China's Electricity Market Reform and Power Plants Efficiency

Chunbo Ma[a*], Xiaoli Zhao[b], Qian Ma[b] and Yue Zhao[b]

[a]School of Agricultural and Resource Economics, Centre for Environmental Economics and Policy, The University of Western Australia, Crawley, WA 6009, Australia
[b]School of Economics and Management, Institute for Low Carbon Economy and Trade, North China Electric Power University, Beijing, China

*E-mail address: chunbo.ma@uwa.edu.au

07 November 2011
Working Paper 1125
School of Agricultural and Resource Economics
http://www.are.uwa.edu.au

THE UNIVERSITY OF WESTERN AUSTRALIA
Achieve International Excellence

Citation: Ma, Chunbo, X.L. Zhao, Q. Ma and Y. Zhao. (2011) *China's Electricity Market Reform and Power Plants Efficiency*, Working Paper 1125, School of Agricultural and Resource Economics, University of Western Australia, Crawley, Australia.

China's Electricity Market Reform and Power Plants Efficiency

Abstract

In the past three decades, Chinese electricity industry has experienced a series of regulatory reforms serving different purposes at different stages. In 2002, the former vertically integrated electricity utility - the State Power Corporation (SPC) – was divested and the generation sector was separated from the transmission and distribution networks in an effort to improve production efficiency. In this paper we study the impact of the reform on efficiency of fossil-fired power plants using plant-level data during 2000-2008. Our results from the data envelopment analysis (DEA) and panel regressions show that: 1) the total factor productivity (TFP) growth mainly comes from technological change; 2) the technical efficiency of previously SPC-managed power plants is converging to that of better-performing independent power producers (IPPs); 3) capacity utilization and unit size are significant factors affecting changes in technical efficiency and the pattern of converging technical efficiency between the two kinds of power plants; 4) most plants operate at increasing returns to scale indicating further cost savings could be achieved through increasing output.

Key words: *Efficiency; DEA; Malmquist Index; China, Electricity*

JEL : *D24, L11, L51, L94, L98*

1. Introduction

Over the past three decades, China's electricity industry has experienced three major reforms in 1985, 1997 and 2002 respectively. Before 1985, the electricity sector was managed by the Ministry of Electricity Power (MEP) and the regional Bureau of Electricity Power (BEP). The reform in 1985 changed the investment institution. Local governments, domestic enterprises and foreign investors have been allowed to form independent power producers (IPPs) since then. The focus of this reform was mainly to remove the capital bottleneck that had constrained the country's electricity sector for decades, and to expand capacity to meet the increasing demand driven mostly by the accelerated economic growth. The second reform in 1997 changed the management system of the electricity industry. The main purpose of this reform was to improve management efficiency and separate the administrative function from the business function of the power plants previously managed by MEP. As a result, a new public utility – SPC – was established as an independent market entity. SPC then took over all generation, transmission and distribution assets previously managed by MEP. MEP was dismantled and its administrative and decision-making functions were transferred to the State Economic and Trade Committee (SETC). The most recent reform was introduced in 2002. The newly established SPC was divested and dismantled into 11 new corporations including five generation groups, two grid operators and four auxiliary corporations. Each of the five generation groups manages a large number of power plants. The reform was to break the vertical monopoly of the SPC and introduce competition on the generation side (Ma and He, 2008). Experiences from other deregulated electricity markets have suggested that restraining the exercise of market power by dominant utility companies is one of the crucial factors for a market reform to be successful (Wolfram, 1999; Borenstein et al., 2002). It is also hoped that the right to dispatch power will be based on economic efficiency and merit order rather than political factors such as protection of state-owned assets and employment. The regulatory authority expects that the divestiture and decentralization reform would eventually increase the competitiveness and improve the overall productivity performance of China's electricity industry.

There have been many studies of these reforms and policies from the perspective of macro policies; however, very few studies have been devoted to quantifying the impacts of the reforms and policies based on detailed micro analyses. The purpose of this paper is to use the data envelopment analysis (DEA) Malmquist approach to estimate relative efficiency gains in the electricity sector and identify significant factors affecting efficiency changes before and after the most recent reform in 2002. The study benefits from a rich collection of plant-level data. The remainder of this paper proceeds as follows. Section 2 reviews previous studies on production efficiency of China's electricity industry. Section 3 introduces the DEA and Malmquist methodology and data. Section 4 presents the DEA results and performs a second-stage analysis and discussion. The last section concludes.

2. Empirical Studies on Efficiency of the Electricity Industry

Over the past half century, different methods have been used to measure technological change and scale economies in power generation. Most early studies measured the technological change of the power industry by studying the shifts in the production and cost functions. Christensen and Greene (1976) used the translog cost function to study the economies of scale for U.S. firms producing electric power and they found that there were significant scale economies in 1955 but such scale economies largely disappeared by 1970. Cowing and Smith (1978) provided an excellent survey of studies of steam electric generation based on production and cost functions. Later studies on electric productivity tended to focus on the effect of ownership and market structure on efficiency (De Alessi, 1974; Meyer, 1975; Pescatrice and Trapani, 1980; Dilorenzo and Robinson, 1982; Atkinson and Halvorsen, 1986; Kwoka, 1996). More recently, Berry and Mixon (1999) used the translog cost function to estimate cost differences in serving different types of buyers. Maloney (2001) also used the translog function to measure economies of capacity utilization in electricity generation. Borenstein et al (2002) used a production function to derive the departures from competitive pricing in California's restructured wholesale electricity market and found significant inefficiency due to market power. Fabrizio et al. (2007) found public owned plants whose owners are largely insulated from market competition, experienced the smallest efficiency gains, while investor-owned plants in states that restructured their wholesale electricity markets improved the most.

Apart from using cost and production functions, Frontier methods such as data envelopment analysis (DEA) and stochastic frontier analysis (SFA) have also been widely used to measure productivity. The use of these non-parametric and parametric approaches not only allows us to compare individual firms to best practice firms, but also to identify sources of inefficiency. Such insights allow policy makers to formulate better policies to improve the efficiency of electricity industry. Färe et al. (1985) were the first to use the DEA approach to compare the efficiency of public and private electric utilities and they found public utilities are more efficient and the inefficiency of private utilities was due to the lack of allocative efficiency. Cote (1989) applied the stochastic frontier cost function to estimate technical efficiency of 62 electric utilities under different ownership structures built between 1965 and 1973. His results suggested that cooperatives were the most efficient type of ownership structure compared with small private and public electric utilities. Färe et al. (1990) used the Malmquist productivity index to study changes in technical efficiency as well as changes in frontier technology of 19 coal-fired generating plants in Illinois during 1975-1981. They found that the average rates of productivity growth were relatively stable and both efficiency changes and technology changes play important roles in productivity growth. Pollitt (1995) also used the DEA approach to look at the ownership-productive efficiency question for both the power plants and the transmission and distribution systems in OECD countries and no significant differences in efficiency were found between different types of ownership or economic organization. Coelli (1997) applied both the DEA and SFA approaches to estimate the productivity change of 13 base-load, coal-fired plants in Australia from 1981/82 to 1990/91. The results suggested a TFP growth of up to 16 percent over the study period. Olatubi and Dismukes (2000) applied the DEA approach to examine efficiency of coal-fired generation facilities in the United States in 1996 and found significant allocative inefficiency. Kleit and Terrell (2001) also studied the efficiency of power generation in the US in 1996 but they applied a Bayesian stochastic frontier model and their results indicate that most plants operate at increasing returns to scale, suggesting further cost savings could be achieved through increasing production. Hiebert (2002) estimated a stochastic frontier cost function together with a model of plant inefficiencies. The paper found significant association between U.S. power plant efficiencies and capacity utilization, the number of plants under utility management, ownership form and state-level restructuring activity over the period 1988-1997. Arocena and Price (2002) applied a Malmquist approach to examine the impacts of different regulatory schemes on performance of publicly owned and privately owned generators in Spain. They found that publicly owned generators are more efficient under cost-of-service regulation while privately owned generators (but not public ones) responded to incentive regulation by increasing efficiency. Abbott (2006) applied a Malmquist approach to estimate the efficiency change of Australian electricity sector over the period 1969-1999 and the paper found significant efficiency improvement before as well as after the substantial restructuring of the industry in the early 1990s. Kwoka and Pollitt (2010) also applied the DEA approach to study the impact of mergers on power plants' efficiencies over the period of 1994 to 2003 and the results suggested that the merger did not consistently improve the cost efficiency. And more recently, Sueyoshi and Goto (2011)'s DEA study found that the unified efficiency of Japanese electricity generation (incorporating undesirable output such as CO_2) has not improved for the period 2004-2008.

Although the scale of China's electricity generation is comparable to that of the US, detailed analyses of the efficiency of this sector have been very limited compared with the case of the US. Given the large scale of China's electricity sector, its coal-dependent nature, and its significance to the global community with regards to the control of climate change, a sound understanding of impacts of recent reforms and productivity performance of the sector becomes increasingly important. However, only a handful of studies have examined the impact of recent reforms in China's electricity sector on the efficiency of power generation using either macro or micro level data. Lam and Shiu (2004) applied a DEA approach to province level data to assess the productivity growth of thermal power industries over the period of 1995 to 2000 with a focus on the regulatory reform in 1997. The results showed that technological change accounts for almost all the TFP growth and provinces not dominated by SPC have achieved higher levels of technical efficiency. Yang and Pollitt (2009) also examined the productivity performance of Chinese coal-fired power plants based on a cross-section sample of 221 plants in 2002; however the focus of the paper was primarily on the relative performance of different DEA-based models when both desirable inputs and outputs and undesirable outputs are incorporated. Du et al.(2009) investigated the impact of the regulatory reform in 2002 on China's electricity generation efficiency using a Differences-in-Differences (DID) approach and plant-level national survey data collected in 1997 and 2004 and they found significant input efficiency improvement in labor and non-fuel materials but not in fuel input. Our study builds on the existing literature and particularly extends Lam and Shiu (2004) and Du et al. (2009). Results from Lam and Shiu (2004) suggested potential efficiency benefits from replacing regulated monopoly with a market-based industry structure. The time is ripe now for an investigation whether such benefits have materialized or not. While Du et al. (2009) was the first to confirm the efficiency improvement due to the 2002 reform, our study differs in several ways. First, our plant-level panel database has data on several years of pre-reform and post-reform periods which is unlike all previous studies. Second, we employ a powerful nonparametric technique – Malmquist index – to examine the sources of TFP changes: changes in pure technical efficiency, scale efficiency or technology frontier. Finally, Lam and Shiu (2004) correctly pointed out that the technical profile of generation units such as age and size could be potentially significant factors affecting efficiency. With a rich collection of plant-level data, we are able to investigate the impacts of these factors**.**

3. Methodology and Data

3.1 Data Envelopment Analysis (DEA) and Malmquist Index

Building on the ideas of Farrell (1957), Data Envelopment Analysis (DEA) method was firstly developed in the seminal work of Charnes, Cooper and Rhodes in 1978 (Charnes et al., 1978). DEA is used to empirically measure the productive efficiency of decision making units (DMUs). Linear programming is used to identify a frontier on which the relative performance of all DMUs in the sample can be compared with. In other words, DEA only benchmarks DMUs against the best performer. If one DMU can produce certain levels of outputs using specific levels of inputs, other DMUs of equal scale should be capable of doing the same. Using higher levels of inputs or producing lower level of outputs are both inefficient. DEA has the advantage of not assuming particular functional forms which in many cases involves subjective judgment; however it does not provide a functional relationship relating output and input. For studies focusing on efficiency measures rather than the functional relationship, DEA is an adequate and powerful approach. There are a number of different DEA approaches with the most basic being the CCR model (Charnes et al., 1978). Later models are able to address variable returns to scale. Seiford and Thrall (1990) provided an excellent account of the methodological developments of DEA in the 1970s and 1980s. Recent DEA models have been developed to incorporate undesirable outputs to address the environmental impacts of economic production (e.g. Bernstein et al. 1990, and, Yaisawarng and Klein, 1994 for power industry; Färe et al., 1989, and, Hailu and Veeman, 2000 and 2001a for pulp and paper industry). Hailu and Veeman (2001b) discussed alternative methods for environmentally adjusted productivity analysis including both parametric methods and nonparametric methods such as DEA. Zhou et al. (2008) conducted a survey of DEA applications in energy and environmental studies. DEA models have also been developed recently to accommodate stochastic elements in a state-contingent setting with random inputs (Chambers et al., 2011).

To introduce the DEA models to be used in this study, we begin with standard notation. We assume that there are k = 1, 2, …, K DMUs (or power plants) in the sample. Let $x^k \in R_+^M$ be a $(M \times 1)$ vector of M different inputs used by DMU k. Let $y^k \in R_+^N$ be a $(N \times 1)$ vector of N different outputs produced by DMU k. Let X, Y be the corresponding $(M \times K)$, $(N \times K)$ matrices of observed inputs and outputs, respectively, for all K DMUs. And let $\lambda \in R_+^K$ be a $(K \times 1)$ vector of intensities that are used to weight the different DMUs in constructing the reference frontier to evaluate DMU k. Then for each DMU k, k = 1, 2, …, K, an output-oriented technical efficiency measure with constant returns to scale (*CRS*) can be computed by firstly solving the following linear programming (LP) problem:

$$
\begin{aligned}
&\max \theta \\
&\text{s.j. } -\theta y^k + Y\lambda \geq 0, \\
&\qquad x^k - X\lambda \geq 0, \\
&\qquad \lambda \geq 0,
\end{aligned}
\tag{1}
$$

where θ is a scalar and $1/\theta$ defines the technical efficiency of DMU k which varies between zero and one with a value of one indicating a point on the frontier and a technically efficient DMU. The *CRS* LP problem can be modified to account for variable returns to scale (*VRS*) by adding the convexity constraint: $K1'\lambda = 1$, where $K1$ is a $(K \times 1)$ vector of ones. To determine the nature of the scale efficiency – increasing, constant or decreasing returns to scale, one can run an additional LP problem by replacing the restriction $K1'\lambda = 1$ with a non-increasing returns to scale (NIRS) restriction: $K1'\lambda \leq 1$. In this paper, the CRS setting and VRS setting will be applied to compute the technical efficiency scores which can then be decomposed into pure efficiency and scale efficiency scores, and the NIRS setting is used to determine the nature of the scale economy.

As standard DEA models only benchmark DMUs against the best performers given existing technology, they do not account for the changes in the technology – i.e. shift in the frontier. In this study, we also use the Malmquist index estimated by DEA-like LP technique to calculate the total factor productivity (TFP) and decompose the TFP into technological change, pure efficiency change and scale efficiency change. The Malmquist index was first suggested by Caves et al. (1982) and further developed by Färe et al. (1989 and 1992) and Färe et al. (1994). The index uses Shephard (1953)'s distance functions that describe multi-input and multi-output production technology. We provide a detailed construction of an output-based Malmquist productivity change index in Appendix A and present the decomposed Malmquist productivity change index in the following:

$$
M_o(y_t, x_t, y_{t+1}, x_{t+1}) = \frac{S_o^t(y_t, x_t)}{S_o^{t+1}(y_{t+1}, x_{t+1})} \cdot \frac{D_{o.vrs}^{t+1}(y_{t+1}, x_{t+1})}{D_{o.vrs}^t(y_t, x_t)} \cdot \left[\frac{D_{o.crs}^t(y_{t+1}, x_{t+1})}{D_{o.crs}^{t+1}(y_{t+1}, x_{t+1})} \cdot \frac{D_{o.crs}^t(y_t, x_t)}{D_{o.crs}^{t+1}(y_t, x_t)}\right]^{\frac{1}{2}} \tag{2}
$$

where $D^{t}_{o.crs}(y_t, x_t)$, $D^{t+1}_{o.crs}(y_{t+1}, x_{t+1})$, $D^{t}_{o.vrs}(y_t, x_t)$, and $D^{t+1}_{o.vrs}(y_{t+1}, x_{t+1})$ are the output distance functions[1] by which production points with input and output vectors are compared to frontier technologies from the same year assuming CRS or VRS technology. $D^{t}_{o.crs}(y_{t+1}, x_{t+1})$ and $D^{t+1}_{o.crs}(y_t, x_t)$ are output distance functions by which production points are compared to frontier technologies at different points of time assuming CRS technology. The CRS or VRS output-oriented LP used to calculate these distance functions are identical to LP problem defined in Equation (1) with or without the convexity (VRS) restriction. The first term and second term outside the bracket measure the change in scale efficiency and the change in pure efficiency between period t and t+1. These two term together measure the change in technical efficiency and describe the "catching-up" to the frontier. The bracketed term measures technological change, i.e. the shift of technological frontier. For all three terms, a value greater than one or less than one denotes an improvement or regression respectively.

3.2 Data, Inputs and Output

Our data covers a sample of 40 power plants from 2000 to 2008. We have chosen to limit our sample to large thermal power plants as consistent data on smaller plants are more difficult to obtain. We managed to collect a consistent dataset of 40 plants. This final sample consists of 26 plants previously owned by SPC and currently owned by the five generation groups (hereafter referred to as "*GROUP"* plants), and 14 plants owned by independent power producers (hereafter referred as "*IPP"* plants). Data on inputs, output and capacity factors are collected from *Statistical Compilation of China's Electricity Industry* (CEC, 2000-2008), which is kindly provided by China's Electricity Council. Information on age and unit size is collected from *A List of Running Desulfurization Facilities on Coal-fired Units* (MEP, 2011) and websites of power plants. More information on data collection is provided in Appendix B.

In our study, each power plant is considered as a DMU. Electricity generated by each DMU is used as the output variable and installed generation capacity, labor and fuel are the three inputs used for electricity generation[2]. Table 1 presents the summary statistics for these input and output variables and some additional variables.

Table 1 - Summary Statistics of Key Variables (Year = 2008)

Variables	*GROUP* plants (obs =26)				*IPP* plants (obs =14)			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
GENERATION (10^8 KWHs[a])	76.54	26.12	45.3	138.28	75.85	20.33	41.26	110.04
CAPACITY (MWs[b])	1444.25	483.79	800	2650	1372.86	407.25	600*	2070

[1] An output distance function measures a maximal proportional expansion or contraction of the output vector compared with a benchmark output vector (the frontier), given an input vector.
[2] In this paper, we do not consider undesirable outputs such as sulfur emission. To the best of our knowledge, there is virtually no data on emissions of power plants in China. While sulfur emission can be estimated using the IPCC reference approach, but this also needs substantial data on the quality of fuels – especially the parameter on sulfur content. In addition, given China's large-scale desulfurization effort in the electricity sector during the past few years, a good estimate of actual sulfur emission should also consider efficiency of different types of desulfurization facilities.

LABOR (Number of Employees)	573	467	265	2186	689	449	327	1909
FUEL (10,000 Tons of SCE[c])	258.16	83.65	162.92	461.43	255.87	63.39	142.09	365.65
UTILIZATION[d]	0.64	0.07	0.47	0.76	0.69	0.08	0.56	0.84
AGE[d] (Years)	15.2	6.12	6.5	31	13.52	4.17	7.5	23.17
UNIT SIZE[d] (MWs)	382	141.7	200	615	366.4	194.7	180	800

[a] KWHs – kilowatt hours; [b] MWs – megawatts; [c] SCE – standard coal equivalent; [d] We use a relative measure of these variables in our regression models; however statistics here are on actual values.

GENERATION

The *Compilation* only reports total gross generation which includes the electricity consumed by the power plant itself. However, it is the net generation that best describes the effective output produced from a combination of all inputs. We thus subtract the self electricity usage from the gross generation and use the net generation as the output variable.

CAPACITY

Total installed nameplate capacity is used as a measure of the DMU's capital input and it may change over time because of closure of outdated units, upgrade of current units, or replacement with larger advanced units.

LABOR

Labour input is measure by the total number of employees. Appendix B provides more details on our figures of labour input.

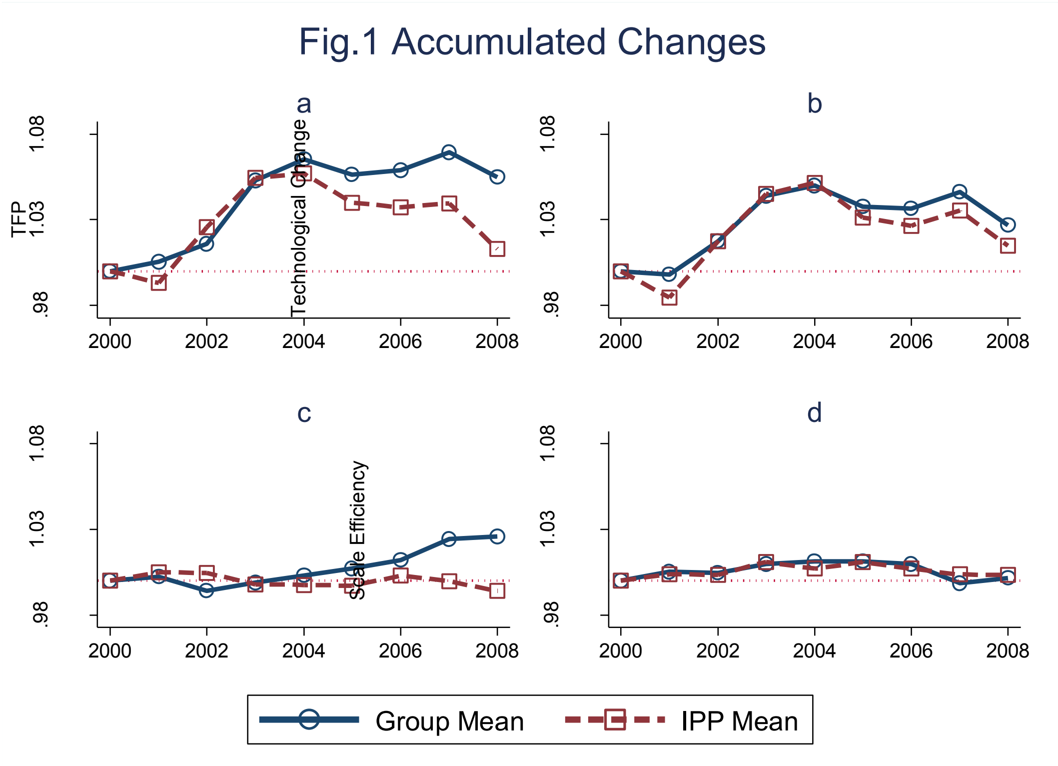
FUEL

In almost all Chinese power plants, oil-fired or gas-fired equipment is also installed for boiler-preheating and standby purposes. The boiler type, design of combustion facilities, and capacity of these equipments vary across plants. Given a certain load of a boiler, the more oil it consumes, the less coal it burns (Yang and Pollitt, 2009). In addition, the quality of coal affects the operating performance of a coal-fired generating unit. As the calorific value of coal falls, the amount of coal consumed increases and the probability of outages and unit derating also increases (Joskow and Schmalensee, 1987). To provide an overall measure of the fuel input, all fuel uses including coal, oil, gas and electricity (self usage) are converted and measured in the same unit – 10,000 tons of standard coal equivalent (SCE), which has adjusted for the type and quality of fuels used for electricity generation.

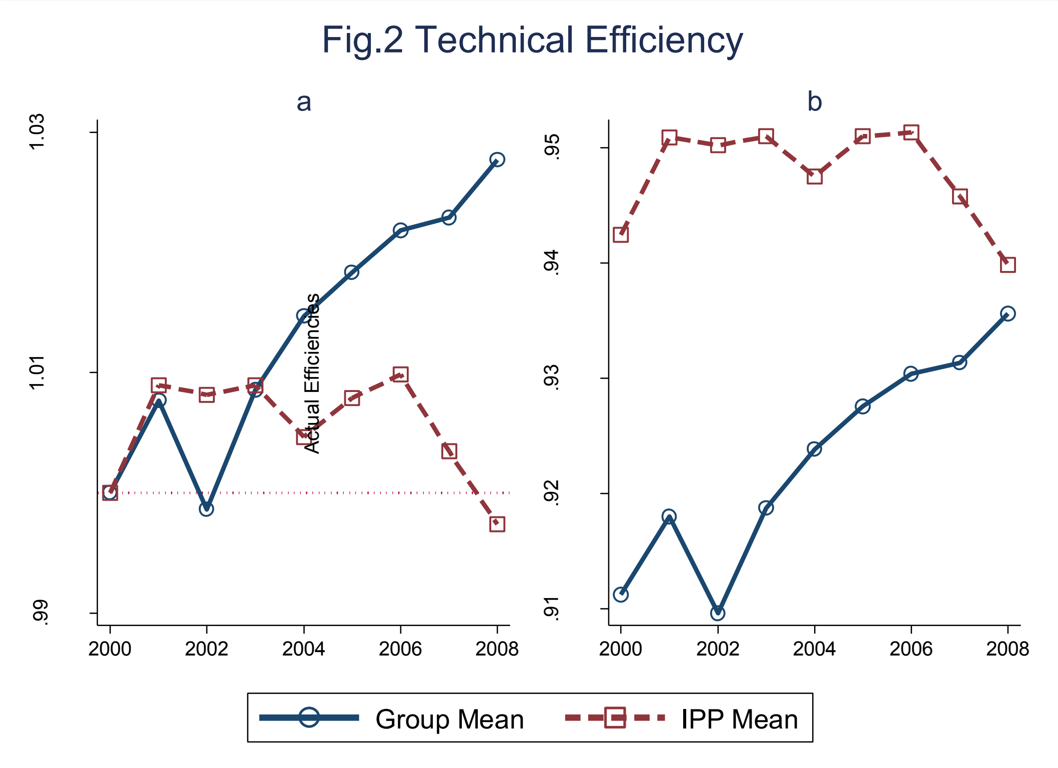
4. Results and Discussions

The results of the Malmquist index decomposition are summarized in Fig.1. The figure presents accumulated annual changes in TFP, technological change (shift of frontier), pure efficiency and scale efficiency with the year of 2000 being the benchmark. The two series in each panel (*a, b, c, d*) are means for *GROUP* and *IPP* plants. We make three observations on Fig.1: 1) the up-trending curves show that plants in our sample have on average experienced positive TFP (*a*) and technological change (*b*) and the growth has been strongest before 2004; 2) higher *GROUP* curves indicate that *GROUP* plants have outperformed *IPP* plants for most efficiency change indicators during this period; 3) the similarity between panel *a* and *b* shows that technological change contributes a significant proportion to the overall TFP change. As the changes in pure efficiency (*c*) and scale efficiency (*d*) together, i.e. the technical efficiency, capture how DMUs have been catching up to the frontier, we provide the combined accumulated technical efficiency (panel *a*) in Fig.2. Fig.2 also presents actual technical efficiency scores. We make two observations on Fig.2: 1) Lam and Shiu (2004) found that provinces and autonomous regions not dominated by SPC have achieved higher levels of technical efficiency during the period of 1995-2000. Our results are consistent to their study and provide micro level evidence that *GROUP* plants which are previously owned and managed by SPC are on average technically less efficient than plants not previously managed by SPC, i.e. *IPP* plants; 2) Fig.2 also shows that there is a clear pattern that the less efficient *GROUP* plants are catching up to the more efficient *IPP* plants. By the end of this period, the efficiency difference between the two has become very limited. Complete results of Malmquist index and technical efficiency for all power plants are listed in Appendix C.

However, it is unclear at this stage whether such "catching up" was due to the reform in 2002 or other factors that might have influence the two kinds of power plants (*GROUP* and *IPP*) in different ways. In order to identify the impacts of the reform in 2002 and identify factors affecting the efficiency change, we perform a second stage regression analysis. Our dependent variable is the estimated technical efficiency scores for the 40 power plants over the period 2000-2008. Given that the technical efficiency score has a value censored at one, the OLS regression does not provide unbiased and consistent estimates. Instead, we employ a panel Tobit regression analysis and control for several time-invariant and time-variant variables.



Source: Malmquist index calculation (The dotted line denotes the benchmark at the value of one).



Sources: Malmquist index and DEA calculations (The dotted line denotes the benchmark at the value of one).

UTILIZATION

Reifschneider and Stevenson (1991) found that departures from a frontier may reflect the systematic effect of conditions that contribute to inefficiency. Factors such as demand induced growth rate in electricity supply or the demand constrained capacity utilization may constrain the ability of the utility to attain the frontier[3]. Because electricity cannot be conveniently stored, generation facilities follow the load across demand cycles. Although total gross capacity can be adjusted in the long run – either by retiring outdated units or installing new units, varying demand is largely met by adjusting capacity utilization of existing units. Maloney (2001) used a two dimensional definition of capacity utilization – generation relative to capacity when a unit is connected to the system and the percent of time the unit is disconnected, and found that both dimensions affected plant efficiencies. Hiebert (2002) found similar results while defining capacity utilization as actual generation output divided by capacity output (nameplate capacity times 8760). In this paper, we follow Reifschneider and Stevenson (1991) and Hiebert (2002)'s definition of capacity utilization. However, given that our dependent variable is a relative efficiency measure, we use a relative utilization variable – actual utilization minus the maximum utilization in that year – in our model.

AGE

It is generally expected that performance eventually to deteriorate as a unit ages; however, units may go through a break-in period early in their lives, which is usually characterized by a high level of forced outrages and derating or cycling of the facility. This means that observed performance may

[3] There are several reasons why a plant may have a capacity utilization factor lower than 100%: 1) a unit may be out of service or operating at reduced output for part of the time due to equipment failures or regular maintenance; 2) output is curtailed because the electricity is not needed (e.g. lower demand); 3) generators choose to reduce output or even shut down because the price of electricity is too low to make generation economical.

actually improve during these earlier years of operation (Joskow and Schmalensee, 1987; Pollitt, 1995). In this study we define the age of a generating unit as calendar year minus year of initial operation. However, since our subject of study is each plant instead of individual unit, the age of each plant is derived as the average age of each plant's all units weighted by each unit's nameplate capacity. Similarly, our *AGE* variable in the models also follows a relative definition – each plant's age minus the maximum plant age in that year. Additionally, we test a squared term for possible nonlinear effect.

UNIT SIZE

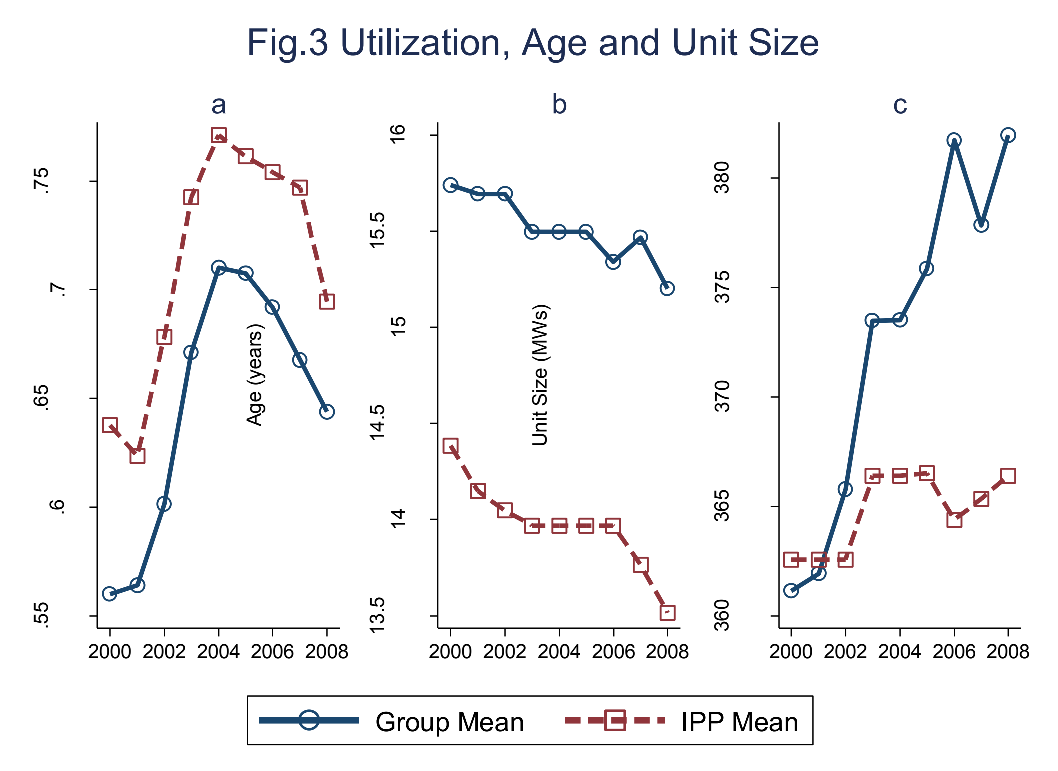
Other things being equal (e.g. steam temperature, pressure and fuel characteristics), larger boiler should reduce the unit's heat rate; however the advantage of larger size should be more significant at small scale than large scale. This is because lager units have poorer availability than smaller units and the advantage of larger units for heat rate may disappear when the costs of poor availability are factored in (Joskow and Schmalensee, 1987). Each plant may have multiple units of different sizes. We thus calculate a plant's unit size as the average size of each plant's all units weighted by each unit's nameplate capacity. Here again, we define our *UNIT SIZE* variable in the models as a relative measure compared to the plant with largest weighted average unit size, and allow this variable to enter with a quadratic specification.

REFORM

The divestiture reform was introduced in 2002 and took effect in 2003. We create a *REFORM* dummy with a value of zero for the period 2000 – 2002 and a value of one for the period 2003-2008 to test whether the reform has in general improved the performance controlling for other factors.

GROUP

Following many other studies on the ownership-efficiency issue (e.g. Boardman and Vining, 1989; Hiebert, 2002; Fabrizio et al., 2007), we also use a dummy to indicate the ownership of the plant. The dummy takes a value of one for *GROUP* plants and zero for IPP plants. As the divestiture directly affected plants previously owned by SPC (i.e. *GROUP* plants) and only indirectly affected the *IPP* plants through increased competition, we expect the impact on efficiency performance would be different for the two categories of plants. We interact the *GROUP* dummy with the *REFORM* dummy to capture possibly different impacts.

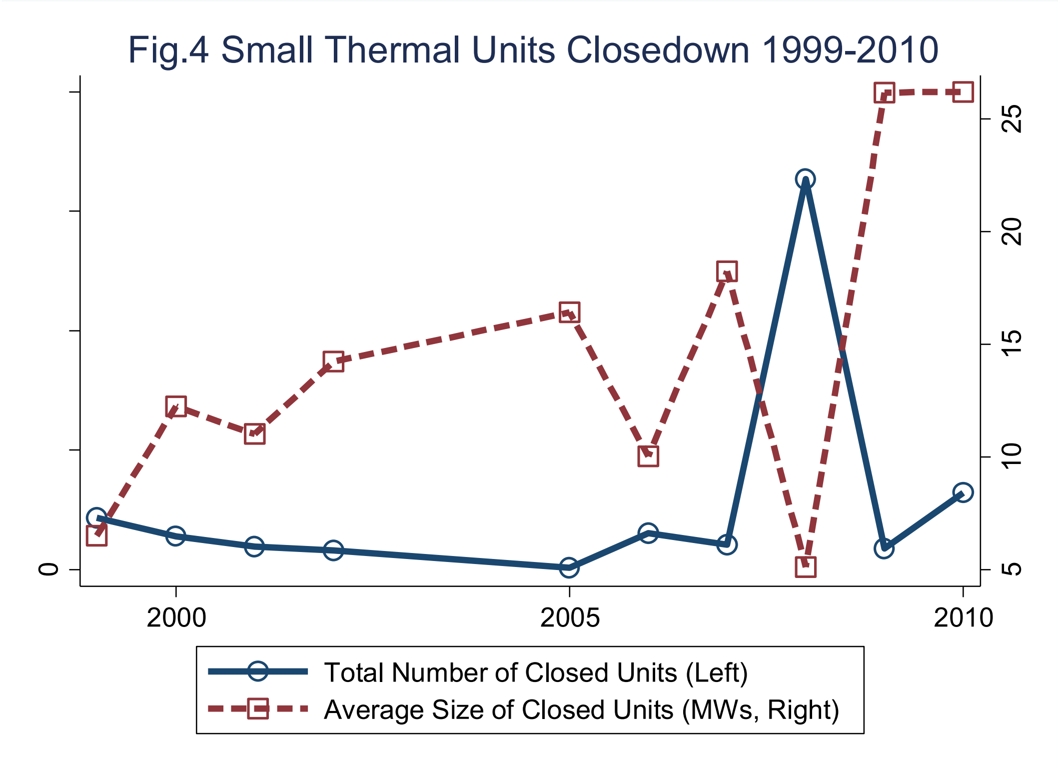


Source: *Statistical Compilation of China's Electricity Industry* (CEC, 2000-2008); *A List of Running Desulfurization Facilities on Coal-fired Units* (MEP, 2011); websites of power plants; authors' calculation

Summary statistics on actual values of *UTILIZATION*, *AGE* and *UNIT SIZE* are provided for the year of 2008 in Table 1. Fig.3 shows the average utilitization, age and unit size for *GROUP* plants and *IPP* plants for the period under study. As expected, the utilization (panel *a*) was highest in 2004 when the shortage of electricity supply was most severe in China. The tension between electricity supply and demand has been relived since 2004. The utilization was higher for *IPP* plants; however the difference became smaller in 2008 compared with 2000. While the average age for both kinds of plants were decreasing, units of *GROUP* plants are on average older than those of *IPP* plants (panel *b*). There was a sharp difference in the change of unit size between the two kinds. While both seemed to have larger units over time, the growth in unit size was much faster for *GROUP* plants (panel *c*). To a large extent, the decreasing age and increasing size were results of China's recent effort to replace outdated small thermal units with new large units. In 1999, China started a national policy effort to shut down small-scale thermal units, where small-scale was defined as a unit with a capacity less than 50 MWs[4]. Due to power shortage in early 2000s, the policy was not fully implemented until the 11th Five Year Plan (2006-2010). In 2006, the Chinese government implemented the Large Substitute for Small program (LSS) with a target of 50 GW of small-scale power plant capacity for closure by the end of this period (2010)[5]. In fact, 76.8GW had been closed by 2010. Fig. 4 illustrates the total number and average size of closed units during the period 1999-2010.

[4] These small units are generally inefficient and also highly polluting. The average total cost per kilowatt hour for small plants is almost three times the cost for large plants. Most of these units were state-owned units built to serve localities that had in the past experienced severe electricity shortages.

[5] According to the new program, the following categories of thermal units are targeted for closure: 1) units below 50 MW; 2) units below 100 MW that have been operating for over 20 years; 3) units below 200 MW that have reached the end of their design lives; 4) units with coal consumption 10% higher than the provincial average or 15% higher than the national average; 5) all other units that fail to meet environmental standards, laws or regulations.



Source: *A List of Closed Small Thermal Units* (NDRC, various issues); authors' calculation.

Note: The large number and small average size in 2008 are due to the closure of a large number of very small oil-fired units; Data for 2009 only includes those closed in Sept. to Dec. as data on units closed during Jan. to Aug. was not released by NDRC.

Table 2 shows the results from three regressions. Model A simply confirms the two observations we make on panel *b* in Fig. 2: 1) *GROUP* plants which are previously owned and managed by SPC are on average technically less efficient than plants not previously managed by SPC, i.e. *IPP* plants; 2) less efficient *GROUP* plants are catching up to the more efficient *IPP* plants after the reform. In Model 2, we control for relative *UTILIZATION*, *AGE* and *UNIT SIZE*. Our results are generally consistent with the findings of previous studies (Joskow and Schmalensee, 1987; Reifschneider and Stevenson, 1991; Maloney, 2001; Hiebert, 2002). First, a plant's technical efficiency is significantly associated with capacity utilization factor. Other things being equal, higher capacity utilization factors are associated with higher technical efficiencies. Second, the impact of a unit's capacity size is significant and nonlinear – technical efficiency first improves with increased unit size; however further increase of unit size may actually decrease efficiency. More importantly, even after such factors are controlled for, we still find the different impacts of the divestiture reform in 2002 on the two kinds of power plants to be significant. A positive interaction term - *GROUP*REFORM* – indicates that previously less efficient *GROUP* plants have converged to more efficient *IPP* plants. Removing the insignificant *AGE* variables in Model C does not change our findings.

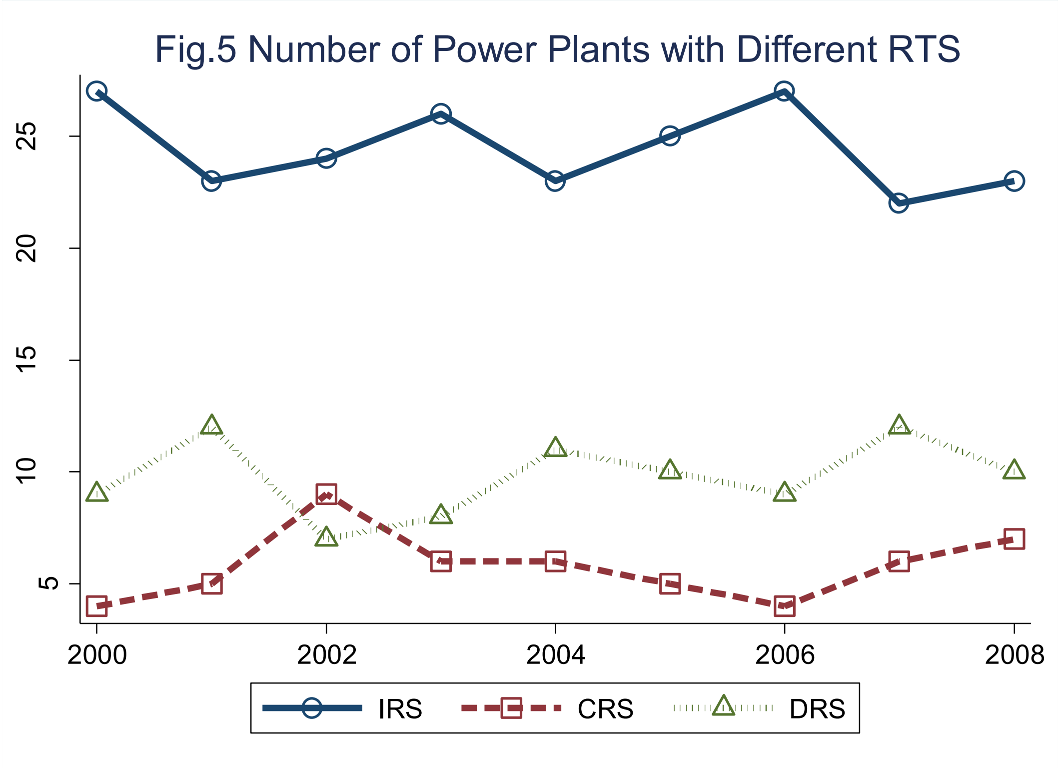
As a final observation, we also examine the scale efficiency of the power plants in our sample. Fig.5 shows the number of plants with increasing returns to scale (IRS), constant returns to scale (CRS) and decreasing returns to scale (DRS) in each year during the period under study. Results show that most plants operate at increasing returns to scale which indicates overall performance can be further improved by increasing output. A comparison between Chinese and U.S. coal-fired power plants shows a substantial gap in capacity utilization factors. During the same period of 2000-2008, U.S. coal-fired power plants have on average achieved a capacity utilization factor of 71.75% while the figure for Chinese ones is only 66.92% (EIA, 2010). Increasing the utilization of existing capacity could improve the sale efficiency.

Table 2 – Random Effects Tobit Regression Results (2000-2008)

Dependent Variable : Technical Efficiency Score

Independent Variables	Model A		Model B		Model C	
	Coefficient	P > |Z|	Coefficient	P > |Z|	Coefficient	P > |Z|
GROUP	-0.0392***	0.019	-0.0370***	0.003	-0.0400***	0.001
REFORM	-0.0015	0.758	-0.0130***	0.005	-0.0132***	0.004
*GROUP*REFORM*	0.0173***	0.004	0.0141***	0.010	0.0143***	0.009
UTILIZATION			0.1605***	0.000	0.1609***	0.000
AGE			-0.0038	0.212		
AGE Squared			-0.0001	0.176		
UNIT SIZE			-0.0028*	0.058	-0.0034**	0.014
UNIT SIZE Squared			-0.0001**	0.003	-0.0001***	0.000
CONSTANT	0.9528***	0.000	0.9773***	0.000	0.9919***	0.000
Sigma_u	0.048***	0.000	0.0314***	0.000	0.0313***	0.000
Wald Chi2	24.24***		145.54***		142.28***	
Log likelihood	645.402		691.7482		690.8215	
Observations	360					

*,**,*** refer to significance at 1%, 5% and 10% respectively.



Sources: DEA calculations

5. Conclusions

In this paper, we investigate the impact of China's divestiture reform in the electricity industry in 2002 on thermal power plants' efficiency performance. We have observed a positive TFP growth during the period 2000-2008 which is largely due to a significant technological change – i.e. a shift of technology frontier. Our plant-level DEA analysis also reveals a pronounced converging pattern. Our results firstly provide plant-level evidence for Lam and Shiu's study (2004) that SPC managed power plants were generally less efficient than *IPP* plants in early 2000s. However, the divestiture reform in 2002 has significantly improved the efficiency of these under-performers who have since converged to the technology frontier mostly represented by the *IPP* plants. This conclusion still holds even after we control for such technical factors as capacity utilization, age and size of units. We also find that the majority of plants in our sample operate at increasing returns to scale, suggesting potential benefits from increasing outputs.

The main purpose of the reform in 2002 was to improve efficiency of power plants by introducing competition mechanism, especially on the generation side. The divestiture reform was crafted to break the natural monopoly and limit the concentration of generation assets. It is also hoped that the right to dispatch power will be eventually based on economic efficiency and merit order rather than political factors such as protection of state-owned assets and employment. Our research has shown that the objective has been partially fulfilled as indicated by efficiency improvement of power plants previously managed by SPC. However, this transition is far from completion. In order to realize the full benefit of the reform, some constraints need to be addressed. A fully functioning national wholesale electricity market is not yet established which is largely constrained by substantial trade barriers across regions as well as inconsistent price mechanisms in the coal and electricity. Since 2004, the Northeast region of China has been selected to perform a trial operation of competitive bidding and dispatch. Zhang and Parsons (2008) show that although the generation asset concentration level is relative low for the whole region but is often much more concentrated at the province level. Given that transmission constraints between provinces are often binding, the full benefit of a regional wholesale market is hard to achieve. In addition, China's current price mechanism in the electricity industry is characterized by completely competitive coal prices in the upstream, partially competitive on-grid electricity prices in the middle (incomplete linking of coal prices and on-grid electricity prices), and regulated retail prices in the downstream. This unbalanced price mechanism further constrains the effectiveness of the market reform.

Appendix A – Mulmquist Productivity Change Index

Firstly suggested by Caves et al. (1982) and further developed by Färe et al. (1989 and 1992) and Färe et al. (1994). The index uses Shephard (1953)'s distance functions that describe multi-input and multi-output production technology. Caves et al (1982) proposed an out-put based Malmquist index relative to a single CRS technology from year t or t+1 as:

$$M_{o.crs} = \frac{D_{o.crs}^{t}(y_{t+1}, x_{t+1})}{D_{o.crs}^{t}(y_t, x_t)} \text{, or} \quad M_{o.crs} = \frac{D_{o.crs}^{t+1}(y_{t+1}, x_{t+1})}{D_{o.crs}^{t+1}(y_t, x_t)} \tag{A1}$$

Färe et al. (1989) suggested using a geometric mean of the above two indexes to avoid an arbitrary choice of referencing frontier:

$$M_o(y_t, x_t, y_{t+1}, x_{t+1}) = \left[\frac{D_{o.crs}^{t}(y_{t+1}, x_{t+1})}{D_{o.crs}^{t}(y_t, x_t)} \cdot \frac{D_{o.crs}^{t+1}(y_{t+1}, x_{t+1})}{D_{o.crs}^{t+1}(y_t, x_t)}\right]^{\frac{1}{2}} \tag{A2}$$

With standard equation manipulations, the above productivity change index can be further decomposed into technological change, pure efficiency change and scale efficiency change (Färe et al., 1989, 1992; Färe et al., 1994):

$$\begin{aligned} M_o(y_t, x_t, y_{t+1}, x_{t+1}) \\ = \left[\frac{D_{o.vrs}^{t}(y_t, x_t)}{D_{o.crs}^{t}(y_t, x_t)} \Big/ \frac{D_{o.vrs}^{t+1}(y_{t+1}, x_{t+1})}{D_{o.crs}^{t+1}(y_{t+1}, x_{t+1})}\right] \cdot \frac{D_{o.vrs}^{t+1}(y_{t+1}, x_{t+1})}{D_{o.vrs}^{t}(y_t, x_t)} \\ \cdot \left[\frac{D_{o.crs}^{t}(y_{t+1}, x_{t+1})}{D_{o.crs}^{t+1}(y_{t+1}, x_{t+1})} \cdot \frac{D_{o.crs}^{t}(y_t, x_t)}{D_{o.crs}^{t+1}(y_t, x_t)}\right]^{\frac{1}{2}} \end{aligned} \tag{A3}$$

As the first bracket term is the chained scale efficiency change, the above index can be simplified to yield the index we used in Equation (2) of the text:

$$M_o(y_t, x_t, y_{t+1}, x_{t+1}) = \frac{S_o^t(y_t, x_t)}{S_o^{t+1}(y_{t+1}, x_{t+1})} \cdot \frac{D_{o.vrs}^{t+1}(y_{t+1}, x_{t+1})}{D_{o.vrs}^t(y_t, x_t)} \cdot \left[\frac{D_{o.crs}^t(y_{t+1}, x_{t+1})}{D_{o.crs}^{t+1}(y_{t+1}, x_{t+1})} \cdot \frac{D_{o.crs}^t(y_t, x_t)}{D_{o.crs}^{t+1}(y_t, x_t)}\right]^{\frac{1}{2}} \qquad \text{(A4)}$$

Appendix B – Data Collection

Chinese electricity authorities have only started to release plant-level information until very recently. Our data has been collected from a range of government publications and documents, supplemented by information disclosed on websites of power plants.

GENERATION / CAPACITY / FUEL / UTILIZATION / GROUP

The major data source for these variables is the *Statistical Compilation of China's Electricity Industry* (CEC, 2000-2008) provided by China's Electricity Council. The *Compilation* was previously considered as confidential internal document and not released to the public. The document provides plant-level data on annual generation, installed capacity, physical volume of different kinds of fuels, standard fuel consumption for power generation and supply, and annual generation hours. The *Compilation* also identifies the ownership structure of each plant. We managed to compile a balanced panel for 40 plants.

AGE / UNIT SIZE

The *Compilation* also provides information on the number of generation units and nameplate capacity of each unit for all plants; however, it does not report the initial operation time of each unit. Such information is included in a recent document released by the Ministry of Environmental Protection - *A List of Running Desulfurization Facilities on Coal-fired Units* (MEP, 2011). This is supplemented by information provided on websites of power plants where a unit is not equipped with desulfurization facilities.

LABOR

None of the above documents provide information on the number of employees for each power plant. In this study, we estimate the number of employees based on standard labor quota in the electricity industry. Specifically, we follow the *Labor Force Quota for Thermal Power Plants* (SPC, 1998) to estimate employee numbers for the period 2000-2002, and the *Labor Force Quota for General Thermal Power Plants* (CHC, 1998) and the *Labor Force Quota for New Thermal Power Plants* (CHC, 2008) to estimate employee numbers for the period 2003-2008. These documents provide estimated employee numbers for typical power plants with different technologies (coal, oil or gas), number of units, unit capacity etc.

Appendix C – Malmquist Productivity Change Index and DEA Technical Efficiency

Malmquist Index for Annual Changes (Geometric Mean for 2000-2008)

Plants		TFP	Technology	Technical Efficiency	Pure Efficiency	Scale Efficiency
GROUP Plants	DMU 1	1.0878	1.0272	1.0585	1.0086	1.0499
	DMU 2	1.0154	1.0128	1.0030	1.0676	0.9397
	DMU 3	1.0013	1.0194	0.9816	0.9978	0.9843
	DMU 4	1.0821	1.0107	1.0702	1.0758	0.9937
	DMU 5	1.0175	1.0478	0.9699	0.9661	1.0044
	DMU 6	1.0850	1.0605	1.0233	0.9469	1.0809
	DMU 7	1.0450	1.0243	1.0191	1.0261	0.9936
	DMU 8	1.0232	1.0209	1.0024	1.0226	0.9811
	DMU 9	1.0883	1.0777	1.0104	1.0314	0.9795
	DMU 10	1.0496	1.0322	1.0177	0.9568	1.0640
	DMU 11	1.0163	1.0187	0.9986	1.0008	0.9976
	DMU 12	1.1162	1.0796	1.0336	1.0337	1.0000
	DMU 13	1.0301	1.0481	0.9832	0.9956	0.9877
	DMU 14	1.0067	1.0143	0.9925	1.0243	0.9696
	DMU 15	1.0097	1.0174	0.9931	1.0009	0.9925
	DMU 16	1.0310	1.0187	1.0124	1.0241	0.9897
	DMU 17	1.0099	1.0156	0.9943	1.0178	0.9773
	DMU 18	1.0054	1.0105	0.9949	0.9958	0.9977
	DMU 19	1.0591	1.0117	1.0475	1.0652	0.9837
	DMU 20	1.0717	1.0207	1.0511	1.0811	0.9720
	DMU 21	1.0359	1.0116	1.0245	0.9875	1.0369
	DMU 22	1.0280	1.0213	1.0083	1.0242	0.9836
	DMU 23	1.0364	1.0209	1.0156	1.0500	0.9668
	DMU 24	1.0117	1.0183	0.9941	0.9998	0.9942
	DMU 25	1.0159	1.0298	0.9872	1.0179	0.9705
	DMU 26	1.1225	1.0508	1.0685	0.8136	1.3132
IPP Plants	DMU 27	1.0785	1.0181	1.0585	1.0057	1.0543
	DMU 28	0.9901	1.0147	0.9739	0.9866	0.9865
	DMU 29	1.0008	1.0162	0.9841	0.9913	0.9920
	DMU 30	1.0113	1.0280	0.9849	0.9642	1.0212
	DMU 31	1.0205	1.0239	0.9967	0.9710	1.0259
	DMU 32	1.0191	1.0227	0.9963	0.9993	0.9970
	DMU 33	1.0014	1.0115	0.9896	1.0000	0.9896
	DMU 34	1.0702	1.0425	1.0256	1.0432	0.9827
	DMU 35	0.9994	1.0079	0.9917	1.0008	0.9911
	DMU 36	1.0220	1.0018	1.0206	1.0307	0.9905
	DMU 37	1.0680	1.0523	1.0150	1.0000	1.0150
	DMU 38	1.1007	1.0442	1.0528	0.9880	1.0671
	DMU 39	1.0074	1.0149	0.9927	1.0197	0.9731
	DMU 40	1.0201	1.0209	0.9983	1.0007	0.9976

DEA Technical Efficiency Scores										
Plants		2000	2001	2002	2003	2004	2005	2006	2007	2008
GROUP Plants	DMU 1	0.855	0.978	0.889	0.882	0.878	0.906	0.927	0.962	0.875
	DMU 2	0.914	0.913	0.908	0.905	0.912	0.924	0.914	0.927	0.93
	DMU 3	0.961	0.954	0.881	0.913	0.944	0.97	0.966	0.945	0.963
	DMU 4	0.854	0.866	0.855	0.953	0.946	0.956	0.97	0.93	0.907
	DMU 5	0.973	0.949	0.939	0.955	0.938	0.95	0.932	0.931	0.938
	DMU 6	0.904	0.794	0.913	0.961	0.957	0.963	0.948	0.949	0.945
	DMU 7	0.923	0.921	0.917	0.926	0.939	0.964	0.953	0.962	0.965
	DMU 8	0.914	0.921	0.903	0.912	0.909	0.923	0.936	0.915	0.911
	DMU 9	0.908	0.911	0.93	0.918	0.915	0.919	0.919	0.91	0.927
	DMU 10	0.909	0.929	0.941	0.91	0.912	0.909	0.921	0.936	0.955
	DMU 11	0.97	0.976	0.966	0.966	0.972	0.964	0.964	0.962	0.973
	DMU 12	0.962	1	0.988	1	1	1	1	0.997	1
	DMU 13	1	1	0.981	0.994	0.993	0.99	0.974	0.952	0.966
	DMU 14	0.91	0.909	0.896	0.898	0.877	0.901	0.902	0.925	0.916
	DMU 15	0.909	0.91	0.887	0.89	0.904	0.901	0.909	0.899	0.924
	DMU 16	0.819	0.82	0.8	0.809	0.803	0.793	0.846	0.911	0.871
	DMU 17	0.916	0.905	0.909	0.9	0.904	0.906	0.917	0.918	0.924
	DMU 18	0.992	0.988	0.972	0.97	0.978	0.983	1	1	0.999
	DMU 19	0.877	0.895	0.903	0.91	0.912	0.933	0.92	0.924	0.998
	DMU 20	0.907	0.935	0.943	0.95	0.951	0.956	0.969	0.964	1
	DMU 21	0.918	0.937	0.935	0.939	0.943	0.94	0.943	0.97	0.941
	DMU 22	0.864	0.876	0.859	0.871	0.874	0.88	0.878	0.859	0.876
	DMU 23	0.909	0.923	0.918	0.917	0.926	0.922	0.926	0.917	0.948
	DMU 24	0.988	0.96	0.927	0.985	1	0.99	0.983	1	1
	DMU 25	0.915	0.915	0.933	0.898	0.897	0.9	0.907	0.888	0.884
	DMU 26	0.721	0.783	0.757	0.755	0.836	0.774	0.766	0.761	0.79
IPP Plants	DMU 27	0.897	0.939	0.951	0.95	0.957	0.955	0.976	0.972	0.953
	DMU 28	0.848	0.845	0.828	0.83	0.786	0.742	0.866	0.843	0.851
	DMU 29	0.992	0.996	0.971	0.969	0.974	0.984	0.97	0.985	0.944
	DMU 30	0.965	0.973	0.935	0.96	0.974	0.962	0.941	0.912	0.927
	DMU 31	0.945	0.942	0.944	0.92	0.95	0.984	0.939	0.921	0.928
	DMU 32	1	1	1	0.992	0.993	0.996	1	1	0.986
	DMU 33	1	1	1	1	1	0.95	0.959	1	1
	DMU 34	0.935	0.959	0.931	0.957	0.964	1	0.974	0.95	0.961
	DMU 35	0.943	0.966	0.958	0.937	0.915	0.944	0.927	0.919	0.906
	DMU 36	0.934	0.947	0.929	0.939	0.97	0.99	0.973	0.954	0.95
	DMU 37	0.984	1	1	1	1	1	1	0.999	1
	DMU 38	0.889	0.883	1	1	0.919	0.949	0.959	0.956	0.884
	DMU 39	0.885	0.883	0.874	0.875	0.877	0.889	0.874	0.855	0.898
	DMU 40	0.977	0.98	0.982	0.985	0.986	0.969	0.961	0.975	0.97

References:

Arocena, P. and C.W. Price., 2002. “Generating efficiency: economic and environmental regulation of public and private electricity generators in Spain”, *International Journal of Industrial Organization*, 20 (1): 41-69.

Bernstein, M. A., S. L. Feldman, and A. P. Schinnar, 1990. "Impact of Pollution Controls on the Productivity of Coal-Fired Power Plants," *Energy Economics*, 12, 11-17.

Chambers, R.G., A. Hailu and J. Quiggin, 2011. “Event-specific data envelopment models and efficiency analysis”, *Australian Journal of Agricultural and Resource Economics*, 55(1): 90-106.

Charnes, A., W.W. Cooper and E. Rhodes, 1978. “Measuring the Efficiency of Decision Making Units”, *European Journal of Operational Research*, 12: 429-444.

Du, L.M., J. Mao, J.C. Shi, 2009. “Assessing the impact of regulatory reforms on China’s electricity generation industry”, *Energy Policy,* 37: 712-720.

EIA, U.S. Energy Information Administration, 2010. Electric Power Annual 2009.

Färe, R, S. Grosskopf, J. Logan, 1985. “The Relative Performance of Publicly- owned and Privately-owned Electric Utilities”, *Journal of Public Economics*, 26: 89-106.

Färe, R., S. Grosskopf, C. A. K. Lovell, and C. Pasurka, 1989. "Multilateral Productivity Comparisons When Some Outputs are Undesirable: A Nonparametric Approach”, *Review of Economics and Statistics,* 71: 90-98.

Hailu, A. and T.S. Veeman. 2000. "Environmentally Sensitive Productivity Analysis of the Canadian Pulp and Paper Industry, 1959-1994: An Input Distance Function Approach," *Journal of Environmental Economics and Management*, 40: 251-74.

Hailu, A. and T.S. Veeman. 2001a. "Nonparametric Productivity Analysis with Undesirable Outputs: An Application to the Canadian Pulp and Paper Industry,” *American Journal of Agricultural Economics*, 83: 605-616.

Hailu, A. and T.S. Veeman, 2001b. “Alternative methods for environmentally adjusted productivity analysis”, *Agricultural Economics*, 25: 211-218.

Joskow, P. and Schmalensee, R., 1987. The performance of coal-burning electric generating units in The United States: 1960–1980. *Journal of Applied Econometrics*, 2, 85–109.

Kwoka, J. and M. Pollitt, 2010. “Do mergers improve efficiency? Evidence from restructuring the US electric power sector”, *International Journal of Industrial Organization*, 28: 645-656.

Lam P. L. and A. Shiu, 2004. “Efficiency and Productivity of China’s Thermal Power Generation”, *Review of Industrial Organization*, 24: 73-93.

Ma, C.B., L.N. He, 2008. “From state monopoly to renewable portfolio: Restructuring China’s electric utility”, *Energy Policy*, 36: 1697-1711.

Meyer, R.A., 1975. “Publicly Owned Versus Privately Owned Utilities: A Policy Choice”, *Review of Economics and Statistics*, 57: 391-399.

Olatubi, W.O and D.E Dismukes, 2000. “A Data Envelopment Analysis of the Levels and Determinants of Coal-fired Electric Power Generation Performance”, *Utilities Policy,* 9: 47-59.

Pollitt, M.G., 1995. Ownership and Performance in Electric Utilities. Oxford University Press.

Reifschneider, D. and R. Stevenson, 1991. “Systematic departures from the frontier: A framework for the analysis of firm inefficiency. *International Economic Review* 32:715-23.

Sueyoshi, T. and M. Goto, 2011. “DEA approach for unified efficiency measurement: Assessment of Japanese fossil fuel power generation”, *Energy Economics*, 33: 292-303.

Seiford, L.M. and R.M. Thrall, 1990, "Recent Developments in DEA: The Mathematical

Programming Approach to Frontier Analysis," *Journal of Econometrics* vol. 46: pp. 7–38.

Yaisawarng, S. and J. D. Klein, 1994. “The effects of sulfur dioxide controls on productivity change in the U.S. electric power industry”, *Review of Economics and Statistics*, 76: 447-460.

Zhang, X.C. and J.E. Parsons, 2008. “Market Power and Electricity Market Reform in Northeast China”, working paper 08-001, Center for Energy and Environmental Policy Research, MIT.

Zhou, P., B.W. Ang and K.L. Poh, 2008. A survey of data envelopment analysis in energy and environmental studies. *European Journal of Operational Research* 189, 1–18.