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ABSTRACT

This paper studies the sensitivity problems of the benchmarking methods used in the regulation practice. Three commonly used methods have been applied to a sample of 52 electricity distribution utilities to estimate their cost efficiency. These methods include stochastic frontier, corrected ordinary least squares and data envelopment analysis. The results indicate that both efficiency scores and ranks are significantly different across various models. Especially considerable differences exist between parametric and non-parametric methods.

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1. INTRODUCTION

Regulatory reform and incentive regulation of power distribution utilities have been used more and more in many countries. 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 efficient companies and punishing the inefficient ones. 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] Such payment systems are usually based on benchmarking that is, identifying the "best-practice" company(ies) to which all companies are compared. Inefficiency can be resulted from technological deficiencies or 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 accounting for a measure of firms' inefficiencies such as X-factors in price cap regulation, in order to reward (or punish) companies accordingly. 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 among the set of legitimate ones. Bauer et al. (1998) have proposed a series of criteria that can be used to evaluate if the results obtained from different methods are mutually "consistent", that is, lead to comparable inefficiency scores and ranks. In particular, it is important that different models identify more or less the same companies as the "best" and "worst" practices. Authors like Jamasb and Pollit (2003) show that there are substantial variations in estimated efficiency scores and rank orders across different methods.[2] These variations may be explained by large estimation errors and inconsistency problems of individual efficiency scores in cross sectional data, as pointed out in Horrace and Schmidt (1996), Street (2003) and Jensen (2000).

The efficiency estimates could be improved using panel data. In contrast with cross-sectional data, panels provide information on same companies over several periods. Citing several examples taken from other industries, Kumbhakar and Lovell (2000)[3] conclude that different panel data models are likely to generate rather similar efficiency rankings, especially at the top and bottom of the distribution. However, as pointed out in Farsi and Filippini (2004), in electricity networks applications, the conventional panel models cannot solve the discrepancies in individual efficiency estimates. Other studies such as Greene (2005, 2004), Farsi et al. (2005, 2006) and Alvarez et al. (2004) applied recently developed alternative panel data models in other industries. However, few studies have applied such models in electricity distribution networks. Moreover, the use of panel data in regulation practice remains extremely rare.

In line with other examples like Jamasb and Pollit (2003), this paper studies the discrepancies in efficiency estimates from cross-sectional data. Several benchmarking models have been applied to a sample of 52 companies operating in Switzerland. Both stochastic and deterministic frontier approaches have been considered. The efficiency scores and ranks as well as the "best" and "worst" practices are compared across different models. The substantial observed variations suggest that consistency criteria such as those proposed by Bauer et al. (1998) are far from satisfied. Such discrepancies may suggest that the efficiency estimates should be used at the sector level rather than for individual companies. However, using an aggregate efficiency score for all companies although more accurate overall, could

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[1] See Joskow and Schmalensee (1986) for a review of regulation models and Jamasb and Pollitt (2001) for an survey of different regulation practices in electricity markets around the world.

[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.

be counterproductive in that it may punish the relatively efficient companies and reward those that are less efficient than average. It is recommended that rather than using the inefficiency estimates in a mechanical way, the benchmarking analysis should be used as a complementary instrument in incentive regulation schemes.

The rest of the paper proceeds as follows: Section 2 provides a discussion of the concept of cost efficiency and an overview of the main benchmarking methods. The model specification along with a brief description of the data is given in Section 3. The estimation results are presented and discussed in Section 4 and the conclusions are summarized at the end.

2. COST EFFICIENCY AND BENCHMARKING METHODS

Inefficiency in production can result from two sources: inefficiency in the adopted technology and the suboptimal allocation of resources. These two efficiency concepts are respectively referred to as technical and allocative efficiency. Overall cost inefficiency of a given company is the sum of these two inefficiencies.[4] Basically, a simple indicator of inefficiency can be defined as the ratio of an output measure to an aggregate measure of inputs. Such indicators do not require a multivariate analysis. However, given that simple indicators cannot account for the environmental factors and other production characteristics, more elaborate methods are generally preferred. These methods are generally based on distance functions. The inefficiency of a production unit is measured as its distance form a frontier (envelope) that is the locus of the optimal production plans. Such distances are

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[3] See page 107.

[4] In benchmarking analysis, the firm's inefficiency is limited to technical and allocative inefficiencies. The inefficiency due to the suboptimal size of the production unit (scale inefficiency) is generally excluded from benchmarking analyses because in regulated industries the company's size is usually determined by demand factors.

measured by distance functions defined in the space of output(s) or input(s), resulting respectively in output-oriented and input-oriented measures of efficiency.[5]

The methods used for measuring inefficiency are commonly referred to as frontier approaches. There are several frontier methods to estimate the efficiency of individual firms. Two main categories are non-parametric methods originated from operations research, and econometric approaches.[6] In non-parametric approaches like DEA, the cost frontier is considered as a deterministic function of the observed variables but no specific functional form is imposed.[7] Moreover, non-parametric approaches are generally easier to estimate and can be implemented on small datasets. Parametric methods on the other hand, allow for a random unobserved heterogeneity among different firms but need to specify a functional form for the cost or production function. The main advantage of such methods over non-parametric approaches is the separation of the inefficiency effect from the statistical noise due to data errors, omitted variables etc. The non-parametric methods' assumption of a unique deterministic frontier for all production units is unrealistic. Another advantage of parametric methods is that these methods allow statistical inference on the significance of the variables included in the model, using standard statistical tests. In non-parametric methods on the other hand, statistical inference requires elaborate and sensitive re-sampling methods like bootstrap techniques.[8]

Apart from a few exceptions, all the parametric methods consider a stochastic frontier. Thus, this group of methods is often labeled as Stochastic Frontier Analysis (SFA). The main exception with a deterministic frontier is the COLS method. In this approach the inefficiencies are defined through a constant shift of the OLS residuals (cf. Greene, 1980). As

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[5] See Kumbhakar and Lovell (2000) for an extensive discussion.

[6] See Coelli et al. (1998), Chapters 6 and 7, and Simar (1992) for an overview of non-parametric approaches and Kumbhakar and Lovell (2000) for a survey of parametric methods.

[7] See Coelli et al. (2003) for more details on DEA.

[8] These methods are available for rather special cases and have not yet been established as standard tests. See Simar and Wilson (2000) for an overview of statistical inference methods in non-parametric models.

the entire stochastic term is considered as inefficiency, the frontier remains deterministic. In SFA models, on the other hand, the residuals are decomposed into two terms, a symmetric component representing statistical noise and an asymmetric one representing inefficiency. This approach is due to Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977).

DEA method is the most commonly used approach in practice. In a sample of N companies with a k-input-m-output production function with variable returns to scale (VRS), the measurement of cost efficiency using DEA method reduces to the following minimization problem:

$$\begin{aligned} &\min_{\lambda, x_i} \; w_i^{'} x_i \\ &\text{st:} \;\; -y_i + Y\lambda \geq 0, \\ &\qquad x_i - X\lambda \geq 0, \\ &\qquad \mathbf{N}^{'}\lambda = 1, \\ &\qquad \lambda \geq 0, \end{aligned} \tag{1}$$

where w_i and x_i are kx1 vectors respectively representing input prices and quantities for firm i (i= 1, 2, ..., N); y_i is an mx1 vector representing the given output bundle; X and Y are respectively input and output matrices namely, a kxN and a mxN matrix consisting of the observed input and output bundles for all the companies in the sample; **N** is an Nx*1* vector of ones; and λ is an Nx*1* vector of non-negative constants to be estimated. The VRS property is satisfied through the convexity constraint ($\mathbf{N}\lambda$=1) that ensures companies are benchmarked against companies with similar size.

The minimization problem given in (1) can be solved by linear programming (LP) methods. The LP algorithm finds a piece-wise linear isoquant in the input space, which corresponds to the minimum costs of producing the given output at any given point. The solution gives the minimum feasible costs for each company namely, $w_i^{'} x_i^*$, where x_i^* is the optimal input bundle for firm i. The cost-efficiency of each production plan is then estimated as its distance to the envelope. Namely, firm i's cost efficiency is therefore obtained by:

$$Eff_i = \frac{w_i^{'} x_i^{*}}{w_i^{'} x_i^{o}}, \tag{2}$$

where x_i^o is the observed input bundle used by company *i*.

COLS approach is based on the OLS estimation of a parametric cost function, usually expressed in logarithms:

$$\ln C_i = f\left(y_i, w_i\right) + \varepsilon_i, \tag{3}$$

where C_i is the actual costs incurred by company *i*, and *f*() is the cost function; and ε_i is the stochastic error term. After correcting this term by shifting the intercept such that all residuals ε_i are positive, the COLS model can be written as:

$$\ln C_i = f\left(y_i, w_i\right) + \min_i \left\{\varepsilon_i\right\} + u_i, \text{ with } u_i = \varepsilon_i - \min_i \left\{\varepsilon_i\right\} \geq 0, \tag{4}$$

where u_i is a non-negative term representing the firm's inefficiency. The cost-efficiency of firm *i* is then given by: $Eff_i = \exp(u_i)$.

The main shortcoming of this method is that it confounds inefficiency with statistical noise: the entire residual is classified as inefficiency, thus the cost frontier is deterministic. In the stochastic frontier model 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, and the second component v_i, 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 assumed to follow a half-normal distribution.[9] The SFA model can be written as:

$$\ln C_i = f\left(y_i, w_i\right) + u_i + v_i, \tag{5}$$

This model with a normal-half-normal composite error term can be estimated using Maximum Likelihood Estimation method. Similarly the cost-efficiency of firm *i* is given by: $Eff_i = \exp(u_i)$.

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[9] Other extensions of this model have also considered exponential and truncated normal distributions for the inefficiency term. See for instance Battese and Coelli (1992).

3. MODEL SPECIFICATION AND DATA

In this section we study a simple example of benchmarking on power distribution utilities to illustrate the potential differences and the resulting problems faced by the regulator. The example has been chosen from the Swiss power distribution sector. The sample consists of 52 utilities operating in 1994. The cost efficiency of these companies has been analyzed by three benchmarking methods: DEA, COLS and SFA.

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.[10] 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.[11] 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.

[10] 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.

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

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

$$C = C(Y, P_K, P_L, P_P, LF, CU, AS) \qquad (6),$$

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.[12]

For the parametric models used in this paper we have chosen a Cobb-Douglas functional form. The condition of linear homogeneity in input prices is imposed by dividing the input prices by the price of purchased electricity. The cost function can therefore be formulated as:

$$\begin{aligned} \ln\left(\frac{C}{P_P}\right)_i &= \beta_0 + \beta_Y \ln Y_{it} + \beta_K \ln\left(\frac{P_K}{P_P}\right)_i + \beta_L \ln\left(\frac{P_L}{P_P}\right)_i \\ &+ \gamma_1 \ln LF_i + \gamma_2 \ln AS_i + \gamma_3 \ln CU_i + r_i, \qquad (7) \\ &\text{with} \quad i = 1, 2, \ldots, N, \end{aligned}$$

where r_i represents the residuals, namely, a mean-zero *iid* error term for COLS and a composite normal-half-normal *iid* term for SFA model, as described respectively in equations (4) and (5). In the case of COLS model the cost function in (6) can be estimated using the OLS method, whereas in the SFA case, Maximum Likelihood Estimation (MLE) method can be used. The SFA model requires a distribution assumption about the residuals. Here we assume a half-normal distribution for the inefficiency term and a normal distribution for the statistical error.

The specification given in (6) can be readily used in the DEA method. In this method there is no need to specify any functional form. The quantities of labor, capital stock and the amount of input energy are considered as input. Labor and capital inputs are respectively measured as the number of full-time equivalent employees and the installed capacity of the transformers.[13] The output (*Y*) and the five output characteristics in (6) are considered as output. With the exception of load factor (*LF*) all these characteristics take resources, thus can be considered as an output. As for the load factor, since a higher *LF* implies a smoother demand, thus lower costs, the corresponding output characteristics in the DEA model is defined as the inverse of *LF*. Therefore, the DEA model can be considered as a production with three inputs and six outputs. We assume variable returns to scale (VRS) for the DEA model.[14] The descriptive statistics are given in Table 1.

Table 1. Descriptive statistics (52 observations)

	Mean	Standard Deviation	Minimum	Maximum
Total annual costs per kWh output (CHF)	.188	.0275	.150	.276
Annual output (*Y*) in GigaWh	258.65	350.01	17	1474.8
Number of customers (*CU*)	26160.5	32260	2648	126,655
Load Factor (*LF*)	.5593	.0628	.3689	.6594
Service Area (*AS*) in km^2	18,558	41,673	176	198,946
Average annual labor price (P_L) per employee (CHF 1000)	101.88	28.38	45.26	204.13
Average capital price (P_K) in CHF per kVoltAmpere installed capacity	95.64	40.23	32.31	199.32
Average price of input power (P_P) in CHF/kWh	.103	.0213	.0613	.139

- All monetary values are in 1996 Swiss Francs (CHF).

12 This specification is a simplified version of the model used in Farsi and Filippini (2004). The dummy variables are excluded.

13 Note that the measurement unit of input factors is not relevant, as long as the prices are defined such that the resulting costs have the same unit.

4. ESTIMATION RESULTS

The three models have been applied to cross sectional data from 52 companies' operation in 1994. The cost frontier parameters for COLS and SFA methods are given in the appendix (Table A.1). Summary statistics of the estimated efficiency scores are given in Table 2. The efficiency scores are normalized to a scale between 0 and 1, where the highest value (1) implies a perfectly efficient company and the difference with 1 approximates the percentage of the total costs that that the company can potentially save. As the results in Table 2 suggest, the studied companies are on average about 86 to 92 percent efficient. The COLS efficiency scores are lower by 6 percent on average, than the other models. COLS and DEA methods are similar in that neither accounts for stochastic variation in the frontier. However, the DEA model has a non-parametric frontier, which can be considered as an almost perfectly flexible functional form. The average efficiency estimate is quite similar between SFA and DEA models, suggesting that a rigid model like COLS can underestimate the efficiency. These results also suggest that in our example, allowing for stochastic variation or a perfectly flexible functional form have at least on average, a similar effect on efficiency estimates.

The correlation coefficients between the efficiency scores obtained from different models are given in Table 3. Although the COLS and SFA estimates show a quite high correlation, their correlation with the DEA estimates is relatively low. These results suggest that the efficiency ranking of the studied companies could considerably change depending on the adopted model. The correlation coefficients between efficiency ranks show a very similar pattern, thus are not reported in the paper.

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[14] The alternative assumption would be constant returns to scale. This assumption is too restrictive because it implies that all companies operate at the optimal scale. See Coelli et al. (1998) for more details.

Table 2. Summary statistics of efficiency scores (1994)

	DEA	SFA	COLS
Minimum	.734	.819	.727
Maximum	1	.977	1
Average	**.917**	**.920**	**.858**
Median	.932	.937	.864
95 percentile	1	.973	.984
N	52	52	52

Table 3. Correlation between efficiency from different models (1994)

	DEA	SFA	COLS
DEA	1	.563	.603
SFA	.563	1	.961

In order to see the differences in ranking individual companies, we studied the rank status of the ten most efficient and least so companies according to the SFA method. Table 4 lists the efficiency ranks of these 20 companies based on the two other models. The results indicate a quite similar ranking across the two parametric methods (SFA and COLS), which is considerably different from that of DEA. However, the differences are less important for the first ten companies. In fact, the DEA model predicts a higher than 98% efficiency for all these companies. Notice that according to this model, 19 companies are perfectly efficient and 24 companies have an efficiency of higher than 95%. But for the ten companies at the bottom of the list, the differences are quite considerable. For instance, two of these companies are evaluated as perfectly efficient by the DEA model. On the other hand among the 19 companies evaluated as 100% efficient by DEA, ten are less than 95% efficient and three are less than 90% efficient.

Overall, our comparison shows that the DEA model predicts perfect efficiency more often than SFA. This might be due to the fact this model has no restriction on the functional form, thus provides more flexibility to account for unobserved differences among companies.

On the other hand, such perfect efficiency scores might be due to the sensitivity of the DEA model to outlier values and/or to the 'curse of dimensionality', a general problem in non-parametric methods with a large number of variables.[15] Unfortunately, there is no simple method to identify the extent of such problems especially for individual companies.

Table 4. Efficiency ranking for the "best" and "worst" practices (1994)

Companies ordered according to SFA	DEA*	COLS
1	22	1
2	1-19	2
3	1-19	4
4	1-19	3
5	1-19	5
6	1-19	6
7	20	7
8	1-19	8
9	1-19	9
10	1-19	10
.	.	.
.	.	.
.	.	.
43	1-19	43
44	47	44
45	41	46
46	39	45
47	45	47
48	46	49
49	1-19	48
50	34	50
51	52	51
52	38	52

* According to DEA method 19 companies are 100% efficient.

The above example illustrates a main problem in benchmarking analysis, that is the discrepancy of the results across different methods. In some cases, the sensitivity of efficiency estimates is so high that a slight change in the model's assumptions or including an additional variable might change the results considerably. Given the extremely large variety

[15] See Simar and Wilson (2000) for a discussion of 'curse of dimensionality' and Simar (2003) for the outliers issue.

of models and specifications, this problem does not appear to have a clear solution. However, as our example suggests the sensitivity problems are less severe if the efficiency is estimated at the sector level rather than for individual companies.

5. CONCLUSION

With a frontier analysis of a cross-section of electricity distribution utilities, we illustrated the sensitivity problems of the benchmarking methods used in the regulation practice. Three commonly used methods have been applied to a sample of 52 electricity distribution utilities to estimate their cost efficiency. The results indicate that the efficiency estimates are significantly different across various models. This discrepancy appears to be high especially when the efficiency scores or ranks are considered for individual companies rather than the entire sector. We observed significant differences across models, in both efficiency ranks and scores. These differences are especially considerable between parametric methods and DEA approach. The results also suggest that the consistency conditions proposed by Bauer et al. (1998) are difficult to satisfy in the context of power distribution utilities.

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Appendix

Table A1. Cost frontier parameters- 1994

	OLS		**SFA**	
	Coeff.	Std. Err.	Coeff.	Std. Err.
ln*Y*	.845*	.052	.867*	.051
ln*CU*	.103	.053	.079	.054
ln*AS*	.048*	.013	.047*	.011
ln*LF*	-.213*	.127	-.210	.119
lnP_L	.145*	.034	.150*	.029
lnP_K	.171*	.029	.169*	.025
Constant	-3.053*	.675	-3.345*	.650
σ_u **(half-normal)**	-	-	.105	.042
σ_v **(normal)**	-	-	.056	.024
R^2	0.995	-	-	-

* significant at p=.05; The sample includes 52 companies.