

Efficiency Analysis Working Papers

WP-EA-06

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On the Sensitivity of US Electric Utilities' Efficiency Estimates – A Distance Function Approach*

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Abstract

Previous applications of different benchmarking techniques, both in academia and regulation practice, have shown substantial differences among the models' results. To analyse the sensitivity of efficiency estimates of a sample of US electricity distribution utilities, we compare the results of the Generalized Least Squares (GLS) frontier model proposed by Schmidt and Sickles (1984) and the Maximum Likelihood Estimation (MLE) frontier model of Pitt and Lee (1981) with the true random effects frontier model introduced by Greene (2004, 2005). We find substantially higher efficiency scores for the Greene model, indicating that the other formulations underestimate firms' efficiency due to an insufficient consideration of firm specific heterogeneity. In contrast to other studies, the efficiency estimates in this paper do not differ considerably.

* The author would like to thank Annika Frohloff and Christian von Hirschhausen for their helpful comments.

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1 Introduction

With the introduction of incentive based regulation mechanisms, efficiency measurement (benchmarking) has been widely applied to electricity distribution utilities, both in academic studies as well as regulatory practice (for an overview, see Jamasb and Pollitt, 2001). Previous applications have found substantial differences among different methods of measurement in electricity distribution. Jamasb and Pollitt (2003), Estache et al. (2004) and Farsi and Filippini (2004) report significant efficiency discrepancies depending on the cross-sectional econometric modelling specification for European, South American and Swiss samples. However, Horrace and Schmidt (1996) and later Jensen (2000) showed that the individual efficiency estimates in cross-sectional data suffer from considerable inconsistency anyway. In a multi-period (panel data) setting, empirical studies are rather scarce yet. In a recent paper, Farsi et al (2006) apply different Stochastic Frontier Analysis (SFA) panel data models on a set of 59 Swiss distribution utilities. The paper addresses two major issues: the consistency of results of different panel data methods and, related to that, the treatment and influence of unobserved firm-specific heterogeneity. Therefore, the authors compare the results of established models such as a Generalized Least Squares (GLS) model proposed by Schmidt and Sickles (1984) as well as a Maximum Likelihood Estimation (MLE) in line with Pitt and Lee (1981) with the ‘true’ random effects model introduced by Greene (2004, 2005). They find that the latter which can distinguish between firm heterogeneity and actual inefficiency delivers much higher average cost efficiency estimates. In addition, the estimates are rather uncorrelated to the GLS and MLE results. These findings are non-trivial. When different econometric models lead to differences among efficiency estimates, which again are used to derive firm individual productivity catch-up targets, regulation imposes high and unforeseeable risks on regulated companies.

In this paper, we apply different parametric SFA panel data models to a broader and somewhat more important sample, a collection of 109 US electricity distribution utilities. In contrast to Farsi et al. (2006), we follow Growitsch et al. (2005) and apply a distance function approach. This allows us to refrain from the limiting behavioural assumptions inherent in cost function approaches, which tends to be much more realistic in a regulated environment (cp. Estache et al., 2004). Moreover, distance functions are less data demanding. By making the use of input prices obsolete, we additionally avoid the complicated definition of cost of capital and the appropriate attribution of labour cost.

The remainder of the paper is organized as follows. Section 2 describes the methodological background and estimation strategy. Section 3 describes the data briefly and presents the results. Section 4 concludes.

2 Methodology and Modelling

There are two advantages in using panel data in efficiency analysis: they produce consistent individual efficiency scores (cp. Horrace and Schmidt, 1996; Jensen, 2000); and they allow for a differentiation of inefficiency and heterogeneity of firms. However, established panel data models, for instance the random effects estimation by Pitt and Lee (1981) or the Schmidt and Sickles (1984) fixed effects model have neglected in doing so. Instead, both strands of models have interpreted time invariant unobserved heterogeneity as inefficiency (cp. Farsi et al., 2006). Only recent research has distinguished between inefficiency as being time-variant¹ and firm heterogeneity being constant over time (Greene, 2001, 2004, 2005). The maximum likelihood estimators proposed by Greene have been referred to as ‘true frontier models’, especially his true random effects model has been applied successfully in network industries’ analyses (Farsi et al., 2005, 2006).

Following the latter, we estimate US electricity distribution utilities’ inefficiency with the MLE model of Pitt and Lee (1981) and the GLS estimator by Schmidt and Sickles (1984) and compare the estimates to those of Greene’s true random effects model. Greene’s model is estimated by the technique of maximum simulated likelihood (cp. Greene, 2001), since its’ likelihood function does not have a closed form for the integral. As suggested by Greene (2005), we use pseudo-random Halton draws in order to achieve an adequate and efficient approximation of the true likelihood function.

In contrast to previous research comparing different estimation methods, we apply a distance function approach. Originally proposed by Shephard (1953, 1970), distance functions have several advantages compared to production or cost functions.² Their major benefit in describing a multi input multi output production technology is that they allow refraining from specifying a behavioural objective (such as cost minimisation or profit maximisation). This is especially advantageous when dealing with regulated industries, where classical behavioural assumptions are likely to be violated

¹ For a discussion of modelling inefficiency as a time-variant stochastic term, see Farsi et al. (2006).

(Rungsuriyawiboon and Coelli, 2004). A second benefit of distance functions – compared to cost functions in particular – is that they render unnecessary the use input prices. Concerning cost of capital, this is advantageous in particular, since the estimation or calculation of cost of capital tends to a general problem in economics and finance (cp. for instance Fama and French, 1999). Estimating firms' cost efficiency without the disadvantages of cost function models is possible by modelling cost, either as total expenditure or split up into operation expenses and capital expenditure, as the relevant input of a decision making unit.

To model electricity distribution utilities' production technology, we specify the input and output variables for the stochastic frontier model following Growitsch et al. (2005). We introduce total expenditures (TOTEX) as a single input in monetary terms, which is defined as the sum of operation and maintenance cost (OPEX) and the capital expenditure (CAPEX). With regard to outputs, we use energy supplied and the number of customers. Although both outputs form one joint service in electricity distribution, they can be treated separately, as they drive different costs (fixed vs. variable) and are marketed individually – at least to a certain extent. Adopting a translog functional form with variables corrected by their sample means the distance function can be written as:

$$\begin{aligned}
-\ln(TOTEX)_{it} = & \alpha_0 + \alpha_1 \ln ENERGY_{it} + \alpha_2 \ln CUSTOMERS_{it} \\
& + \frac{1}{2} \alpha_{11} (\ln ENERGY_{it})^2 + \frac{1}{2} \alpha_{22} (\ln CUSTOMERS_{it})^2 \\
& + \alpha_{12} \ln ENERGY_{it} * \ln CUSTOMERS_{it} + \alpha_t t + r_{it}.
\end{aligned} \tag{1}$$

with $i=1, \dots, N$ and $t=1, \dots, T$, where subscripts i denotes the individual company and t the corresponding year. α are unknown parameters to be estimated and r_{it} is the total residual. It can be decomposed into the firm specific component α_i and into time and observation varying term ε_{it} . We estimate all three models based on this specification. Differences among the models' estimation results occur due to different distributional assumptions concerning the firm specific and the time component as well as the estimation procedure for the efficiency scores. The different assumptions applied to a distance function are shown in Table 1. The efficiency scores are bounded between 0 and 1; a value of 1 indicating relative efficiency.

² For an excellent overview of parametric estimation techniques in efficiency measurement, the interested reader may be referred to Kumbhakar and Lovell (2000).

[Insert Table 1 here]

3 Data and Results

The dataset used for this study consists of 109 US electric utilities and was taken from FERC Form 1 filings for the years 1994-2005.³ In order to create a balanced panel, we had to reduce the original data of 295 investor owned utilities to 109 IOUs due to a lack of data resulting in a total number of 1308 observations.⁴ The sample accounts for 68% of total electricity sold and for 52% of total customers in the year 2004 in the US. For the sample period, these fractions are rather constant over time.

Table 2 presents the parameter estimates for the fixed effects GLS model of Schmidt and Sickles (1984) (Model I), the MLE random effects frontier model of Pitt and Lee (1981) (Model II), and the true random effects frontier models of Greene (2005) (Model III). The results show almost all coefficients to be highly significant and to have the expected signs.⁵ In addition, the estimation outcome supports the findings of Farsi et al. (2006) of quite similar coefficients across the considered models. Only the GLS model suggests production elasticities of the number of customers being low compared to the other models.

[Insert Table 2 here]

A summary of the model-specific efficiency estimates is shown in Table 3. Interestingly, the mean efficiency scores differ notably between all three models. This contrasts – at least partly – Farsi et al.’s findings of similar efficiency distribution between the GLS and MLE models. As expected, the true random effects model shows not only a substantially higher average efficiency scores but also a smaller variation of the individual efficiencies. By separating (time variant) inefficiency and firm-specific unobserved heterogeneity, the true random effects estimator identifies productivity disadvantages beyond managerial control. The other models not accounting for these effects tend to underestimate efficiency, therefore.

³ A detailed description of the construction of the data set can be found in Hess (2006).

⁴ For a few missing observations we approximated operation and maintenance cost and the number of employees for a single year averaging over the variable values of the previous and the following year.

[Insert Table 3 here]

To analyse the different estimation results in more detail, we computed Pearson correlation coefficients between the model estimates as well as the Spearman rank-order correlation coefficients. Despite the significant differences of efficiency measures among the models, the correlations between the inefficiencies are significant with values between 52 and 77 percent. Moreover, the correlation between the ranks is significant and even higher with coefficients lying in the band width of 56 and 86 percent, especially the correlation of the true random effects model improves notably. These outcomes contradict the results of Farsi et al. (2006) who found that the efficiency estimates of the true random effects model did not correlate much with the other models.

4 Conclusions

Previous applications of different benchmarking techniques, both in academia and regulation practice, have shown substantial differences among the models' results. These experiences provoked serious concerns about the sensitivity of efficiency measurement methods and the related policy recommendations. Especially for network industries, where efficiency estimates are used to derive firm specific productivity targets, the problem is of major economic importance.

In this paper, we applied different parametric SFA panel data models to analyse the sensitivity of efficiency scores of a dataset consisting of 109 US electricity distribution utilities. Following Farsi et al (2006), we compared the results of three different stochastic frontier models, namely the fixed effects GLS model of Schmidt and Sickles (1984), the MLE random effects model of Pitt and Lee (1981), and the true random effects model of Greene (2005). However, to refrain from limiting – and for regulated industries somewhat unrealistic – behavioural assumptions inherent in cost function approaches (as profit maximization or cost minimization), we applied a distance function approach. Analogous to previous research, we found substantially higher efficiency scores for the Greene model, indicating that the other formulations underestimate firms' efficiency due to an insufficient consideration of firm specific heterogeneity. In contrast to other studies, the efficiency estimates in our

⁵ Note that in our distance functions setting, the first order coefficients satisfy the monotonicity requirements and can be interpreted as partial production elasticities with regard to output.

paper do not differ considerably. As the distance function's coefficients are however rather similar to Farsi et al's cost function's results, we suggest that efficiency estimates are more sensitive to the underlying data set than to the assumptions about the inefficiency and heterogeneity terms. Nevertheless, the applied techniques seem to have only an impact on the level of efficiency, not the ranking.

Future research should analyse the sensitivity of efficiency estimates for other samples from various industries and under different production technology models. Our and prospect findings should be taken into account in the further development of incentive regulation mechanisms.

Appendix

Table 1: Econometric specifications of the stochastic cost frontier

$r_{it} = \alpha_i + \varepsilon_{it}$	Model I GLS	Model II MLE	Model III True RE
Firm-specific component α_i	iid $(0, \sigma_\alpha^2)$	Half-normal $N^+(0, \sigma_\alpha^2)$	$N(0, \sigma_\alpha^2)$
Time-variant component ε_{it}	iid $(0, \sigma_\varepsilon^2)$	$N(0, \sigma_\varepsilon^2)$	$\varepsilon_{it} = u_{it} + v_{it}$ $u_{it} \sim N^+(0, \sigma_u^2)$ $v_{it} \sim N(0, \sigma_v^2)$
Inefficiency	$\max\{\hat{\alpha}_i\} - \hat{\alpha}_i$	$E[u_i \hat{r}_{i1}, \hat{r}_{i2}, \dots, \hat{r}_{iT}]$	$E[u_{it} \hat{r}_{it}]$
Relative efficiency (0-1)	$\exp[-(\max\{\hat{\alpha}_i\} - \hat{\alpha}_i)]$	$E[\exp(-u_i \hat{r}_{i1}, \hat{r}_{i2}, \dots, \hat{r}_{iT})]$	$E[\exp(-u_{it} \hat{r}_{it})]$

Table 2: Distance function parameters: Panel data (1994-2005)

Coefficient	Model I GLS	Model II MLE	Model III True RE
$\ln ENERGY$	-0.125*** (0.025)	-0.118*** (0.014)	-0.113*** (0.006)
$\ln CUSTOMERS$	-0.377*** (0.090)	-0.837*** (0.029)	-0.814*** (0.006)
$\ln ENERGY^2$	0.127*** (0.027)	0.132*** (0.222)	0.132*** (0.008)
$\ln CUSTOMERS^2$	-0.050 (0.084)	-0.085*** (0.023)	-0.059*** (0.011)
$\ln ENERGY * \ln CUSTOMERS$	0.026 (0.037)	-0.017 (0.018)	-0.034*** (0.009)
t	-0.019*** (0.001)	-0.014*** (0.001)	-0.015*** (0.000)
Constant	–	0.595*** (0.022)	0.273*** (0.004)
σ_α (normal)	–	–	0.238
σ_u (half-normal)	–	0.525	0.127
σ_v (normal)	–	0.069	0.111

Significance on 1%-level: ***, standard error in parentheses.

Table 3: Summary of efficiency measures

	Model I GLS	Model II MLE	Model III True RE
Mean	0.322	0.647	0.885
Median	0.307	0.634	0.911
Max	1.000	0.994	0.986
Min	0.073	0.334	0.562
95th Percentile	0.615	0.952	0.973

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