FONDAZIONE ENI ENRICO MATTEI

NOTA DI LAVORO

12.2017

What Factors Affect the Competiveness of Power Generation Sector in China? An Analysis Based on Game Cross-efficiency

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Mitigation, Innovation & Transformation Pathways
Series Editor: Massimo Tavoni

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Summary

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Keywords: Game Cross-efficiency, Data Envelopment Analysis, Generalized Method of Moments, Power Industry, Environmental Efficiency, China

JEL Classification: Q54, Q55, Q58, Q43, Q48, O13, O44, R11

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What factors affect the competiveness of power generation sector in China? An analysis based on game cross-efficiency

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Abstract

China's unbundling reform in 2002 aimed to introduce competitiveness into the power industry, especially the generation sector, to improve its operational efficiency. Meanwhile, great concern about a range of environmental problems and global climate change increasingly calls for saving energy and abating emissions. Thus, the ability to balance the reduction of carbon emissions with economic benefits may to a great extent determine the competitiveness of power generation sector. This study first adopts the game cross-efficiency approach to evaluate the environmental efficiency of the generation sectors in China's 30 provinces. It then employs a system generalized method of moments model to explore the determinants of their performance while eliminating the associated endogeneity problem. The results of this first study combining the two methods indicate that efficiency gaps do exist among the regions even though overall efficiency has been improved. Despite the negative correlation between environmental efficiency and the thermal power ratio, the power mix should be adjusted gradually. The average firm size and capacity utilization rates are positive factors boosting the environmental efficiency. The incentive policies for clean energy development should be differentiated across regions according to their power mix and self-sufficiency ratio.

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1. Introduction

The history of power system reform reveals a process aimed at improving market mechanisms and building good competition systems. Such reforms not only take place in the developed world, such as the power reforms in England in the early 1990s (Stagliano, 1997) and the first pilot reform in California, USA in 1996 (Wiser et al., 1998). Similar reforms are also undertaken in developing countries, such as Argentina, Brazil, Chile (Rudnick et al., 2005), and Iran (Arabi et al., 2014). Introducing market-oriented mechanisms has always been the aim of China's power reforms in recent decades. In the 1980s China began to implement the policy of “open the industry to the public to raise funds” in the generation sector to overcome the nationwide power shortage. This led to a trend of establishing joint-stock power companies.[1] Later reforms further encouraged foreign companies to invest in the power industry. With the abolition of the Ministry of Power Industry, the government began to implement the policy of "separation of government and enterprises" and established the State Power Corporation; simultaneously, it also encouraged the local governments to be investors in the power industry. This policy completely broke down the unified management system and the corresponding management functions were transferred from the Ministry of Power Industry to the national and local Economic and Trade departments concerned.

In 2002 the State Council issued the unbundling reform of “separating power-generating plants from grids”. This was the first attempt to establish a market-oriented mechanism and framed China’s power management system over the following 15 years. By dismantling the vertically integrated management system into independent companies, this policy aims to develop

[1] The first central and local co-funded power plant, Shandong Centennial Power Development Co., Ltd., was established in Longkou, Shandong province in 1984.

a competitive regional or even national wholesale electricity market where power plants would place bids into the market and gain grid-access priority according to the economic merit. In 2003 the State Power Corporation was dismantled and reorganized into 11 corporations according to the nature of their business, among which five were generation groups,[2] in an effort to intensify the competition and improve the economic efficiency. To achieve a fair competitive environment, all of the five generation groups were roughly the same size with an installed capacity of 32 million kilowatts, with each of them occupying no more than 20% of the regional electricity market. This guaranteed a basic pattern of equal competition for China's generation market (Du et al., 2013). At the same time, more and more generation enterprises, including local enterprises, four national enterprises,[3] and foreign-funded enterprises, were established all over the country. These progress had broken down the old monopoly on power generation side. Along with the development of the power market, price mechanism reforms have also been carried out.[4]

Generally speaking, China's unbundling reform has accomplished a degree of success in the generation sector (Duan et al., 2016; Xie et al., 2012; Zhao and Ma, 2013), and it has had significant positive effects in enhancing the efficiency of fossil-fired power plants (Arabi et al., 2014; Du et al., 2013; Ghosh and Kathuria, 2016; Meng et al., 2016). Nevertheless, with significant increase in installed power capacity, the power supply has exceeded demand since 2012 on the whole, especially in the north, northeast, and northwest of China where the wind resources are abundant but the wind power is frequently curtailed. In this case the provinces with

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[2] They are Datang Corporation, Huaneng Group, Guodian Corporation, Huadian Corporation, and State Power Investment Corporation.

[3] They are China Resource Power Holdings Co., Ltd., SDIC Power Holdings Co., Ltd., China General Nuclear Power Corporation, and Guohua Electric Power Company.

[4] In 2004 China announced a unified feed-in tariff policy for coal-fired units across the country for the first time, which was adjusted in accordance with changes in the generation cost. In 2006 China promulgated the "renewable energy power generation price and cost-sharing management pilot scheme," which defined the tariff and cost-sharing management approach for the construction of renewable energy power generation projects.

excess power supplies have to face fierce competition when they endeavor to export their surplus power to the importing provinces to increase their efficiency. Both the trend of developing an open, orderly, and competitive electricity market for further electricity market reform (Meng et al., 2016; Mou, 2014) and the unbalanced power supply-demand situation show that the electricity sector is facing increasingly fierce competition. It is necessary to objectively examine the performance of the generation sector in a competitive environment to improve its efficiency and provide some guidance on further reform.

To cope with the deterioration of the environment, there is a growing trend in recent years of incorporating environmental factors when analyzing the operational efficiencies of the generation sector. Despite the pillar role of the power industry in China's economy, it also contributes to a large share of the national carbon emissions. Since the beginning of the 21st century, the corresponding proportion has remained at a level of over 40% (Yan et al., 2016; Yang and Lin, 2016). To reduce fuel consumption and air pollution, the 12th Five-Year Energy Development Plan set the power consumption goal for 2015 for the first time, and the power industry came into a new era of dual control for both generation and carbon emissions. Furthermore, under the joint China-US climate statement in November 2014, China committed to capping its GHG emissions around 2030, and to trying to peak early, and increasing the share of non-fossil fuel use to around 20% by 2030.[5] These commitments were officially incorporated into China's Intended Nationally Determined Contributions submission to the United Nations Framework Convention on Climate Change Secretariat. In addition, China pledged to reduce the carbon intensity of its economy by 60–65% by 2030 compared to 2005 levels (see Zhang (2017) for further discussion on China's

[5] See "US-China joint announcement on climate change" published by White House in November 2014.

2030 commitments).[6] Yan et al. (2016) estimated that China's CO_2 emissions would rise to 5596 Mt by 2020 if no effective measures were adopted after 2012, which would run counter to the national emission reduction commitment. From 2014 the state government officially included the CO_2 emission intensity reduction goals in the regional or industry indexes for the first time.[7] As one of the key industries for emission abatement, the electricity industry has introduced a quota control mechanism in implementing its development plan and allocating emission shares.[8] Under the circumstance it is essential to supplement the productivity performance with environmental efficiency in evaluating the development of the generation sector.

This study adopts a data envelopment analysis (DEA) game cross-efficiency model to assess the environmental performance of the power generation sectors under dual control of generation and carbon emissions. Considering the differences in fuel quality, energy structure, and technology, it further explores the determinants affecting the competitiveness of the generation sector. Although the power plants are operated by the generation groups following the unbundling reform in 2002, the power generation is determined by the provincial grids where the plants are located. Moreover, the production plans and emission quotas are all implemented by the provinces, so the studies of the generation sector in China mainly involve provincial analysis (Lin and Yang, 2014; Sueyoshi and Yuan, 2015; Zhou et al., 2013). To the best of our knowledge, this is the first attempt to take the competitiveness into consideration in evaluating the performance of the generation industry. Other contribution lies in introducing the system generalized method of moments

[6] See "Enhanced actions on climate change: China's intended nationally determined contributions" by National Development and Reform Commission in June 2015.

[7] See the "Carbon dioxide emission reduction per unit of GDP target responsibility assessment approach" issued by the National Development and Reform Commission in August 2014, in which the provincial CO_2 emission reduction per unit of GDP target is among the most important assessment indicators.

[8] The "Greenhouse gas emissions control program during 13th Five Year Plan" by the State Council in November 2016.

(SGMM) to eliminate the endogeneity problem among the provincial factors affecting their performance. The rest of our paper proceeds as follows. Section 2 reviews the related literature. Section 3 introduces the concept of game cross-efficiency and SGMM. Sections 4 and 5 present the empirical results and discussions. Section 6 presents our conclusions and puts forward some policy recommendations.

2. Literature review

DEA is a widely used and effective method to conduct efficiency evaluation due to its advantages in measuring efficiency for multiple inputs and outputs without assigning weights and specifying any function form (Cook and Seiford, 2009; Liu et al., 2013; Zhou et al., 2008). A typical characteristic of the energy and electricity industries is that undesirable outputs, which causes environmental problems, are produced in addition to desirable outputs. Thus it should come no surprise that energy and electricity are among the most widely applied DEA areas (Zhou et al., 2008). With regard to the issues that are combined with environmental problems, the economic index and environmental index are separated into input and output. If pollution exists in the output, this output becomes an undesirable output and should be minimized. Generally, the undesirable output can be solved through function variation and then combined with DEA models. Sueyoshi et al. (2017) summarized DEA applications from the 1980s to the 2010s, and suggested that of 185 papers on electricity, 75 ones were combined analyses dealing with various environmental issues, such as greenhouse gas emissions and waste discharges.

Färe et al. (1996) evaluated the environmental performance of American fossil fuel-fired electric utilities where CO_2 emissions are considered in addition to emissions of SO_2 and NO_x. In recent years, with the increasing concern about global climate change, CO_2 emissions have become the main and even the only undesirable output in work on the power sector's environmental efficiency. These studies can probably be classified into four groups: comparison between countries and analysis based on a regional, firm, or plant level. In the comparative analysis between countries, the Organization for Economic Cooperation and Development (OECD), European Union, and Brazil, Russia, India, and China (BRIC) countries and other international organizations are common objects of research. For example, Xie et al. (2014) employed the environmental Malmquist index to measure the environmental efficiency of the electric power industries in 26 OECD and BRIC countries, and Ewertowska et al. (2016) combined DEA with life cycle assessment to analyze the environmental performance of the power sector in 27 top European economies. At the regional level, most of the studies involved the environmental performance of the provincial power industry and analyses of the regional differences (Bian et al., 2013; Lin and Yang, 2014; Zhou et al., 2013). At the firm or plant level, Korhonen and Luptacik (2004) presented the performance of power plants when evaluating technological and ecological efficiencies. Sueyoshi and Goto (2011) discussed a new non-radial DEA approach to measure the unified (operational and environmental) efficiency of Japanese fossil fuel power generation from 2004 to 2008 and made methodological comparisons between the different DEA models. Arabi et al. (2014) compared the eco-efficiency of different types of thermal power plants (steam, gas, and combined cycle) in Iran under the background of power reform; the results showed that restructuring succeeded in improving the power generation facilities' performance. Du and Mao (2015) estimated the environmental efficiency of thermal power plants in China using the data from the China Economic Census in 2004 and 2008.

The ultimate aim of efficiency evaluation for the power generation sector is to find the influencing factors and then put forward targeted measures to improve the performance. Many DEA studies have advocated a two-step approach where efficiency is estimated in the first step using linear programming, and then the estimated efficiencies are regressed on explanatory variables in the second step (Nakano and Managi, 2008). For example, Yang and Pollitt (2009) analyzed the impact of the calorific value of coal and the unit scale on the environmental efficiency of power plants. Fleishman et al. (2009) presented the effect of air quality policies on the efficiency of US power plants. Du and Mao (2015) analyzed the effect of several factors: the ownership, scale, age, energy consumption structure, subsidy, location, and time trend.

However, the aforementioned literature did not consider the competition in the power industry, which will influence its performance during the efficiency evaluation by DEA. In reality, the competition is ubiquitous, especially in the situation where the generation sector is under the constraints of energy consumption and carbon reduction and the power supply-demand is imbalanced. At the beginning of plant-grid separation, China was in a power shortage, and provincial governments were competing for the construction of power generation projects. After 2012, the power supply situation began to ease, especially in the northeast, northwest, and other regions where wind power curtailment frequently happens, thereby stimulating the construction of high-voltage transmission networks to export surplus electricity. However, the DEA models used to estimate environmental performance mainly include the traditional CCR (Charnes, Cooper and Rhodes) model (Zhou and Ang, 2008), slacks-based measure (Bi et al., 2014), the Malmquist index (Chen and Golley, 2014; Woo et al., 2015), non-radial DEA (Bian et al., 2013), and DEA cross-efficiency (Liu et al., 2017). None of these models can incorporate competition between different provincial generation sectors. Wu et al. (2009) and Roboredo et al. (2015) adopted a new DEA model, game cross-efficiency, which was pioneered by Liang et al. (2008), to measure the efficiency of decision-making units (DMUs) and rank them in a competitive environment; it has been proved to be an effective method in this situation. Until now game cross-efficiency has been mainly applied in studies about sporting events and has never been involved in the studies regarding the power industry.

Measuring efficiency without considering competition among provinces does not seem to provide an equitable score for efficiency benchmarking and comparisons. Hence, we adopt the game cross-efficiency model to measure the environmental performance and give a specific rank of the generation sectors in a competitive power market. Compared to basic DEA, game cross-efficiency follows the peer evaluation concept of cross-efficiency in view of the similar features of the provincial generation sectors. In common with branches, peer evaluation can better reflect the relative environmental performance among provinces. The efficiency values and rankings obtained from game cross-efficiency can properly reflect the competitiveness of the provincial generation sectors. For the determinants analysis the previous studies mainly used Tobit regression (Fleishman et al., 2009; Zhao et al., 2014; Zhao et al., 2015; Zhou et al., 2013), neglecting the endogenous problem in the variables when the dependent variables were obtained from DEA; in particular, the lagged independent variable in the regression model can lead to the endogenous problem because of the correlation between the independent variable and the error term (Fan et al., 2015). To avoid this problem, some studies adopted the SGMM estimator in the second step (Chen and Golley, 2014; Fan et al., 2015). Meanwhile, SGMM is suitable for situations with “small T, large N” panels, meaning few time periods and many individuals (Roodman, 2006). To the best of our knowledge, this study is the first attempt to adopt game cross-efficiency approach in the electricity industry. Also, we believe that it is the first time that SGMM has been used to analyze the determinants of the Chinese generation sector’s environmental efficiency.

3. Methodology

In this section we first introduce game cross-efficiency, which is used to measure the environmental efficiency of the generation sector in China, and we then introduce SGMM to analyze the influence factors.

3.1 The game cross-efficiency method

DEA is a non-parameter linear programming technique that is used to assess the relative efficiency of DMUs. However, the basic DEA method groups the DMUs into two sets: those that are efficient and those that are inefficient. This method cannot discriminate further, and it is apt to benefit itself in the choice of weight (Adler et al., 2002). The decision-makers are often interested in a complete ranking in order to refine the efficiency, and DEA cross-efficiency is commonly used among the different ranking methods (Liu et al., 2017). This approach was originated by Sexton et al. (1986), and further developed by Doyle and Green (1994). They argued that cross-efficiency is a democratic process with less of the arbitrariness of additional weight restrictions.

Supposing that there are n DMUs, the cross-efficiency method simply calculates the efficiency score of each DMU n times using the optimal weights evaluated by the n linear programming and then averages the results to get an average cross-efficiency score. It can avoid the disadvantages of basic DEA by both self and peer evaluation, whereas the cross-efficiency score may not be unique. To eliminate the non-uniqueness of cross-efficiency scores, aggressive and benevolent strategies have been proposed as secondary goals by minimizing or maximizing other DMU's efficiency values at a second level. The way the weight is chosen is affected by the bias of the decision makers, and this will affect the objectivity of the evaluation results to some extent. In addition, each DMU is not independent but competes with others directly or indirectly in many cases. Liang et al. (2008) proposed a game cross-efficiency model based on the idea of cross-efficiency using game theoretic constructs, and it has been proved that this model can get a unique Nash equilibrium solution.

In a competitive electricity market each provincial generation sector can be treated as a competitor (i.e. the DMU in a DEA model) with m inputs and s outputs, then $x_{ij}\left(i=1,2,\cdots,m\right)$ and $y_{rj}(r=1,2,\cdots,s)$ represent the i th input and r th output of $DMU_j\left(j=1,2,\cdots,n\right)$. The game cross-efficiency model is given as follows:

$$\begin{aligned}
Max \quad & \sum_{r=1}^{s}\mu_{rj}^{d}y_{rj} \\
s.t. \quad & \sum_{i=1}^{m}\omega_{ij}^{d}x_{il}-\sum_{r=1}^{s}\mu_{rj}^{d}y_{rl}\geq 0, \quad l=1,2,\ldots,n, \\
& \sum_{i=1}^{m}\omega_{ij}^{d}x_{ij}=1, \\
& \alpha_{d}\times\sum_{i=1}^{m}\omega_{ij}^{d}x_{id}-\sum_{r=1}^{s}\mu_{rj}^{d}y_{rd}\leq 0, \\
& \omega_{ij}^{d}\geq 0, \quad i=1,2,\ldots,m, \\
& \mu_{rj}^{d}\geq 0, \quad r=1,2,\ldots,s.
\end{aligned} \tag{1}$$

where α_d is a parameter with an initial value given by the average original cross-efficiency of

DMU_d, and finally it converges to the best (average) game cross-efficiency score; $\alpha_d \times \sum_{i=1}^{m} \omega_{ij}^d x_{id} - \sum_{r=1}^{s} \mu_{rj}^d y_{rd} \le 0$ ensures that, for each competing DMU_j, a multiplier bundle to optimize the efficiency score for j is determined with the additional constraint that the resulting score for d should be at or above d's estimated best performance. Therefore, this approach can be regarded as a form of a generalized benevolent approach.

For each DMU_j, Model (1) is solved n times, once for each $d = 1, 2, \cdots, n$, and for each d, it holds the constraint $\sum_{i=1}^{m} \omega_{ij}^d x_{ij} = 1$ for $DMU_j \left(j = 1, 2, \cdots, n \right)$. Hence, the game d-cross-efficiency score for each DMU_j can be defined as follows:

$$\alpha_{dj} = \frac{\sum_{r=1}^{s} \mu_{rj}^d y_{rj}}{\sum_{i=1}^{m} \omega_{ij}^d x_{ij}}, \qquad d = 1, 2, \cdots, n, \tag{2}$$

where μ_{rj}^d and ω_{ij}^d are the optimal weights for $x_{ij} \left(i = 1, 2, \cdots, m \right)$ and $y_{rj} (r = 1, 2, \cdots, s)$, respectively, in Model (1). Then the average game cross-efficiency score of DMU_j is:

$$\alpha_j = \frac{1}{n} \sum_{d=1}^{n} \sum_{r=1}^{s} \mu_{rj}^{d*} \left(\alpha_d \right) y_{rj} \tag{3}$$

In this study we aim to evaluate the whole performance of the generation sector. As well as the operational performance, it is also necessary to take into account some byproducts that have an adverse effect on the environment.[9] In this case we incorporated undesirable outputs into the game cross-efficiency model to maximize the reduction of CO_2 emissions when maximizing the power generated. Scheel (2001) summarized the DEA approaches with undesirable outputs and classified them as direct and indirect approaches. The indirect approaches use a monotone decreasing function f to transform the values of undesirable outputs into "normal" outputs, since after transformation increasing the transformed data means decreasing the original undesirable outputs. We follow the indirect approaches and apply the conversion function

[9] This study mainly considers the environmental efficiency of the generation sector under the constraints of carbon abatement, and so CO_2 is treated as the only undesirable output.

$f\left(U\right)=-U$, where U represents the set of undesirable outputs, then we perform the following mathematical programming for each DMU_j with undesirable outputs:

$$
\begin{aligned}
Max \quad & \sum_{r=1}^{s}\mu_{rj}^{d}y_{rj}-\sum_{k=1}^{q}\nu_{kj}^{d}b_{kj} \\
s.t. \quad & \sum_{i=1}^{m}\omega_{ij}^{d}x_{il}-\left(\sum_{r=1}^{s}\mu_{rj}^{d}y_{rl}-\sum_{k=1}^{q}\nu_{kj}^{d}b_{kl}\right)\geq 0, \quad l=1,2,\ldots,n, \\
& \sum_{i=1}^{m}\omega_{ij}^{d}x_{ij}=1, \\
& \alpha_d\times\sum_{i=1}^{m}\omega_{ij}^{d}x_{id}-\left(\sum_{r=1}^{s}\mu_{rj}^{d}y_{rd}-\sum_{k=1}^{q}\nu_{kj}^{d}b_{kd}\right)\leq 0, \\
& \omega_{ij}^{d}\geq 0, \quad i=1,2,\ldots,m, \\
& \mu_{rj}^{d}\geq 0, \quad r=1,2,\ldots,s, \\
& \nu_{kj}^{d}\geq 0, \quad k=1,2,\ldots,q.
\end{aligned}
\tag{4}
$$

where $b_{kj}\left(k=1,2,\cdots q\right)$ represents the k th undesirable outputs of $DMU_j\left(j=1,2,\cdots,n\right)$, and ν is the corresponding weighting vector; the other settings are the same as for Model (1). In Model (4) the transformed undesirable outputs are handled as desirable outputs in the mathematical programming, and we can find that this treatment is able to achieve the expected results to minimize the undesirable outputs when maximizing the desirable outputs.

The game *d*-cross-efficiency of DMU_j in this situation can be defined as follows:

$$
\alpha_{dj}=\frac{\sum_{r=1}^{s}\mu_{rj}^{d}y_{rj}-\sum_{k=1}^{q}\nu_{kj}^{d}b_{kj}}{\sum_{i=1}^{m}\omega_{ij}^{d}x_{ij}}, \quad d=1,2,\ldots,n,
\tag{5}
$$

and the average game cross environmental efficiency score of DMU_j is：

$$
\alpha_j=\frac{1}{n}\sum_{d=1}^{n}\left(\sum_{r=1}^{s}\mu_{rj}^{d*}\left(\alpha_d\right)y_{rj}-\sum_{k=1}^{q}\nu_{kj}^{d*}\left(\alpha_d\right)b_{kj}\right)
\tag{6}
$$

3.2 Driving factor analysis on SGMM

To avoid unobserved heterogeneity, omitted variable bias, and measurement errors when using the pooled ordinary least squares and fixed effect method, we use SGMM to analyze the driving factor of environmental efficiency (Zhang et al., 2017). Arellano and Bond (1991) first proposed the difference GMM (DGMM) estimator, in which the first difference taking the levels of past values as instruments is used. The SGMM estimator, an improvement of the DGMM estimator, was developed by Arellano and Bover (1995) and Blundell and Bond (1998). Compared to DGMM the SGMM allows more instruments to be introduced, thereby significantly improving the efficiency (Roodman, 2006). SGMM is a dynamic panel regression model that is suitable for "small T, large N" panels, which aligns nicely with this study of China's generation sectors with many provinces but a relatively short span. Meanwhile, the efficiency results achieved from game cross-efficiency and the explanatory variables might not be strictly exogenous. Thus, the SGMM is employed to do a second step analysis.

The SGMM model can be specified as follows:

$$E_{i,t} = \alpha + \beta_0 E_{i,t-1} + \beta X_{i,t} + \mu_{i,t} \quad \textbf{(7)}$$

$$\mu_{i,t} = \nu_i + \varepsilon_{i,t} \quad \textbf{(8)}$$

where $E_{i,t}$ represents the environmental efficiency of the i th province in year t, which is obtained from the game cross-efficiency model, and $E_{i,t-1}$ represents the lagged dependent variable. The lagged dependent variable is used as an explanatory variable to exclude the history of the other independent variables so that the results represent the influence in the current period. $X_{i,t}$ refers to the vector of different environmental explanatory variables, and $\mu_{i,t}$ is an error term representing the individual (provincial) influence, including the time-invariant individual characteristics ν_i and observed specific influence $\varepsilon_{i,t}$.

Several tests need to be carried out for SGMM: first, we need to use the Arellano–Bond test to test whether the residual series autocorrelation exists, and the null hypothesis is that the residual series has no autocorrelation. SGMM is insensitive to first-order autocorrelation, but no significant second-order autocorrelation in the residual series should be satisfied, because such an autocorrelation will make the lags of endogenous variables inappropriate instruments. Besides, it is necessary to test the instrument validity using the Sargan (Sargan, 1958) or Hansen (Hansen, 1982) tests. In this study the two tests are performed simultaneously to ensure the validity of the results, and their null hypotheses indicate that these instrumental variables are valid.

4. Empirical study

4.1 Data

In this section we adopt game cross-efficiency to calculate the environmental efficiency of the provincial generation sector from 2003 to 2013. This study includes 30 provinces, and does not cover Taiwan, Hong Kong, Macao, and Tibet. We selected 2003 as the starting year of the study since the competitive mechanism was introduced after the reform of the Plant-Grid Separation in 2002. The non-energy inputs include capital and the labor force. Capital is measured in terms of the installed generating capacity (Bi et al., 2014; Mou, 2014; Zhou et al., 2013), which is derived from China's Electric Power Industry Statistics Compiled. For the labor force, previous studies usually took the labor force in the power and thermal generation and supply industry as proxy (Bi et al., 2014; Lin and Yang, 2014). This treatment does not accurately reflect the input of the labor force in the generation sector. Hence, we collect the annual average of the total number of employees in the provincial generation sector from the Macro China Industry Database,[10] the

[10] http://mcid.macrochina.com.cn/.

statistical caliber of which is consistent with the rest of the inputs and outputs data. But because data in this Database ended in 2013, the time span for our research is set to range from 2003 to 2013. The energy input is total energy consumption, which is calculated on standard coal equivalent and is gathered from the China Energy Statistical Yearbook 2004–2014. Annual net electricity generated, which is collected from China's Electric Power Industry Statistics Compiled 2004–2014, is used as the single desirable output. Although some studies have used SO_2, $NO_{x,}$ and soot as undesirable outputs (Bi et al., 2014; Zhou et al., 2013), other studies have mainly been concerned about carbon emissions, so they have chosen CO_2 emissions as the undesirable output (Du and Mao, 2015; Lin and Yang, 2014; Sueyoshi and Goto, 2011). This study adopts CO_2 emissions as the only undesirable output, since our focus is on the performance level under the pressure for carbon emissions reduction. Because the data for CO_2 emissions are not directly available, so we multiplied the various types of fossil fuels consumed by the power generation sectors by the corresponding CO_2 emission coefficients to get the emission data required; the CO_2 emission factors are derived from the IPCC (2006). **Table 1** shows the basic statistics of inputs and outputs indicators.

[Insert Table 1 about here]

4.2 Results

The efficiency scores and statistics of the rankings obtained from the game cross-efficiency model are shown in **Table 2**. The results show that this method has an excellent discrimination for efficiency and can sort the results in a specific order. Meanwhile, **Fig. 1** displays the statistical properties of the environmental efficiency in different provinces, and we can see that the variation range of the efficiency value shrinks at first and then expands and shrinks again. The ceiling of the environmental efficiency calculated by game cross-efficiency is one; thus, the variation range is determined by the floor. If we combine the efficiency and electricity supply–demand, we can draw the conclusion that the efficiency value is relatively high during the periods of power shortage and vice versa. When the power supply is insufficient, all the provinces must be fully productive to get a higher level of efficiency, even if the technical level and management level are limited, whereas the differences in the efficiency across provinces widened. In brief, the game cross-efficiency can exactly capture the influence of the external situation and reflect the competitiveness of the power system. It has proved to be an extremely effective method to analyze the efficiency of the power system in a competitive market.

Of all the 330 samples, 37.2% of the provinces stay at more than 0.9 in terms of environmental efficiency, and the proportion of provinces that are more than 0.75 reaches 89.7%, indicating that the efficiencies of the generation sector in most provinces are not very different. As can be seen from **Fig. 2**, the average environmental efficiency of all provinces changes from 0.838 in 2003 to 0.875 in 2008 before slipping to 0.852 in 2009. Another low point appears in 2012, and then there is a rise to 0.883 in 2013, showing a rising trend in fluctuations. After the implementation of the Plant-Grid Separation, the power-generation enterprises had to participate in the market competition, which mobilized the enthusiasm for production and enhanced the power efficiency. In addition, the high GDP growth rate of more than 10%, along with the continuously increasing electricity demand, facilitated the improvement of capacity utilization in the power industry and further promoted the efficiency of the industry. However, after the outbreak of the U.S. subprime mortgage crisis, the economies of various countries were generally adversely affected due to economic globalization, and China was no exception. At the end of 2008 economic growth began to decline, and the electricity consumption growth rate dropped from the previous year’s 14.4% to 5.6%. Despite the introduction of the country's four trillion yuan economic stimulus plan, China's economic growth was still unavoidably affected, and the electricity consumption growth rate rapidly declined, so the average production efficiency of the power industry fell to its lowest value again. With economic growth back on track, the average efficiency has gradually picked up. However, the average efficiency in 2012 reduces to another low point. Not surprisingly, the GDP growth rate in 2012 is lower than before. Based on the aforementioned analysis, we can find that the efficiency values have the same trend as the economic growth rate with a certain lag.

It is noteworthy that there are outliers below normal levels during 2011 to 2013. Jilin has abnormal values for these three years, and the abnormal value in 2012 also includes Heilongjiang. The outliers indicate that the efficiency of each of these provinces has a large gap to the normal level, and Jilin happens to be the area with the most severe wind power curtailment in these three years (the specific analysis is given in Section 5.1). Several outliers occurred only after 2011 when there was an oversupply of electricity. This suggests that an unreasonable allocation of capacity not only failed to improve efficiency but widened the gap with other provinces. In addition, technological progress leads to the improvement of the overall efficiency, and this also widens the gap between the backward provinces and the frontier. In 2005–2008, when the tensions of power supply had emerged, the distribution of efficiency values is compact even though the lowest value exceeds 0.7. The first quartiles show an overall increasing trend, and they are over 0.8 in the research period except for the first two years; the third quartiles remain basically stable and have been fluctuating around 0.92; the medians change very slightly, ranging from 0.86 to 0.89. All of these three indicators are increasing during 2009–2013 except for 2012. The gap between the first and third quartiles narrows, indicating that the efficiencies of the provinces are in a convergence trend, and the differences among the provinces are gradually reducing. This implies that the corresponding measures, such as eliminating outdated power generation equipment, have achieved their initial results under the constraints of both energy saving and emission abatement.

[Insert Table 2 about here]

[Insert Fig. 1 about here]

[Insert Fig. 2 about here]

5. Discussions

5.1 Environmental efficiency gaps

In order to reflect the socio-economic development level of different regions more scientifically and better formulate regional development policies, all the provinces are usually classified into four regions: the eastern, middle, western, and northeastern regions.[11] In this study, in accordance with this regional division, we calculate the average values of the environment efficiencies and rankings of the provinces in the eastern, middle, western, and northeastern regions to explore the differences among them (**Table 3**) and present the average ranking change for different regions (**Fig. 3**). Overall, all the statistical data, including the minimum, average, and

[11] The eastern region includes: Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; Central: Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan; Western: Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang; Northeast: Liaoning, Jilin and Heilongjiang.

quartile of efficiency values, are the highest in the eastern region, followed by the west and the middle, and the lowest are in the northeast. This suggests that the generation sectors in the eastern region have the best environmental performance, with the average efficiency of 0.89 and the maximum value of over 0.9 in that region. Slightly unexpectedly, the performance of the generation sectors in the western region is better than that in the middle region, and the worst environmental performance is in the northeastern region. Even the minimum value of the eastern region is more than the maximum value of the northeastern region.

[Please Insert Table 3 about here]

[Insert Fig. 3 about here]

The differences in the environmental performance of the generation sectors across regions are closely related to the level of regional economic development. The eastern region was the first to carry out the process of reform and opening up and now is the most developed area in China. The economies of the middle and western regions are relatively backward, but the implementation of the “Rising of Middle China” and “Great Western development” strategies have promoted the economic development of the middle and western regions and narrowed the gap between them. The northeastern region, as the old industrial base, relies heavily on the petroleum and coal industries. In recent years the traditional heavy industries have suffered from serious overcapacities, and as they are the main power consumers, the economic downtrend is the most obvious in the northeastern region. This has resulted in the low efficiency of the generation sector in that region. The developed regions are in the better position to retrofit outdated capacity and to innovate and install advanced CO_2 emission abatement technologies (Bian et al., 2013). For example, there are 24 ultra-supercritical thermal power units over 1000 MW that were installed by

2013, of which 22 are located in Zhejiang, Shandong, Jiangsu, Guangdong, Tianjin, and other eastern provinces.[12] There are 139 thermal power units with an installed capacity of more than 600 MW in the eastern region, 49 in the western region, 42 in the middle region, and only 14 in the northeastern region.[13] This is why the environmental efficiencies of the eastern provinces, such as Zhejiang and Jiangsu, have improved in recent years. In addition, the proportion of tertiary industries tends to be relatively large in the developed areas, and since the electricity consumption of tertiary industries is much less than that of secondary industries, it has only a slight influence on the generation sector.

Moreover, the generation structure has large effects on the environmental efficiency. Hydropower, wind power, and other clean energy does not produce carbon emissions, so the areas where clean energy accounts for a large proportion of the generation structure usually have a higher environmental efficiency (Bi et al., 2014; Xie et al., 2012). The economic development of the western region is close to or even lower than that of the middle region, but the overall efficiency is slightly higher than that of the middle region, which is due to its more optimized power structure. Because of its special geographic and climatic conditions, the western region is abundant in water and wind resources, so the proportion of thermal power is relatively low. Taking Qinghai as an example, more than 70% of the power generated come from hydropower, which is rare in China where the energy mix is dominated by coal. Thus, the environmental performance of Qinghai province has ranked first in the country on several occasions. There are 31 hydropower plants with an installed capacity of more than 1000 MW in the western region, 9 and 10 in eastern and middle regions, respectively, and only two in the northeast. A similar situation has occurred in

[12] See China's Electric Power Industry Statistics Compiled 2014.
[13] See China Electric Power Yearbook 2014.

the eastern region; the proportion of thermal power in Jiangsu has declined due to the promotion of renewable energy and "green power" since the 11^{th} Five-Year Plan period, which has led to a very high rise in environmental efficiency after 2008.

[Please Insert Fig. 4 about here]

Furthermore, the power supply and demand situation is a crucial factor affecting the environmental efficiency of the generation sector. In the provinces with excess power generation, especially in the years with more frequent instances of wind power curtailment, the efficiency is generally low (Xie et al., 2012). From the ranking of provinces with high wind power curtailment rates in recent years **(Fig. 4)**, we can see that almost all the provinces are in a declining trend, and most provinces have fallen significantly. The environmental efficiency values of the aforementioned provinces were lower than the national average during the same period except for only a few provinces in the earlier years. Because of the outbreak of the economic crisis in 2008, China has implemented a four trillion yuan investment plan, which has stimulated power investment in most of the provinces, especially wind power investment. However, it is hard for wind power to provide for peak loads or to be used for heating, so the waste is more serious in winter when wind resources are abundant; at the same time, the economic downturn caused industrial electricity consumption to decrease. With the increase in supply and decrease in demand, it has been difficult to absorb the power generated, which explains the decline in efficiency from 2008 for most of the provinces mentioned previously. A province with a power surplus can only sell its electricity to large enterprises at a very low price or send it to other provinces; as a result, the power generation sectors of these provinces are at a disadvantage in a competitive market and their efficiencies and rankings are lower than others. The environmental efficiency changes resulting from the power supply-demand situation are not only reflected at the provincial level but also at the national level, which is discussed also in Section 4.2.

5.2 Determinants of environmental efficiency

In Section 5.1 we briefly analyzed the reasons behind the environmental efficiency changes of the generation sectors. Furthermore, in-depth research is warranted to identify the determinants of environmental performance, thereby enabling us to put forward some targeted improvement measures. From the aforementioned analysis it can be concluded that the level of economic development, the generation structure, and the power supply–demand situation may affect the overall performance of a power generation sector. In addition, the overall performance may be influenced by the scale of the generation enterprises and the industrial structure. Accordingly, some relevant variables are introduced in this section and the detailed explanations are as follows.

Generation structure (GS): in the power industry there are large differences in efficiency among different modes of electricity generation. China has a coal-dominant energy mix on the whole, but there are obviously differences in the generation structure between different provinces. This is a major concern in the studies regarding electricity efficiency (Lin and Yang, 2014; Zhou et al., 2013).

Regional gross domestic product (RGDP): based on the analysis in Section 5.1 and other research results (Bi et al., 2014; Zhou et al., 2013), the regional economic development, represented by regional gross domestic product (RGDP) in this paper, can affect the operational and environmental efficiency of the power industry. In general, the developed regions have more advantages in R & D and equipment renewal than the less developed regions.

Average firm size (AFS): many studies have advocated the unit scale as an indicator of the plant level (Du and Mao, 2015; Yang and Pollitt, 2009). In terms of the provincial level, Lin and Yang (2014) proposed industry concentration as a substitute for the average scale of single enterprises in the electricity industry, and the higher the industry concentration is, the larger the average scale of single enterprise is. In this study we adopt a similar concept but we name it the average firm size.

Capacity utilization rate (CUR): considering the oversupply of electricity and the increasing generation capacity in recent years, it is essential to explore the impact of capacity utilization on the competitiveness of the generation sector. We propose the capacity utilization rate to indicate whether the generation capacity is fully utilized, and the higher it is, the less waste there is in the installed capacity.

Industry structure (IS): the electricity consumption of the primary, secondary, and tertiary industries are quite different, especially in the secondary industry that includes a lot of enterprises with high energy consumption. The electricity consumption will affect the electricity absorption at the provincial level, which is expected to influence the environmental efficiency of the generation sector.

The detailed definitions and symbols of the regression variables are shown in **Table 4**. The data are collected from China's Electric Power Industry Statistics Compiled, National Bureau of Statistics, and Macro China Industry Database.[14]

[Insert Table 4 about here]

In order to unify the dimension, the aforementioned variables are normalized, and we run the

[14] http://data.stats.gov.cn/

following regression:

$$E_{i,t} = \alpha + \beta_0 E_{i,t-1} + \beta_1 GS_{i,t} + \beta_2 RGDP_{i,t} + \beta_3 AFS_{i,t} + \beta_4 CUR_{i,t} + \beta_5 IS_{i,t} + v_i + \varepsilon_{i,t} \qquad \textbf{(9)}$$

According to Eq. (9) this study estimates the determinants of China's power industry environmental efficiency in 30 provinces from 2003 to 2013. The results are shown in **Table 5.**[15] The results of the tests are also reported: the results of the Arellano–Bond test indicate that the error terms are significantly first-order serial correlated at the 1% level but not second-order serial correlated, which satisfies the hypothesis of SGMM; both the Sargan and Hansen tests accept the null hypothesis due to the insignificant P-values at the 10% level, demonstrating that the instrumental variables are valid; the Wald chi-square test confirms the overall significance of the regression specification.

[Insert Table 5 about here]

As Table 5 shows, the external factors vary among regions, and they do affect the environmental efficiency of the generation sector. The coefficient of GS is negative at the 1% level significantly, implying a negative correlation between the environmental efficiency and GS. Obviously, the environmental efficiency of the generation sector has a strong relationship with its energy structure, and thermal power contributes to the main CO_2 emissions in the power industry; thus, the environmental efficiency declines with the increase in the proportion of thermal power.

$RGDP$, AFS, CUR, and IS have positive relationships with E. E increases by 0.166% as $RGDP$ increases by 1%. The trend of the energy demand, especially the power demand, is often consistent with the change in GDP. The more developed provinces have a greater energy demand, so it is more necessary to improve their electricity efficiency to meet the increased

[15] See appendix A for the correlation coefficient matrix.

demand (Chen et al., 2013). Meanwhile, the demand for environmental quality is relatively high in the developed provinces, and they have both driving force and abilities to introduce or develop the advanced technology; provinces with larger AFS usually have a more optimized resource integration and eliminate outdated power units and launch advanced ones in a timely manner. In other words, AFS can represent the technical level to some extent. Outdated small thermal power units are energy inefficient and heavy polluting, so the policy of "developing large units and suppressing small ones" carried out in the electricity industry is conducive to the improvement of the environmental performance. As for CUR, the efficiency is higher if the generation capacity is fully used and less wasted, as expected, and too much capacity may lead to low utilization rates and over competitiveness in the generation sector. As we can see from **Table 5**, E increases by approximately 0.266% as CUR increases by 1%. Surprisingly, the IS, which refers to the proportion of secondary industry, has a positive role in promoting the efficiency of the generation sector. This is mainly because China is still in the post-industrialization period, so economic growth is largely driven by industrial expansion, and the power consumption required for this is more concentrated in the secondary industry, indicating that the provinces in which the secondary industry accounted for a higher proportion have scale advantages in electricity consumption and are more balanced in terms of power supply-demand. The results also show that there is no direct correlation between the efficiency of the generation sector and the growth of tertiary industry.

GS, AFS, and IS are all of statistical significance at the 1% level, and the coefficients have slight differences. The E increases by approximately 0.153% and 0.163%, respectively, as AFS and IS increase by 1%, and decreases by 0.147% as GS increases by 1%. Comparatively speaking, IS has a greater impact on the environmental efficiency, implying that the efficiency revealed by the game cross-efficiency model is more affected by the power supply situation than other factors, and a power surplus always detracts from the operations of low-efficiency provinces. This is because the provinces with excess power generated do not prevail in the increasingly competitive electricity market. There is no doubt that an appropriate increase in the proportion of clean energy generation will improve environmental efficiency, but an overreliance on clean power may damage the stability of the grids and do harm to the development of the economy.

Remarkably, the coefficient of $E_{i,t-1}$ is significantly negative, indicating the negative relationship between the environmental efficiencies over two adjacent periods. Due to the constraints of technical bottlenecks and output growth targets, it is difficult to continuously reduce a great amount of CO_2 emissions in a short time, which make improvement of the environmental efficiency slow and tortuous (Fan et al., 2015). Meanwhile, phased emission reduction targets may heavily incentivize the local governments to reduce their emissions in the short term; enterprises do not have any impetus to carry out sustained emission-reduction activities under the existing policy.

6. Conclusions and policy suggestions

6.1 Conclusions

This study employs a game cross-efficiency model to measure the environmental efficiency of China's generation sector. The competitiveness among provinces is considered for the period from 2003 to 2013. Furthermore, it has adopted the SGMM method to eliminate the endogenous problem among the provincial factors affecting their performance and to analyze the determinants of environmental efficiency. We reach several conclusions as follows.

Our study shows that incorporating game cross-efficiency with SGMM is an effective approach to measure the environmental efficiency of the generation industry. The game cross-efficiency results combining self-evaluation with peer-evaluation performed well in terms of discrimination and objectiveness. The number of efficient DMUs decreased significantly and the competitiveness is reflected in the results. In contrast to other regression models, the SGMM may eliminate the influence of endogenous factors on efficiency. It is foreseeable to indicate that the competitiveness in the generation sector will be strengthened with the deepening of reforms, and this approach may gain popularity in not only the generation sector but also the transmission and distribution sectors.

Even though the efficiency gaps among regions decrease, it is hard to achieve simultaneous nationwide improvement of environmental efficiency. There is a relatively large amount of room to promote the efficiency of China's generation industry. The average environmental efficiencies were less than 0.88 during 2003–2011; some efficiencies were even lower than 0.6, and there are abnormal efficiencies below the average during 2011–2013. In addition, the performance of the generation sector is heavily dependent on the power supply situation. A power shortage always leads to a smaller gap, whereas a power surplus always makes the operation of low efficiency provinces worse.

Our results suggest that $RGDP$, AFS, CUR, and IS are conducive to improving the environmental efficiency significantly, whereas GS is negatively related to the efficiency. The power consumption is determined by $RGDP$ and IS to a great extent, which are the main drivers beyond the power system control for efficiency improvement. The AFS is an important indicator for technology, while *CUR* reflects the utilization rate of equipment, and these are also driving forces for performance improvement that the industry may adopt measures to improve. In addition, the development of clean energy may improve the environmental efficiency of the generation sector due to its significant contribution in reducing emissions.

6.2 Policy Implications

Based on the aforementioned analysis, we suggest the following measures to improve the environmental efficiency of the generation sectors.

First, it is urgent to adjust the efficiency evaluation mechanism to improve the environmental performance of the generation industry. Comparatively, both power system development, energy-saving, and emissions reduction are long term tasks. It is not advisable to adopt all possible measures to achieve the goals at the cost of sustainable development. A well-designed power management mechanism taking long-term and short-term factors as well as regional differences into consideration may help to achieve the sound development of the generation sector. For the middle and western areas of underdeveloped economies, favorable policies for investment, as well as subsidies, are effective measures to accelerate the development of green power, which in turn may narrow the differences in environmental performance for the generation sectors.

Second, the power mix should be adjusted in step with the technology and local economic development. The improvement of the generation structure cannot be simplified to monotonically decrease the thermal power ratio – a balanced and coordinated power system with multiple generation forms could not only fulfill the power demands but also achieve environmental efficiency improvement. There is no doubt that it is important to control the thermal power ratio within a reasonable range for newly installed capacity. Of course, this does not mean that the green power ratio in the power mix should be randomly increased. The incentive policies for clean energy should be weakened in the power-exporting regions and strengthened in the power-importing provinces.

Finally, innovation is an effective measure to improve the environmental efficiency of the generation sector. The average firm size is the main driving factor analyzed in SGMM that the power industry may be able to improve by its own efforts. The introduction of supercritical and ultra-supercritical technologies has resulted in an increase of the average firm size in the thermal power industry and has changed the generation sector fundamentally. On the other hand, stability is one of the main obstacles hindering clean power development. In general, incentive policies for research & development may have better effects than subsidies from a long-term perspective.

However, there are also several aspects needing to be improved. For example, this study has not included other pollutants, such as SO_2 and NO_x, in examining the environmental efficiency of the power industry. In addition, we conducted the analysis with the provincial data rather than the plant level data, which is the actual operator of the generation sectors. Furthermore, the study has not examined the dynamic efficiency of the power industry. These issues will be studied in future research.

Acknowledgments

This work is financially supported by the National Natural Science Foundation of China under grant Nos. 71373172, 71271147, 71431005 and 71373055, the Humanities and Social Science

Planning Fund Project of Ministry of Education under grant No. 15YJA790091 and the Ministry of Housing and Urban-rural Development of China under grant No.11-R1-338.

Appendix A

Table A1.

[Insert Table A1 about here]

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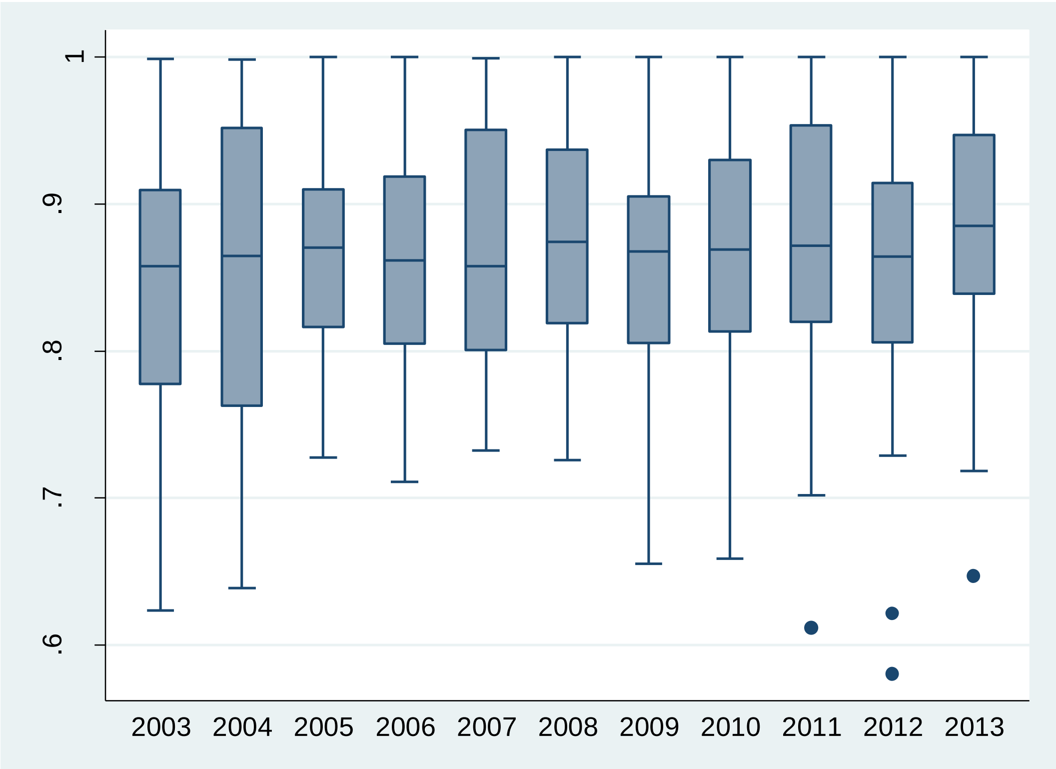

Fig. 1 Statistic properties of environmental efficiency in China's generation sector from 2003 to 2013

Note: The box-chart gives the median, first quartile (x0.25) and third quartile (x0.75) of the data by using the lines in a box in Fig. 1. The interquartile rage (IQR) is calculated by subtracting the first quartile from the third quartile (x0.75 - x0.25). The smallest, largest and the average values line inside the figure with symbols.

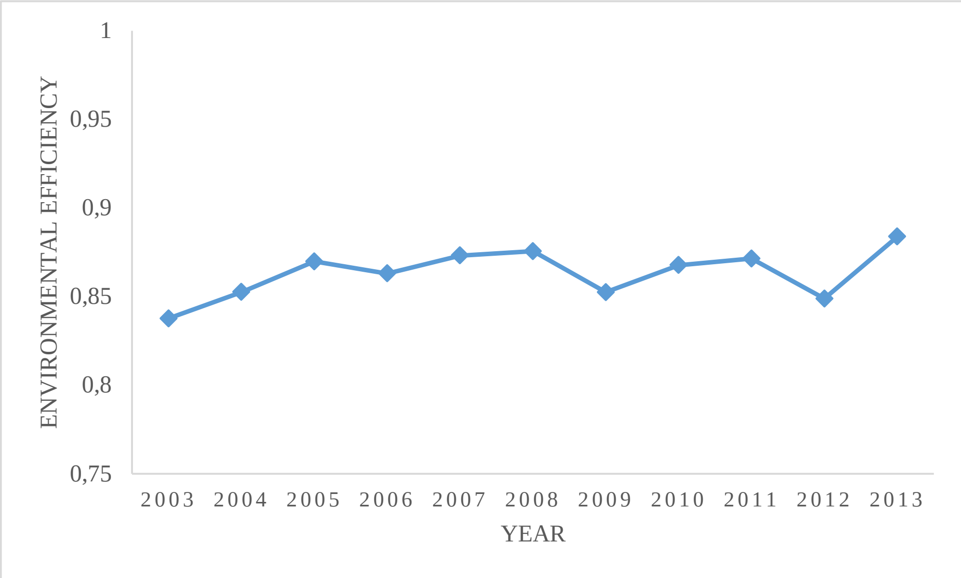

Fig. 2 The average environmental efficiencies of all provinces

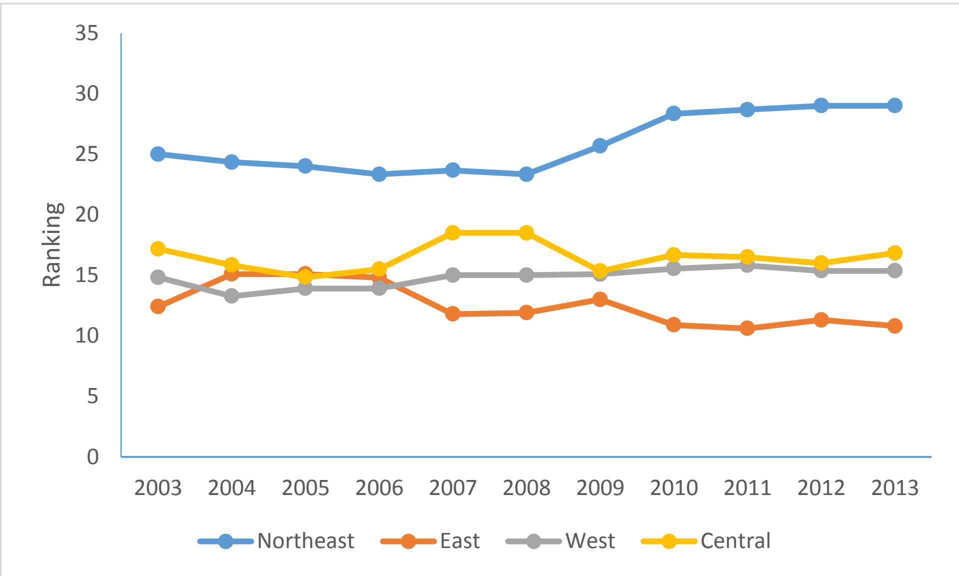

Fig. 3 The average ranking of regions

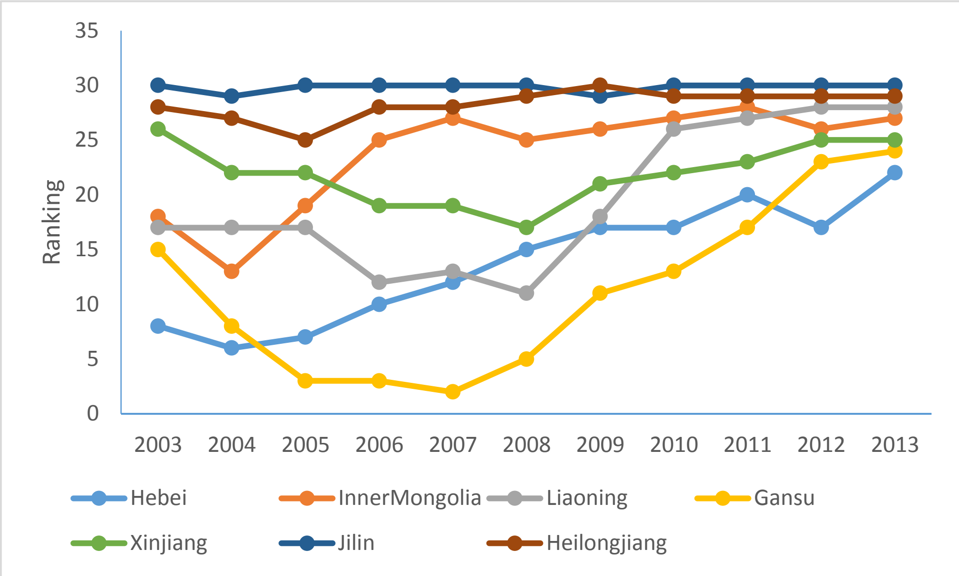

Fig. 4 The ranking of provinces with high wind power curtailment rate

Table 1 Summary statistics of inputs and outputs

Variable	Units	Max	Min	S.D.	Mean
Labor	P	120395	3020.25	24075.77	34831.89
Installed capacity	10^4 kW	8598	175.96	1918.604	2661.684
Energy	10^4 tce	14802.01	142.229	2942.126	3544.792
Power generation	10^2 MkW h	4405	59.42	880.8375	1185.744
CO_2	10^4 t	39711.12	381.7948	7635.239	9242.663

Table 2 Efficiency and ranking of provinces 2003-2013

Province	Efficiency (Year)											Ranking		
	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	Mean	Max	Min
Beijing	0.777	0.735	0.782	0.78	0.858	0.851	0.835	0.847	0.867	0.814	0.919	20.5	27	13
Tianjin	0.999	0.993	1.000	0.968	0.999	0.965	0.805	0.910	0.940	0.907	0.947	7.1	23	1
Hebei	0.909	0.957	0.935	0.899	0.913	0.878	0.847	0.859	0.841	0.84	0.840	13.7	22	6
Shanghai	0.971	0.977	0.946	0.914	0.943	0.937	0.961	0.972	0.991	0.961	0.924	6	12	2
Jiangsu	0.940	0.954	0.872	0.894	0.957	1.000	1.000	1.000	1.000	1.000	1.000	4.6	11	1
Zhejiang	0.870	0.770	0.785	0.805	0.864	0.870	0.902	0.966	0.954	0.965	0.997	12.6	26	2
Fujian	0.884	0.808	0.906	0.919	0.939	0.908	0.871	0.906	0.925	0.902	0.929	11.6	19	8
Shandong	0.759	0.827	0.845	0.823	0.854	0.881	0.883	0.876	0.823	0.803	0.883	18.5	24	12
Guangdong	0.935	0.859	0.902	0.929	0.941	0.935	0.916	0.945	0.982	0.914	0.883	9.2	17	3
Hainan	0.670	0.639	0.741	0.724	0.801	0.866	0.794	0.858	0.892	0.854	0.958	21.4	30	6
InnerMongolia	0.819	0.880	0.850	0.789	0.786	0.780	0.776	0.750	0.720	0.763	0.807	23.7	28	13
Guangxi	0.964	0.755	0.816	0.878	0.797	0.852	0.866	0.927	0.876	0.836	0.887	16.5	25	4
Chongqing	0.806	0.87	0.857	0.770	0.819	0.804	0.810	0.854	0.818	0.810	0.809	21.5	26	15
Sichuan	0.872	0.875	0.904	0.870	0.855	0.825	0.875	0.944	0.974	0.885	0.982	11.9	22	3
Guizhou	0.870	0.922	0.880	0.877	0.951	0.944	0.968	0.862	0.824	0.899	0.874	12.5	21	3
Yunnan	0.861	0.998	0.910	0.845	0.857	0.899	0.870	0.923	0.936	0.903	0.976	10.7	17	1
Shaanxi	0.806	0.899	0.840	0.838	0.792	0.768	0.747	0.805	0.904	0.883	0.888	19.5	27	12
Gansu	0.859	0.952	0.987	0.987	0.999	0.971	0.890	0.903	0.863	0.806	0.817	11.3	24	2
Qinghai	0.787	0.763	0.906	1.000	0.990	0.990	0.968	0.983	0.966	0.983	0.972	7.5	23	1
Ningxia	0.999	0.996	0.979	1.000	0.998	0.986	0.905	0.844	0.919	0.921	0.950	6.2	21	1
Xinjiang	0.722	0.766	0.829	0.824	0.847	0.868	0.822	0.825	0.819	0.785	0.813	21.9	26	17

Province	Efficiency(Year)											Ranking		
	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	Mean	Max	Min
Shanxi	0.944	0.931	0.935	0.940	0.950	0.919	0.894	0.896	0.851	0.875	0.871	11.3	21	5
Anhui	0.896	0.982	0.884	0.853	0.827	0.835	0.911	0.930	0.975	0.918	0.935	10.7	21	4
Jiangxi	0.710	0.713	0.754	0.818	0.738	0.759	0.707	0.743	0.817	0.818	0.871	25.5	29	19
Henan	0.791	0.762	0.798	0.789	0.801	0.819	0.826	0.813	0.852	0.809	0.875	21.8	24	18
Hubei	0.856	0.934	0.996	0.983	0.961	0.994	0.991	0.985	0.955	0.917	0.936	5.9	16	2
Hunan	0.727	0.802	0.868	0.818	0.792	0.765	0.781	0.804	0.800	0.760	0.839	23.8	27	16
Liaoning	0.829	0.845	0.867	0.888	0.877	0.918	0.840	0.763	0.743	0.729	0.767	19.5	28	11
Jilin	0.624	0.693	0.728	0.711	0.732	0.726	0.656	0.659	0.612	0.580	0.647	29.8	30	29
Heilongjiang	0.673	0.719	0.793	0.759	0.754	0.757	0.655	0.681	0.702	0.622	0.718	28.3	30	25

Table 3 Average efficiencies and ranking for regions 2003-2013

Region	Min		1st Qu.		Middle		Mean		3rd Qu.		Max		N
	E	R	E	R	E	R	E	R	E	R	E	R	
East	0.852	10.6	0.871	11.1	0.896	11.9	0.892	12.5	0.911	13.9	0.928	15.1	11
West	0.851	13.3	0.869	14.4	0.879	15	0.875	14.8	0.881	15.4	0.889	15.8	11
Middle	0.821	14.8	0.849	15.7	0.854	16.5	0.857	16.5	0.87	17	0.888	18.5	11
Northeast	0.644	23.3	0.705	23.8	0.717	25	0.735	25.8	0.787	28.5	0.8	29	11

Note: E denotes environmental efficiency and R denotes ranking.

Table 4 Definition of regression variables

Variables	Symbols	Unit	Definition
Environmental efficiency	*E*		gained from game cross-efficiency model
Generation structure	*GS*	%	thermal power generation/total power generation
Region gross domestic product	*RGDP*	10^2 Million Yuan	region gross domestic product of each province
Average firm size	*AFS*	10^3 Yuan	total fixed-asset investment/ number of enterprises
Capacity utilization rate	*CUR*	h/10MW	total generation time/ total installed capacity
Industry structure	*IS*	%	the value-added of the second industry / total value-added of industry

Table 5 Dynamic panel-data estimation, two-step system GMM

Dependent variables	E	
	Coef.	Std. Err.
E_lag1	-0 .602***	0 .083
GS	-0 147***	0 .046
RGDP	0.166*	0.086
AFS	0 .153***	0 .058
CUR	0.266**	0 .133
IS	0.163***	0.061
Constant	1.283***	0. 102
Diagnostic tests	Statistic	p value
AR(1) test	2.76	0.006
AR(2) test	-1.23	0.220
Wald test	100.93	0.000
Sargan test	2.63	0.268
Hansen test	0.42	0.811

Note: * Denotes statistical significance at the 10% level.

** Denotes statistical significance at the 5% level.

*** Denotes statistical significance at the 1% level.

Table A1 Correlation coefficients among independent variables in Eq.(9)

Variable	GS	RGDP	CUR	AFS	IS
GS	1.0000				
RGDP	0.1660	1.0000			
CUR	0.1374	-0.4882	1.0000		
AFS	0.1206	0.2355	-0.1853	1.0000	
IS	0.1221	0.2811	-0.5269	0.0144	1.0000

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