REGULATION AND MEASURING COST EFFICIENCY WITH PANEL DATA MODELS: APPLICATION TO ELECTRICITY DISTRIBUTION UTILITIES

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ABSTRACT

This paper examines the application of different parametric methods to measure cost efficiency of electricity distribution utilities. The cost frontier model is estimated using four methods: Displaced Ordinary Least Squares, Fixed Effects, Random Effects and Maximum Likelihood Estimation. These methods are applied to a sample of 59 distribution utilities in Switzerland. The data consist of an unbalanced panel over a nine-year period from 1988 to 1996. Different specifications are compared with regards to the estimation of cost frontier characteristics and inefficiency scores. The results point to some advantages for the FE model in the estimation of cost function's characteristics. The mutual consistency of different methods with regard to efficiency measures is analyzed. The results are mixed. The summary statistics of inefficiency estimates are not sensitive to the specification. However, the ranking changes significantly from one model to another. In particular, the least and most efficient companies are not identical across different methods. These results suggest that a valid benchmarking analysis should be applied with special care. It is recommended that the regulator use several specifications and perform a (mutual) consistency analysis. Finally, the out-of-sample prediction errors of different models are analyzed. The results suggest that benchmarking methods can be used as a control instrument in order to narrow the information gap between the regulator and regulated companies.

1. INTRODUCTION

Transmission and distribution of electricity have been considered as natural monopolies, thus less affected by the recent waves of deregulation in power industry. However, as competition is introduced into generation sector, regulatory reform and incentive regulation of distribution utilities have become more common. In traditional cost-of-service regulation systems companies recover their costs with a risk-free fixed rate of return and therefore have little incentive to minimize costs. The incentive-based schemes on the other hand, are designed to provide incentive for cost-efficiency by compensating the company with its savings. A variety of methods are proposed in the literature. Main categories of incentive-based schemes used for electricity utilities are: price or revenue cap regulation schemes, sliding-scale rate of return, partial cost adjustment, menu of contracts, and yardstick regulation.[1] Jamasb and Pollitt (2001) provide an extensive survey of different regulation practices in electricity markets around the world. Virtually all the models used in practice, are based on *benchmarking* that is, measuring a company's efficiency against a reference performance. Inefficiency is a deviation from the optimal point on the production or cost frontier. This deviation can be resulted from two sources: technological deficiencies and problems due to a non-optimal allocation of resources into production. Both *technical* and *allocative* inefficiencies are included in cost-inefficiency, which is by definition, the deviation from minimum costs to produce a given level of output with given input prices. In benchmarking applications the regulator is generally interested in obtaining a measure of firms' inefficiency in order to reward (or punish) companies accordingly. The reliability of inefficiency scores is therefore crucial for the regulator. In particular, if the estimated inefficiency scores are sensitive to the benchmarking method, a more detailed analysis to justify the adopted model is required. However, in most cases it is difficult to identify the "right" model and the regulator should not use the results in a mechanical way. Rather, the benchmarking analysis can be used as a complementary instrument in the regulation.

There are a wide variety of methods to measure cost-efficiency. These measures range from basic indicators to more complex measures obtained from a multivariate analysis. Simple measures such as average unit cost or average labor productivity are commonly used in practice but fail to account for the differences among conditions and opportunities that different companies face. Multivariate analyses however adjust the measures with respect to factors that are beyond companies' control. These methods can be classified into two main

[1] See Jamasb and Pollitt (2000) and Joskow and Schmalensee (1986) for reviews of regulation models.

categories: non-parametric or deterministic methods such as data envelopment analysis, and parametric or stochastic methods such as least squares method and stochastic frontier analysis. Rossi and Ruzzier (2000) provide a comparative discussion of different approaches used in cross-sectional and panel data.

One of the main advantages of parametric methods is their ability to control for unobserved heterogeneity among companies. In particular, panel data models give a better possibility to control for such heterogeneities. This turns out to be an important issue in network industries like electricity distribution sector, where different companies deal with networks with different shapes and consumer densities and various topographical conditions. These factors as well as other potentially unobserved characteristics do affect the production costs but are not necessarily indicative of different efficiencies. The inefficiency measures may therefore be affected by these confounding factors. In this case companies that face more difficult conditions may be classified as inefficient producers.

The theoretical development of stochastic frontier models in panel data has been subject of a great body of literature.[2] Many studies compared the inefficiency scores obtained from different models. After reviewing their previous studies, Kumbhakar and Lovell (2000)[3] conclude that different approaches are likely to generate rather similar efficiency rankings, especially at the top and bottom of the distribution. However, using Monte Carlo simulations, Gong and Sickles (1989) find that with complex production functions all models show a poor performance. Their results suggest that the reliability of different models depends on the nature of production. We argue that in industries such as electricity distribution, the production technology is a rather complex function that depends on a variety of external parameters associated with the production environment and demand characteristics.

In practice, regulators have used virtually all measures including simple univariate indicators. The effect of unobserved differences among companies is often ignored. This issue may however be crucial in network industries. The main goal of this paper is to study how and to what extent the unobserved differences among companies affect the inefficiency measures. Focusing on parametric methods and using different panel data models, it is shown that the inefficiency scores and rankings are quite sensitive to whether and how the heterogeneity of production conditions is accounted for. Moreover, there is no unique model with a decisive advantage over all other methods.

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[2] See Kumbhakar and Lovell (2000) for a review and Greene (2002) and Tsionas (2002) for some recent developments.

[3] See page 107.

In this paper, different stochastic frontier models are applied to a sample of distribution utilities in Switzerland. The sample is an unbalanced panel of 59 companies over a period of 9 years (a total of 380 observations). The inefficiency scores estimated from four different models are compared. In particular, the resulted efficiency rankings obtained from random effect and fixed effect models are analyzed. Although there is a reasonably good correlation between the estimates obtained from certain models, individual inefficiency scores and ranks change quite significantly from one model to another. The estimated measures of inefficiency are therefore sensitive to econometric specification and should not be used as a direct and firm instrument in benchmarking.

However, benchmarking methods can be used as a control instrument in addition to other tools. An interesting example is provided by Antonioli and Filippini (2003) in the regulation of water supply in Italy. There, the regulation 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 heterogeneity. The proposed tariff is approved if it does not exceed an "acceptable" range from the estimated price cap.[4] Otherwise, the tariffs can be renegotiated with the requirement that the company justify its excessive tariff before any revision. The contrasting difference with Schleifer (1985)'s *yardstick competition* model is the possibility of renegotiation.[5] The interaction between the regulator and companies may be helpful in the face of information asymmetry. In order to provide a disincentive to renegotiate a penalty can be imposed on the companies that do not accept the first-stage prices. In case of disagreement the regulator performs a more detailed analysis with additional information from the individual company and offers a new price. The probability of disagreement and the flexibility of the regulator depend on the prediction power of the adopted econometric model in benchmarking.

The rest of the paper proceeds as follows: Section 2 provides a brief review of cost-frontier models and presents the specification used in this paper. Section 3 describes the data, and section 4 presents the estimation results. A discussion of the main results in section 5 concludes.

[4] In the example of Italy's water supply, the regulation authorities accept tariffs that differ by at most 30 percent from their estimated benchmark prices.

[5] In Schleifer's model the regulator's commitment to a fixed price is crucial in obtaining an efficient outcome.

2. METHODOLOGY

A frontier cost function defines minimum costs given output level, input prices and the existing production technology. It is unlikely that all firms will operate at the frontier. Failure to attain the cost frontier implies the existence of technical and allocative inefficiency. Different approaches can be used to estimate a frontier cost function with panel data. Battese (1992) and Simar (1992) give general overviews of these methods. This section provides a description of the cost frontier models and the specification used in this paper. The adopted methodology is based on a comparison of different models with respect to the estimated cost function parameters, estimated inefficiency scores, and the out-of-sample prediction errors. The main goal is to study the limitations of different models in benchmarking and the extent to which the inefficiency scores are sensitive to model selection.

2.1. Cost frontier models

In this paper we consider the estimation of a deterministic and three versions of a stochastic frontier cost function using panel data. The deterministic approach constrains the error term of the cost function to be non-negative. This model can be formulated as:

$$\ln C_{it} = \ln C(y_{it}, w_{it}) + u_{it} \qquad u_{it} \geq 0 \qquad i= 1, 2, ..., N \quad and \quad t = 1,2,...,T \qquad (1)$$

where C_{it} is observed total cost in year t, y_{it} is a vector of outputs, w_{it} is an input price vector and u_{it} is a positive one-sided disturbance capturing the effect of inefficiency. N represents the number of firms and T the number of years in the sample. Firms can therefore operate on or above the cost frontier but not below it. One interesting method proposed for estimating equation (1) is Greene's (1980) version of Richmond's (1974) "Corrected Ordinary Least Squares" (COLS). A functional form for the cost function is assumed, and parameter estimates are obtained using Ordinary Least Squares (OLS) method. The intercept is corrected by shifting the value of the intercept such that all residuals are positive and at least one is zero. This method is also known as Displaced Ordinary Least Squares (DOLS).

Greene (1980) has shown that the resulting constant term is consistent but biased and of unreliable efficiency. The main shortcoming of this method is that it confounds inefficiency with statistical noise: the entire residual is classified as inefficiency. Nevertheless many studies have used this approach.[6]

This problem can be overcome using the stochastic cost frontier approach suggested by Aigner et al. (1977):

$$\ln C_{it} = \ln C(y_{it}, w_{it}) + u_i + v_{it} \quad u_i \geq 0 \qquad i = 1, 2, ..., N \text{ and } t = 1,2,...,T \qquad (2)$$

In this specification the error term is composed of two uncorrelated parts: The first part u_i, is a one-sided non negative disturbance reflecting the effect of inefficiency (including both allocative and technical inefficiencies), and the second component v_{it} , is a symmetric disturbance capturing the effect of noise. Usually the statistical noise is assumed to be normally distributed, while the inefficiency term u_i is generally assumed to follow an exponential or a truncated normal distribution.

The main advantage of the stochastic cost frontier approach compared to the deterministic approach is the separation of the inefficiency effect from the statistical noise. However, this method is subject to the potential criticism of having an arbitrary assumption about the distribution of the random terms. These assumptions can be however, relaxed by rewriting equation 2 as:

$$\ln C_{it} = \ln C(y_{it}, w_{it}) + \alpha + u_i^* + v_{it} \quad \text{with} \quad u_i = u_i^* - \min\{u_i^*\}, \qquad (3)$$

and using a feasible Generalized Least Squares (GLS) method as proposed by Schmidt and Sickles (1984).[7] Notice that the only required assumption is that both random terms have zero means.

The remaining restrictive assumption is that the two random components be uncorrelated with each one of the explanatory variables. This implies that firm's inefficiency is uncorrelated with its observed characteristics included in the cost function. In the real world however, many of these factors may affect the firm's inefficiency. Schmidt and Sickles (1984) propose a solution around this assumption.[8] In their model the overall residual w_{it} is composed of two terms ($w_{it} = u_i + v_{it}$): a symmetric disturbance v_{it}, like previous models, and a one-sided fixed component u_i, that represents cost inefficiency. The latter component

[6] See for example Wagstaff (1989) and Filippini and Maggi (1993).
[7] See also Kumbhakar and Lovell (2000).
[8] For a presentation of this method see also Simar (1992).

can be identified by a fixed effects specification with no assumption on the distribution of u_i.[9] Inefficiency scores are estimated as the distance to the firm with the minimum fixed effect, that is: $u_i - \min\{u_i\}$. The fixed effects approach controls for unobservable firm specific effects, such as inefficiency, that are not captured by control variables. There are however, two limits to this approach: First, the time invariant variables are captured by the fixed effects and cannot be included in the model. This implies that the inefficiency estimators include the variations in time-invariant firm characteristics. Moreover, inefficiency is assumed to be constant over time. Notice that this assumption can be relaxed in the random effects models discussed above.[10]

The main advantage of the fixed-effects specification is that the estimations are unbiased even if explanatory variables are correlated with firm-specific dummies. However, the inefficiency measures are confounded with other factors. The choice between random effects and fixed effects models depends on whether or not firms belong to the same population.[11] To the extent that the heterogeneity among companies is limited to a single population random effects model is a legitimate specification. Given that benchmarking is based on the concept of comparing comparable firms one may argue that the single-population assumption is required in the first place and a random effects specification is justified.

2.2. Specification of the Frontier Cost Function

Electricity distribution utilities operate in networks with different shapes, which directly affect the costs. As discussed in Robert (1986), Salvanes and Tjϕota (1994) and Thompson (1997), the cost function should take into account differences in network characteristics, load factor and other factors that are unrelated to cost-efficiency but affect the costs. The specification used here draws basically from the model used by Filippini (1998). The output is measured by the total number of kWh delivered. Inputs to the electricity distribution process consist primarily of labor, capital and the power purchased from the generator. The firm's total cost of distributing electricity can be represented by:

$$\mathrm{C} = \mathrm{C}(Y, P_K, P_L, P_P, LF, CU, AS, HGRID, DOT, DW, T) \qquad (4)$$

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[9] In this approach the term stochastic is referred to the fact that the model is stochastic (presence of a symmetric component of the disturbance v_{it}) but not the inefficiency term u_i. In the approach suggested by Aigner et al. (1977) both the model and the inefficiency term are stochastic.

[10] Battese and Coelli (1992) propose a method. See also Coelli, Rao and Battese (1998) for a summary.

[11] See Baltagi (2001) and Hsiao and Sun (2000) for detailed discussions on fixed *vs* random effects.

where C represents total cost, Y is the output in kWh, and 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 peak demand on its maximum capacity, AS the size of the service area served by the distribution utility, and CU is the number of customers. These variables are introduced in the model as output characteristics. The load factor captures the impact of the intensity of use on costs.[12] *HGRID* is a binary indicator to distinguish the utilities that operate a high-voltage transmission network in addition to their distribution network. Some of the utilities in our sample are involved in auxiliary services such as installation of electric appliances. Those companies whose share of auxiliary revenues is more than 25 percent of total revenues are distinguished by dummy variable *DOT*. The maintenance costs and damage risks of power lines are generally higher in forests. Binary indictor *DW* represents the cases in which more than 40 percent of the service area is covered by forests. T is a time variable representing the linear trend in technological progress.

The regularity conditions require that the cost function in equation (4) be linearly homogeneous in input prices, non-decreasing in input prices and concave.[13] The translog model and Cobb-Douglas form are two main functional forms commonly used in the literature. Translog form does not impose any technological restriction and allows the economies of scale, size and density vary with output. These values are assumed constant in the Cobb-Douglas functional form. In this paper, the Cobb-Douglas form is used for two main reasons. First, because of the large number of parameters[14] in translog model there is a considerable risk of near-multicollinearity, especially given that different output variables Y, AS and CU are highly correlated.[15] Moreover, the estimation of scale economies is of secondary importance in this paper. The assumption that scale-economies do not vary with output (implicit in Cobb-Douglas form) can therefore be justified to the extent that it does not affect the inefficiency estimators.

[12] See Foreman-Peck and Waterson (1985) for a discussion of the role of load factor in cost models.
[13] See Cornes (1992) for a discussion of the properties of cost functions.
[14] In our specification the number of parameters in translog model would be 40.
[15] Our preliminary analysis suggests that this problem creates technical difficulties in our maximum likelihood estimations.

The Cobb-Douglas specification of the cost function in (4) can be written as:

$$\ln\left(\frac{C}{P_P}\right) = \beta_0 + \beta_Y \ln Y + \beta_K \ln\left(\frac{P_K}{P_P}\right) + \beta_L \ln\left(\frac{P_L}{P_P}\right) + \gamma_1 \ln LF$$

$$+ \gamma_2 \ln AS + \gamma_3 \ln CU + \delta_1 HGRID + \delta_2 DOT + \delta_3 DW + \tau_T T \qquad (5)$$

Linear homogeneity in input prices is imposed by dividing money values by the price of the input power.

3. DATA

The data used in this paper consists 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. The original data set has been prepared and analyzed by Filippini (1998) and completed by Wild (2001) and Filippini and Wild (2001). These data are mainly based on the information from the annual reports of the Swiss Federal Statistical Office, the Swiss Federal Energy Office, and the Swiss Cities Association. A mail survey from the utilities has been used to complete the data.[16] The sample does not include the utilities that generate more than 20 percent of their input power. There are about 900 electricity distribution companies in Switzerland. This sector is characterized by a large number of small companies along with a relatively small number of large firms. The 59 companies included in this study deliver about a third of Switzerland's electricity consumption. The sample used in this study can therefore be considered as a representative sample of relatively large distribution utilities in the country. In spite of a considerable degree of variation in costs and other characteristics, the sample represents relatively similar companies compared to the entire sector.

Table 1 gives the summary statistics of the key variables used in the analysis. All money values are converted to 1996 Swiss Francs using the global consumer price index. The cost of purchased electricity is included in total costs. 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. Labor price is defined as the average annual salary of the firm's employees. Capital expenditure is approximated by the *residual* costs that is, total costs minus labor and purchased power costs. Because of the lack of inventory data the capital stock is measured by the capacity of transformers.[17] The capital price is obtained by dividing the capital costs by the total capacity of the installed transformers.

Table 1. Descriptive statistics (380 observations)

	Mean	Standard Deviation	Minimum	Maximum
Total annual costs per kWh output (CHF)	.188	.0303	.128	.323
Total annual output in GigaWh *(Y)*	263.51	390.36	17	2301.5
Number of customers	26975.6	36935.8	2461	220060
Load Factor	.5541	.0727	.3219	.9817
Service area (km^2)	15,467	35,376	176	198,946
Average annual labor price (P_L) per employee (1000 CHF)	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
Share of forest area more than 40% *(DW)*	.261	.440	0	1

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

4. ESTIMATION RESULTS

The estimated parameters of the cost frontier are listed in table 2. In the OLS model data are pooled across different years and the estimators are based on an implicit assumption that the unobserved random variations are not firm-specific. The other three models have the advantage of accounting for firms' heterogeneity. In the random-effects model (GLS) it is assumed that firms' unobserved heterogeneity is uncorrelated with their observed characteristics. The MLE model imposes an additional restriction that firms' unobserved heterogeneity has a half-normal distribution. The fixed-effects specification is robust to both these assumptions. This model however is mainly based on the variations within firms and cannot estimate the effect of time-invariant factors.

[16] See Filippini and Wild (2001) for a more detailed description of data sources.

As it can be seen in the table, the fixed-effect estimators for output (*Y*) and costumers (*CU*) coefficients are quite different from other models. This contrasting difference suggests that the estimations could be sensitive to firm-specific characteristics. This result is not surprising in network industries. Any correlation between random effects and other explanatory variables may result in a bias in estimations. Therefore, in the absence of information regarding the unobserved heterogeneity among firms, the fixed-effect model can provide more reliable estimates for the factors that vary over time.[18] This advantage however, is hardly clear in our sample: A more careful examination of the results shows that other coefficients are very similar among different models. Moreover, even though output coefficients *Y* and *CU* are different in the FE model, their sum is quite similar among different models. This result suggests that the value of economies of scale is robust to specification. Finally, the results of the Hausman specification test indicate that the FE and RE estimates are not significantly different at 5 percent significance level (p-value of .055). Overall, these results suggest that the cost function estimations are not sensitive to the unobserved heterogeneity among companies.

Table 2. Cost frontier parameters

	OLS		**Random-Effects (GLS)**		**Random-Effects MLE (Half-Normal)**		**Fixed-Effects**	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
lnY	0.851	0.017	0.780	0.032	0.767	0.040	0.677	0.055
lnCU	0.084	0.017	0.153	0.033	0.163	0.048	0.251	0.096
lnAS	0.044	0.004	0.051	0.009	0.047	0.013	-	-
lnLF	-0.243	0.037	-0.239	0.039	-0.230	0.023	-0.213	0.044
lnPL	0.067	0.011	0.041	0.014	0.039	0.014	0.038	0.016
lnPK	0.200	0.009	0.174	0.010	0.171	0.005	0.169	0.010
HGRID	0.063	0.012	0.075	0.027	0.098	0.039	-	-
DOT	0.033	0.010	0.050	0.022	0.040	0.028	-	-
DW	0.014	0.010	0.012	0.023	0.062	0.028	-	-
T	0.001	0.002	0.001	0.001	0.001	0.001	0.001	0.002
Constant	-2.236	0.233	-0.793	0.369	-0.653	0.430	-	-
R Square	0.995		0.995				0.991	

[17] Transformer is the main device used to transfer electricity in the network. This is basically a device to convert current variations to voltage variations and vice versa.

[18] Of course the precision of such estimations directly depends on the amount of within-firm variation.

In cost frontier framework both random and fixed effects models assume that the unobserved heterogeneity among firms is completely due to their differences in efficiency.[19] This assumption leads to an overestimation of inefficiency in fixed-effects models for the following reasons. First, the fixed firm-specific effects capture both observed and unobserved time-invariant factors. Moreover, since the fixed effects do not follow any distribution and efficiency is estimated compared to the best observed practice (the firm with the minimum fixed effect), the estimators are sensitive to outliers. In fact, the problem of outlier firms is transferred from the cost function to efficiency estimators. To illustrate this fact, several specifications are compared. We start from a "naïve" OLS model that ignores the time-invariant factors and refine this model in several steps until all time-invariant factors are included. The inefficiency scores obtained from these models are compared to those obtained from a fixed-effects model. The results (not given here) indicate that as the OLS model becomes more "refined" the estimated inefficiency scores show less correlation with those obtained from the fixed-effects model.[20] These results suggest that as far as inefficiency scores are concerned the performance of a fixed-effect model is quite poor (even compared to a naïve OLS model).

Table 3. Summary statistics of inefficiency scores

	DOLS	RE (GLS)	FE	ML
Minimum	1.07	1	1	1.07
Maximum	1.46	1.38	2.14	1.36
Average	1.23	1.16	1.35	1.15
Median	1.22	1.16	1.31	1.13
95 percentile	1.41	1.32	1.66	1.30
Number of firms	59	59	59	59

In order to see the limitations of these models we also study the inefficiency estimates obtained from different models. Table 3 gives the summary statistics of the inefficiency scores resulted from different models. The inefficiency score is defined as exp(*Ui*), where *Ui* is the inefficiency term obtained from the regression model.[21] The scores therefore represent the ratio of a company's actual costs to a minimum level that would have been achieved had

[19] There exist some recent developments that account for an additional random term in the random of fixed effects model to represent the inefficiency variations. The discussion of these models is beyond the scope of the present paper. See Greene (2002) and Tsiona (2002) for more information on these models.

[20] This is also the case for the mean and median inefficiency scores (and other quantiles). That is, as the OLS model get more refined the summary statistics decrease and get farther from that of the fixed-effects model.

[21] In the DOLS model where the inefficiency term is time-variant, the company's inefficiency *Ui* is assumed to be the average of u_{it} over the entire sample period.

the company operated as cost-efficient as the "best practice" observed in the sample. The excessively large values resulted from the fixed-effect model confirms the poor performance of this model in estimating inefficiencies. In practice, benchmarking is usually based on efficiency ranking of companies. The correlation matrix between the ranks obtained from different models is given in table 4. These results indicate a relatively high correlation between rankings from RE and MLE models.

Table 4. Correlation between inefficiency ranks from different models

	DOLS	RE (GLS)	FE	ML
DOLS	1			
RE (GLS)	0.936	1		
FE	0.447	0.514	1	
ML	0.838	0.895	0.417	1

To see the individual differences RE and MLE models are compared regarding the inefficiency scores. The FE model is not considered here because as discussed above, its efficiency scores are significantly different from other models. Table 5 summarizes the results. These results indicate that the maximum difference of cost-inefficiency between the two models is about 9 percent. This difference is quite significant noting that both models are based on the same Cobb-Douglas specification and their only difference is in the distribution of the efficiency term. A closer look to the rankings highlights these differences. Our results show that changing from one model to another results in significant changes in rankings. For instance for more than half of the companies in the sample changing the model from RE to MLE implies a change of 4 places or more in their ranks, and for about 25 percent of companies this means a change of 9 places or more. Even the ranking quartile changes considerably. Change of the model from MLE to RE results in a change in ranking quartile for 20 companies out of 59. This change results in a change of quartile for about a third of the companies in the first quartile (the 25 percent most efficient firms). Moreover, different models do not identify the same companies as the best and worst practices. The best practice as identified by the ML method is ranked 17 in the RE model whereas the RE model's best practice is ranked 7 by the ML model. These differences are as more striking as the two models differ only in their assumption on the distribution of the inefficiency term.

Therefore, the *mutual consistency conditions* proposed by Bauer et al. (1998)[22] are not satisfied. These results show the sensitivity of the benchmarking method in our sample. In contrast with the general contention in previous studies that different approaches give rather similar inefficiency rankings, this analysis suggests that rankings may be sensitive to the adopted model. Therefore, a direct use of inefficiency estimates in benchmarking regulation of network industries may be misleading. In usual cases where the choice of the appropriate model is not clear, a sensitivity analysis could be used to study the robustness of the results and the limitations of different models.

Table 5. Summary statistics of the absolute value of difference in inefficiency scores

Models:	RE and DOLS	RE and MLE
Minimum	0.01	0.00
Maximum	0.14	0.09
Mean	0.07	0.03
Median	0.07	0.02
95 percentile	0.12	0.08
N	59	59

Cost frontier models can also be used by the regulator to "predict" the costs of individual companies. Three specifications OLS, fixed effects (FE) and random effects (RE) are compared with respect to their predictive power. Predictions are considered in two directions: out-of-sample prediction which consists of predicting the costs of a given firm using the estimations obtained from other firms, and forecasting that involves the prediction of costs in a year using the estimation based on the data previous to that year. One, two and three-year-ahead forecasts are considered. In all predictions the actual values of explanatory variables are used. Prediction errors are defined as the predicted total costs minus the actual costs divided by the actual costs. In the RE model the forecasts are based on the optimal predictor given in Bailli and Baltagi (2000).[23] The prediction errors of different models are compared. The results are summarized in table 6. The 2-year ahead forecast errors are not listed.

As expected, the out-of-sample estimation errors are significantly higher in fixed-effects model. Interestingly, even the forecasting performance of the random effects model is comparable to that of the fixed effects model. This implies that in our sample the fixed effects

[22] According to Bauer et al., to be mutually consistent, different approaches should have the following conditions: inefficiency scores should have comparable means, standard deviations and other distributional properties; the ranking order of the firms should be approximately the same; and the "best-practice" and "worst-practice" firms should be mostly the same.

model does not provide a significant predictive advantage over other models.[24] The results show that the prediction errors are generally within an acceptable range from a practical point of view. In particular the random-effects model shows the best performance.

The results suggest that in panel data models the prediction capacity of different models can be used to identify the specification that best fits the data. Moreover, such analyses can be used to predict a confidence interval for the costs of any individual firm. In particular, a frontier approach can estimate a reference confidence interval for the costs of any given firm provided that the firm adopts the "most efficient" production strategy. Using such predictions, the regulator can hold companies in a reasonable range of cost-efficiency.

Table 6. Prediction errors

Type of prediction	Out-of-sample			1-year-ahead			3-year-ahead		
Model	OLS	RE	FE	OLS	RE	FE	OLS	RE	FE
Average absolute error	7.37	7.57	11.8	5.91	3.02	3.10	6.24	4.18	4.58
Maximum absolute error	25.2	27.3	39.0	17.0	10.3	10.3	16.7	14.6	16.4
95 percentile absolute error	17.8	20.1	31.1	13.5	6.82	7.66	14.1	10.9	13.0
Average prediction bias	.34	.98	1.08	-.03	0.08	.24	-1.89	-1.87	-1.39
Number of predictions	380	380	380	52	52	52	52	52	52

- Errors are given in percentage of the actual costs.

5. CONCLUSION

Four different stochastic cost frontier models are applied to a panel data set of electricity distribution utilities in Switzerland. A comparison of the estimation results indicates significant differences among different models. This result can be explained by the strong unobserved heterogeneity among distribution companies, which is a common characteristic of network industries. These differences are particularly important for the estimates of inefficiency scores. While the summary statistics of inefficiency estimates are not sensitive to model specification, the ranks change quite significantly from one model to another. Different models are not found to be "mutually consistent" with respect to

[23] See page 256 of Bailli and Baltagi (1999) for more details.

[24] This result is more or less confirmed by a p-value of .055 resulted from Hausman specification test.

inefficiency measures. These results point to an important shortcoming of the benchmarking methods in network industries. Given that the regulators actually use these methods in practice, the analysis in this paper has an important implication suggesting that benchmarking analysis should be applied with caution. In particular, it is recommended that several models be used and compared. A sensitivity analysis should be performed to identify the limitations of different models.

The paper also uses different cost frontier panel data models to predict the firms' costs. In particular, the out-of-sample prediction performance of different models is studied. The prediction errors are within acceptable limits from a practical point of view. The results suggest that stochastic frontier models can be used to gain information about costs of individual firms. Moreover, certain models with apparent limitations in the estimation of cost-frontier characteristics have a relatively good performance in predicting costs. Although this conclusion may be limited to the data used in this paper, the results suggest that cost frontier models can be used as a control instrument in order to narrow the information gap between the regulator and regulated companies. The stochastic frontier model can also be used to estimate a confidence interval for the costs of individual companies provided that they are cost-efficient. Moreover, the adopted methodology can be used in panel data to specify the appropriate model among several specifications.

References

Aigner, D., C. A. K. Lovell and P. Schmidt (1977), 'Formulation and Estimation of Stochastic Frontier Production Function Models', *Journal of Econometrics*, 6, 21-37.

Antonioli, B. and M. Filippini (2003) "The use of a variable cost function in the regulation of the Italian water industry", *Utilitis Policy*, 2003, Forthcoming.

Baillie, Richard T. and Badi H. Baltagi (1999) "Prediction from the regression model with one-way error component" Chapter 10 in *Analysis of Panels and Limited Dependent Variable Models* (C. Hsiao, K. Lahiri, L-F. Lee, and M. H. Pesaran, eds.), Cambridge University Press, 255-267.

Baltagi, Badi H. (2001) *Econometric Analysis of Panel Data*, Second Edition, John Wiley and Sons.

Battese, George E. (1992) 'Frontier Production Functions and Technical Efficiency: A Survey of Empirical Applications in Agricultural Economics*', Agricultural Economics*, 7, 185-208.

Battese, George E. and Tim Coelli (1992) "Frontier production functions, technical efficiency and panel data: with application to paddy farmers in India", *Journal of Productivity Analysis*, 3: 153-169.

Bauer, Paul W., Allen N. Berger, Gary D. Ferrier, and David B. Humphrey (1998) "Consistency conditions for regulatory analysis of financial institutions: A comparison of frontier efficiency methods", *Journal of Economics and Business*, 50: 85-114.

Coelli, Tim, D. S. Prasada Rao, and George E. Battese (1998) *An Introduction to Efficiency and Productivity Analysis*, Kluwer Academic Publishers.

Cornes, R. (1992) *Duality and Modern Economics*, Cambridge University Press.

Filippini, Massimo (1998) "Are municipal electricity distribution utilities natural monopolies?", *Annals of Public and Cooperative* Economics, 2: 157-174.

Filippini, M. and R. Maggi (1993) "Efficiency and Regulation in the case of the Swiss Private Railways", *Journal of regulatory Economics*, 5, 199-216.

Filippini, Massimo and Jörg Wild (2001) "Regional differences in electricity distribution costs and their consequences for yardstick regulation of access prices", *Energy Economics*, 23: 477-488.

Foreman-Peck, J. and M. Waterson (1985) "The comparative efficiency of public and private enterprise in Britain: electricity generation between the world wars", *Economic Journal*, 95: 83-95.

Gong, B. H., and R. C. Sickles (1989) "Finite sample evidence on the performance of stochastic frontier models using panel data", *Journal of Productivity Analysis*, 1 (3): 229-261.

Greene, William (2002) "Alternative panel data estimators for stochastic frontier models", Unpublished manuscript (Septemebr 1, 2002), Department of Economics, New York University.

Greene, William H. (1980), 'Maximum Likelihood Estimation of Econometric Frontier Functions', *Journal of Econometrics*, 13, pp. 27-56.

Hsiao, Cheng and Baohong Sun (2000) "To pool or not to pool panel data", Chaper 9 in *Panel Data Econometrics: Future Directions* (Krishnakumar, J. and E. Ronchetti, eds.), North-Holland, 181-198.

Kumbhakar, Subal C. and C. A. Knox Lovell (2000) *Stochastic Frontier Analysis*, Cambridge University Press, Cambridge.

Jamasb, T. and M. Pollitt (2001) "Benchmarking and regulation: international electricity experience" *Utilities Policy*, 9 (3), 107-130.

Jamasb, T. and M. Pollitt (2000) "Benchmarking and regulation of electricity transmission and distribution utilities: lessons from international experience", Working paper, Department of Applied Economics, University of Cambridge.

Joskow, P. J., and R. Schmalensee (1986) "Incentive regulation for electric utilities", *Yale Journal of Regulation*, 4 (1): 1-49.

Richmond, J. (1974), 'Estimating the Efficiency of Production', *International Economic Review*, 15, pp. 515-521.

Roberts, M. J. (1986) "Economies of Density and size in the Transmission and Distribution of Electric Power", *Land Economics*, 62, 378-387.

Rossi, Martin A. and Christan A. Ruzzier (2000) "On the regulatory application of efficiency measures" *Utilities Policy*, 9 (2), 81-92.

Salvanes, K.G. and Tjϕota, S. (1994) "Productivity Differences in Multiple Output Industries: An Empirical Application to Electricity Distribution", *The Journal of Productivity Analysis*, 5, 23-43.

Schleifer, Andrei (1985) "A theory of yardstick competition", *Rand Journal of Economics*, Autumn 1985, 16 (3): 319-327.

Schmidt, P. and R.E. Sickles, (1984), Production Frontiers and Panel Data, *Journal of Business and Economic Statistics*, 2, 367-374.

Simar, L., (1992), 'Estimating Efficiencies from Frontier Models with Panel Data: A Comparison of Parametric, Non-parametric and Semi-parametric Methods with Bootstapping', *The Journal of Productivity Analysis*, 3, 171-203.

Thompson, H.G. (1997) "Cost efficiency in Power Procurement and Delivery Service in the Electric Utility Industry", Land Economics, 73, 287-296.

Tsiona, Efhtymios G. (2002) "Stochastic frontier models with random coefficients" *Journal of Applied Econometrics*, 17: 127-147.

Wagstaff, A. (1989) "Estimating Efficiency in the Hospital Sector: a Comparison of three Statistical Cost Frontier Models", *Applied Economics*, 21, pp. 659-672.

Wild, Jörg (2001) *Deregulierung und Regulierung der Elektrizitätsverteilung, Eine mikro-ökonomische Analyse mit empirischer Anwendung für die Schweiz.* vdf Hochschulverlag AG an der ETH Zürich, Zürich.