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A Bayesian stochastic frontier analysis of Chinese fossil-fuel electricity generation companies

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ABSTRACT

This paper analyses the technical efficiency of Chinese fossil-fuel electricity generation companies from 1999 to 2011, using a Bayesian stochastic frontier model. The results reveal that efficiency varies among the fossil-fuel electricity generation companies that were analysed. We also focus on the factors of size, location, government ownership and mixed sources of electricity generation for the fossil-fuel electricity generation companies, and also examine their effects on the efficiency of these companies. Policy implications are derived.

1. Introduction

With the onset of reform and the “Open-door” policy that has been in place since 1978, China's economy began to prosper with impressive growth over the following decades. A boom in electric power industry in China was witnessed to cater for the tremendous demand for power (Shiu and Lam, 2004; Yeoh and Rajaraman, 2004). The installed electricity capacity leapt from 65.87 million kilowatts in 1980 to 1100.49 million kilowatts in 2011, whilst total net electricity generation soared from 285.47 billion kilowatt hours to 4490.54 billion kilowatt hours during the same period. China has now become the largest electricity consuming country in the world, since 2011.

The main cause of this impressive growth was the reform of the power sector, which was launched in three main stages by government authorities over the last three decades. Before the reform, Chinese electricity generation plants were vertically integrated as state-owned utilities, in the form of an absolute monopoly. The administration, investment and price levels were completely controlled by the central government (Wang and Chen, 2012). Since 1985, the government gradually introduced three waves of reform to deregulate the power industry in China and established modern electricity generation companies. However, there are still some operational distortions that have not been corrected. Firstly, the monopolistic situation has still not been significantly dismantled and the Big Five[1] control the majority share of electricity generation, which causes a loss of welfare (Wang and Chen, 2012). Secondly, the price of electricity is inflexible, given the government's regulation and inflation concerns, whilst the price of coal is determined by the open market. The booming economy and expansion of the manufacturing sector have pushed up the price of coal, as well as the cost to these companies, which takes them to the brink of bankruptcy, although the government has formulated a plan to supply coal at a lower price in order to subsidise fossil-fuel electricity generation companies.

Compared to other sources, including hydroelectric power, nuclear power, wind power, solar power, and bio-energy, fossil-fuel power plays the most important role and provides the majority of China's

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[1] i.e., China Huaneng Group, China Guodian Corporation, China Datang Corporation, China Huadian Corporation and China Power Investment Corporation. They are all big state-owned electricity generation companies.

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electricity.[2] The clean energy sources, i.e., nuclear and other non-hydroelectric renewable energies, were not developed greatly, until recent years.

Motivated by the important status of fossil-fuel power and the series of complicated reforms that electricity generation companies in China have undergone (Zhou et al., 2010a, 2010b; Du et al., 2013; Elliott et al., 2013), this paper examines the technical efficiency of a sample of Chinese fossil-fuel electricity generation companies which produce electricity with coal turbines, gas turbines or diesel turbines. Meanwhile, monitoring the efficiency performance of Chinese fossil-fuel electricity generation companies can provide useful information for assessing the effectiveness of energy efficiency policies and measures, as a means of improving energy efficiency and productivity, and also as a way to achieve sustainable development in the most cost-effective way (Ang, 2006; Ang et al., 2010; Wang et al., 2013). Furthermore, restrictions of energy sources and environmental protection have boosted the development of renewable energy sources to produce clean energy, in line with the Kyoto protocol (Gorecki et al., 2010). The Eleventh Five-Year Plan of the Chinese central government sets the target to control energy consumption and promotes low-carbon development (Wang et al., 2013). This competition is also forcing the Chinese fossil-fuel electricity generation companies to upgrade their efficiency when competing for market share (Barros and Peypoch, 2008).

Several methods have been widely adopted to measure the efficiency of electricity generation companies and plants (Barros and Peypoch, 2007; Barros, 2008; Ang et al., 2010; Briec et al., 2011; See and Coelli, 2012), including data envelop analysis (DEA) models (Barros, 2008; Briec et al., 2011; Sueyoshi and Goto, 2011) and stochastic frontier analysis (SFA) models (Aigner et al., 1977; Barros and Peypoch, 2007; Huang et al., 2010; Growitsch et al., 2012; See and Coelli, 2012), blended DEA and stochastic frontier models (Jaraitė and Di Maria, 2012) and recently the StoNED—stochastic Non-Smooth Envelopment of Data (Kuosmanen, 2012; Mekaroonreung and Johnson, 2012; Saastamoinen and Kuosmanen, 2015). This paper adopted the Bayesian stochastic frontier model to estimate the efficiency of Chinese fossil-fuel electricity generation companies for the first time. The Bayesian stochastic frontier model (Orea and Kumbhakar, 2004; Greene, 2005) has an advantage, in that the technique incorporates informative priors, so that prior knowledge, or results of a previous model, can be used to inform the current model. Furthermore, small sample inference is carried out in the same way as if one had access to a large sample, and all inferences follow logically from Bayes' theorem. Therefore, any sample size can be accommodated, no matter how small. The estimation is unbiased with respect to sample size. This is in contrast to frequentist inference, which becomes more biased as the sample size decreases from infinity. In addition, it obeys the likelihood principle. Bayesian inference is consistent with much of the philosophy of science regarding epistemology, where knowledge cannot be built entirely through experimentation, but requires prior knowledge (Koop et al., 1997; Griffin and Steel, 2007).

A cost function is adopted and the translog form is used, which is flexible and leads to a robust cost efficiency measure (O'Donnell and Coelli, 2005). The main issue in efficiency analysis is the choice benchmark by which fossil-fuel electricity generation companies can be analysed.

The rest of this paper is organised as follows. After this introduction, the literature survey is presented, followed by research hypotheses. Then the methodology is outlined, followed by the data, results and robustness tests. The final sections present the conclusions.

[2] According to the statistics of EIA (U.S. Energy Information Administration), electricity produced by fossil-fuel electricity generation companies accounts for 79.58% of total electricity generation on average during the period from 1980 to 2011.

2. Literature survey

We divide this section into two parts. Firstly, we review other widely-used methods for estimating the efficiency of electricity generation companies and plants, in order to further justify the choice of the Bayesian stochastic frontier model in this paper. Secondly, we summarise the literature on the Chinese power sector, and highlight the significance of this present research.

2.1. Review of alternative methods

There are many alternative approaches for estimating the efficiency of electricity generation companies and plants, such as: the SFA—stochastic frontier analysis (Hattori, 2002; Farsi and Filippini, 2004; Barros and Managi, 2009; Barros and Peypoch, 2007, 2008; Barros and Antunes, 2011; Kopsakangas-Savolainen and Svento, 2011; See and Coelli, 2012); the DEA—data envelopment analysis (Nakano and Managi, 2008; Arocena, 2008; Zhou and Ang, 2008) and StoNED—stochastic Non-Smooth Envelopment of Data (Kuosmanen, 2012; Mekaroonreung and Johnson, 2012; Kuosmanen et al., 2013; Saastamoinen and Kuosmanen, 2015). However, classic data envelop analysis (DEA) and stochastic frontier analysis (SFA) assume that all the analysed units operate under the same production or cost technology for the estimation of efficiency. Tsionas (2002) argues that these methods have limitations which may lead to incorrect efficiency estimates and thus it is inappropriate to use them in isolation. The Bayesian SF model caters for heterogeneity, and is closer to reality, thus ensuring that efficiency is correctly estimated. The new StoNED method proposes a two-step estimator which combines the axiomatic DEA-style non-parametric frontier with the probabilistic SFA-style treatment of noise, and does not make any assumptions about the functional form, neither its smoothness (Kuosmanen and Kortelainen, 2012; Dai and Kuosmanen, 2014). However, StoNED still has its own limitations, which highlights the need for further investigation of the underlying axiomatic foundation, statistical properties and performance of the technique, as it is very restrictive (Lin et al., 2013; Simar et al., 2013; Martins-Filho and Yao, 2015).

2.2. Research on the Chinese power sector

The analysis of energy efficiency in power generation is a well-established field of research (Knittel, 2002; Farsi and Filippini, 2004, Managi et al., 2006; Vaninsky, 2006), which enables significant insight into the performance of power plants and their potential for increasing productivity and for improving resource-use (See and Coelli, 2012). However, rarely has research paid attention to the Chinese power sector.

Up until recent years, a growing strand of literature began to focus on energy efficiency in China. In the early stage, some authors only researched and introduced the background and the situation of the power sector of China (Yang and Yu, 1996; Shiu and Lam, 2004; Xu and Chen, 2006; Ma and He, 2008; Chai et al., 2009). Later on, academics placed more emphasis on energy efficiency. Lam and Shiu (2001, 2004), Hu and Wang (2006), Wei et al. (2009) and Shi et al. (2010) apply the DEA as a means of analysing the technical efficiency of fossil-fuel electricity generation, with province-level data from China. Wu et al. (2012), Zhou et al. (2012a, 2014), Wang et al. (2013) and Bi et al. (2014) all further consider the undesirable output or environmental constraints when evaluating the efficiency performance in China's fossil-fuel power sector; and Choi et al. (2012) further improve the above-mentioned research with replacing the radial DEA for a non-radial slack-based DEA. Yang and Pollitt (2009) estimate the efficiency of the Chinese coal-fired power plants with DEA, incorporating both undesirable outputs and uncontrollable variables; and Du et al. (2013) assess the TFP of Chinese fossil-fired power plants following traditional SFA and conclude that the reform in the power sector had improved the efficiency. These studies reflect the dynamics of the efficiency of

China's fossil-fuel power sector. However, the researcher has seldom utilised the SFA parametric method, or even Bayesian SF, to compare this efficiency. This may lead to problems, as mentioned in the first part of this section (Zhou et al., 2012b; Du et al., 2013). Furthermore, most of the papers use the province-level data to examine the efficiency of thermal electricity generation in China. Some research investigates the energy efficiency of China with city-level or plant-level data (Du et al., 2013; Elliott et al., 2013). However, there are hardly any papers that focus on fossil-fuel electricity generation companies that use firm-level data; and the firm-level efficiency research will be more useful for energy companies to manage their relative performance, which is therefore a major issue of competitiveness management (Barros and Peypoch, 2007; Barros, 2008; Briec et al., 2011; See and Coelli, 2012). The present research is designed in this context.

3. Research hypotheses

Despite the power sector reforms that span nearly three decades, China is still undergoing reform and development. There are many transitional characteristics in the country's energy system, including scale, location, government ownership, sources diversification with clean energy and so forth. Therefore, our aim is to test the relationship between Chinese fossil-fuel electricity generation companies' technical efficiency and the following covariates: company size, coastal location, government ownership and mixed energy sources. The justification for the selection of each of these covariates is explained in the following subsections.

3.1. Size of fossil-fuel electricity generation companies

It is often argued that large firms are possibly more efficient, as they can use more specialised inputs, coordinate their resources better and reap the advantages of economies of scale (Alvarez and Crespi, 2003). In the context of this research, firm size might also take on additional importance, as Chinese fossil-fuel electricity generation companies are characterised by distinct market values. These plants might thus be more profitable, if they were to increase their size, in order to achieve economies of scale and to make up for external market failures (Khanna and Palepu, 2000; Ghemawat and Khanna, 1998). As related studies on energy plants also indicate that firm size contributes to higher efficiency, we thus assume H1: that firm size has a positive impact on the efficiency of the Chinese fossil-fuel electricity generation companies. The dummy variable “big”, which reflects the size, or scale, of Chinese fossil-fuel electricity generation companies, is defined as whether they are the members of the “Big Five”. As mentioned in the introduction, the “Big Five” own many more assets compared to all the other Chinese fossil-fuel electricity generation companies and they have the majority share of the market:

H1. The size of fossil-fuel electricity generation companies has a positive impact on the efficiency of Chinese fossil-fuel electricity generation companies, by reducing their costs. This hypothesis is tested with the variable “big”.

3.2. Coastal fossil-fuel electricity generation companies

It is often argued that location plays a role in efficiency (Wei et al., 2009; Shi et al., 2010; Du et al., 2013; Elliott et al., 2013; Bi et al., 2014), whereby the coastal location of fossil-fuel electricity generation companies is hypothesised as having an effect on their efficiency. A coastal location corresponds to an easier access to more populated markets. Moreover, the reforms were first initiated in the coastal provinces of China, which may enhance the management and incentives in the power industry through deregulation. The majority of FDI in China invested in the coastal provinces, and thus made manufacturing prosperous in these areas. This also increases the demand for electricity and compels these fossil-fuel electricity generation companies to be more efficient, in order to be able to supply sufficient electricity (Elliott et al., 2013). Therefore, we assume H2: that a coastal location of Chinese fossil-fuel electricity generation companies has a positive impact on its efficiency. The coastal location is defined according to whether the fossil-fuel electricity generation company is located in the coastal provinces of China, which include Liaoning, Tianjin, Hebei, Shandong, Jiangsu, Zhejiang, Fujian, Guangdong, Guangxi and Hainan:

H2. A coastal location has a positive impact on the Chinese fossil-fuel electricity generation companies, reducing their costs. This hypothesis is tested with the variable “coastal”.

3.3. Government ownership of fossil-fuel electricity generation companies

Before 1978, all corporations in China were State-owned. Thereafter, China gradually transformed from a centrally-planned economy to a market-orientated one, leading to the creation of many private and joint-venture companies. In this contextual setting, after reform, many private and joint-venture fossil-fuel electricity generation companies were founded. Since 1992, China initiated a joint-stock reform across the whole nation and aimed to transform State-owned enterprises into modern, profit-oriented corporations. However, the government still holds shares in these corporations, and sometimes even has the majority share. The World Bank (2012), Brandt and Zhu (2010) and Bai et al. (1997) argue that the government intervened because of the fact that industry supplies public goods and services, but this has led production to be quite inefficient. Sarıca and Or (2007) and Pollitt (1996) also note that public power plants in Turkey and the UK are less efficient. Therefore, we assume H3: that majority ownership by the government will decrease the efficiency of Chinese fossil-fuel electricity generation companies. Once the fossil-fuel electricity generation company's majority ownership is acquired by the central government, the dummy variable is equal to 1:

H3. Majority ownership by the government has a negative impact on Chinese fossil-fuel electricity generation companies' cost reduction. This hypothesis is tested with the “control” variable.

3.4. Energy sources of fossil-fuel electricity generation companies

Different energy sources have different costs and therefore also have different impacts on company efficiency and the country's GDP (Ohler and Fetters, 2014). As pointed out in the Introduction, most fossil-fuel electricity generation companies in China use coal to generate power. Some other fossil-fuel electricity generation companies use fuel oil. When the government called for anti-pollution and environmental protection, some of China's fossil-fuel electricity generation companies began to build hydroelectric plants. Compared to thermoelectric power options, hydroelectric plants are invulnerable to rises in the price of coal and fuel oil. Therefore, we assume H4: that hydroelectricity has a positive impact on the cost efficiency of Chinese fossil-fuel electricity generation companies. When the dummy variable “hydro” is equal to 1, it indicates that the fossil-fuel electricity generation companies have built hydroelectric plants.

H4. The building of hydroelectric plants has a positive impact on Chinese fossil-fuel electricity generation companies, thus reducing their costs. This hypothesis is tested with the “hydro” variable.

4. Methodology

The Bayesian stochastic random frontier model was introduced by Tsionas (2002) and it assumes that each firm is allowed different intercepts, as well as slope coefficients. The main purpose of the model is to improve the accuracy of the efficiency estimation by separating the cost efficiency estimates from heterogeneity among firms. This model is different from the Bayesian fixed frontier model introduced by Koop et al. (1997), which assumes that all units share exactly the same production possibilities (i.e., no heterogeneity between firms). To illustrate the Tsionas model, we consider the following cost equation (Kumbhakar and Lovell, 2000):

$$C_{it} = \alpha + X_{it}\beta_i + v_{it} + \mu_{it}; \quad i = 1, 2, \ldots N, \ \ t = 1, 2, \ldots T \tag{1}$$

where C_{it} is a vector of the dependent variable for the ith observation of year t, x_{it} is a vector of explanatory variables, v_{it} is a random error identically and independently distributed as $N(0,\sigma_{2n})$, μ_{it} is a non-negative random error which captures the level of cost inefficiency and ensures that each firm's cost-efficiency lies on or below the frontier model, β_i is a vector of random coefficients, and α is a non-random intercept. In the Bayesian context, it is common to assume that the inefficiency term μ_{it} is exponentially distributed (other distributions such as truncated and gamma are also possible, but the exponential distribution is generally the most common one in the Bayesian framework, for more details see Koop (2003)) with a parameter θ, and which can be expressed as follows:

$$f(\mu_{it}) = \theta\exp(-\theta\mu_{it}). \tag{2}$$

To complete the model's assumptions, the β_i parameters follow a multivariate normal distribution, where $\overline{\beta}$ is a vector of parameter means and Ω is a positive-definite covariance matrix.

$$\beta_i \sim N\left(\overline{\beta}, \Omega\right) \tag{3}$$

Under the specification that μ is drawn from an exponential distribution with parameter θ, where the prior mean for θ is, in turn, $q = -\ln r^*$, the Gibbs sample for the Tsionas (2002) model for exponential distributed μ is: (i) draw β_i from the conditional normal distribution; (ii) draw σ from the conditional gamma distribution; (iii) draw (a,b) from the conditional normal distribution; (iv) draw Ω from the conditional Wishart distribution; (v) draw μ_{it} from the conditional truncated normal distribution; and (vi) draw θ from the conditional gamma distribution (Greene, 2007a).

This makes it a hierarchical model, with two levels of latent variables, β_i and μ_{it}. Each firm under consideration has its own specific cost function with β_i parameters, which account for the heterogeneity or technological differences between fossil-fuel electricity generation companies. The procedure involves the following steps:

Step 1: The choice of distribution for the non-informative priors.
The Bayesian estimation of the model requires prior information about the parameters. A common practice is to choose the priors for α and β as flat (i.e., imposing no prior information about the parameter mean). The general priors for the model follow Tsionas (2002), α_i, $\beta_i \sim N[(a, b), \Omega)]$, $i = 1, \ldots N$; $(a, b) \sim N[(0, 0), W]$ with $\Omega \sim$ Inverted Wishart; $\theta \sim$ two parameter gamma; and $\sigma \sim$ inverted gamma.

Step 2: A prior statistical distribution for the cost function is chosen, in this case an exponential distribution based on the Deviation Information Criteria (DIC). The DIC is a hierarchical modelling generalisation of the AIC (Akaike Information Criterion) and BIC (Schwarz Criterion) and it is the most popular criterion for Bayesian model selection and model comparison.
From Step 2 from the joint density equation and after marginalising over μ, the likelihood of the joint model in Eq. (1) can be expressed as:

$$L = NT\ln\theta + \left(\frac{\theta^2}{2}\right)\sum_{t=1}^{T}\sum_{i=1}^{N}W_{it} + \sum_{t=1}^{T}\sum_{i=1}^{N}\left[\ln\Phi\left(\frac{-\varepsilon_{it}-\theta W_{it}}{W_{it}^{1/2}}\right) + \theta\varepsilon_{it}\right] \tag{4}$$

where $\varepsilon_{it} \equiv C_{it} - \alpha - X_{it}'\overline{\beta}$; $W_{it} \equiv \sigma^2 + X_{it}'\Omega X_{it}$; $\Phi(\cdot)$ denotes the standard normal cumulative distribution function, and X is a matrix of explanatory variables (Tsionas, 2002).

Step 3: Using acquired information about the likelihood and the priors, the conditional posterior of each of the model parameters can then be estimated and the cost equation is also estimated from the conditional equation, using Winbugs software. See Tsionas (2002) for the conditional equation details.

Using these conditional densities, the Gibbs sampler in Winbugs programme is used. When the iterations approach infinity, the Gibbs sampling methods converge to the actual joint posterior density function. In this article, we generate 11,000 parameter vectors and drop the first 1000 to avoid the sensitivity of starting values.

5. Data

We use a balanced data panel, comprising twenty-seven Chinese fossil-fuel electricity generation companies, listed in Table 1, over a period of thirteen years from 1999 to 2011 (351 observations), which was obtained from the Shanghai Stock Exchange (www.sse.com.cn) and the Shenzhen Stock Exchange (www.szse.cn). The sample period of 1999–2011 was adopted on account of the data availability. Before 1999, many fossil-fuel electricity generation companies were not listed on the stock market and hence their financial reports were not published. The variables were transformed as described in Table 2, where monetary magnitudes are expressed in units of ¥1000 Renminbi, deflated by the GDP deflator and denoted at 2008 prices. Moreover, the model specification in the paper, e.g., the input and output variables, is mentioned in a large strand of literature on efficiency analysis. For example, the literature always uses the installed capacity, rather than the number of generators (Lam and Shiu, 2001; Yang and Pollitt, 2009; Bi et al., 2014). Secondly, the data availability sometimes restricts the adopted variables and hence the specification of the model. The price of fuel oil and coal is not disclosed. If we use the market price of fuel and coal as a proxy variable, then it is not necessary, as all the firms are the same. As for the undesirable outputs, such as CO_2, SO_2 and NO_x emissions, we also take into account their significance for the efficiency analysis. These papers, as well as those of Yang and Pollitt (2009), Bi et al. (2014), etc., have also inspired our research. However, the pollution and emission data of these fossil-fuel electricity generation companies have never been published. Although Yang and Pollitt (2009) said they used the undesirable output data, they never declared the sources. Bi et al. (2014) used province-level data (each province in China may have several fossil-fuel electricity generation companies), rather than firm-level, as we did in our paper.

The stochastic cost frontier model used in this study is in restricted translog form and can be expressed as follows: where C_{it} is the total cost, which is chosen according to literature of cost efficiency analysis (Kleit and Terrell, 2001; Huang et al., 2010; Growitsch et al., 2012); $Prod_{it}$ is the total production (kWh); $Capac_{it}$ is the total capacity (kW); $Profit_{it}$ is the net profit; PL_{it} is the price of labour, measured by dividing total wages by the number of workers; PK_{it} is the price of capital premises, measured by dividing the total amortisation by the value of total assets; big, coastal, control and hydro are dummy variables which take the value of 1 for Chinese fossil-fuel electricity generation companies that have the characteristic and zero elsewhere; Trend is a time trend variable; v_{it} is a random error identically and independently distributed as $N(0,\sigma_{2n})$; and μ_{it} is a non-negative random error, which

Table 1
Characteristics of Chinese thermal power companies, 2011.
Sources: Shanghai Stock Exchange (www.sse.com.cn); Shenzhen Stock Exchange (www.szse.cn).

Nobs	Plants	Names	Operational costs (yuan)	Production (MW)	Capacity (100 M kWh)
1	SZE	Shenzhen Energy Group Co., Ltd.	12,937,657,154.70	4327.26	215.85
2	SZNS	Shenzhen Nanshan Power Co., Ltd.	3,688,061,569.69	946.71	37.32
3	GZE	Guangzhou Hengyun Enterprises Holding Ltd.	2,939,485,705.55	1362.07	67.75
4	GED	Guangdong Electric Power Development Co., Ltd.	13,815,088,321.00	6680.00	337.82
5	AHE	Anhui Wenergy Company, Limited	5,150,040,025.71	1938.50	140.91
6	JEI	Jointo Energy Investment Co., Ltd. Hebei	5,698,617,477.69	2871.00	154.83
7	BXNY	Guangdong Baolihua New Energy Stock Co., Ltd.	2,966,565,608.68	1588.48	85.67
8	SXZZ	Shanxi Zhangze Electric Power Co., Ltd.	4,612,675,809.77	3188.50	140.70
9	JPSC	Jilin Power Share Co., Ltd.	4,041,693,634.79	3283.00	91.04
10	JXGN	Jiangxi Ganneng Co., Ltd.	2,616,200,359.76	1500.00	67.87
11	GDCY	Guodian Changyuan Electric Power Co., Ltd.	7,857,538,495.27	4080.00	207.74
12	HNYN	Henan Yuneng Holdings Co., Ltd.	4,085,803,648.79	1585.00	361.00
13	HPI	Huaneng Power International, Inc.	124,742,023,369.00	55,350.00	3135.54
14	SEP	Shanghai Electric Power Company Limited	16,197,103,346.09	7009.30	345.68
15	HDPI	Huadian Power International Corporation Limited	50,984,641,000.00	25,785.20	1507.60
16	GDIH	Guangzhou Development Industry (Holdings) Co., Ltd.	9,924,670,866.92	3170.00	405.10
17	SYJS	Shenyang Jinshan Energy Co., Ltd.	2,618,744,500.22	838.93	69.72
18	XJTF	Xinjiang Tianfu Thermoelectric Power Co., Ltd.	1,920,798,923.19	562.00	35.58
19	BJTP	Beijing Jingneng Thermal Power Co., Ltd.	2,650,665,397.47	2118.50	95.47
20	SHEN	Shenergy Company Limited	21,022,356,009.26	7000.00	312.00
21	HDEC	Huadian Energy Company Limited	9,120,510,932.15	5709.50	288.62
22	DHEP	DaTang HuaYin Electric Power Co., Ltd.	9,547,675,039.31	4451.45	121.53
23	TEC	Top Energy Company Ltd. Shanxi	4,857,096,596.23	1548.80	73.61
24	GDPD	GD Power Development Co., Ltd.	43,265,686,516.42	32,040.40	1496.04
25	NMHD	Inner Mongolia MengDian HuaNeng Thermal Power Corporation Limited	5,719,445,831.22	6580.00	251.53
26	SDIC	SDIC Huajing Power Holdings Co., Ltd.	18,596,390,585.55	8520.00	657.25
27	DTP	Datang International Power Generation Co., Ltd.	62,645,331,000.00	38,484.20	2037.16

captures the cost inefficiency level. Note that we divided the total cost, price of labour and the price of capital-premise by the PM—price of materials, to ensure homogeneity in price for the cost function.

Table 2 presents some descriptive statistics of the variables:

$$
\begin{aligned}
\ln\left(\frac{C_{it}}{PM_{it}}\right) &= \beta_1+\beta_2\text{Trend}+\beta_3\text{Trend}^2+\beta_4\ln\frac{PL_{it}}{PM_{it}}+\beta_5\ln\frac{PK_{it}}{PM_{it}}\\
&+\beta_6\ln\text{Capac}_{it}+\beta_7\ln\text{Prod}_{it}+\beta_8\ln\text{Profit}_{it}+\beta_9\text{big}+\beta_{10}\text{coastal}\\
&+\beta_{11}\text{control}+\beta_{12}\text{hydro}+\beta_{13}\left(\frac{PL_{it}}{PM_{it}}\right)^2+\beta_{14}\left(\ln\frac{PK_{it}}{PM_{it}}\right)^2+\beta_{15}(\ln\text{Capac}_{it})^2\\
&+\beta_{16}(\ln\text{Prod}_{it})^2+\beta_{17}(\ln\text{Profit}_{it})^2+\beta_{18}\ln\frac{PL_{it}}{PM_{it}}*\ln\frac{PK_{it}}{PM_{it}}+\beta_{19}\ln\frac{PL_{it}}{PM_{it}}*\ln\text{Capac}_{it}\\
&+\beta_{20}\ln\frac{PL_{it}}{PM_{it}}*\ln\text{Prod}_{it}+\beta_{21}\ln\frac{PL_{it}}{PM_{it}}*\ln\text{Profit}_{it}+\beta_{22}\ln\frac{PK_{it}}{PM_{it}}*\ln\text{Capac}_{it}\\
&+\beta_{23}\ln\frac{PK_{it}}{PM_{it}}*\ln\text{Prod}_{it}+\beta_{24}\ln\frac{PK_{it}}{PM_{it}}*\ln\text{Profit}_{it}+\beta_{25}\ln\text{Capac}_{it}*\ln\text{Prod}_{it}\\
&+\beta_{26}\ln\text{Capac}_{it}*\ln\text{Profit}_{it}+\beta_{27}\ln\text{Prod}_{it}*\ln\text{Profit}_{it}+\ln v_{it}+\ln\mu_{it}
\end{aligned}
\tag{5}
$$

where v is a random error which reflects the statistical noise and is assumed to follow a normal distribution centred at zero, whilst μ reflects inefficiency, and is assumed to follow a half-normal distribution.

6. Results

The specification of the cost function follows the microeconomic theory (Varian, 1987). The costs are regressed in input prices and output descriptors. Frontier models require the identification of inputs (resources) and outputs (transformation of resources). Several criteria can be used in their selection. The first is the empirical availability of the data. The second is the literature survey to ensure the validity of the research. The last is the professional opinion of the plant manager.

The empirical specification of the cost function is the translog. We have chosen a flexible functional form in order to avoid imposing

Table 2
Descriptive statistics of the data.
Sources: Shanghai Stock Exchange (www.sse.com.cn); Shenzhen Stock Exchange (www.szse.cn).

Variable	Description	Minimum	Maximum	Mean	Standard deviation
lnCost	Logarithm of operational cost in Renminbi at constant price 2008 = 100	7.785	11.113	9.430	0.616
Trend	Trend variable	1	13	7	3.746
Trend^2	Square Trend	1	169	63	53.909
lnPL	Logarithm of price of workers, measured by dividing total wages between the number of workers	3.662	5.804	4.871	0.391
lnPK	Logarithm of price of capital-premises, measured by the amortisations divided by the value of the total assets	0.003	1.099	0.107	0.075
lnProd	Logarithm of the production in MWH	0.055	3.496	1.967	0.567
lnCapac	Logarithm of the capacity in MW	2.032	4.743	3.276	0.503
ln Profit	Logarithm of the net profit in Renminbi at constant price 2008 = 100	5.214	9.809	8.341	0.689
Big	Dummy variable which is one for big fossil-fuel generation companies and zero elsewhere	0	1	0.185	0.389
Coastal	Dummy variable which is one for coastal located fossil-fuel generation companies and zero elsewhere	0	1	0.296	0.457
Control	Dummy variable which is one for central government controlled thermal power companies and zero elsewhere	0	1	0.481	0.500
Hydro	Dummy variable which is one for the fossil-fuel generation companies that also own hydroelectric plants and zero elsewhere	0	1	0.370	0.483

Table 3
Posterior mean parameter estimates.

	Bayesian stochastic frontier model				Standard stochastic frontier model	
Variables	Parameters	Posterior mean	SD	Monte Carlo error	Parameters	Std. Err.
Constant	β1	**0.7864**	2.3220	1.039E−02	**6.3876**	2.3145
Trend	β2	**0.0360**	0.0119	5.133E−05	**0.0326**	0.0111
Trend^2	β3	**0.0007**	0.0008	3.305E−06	0.0009	0.0007
lnPL	β4	1.7130	0.6468	2.687E−03	0.9069	0.6208
lnPK	β5	**0.0700**	3.1460	1.288E−02	**0.0994**	0.0461
lnCapac	β6	3.3780	1.3640	5.686E−03	0.4938	1.3669
lnProd	β7	−3.4810	1.2110	4.716E−03	−2.1754	1.1924
lnProfit	β8	−0.2765	0.2734	1.057E−03	0.0254	0.2643
Big	β9	**0.0331**	0.0547	2.412E−04	**0.1832**	0.0506
Coastal	β10	**0.0119**	0.0320	1.284E−04	0.0518	0.0328
Control	β11	**0.1365**	0.0268	1.112E−04	**0.1589**	0.0257
Hydro	β12	**0.0615**	0.0285	1.080E−04	**0.0633**	0.0266
(lnPL ∗ lnPL)	β13	**−0.0282**	0.0587	2.757E−04	−0.0689	0.0546
(lnPK ∗ lnPK)	β14	−2.3160	0.5441	2.092E−03	−0.5961	0.5221
(lnCapac ∗ lnCapac)	β15	**0.0691**	0.1925	7.523E−04	**0.4009**	0.1861
(lnProd ∗ lnProd)	β16	−0.4390	0.1420	5.096E−04	**−0.3896**	0.1395
(lnProfit ∗ lnProfit)	β17	**0.1078**	0.0239	8.803E−05	**0.0629**	0.0234
lnPL ∗ lnPK	β18	−2.6370	0.7200	2.636E−03	−0.6453	0.5928
lnPL ∗ lnCapac	β19	−0.3292	0.1846	7.057E−04	−0.0768	0.1797
lnPL ∗ lnProd	β20	**0.3803**	0.1589	6.124E−04	**0.3263**	0.1570
lnPL ∗ lnProfit	β21	**−0.0604**	0.0520	2.181E−04	−0.0216	0.0513
lnPK ∗ lnCapac	β22	−1.8090	1.1240	4.430E−03	−0.6840	0.9268
lnPK ∗ lnProd	β23	**4.9470**	1.0950	4.357E−03	**3.6641**	0.9394
lnPK ∗ lnProfit	β24	−0.3043	0.3912	1.488E−03	−0.0189	0.3963
lnCapac ∗ lnProd	β25	0.7016	0.2997	1.128E−03	0.2543	0.2943
lnCapac ∗ lnProfit	β26	**−0.3892**	0.1079	4.097E−04	**−0.3637**	0.0831
lnProd ∗ lnProfit	β27	0.1121	0.0951	3.581E−04	0.1509	0.0786
σ^2		**0.0208**	0.0427	1.535E−04	**0.7137**	0.2757
θ		**12.4600**	2.1690	3.359E−02	**5.5044**	0.2774
Number of observations	Nobs	351			351	
Number of iterations	Iterations	110,000				

Notes: Statistical significant parameters at 5% level are in bold.

unnecessary a priori restrictions on the technologies to be estimated. Each explanatory variable is divided by its geometric mean. In this way, the translog can be considered as an approximation to an unknown function and the first order coefficients can be interpreted as the production elasticities evaluated at the sample geometric mean. We also include both a time trend and a squared time trend, in order to obtain some temporal changes.

The posterior estimates, posterior standard deviations and the Monte Carlo error are reported in Table 3.

The results in Table 3 show that the parameters reveal a cost increase in the observation period in line with the trend and at an increasing rate according to the square rate. The cost increase as theoretically expected with the inputs (PL, PK and capacity) and the outputs, signifying that it is costly to produce energy. Production and profits come at a lower cost, signifying that these variables help reduce costs. Relative to the dummies, we find that only one hypothesis is valid and accepted for the Chinese fossil-fuel electricity generation companies, i.e., costs were found to increase with government control. In contrast, the other three hypotheses are rejected. Size, location and mixed energy sources all increase cost inefficiency.

This paper has proposed a framework for the comparative evaluation of a sample of Chinese fossil-fuel electricity generation companies quoted on the stock exchange and the rationalisation of their operational activities. The analysis was carried out by implementing the Bayesian stochastic frontier model (Tsionas, 2002), which allows the incorporation of multiple inputs and outputs to determine the relative efficiencies and the inclusion of heterogeneity in the data.

The main policy implication of the findings of this analysis is that heterogeneity must be considered a major issue for the Chinese fossil-fuel electricity generation companies. The variable “big”, reflecting economies of scale, emerges as one of drivers of cost inefficiency, which differs from that which was found by the previous research on Chinese hydroelectric power generation companies (Barros et al., 2013). The “Big Five” have a huge amount of assets, as well as a large monopoly of China's electricity industry. These giants of electricity generation have not invested in increasing technological innovation, neither in competition.

Coastal location is also an important factor for defining the efficiency of Chinese fossil-fuel electricity generation companies, confirming the previous research on China (Wei et al., 2009; Shi et al., 2010; Bi et al., 2014). The coastal area of mainland China first implemented the “reform and open up” policy and is contiguous to Hong Kong, Macau, Taiwan, Japan, South Korea, etc., which led to many factories being concentrated there and, as the manufacturing sector was booming, the demand for electricity exploded. However, the advantage of location has not improved the efficiency of fossil-fuel electricity generation companies. This may result from the enhanced infrastructure of power distribution, which includes the unified grid that covers the whole country, and the West–east Electricity Transfer Project, which was initiated in 2000 (http://wilsoncenter.org/wilsonweekly/chinas-west-east-electricity-transfer-project.html). This result is diametrically opposite to that of Wei et al. (2009), Shi et al. (2010) and Bi et al. (2014).

The majority ownership of central government in fossil-fuel electricity generation companies has reduced their cost efficiency, which is the same finding as other research (Sarıca and Or, 2007; Pollitt, 1996, etc.). As explained in the Introduction and also by the World Bank (2012), State-controlled companies, which were former State-owned enterprises, have always been subject to government intervention, because they offer public goods and services, which affect factors such as low inflation and high employment. Moreover, controlled electricity prices and soaring coal/fuel oil prices have always afflicted Chinese fossil-fuel electricity generation companies. This distortion could lead to the inefficient allocation of resources.

Table 4
Efficient scores.

Nobs	Chinese fossil-fuel generation companies	Bayesian mean efficiency ranks	Standard SFA model mean efficiency ranks
1	SZE	0.9433	0.9374
2	SZNS	0.9465	0.9350
3	GZE	0.9427	0.9053
4	GED	0.9165	0.9174
5	AHE	0.8912	0.9207
6	JEI	0.9162	0.9016
7	BXNY	0.9315	0.8033
8	SXZZ	0.9562	0.9185
9	JPSC	0.9231	0.9093
10	JXGN	0.9507	0.9111
11	GDCY	0.9311	0.9001
12	HNYN	0.9536	0.9133
13	HPI	0.9129	0.9243
14	SEP	0.9437	0.9111
15	HDPI	0.8772	0.9411
16	GDIH	0.9400	0.9384
17	SYJS	0.9099	0.8669
18	XJTF	0.9389	0.9456
19	BJTP	0.9485	0.9066
20	SHEN	0.8567	0.9278
21	HDEC	0.8429	0.9389
22	DHEP	0.9482	0.9424
23	TEC	0.9457	0.8953
24	GDPD	0.9480	0.8878
25	NMHD	0.9424	0.9148
26	SDIC	0.9202	0.8876
27	DTP	0.9322	0.9093
	Mean	0.9262	0.9115
	Median	0.9389	0.9133
	Std. dev.	0.0291	0.0288

Finally, mixed energy sources decrease energy efficiency. Although hydro-energy sources are nearly free of costs, they require large investments to build the dams. For Chinese fossil-fuel electricity generation companies, the share of hydroelectricity is still too small to recover the investment and offset the significantly increasing costs incurred by the fossil-fuel electricity generation companies.

Table 4 below shows the cost average/cost efficiency for each fossil-fuel electricity generation company throughout the period. Cost efficiency is defined as the ratio between the minimum cost and the actual cost, and takes values of between 0 and 1. According to this definition, the closer the efficiency measure is to 1, the more efficient the fossil-fuel electricity generation companies can be considered to be. Given that the dependent variable is expressed in logarithms, it was calculated as:

$$EC = \exp(-\hat{\mu}) \tag{6}$$

where the estimated value of the inefficiency ($\hat{\mu}$) is separated from the random error term ($\hat{v}$) using the Jondrow et al. (1982) formula.

According to the scores in Table 4, SXZZ (Shanxi Zhangze Electric Power Co., Ltd.) is the most efficient company, whilst HDEC (Huadian Energy Company Limited) has the lowest efficiency score.

There is a tradition in analysing the time paths of the betas in the estimation for the empirical model, aiming to detect whether the parameters are time invariant; see Stock (1994) and Dufour and Ghysels (1996) for surveys. In Bayesian econometrics, the inference is to update parameters over time in a sequential analysis that allows for the updating of estimates as new observations are observed. Uncertainty is addressed by updating prior opinions about estimated quantities and parameters, as new data is observed. The process of moving from Prior, to Posterior, information is called Bayesian Learning. In our research, the betas were stable and time variant, without structural breaks over time, signifying that the data is sound for modelling purpose.

7. Robustness tests

7.1. Comparing with standard stochastic frontier model

To check the robustness (i.e., correctness) of the Bayesian results, a first check is made as to whether the results do not change when a standard stochastic frontier model is adopted. Furthermore, we also check whether the fossil-fuel electricity generation company ranks do not change with an alternative stochastic frontier model. These tests are commonly used in literature (Mutter et al., 2013). Following Belotti et al. (2013) the Battese and Coelli (1992) stochastic frontier model will be adopted. The results are presented in Table 3. These results reveal that the parameter estimation is in line with the Bayesian frontier model estimated with the same signs, but the Battese and Coelli (1992) stochastic frontier model has less statistical significant parameters, probably due to the replications adopted in the Bayesian approach. Furthermore, the results in this paper are comparable to the one in Tsionas (2002). The coefficients are reasonably close for alternative models. However, σ_2 (the standard errors of cost function parameters) and θ are significantly different between the two models. Differences in σ_2 and standard errors can be attributed to the heteroscedastic nature of the stochastic frontier model, and the differences in θ are more important and carry implications for efficiency measurement (Tsionas, 2002). According to the results in Table 3, the σ_2 of the Bayesian stochastic frontier model is 0.0208 whilst it is 0.7137 under the standard stochastic frontier model. Meanwhile, the θ of the Bayesian stochastic frontier model is 12.4600 whilst it is 5.5044 in the standard stochastic frontier model.

As for the parameter θ of Bayesian stochastic frontier model is two times bigger than the one in the standard stochastic frontier model, it implies that near-perfect efficiency under the former model is about two times more likely compared to the latter one (Tsionas, 2002). Therefore, the mean and median of the efficient scores for the Battese and Coelli (1992) stochastic frontier model is lower than the one for Bayesian stochastic frontier models (see Table 4). After comparing with the standard stochastic frontier model, it implies that the Bayesian stochastic model seems more suitable for the analysis for the Chinese fossil-fuel electricity generation company.

7.2. Endogeneity in stochastic frontier models

Endogeneity may arise in stochastic frontier models. Endogeneity may be due to biased omitted variables, measurement errors and simultaneity/reverse causation. Endogeneity refers to the fact that an independent variable included in the model is potentially a variable correlated with unobservable variables, which are relegated to the error term. Some factors, such as profit, may be affected by the dependent variable ‘cost’, and may be endogenous if the profit is correlated with unobservable variables that affect the cost. Investigation of endogeneity in stochastic frontier models is a recent research topic and the generic idea is that one either omits the endogenous variable, or includes a proxy (Greene, 2007b).

When using additional variables such as quality or weather, these common variables are endogenous (Mutter et al., 2013). But there is no variable for quality or weather in the context of this paper. We have a possible endogenous variable, control, which stands for government's ownership. However, the government regulation variable “control” is not common to all companies, only to government-owned ones. Moreover, this variable is a dummy, and it only affects some companies (Ngan, 2010).

In addition, so far there is no statistical test to detect endogeneity in stochastic frontier models, such as that of Hausman (1978), or the Smith–Blundell test of exogeneity in panel data (Smith and Blundell, 1986). Therefore detection is based in implausibly large returns of scale (Tran and Tsionas, 2013). The Regulation variable has no large implausible results. The GMM—general method of moments was proposed to handle the endogeneity with instrumental variables (Tran and Tsionas, 2013); and Kutlu (2010) proposes a Battese and Coelli (1992) endogenous model, decomposing the irregular term into two parts: one part is correlated with the regressors, and the other one is not correlated with the regressors. The correlated part is used as a bias correction term, and the other part remained as an irregular term.

As there is no qualitative variable that is common to all companies in our data set, as there are neither implausibly large or small values in our results, and as the standard microeconomic models such as the one we use in the present research are usually not endogenous for they rooted in Microeconomic Theory (Varian, 1987), there is no theoretical evidence of endogeneity in this paper. However, we have further checked the endogeneity by estimating the frontier model with GMM (Tran and Tsionas, 2013). The parameters did not change and, based on Tsionas' advice, we have not included it in this paper, as it is redundant in the present case.

8. Conclusion

A comparison of this model with alternative homogenous frontier models, leads to a clearer view of the causes of efficiency than that provided by the DEA model (Shi et al., 2010). Therefore, this model enlarges the view of the causes of heterogeneity in energy companies.

The overall conclusion of this research is that size, coastal location, government control and hydro-energy sources are the main underlying factors of efficiency in the case presented, as they all increase costs. In addition, unobserved heterogeneity is captured by the error terms and by the separation between the error term and the inefficient term. Finally, the hypotheses are all rejected except one. Thus, the main conclusion is that Chinese fossil-fuel electricity generation companies should take these results into consideration to bring about better management of their relative efficiency.

With regard to the causes of inefficiency in Chinese fossil-fuel electricity generation companies, the main cause is the mismatch between inputs and outputs, which is reflected by the price of labour and capital, as well as by capacity and outputs.

The policy implication of this research is that efficiency checks should be applied regularly to Chinese fossil-fuel electricity generation companies, in order to promote a regular efficiency increase over the years. There was some improvement in the efficiency over the period analysed, but more active policies are needed. Based on the results, it can be observed that there is no common policy among Chinese fossil-fuel electricity generation companies and that each company is driven by its local situation. In this context, it may thus be observed that some companies decrease their efficiency, whilst others increase it. This heterogeneous behaviour suggests that there is no common policy for improving the efficiency of all Chinese fossil-fuel electricity generation companies that has a common adjustment to the contextual setting changes. In the competitive context within which the Chinese fossil-fuel electricity generation companies operate, each company should adopt a focus on efficiency promotion, which leads to improvement. The changes required in terms of efficiency are clear: better management practices. The regulation must be applied to embrace heterogeneity when implementing a regulation policy. Furthermore, Chinese authorities, such as the central government and SERC, should abandon a policy of intervention and instead opt for market-driven measures. Given that the price of electricity is controlled by the government, and that the market-driven price of coal and fuel oil has soared, the bigger size of companies has not been favourable for higher efficiency. In addition, the monopoly still undermines the efficiency of fossil-fuel electricity generation companies in China. The government should encourage the "Big Five" to invest more resources in more sophisticated equipment, personnel training and technology innovation, to promote more efficient power production. When the market pushed the price of coal or fuel oil to new highs, the fossil-fuel electricity generation companies increased their use of hydroelectric plants to reduce costs. However, the effect is very limited at present. When China implements a new reform in the electricity industry, this analysis could be used as a reference.

The use of this methodology is in line with the resource-based theory of Barney (1986) and Teece et al. (1997), which explains that Chinese fossil-fuel electricity generation companies are heterogeneous in terms of the resources and capabilities on which they base their managerial practices, and thus heterogeneity is expected to interfere with efficiency. How does this paper compare with other research on China's energy efficiency? This paper is directly comparable to Barros et al. (2013), who analysed Chinese hydroelectricity companies by using a standard stochastic frontier model, but it gives a broader view of the causes of efficiency, namely heterogeneity. Furthermore, this paper focuses on novel issues such as size, coastal location, government ownership and hydroelectric plants for fossil-fuel electricity generation companies. Given that this methodology is used for the first time in this area, it is difficult to make a direct comparison between the results of this study and other related studies.

This paper is clearly not comparable to homogenous energy studies, since those studies do not take into consideration the aforementioned heterogeneity. Likewise, this paper is not comparable to DEA-modelled research, as these models neither allow for clusters, nor for statistically estimated parameters.

This paper has two main limitations, which are both related to the dataset. Firstly, the data span is relatively short, but Bayes' theorem allows the data to be handled accurately. Secondly, the sample procedure adopted was restricted to a single country, thus the conclusions cannot be extended beyond China. Moreover, since this research is an exploratory study, the intention is not to obtain definitive results for direct use by fossil-fuel electricity generation companies or regulatory agencies, but rather it draws their attention to the value of identifying heterogeneity among fossil-fuel electricity generation companies, and of defining business strategies for each cluster, in order to satisfy the characteristics of each company. In order to draw more generalised conclusions, a larger data set would be necessary, with the inclusion of more countries (Zhu et al., 2012b).

The limitations of this paper suggest directions for new research. Firstly, additional research is needed to confirm the results of this paper, as well as to clarify the above-mentioned issues. Secondly, research concerning fossil-fuel electricity generation companies' efficiency in the context of heterogeneity should be expanded to include other energy sectors.

Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.eneco.2014.12.020.

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