0.9040	18	0.9967	16	DF	0.8564	24	0.9957	18	DF
Gansu/ GS	0.9537	16	0.9982	3	L	1.0000	1	0.9969	14	L
Qinghai/ QH	1.0000	1	0.9448	25	PF	0.9960	12	0.9091	28	PF
Ningxia/ NX	0.9866	9	0.9976	12	L	0.8429	26	0.9959	17	DF
Xinjiang/ XJ	0.8916	22	0.9963	17	DF	1.0000	1	0.9955	19	L

Table 2 Operational performance before reallocation (BR) and after reallocation (AR)

Province	Efficiency		Effectiveness BR		Effectiveness AR		SP	SP
	Score	Rank	Score	Rank	Score	Rank	BR	AR
Beijing	0.9769	11	0.4940	30	0.9993	21	PF	PF
Tianjin	0.9885	10	0.9468	25	0.9994	17	L	PF
Hebei	0.9423	14	0.9197	28	0.9995	6	L	L
Shanxi	0.9497	13	0.9951	19	0.9993	22	L	PF
Inner Mongolia	0.8432	27	0.9947	21	0.9995	3	DF	DF
Liaoning	0.8492	26	0.9851	23	0.9994	16	DF	DF
Jilin	0.6794	30	0.9970	13	0.9994	18	DF	Lag
Heilongjiang	0.7925	29	0.9969	15	0.9993	24	DF	Lag
Shanghai	1.0000	1	0.8801	29	0.9994	12	PF	L
Jiangsu	1.0000	1	0.9987	2	0.9992	25	L	PF
Zhejiang	0.9976	7	0.9992	1	0.9995	4	L	L
Anhui	0.9360	16	0.9960	18	0.9993	23	L	PF
Fujian	0.9996	6	0.9976	10	0.9995	9	L	L
Jiangxi	0.8124	28	0.9984	3	0.9994	11	DF	DF
Shandong	0.9358	17	0.9979	5	0.9994	14	L	L
Henan	0.8787	24	0.9981	4	0.9995	8	DF	DF
Hubei	0.9961	8	0.9950	20	0.9994	20	L	PF
Hunan	0.8923	23	0.9977	9	0.9991	29	DF	Lag
Guangdong	1.0000	1	0.9226	27	0.9994	13	PF	L
Guangxi	0.8971	22	0.9921	22	0.9994	15	DF	DF
Hainan	1.0000	1	0.9975	11	0.9992	28	L	PF
Chongqing	0.9062	21	0.9594	24	0.9992	27	Lag	Lag
Sichuan	0.9743	12	0.9973	12	0.9990	30	L	PF
Guizhou	0.9372	15	0.9977	8	0.9995	5	L	L
Yunnan	0.9258	18	0.9978	6	0.9995	10	DF	DF
Shaanxi	0.9162	20	0.9963	16	0.9994	19	DF	Lag
Gansu	0.9172	19	0.9977	7	0.9995	7	DF	DF
Qinghai	1.0000	1	0.9314	26	0.9996	1	PF	L
Ningxia	0.9902	9	0.9970	14	0.9996	2	L	L
Xinjiang	0.8734	25	0.9960	17	0.9992	26	DF	Lag

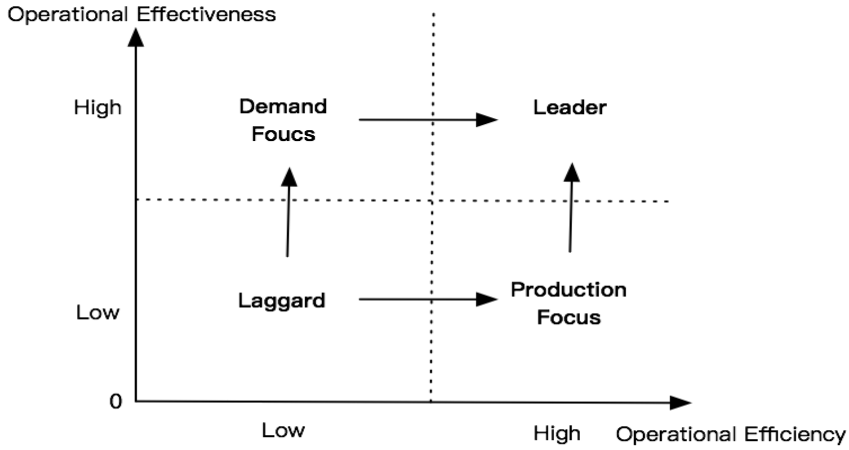

Figure 1 Strategic positions from perspective of operational performance improvement

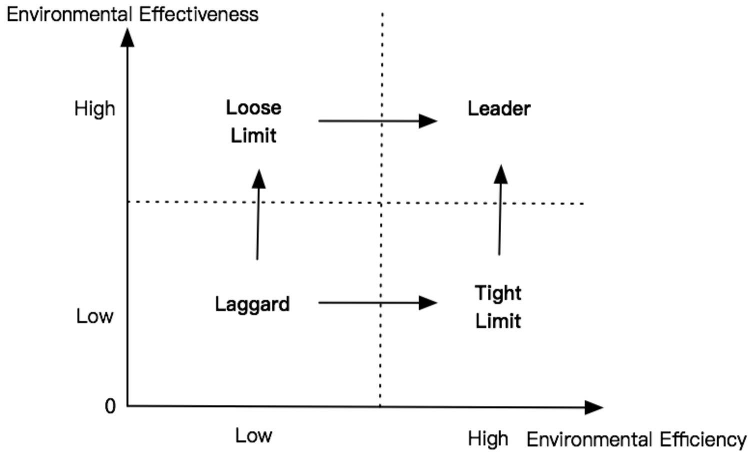

Figure 2 Strategic positions from perspective of environmental performance improvement

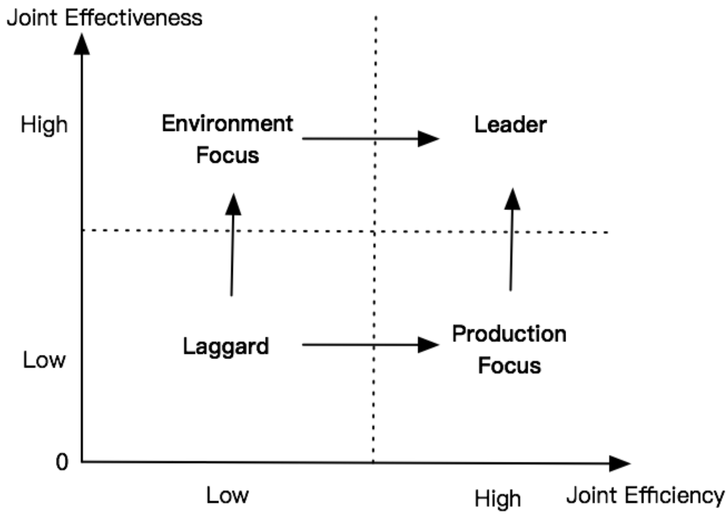

Figure 3 Strategic positions from perspective of joint performance improvement

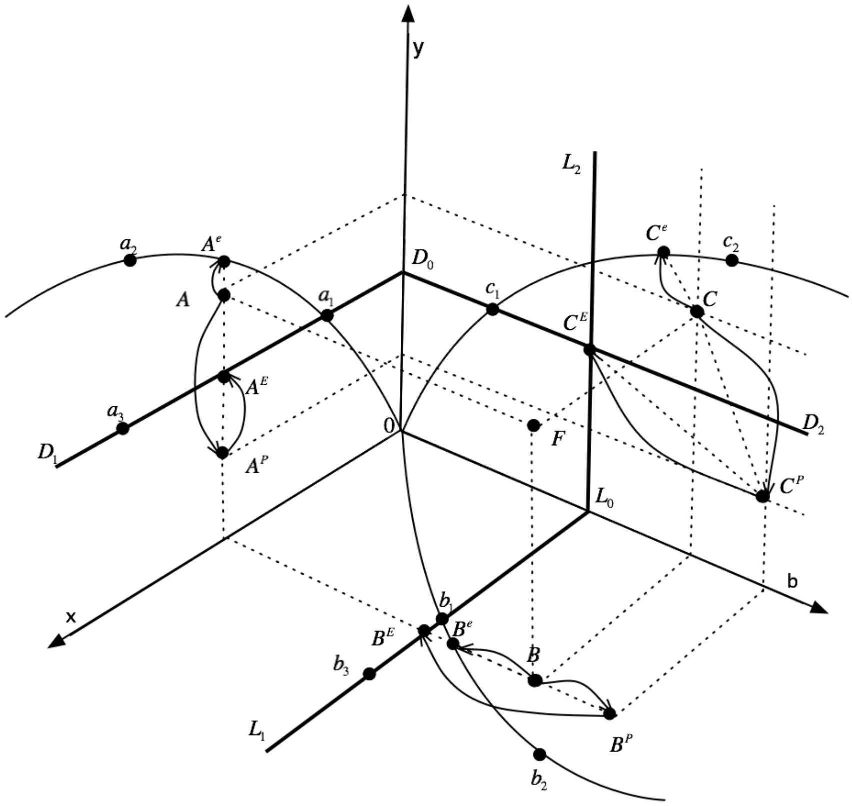

Figure 4 Operational, environmental and joint performance measurements

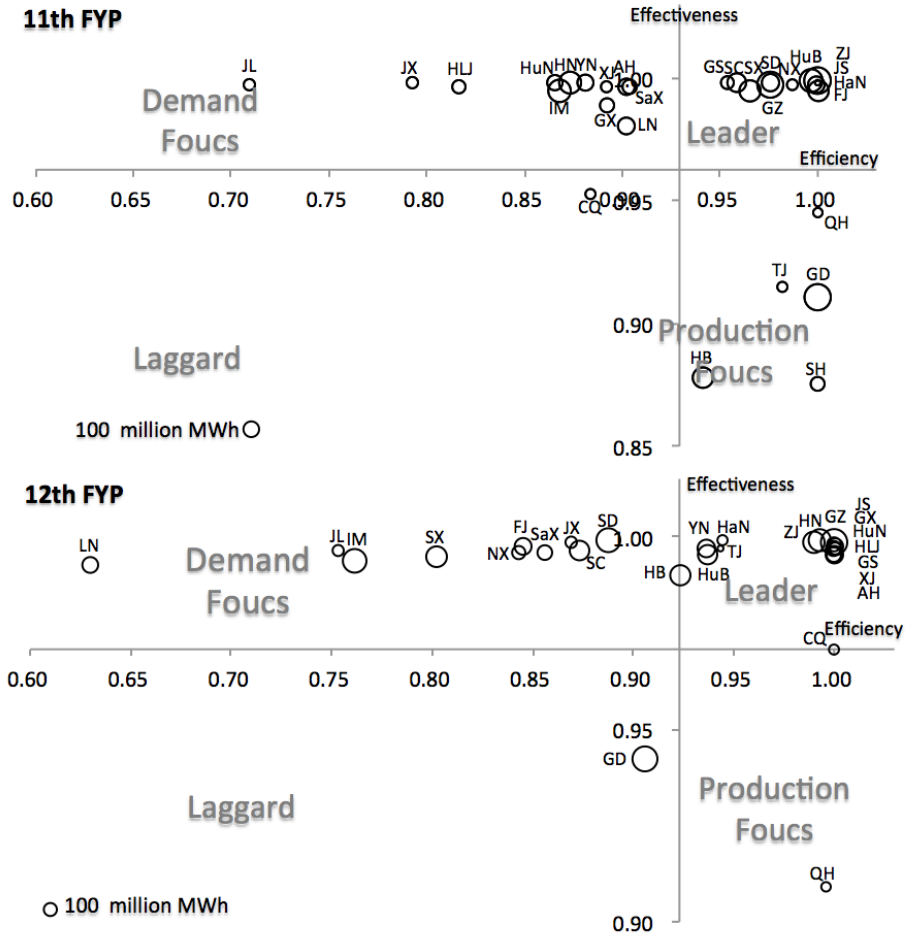

Figure 5 Strategic positions in terms of operational performance

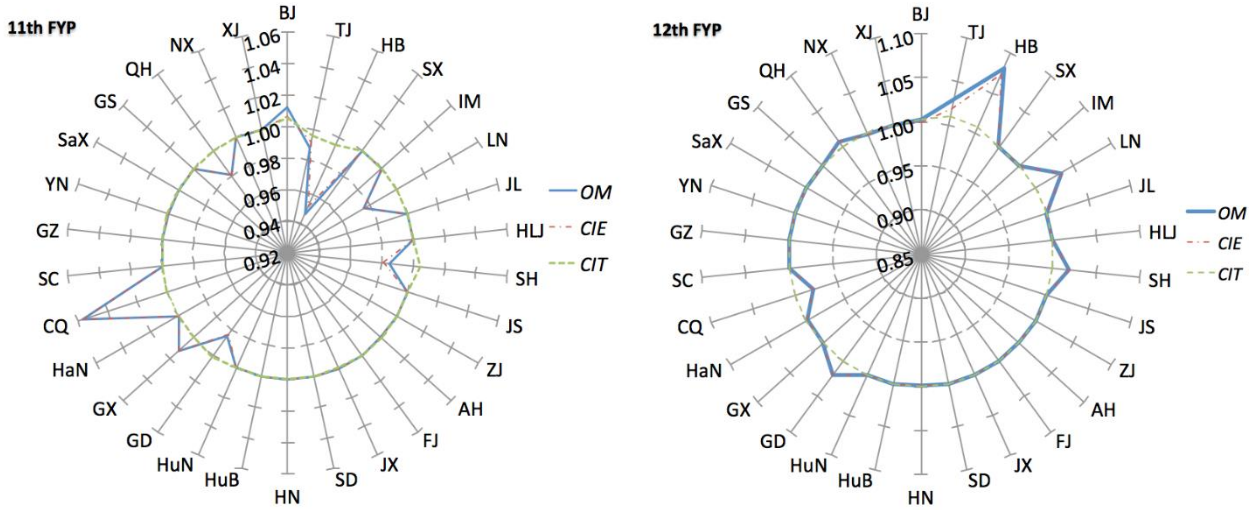

Figure 6 Productivity change in terms of operational performance

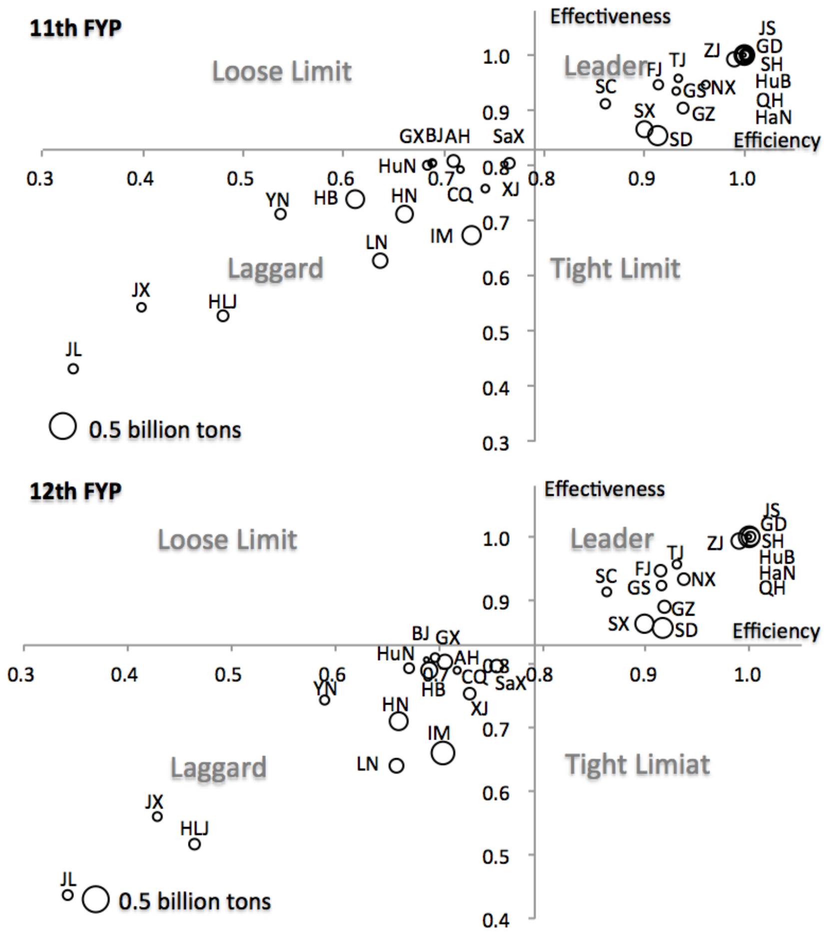

Figure 7 Strategic positions in terms of CO_2 emissions reduction performance

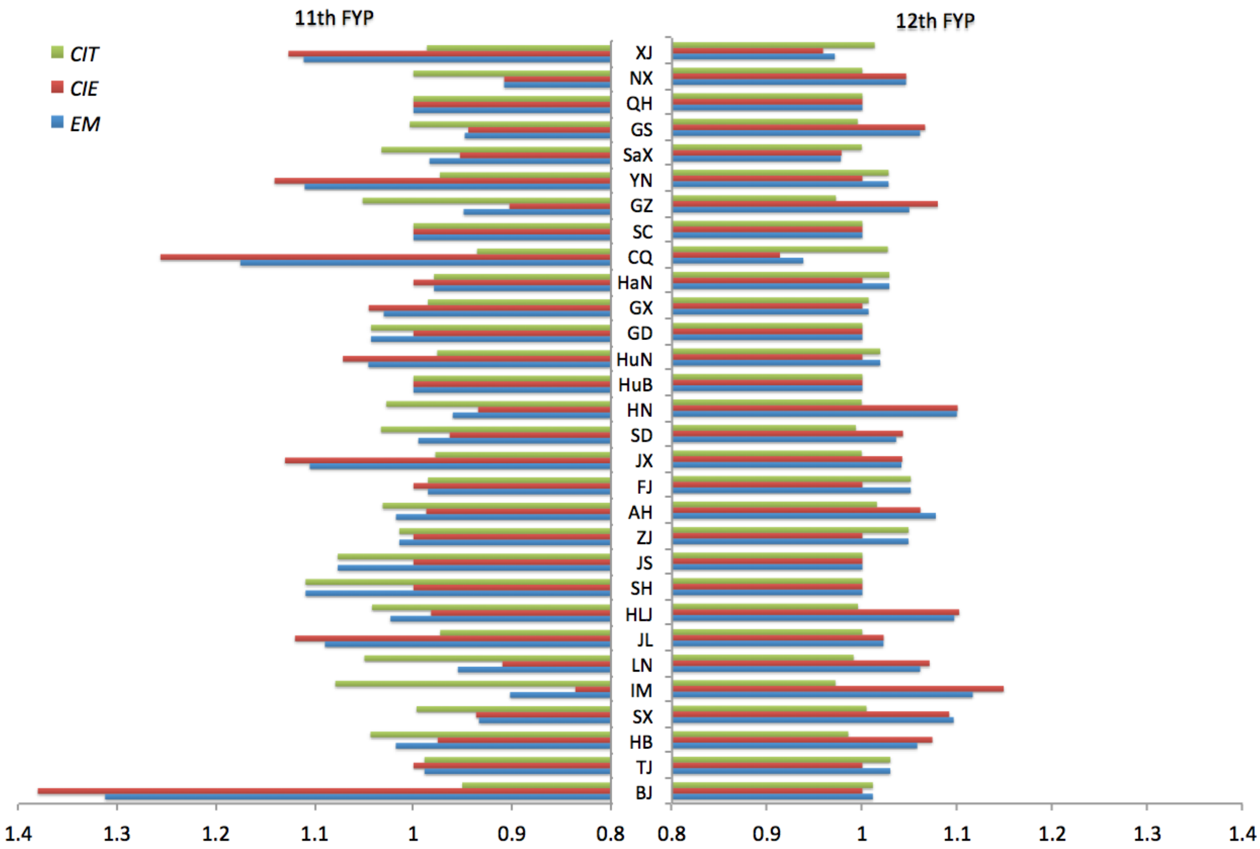

Figure 8 Productivity change in terms of CO_2 emissions reduction performance

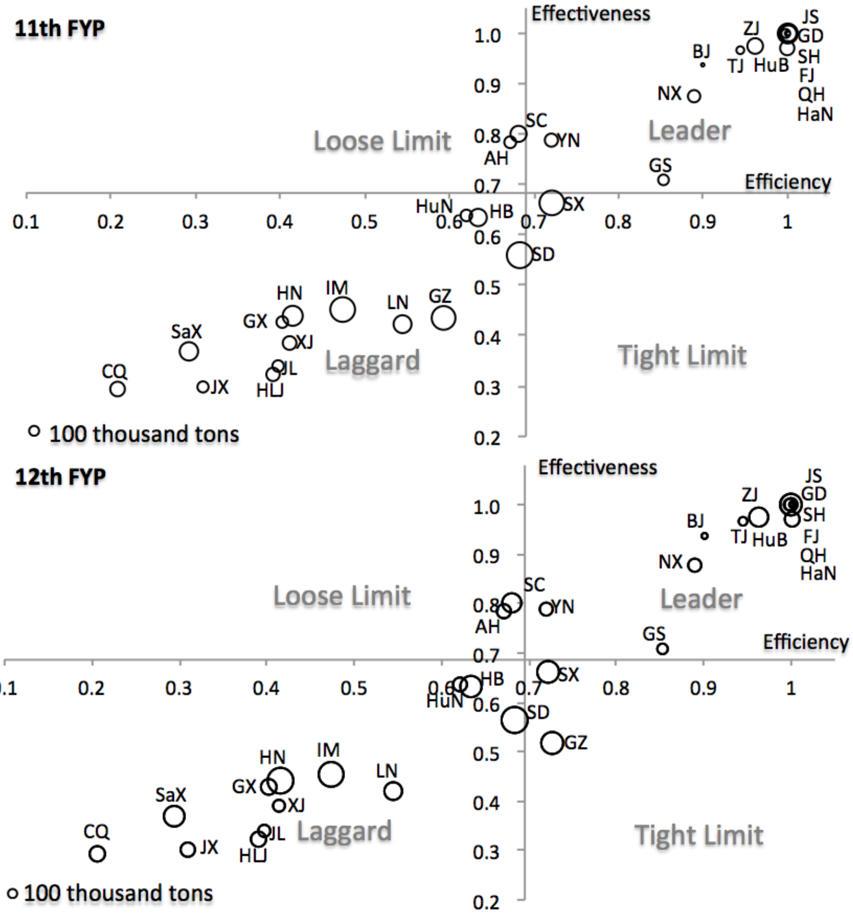

Figure 9 Strategic positions in terms of SO_2 emissions reduction performance

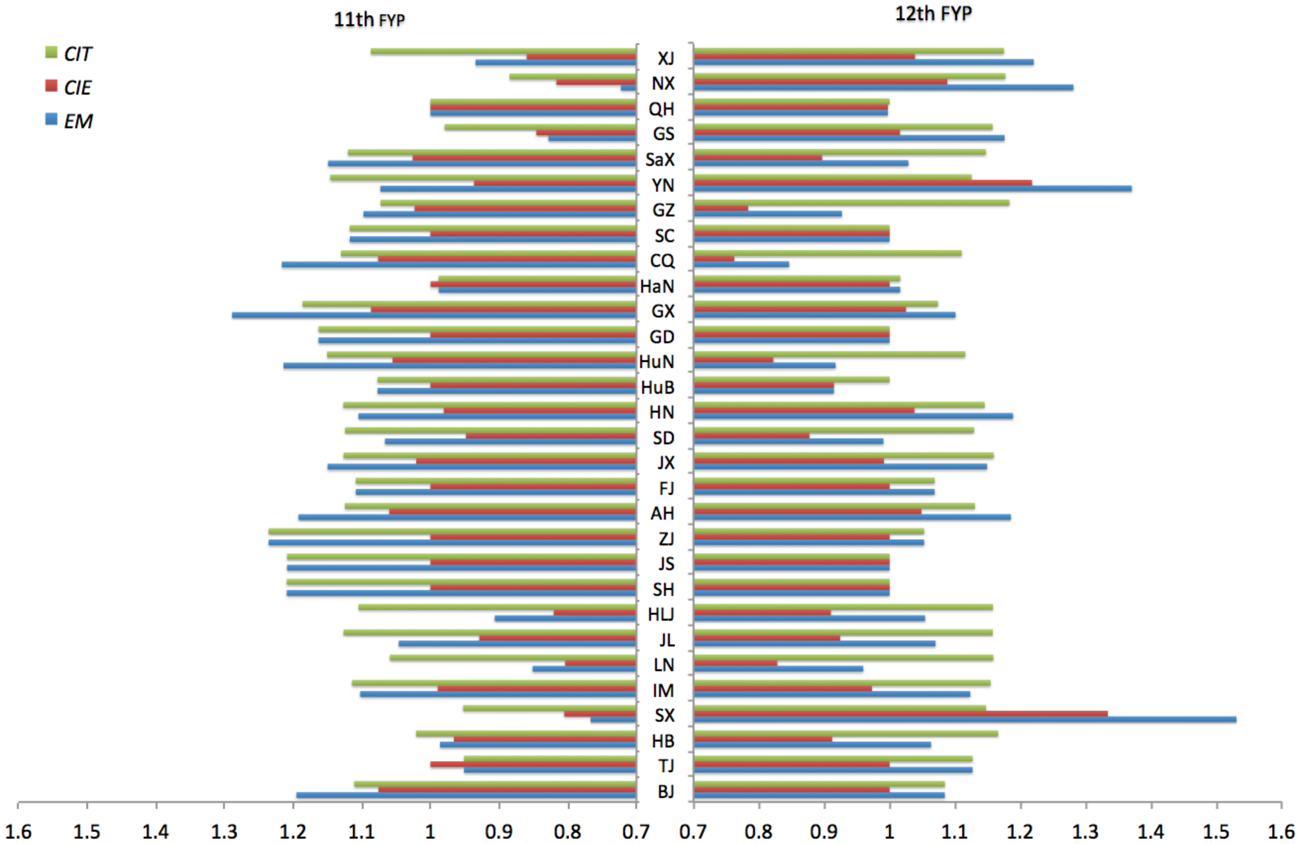

Figure 10 Productivity change in terms of SO_2 emissions reduction performance

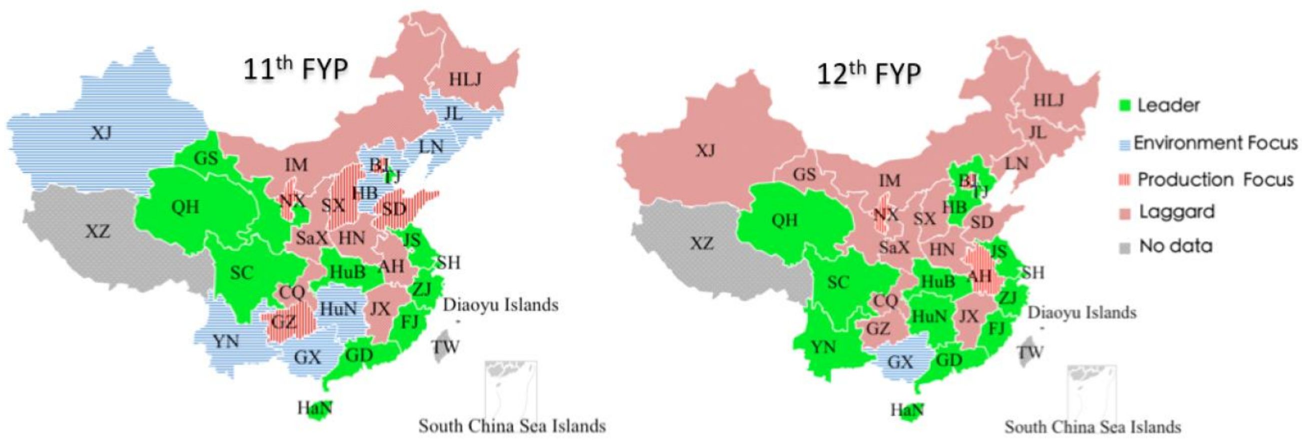

Figure 11 Strategic positions in terms of joint performance

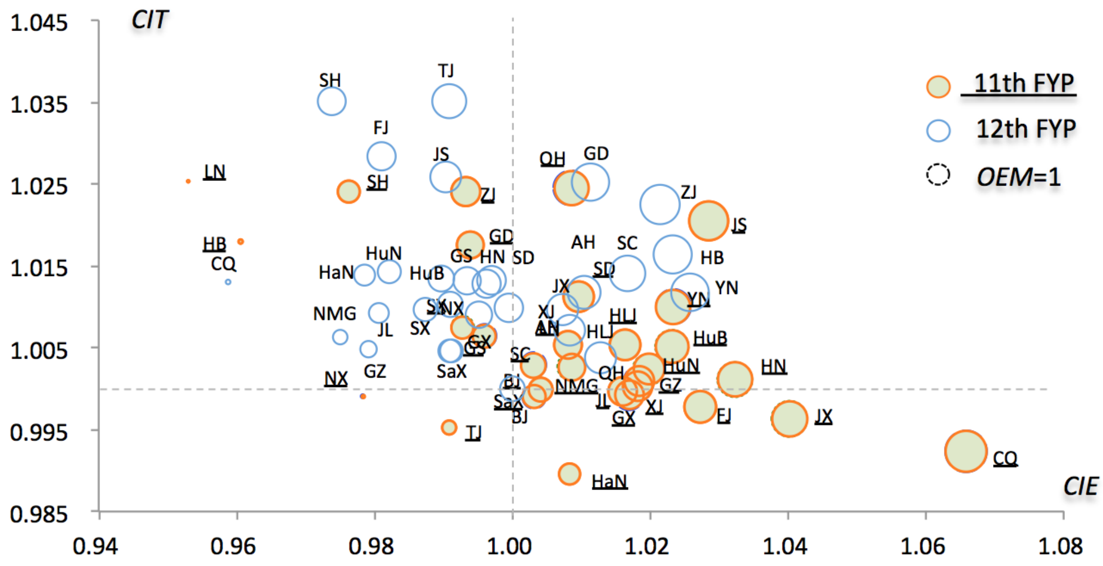

Figure 12 Productivity change in terms of joint performance