APPLICATION OF PANEL DATA MODELS IN BENCHMARKING ANALYSIS OF THE ELECTRICITY DISTRIBUTION SECTOR*

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ABSTRACT

This paper explores the application of several panel data models in measuring productive efficiency of the electricity distribution sector. Stochastic Frontier Analysis has been used to estimate the cost-efficiency of 59 distribution utilities operating over a nine-year period in Switzerland. The estimated coefficients and inefficiency scores are compared across three different panel data models. The results indicate that individual efficiency estimates are sensitive to the econometric specification of unobserved firm-specific heterogeneity. This paper shows that alternative panel models such as the "true" random effects model proposed by Greene (2005) could be used to explore the possible impacts of unobserved firm-specific factors on efficiency estimates. When these factors are specified as a separate stochastic term, the efficiency estimates are substantially higher suggesting that conventional models could confound efficiency differences with other unobserved variations among companies. On the other hand, refined specification of unobserved heterogeneity might lead to an underestimation of inefficiencies by mistaking potential persistent inefficiencies as external factors. Given that specification of inefficiency and heterogeneity relies on non-testable assumptions, there is no conclusive evidence in favor of one or the other specification. However, this paper argues that alternative panel data models along with conventional estimators can be used to obtain approximate lower and upper bounds for companies' efficiency scores.

1. INTRODUCTION

During the past two decades many countries have introduced regulatory reforms and incentive regulation in their electricity distribution sector. Though being practiced in a wide variety (Jamasb and Pollitt, 2001; Joskow and Schmalensee, 1986) of forms, most incentive-based regulation schemes use benchmarking in one way or another. Benchmarking consists of measuring a company's performance against a reference or benchmark performance. Performance measures in electricity sector are often related to companies' productive efficiency namely, technical and/or cost efficiency.[1] There exist a variety of methods for efficiency measurement. Kumbhakar and Lovell (2000), Coelli et al. (2005) and Murillo-Zamorano (2004) provide extensive presentations of these methods. Many studies report discrepancies in individual efficiency estimates across different methods. Jamasb and Pollit (2003) report substantial variations in estimated efficiency scores and rank orders across different approaches (parametric and non-parametric) and among different econometric models applied to a cross sectional sample of European power distribution utilities. More or less similar discrepancies have been reported by Estache et al. (2004) and Farsi and Filippini (2004, 2005) in two samples of power distributors respectively from Switzerland and South America.[2] This problem is especially important for in most cases, there is no clear criterion for choosing a unique method among several legitimate models. Moreover, the efficiency estimates could have great financial consequences for the regulated companies and therefore, their reliability is crucial for an effective regulation system. In particular, if the efficiency estimates are sensitive to the benchmarking method, a more detailed analysis to justify the

[1] Other measures of performance such as quality and productivity are not considered here.This paper focuses on productive (in)efficiency, namely technical and allocative (in)efficiencies (cf. Kumbhakar and Lovell, 2000). Scale inefficiency due to suboptimal size (scale) of the production unit, is generally not considered in benchmarking because it is often beyond the firm's control.

[2] Other authors like Horrace and Schmidt (1996), Street (2003) and Jensen (2000) reported substantial errors and inconsistency problems in the estimation of individual efficiency scores in cross sectional data from other industries.

adopted approach is required. For instance, Bauer et al. (1998) have proposed a series of criteria that can be used to evaluate if the efficiency levels obtained from different approaches and models are mutually “consistent”, that is, lead to comparable efficiency scores and ranks. However, in many cases because of a considerable discrepancy, these criteria are not satisfied.

In their comparative analysis of a sample of generating companies, Kopp and Smith (1980) conclude that the differences in efficiency estimates are related to the estimation method rather than the adopted functional form of the production frontier. Similarly in this paper, we argue that a major part of these discrepancies is related to the specification of unobserved factors and the model’s assumptions required for distinguishing those factors from efficiency differences. In particular, this paper explores how some of the recently developed panel data models can be used to explain some of these discrepancies and attempts to provide a guideline for a better utilization of benchmarking methods.

As opposed to cross-sectional data, panels provide information on same companies over several periods. Repeated observation of the same company over time allows an estimation of unobserved firm-specific factors, which might affect costs but are not under the firm’s control. Individual companies operate in different regions with various environmental and network characteristics that are only partially observed. It is crucial for the regulator to distinguish between inefficiency and such exogenous heterogeneity. Several recently developed models such as Greene (2005, 2004), Alvarez, Arias and Greene (2004) and Tsionas (2002) have addressed this issue using alternative panel data models. Some of these models have proved a certain success in other applications such as public transportation networks in that they give more plausible efficiency estimates.[3] These results raise an important question as to whether (or to what extent) the sensitivity problems can be solved by using panel data and the adapted frontier models. This question is especially important in the electricity sector, in which the application of benchmarking has been frequently criticized based on reliability of efficiency estimates.[4] Moreover, given that in many countries the regulatory reforms have been in effect for several years, an increasing number of regulators have access to panel data. However, the number of empirical studies is still insufficient to provide a general answer to this question. This paper provides a contribution to this debate by a comparative analysis of efficiency in a sample of electricity distribution utilities. We focus on econometric methods (as opposed to non-parametric approaches)[5] as they can be relatively easily adapted to panel data. Productive efficiency can be estimated using production or cost frontiers. This study focuses on the latter category that can be readily used to estimate cost-efficiency.

The results underline the importance of modeling unobserved heterogeneity and the assumptions used to separate these factors from inefficiencies. The results also suggest that the alternative panel data models can be used to separate part of the unobserved heterogeneity from efficiency estimates thus can be considered as a promising complement to other regulatory instruments such as case-by-case analyses or cost prediction. In a previous paper Farsi and Filippini (2004) discussed the application of conventional models in prediction of companies' costs without exploring the effect of unobserved firm-specific heterogeneity. This paper uses an alternative panel data model that allows a better distinction of these unobserved factors from inefficiency. The rest of the paper proceeds as follows: Section 2 discusses the application of stochastic frontier models in panel data. The model specification and the

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[3] See Farsi, Filippini and Kuenzle (2006) and Farsi, Filippini and Greene (2005) for applications in bus and railway transports respectively.

[4] See for instance, Shuttlewoth (2003) and Irastorza (2003).

[5] The literature provides two main approaches to measure efficiency – the econometric (parametric) approach and the linear programming (non-parametric) method. While the latter category, particularly Data Envelopment Analysis, has become popular among electricity regulators, both approaches have advocates in the scientific community. The purpose of this paper is not to stress the advantages and drawbacks of these two approaches, but to explore if some limitations of frontier models can be overcome if panel data are available.

adopted econometric methods are described in Section 3. Following a brief description of the data, the estimation results are presented and discussed in Section 4. And Section 5 summarizes the main conclusions.

2. PANEL DATA AND STOCHASTIC FRONTIER MODELS

The first use of panel data models in stochastic frontier models goes back to Pitt and Lee (1981) who interpreted the panel data random effects as inefficiency rather than heterogeneity.[6] This tradition continued with Schmidt and Sickles (1984) who used a similar interpretation applied to a panel data model with fixed effects. Both models have been extensively used in the literature. A main shortcoming of these models is that any unobserved, time-invariant, firm-specific heterogeneity is considered as (in)efficiency. The discrepancies in efficiency estimates from conventional panel data models have been illustrated in Horrace and Schmidt (1996) and Farsi and Filippini (2004). A common feature of all these models is that they do not fully separate the sources of heterogeneity and inefficiency at the firm level. In fact, the time-variant error term in these models could include a major part of inefficiencies whereas the firm-specific effects that are interpreted as inefficiency could be mainly due to time-invariant heterogeneity.

Battese and Coelli (1992) and Cornwell, Schmidt and Sickles (1990) have extended the random effects model (Pitt and Lee, 1981) to include time-variant inefficiency. In particular the latter paper proposes a model in which efficiency is defined as a deterministic function of time with parameters varying among firms. In a more recent development, Sickles (2005) has proposed a semi-parametric model that allows a relatively unrestricted specification of time-variant efficiency across firms. In principle with slight modifications some of these models especially Sickles (2005)'s semi-parametric model can accommodate a distinction of

[6] Pitt and Lee (1981)'s model is different from the conventional random-effects model in that the individual specific effects are assumed to follow a half-normal distribution. Important variations of this model were

unobserved time-invariant heterogeneity across firms from efficiency. However, in their present forms they interpret such unobserved factors as (in)efficiency. This distinction could be important in many network industries where part of the time-invariant factors is related to unobserved environmental and network characteristics that are beyond the firm's control.

An alternative approach is to include an additional stochastic firm-specific term (fixed or random effect) to the stochastic frontier model in its original form as in Aigner, Lovell and Schmidt (1977). There are a few papers that have explored this possibility. The first development can be attributed to Kumbhakar (1991) who proposed a three-stage estimation procedure to solve the model with time- and firm-specific effects.[7] Polachek and Yoon (1996) attempted to estimate a panel data frontier model with firm dummies using a one-step procedure. Greene (2002a) discussed the numerical obstacles that have apparently delayed such a development.

As shown by Greene (2002a), assuming that the inefficiency term follows a distributional form, both models with random and fixed effects can be estimated using maximum likelihood estimation methods. These models are referred to as "true frontier models" in that they are a straight extension of original frontier framework (in line with Aigner et al., 1977) to panel data. He proposed numerical solutions for both models, which he respectively refers to as 'true' fixed and random effects models (see also Greene, 2005). In particular, Greene's true random effects model has proved useful in efficiency measurement of network industries (Farsi, Filippini and Greene, 2005).

Alvarez, Arias and Greene (2004) show that even in cases where inefficiency is due to time-invariant factors such as constant managers' capability, the resulting inefficiencies can vary over time. Those authors assume that the management skills are one of the inputs that

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presented by Schmidt and Sickles (1984) who relaxed the distribution assumption and used the GLS estimator, and by Battese and Coelli (1988) who assumed a truncated normal distribution.

can interact with other time-variant input factors thus, create time-variant cost inefficiency. This result is consistent with the economic theory in that a firm's inefficiency is a dynamic phenomenon and cannot be constant. Firms constantly face new events and technologies, which they gradually learn how to deal with and apply. As the learning process continues, inefficiency with regards to the existing technologies decrease but other new events and technologies appear. Therefore the overall inefficiency of a firm depends on not only the managers' efforts but on the effect of new technologies and events on the production process. Based on this argument, the inefficiency can be modeled as a time-variant stochastic term. On the other hand a major part of the unobserved heterogeneity such as network and location-related factors can be considered as constant over time.

Based on above contentions, we adopt the true random effect model for our analysis. This model is not a unique choice for accounting for unobserved heterogeneity. However, we have excluded alternatives such as the semi-parametric model proposed by Sickles (2005), mainly because this model is computationally intensive. Moreover, for the purpose of this paper a parsimonious and accessible model is preferable as it can be used and understood more easily in the regulatory practice. The estimates of true random effects model will be compared with two other conventional models with constant inefficiency.

3. MODEL SPECIFICATION

To illustrate the differences across models, we focus on three panel data models: GLS model in line with Schmidt and Sickles (1984), MLE model as in Pitt and Lee (1981), and the True Random Effects (TRE) model as proposed by Greene (2005, 2004). As the TRE model's likelihood function does not have a closed from, this model is estimated using Maximum Simulated Likelihood Estimation method. We use pseudo-random Halton draws to minimize

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[7] See also Heshmati and Kumbhakar (1994) and Kumbhakar and Hjalmarsson (1995) for two applications of

the potential sensitivity of the results to simulation process. The three models have been applied to a panel of 59 Swiss distribution utilities.[8] A triple-input single-output production function has been considered. The output is measured as the total number of delivered electricity in kWh, and the three input factors are set as capital, labor and the input power purchased from the generator. Capital price is measured as the ratio of capital expenses (depreciation plus interest) to the total installed capacity of the utility's transformers in kVA.[9] The capital costs are approximated by the residual costs that is, total costs minus labor and purchased power costs. Labor price is defined as the average annual salary of the firm's employees. For those companies that produce part of their power the average price of input electricity is assumed to be equal to the price of purchased power.

The costs of distribution utilities consist of two main parts: the costs of the purchased power and the network costs including labor and capital costs. There are therefore two alternatives for measuring cost efficiency in power distribution utilities: total costs approach and network costs approach. The network costs approach has a practical advantage in that the estimated average costs can be directly used in a price-cap formula.[10] However, this approach neglects the potential inefficiencies in the choice of the generator and also in the possibilities of substitution between capital and input energy. In this paper we use the first approach based on the total costs.

In addition to input prices and output, several output characteristics are included. The resulting specification of the cost function can be written as:

$$C = C(Y, P_K , P_L , P_P , LF, CU, AS, HGRID, DOT) \qquad (1),$$

this model. Note that in the latter paper, it is assumed that both time- and firm- specific effects are part of inefficiency.

[8] The sample used in this study is similar to the one used by Farsi and Filippini (2004).

[9] Because of the lack of inventory data the capital stock is measured by the capacity of transformers, which are the main device used to transfer electricity in the network.

[10] Notice that the price cap is generally applied to the network access.

where C represents total cost; Y is the output in kWh; P_K , P_L and P_P are respectively the prices of capital, labor and input power; *LF* is the 'load factor' defined as the ratio of utility's average load on its peak load; *CU* is the number of customers; and *AS* the size of the service area served by the distribution utility. *HGRID* is a binary indicator to distinguish the utilities that operate a high-voltage transmission network in addition to their distribution network and *DOT* is a dummy variable representing the utilities whose share of auxiliary revenues is more than 25 percent of total revenues. Quality of service usually measured by the number of interruptions is among the excluded variables. Given that in Switzerland, practically there have been no outage cases, we can assume that all the utilities operate at a sufficient level of quality reinforced by a tight regulation system. Therefore, we contend that the quality differences are not significant. Another excluded variable is the network length. In our model, this variable is proxied by the service area.

A Cobb-Douglas functional form has been adopted. We excluded the flexible forms like translog to avoid the potential risk of multicollinearity among second order terms due to strong correlation between output characteristics. Moreover, given the purpose of this study and the small sample size, we want to use a simple specification and avoid an excessive number of parameters required in the flexible functional forms. Our preliminary analyses have shown that when a large number of variables are included in the model, the TRE model's simulated likelihood estimator does not converge to a reasonable solution with non-zero variances. This can be explained by the fact that the problems related to small sample size and multicollinearity could be exacerbated in models with multiple error components. Therefore we focused on a parsimonious specification with Cobb-Douglas functional form. This specification is similar to that used in Farsi and Filippini (2004) with the only difference that here we excluded two explanatory variables whose effects proved to be statistically insignificant.[11] After imposing the linear homogeneity in input prices the adopted cost function can be written as:

$$\ln\left(\frac{C}{P_P}\right)_{it} = \beta_0 + \beta_Y \ln Y_{it} + \beta_K \ln\left(\frac{P_K}{P_P}\right)_{it} + \beta_L \ln\left(\frac{P_L}{P_P}\right)_{it} + \gamma_1 \ln LF_{it}$$

$$+ \gamma_2 \ln AS_{it} + \gamma_3 \ln CU_{it} + \delta_1 HGRID_{it} + \delta_2 DOT_{it} + r_{it} \qquad (2),$$

$$\text{with} \quad i = 1, 2, \ldots, N \text{ and } t = 1, 2, \ldots, T_i$$

where subscripts i and t denote the company and year respectively; and r_{it} is the total residual.

All the three models are based on the specification given in equation (2). The differences are in the specification of the residuals (r_{it}). This term is composed of two components, one of which (α_i) being time-invariant (firm-specific) and the other (ε_{it}) varying across observations. Table 2 summarizes the econometric specification of the models used in this study. The table also provides the estimation procedure for the efficiency scores. These scores are relative efficiencies on a scale of 0 to 1 against the best practice. The conditional expectations are estimated using the procedure proposed by Jondrow et al. (1982).[12]

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[11] The excluded variables are a linear trend and the dummy variable representing forest areas. As seen in that paper, including these variables in conventional models does not affect the estimation results. In this paper however, we decided to exclude all insignificant variables to avoid potential numerical problems.

[12] See also Battese and Coelli (1992). Note that in TRE model the conditional expectations are based on simulations (see Greene, 2002b).

Table 2. Econometric specifications of the stochastic cost frontier

$r_{it} = \alpha_i + \varepsilon_{it}$	*Model I* **GLS**	*Model II* **MLE**	*Model III* **TRE**
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	$\hat{\alpha}_i - \min\{\hat{\alpha}_i\}$	$\mathrm{E}\left[u_i \mid \hat{r}_{i1}, \hat{r}_{i2}, .., \hat{r}_{iT}\right]$	$\mathrm{E}\left[u_{it} \mid \hat{r}_{it}\right]$
Relative efficiency (0-1)	$e^{-(\hat{\alpha}_i - \min\{\hat{\alpha}_i\})}$	$\mathrm{E}\left[e^{-u_i} \mid \hat{r}_{i1}, \hat{r}_{i2}, .., \hat{r}_{iT}\right]$	$\mathrm{E}\left[e^{-u_{it}} \mid \hat{r}_{it}\right]$

4. DATA AND ESTIMATION RESULTS

The data consist of an unbalanced panel of 59 Switzerland's distribution utilities over a 9-year period from 1988 to 1996. The sample includes 380 observations with a minimum of four observations per company. From about 900 power distribution companies in Switzerland, the companies included in the sample deliver about a third of Switzerland's electricity consumption, thus can be considered as representative of relatively large distribution utilities in the country.[13] The descriptive statistics are given in Table 3.

[13] See Farsi and Filippini (2004) for more details on the data set and a general description of the Swiss power distribution sector in Switzerland.

Table 3. Descriptive statistics (380 observations)

	Mean	Standard Deviation	Minimum	Maximum
Total annual costs per kWh output (CHF)	.188	.0303	.128	.323
Annual output (Y) in GigaWh	263.51	390.36	17	2301.5
Number of customers (CU)	26975.6	36935.8	2461	220060
Load Factor (LF)	.5541	.0727	.3219	.9817
Service Area (AS) in km^2	15,467	35,376	176	198,946
Average annual labor price (P_L) per employee (CHF 1000)	101.27	32.55	43.36	253.89
Average capital price (P_K) in CHF per kVoltAmpere installed capacity	95.06	39.35	32.08	257.98
Average price of input power (P_P) in CHF/kWh	.105	.0210	.0583	.161
High-voltage network dummy ($HGRID$)	.35	.4776	0	1
Auxiliary revenues more than 25% (DOT)	.397	.490	0	1

- All monetary values are in 1996 Swiss Francs (CHF), adjusted for inflation by Switzerland's global consumer price index.

The estimated parameters of the cost frontier are listed in Table 4. This table shows that almost all the coefficients are highly significant and have the expected signs. The results are more or less similar across different models. It should be noted that the three models are similar in the sense that they all have a firm-specific and a time-variant stochastic term, but differ in the distribution of these terms. Moreover, in all the models it is assumed that the firm-specific term is uncorrelated with the time-variant one.[14]

[14] Potential correlations may bias the coefficients. The assumption of no correlation can be relaxed using a fixed effects model (cf. Farsi and Filippini, 2004). However, given that in this paper the main focus is on the efficiency estimates and the coefficients have only a secondary importance, we decided to focus on random-effects models.

Table 4. Cost frontier parameters- Panel data (1988-1996)

	GLS		MLE		True RE	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
$\ln Y$	.783*	.031	.789*	.037	.754*	.004
$\ln CU$	.150*	.033	.145*	.048	.185*	.004
$\ln AS$	.052*	.009	.046*	.014	.056*	.001
$\ln LF$	-.234*	.038	-.211*	.022	-.155*	.007
$\ln P_L$	.044*	.013	.044*	.014	.033*	.003
$\ln P_K$	.173*	.009	.166*	.005	.164*	.002
HGRID	.074*	.026	.108*	.047	.066*	.003
DOT	.049*	.021	.033	.032	.032*	.002
Constant	-.854*	.360	-.870*	.355	-.345*	.058
σ_α (normal)	-	-	-	-	.083*	.001
σ_u (half-normal)	-	-	.146*	.022	.063*	.001
σ_v (normal)	-	-	.040*	.013	.008*	.001

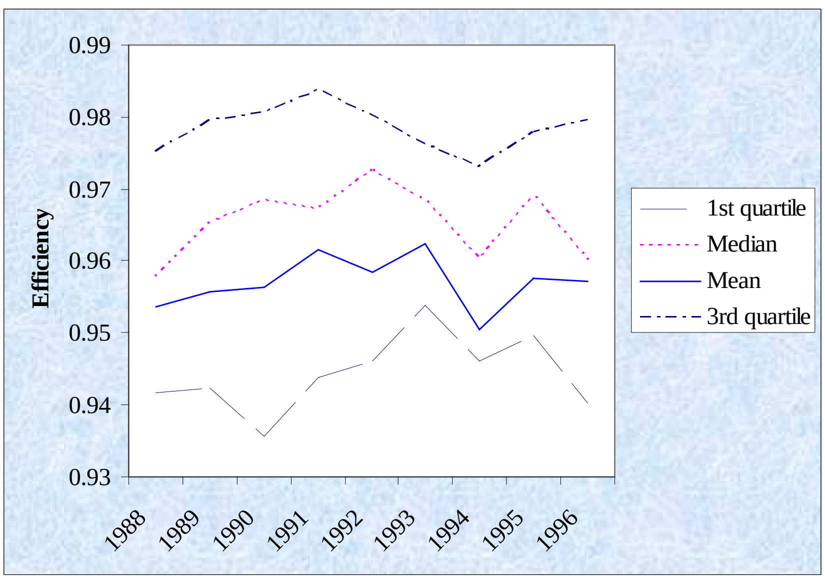
* Significant at p=.05; The sample includes 380 observations from 59 companies.

A descriptive summary of the efficiency estimates from different models is given in Table 5. The results indicate quite similar estimates for the GLS and MLE models, with a difference of about .02 in the median and average values. This can be explained by the fact that these models have a similar interpretation of inefficiency as a time-invariant factor. The True RE model predicts on the other hand, a much higher average efficiency rate. According to this model, the companies are on average 96% efficient. Noting that this model assumes a time-variant inefficiency term and a separate stochastic term for firm-specific unobserved heterogeneity, these results suggest that the other models underestimate the efficiency. This conclusion is valid to the extent that inefficiencies do not remain constant over time. On the other hand one can argue that the TRE model tends to overestimate efficiency, because at least part of the time-invariant factors that are considered as external heterogeneity might be related to inefficiency. The variation of efficiency over the study period is plotted in Figure 1. These results are based on the TRE model's estimates.

Table 5. Summary statistics of efficiency scores (1988-96)

	GLS	MLE	TRE
Minimum	.723	.735	.861
Maximum	1	.993	.996
Average	**.868**	**.887**	**.957**
Median	.857	.877	.966
95 percentile	.981	.990	.990
N	380	380	380

Figure 1: Variation of efficiency over the study period (based on TRE model)



The correlation coefficients between the efficiency estimates from different models are listed in Table 6. As expected these results indicate a high correlation between the GLS and MLE estimates. However, the TRE estimates are only weakly correlated with those of the two other models. The correlation between efficiency ranks shows a similar pattern, thus excluded from the paper. The results in Table 6 indicate that the estimated efficiencies change considerably from one model to the other, suggesting that the assumption about the inefficiency and heterogeneity terms is crucial for the estimations.

Table 6. Correlation between efficiency from different models (1988-96)

	GLS	MLE	TRE
GLS	1	.970	.042
MLE	.970	1	.055

The assumption that inefficiencies are random over time is more realistic than considering constant inefficiency. In fact, the regulated firms cannot sustain a constant level of inefficiency for a long period of time. Not only are they presumably induced to improve their efficiency they constantly face new technological and organizational problems. On the other hand there are a host of parameters such as network characteristics and location related factors that remain more or less constant. Therefore, the assumptions of the TRE model appear to be more consistent with the real world. However, it should be pointed out that the inefficiencies might be understated in the TRE model because this model considers persistent inefficiencies as external heterogeneity.

5. DISCUSSION

The results of frontier analyses of electricity distribution utilities presented in the literature point to sensitivity problems in the benchmarking methods commonly used in the regulation practice. The discrepancy appears to be high when the efficiency scores or ranks are considered for individual companies, whereas the efficiency of the whole sector or large groups of utilities prove to be more or less robust. This general result applies to both parametric and non-parametric methods. A possible explanation of this inconsistency problem can be related to the difficulty of benchmarking models in accounting for unobserved heterogeneity in environmental and network characteristics across companies. Parametric panel data models could be helpful to shed some light on this heterogeneity problem. In this paper we applied several stochastic frontier models to a panel of Swiss distribution utilities.

This study along with the previous empirical literature suggests that the estimation errors for individual efficiency scores are rather high. Given these possible errors, the direct use of benchmarking results in regulation could have undesired financial consequences for the companies. Therefore, the benchmarking results should not be directly applied to discriminate companies through different individual X-factors. Such differentiations require a complementary study of individual cases. However, the results can be used as an instrument to minimize the information asymmetry between the regulator and the regulated companies. For instance benchmarking can be used as a guide to classify the companies into several efficiency groups or estimating efficiency intervals for individual companies. In particular, this paper provides a methodology to determine approximate lower and upper bounds for efficiency levels, based on two different specifications of unobserved heterogeneity.

Consistent with previous research, the results of this paper suggest that alternative panel data models such as 'true' random effect model (Greene, 2005) can be used to explore different assumptions regarding heterogeneity and inefficiency. Assuming that the inefficiency is a transient and time-variant phenomenon and that unobserved network characteristics are more or less constant over time, these models can be helpful to disentangle unobserved heterogeneity from inefficiency. However, as these models consider the potential persistent inefficiencies as external factors, they might underestimate the companies' inefficiency. On the other hand conventional panel data models can provide an upper bound estimate of inefficiency as they assumes that all the unobserved firm-specific factors are associated with inefficiency. These two approaches based on two different assumptions can therefore provide an approximate interval for companies' efficiency scores.

It should be pointed out that the assumptions regarding heterogeneity and inefficiency are not testable. Therefore, there is no conclusive evidence in favor of one or the other econometric specification. However, Monte Carlo simulation studies could be used to assess the relative performance of these models in various cases of misspecification. This is left for future research.

An interesting feature of parametric methods is that they can be used to predict the costs/revenues for each company within a confidence interval. Therefore, such methods can be employed to implement a yardstick regulation framework in line with Schleifer (1985). The prediction power of these models can be considerably improved by using panel data. For instance, Farsi and Filippini (2004) show that panel data models can have a reasonably low out-of-sample prediction error.[15]. This method could be used as an alternative to conventional use of benchmarking methods. In practice this regulation approach implies that the regulator predicts a confidence interval of the expected costs of a given utility accounting for its unobserved characteristics and considering a level of efficiency. The utilities are then required to justify any costs in excess of the predicted range.

A similar approach has been used in the regulation of water supply in Italy, where a yardstick competition model has been applied (cf. Antonioli and Filippini, 2001). This regulation method is based on an interactive approach: The company proposes its tariff in the first stage. The regulator estimates a price cap for the firm using a benchmarking analysis and adjusting for observed differences among companies. The proposed tariff is approved if it does not exceed an acceptable range around the estimated price cap. Otherwise, the tariffs can

[15] For instance that study reports that a GLS model (similar to the one used in this paper) can achieve a one-year ahead prediction error of 3 percent on average while keeping the maximum error at 10 percent level.

be renegotiated with the requirement that the company justify its excessive tariff before any revision.

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