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Keywords Grid industry; Efficiency estimation; Stochastic frontier analysis; Environmental heterogeneity; China

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Does environmental heterogeneity affect the productive efficiency of grid utilities in China?

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Abstract

China's electricity industry has experienced a reform whereby the generation sector is being opened up to competition but the transmission and distribution sectors are still regulated. Efficiency and benchmarking analyses are widely used for improving the performance of regulated segments, and the impact on efficiency of observable environmental factors, together with unobservable characteristics, has gained increasing attention in recent years. This study uses alternative stochastic frontier models combined with input distance functions to study the productive efficiency of 29 grid firms of China over the period 1993–2014 and investigates the effect of observed environmental factors and unobserved heterogeneity. The results indicate that efficiency is sensitive to model specification and illustrates the presence of observed and unobserved heterogeneity. The number of customers, power delivered and network length are demonstrated to have positive impacts on the utilities' efficiency while adverse environmental conditions harm the operation of grid utilities, but policy regulations may offset the negative impact. Finally, we suggest that there is room for efficiency improvement in the distribution grid, which could be encouraged by incentive regulation,

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1. Introduction

Since the 1980s, many countries have experienced market-oriented reforms in their electricity sectors (Wang and Chen, 2012). These reforms have been aimed at strengthening competition and improving efficiency. The vertically integrated power systems include segments for generation, transmission, distribution, and retailing. Market mechanisms have been introduced in the generation and retailing sectors to improve their operating and investment efficiency, but the transmission and distribution sectors are still regulated in most countries because of their natural monopoly characteristics (Joskow, 2014). The generation and retailing sectors have benefited from de-regulation and competition, whereas by contrast for the natural monopoly networks, the adoption of effective incentive regulation (i.e. re-regulation) has been necessary to ensure efficiency improvements. China implemented a reform called "Separate power plants from grids" in 2002, which has been a success in the generation sector (Du et al., 2013; Zhao and Ma, 2013). This reform also proposed the separation of distribution from transmission when the circumstances are appropriate, but this proposal is still under discussion, even after recent reforms in 2015.

Efficiency analysis has played a crucial role in defining adequate regulatory policies, especially in industries characterized by natural monopolies and/or by public ownership (Christian von Hirschhausen et al., 2006). The performance assessment of the grid industry has gained increasing attention in recent years. For example, Christian von Hirschhausen et al.(2006), Nemoto and Goto (2006), and Ter-Martirosyan and Kwoka (2010) and Filippini and Wetzel (2014) have applied benchmarking techniques to measure the efficiency of network utilities, while Mullarkey et al.(2015) and Pérez-Reyes and Tovar(2009) further depict the efficiency change trends over time. One of the main assumptions underlying frontier analysis and technical efficiency measurement is that all the firms in an industry share the same production technology and face a similar operating environment. However, this is not entirely true for the grid industry, as it is an interconnected network and is more prone to the influence of the conditions of the operating area or technical characteristics (Cullmann, 2012). If such heterogeneity factors are ignored, considerable bias can be created in the inefficiency estimates (Kopsakangas-Savolainen and Svento, 2011).

There are two commonly used benchmarking methods to model frontier efficiency, namely data envelopment analysis (DEA) and stochastic frontier analysis (SFA). DEA is a non-parametric, deterministic programming model under which a frontier is constructed for each period, while SFA is a parametric, stochastic econometric model. The stochastic frontier models assume specific parametric functional forms for the production or cost frontiers, and use distributional assumptions on the noise and inefficiency components, but DEA models do not make such assumptions (Kumbhakar andTsionas, 2008). Moreover, the stochastic frontier model has the advantage of producing standard errors for frontier parameters and including environmental variables easily, and it is more applicable to a situation when heterogeneity factors are taken into consideration, due to its flexibility in dealing with time-variant efficiency specifications. It is used in various fields, including banks, sports and utilities, etc. (Barros andRossi, 2014; Battese et al., 2000; Gil-Alana et al., 2017; Li andLopez, 2016).

In the past few decades, a number of studies have been dedicated to evaluating the performance of power enterprises. Of these, Pollitt(1995) was the first one to apply SFA to efficiency benchmarking for the grid industry. Previous studies adopting stochastic frontier models involved three perspectives: decomposing efficiency into efficiency change and technical progress (See and Coelli, 2013; Tovar et al., 2011), estimating efficiency with dynamic stochastic models (Emvalomatis, 2011; Galán and Pollitt, 2014), and distinguishing heterogeneity in efficiency measurement (Coelli et al., 1999; Kopsakangas-Savolainen and Svento, 2011). Given the significance of the heterogeneity in efficiency measurement (Growitsch et al., 2012), this study will analyze the influence of both observed and unobserved heterogeneities on the operational efficiency of the grid industry. Although modeling heterogeneity in measuring efficiency in the electricity transportation sector has notable effects (Farsi et al., 2006a), studies focusing on this aspect are relatively rare. Kopsakangas-Savolainen and Svento(2011) analyzed the effect of observed and unobserved heterogeneity on distribution utilities in Finland. Galán and Pollitt(2014) found the existence of persistent high inefficiency in the Colombian distribution sector, and Llorca et al.(2016) demonstrated the influence of environmental factors on the efficiency of the US electricity transmission industry. As can be seen, most of the studies have just focused on the transmission or distribution sector; this study will explore whether their results are applicable to the integrated power grid system in China.

Among environmental factors, the weather and geographic conditions are some of the most commonly debated factors that are perceived to affect the performance of utilities (Yu et al., 2009). Geographical, weather, and some unobservable factors vary with grid utilities and time, and the increasing adoption of incentive regulation and benchmarking of grid utilities requires close attention to the role and treatment of such external factors. Domijan et al.(2003) found a significant correlation between power interruptions and weather parameters such as rain, wind, and temperature. Rothstein and Halbig(2010) indicated that many atmospheric and hydrological factors can affect electricity transmission, and Cambini et al.(2014) further demonstrated that the heterogeneity associated with contextual variables had significant effects on efficiency. However, it is argued that utilities often adapt their operating and investment practices to adverse environmental conditions, and hence the measured environmental effects may not be significant. Nillesen and Pollitt(2010) found that US electricity distribution firms that operated in unfavorable conditions often operated at best-practice levels before adjusting for environmental effects. By analysing the influence of weather variables on the efficiency of electricity distribution companies in Argentina, Brazil, Chile and Peru, Anaya and Pollitt(2017) found that on average there is a significant increase in measured efficiency when weather is incorporated. Whether environmental factors affect the efficiency of grid utilities is still a controversial issue in China. Since environmental variables are beyond the control of grid utilities, these variables should be controlled for in efficiency modelling.

This study aims to analyze the performance of China's grid system[1] while taking into account the effect of observed heterogeneity, including geographic and weather conditions, as well as unobserved heterogeneity. It adopts alternative stochastic frontier models to estimate efficiency utilizing a panel dataset of 29 Chinese grid utilities for the period 1993–2014. With different specifications under which either (or both) of the observed or unobserved heterogeneity is taken

[1] As mentioned above, the separation of distribution from transmission is still under discussion, thus the grid system here means utilities that operate and own both transmission and distribution businesses.

into account, we are not only able to examine the productive inefficiency of the grid firms and depict trends in the development of their efficiencies, but we can also identify whether the environmental factors are determinants of firms' performance. To the best of our knowledge, this is the first empirical study measuring the operational efficiency of grid utilities in China that takes environmental factors into consideration, and the study is based on a more recent large-scale panel dataset covering almost all of China's grid industry. In addition, this study is unique in two ways: it adapts the capital stock to better represent the resources the grid company is using, and it adjusts the network length comprehensively by taking the voltage levels as weights, which allows us to analyze the correlation between the operational efficiency and grid size. The rest of this paper is organized as follows. Section 2 provides an outline of the grid system in China. Section 3 describes the theoretical functions that we estimate as well as the empirical specifications of the estimated models. Section 4 illustrates the data and variables. Section 5 discusses the results obtained from those estimates and Section 6 presents the main conclusions.

2. Development of China's grid system

China's electric power industry has been growing at a rapid pace in recent decades in order to support the country's economy, which has boomed as a result of increased industrialization and economic reforms. Figure 1 shows the rapid growth of China's national electric power generation from 2002 to 2016. To keep pace with economic growth, the electricity supply industry has been reformed to dismantle the previous monopolistic structure of the industry and to provide incentives for its efficiency (Yeoh and Rajaraman, 2004). With the changes in the situation of power supply and demand in recent years, promoting the quality and efficiency of electricity transportation has become one of the most critical issues facing the sector. Figure 1 also shows the development of network length for transmission and distribution circuits from 2002 to 2016. Indeed, annual investment in the transmission and distribution sector has exceeded that of the generation sector since 2014.[2]

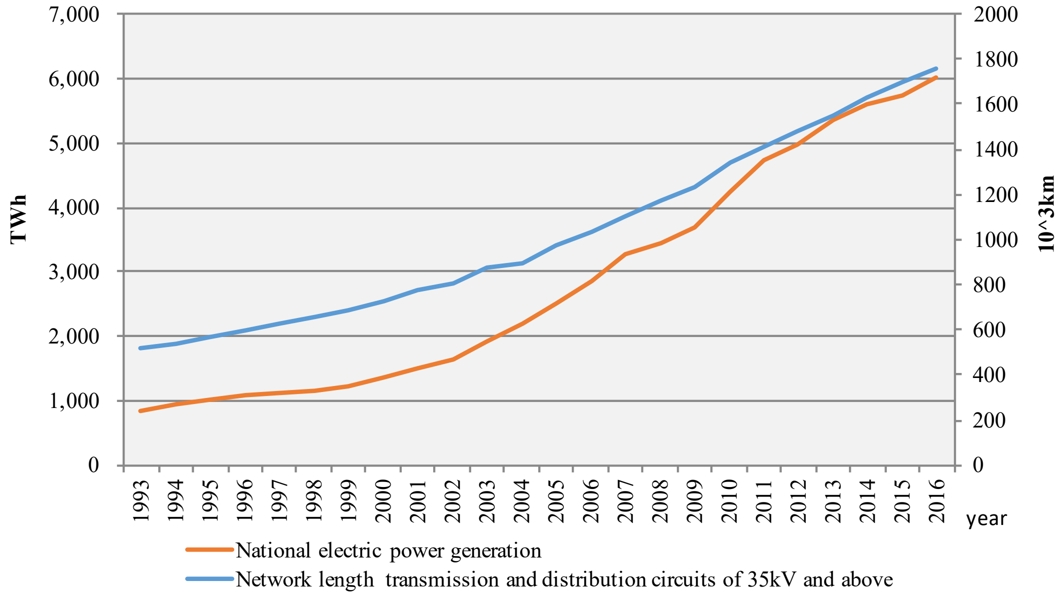

Fig.1 The development of China's electric power sector from 1993 to 2016

Starting in 1997, China began its market-oriented reforms in the power industry by establishing the State Power Corporation to oversee the business operations of the electricity system. Along with the abolition of the former Ministry of Electric Power, power industry regulations became part of the responsibilities of the State Economic and Trade Commission. Later, under the *Scheme of the Reform for Power Industry* issued by the State Council in 2002, the vertically integrated national monopolist that was the State Power Corporation was unbundled into five big generation

[2] For a discussion of China's most recent electricity reform see Pollitt et al.(2017).

corporations, two grid corporations, and four corporations operating the auxiliary businesses[3].

Even though China stated its plan to separate the distribution from the transmission sector[4] in 2002, it has not been put into practice yet. Most of the transmission and distribution businesses are mainly operated by two legally independent state-owned limited liability corporations, namely the China Southern Power Grid Corporation and the State Grid Corporation of China. The China Southern Power Grid Corporation is in charge of power grid construction, maintenance, power transmission, distribution, and sales in the five southern provinces[5], and the State Grid Corporation is responsible for the same businesses in the other 26 provinces on the mainland[6].

China presents a particularly interesting case to study the effect of observed and unobserved

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[3] The five big generation corporations consist of China Huaneng Group, China Guodian Corporation, China Datang Corporation, China Huadian Corporation, and China Power Investment Corporation. The four corporations operating the auxiliary businesses are SDIC Huajing Power Holdings Co Ltd, Guohua Electric Power Corporation, China Resources Power Holdings Company Limited, and China General Nuclear Power Group. The two grid corporations will be introduced later in this paper.

[4] The electricity transmission utilities, in general, provide electricity transport services across long-distance high voltage wires, whereas the distribution utilities operate at lower voltages and connect to the final consumers.

[5] China South Power Grid Corporation operates the grid businesses in Guangdong, Guangxi, Guizhou, Yunnan, and Hainan.

[6] China's grid system consists of six parts: The north regional grid branch operates the businesses in Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, and Shandong. The utilities in Liaoning, Jilin, Heilongjiang, and Eastern Inner Mongolia are managed by the northeastern regional branch. The east regional grid covers Shanghai, Jiangsu, Zhejiang, Fujian, and Anhui. The central grid branch covers Henan, Hubei, Hunan, Sichuan, and Chongqing. The northwest regional grid branch operates the business in Shaanxi, Gansu, Ningxia, Qinghai, and Xinjiang. Note that the power grid in the eastern Inner Mongolia is under the management of the State Grid Corporation of China, while the western part is managed by the Inner Mongolia Power Group Corporation, which is independent of the aforementioned two companies.

heterogeneity. First, it is a large country with unbalanced development of its regional economies. These disparities may affect network investment, infrastructure facilities construction, and the behaviors of the customers, all of which have indirect influences on the efficiency of the grid system. Second, macroeconomic policy may play a dominant role in the power grid. The desire of the government to stimulate provincial GDP via power sector investment may influence measured efficiency. Third, the grid system in China involves long-distance transportation as well as complex climatic and topographic conditions. Power interruptions and failure rates have significant correlations with weather parameters (Coelho et al., 2003; Domijan et al., 2003), and adverse landform characteristics can increase the difficulty of repairs and maintenance. A notable example was the heavy snow storm in southern China in 2008, which led to serious damage to electric network equipment. Although the financial and political characteristics are unobserved, whereas the climatic and geographic factors are observed, they may be correlated with each other, and result in reducing unobserved heterogeneity.

For the power grid, heterogeneity has become more and more significant with the implementation of the "extending power coverage to every village" project and the construction of ultra-high voltage[7] (UHV hereafter) power grids. The first project aimed at electrifying some rural areas that previously had absolutely no access to electricity. Related projects usually locate in areas with severe natural environmental conditions, which may result in lower operational efficiency. China has also devoted efforts towards raising the technology level of the power grids. Regarding

[7] Ultra-high voltage power grids refer to super giant power grids that consist of ultra-high voltage backbone networks with 1000 kV alternating current transmission systems and 600 kV direct current transmission networks.

the second, the first commercial operating ultra-high voltage (UHV) project worldwide was completed in China in 2008. This gave China a leading role in the world in this technology. The network starts at the Changzhi substation in Shanxi and ends at the Jingmen substation in Hubei, thereby interconnecting the North China Power Grid and the Central China Power Grid. UHV power grids, bringing power from the net exporting areas in the west to importing areas in the east and south, can not only satisfy the need for long-distance transportation but can substantially improve the reliability and vulnerability of the network and further increase its efficiency as well. Simultaneously, it further increases the heterogeneities among grid branches, which may further broaden their efficiency gaps.

3. Methodology

3.1 The involvement of heterogeneity in stochastic frontier analysis

SFA is a widely used frontier efficiency model that was introduced by Aigner et al.(1977) and Meeusen andvan den Broeck(1977); after this came the panel data models in the form of random (Pitt and Lee, 1981) and fixed effects (Schmidt and Sickles, 1984). However, it is hard to satisfy the strong assumptions stated in these models, in which inefficiency is time invariant and both inefficiency and noise terms are independently and identically distributed. Since the utilities may adapt their operating and investment practices over time to counteract the adverse effects caused by the environment, Kumbhakar(1990) and Battese and Coelli(1992) specified a quadratic and exponential function, respectively, to relax this time-invariant assumption.

Even though these deterministic functions are able to describe the time path of efficiencies for an industry on average, they cannot model firm-specific behavior by restricting the time paths to have the same structure across firms. Accordingly, extensions to the originally proposed stochastic frontier models were introduced, in which firm-specific heterogeneity can be modeled explicitly. Battese and Coelli(1995) expressed time-varying inefficiency as a function of the exogenous variables, but it is understandable that not all of the exogenous factors might be observable or quantifiable, and unobserved residual heterogeneity always exists. Greene(2005) then proposed an approach that integrates an additional stochastic term in both the fixed and random effects models to distinguish the unobservable heterogeneities from inefficiency. Kumbhakar et al.(2014) further split the time-invariant firm-specific term into two parts, one involving unobserved heterogeneity and the other representing time-invariant inefficiency. In this section, we specify alternative models for estimating the operational efficiency of grid utilities that take into account the observed and/or unobserved heterogeneity.

3.2 Translog distance functions

Efficiency is an index that is often employed to measure the relative performance of a decision-making unit (company, region, etc.). It is usually defined as the ratio of the observed outputs to the potentially optimal values. To address the issue that basic stochastic frontier models can only solve single-output issues, we use multi-input, multi-output distance functions to estimate the relative efficiency of utilities in relation to the technical frontier. Since the outputs of grids are determined by electricity consumption and the number of customers, which are exogenous factors, and the main objective of a grid company is to minimize the inputs for given outputs, we measure firm-specific technical efficiency within an input distance function framework defined as:

$$D^I(x,y,g) = \max\{\rho | (x/\rho) \in L(y), \rho \geq 1\} \tag{1}$$

where the input set $L(y)$ represents all input vectors x that can produce the output vector y, and ρ measures the maximum amount by which an input vector can be radially contracted while the output vector remains constant. The input distance function has the following properties: it is homogeneous of degree one and has a non-decreasing concave function of inputs and a non-increasing quasi-concave function of outputs (Färe and Primont, 1995).

The properties above allow us to calculate input-oriented technical efficiency (*TE*) as the reciprocal of the value of the distance function and gets values from 0 to 1, with a value of 1 meaning a firm operating on the frontier. Following Farrell(1957):

$$TE_I(x,y,g) = 1/D^I(x,y,g). \tag{2}$$

Specifically, we use a more flexible translog function to parameterize the distance function. It is easy to calculate and allows the imposition of the homogeneous condition. For the case of M outputs and K inputs, the translog function is specified as follows (Coelli et al., 2003):

$$\begin{aligned}\ln D_{it}^I = {} & \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln y_{mit} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \alpha_{mn} \ln y_{mit} \ln y_{nit} + \sum_{k=1}^{K} \beta_k \ln x_{kit} \\ & + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl} \ln x_{kit} \ln x_{lit} + \sum_{k=1}^{K}\sum_{m=1}^{M} \delta_{km} \ln x_{kit} \ln y_{mit} + \varphi t + v_{it},\end{aligned} \tag{3}$$

where subscripts $i(i = 1,2,...,N)$ and $t(t = 1,2,...,T)$ denote the firm and time period, respectively, and v_{it} is the normally distributed error term with variance σ_v^2, and α,β,δ and φ are unknown parameters to be estimated. Homogeneity of degree one in inputs is imposed by the constraints:

$$\sum_{k=1}^{K} \beta_k = 1, \quad \sum_{l=1}^{K} \beta_{kl} = 0, k = 1,2,...,K \text{ and } \sum_{k=1}^{K} \delta_{km} = 0, m = 1,2,...,M, \tag{4}$$

Symmetry is given if the second order coefficients satisfy:

$$\alpha_{mn} = \alpha_{nm}, \quad m,n = 1,2,...,M \quad \text{and} \quad \beta_{kl} = \beta_{lk}, \quad k,l = 1,2,...,K. \tag{5}$$

In this study, we apply the SFA techniques to estimate the presented translog input distance function, and the feature of linear homogeneity allows us to normalize all the inputs in the distance function by a specific input x_{Kit} to make it easily estimated.

$$-\ln x_{Kit} = TL\left(\ln x_{kit}^{*}, \ln y_{mit}, t\right) + v_{it} - u_{it} \tag{6}$$

where $TL(\cdot)$ is the translog input function form, and $x_{kit}^{*} = x_{kit} / x_{Kit}$, $u_{it} \equiv \ln D_{t}$ is a half normally distributed non-negative technical inefficiency term with mean 0 and variance σ_u^2.

3.3 Specification of estimated models

Most traditional studies focusing on inefficiency analysis assume that all decision-making units (DMU) share a similar operating environment, but this does not conform to reality, since the DMUs might be heterogeneous due to their individual characteristics, such as their resource endowments, institutional environment, and background level of economic development (Lin and Du, 2014). Both observed and unobserved heterogeneity would cause a bias in inefficiency estimation, so it is important to determine their roles in estimating the relative performance of utilities. This study employs a panel dataset of China's grid utilities and applies five alternative stochastic frontier models to measure the level the inefficiency variance over time, which allows us to analyze the effect of heterogeneity represented by a set of environmental variables on the efficiency.

The first estimated model (REH) proposed by Battese and Coelli(1995) is the most frequently used model in past studies. As this model assumes that the mean of the pre-truncated normal variable depends on external variables, it can investigate the influence of environmental variables on inefficiency. Although it is designed for cross-sectional data, it can readily be used for panel models (Kumbhakar et al., 2014).

$$
\begin{aligned}
&-\ln x_{Kit} = \alpha + TL\left(\ln x_{kit}^{*}, \ln y_{mit}, t\right) + v_{it} - u_{it} \\
&u_{it} \sim N^{+}\left(\mu_{it}, \sigma_u^2\right) = N^{+}\left(\delta_0 + z_{it}^{'}\delta, \sigma_u^2\right) \\
&v_{it} \sim N\left(0, \sigma_v^2\right)
\end{aligned} \tag{7}
$$

where z_{it} is a vector of the environmental factors expected to influence the inefficiency. Regardless of the observed environmental factors, this model suffers from the issue that the unobserved heterogeneity still remains in the inefficiency term and is not distributed independently of the explanatory variables. Farsi and Filippini(2006) argue that if the unobserved heterogeneity exists, this model may overestimate the inefficiency.

In order to address the unobserved heterogeneity bias, Greene(2005) developed the “true” random-effects (TRE) model with the addition of a firm-specific time-invariant random effect representing the unobserved heterogeneity among utilities; in this way, we can disentangle the firm heterogeneity from the technical inefficiency.

$$
\begin{aligned}
&-\ln x_{Kit} = \left(\alpha + \omega_i\right) + TL\left(\ln x_{kit}^{*}, \ln y_{mit}, t\right) + v_{it} - u_{it} \\
&u_{it} \sim \mathrm{N}^{+}\left(0, \sigma_u^2\right), v_{it} \sim iid\mathrm{N}\left(0, \sigma_v^2\right), \\
&\omega_i \sim iid\mathrm{N}\left(0, \sigma_\omega^2\right)
\end{aligned} \tag{8}
$$

where ω_i is a normally distributed random term that captures unobserved individual characteristics. The TRE model usually performs better than the REH model as it can separate unobserved heterogeneity bias from the non-negative technical inefficiency term.

This study extends the TRE model by adding the effects of environmental factors to get the third model, TREH1, which has a similar specification but the mean of the inefficiency is a function of the heterogeneity explaining covariate. The TREH1 model is then comparable to the REH model, with the main difference being that the former is estimated by a simulated maximum likelihood approach with no unobserved firm-specific effects considered, whereas the latter is estimated by a maximum likelihood approach when separating the unobserved heterogeneity from the inefficiency.

The third model is specified as follows:

$$
\begin{aligned}
&-\ln x_{Kit} = (\alpha + \omega_i) + TL\left(\ln x^*_{kit}, \ln y_{mit}, t\right) + v_{it} - u_{it} \\
&u_{it} \sim \mathrm{N}^+\left(\mu_{it}, \sigma_u^2\right) = \mathrm{N}^+\left(\delta_0 + z_{it}^{'}\delta, \sigma_u^2\right) \\
&v_{it} \sim iid\mathrm{N}\left(0, \sigma_v^2\right), \omega_i \sim iid\mathrm{N}\left(0, \sigma_\omega^2\right)
\end{aligned}
\tag{9}
$$

All the models above treat the error term as homoscedastic; however, Kumbhakar and Lovell(2000) pointed out that ignoring the heteroscedasticity of the symmetric error term would lead to bias in estimating the technical efficiency. In order to determine the extent of the impact of the distribution hypothesis about the error term on the inefficiency, we further adopt the fourth model (TREH2) introduced by Alvarez et al.(2006) into our efficiency analysis. TREH2 includes a heterogeneity component into the variance of the distribution of inefficiency; in this way, both the pre-truncation mean and variance of the inefficiency term are involved in the environmental variables.

$$
\begin{aligned}
&-\ln x_{Kit} = (\alpha + \omega_i) + TL\left(\ln x^*_{kit}, \ln y_{mit}, t\right) + v_{it} - u_{it} \\
&u_{it} \sim \mathrm{N}^+\left(\mu_{it}, \sigma_{uit}^2\right) = \mathrm{N}^+\left(\delta_0 + z_{it}^{'}\delta, \exp(\gamma_0 + z_{it}^{'}\gamma)^2\right) \\
&v_{it} \sim \mathrm{N}\left(0, \sigma_v^2\right), \omega_i \sim iid\mathrm{N}\left(0, \sigma_\omega^2\right)
\end{aligned}
\tag{10}
$$

In the TRE models it is assumed that the unobserved differences across firms that remain constant over time capture the persistent unobserved firm level heterogeneity, rather than being understood as the inefficiency. Nevertheless, it may be argued that the firm-specific term may capture the possible time-invariant structural or persistent component of the inefficiency. If there is a possibility of a time-invariant structural element in the inefficiency, Greene's model may underestimate the overall inefficiency and the fifth model (GTRE) proposed by Kumbhakar et al.(2014) may be useful:

$$
\begin{aligned}
&-\ln x_{Kit} = (\alpha + \omega_i + \eta_i) + TL\left(\ln x_{kit}^{*}, \ln y_{mit}, t\right) + v_{it} - u_{it} \\
&u_{it} \sim \mathrm{N}^{+}\left(0, \sigma_u^2\right), v_{it} \sim \mathrm{N}\left(0, \sigma_v^2\right) \\
&\omega_i \sim \mathrm{N}\left(0, \sigma_\omega^2\right), \eta_i \sim iid\mathrm{N}\left(0, \sigma_\eta^2\right)
\end{aligned}
\tag{11}
$$

The GTRE model overcomes the aforementioned problems by decomposing the time-invariant component into a firm effect and persistent inefficiency, the inefficiency then consists of a time-invariant part η_i and a time-varying part u_{it}, while the rest are the unobserved permanent firm-specific heterogeneity (ω_i) and the noise term (v_{it}). This model can be estimated in three steps as described in Kumbhakar et al.(2014).

The main features of the five models specified above are summarized in Table 1. The models are different in the way they model the observed and unobserved heterogeneity, and as there is no prior knowledge of the superiority of these models in efficiency measurements, here we apply them to the same dataset with the aim of analyzing the extent to which inefficiency is sensitive to different models. Explicit allowance for heterogeneity likely overestimates efficiency whereas failure to allow for heterogeneity is likely to underestimate efficiency. To some extent, TREH2 model usually performs better than REH, TRE and TREH 1 models in discriminating the heterogeneity component, while GTRE is good at analyzing the time-invariant firm specific heterogeneities. It is hard to compare the results of REH2 and GTRE, which may provide more information than other models.

Table 1
Summary table of the models estimated.

Model	Observed external heterogeneity	Unobserved firm specific heterogeneity
REH	Observed environmental factors included in the mean of the distribution of inefficiency	Not included in the model
TRE	Not included in the model	Time invariant random component
TREH1	Observed environmental factors included in the mean of the distribution of inefficiency	Time invariant random component
TREH2	Observed environmental factors included in the mean and variance of the distribution of inefficiency	Time invariant random component
GTRE	Not included in the model	Time invariant random component after removal of time invariant inefficiency

4. Data and samples

The data used in this study consist of a panel of 29 provincial grid companies[8], covering a 22-year period from 1993 to 2014. As there are only several small local grid companies in Shanxi, Jilin Sichuan, Guangxi and other provinces that are not included in this study, the studied samples serve about 98% customers of China's grid sector whose electricity consumption amounts to 98.5% of the national total. The data mainly come from Chinese power industry statistics compilations, yearbooks for China Electric Power, State Grid Corporation, and Southern Power Grid Company, China Energy Statistics, China Statistics, and the China Meteorological Data Network. The dataset is an unbalanced panel with a total of 659 observations[9].

Pollitt(1995) pointed out that it might be desirable to take every specific factor of the company

[8] This study does not include Tibet in the sample as it was not involved in the 2002 unbundling reform. The Chongqing and Eastern Inner Mongolia grid companies are also included after their establishment in 1997 and 2009, respectively. Hong Kong, Macao, and Taiwan are also not included because of differences in their management mechanisms and the nature of their statistical reporting.

[9] For the missing data, we use the linear interpolation method to adjust.

into account due to the complexity of the network, but with the limitation on the availability of data and the complexity of the models, we cannot cover all the aspects of the grid system. In this study we select two inputs and three outputs to specify the translog distance function. The inputs are labor (x_1) and capital (x_2). As there are no costs or income information for the employees of the grid industry in China, we adopt the number of employees as an approximation. Hattori(2002), Çelen(2013), and Kumbhakar et al.(2014) also took it as an input. Kumbhakar and Hjalmarsson(1998) defined the capital as the total transformer capacity, which is actually only part of the resources adopted, with the transport distance also constituting a significant part (Kumbhakar et al., 2014). Hossain and Karunaratne(2004) defined the capital input as the gross fixed assets aggregated from book values of various materials. However, the depreciation used in the accounts may not represent the real decline in the value of the capital assets (Kumbhakar et al., 2014). We measure here the capital input by the capital stock in the real value of 2000, which can better reflect the true value of capital. We adopt the perpetual inventory method (PIM)[10] just as Lin and Wang(2014) did, to calculate the capital stock level for the grid companies annually.

The number of customers (y_1) is chosen as the first output, including billed residential

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[10] The PIM was first applied by Goldsmith (1951), and it can be expressed as: $K_t = K_{t-1}(1-\delta_t) + I_t$ where K_t and K_{t-1} represent capital stock in year t and (t–1), respectively. I_t represents investment in year t, and δ_t represents depreciation rate in year t. This paper selects 1993 as the base year and sets the fixed assets price index in 1997 to 100. Following *Ratification Methods for Western Inner Mongolia Power Grid Transmission and Distribution Approval Costs*, the average residuals rate is set to 5% and the equipment life period to 25 years, so the average depreciation rate per year is (1–5%)/25=3.8%. Then we derive the fixed capital stock for grid companies from 1994 to 2014 by iteration.

customers and non- residential customers. This variable can reflect the number of connection points (Jamasb and Pollitt, 2003) and important differences in the average levels of consumption (Tovar et al., 2011). The second output is power delivered (y_2), which is measured in megawatt-hours (MWh). These two variables are the most commonly used outputs in benchmarking electrical network utilities and are assumed to reflect the network connection and electricity supply of the grid sector (Neuberg, 1977). We also include the network length (y_3) of the grid sector for transmission and distribution business as the third output, which is comprehensively calculated by taking the voltage levels as weights. This reflects both geographical spread (across space) and capacity to deliver (in terms of maximum amounts of power). For the same distance of physical network length, we take the voltage levels as weights to reflect not only the size of the transportation task but the organization of the services as well[11].

In addition to the above inputs and outputs, regulatory, geographic, climatic, and other conditions may all affect the performance of grid utilities (Growitsch et al., 2012), consequently, we incorporate another dummy variable as well as some weather and geographic variables into the following analysis. The dummy variable, denoted as unbundling (d_1), may measure the impact of the unbundling policy on the grid companies (Çelen, 2013; Filippini and Wetzel, 2014). The policy was implemented in 2002, and most provincial grid companies had finished the reform by the end of 2003, so we set the dummy variable as 1 for all companies after 2004 and 0 otherwise. As for the environmental variables, Domijan et al.(2005) found that weather conditions, such as rainfall and

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[11] This study has only included the network 35kV above as the output, for an output of 100km length of 500kV network, it will be counted as 500kV*100km=50 GVm.

wind, are the most significant factors affecting the power outages. According to Llorca et al.(2016), it is more difficult to manage a firm operating in a region with bad weather where the wind speed and precipitation are high and the minimum temperature is low. We include these above mentioned factors such as the temperature range (z_1), annual precipitation (z_2), and wind speed (z_3) as the weather factors. A further correlation test also verify their effectiveness. In addition, we determine the influence of the topographic features, hence the proportion of mountains (z_4) is included as a geographic factor. The temperature variable is the annual maximum temperature minus the minimum temperature in degrees Celsius. The annual precipitation is the average of the annual precipitation in millimeters, and the wind speed is the average of the daily mean wind speeds. Since the grid utilities' server areas may enclose large numbers of meteorological stations, the environmental data are collected from and represented by the capital cities of the corresponding provinces. It can be assumed that more adverse conditions appear when all the four environmental variables exhibit high values.

Table 2 presents a summary of the descriptive statistics of the variables used in this study.

Table 2
Descriptive statistics.

	Variable	Nomenclature	Unit	Mean	Std.	Min	Max
Capital stock	Input	x1	10^4 yuan	234.857	269.916	18.866	1979.849
Number of employees	Input	x2	person	26512.305	17830.647	2052.000	117337.000
Number of customers	Output	y1	10^4	1214.831	882.591	0.002	8687.648
Electricity consumption	Output	y2	10^8 kwh	828.254	819.350	19.411	4960.650
Network length	Output	y3	10^4 km•kV	407.050	323.478	0.017	1563.573
Unbundling	Dummy	d1	—	0.499	0.500	0.000	1.000
Temperature range	Environment	z1	℃	45.735	11.975	17.375	84.500
Annual precipitation	Environment	z2	mm	710.802	512.773	2.500	5643.083
Wind speed	Environment	z3	m/s	23 .028	5.745	11.313	38.417
Rate of mountains	Environment	z4	%	39.315	17.359	7.000	78.200

5. Factors affecting the efficiencies under different models

5.1 Coefficients

Table 3 presents the coefficients of variables and returns to scale based on our alternative models. All the variables included in the models are in logarithms and are normalized by their mean, with the exception of the dummy variable and the time period. Hence, the first-order coefficients in the model can be interpreted as the elasticity of the outputs. Just as we expected, the number of customers and network length have a positive influence (negative coefficients) on the operational efficiency[12]. Increasing customer numbers and network length would bring economics of scale and, ceteris paribus, further enhance the efficiency of grid companies. Even though the coefficient of power delivered has a negative influence (positive coefficient) on the operational efficiency, the sum of the coefficients of the number of customers, power delivered and network length is negative, which means the outputs are positive correlated with the operation efficiency. The results coincides with Galán and Pollitt (2014), and Anaya and Pollitt(2017). The coefficient of unbundling is positive, which means that on the whole the unbundling reform has decreased the efficiency of the power grid system.

[12] Though some positive coefficients appear in the model except TREH2, they are not significant on 10% level.

Table 3
Parameter estimates of the translog function.

		REH		TRE		TREH1		TREH2		GTRE	
		Coef.	Std.	Coef.	Std.	Coef.	Std.	Coef.	Std.	Coef.	Std.
frontier	ln(x2/x1)	-0.564***	0.208	-0.632***	0.120	-0.645***	0.139	-0.622***	0.137	-0.574***	0.195
	lny1	-2.369***	0.773	-6.151***	0.349	-2.522***	0.663	-2.435***	0.346	-3.193***	0.782
	lny2	4.425***	1.113	1.248**	0.361	0.689**	0.497	0.549*	0.178	0.361**	0.137
	lny3	-6.524***	1.154	-0.599*	0.330	-1.019**	0.515	-1.236***	0.211	-1.026**	0.813
	1/2ln(x2/x1)^2	-0.004	0.054	0.134	0.038	-0.255	0.162	-0.784***	0.205	-0.052	0.184
	ln(x2/x1)*lny1	1.177***	0.275	1.112***	0.169	3.389***	0.652	0.495	0.502	3.344***	0.634
	ln(x2/x1)*lny2	0.755*	0.436	-0.010	0.226	0.330	0.289	0.044	0.250	-0.457	0.372
	ln(x2/x1)*lny3	-1.602***	0.406	-0.790***	0.227	-1.980***	0.562	-0.023	0.292	-2.494***	0.631
	1/2(lny1)^2	0.349	0.358	1.082***	0.206	2.075***	0.569	0.184	0.575	1.903***	0.672
	lny1*lny2	-2.757**	1.322	1.418*	0.343	-0.455	0.602	-0.195	0.758	0.344	1.003
	1/2(lny2)^2	-1.026	1.347	2.344***	0.300	2.181***	0.207	1.511***	0.421	2.127***	0.260
	lny1*lny3	3.240**	1.282	1.347	0.348	-0.072	1.311	0.578	0.366	1.238	1.304
	lny2*lny3	0.386	2.252	-4.553***	0.424	0.082	0.478	-0.267	0.453	0.240	0.754
	1/2(lny3)^2	2.450**	1.136	1.506***	0.302	1.195	1.062	0.208	0.225	0.729	1.160
	d1	0.014***	0.004	0.148***	0.003	0.234***	0.039	0.260***	0.036	0.284***	0.053
	t	-0.012***	0.004	-0.001***	0.000	-0.010**	0.005	0.120**	0.085	0.005	0.006
	cons	3.057***	0.350	3.643	0.217	-0.577***	0.067	-0.515***	0.118	-0.499***	0.380
mu	z1	-8.086**	3.468			-0.508***	0.064	-0.432***	0.166		
	z2	6.263***	1.349			0.335***	0.048	0.144	0.108		
	z3	8.833***	2.055			0.406***	0.057	0.352***	0.095		
	z4	7.731***	1.621			-0.157	0.146	0.177	0.108		
	t	0.103**	0.421			0.125***	0.011	-0.035*	0.020		

Table 3
Parameter estimates of the translog function. *(continued)*

		REH		TRE		TREH1		TREH2		GTRE	
		Coef.	Std.	Coef.	Std.	Coef.	Std.	Coef.	Std.	Coef.	Std.
	cons	-1.831***	0.045	-0.847**	0.075	-1.957***	0.241	0.500**	0.245		
usigma	z1							-1.057***	0.166		
	z2							-0.452***	0.105		
	z3							-0.090	0.191		
	z4							-0.584***	0.164		
	t							0.275***	0.022		
	cons	-3.740***	0.227	4.530***	0.100	-2.432***	0.237	-5.515***	0.498		
vsigma	cons	-7.543***	0.071	-3.023***	0.203	-3.419***	0.162	-3.514***	0.211		
Return to scale		5.032		6.134		3.497		3.744		4.432	

*** Significant at 1% significance level.
** Significant at 5% significance level.
*Significant at 10% significance level.

With regard to the external variables in the pre-truncated inefficiency component, we get positive coefficients for annual precipitation, wind speed and mountain rates, which illustrates that bigger observed values would generate lower levels of efficiency; similar results have also been obtained by Llorca et al.(2016). It is somewhat surprising to find that the temperature range gains a negative sign, indicating that for utilities that are operated in a region with a larger temperature range, it is easy to achieve higher efficiency. This result is reasonable to some extent because most regions with a larger temperature range are located in the north of China. The grids in these regions are usually designed to take into consideration the likelihood of extremely low temperatures. In addition, the customers in these regions have easy access to central heating services in the winter, which may effectively prevent the excessive growth of electricity demand and result in relatively steady power consumption. These measures all benefit the operation of grid systems. In general, adverse weather conditions may block the improvement of efficiency, whereas the policy and grid design seem to have the ability to offset the negative effects of cold weather. As for the time trend, it seems that the negative value through the input distance function of TREH2 cannot counterbalance its negative value for the pre-truncation mean of inefficiency, which is also consistent with Llorca et al.(2016).

5.2 Efficiency estimation based on different models

Table 4 presents the basic statistics of the efficiencies under different models. The highest efficiency mean (0.795) occurs under the TREH2 model, while the lowest (0.594) occurs under GTRE. In general, the efficiency we get is a little lower than that of Li et al.(2016), which may be due to their ignoring several provinces with adverse environmental conditions and, accordingly, lower efficiency. These provinces included the Xinjiang Autonomous Region and the Yunnan and Hainan provinces of China Southern Power Grid Corporation.

Table 4
Statistics of efficiency under different models.

	REH	TRE	TREH1	TREH2	GTRE
Mean	0.764	0.783	0.787	0.795	0.594
Std.Dev.	0.134	0.139	0.219	0.220	0.148
Minimum	0.188	0.274	0.149	0.120	0.208
Maximum	0.936	0.956	0.975	0.998	0.844

Results in Table 4 show that the model specifications may influence the average efficiency estimates. The REH model has lower efficiency scores than TREH1, Since the inefficiency in the former model is a compound of time-invariant firm-specific heterogeneity and “real” inefficiency, whereas the latter model separates them, it is reasonable that the first model has a relatively higher inefficiency and a correspondingly lower efficiency (Filippini and Wetzel, 2014). The efficiency under TREH1 is lower than that of TREH2, but it is almost the same as TRE. This coincides with the results of previous studies that TREH2 usually reach more objective results (Filippini and Wetzel, 2014). Next, we turn to the last model, which has a lower efficiency score than all the models above. This result is predictable as well, since the GTRE model treats inefficiency as a mix of the persistent and transient part, and the addition of the persistent part leads to lower efficiency than those from the TRE models (Li et al., 2016).

As for the divergence between the results of the models, the deviations between TREH1 and TREH2, which have taken both observed and unobserved heterogeneity into consideration, are larger than those of the other models, and their efficiency gaps have increased over the period. The lack of convergence in companies' efficiency further illustrates the importance of accounting for firm-specific persistence parameters. Most of the observed heterogeneity, such as the weather and geographic conditions, is hard to improve, whereas the companies can strengthen their management to counteract the unobserved heterogeneities to some extent.

This study also conducts Spearman correlation tests to investigate the consistency of the efficiency ranks for the different models, and the detailed information about the correlation matrix can be seen in Table 5. The low correlation coefficients between the models indicate that the efficiency ranks of grid utilities seem to differ significantly between the models. A possible explanation lies in the fact that the models impose different assumptions on the inefficiency distribution form and on the contents of the inefficiency term. The inconsistent correlation also reminds us that efficiency benchmarking analysis should be carefully conducted on the grid utilities, especially when the results for individual units are part of the determination of their allowed revenue by the regulator.

Table 5
Spearman rank correlations between efficiency estimates.

	REH	TRE	TREH1
REH	1		
TRE	0.644*	1	
TREH1	0.220*	0.300*	1
TREH2	0.330*	0.374*	0.765*
GTRE	0.621*	0.254*	0.195*

*: Significant on the 1%-level.

5.3 The influence of unbundling reform

This study has compared the average posterior distribution of the operational efficiency of grid utilities before and after the unbundling reform. Figure 2 depicts the efficiency tendencies measured in different specifications. As can be seen, the results for different models vary significantly. There are no obvious trends in efficiency under models considering either observed heterogeneity (REH) or unobserved heterogeneity (TRE), and the efficiency of GTRE model has a similar trend except that the efficiency value is smaller. The models considering both observed and unobserved heterogeneity (TREH1 and TREH2) lead to continuous declining efficiency after the unbundling reform, indicating that the unbundling reform does not seem to create favorable conditions for the power grid utilities. Further, when the dummy variable is excluded from the analysis, the efficiency trends of TREH1 and TREH2 models are as shown in Figure A.1. The efficiency of TREH1 and TREH2 witness constantly increasing trends after excluding the dummy variable, and possible reasons for the different trends may come from the large cross subsidies that exist in China's grid system(Li et al., 2017). It demonstrates that the unbundling reform has to be considered in the efficiency evaluation. In addition, the descending efficiency may be the result of other circumstances, including management and assessment, and may be traced to the extensions of the network into more challenging weather and geographical conditions.

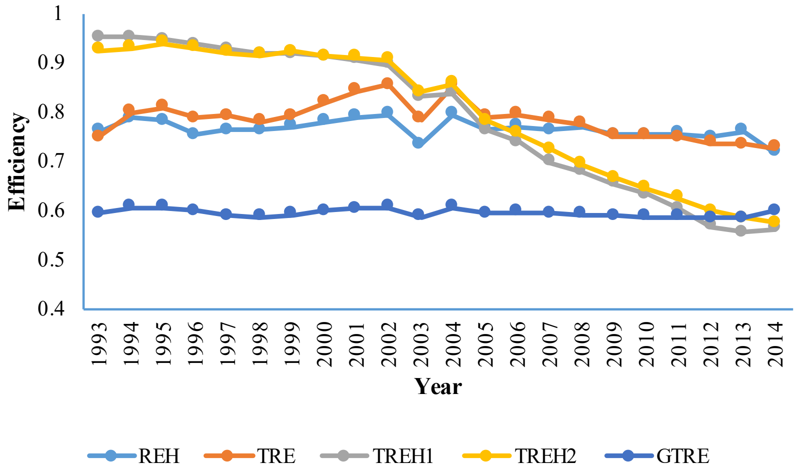

Figure 2. Annual evolution of the grid utilities' average efficiency for all models.

5.4 The efficiency differences between regions

The grid corporations are classified into six groups, according to their regions, mentioned in Section 2, namely the Northeast China Power Grid, the Northwest China Power Grid, the Northern China Power Grid, the Central China Power Grid, the Eastern China Power Grid and the Southern Power Grid. Considering that the first three models are all special cases of the TREH2 model, this study only presents the results of the last two models. Figures 3 and 4 show the average efficiency of these groups over the study period under TREH2 and GTRE model, respectively.

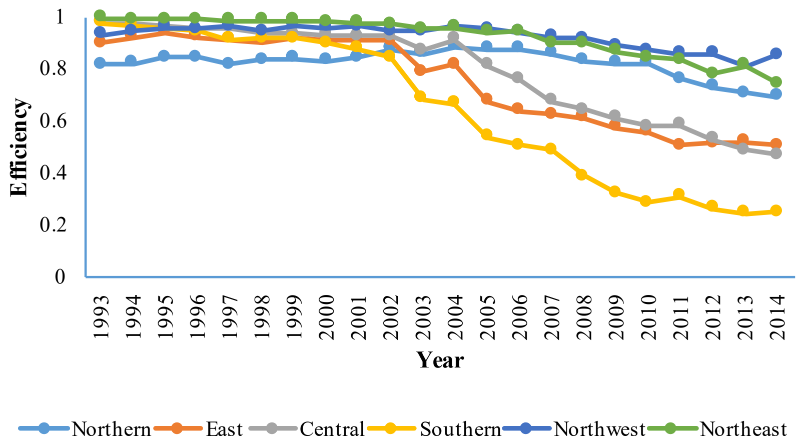

Figure 3. Average efficiency by groups of utilities under TREH2 model.

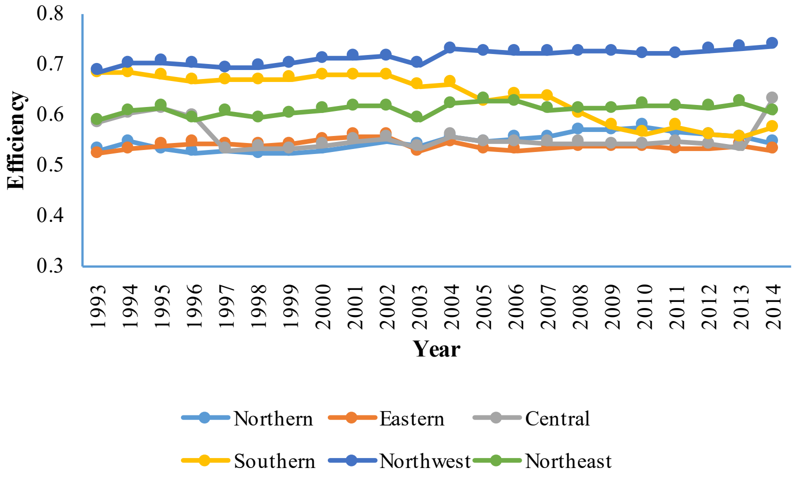

Figure 4. Average efficiency by groups of utilities under GTRE model.

From Figure 3 and 4, it can be seen that the Northeast and Northwest China Power Grids show higher efficiencies during the study period, and the efficiency changes in the northern areas (the Northeast, Northwest, and Northern China Power Grids) are relatively small. However, some relatively developed regions usually have lower efficiencies, such as Tianjin, Guangdong and the Yangtze River delta region. It is a common phenomenon that capital investment is growing fast in these regions and suggests that there might be excessive investment, which contributes to the difficulty in improving the measured performance of grids. Excessive investment is the product of monopoly, however, it may have the advantage of improving GDP growth and service quality of the grids (which we do not consider due to a lack of data).

Thus by contrast to the northern regions, the Southern Power Grid exhibits a significant decrease in efficiency after unbundling. This is mainly due to a decline in the ratio of customer numbers to capital input witnessed in the study period, as shown in Figure 5. The downward trend may also because of the following reasons. First, the underdevelopment of the economies in more than half of the southern provinces, such as Yunnan, Guizhou, and Guangxi etc., has put local companies at a disadvantage in measuring unobserved heterogeneity. Second, the lack of advanced stability in power sources such as thermal power, together with the higher rate of interregional power dispatching, has impeded the improvement of efficiency to some extent. Third, all of these provinces are located in relatively harsh conditions where the rates of mountainous terrain are higher, which poses additional operational challenges. The efficiency of the branches of the Southern Power Grid group even dropped during the power-hungry period after the unbundling reform, which suggests that the Southern Power Grid branches need to do more to enhance their efficiency, and the government should place more emphasis on incentive regulation in these provinces.

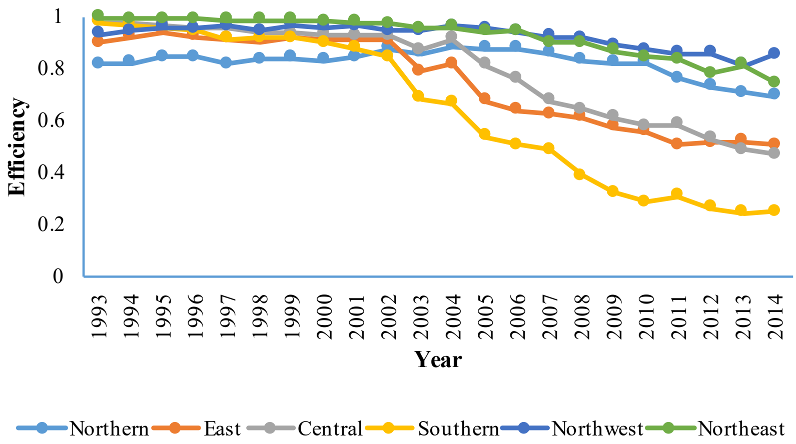

Figure 3. Average efficiency by groups of utilities under TREH2 model.

6. Conclusions

In recent years efficiency analysis has been widely used in designing reforms and benchmarking the performance of grid utilities. China implemented the unbundling reform of separating power plants from grids in 2002 with the aim of improving the service quality and promoting competition. This study has adopted alternative stochastic frontier models to investigate the impact of observed heterogeneity, in terms of weather and geographic factors, and unobserved heterogeneity on the performance of grid utilities before and after the unbundling reform.

Both the observed and unobserved environmental heterogeneities need to be taken into account in measuring the efficiency of the grid industry. We first apply the conventional REH and TRE models, which capture observed and unobserved heterogeneity, respectively. By combining these two features, models TREH1 and TREH2 are estimated with different assumptions about the inefficiency term. In another version of the extended model (GTRE), the inefficiency consists of two parts: time-varying and time-invariant parts. These results indicate that the estimated efficiencies are sensitive to model specification, and the models considering both observed and unobserved heterogeneity (TREH1 and TREH2) have a larger divergence than the others. The efficiency rank orders are quite different among the different models; thus, an efficiency-based regulation scheme should consider the role of benchmarking carefully. The lack of convergence in efficiency illustrates the necessity of taking firm-specific heterogeneity into consideration.

In addition, whatever model is selected, the number of customers and the network length are demonstrated to have positive impacts on the utilities' efficiency, and the effects of these two factors and power delivered is also positive. This is because the marginal inputs required to support the growth of customers, the extension of the network are limited, and economies of scale exist in China's grid industry. In general, regardless of whether observed or unobserved heterogeneity is included or not, the results from the alternative models all indicate the existence of economies of scale. This may be explained by the industry's natural monopoly, which calls for sustained public intervention and incentive-based monopoly regulation. As a result, further unbundling reform to introduce competitiveness and adjust the firms to proper scale will be a long-term project for the grid industry. Though we note that our sample bundles transmission and distribution, which may have different optimal scales (e.g. larger for transmission than distribution). It also ignores lower voltages which may also have a different – smaller - optimal scale. The results also indicate that adverse weather and geographic conditions are indeed obstacles to be overcome on the path towards the efficient operation of China's grid utilities.

Finally, there is still room to improve China's grid system's relative performance, and more management effort and more effective policies should be put into practice to address apparent provincial under-performance. With regard to the unbundling reform of 2002, this study has found no evidence of significant improvements in efficiency (though we do not focus on the different but related issue of general productivity effects), although large differences in efficiency have been found among companies. The differences may have arisen because of the drive to meet investment targets and demand requirements and/or from China's strong intervention in the grid industry. In-depth analysis of the regional efficiency differences shows that the Northeast and Northwest China Power Grids show higher efficiencies, but the China Southern Power Grid witnesses a significant decrease after the unbundling reform. Thus, the independently operating China Southern Power Grid Corporation needs to consider the reasons behind its relative decline in performance since 2002. One of the practical ways is to implement regional specific policy reforms or pilot projects in a few provinces, so that lessons for national policy can be learned and regulatory decisions can be made more scientifically.

This study has some limitations of course. Operational cost information is not available for grid companies in China, so it is regrettable that the operational performance of firms was evaluated without including the effect of environmental heterogeneity on financial cost. Further studies could also add other extreme weather conditions and geographic factors to the sample and conduct dynamic stochastic frontier models.

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Appendix

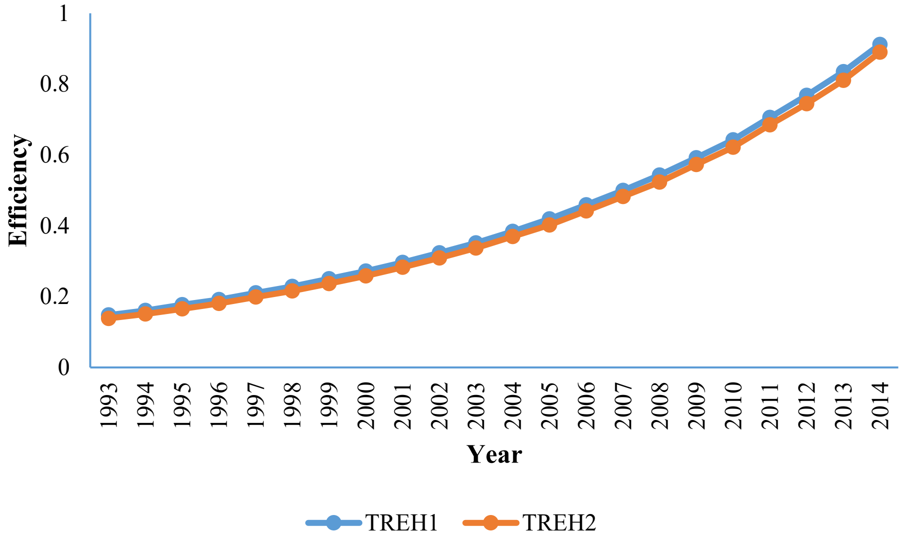

Figure A.1. Annual evolution of the grid utilities' average efficiency for TREH1 and TREH2 models after excluding dummy variable.