Energy-saving and emission-abatement potential of Chinese coal-fired power enterprise: a non-parametric analysis

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ABSTRACT

In the context of soaring demand for electricity, mitigating and controlling greenhouse gas emissions is a great challenge for China's power sector. Increasing attention has been placed on the evaluation of energy efficiency and CO_2 abatement potential in the power sector. However, studies at the micro-level are relatively rare due to serious data limitations. This study uses the 2004 and 2008 Census data of Zhejiang province to construct a non-parametric frontier in order to assess the abatement space of energy and associated CO_2 emission from China's coal-fired power enterprises. A Weighted Russell Directional Distance Function (WRDDF) is applied to construct an energy-saving potential index and a CO_2 emission-abatement potential index. Both indicators depict the inefficiency level in terms of energy utilization and CO_2 emissions of electric power plants. Our results show a substantial variation of energy-saving potential and CO_2 abatement potential among enterprises. We find that large power enterprises are less efficient in 2004, but become more efficient than smaller enterprises in 2008. State-owned enterprises (SOE) are not significantly different in 2008 from 2004, but perform better than their non-SOE counterparts in 2008. This change in performance for large enterprises and SOE might be driven by the "top-1000 Enterprise Energy Conservation Action" that was implemented in 2006.

Keywords: Energy-saving potential; CO_2 abatement potential; Weighted Russell Directional Distance Function; Coal-fired power enterprise

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1. Introduction

The expansion of China's power sector raises worldwide concerns due to its significant role in global greenhouse gas (GHG) emissions. In 2011, China's power sector produced about 3981 million tons of CO_2 equivalent ($MtCO_2e$), accounting for almost 50% of China's and about 13% of the worldwide emissions from fuel, respectively (IEA, 2013). China's booming power generating capacity —950 gigawatt (GW) in 2010, and expected to hit 1760 GW by 2020, still can't keep up with its rapidly increasing electricity demand (Reuters, 2011). Given the rapid expansion of the power sector in China, problems might be further exacerbated in the future.

To reverse this trend, China has made great efforts to reduce its energy intensity by 19.1% during the 11th Five-Year Plan (FYP) from 2006 to 2010 (NDRC, 2011). New targets for reducing its energy intensity and carbon intensity by 16% and 17% relative to its 2010 levels by 2015 were set in the 12th FYP (2011-2015), respectively (Zhang, 2011). To achieve this national goal, a key program is the Top-1000 Enterprises Energy Conservation Action launched by the National Development and Reform Commission (NDRC), the National Bureau of Statistics (NBS), the State-owned Assets Supervision and Administration Commission, the Office of National Energy Leading Group and the General Administration of Quality Supervision, Inspection and Quarantine in 2006 (Price et al., 2010). The aggregated energy consumption for these Top-1000 enterprises accounts for 47% of total industrial sector and 33% of total national energy consumption in 2005. Whether these top-1000 enterprises can achieve their energy-saving targets, i.e. 100 Mtce (Millions of tons of coal equivalent) by 2010, is thus crucial for achieving the national goal. To create strong incentives for decision-makers, large-scale enterprises, mostly state-owned enterprises (SOE) with a minimum of 180,000 tons of coal equivalents (tce) energy consumption from nine major energy-intensive sectors[1], must sign an energy conservation agreement with local governments. To meet the program's requirement, the top-1000 enterprises are required to establish an energy-saving organization, set up an energy-saving target, submit their quarterly fuel utilization information online to NBS directly, invest in energy efficiency improvements and conduct energy auditing and training. Additionally, the enterprise managers and local officials cannot be promoted without achieving their goal. Under this strict regulation, the top-1000 enterprises reached its target at the end of 2008. However, the cost-effectiveness of the program is unclear. There exists neither a bottom-up analysis nor an evaluation of energy-saving and emission-reduction potentials at the enterprise level in China (Price et al., 2011; WorldBank, 2009). Hence, the distribution of energy-savings and emission-abatement potential among large enterprises or SOEs is unknown.

Given this background, one question we are interested in is whether a large power enterprise has greater energy-saving potential and associated CO_2 abatement potential than a smaller enterprise. The existing literature does not provide a clear linkage between firm size and energy (in)efficiency. On the one hand, large firms can benefit from economies of scale and the formalization of procedures, which allow them to gain superior performance relative to smaller ones. On the other hand, large firms might be characterized by complex hierarchical management structures, failure to minimize production costs and lack of competition, which lead to X-inefficiency (Leibenstein, 1975). Empirical studies are also equivocal. For example, some studies support a positive relationship between efficiency and firm size (Kalaitzandonakes et al., 1992; Lundvall and Battese, 2000; Pagano and Schivardi, 2003). Contrarily, Page (1984) finds little

[1] These nine sectors include: iron and steel, chemical, electricity power generation, petroleum, construction materials, non-ferrous metals, coal mining, paper, textile

evidence of a systematic relationship between firm size and efficiency. Majumdar (1997) offers the opposite evidence and finds larger firms to be less productive than small ones.

As for ownership, the debate on relative efficiency of public versus private enterprises also has a long history in economics. The property rights view suggests that publicly owned enterprises perform less efficient than privately owned enterprises since the public ownership attenuates property rights and reduces the manager's incentive to minimize costs. Consequently, state-owned enterprises (SOE) perform less efficiently and hence have a higher abatement potential than private firms. However, the existing empirical evidence provides weak support for this hypothesis. For example, Atkinson and Halvorsen (1986) find no significant difference between publicly and privately owned electric utilities in the U.S.

Given the crucial role that the power sector plays in climate change mitigation and the debates on current practices, several important questions naturally arise: How large are coal-fired power enterprises' reduction potential of energy usage and associated CO_2 emission in China? Are these potentials associated with enterprise scale and ownership? This paper attempts to respond to these questions by analyzing data from coal-fired power enterprises in China's Zhejiang province of the years 2004 and 2008. Since the energy-saving regulation for these enterprises was implemented in 2006, this unique firm-level data also provides an opportunity to examine whether the energy reduction potential and its associated CO2 abatement potential changed.

The non-parametric approach of data envelopment analysis (DEA) has been widely used in the literature. A key advantage of DEA over other approaches is that it does not need a specific pre-assumed functional form and can easily accommodate both multiple inputs and multiple outputs. This technique has been applied to evaluate, e.g., the relative energy and environmental efficiency of U.S. power plants (Färe et al., 1989; Färe et al., 2007; Pasurka, 2006; Tyteca, 1997).

Zhou et al. (2008) and Zhang and Choi (2014) provide a comprehensive overview on the use of DEA model in energy and environmental studies. Recently, DEA has been used with increasing frequency in studies of the Chinese power sector: Choi et al. (2012) apply a non-radial slacks-based DEA model to estimate the energy efficiency and shadow price of energy-related CO_2 emissions at the province level for the period 2001 to 2010. Xie et al. (2012) use a two-stage network DEA model to evaluate the provincial environmental performance in China and explore the linkage between the environmental efficiency and generation forms. Yang and Pollitt (2009) apply three multiplicative DEA models to 582 Chinese coal-fired power plants in 2002 to gauge their environmental performance. They also employ an unbalanced panel of 796 power plants during 1996-2002 to calculate the Malmquist TFP indices (Yang and Pollitt, 2012). Using an output-oriented DEA technique, Zhao and Ma (2013) estimate the technical and scale efficiency score of 34 power plants during 1997-2010 and then examine the impact of deregulation on performance.

Apart from these previous studies, this paper applies the non-radial Weighted Russell directional distance function approach to measure the energy-saving potential index and CO_2 emission-abatement potential index for coal-fired power enterprises in 2004 and 2008. This approach is first developed by Chen et al. (2011) which mirrors the strategy employed by Chung et al. (1997) and extended the work of Fukuyama and Weber (2009). It recently has been applied for Japanese banks (Barros et al., 2012), Indian banks (Fujii et al., 2014) and Korean power plants (Zhang et al., 2013). One advantage of this methodology is that it provides the specific-factor efficiency (such as energy efficiency and CO_2 emission efficiency) in addition to the overall efficiency score in the radial directional distance function (DDF) model (Sueyoshi and Goto, 2011). Moreover, it can avoid the overestimation the efficiency value as it takes account the nonzero slacks, which are ignored in the radial DDF model (Fukuyama and Weber, 2010)[2]. To our knowledge the current paper is the first micro-level study using this innovative methodological approach to assess the energy-saving potential and CO_2 abatement potential in China. Our results suggest that the top-1000 enterprise program, which started in 2006, significantly affected the performance of large and SOE power enterprises. These enterprises become more efficient in terms of energy utilization and CO_2 emissions when compared to small and non-SOE enterprises, respectively. As smaller-size and non-SOE enterprises are associated with higher potentials for energy savings and CO_2 emission reductions, energy conservation programs might change their scope accordingly.

The remainder of this paper is organized as follows. Section 2 introduces Zhejiang's power sector. Section 3 presents the methodology and data. In section 4, we derive and discuss the results. Finally, we present conclusions and draw some policy implications.

2. Description of Zhejiang's Power Sector

We select Zhejiang province as our sample region. It has a developed economy characterized by high energy demand and high productivity. With a population of 51.8 million it is situated in the Yangtze River Delta. In 2009, Zhejiang ranked 4th in terms of per capita GDP among 31 Chinese provinces, accounting for 6.8% of national GDP and 11.1% of China's exports (NBS, 2010). However, like most of the other provinces, it suffers from serious shortages of energy due

[2] Zhou et al. (2012a) present a formal definition of the non-radial directional distance function to modeling energy and CO_2 emission performance in the electric power sector. The non-radial models fall into three categories: Russell measure, Additive model and Slacks-based model (SBM). In general, the non-radial efficiency measures have a higher discriminating power relative to the standard formulation of DEA-based models. However, the setting of a weight vector *w* may depend on the purpose of the research. More discussion and a comparison for these models can be found in Barros et al. (2012)

to its rapid industrialization and increased urbanization. The maximum power supply capacity shortages in Zhejiang were estimated at around 3.6 GW during the summer of 2010 when the local grid operator had to cut the power supply to energy-intensive sectors (Reuters, 2010). Driven by market opportunities, substantial investments have flowed to the construction of power generation projects. Figure 1 presents the historical trend of total generation, thermal power generation and total installed capacity in Zhejiang from 2002-2009. Its installed capacity, as shown in the left vertical axis, indicates a steady increase from 20.7 GW in 2002 to 56.2 GW in 2009, with an annual growth rate of 15.3%. The total power generation in 2009 reaches 224.6 TWh, 2.5 times the 2002 level with a 14.2% growth rate.

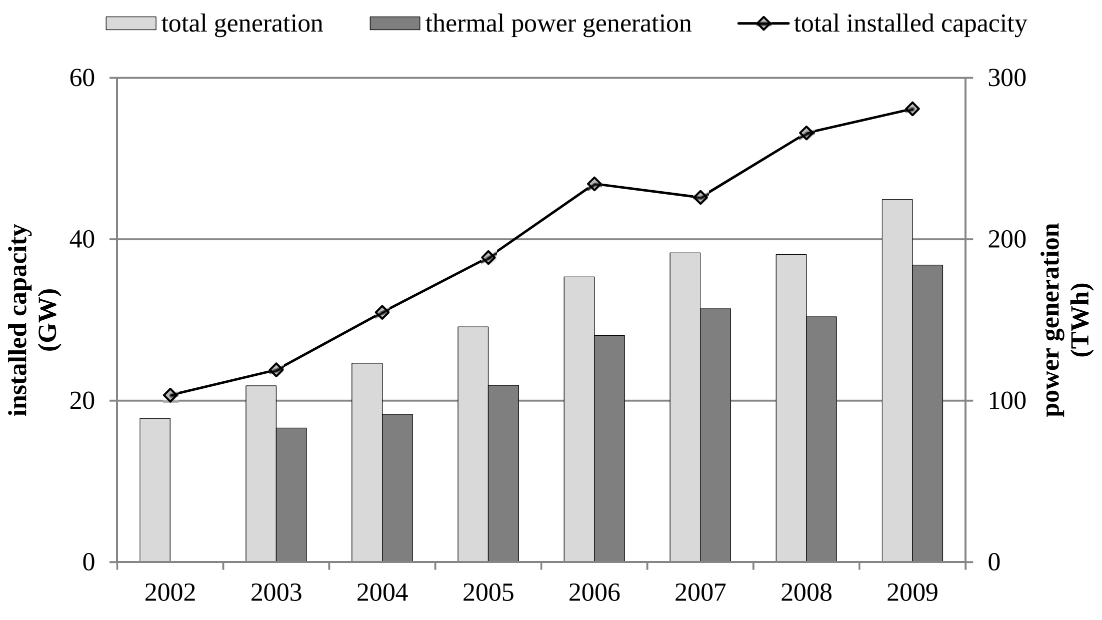

Figure 1 Power generation and installed capacity in Zhejiang (2002-2009)

Source: The power generation data is taken from the China Energy Statistical Yearbook (NBS,2009); the installed capacity data is taken from the White Paper of Energy in Zhejiang (Zhejiang Province Economic and Information Commission and Zhejiang Provincial Bureau of Statistics, 2010).

Figure 1 also reveals that thermal power generation contributes around 80% of the total generation capacity in Zhejiang. Consequently, the power sector in the Zhejiang province is a major source of GHG. In 2007, it produced 314 $MtCO_2e$, which accounts for 81.6% of Zhejiang's and 2.1% of the national GHG emissions (Province, 2010). The resource utilization efficiency in Zhejiang's power sector remains high due to a high proportion of larger-scale generating units. Table 1 lists the energy intensity of thermal power generation in China and Zhejiang province. Energy consumption in Zhejiang's thermal power enterprises to generate one kWh is noticeably less than the national average level. However, if we compare it to the international advanced level, the thermal power enterprises in Zhejiang province still have 6.7-11.5% improvement potential in energy efficiency.

Table 1 Comparison of energy intensity of thermal power generation

			China		Zhejiang	
Indicator	Units	International advanced level	average level (2006)	top-1000 enterprises (144 thermal power plants, 2006)	Large & medium size thermal power plants (2005)	Smaller thermal power plants above 6MW (2006)
Coal consumption per unit of thermal power generation	Grams of coal equivalents / kWh	312	366	365	333	348

Source: All data except Zhejiang are taken from the Report on the State Energy use of the Top-1000 Enterprises (NDRC and NBS, 2007). The last two columns refer to the White Paper of Energy in Zhejiang(Zhejiang Province Economic and Information Commission and Zhejiang Provincial Bureau of Statistics, 2010).

Table 2 presents several macro-level single-factor productivity indicators. In 2009, one unit of tce in Zhejiang generated 13,500 Yuan GDP and 8,900 Yuan industrial value-added, ranked 4th and 6th in terms of the productivity level among 31 provinces, respectively. The GDP per unit of CO_2 emissions of the Zhejiang province is 1.43 times the national level and ranked 8th in 2007.

Table 2 Energy productivity and CO_2 productivity of Zhejiang

Indicators	Units	Year	Zhejiang province	Ratio to national level	Rank among 31 provinces
GDP per unit of energy consumption	10,000 Yuan/ tce, 2005 price	2009	1.35	1.45	4
Industrial value-added per unit of energy consumption	10,000 Yuan/ tce, 2005 price	2009	0.89	-	6
GDP per unit of CO_2 emission	10,000 Yuan /ton, 2007 price	2007	1.29	1.43	8

Source: The data in the second and third row is taken from China Statistical Yearbook (NBS, 2010). The data in the last row derives from the Climate Change Program of Zhejiang Province (Zhejiang Provincial Government, 2010).

Zhejiang seems to be a particularly interesting region to study the performance of coal-fired power plants in China. Our estimated result for energy-saving and emission-abatement potentials in Zhejiang will provide a valuable reference for China’s situation.

3. Methodology and Data

3.1 The Analytical Framework

Our analytical framework is based on a directional distance function combined with a non-parametric DEA approach. We consider a productive process that uses a vector of inputs $x \in \mathrm{R}_{+}^{N}$ to produce two kinds of outputs: Good output and bad output, which are denoted by the vector $y \in \mathrm{R}_{+}^{M}$ and $b \in \mathrm{R}_{+}^{J}$, respectively. The relationship between inputs and outputs is represented by an output set:

$$P(x) = \left\{ (y,b) : x \in \Re_{+}^{N} \; can\; produce \; (y,b) \in \Re_{+}^{M} \times \Re_{+}^{J} \right\} \tag{1}$$

Apart from the standard convex and compact assumptions, the output set (1) satisfies free disposability of good outputs, that is: $(y,b) \in P(x) \, and \; y' \leq y \Rightarrow (y',b) \in P(x)$. This indicates that it is possible to reduce good output without reducing bad output. Also, the input is freely disposable if $x' \geq x \in \Re_{+}^{N} \Rightarrow P(x') \supseteq P(x)$. Furthermore, we assume that bad outputs and good outputs satisfy joint weak disposability: $if\,(y,b) \in P(x) \, and \, 0 \leq \theta \leq 1, then\, (\theta y, \theta b) \in P(x)$. Weak disposability implies that it is feasible to reduce both good and bad output proportionally by θ. The idea is to make sure that it is 'costly' to reduce bad output[3]. Finally, good and bad outputs are

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[3] The concept of weak disposability is first introduced by Färe et al. (1989) when modeling an environmental production technology. However, it faces criticism recently in energy and environmental economics studies. Kuosmanen (2005) suggests that the weak disposability in DEA analyses may unintentionally assume that all firms apply uniform abatement factors. Yang and Pollitt (2010) argue that the weak disposability assumption may not suit for the SO_2 case in the electricity sector. They also find that the imposition of this assumption significantly alters results. Chen (2013) re-examine the weak disposability assumption and finds that the non-additive efficiency model violates the monotonic axiom in pollution quantities. Sueyoshi and Goto (2012) review the weak and strong disposability concepts and confirm that the weak disposability cannot properly measure an occurrence of undesirable congestion. They suggest to replace the weak/strong disposability with a newly proposed natural/managerial disposability. Recently, Aparicio et al. (2013) and Färe et al. (2014) modify the specification of weak disposability that eliminates the downward sloping good-bad output production frontier. In the present paper, we still model weak disposability as our bad

assumed to satisfy the null-jointness or byproduct axiom, that is:

$if\,(y,b) \in P(x)\, and\, b = 0, then\, y = 0$, which implies that good output cannot be produced without producing bad output. In other words, bad output is jointly produced with good output.

The general directional output distance function can be defined as follows:

$$\vec{D}_o(x, y, b; g_x, g_y, g_b) = \sup\left\{\beta : (y + \beta g_y, b + \beta g_b) \in P(x + \beta g_x)\right\} \tag{2}$$

The direction vector $g= (g_x, g_y, g_b)$($g \in \mathrm{R}_+^N \times \mathrm{R}_+^M \times \mathrm{R}_+^J$) indicates that we intend to expand the good output and contract both the input and the bad output. Its components g_x , g_y and g_b determine the direction for input, good and bad outputs, respectively. Given the production technology $P(x)$ and the direction vector g, the directional distance function aims at the maximum feasible expansion of good outputs and contraction of input and bad outputs along the direction vector g_y , g_b and g_x. The value of β is the distance between the observation and the boundary. If one observation lies on the frontier, it is the most efficient observation compared with others and yields a zero value of β. As the value β increase, the observation becomes less efficient.

Since our focus is the specific-factor inefficiency (such as the energy-saving potential and the CO_2-abatement potential) rather than the overall inefficiency, we apply the weighted Russell directional distance model (WRDDM) following Barros et al. (2012) and Fujii et al. (2014). Assume there are $k=1,\ldots,K$ observations using $n=1,\ldots,N$ inputs to obtain a vector of $m=1,\ldots,M$ good outputs and a vector of $j=1,\ldots,J$ bad outputs. The production technology exhibits constant returns to scale. The value of $\vec{D}_o(x, y, b)$ for the *k'-th* firm can be computed by solving the following programming problem:

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output is CO_2. The non-radial additive model doesn't violate monotonicity assumption in this case and it allows for non-uniform scale factors.

$$\vec{D}_o(x^{k'}, y^{k'}, b^{k'}; g_x, g_y, g_b) = \max\left(\omega_n^{k'}\beta_n^{k'} + \omega_m^{k'}\beta_m^{k'} + \omega_j^{k'}\beta_j^{k'}\right) \tag{3}$$

$s.t.$

$$\sum_{k=1}^{K} z^k y_m^k \geq (y_m^{k'} + \beta_m^{k'} \cdot g_{y_m}),\ m = 1,...,M \qquad \text{(i)}$$

$$\sum_{k=1}^{K} z^k b_j^k = (b_j^{k'} - \beta_j^{k'} \cdot g_{b_j}),\ j = 1,...,J \qquad \text{(ii)}$$

$$\sum_{k=1}^{K} z^k x_n^k \leq (x_n^{k'} - \beta_n^{k'} \cdot g_{x_n}),\ n = 1,...,N \qquad \text{(iii)}$$

$$z^k \geq 0, k = 1,...,K \qquad \text{(iv)}$$

where z^k are the intensity variables that weight the observations to construct the production set. The left-hand and right-hand sides for constraints (i)-(iii) for model (3) represent the theoretical efficient enterprise and the actual observation. The coefficient vector $\omega=(\omega_n, \omega_m , \omega_j)^T$ denotes a normalized weight vector relevant to the number of inputs and outputs. The coefficient β_n, β_m and β_j denote the individual inefficiency measures for the n-th input, m-th good output and j-th bad output, respectively. Note that the inequality sign in (i) and (iii) in both models represents the free disposability of good outputs and inputs. The constraint (ii) shows that the bad outputs are weakly disposable and meet the theoretical assumption of null-jointness. The last constraint (iv) is used to ensure that all intensity variables are non-negative. In the present paper, we have three inputs, one good output and one bad output, thus the normalized weight vector ω is set as (1/9,1/9,1/9,1/3,1/3) since it is more reasonable for an economic power utility (Zhang et al., 2013). Following previous empirical studies, the directional vector is set as $g=(g_x , g_y , g_b)=(-x_n, y_m,-b_j)$, which suggests the inefficient firm can simultaneously scale the input/output vector in proportion to its initial combination of actual inputs and outputs (Barros et al., 2012; Fujii et al., 2014)[4].

3.2 Energy-saving Potential Index and Emission-abatement Potential Index

One of the advantages of WRDDM is that it can expand each good output and contract each input and bad output with different proportion rates. In other words, it can assist us to find the maximum distance (potential) for each input/output vector toward the frontier. Consequently, one may derive specific factor's inefficiency measures and examine each factor's contribution to overall inefficiency.

Suppose that $\beta_{energy}^{k'}$ is the optimal solution to the energy input in model (3), we introduce the *k'*-th firm's Energy-Saving Potential Index (*ESPI*) as:

$$ESPI^{k'} = \frac{\beta_{energy}^{k'} \cdot g_{energy}^{k'}}{x_{energy}^{k'}} \tag{4}$$

The *ESPI* measures the maximum feasible saving potential compared with the best-performing firms and reflects the inefficiency level with respect to the energy factor. The value of the *ESPI* is non-negative and less than or equal to 1. A higher value of the *ESPI* indicates a larger inefficiency

[4] As Vardanyan and Noh (2006) explored, different directional vectors for good and bad outputs affect results. The choice of the directional vector depends on the research purpose and policy goals. One may treat the good and bad output asymmetrically or symmetrically. It is also possible to credit a producer for expanding good output production while holding bad outputs production constant. Energy efficiency studies adopt the strategy to minimize energy use while holding the good/bad output and non-energy inputs constant either by DEA (Blomberg et al., 2012; Mandal, 2010; Shi et al., 2010) or stochastic frontiers techniques (Boyd, 2005; Zhou et al., 2012b). The directional vector in this case is (g_x, g_y, g_b)=($-x_{energy}$, 0, 0) and it is essentially equivalent to an input-oriented DEA model. If the focus is on reducing bad output production, one may minimize the bad output while holding the good output and inputs constant. In this case, the directional vector is (g_x, g_y, g_b)=(0, 0, $-b$) and it is essentially equivalent to an output-oriented DEA model. Following Zhou et al. (2012a) and Zhang et al. (2014), the present assumption of directional vector seeks to simultaneously reduce inputs and bad output and expand good output non-proportionally

and a greater potential to remove excessive energy input through efficiency improvement. It should be noted that a zero value of the *ESPI* does not imply that the firms are perfect and without any excessive energy or inefficiency during the production process. Rather, it indicates that the firms are Pareto-Koopmans efficient among all of the observations in the sample (Charnes et al., 1985).

Moreover, the *k'*-th firm's total-factor energy efficiency (*TFEE*) can be defined (Hu and Wang, 2006) as:

$$TFEE_{energy}^{k'} = \frac{x_{energy}^{k'} - \beta_{energy}^{k'} \cdot g_{energy}^{k'}}{x_{energy}^{k'}} = 1 - \frac{\beta_{energy}^{k'} \cdot g_{energy}^{k'}}{x_{energy}^{k'}} = 1 - ESPI^{k'} \tag{5}$$

Similarly, we introduce the CO_2 Abatement Potential Index (*CAPI*) as the ratio of maximum feasible reduction volume to its actual emission level (Wei et al., 2012). That is:

$$CAPI^{k'} = \frac{\beta_{CO_2}^{k'} \cdot g_{CO_2}^{k'}}{b_{CO_2}^{k'}} \tag{6}$$

CAPI in equation (6) is used to measures the relative degree of CO_2 reduction for plant *k'*. It has a non-negative value and is not higher than 1. A zero value of *CAPI* indicates that the firm performs best in terms of emission. Conversely, a higher value indicates greater inefficiency and larger potential to remove excessive undesirable outputs.

Also, the *k'*-th firm's total-factor CO_2 efficiency (*TFCE*) is given as below, that is:

$$TFCE_{CO_2}^{k'} = \frac{b_{CO_2}^{k'} - \beta_{CO_2}^{k'} \cdot g_{CO_2}^{k'}}{b_{CO_2}^{k'}} = 1 - \frac{\beta_{CO_2}^{k'} \cdot g_{CO_2}^{k'}}{b_{CO_2}^{k'}} = 1 - CAPI^{k'} \tag{7}$$

3.3 Data

The novel data set used in this study is taken from the First and Second National Economic Census (NECC) of the Zhejiang province that was conducted in 2004 and 2008, respectively[5]. It covers the basic characteristics of coal-fired power enterprise units, including the number of employees, financial situation, production and business operation situation, production capacity, consumption of raw materials and energy as well as scientific and technology-oriented activities.

All state-owned industrial corporations and non-state-owned industrial enterprises in the Zhejiang province with annual sales from principal activity of five million Yuan or more in the power sector are analyzed. The input data consists of labor, capital stock and energy consumption. The average number of employees is used to represent the productive labor force. As for capital, we use the value of fixed assets in the power enterprise derived from independent accounting systems. The price indices of investment in fixed assets are used to deflate the capital value in 2008's constant price. The energy data in 2004 comes from the first NECC. The 2008's energy data comes from the Compilation of Statistical Data of Electric Power Industry (CEC, 2009). The aggregate heat content of coal, oil and natural gas are used to represent the energy input. They are all converted to standard coal equivalents. There are two outputs: one good output, given by the electricity generation (gigawatt hour, GWh), and one bad output, measured by estimated CO_2 emission. We follow Du et al. (2012) to estimate the CO_2 emissions from fossil fuel consumption[6].

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[5] The major purpose of the National Economic Census of China (NECC) is to keep abreast of the development of the secondary and tertiary industries of China. The data of the first and second NECC covered the whole year of 2004 and 2008, respectively. The detailed introduction of the first NECC (2004) can be found at: http://www.stats.gov.cn/english/NewsEvents/200603/t20060301_25734.html; the information for the second NECC(2008) can be found at: http://www.stats.gov.cn/english/NewsEvents/200912/t20091225_26264.html

[6] The IPCC guideline provides the reference value for the emission factor. The average calorific value for each fuel can be obtained from NBS (2009).

To ensure that all units under the DEA assessment are homogeneous and employ the same production technology (Dyson et al., 2001), we select for our sample those units whose primary output is electricity and exclude power enterprises where the coal share in fuel input is less than 95% (Färe et al., 2007). Finally, the data set covers 106 coal-fired power enterprises in 2004 and 76 enterprises in 2008, totally 182 observations[7]. Since private information of enterprises (such as ID, name, geographical location etc) is unavailable, we cannot assess which enterprises appear in both years. Descriptive statistics for all variables are presented in Table 3. From Table 3 a rough first impression is that the average sample enterprise in 2008 doubled its capital input in order to double its electricity and CO_2 production compared to 2004. However, energy consumption increases by less and labor input even decreases.

The study sample provides a rather representative picture. In 2004, the 106 sample power enterprises consumed 32.7 million tce, about 30% of total energy in Zhejiang to generate 83.9 TWh electricity, which accounts for 68.2% of total generation. Compared with 2004, the number of power enterprise in the 2008 sample decreased to 76. But they accounted for an even higher share of total generation (68.5%) and a slightly smaller share in energy consumption (26.4%).

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[7] Some of the power enterprises may have more than one plant. However, this information is unavailable in NECC 2004 and 2008.

Table 3 Descriptive statistics of coal-fired power enterprises in Zhejiang

Variable	**Description**	**Units**	**Mean**	**Std. Dev.**	**Min**	**Max**
2004 (n=106)						
Y	Electricity	GWh	792.08	2059.34	2.27	13000
B	CO_2	10,000 tonnes	85.68	169.89	1.62	1100
L	Labor	Persons	314.69	417.63	21.00	2528
K	Capital stock	Million Yuan	464.25	1130.22	3.55	7600
E	Heat content of fuel	10,000 tce	30.82	63.08	0.59	410
2008 (n=76)						
Y	Electricity	GWh	1717.58	3742.94	11.72	15000
B	CO_2	10,000 tonnes	145.30	309.33	1.18	1200
L	Labor	Persons	290.80	361.21	22.00	2059
K	Capital stock	Million Yuan	940.34	1812.52	2.42	7600
E	Heat content of fuel	10,000 tce	52.53	112.13	0.43	450

4. Empirical Results

The GAMS/MINOS solver was employed to estimate the WRDDM in equation (3). We first report *ESPI* and *CAPI* according to equation (4) and (6), respectively. Thereafter we conduct statistical tests.

4.1 Measure ESPI and CAPI

The left vertical axis in Figure 2 shows the projected minimum energy input and excess energy usage due to inefficiency for each power enterprise in 2004. The total length of a bar comprises projected and excess energy. The right vertical axis shows the *ESPI* score which is derived by dividing the excess energy input by the observed energy level. Similarly, the left vertical axis in Figure 3 depicts the observed CO_2 emission and the excess CO_2 emission resulting from inefficiency for year 2004. The right axis is the *CAPI* that is used to measure the relative abatement potential of CO_2. 62 out of 106 enterprises in 2004 have a zero value of ESPI, which suggests that these enterprises perform better than others in terms of energy utilization, or they cannot reduce energy input further if all other things remain unchanged. 12 out of 106 enterprises in 2004 have a zero value of *CAPI*, which suggests that these enterprises cannot reduce CO_2 emissions further if other things are fixed.

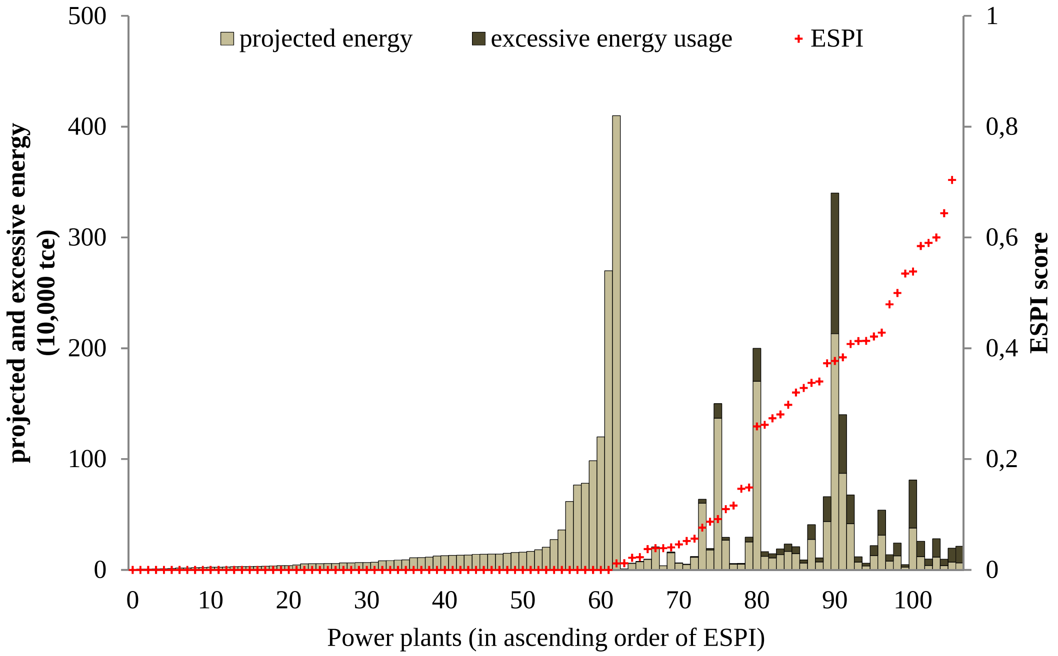

Figure 2 Projected energy, excessive energy and ESPI (2004)

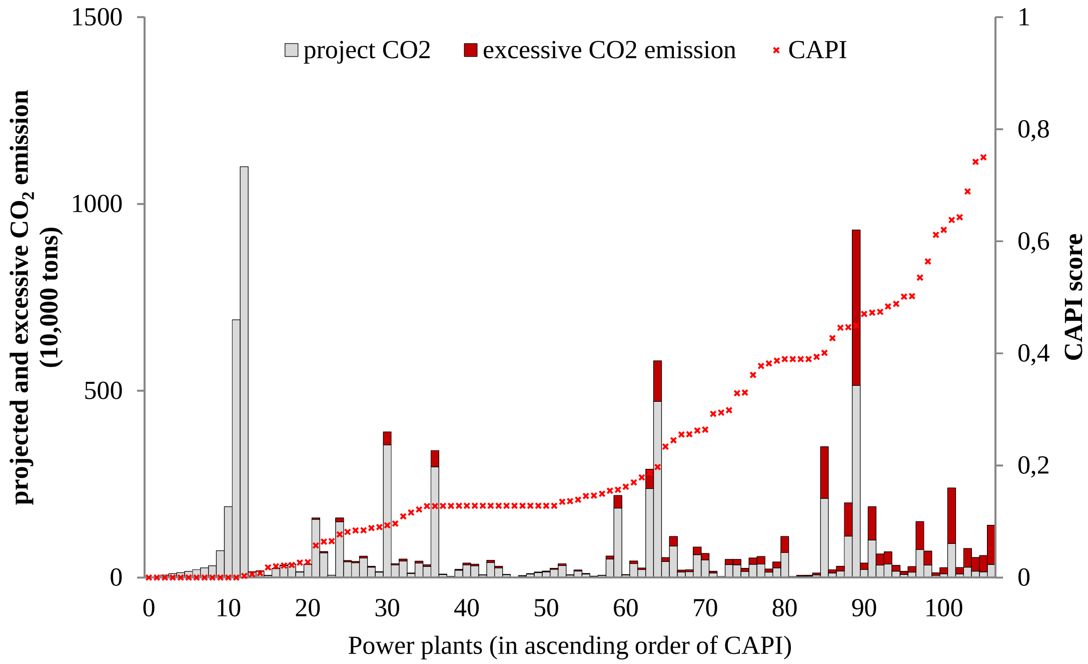

Figure 3 Projected CO_2, excessive CO_2 and CAPI (2004)

It should be kept in mind that the zero value of *ESPI* or *CAPI* for these power enterprises is a relative concept. It indicates that they are relatively efficient in terms of energy use or emissions when compared to other enterprises. If all inefficiency measures, β_n, β_m and β_j equal zero, the power enterprise is globally efficient and lies on the best-practice frontier[8].

Figure 4 and 5 present the ESPI and CAPI in the year 2008. It can be seen that 24 of the 76 enterprises are efficient in terms of their energy utilization since the ESPI score is zero. As for the CO_2 emission, 18 of 76 enterprises are relatively efficient with a zero value of CAPI. If we compare the 2004 and 2008 results, we notice that the power enterprises in 2004 have a larger ESPI and CAPI value than the power enterprises in 2008. This may suggest that the energy

[8] There are 5 of 106 enterprises in 2004 and 10 of 76 enterprises in 2008 that are overall efficient in terms of input utilization, electricity generation and CO_2 emission, respectively.

saving potential and the emission abatement potential of our 106 enterprise sample in 2004 is higher than our 76 enterprise sample in 2008.

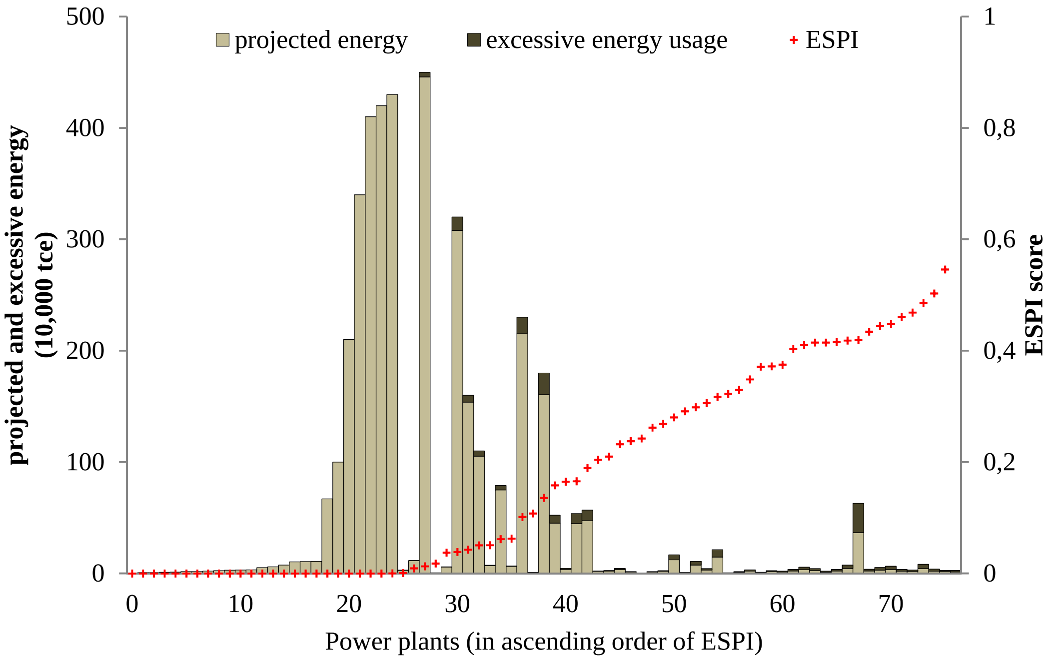

Figure 4 Projected energy, excessive energy and ESPI (2008)

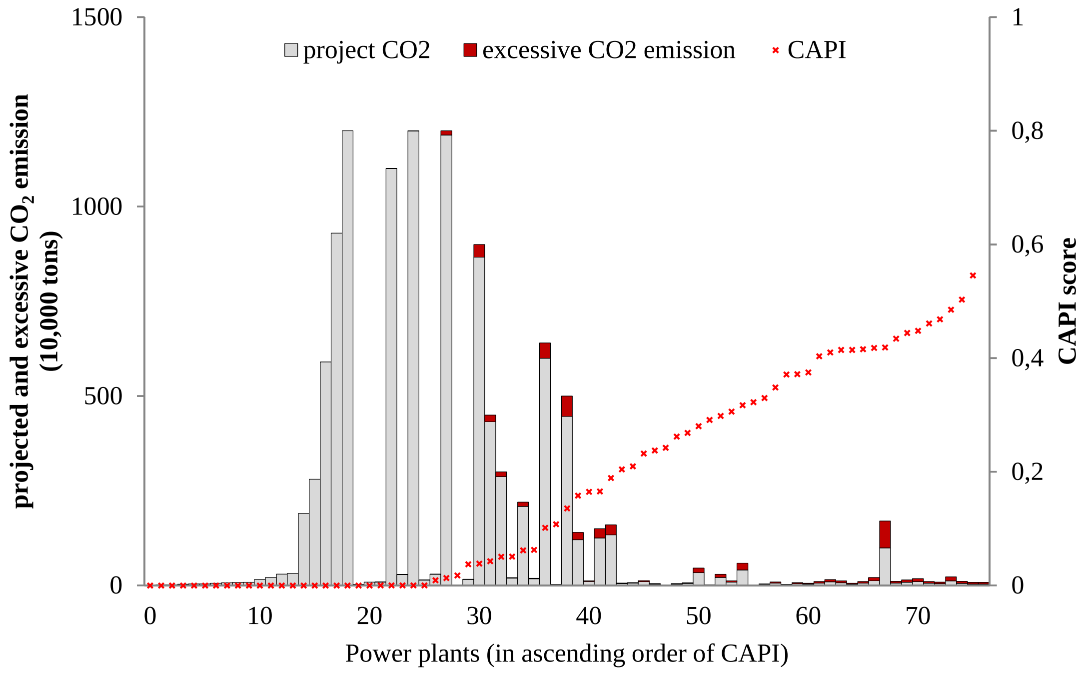

Figure 5 Projected CO_2, excessive CO_2 and CAPI (2008)

[insert Figure 5 here]

Table 4 reports the summary statistics for *ESPI* and *CAPI*. The results show that an excess of 15.5% of the energy input is used and an excess of 22.6% of CO_2 is emitted by our 106 power enterprises due to inefficiency in 2004. Alternatively, if all enterprises would have performed efficiently in 2004, about 5.04 Mtce energy could be saved with a simultaneous 20.52 $MtCO_2$ reduction of CO_2 emission. This result is consistent with Wei et al. (2013)'s finding, in which they report an overall inefficiency level of 18.9% for power enterprises in 2004 using a parametric approach. The reduction potential to save energy use and CO_2 emission in 2008 seems much less than that of 2004 in absolute and relative values. In 2008, around 1.71 Mtce energy and associated 4.73 $MtCO_2$ emission for our 76 sample enterprises potentially could have been reduced if all enterprises performed efficiently[9].

Table 4 Summary statistics of ESPI and CAPI

		Energy-saving			Emission-abatement		
		ESPI	feasible reduction of energy (10,000 tce)	minimum energy input (10,000 tce)	CAPI	feasible abatement of CO_2 (10,000 tonnes)	minimum CO_2 emission (10,000 tonnes)
Mean (std)	2004	0.116 (0.191)	4.76 (14.7)	26.06 (56.16)	0.222 (0.197)	19.36 (48.02)	66.31 (146.44)
	2008	0.176 (0.18)	2.25 (4.46)	50.28 (111.16)	0.176 (0.18)	6.23 (12.27)	139.07 (306.63)
Aggregate	2004	0.155	504.89	2762.18	0.226	2052.42	7029.21
	2008	0.043	171.21	3821.36	0.043	473.1	10569.37

In Table 5, we compare our results with previous studies. The results differ depending on the samples, the model assumptions, the setting of the direction vector, as well as the selection of input and output variables. To make these results comparable, we concentrate on the partial technical efficiency of good/bad output. Our estimation of partial technical efficiency is close to Yang and Pollitt (2010)'s result who use similar data but a different model, but higher than that of (Zhou et al., 2012a) who use a similar model but with nation level data. Our result is lower than other studies which may occur due to two reasons: First, the number of input/output

[9] One referee mentions the close link between fuel consumption and CO_2 emissions due to the lack of lower-cost abatement technologies for CO_2 emissions. The difference between ESPI and CAPI may hence result from changes in the fuel mix. Given the same heat content, a higher use of non-coal fuel is associated with higher electricity generation, but lower emission compared to a higher coal dependence.

variables can affect the frontier estimation. A higher number of inputs and outputs in other studies will increase the number of constraints in the LP problem. This change leads to more observations being on the frontier and a relatively higher score of technical efficiency. Second, the choice between a constant or variable returns to scale can alter the result. In case of a variable returns-to-scale production technology more observations lie on the frontier. This lead to a relatively lower inefficiency value[10].

Table 5 Comparison with other DEA-based studies

Author	Samples	DEA Model			Number of input/output	Result
		type	return to scale	setting of (g_y,g_b,g_x)		
Picazo-Tadeo et al. (2005)	35 Spanish ceramic tile producers in 1995	Additive DDF	VRS	(1,0,1)	3 inputs 1 good output 2 bad output	pTE$_y$: 0.978
Färe et al. (2007)	92 U.S. coal-fired power plants in 1995	Multiplicative DEA	CRS	Max *y* *b,x* fixed	5 inputs 1 good output 2 bad output	pTE$_y$: 0.911
		Additive DDF	CRS	(1,1,0)		pTE$_y$: 0.999
Yang and Pollitt (2010)	582 Chinese coal-fired power plants in 2002	Multiplicative DEA	CRS	Min *b,x* *y* fixed	3 inputs 1 good output 3 bad output	pTE$_y$:0.803-0.853[1]
Zhou et al. (2012a)	126 countries in 2005	Non-radial DDF	CRS	(-*x*,*y*,-*b*)	1 inputs 1 good output 1 bad output	Energy-carbon performance index: 0.619
This study	106 Chinese coal-fired power enterprises in 2004, 76 enterprise in 2008	Non-radial DDF	CRS	(-*x*,*y*,-*b*)	3 inputs 1 good output 1 bad output	2004: pTE$_b$:0.778 2008: pTE$_b$:0.824

Note: DDF denotes the directional distance function. CRS and VRS represent constant return-to-scale and variable return-to-scale, respectively. pTE$_y$ and pTE$_b$ is the partial technical efficiency of good output *y* and bad output *b*, respectively.

[10] Both interpretation benefits from the discussion with Dr. Pasurka. Under the VRS assumption, the mean value of the ESPI is 0.102 and 0.124, which is lower than the result under CRS (0.116 and 0.176) in 2004 and 2008, respectively. There are also some studies specifies the VRS technology when weak disposability is imposed on the outputs (Färe et al., 1986; Picazo-Tadeo and Prior, 2009; Picazo-Tadeo et al., 2005)

[1]: Yang and Pollitt (2010) analyze three scenarios for weak and free disposability among SO_2, NO_x and CO_2. In the case of weak disposability and free disposability among all these pollutants, the TE is 0.881 and 0.803, respectively. If only CO_2 is weakly disposable, the value of TE is 0.853.

4.2 ESPI, CAPI and enterprise characteristics

To classify the enterprise size, we follow the criteria of the National Top-1000 enterprises program and define a coal-fired power enterprise as large if its annual energy consumption exceeds 180000 tce[11]. Figure 6 plots the *ESPI* and *CAPI* score by enterprise scale for year 2004 and 2008. It is clear that in 2004 the large enterprises have a higher median value and larger variation of *ESPI* and *CAPI* than their small counterparts. It indicates that large power enterprises in our 2004 sample perform less efficient than others in terms of energy utilization and CO_2 emissions. However, this pattern reverses in 2008. This may suggest that the larger power enterprises became more efficient.

[11] In accordance with this classification, there are 34 large and 72 small enterprises in 2004 and 19 larger and 57 small enterprises in 2008, respectively.

Figure 6 Box plot of ESPI and CAPI by size in 2004 and 2008

Next we would like to examine whether the type of ownership of power enterprises implies a significant difference in energy utilization and CO_2 emissions. We divide our sample into two groups: SOE (state-owned enterprises) and non-SOE[12]. The plot of ESPI and CAPI by ownership is displayed in Figure 7. We note that in 2004 the SOE group holds a similar median value of ESPI and CAPI, but a larger variation when compared with the non-SOE group, respectively. The distribution in 2008 shows a different pattern. The SOE group is now significantly lower in terms of ESPI and CAPI than the non-SOE group, respectively. It suggests that the SOE operate in a

[12] There are 18 SOE and 88 non-SOE in our 2004's sample. In 2008, the number of SOE and non-SOE power enterprises is 8 and 68, respectively.

similar efficiency compared to non-SOE in 2004, but operate more efficient than non-SOE in 2008.

Figure 7 Box plot of ESPI and CAPI by ownership in 2004 and 2008

Is this gap between SOE and non-SOE statistically significant? In order to shed light on the significance of the difference between large and small enterprises and between SOE and non-SOE enterprises we perform non-parametric tests for *ESPI* and *CAPI*. The reason to use a non-parametric test rather than a classic t-test is that the former test is distribution-free and suitable for a statistical test in a DEA analysis (Cooper et al., 2007). The Kolmogorov-Smirnov test is used to test for equality of distribution between large group and small groups. The null hypothesis of the Wilcoxon-Mann-Whitney test is that the rank sums of the large and small samples are the same.

Table 6 Statistical test

Null hypothesis (H_0)	Kolmogorov-Smirnov test D (p-value)	Mann-Whitney test Z (prob > |Z|)
For year 2004		
ESPI(large)= ESPI(small)	0.480*** (0.000)	4.211*** (0.000)
CAPI(large)=CAPI(small)	0.315** (0.02)	1.978** (0.048)
ESPI(SOE)= ESPI(non-SOE)	0.119 (0.984)	0.033 (0.974)
CAPI(SOE)=CAPI(non-SOE)	0.197 (0.608)	-0.75 (0.454)
For year 2008		
ESPI(large)= ESPI(small)	0.456*** (0.005)	-2.109** (0.035)
CAPI(large)=CAPI(small)	0.456*** (0.005)	-2.017** (0.044)
ESPI(SOE)= ESPI(non-SOE)	0.544** (0.029)	-2.588*** (0.009)
CAPI(SOE)=CAPI(non-SOE)	0.544** (0.029)	-2.377** (0.018)
For all enterprise		
ESPI(2004)= ESPI(2008)	0.269*** (0.003)	-3.104*** (0.002)
CAPI(2004)=CAPI(2008)	0.266*** (0.004)	1.85* (0.064)

Note: ***, ** and * denote 1%, 5% and 10% significant level, respectively.

Based on the test statistics shown in Table 6, we can reject the null hypothesis that ESPI and CAPI are identical for large and small power enterprises in both 2004 and 2008. That is to say, large coal-fired power enterprises in our sample are associated with larger energy-saving potential and CO_2 abatement potential in 2004, while in 2008 the opposite is the case. This change between 2004 and 2008 may result from the environmental pressure mainly imposed on large power enterprises. As for the difference between SOE and non-SOE, our results indicate that the hypothesis of no difference of ESPI and CAPI between SOE and non-SOE cannot be rejected in 2004. However, the gap between SOE and non-SOE is statistical significant in 2008. In short, the inefficiency in terms of energy utilization and CO_2 emission for state-owned coal-fired power enterprises is not systematically different from those for their non-SOE counterparts in 2004, but in 2008 the SOE perform better than non-SOE. This finding partially supports

Atkinson and Halvorsen (1986) and Färe et al. (1985)'s conclusions for the U.S which suggest that publicly-owned electric utilities are slightly, but insignificantly more efficient than their non-SOE counterparts. Moreover, the result shows that both ESPI and CAPI in 2004 are significantly different from 2008.

Several reasons may help to better understand this result. First, large enterprises are relatively inefficient in 2004, which may be associated with serious X-inefficiency problem. But these large enterprises which fall into the "Top-1000 Enterprises Energy Conservation Action" were more efficient in 2008 than the small power companies who had not faced this energy-use regulation. The "Top-1000 Enterprises Energy Conservation Action" seems to have an important impact on the regulated large enterprises. Moreover, small enterprises seem to possess a greater energy-saving potential and emission-abatement space. Based on the empirical results, attention should be paid especially to those power enterprises that are not covered by the top-1000 program. The 11th FYP also set targets for shutting down inefficient small plants: In the power sector, small-size plants with capacity of less than 50 MW (with capacity of less than 100 MW if operated over 20 years or with capacity of less than 200 MW if the operation year exceeds the life cycle) as well as plants whose coal consumption per kWh is 15% higher than the national average are expected to be phased out. However, closures of small coal-fired power plants face many difficulties for implementation in practice. Closures might be suspended in certain years due to power supply shortages. Also, local governments are not only concerned about inefficient electricity production, but care about employment and social stability (Price et al., 2011).

Our results show that in 2004, SOE are not significantly different from non-SOE, while in 2008 the SOE outperform non-SOE in terms of energy utilization and emission. This seems to favor the claim by Dewenter and Malatesta (2001) that the change of ownership from SOE to non-SOE, i.e. private-ownership, does not give rise to further efficiency gains. SOE reforms in China which started in late 1978 adopt a policy of “grasping the large and releasing the small” (Qian, 2002). This strategy enables the privatization and sale of small or non-profitable SOEs. In contrast, those remaining SOEs in the power generation sector are highly competitive. Moreover, as Tyteca (1996) argued, privately owned enterprises are most likely efficient in production, but presumably not as efficient as SOE from an environmental perspective due to the absence of internal environmental motivation. State-owned coal-fired power enterprises are more likely to be regulated by the government to meet the soaring electricity demand and achieve more strict environmental targets. Consequently, SOE readily intend to equip with larger generating units and desulfurization equipment under strict energy or environmental standard. Hence they perform better in both energy utilization and environment aspects.

5. Conclusion

To investigate whether a large SOE is associated with higher energy-saving potential and CO_2 abatement potential in China’s power sector, we employ a Weighted Russell Directional Distance Function. This non-parametric non-radial DEA approach enables us to model bad output within an environmental production framework. The major strength of WRDDF is that it allows for non-proportionally adjustments of inputs and outputs. It thus makes it possible to investigate specific factor’s inefficiency levels. This innovative methodology is applied to a unique sample of Chinese coal-fired power enterprises located in the Zhejiang province in the years 2004 and 2008. Each power enterprise is assumed to produce electricity and CO_2 with labor, capital and energy input. By comparing with the target reference on the piecewise frontier under the DEA technology, the maximum feasible energy-saving potential index (ESPI) and CO_2 emission-abatement potential index (CAPI) for each power enterprise is estimated. Moreover, we perform statistical tests and find that large power enterprises are less efficient in 2004, but become more efficient in 2008 than small power enterprises in terms of energy utilization and CO_2 emission. For the SOE, there is no statistical evidence on an inferior performance compared to non-SOE in 2004, but SOE exhibit higher efficiency than non-SOE in 2008. This dramatic change between 2004 and 2008 may result from the implementation of the “Top-1000 program” which set strict energy-saving targets for large power plants and SOE.

We found that about 15.5% of energy (5.04 Mtce) and an associated 22.6% of CO_2 (20.52 MtCO2) could be reduced if all enterprises would have performed efficiently in 2004. The energy-saving potential and emission reduction potential for power enterprise in 2008 decreased to 1.71 Mtce and 4.73 MtCO2, respectively. This change on the one hand highlights the urgency for China’s coal-fired power enterprises to eliminate their inefficient production and emission levels (Yang and Pollitt, 2010) . On the other hand, it confirmed the impact of the national energy-saving and emission-abatement strategy implemented since 2006 on the performance of enterprises. However, it also indicates that it is getting more and more difficult to further reduce the energy use and emission levels through efficiency improvements.

The measurement and analysis of the energy-saving potential and CO_2 abatement potential index provide decision makers with important information to design environmental regulation and assess its potential impact. If energy and climate policies are not market-based (like in general superior energy/climate taxes or emissions trading schemes), but rather based on command and control approaches, these indices help policy makers to set regulations based on enterprise characteristics, to identify enterprises with more capacity to save energy and cut inefficient emissions, and to allocate proper energy-saving and emission-reduction targets. Similar to Zhou et al. (2010)'s claim, small-sized, non-SOE power enterprises beyond the top-1000 enterprise program in 11th FYP should be included in future initiatives as they have a relatively greater space to eliminate inefficient energy utilization and associated CO_2 emissions. Actually some provinces, i.e., Guangdong in the 11th FYP, had designed a similar top-1000 program and extended the program to a wider scope of enterprise. Also the central government formulated in the 12th FYP another "Top-10,000 Enterprise Energy Conservation Action", which can be seen as a ramp up of the "Top-1000 program". It will cover around 17,000 enterprises with annual energy consumption excess 5,000 tce. Nevertheless, policy implications have to be drawn very cautiously as our study faces important limitations. For example, the lack of information on generators and boilers prevents us from examining the effect of technology differences on abatement potentials which might play an important role.

Acknowledgement

This work was financially supported by the National Science Foundation of China (No.41201582, 71203116), the Beijing Natural Science Foundation (9152011), the Mingde Scholar Program of Renmin University (13XNJ016), the Gottfried Wilhelm Leibniz Scientific Community and the Alexander von Humboldt Foundation.

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