BENCHMARKING AND REGULATION IN THE ELECTRICITY DISTRIBUTION SECTOR*

Mehdi Farsi Aurelio Fetz Massimo Filippini

Department of Management, Technology and Economics

ETH Zurich, Switzerland

Correspondence: Massimo Filippini, ZUE E15, Zürichbergstr. 18, 8032 Zurich, Switzerland

Phone: +41-1-632-0649, Fax: +41-1-632-1050, E-mail: mfilippini@ethz.ch

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ABSTRACT

In the last two decades electricity distribution sector have witnessed a wave of regulatory reforms aimed at improving efficiency through incentive regulation. Most of these regulation schemes use *benchmarking* namely measuring a company's efficiency and rewarding them accordingly. The reliability of efficiency estimates is crucial for an effective implementation of those incentive mechanisms. A main problem faced by the regulators is the choice among several legitimate benchmarking models that usually produce different results. After a brief overview of the benchmarking methodologies, this paper summarizes the methods used in the regulation practice in several OECD countries, in which the benchmarking practice is relatively widespread. Repeated observation of similar companies over time namely panel data, allows a better understanding of unobserved firm-specific factors and disentangling them from efficiency estimates. Focusing on parametric cost frontier models, this paper presents two alternative approaches that could be used to improve the reliability of benchmarking methods, and based on recent empirical evidence, draws some recommendations for regulatory practice in power distribution networks.

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 being 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- or performance-based schemes on the other hand, are designed to provide incentive for productive efficiency by compensating the company with part of its cost savings. A variety of methods have been proposed in the literature.[1] Main categories of incentive regulation systems used for electricity utilities are: price/revenue cap schemes, sliding-scale rate of return, partial cost adjustment, menu of contracts, and yardstick competition.[2] One of the most widely used methods in electricity networks is price cap regulation (RPI-X). This method sets the maximum rate of increase for the regulated prices equal to the inflation rate of retail prices index (RPI) minus a productivity growth offset referred to as X-factor.[3] The regulated companies can therefore increase (lose) their profits if they improve their productivity at a higher (lower) rate than the assigned X-factor.

For the definition of X-factor the regulators around the world have used several options. In the first option based on the original price-cap approach (cf. Beesley and

[1] See Joskow (2006) and Joskow and Schmalensee (1986) for a review of regulation models.
[2] Jamasb and Pollitt (2001) provide an extensive survey of different regulation practices in electricity markets around the world.
[3] In addition to inflation, the changes beyond companies' control may include changes in input factor prices and exogenous changes in demand and network characteristics generally referred to as Z-factors.

Littlechild, 1989; Brennan, 1989), X-factor is set equal to the annual expected or target growth rate of the total factor productivity (TFP) in the entire sector. This option has been employed mostly by the US regulators. In the second option used in relatively new regulatory regimes (mostly adopted by European regulators) X-factors are set equal to the annual target change in productive efficiency for each individual company. Therefore, the regulator can set differentiated price caps based on the companies' efficiency performance estimated from a benchmarking analysis. In the latter case, there is differentiation between the companies based on 'benchmarking' that is, measuring a company's productive efficiency against a reference performance.[4]

The increasing use of benchmarking analysis in electricity industry has raised serious concerns among regulators and companies regarding the reliability of efficiency estimates.[5] In fact the empirical evidence suggests that the estimates are sensitive to the adopted benchmarking approach.[6] This implies that the choice of the approach can have important effects on the financial situation of the companies.

There are however, alternative strategies that can be used to improve benchmarking methodology regarding the sensitivity issues and to provide the regulator with complementary tools. The purpose of this chapter is to explore some of these

[4] Both these alternatives have certain drawbacks. While the latter option does not account for the TFP growth, in the former case, there is a risk of inducing undesired incentive effects. Namely relatively inefficient companies can benefit much more than already efficient companies that cannot further improve their productivity. A third alternative would consist of decomposing the TFP growth into two components: one due to technical progress and the other related to the firm-specific efficiency improvements. The X-factor for each company is then taken as the sum of the first component (common for the entire sector) and the annual target change in the company's efficiency. This approach has the advantage that it tailors the price caps to individual companies' performance. For a discussion of this issue see Coelli et al. (2003).

[5] See Shuttleworth (2005) for a critical overview of the usage of benchmarking in regulation of electricity networks.

[6] See Jamasb and Pollit (2003) and Estache et al. (2004) for examples.

possibilities, discuss their effectiveness in the light of the recent empirical findings, and draw recommendations for regulatory practice.

The rest of the chapter proceeds as follows: Section 2 discusses the application of benchmarking in regulation practice with a focus on selected OECD countries. Section 3 provides a general picture of different benchmarking methods and their problems. The alternative methods using panel data are presented in Section 4. This section also uses an example to illustrate some of the advantages of panel data models. Section 5 concludes the paper with a final discussion and policy recommendations.

2. BENCHMARKING AND REGULATORY PRACTICE IN OECD COUNTRIES

The regulatory approaches show an important variation across countries. Table 1 provides a summary of current regulatory approaches and benchmarking practices for a selection of OECD countries.[7] This summary focuses mainly on countries that use the incentive regulation schemes in one way or another. The main systems used in practice are price/revenue cap regulation and Yardstick competition.[8] Moreover, several regulators use the results obtained from benchmarking analysis in the application of these regulation systems. The conventional rate-of-return (ROR) or cost-of-service regulation, while still being used in many countries,[9] is not considered in this review. It should be

[7] See Jamasb and Pollitt (2001) for a previous summary of benchmarking methods in a selection of countries. It is worth noting that in several countries the regulation practice has considerably changed since the publication of that paper.

[8] Yardstick competition is a regulation model proposed by Schleifer (1985). In his model the price of each local monopolist is regulated based on average costs of other identical firms producing the same homogeneous good.

[9] The use of ROR is still widespread even in Europe. According to Eurelectric (2004), Belgium, Denmark, Greece, Ireland, Portugal, Germany and Romania use ROR method.

noted however that in a few cases such as Finland and Sweden, the regulators combine the ROR method with other incentive regulation approaches. For instance, benchmarking analyses can be used to estimate a reasonable return rate. In this case the ROR is calculated on the costs of an average typical firm or a fully efficient firm and not on the reported company's own costs. This approach is in line with the yardstick competition model.

Generally, the regulation terms could be set before or after the regulation period. In *ex ante* regulation the companies' financial records in previous years are used to set the regulatory scheme namely price/revenue caps or budget limits at the beginning of the period. In *ex post* regulation on the other hand, the regulator examines the companies' expenditures and revenues during the regulation period and compensates them accordingly.[10] The *ex post* regulation allows a more flexible approach and therefore cannot provide as high-powered incentive mechanism as in *ex ante* regulation. The *ex post* regulation is practiced in a few countries such as Sweden and Finland. However, according to the new EU electricity directive approved in 2003, the *ex ante* regulation will become the norm throughout the European Union (Eurelectric, 2004).

[10] See Kinnunen (2005) for more details.

Table 1: Characteristics of regulatory practices in a selection of OECD [a] countries

Country	Regulation method	Approach	Explicit use of benchmarking	Benchmarking level	Benchmarking methods
Australia (New South Wales)	Revenue-cap until 2004, weighted average price cap from 2004	Ex ante	No	Individual	DEA, SFA, TFP
Chile	Special case of Yardstick	Ex ante	Yes	For 5 typical zones	Engineering economic analysis (efficient model company is defined)
Finland	Expenditure-cap and Rate of Return	Ex post	No	Generic [b]	DEA
Netherlands	Yardstick	Ex ante	Yes	Generic	DEA
Norway	Revenue-cap	Ex ante	Yes	Generic and individual	DEA
Sweden	Special case of Yardstick	Ex post	Yes	Individual	DEA, Performance assessment model (engineering analysis)
United Kingdom	Price-cap	Ex ante	Yes	Generic and individual	COLS, Bottom-up engineering analysis
United States (California)	Price-cap with earnings sharing	Various	No	Individual	TFP studies
United States (Maine)	Price-cap with earnings sharing	Various	No	Individual	TFP studies

[a] Except Chile: As one of the first countries that has de-regulated its electricity networks, Chile represents an interesting non-OECD case.
[b] Planning for the use of individual efficiency scores starting from 2008.

References: Jamasb and Pollitt (2001), **Australia**: IPART (2004), Irastorza (2003); **Chile**: Rudnick, Doloso (2000); **Finland**: Honkapuro et al. (2004), Energiamarkkinavirasto (2004); **Netherlands**: DTe (2005), Wals et al. (2003), Nillesen and Pollitt (2004); **Norway**: Ajodhia et al. (2003), Plaut (2002); **Sweden**: Viljainen et al. (2004), Sand and Nordgard (2004); **United Kingdom**: CEPA (2003), Irastorza (2003), Pollitt (2005); **USA**: CPUC (2000), MPUC (2005), Sappington et al. (2001).

As can be seen in Table 1, an important aspect of regulation is in the use of efficiency scores in the regulation schemes, such as X-factors in the price/revenue cap formula or the efficiency adjustment in yardstick rules. The efficiency scores can be considered as a generic value for all companies or as individual firm-specific values. While both approaches have been used in practice, there is a general tendency to use different scores for individual companies (Table 1). However, this practice which has become commonplace in a few countries like Norway (Ajodhia et al., 2003), has faced a court's objection in a lawsuit in Netherlands that consequently dismissed the method in favor of generic values (Riechmann, 2003).

In general, there exist two approaches concerning the use of benchmarking results. Regulators in many countries like Chile, Norway, UK and Netherlands use in a rather "mechanical" way the efficiency results as an explicit part of the regulation process. In other countries such as US, Australia and Finland the benchmarking analysis is used only as an additional instrument for regulatory decisions. As for measuring efficiency, the deterministic methods like DEA and COLS are most commonly used. There is a growing interest however, in using Stochastic Frontier Analysis as a complementary method.

3. BENCHMARKING METHODS

Benchmarking can be defined as a process of comparison of some measure of actual performance against a reference or benchmark. The performance of a company can be regarded in three main aspects: productivity, efficiency and quality. Efficiency and productivity are the most commonly used measure of performance in the electricity sector.[11] The focus of this paper is on productive efficiency in particular cost efficiency.[12] The

[11] See Giannakis et al. (2004) for a discussion on quality benchmarking.

[12] In addition to cost and technical efficiency, another source of inefficiency is related to deviations from optimal size, defined as the output level that minimizes the average costs (Chambers, 1988).

methods used for measuring efficiency are commonly referred to as frontier approaches.[13] A common measure of technical inefficiency is the distance, in the output space, to the production frontier. This measure does not include allocative inefficiency namely, the potential savings by reallocating input factors. Cost-inefficiency is an input-oriented measure overall inefficiency, which is defined as the distance from the cost frontier.[14] Each of the above-mentioned measures has their respective advantages and drawbacks. Estimating technical efficiency does not require any data on costs and prices, usually difficult to obtain, but it does not provide any information on cost minimization process, which is more appealing form an economic standpoint. The cost-inefficiency measure includes both allocative and technical inefficiencies but does not provide an easy way to separate these two components.[15] An advantage of the cost efficiency approach is that it treats the output as given, a realistic assumption in most regulated industries where the level of output is set by the regulator or determined by the demand factors.

The estimation of efficiency can be performed using a wide variety of models classified into to two main categories of parametric and non-parametric approaches.[16] Figure 1 presents a general classification of efficiency measurement methods. Non-parametric approaches such as Data Envelopment Analysis (DEA) and Free Disposal Hull (FDH) use linear programming to determine a company's efficiency frontier. In these approaches the cost frontier is considered as a deterministic function of the observed variables and no specific functional

[13] There exist alternative approaches like Engineering Economic Analysis and Process Benchmarking, which use a bottom-up methodology to calculate optimal costs and efficiency.

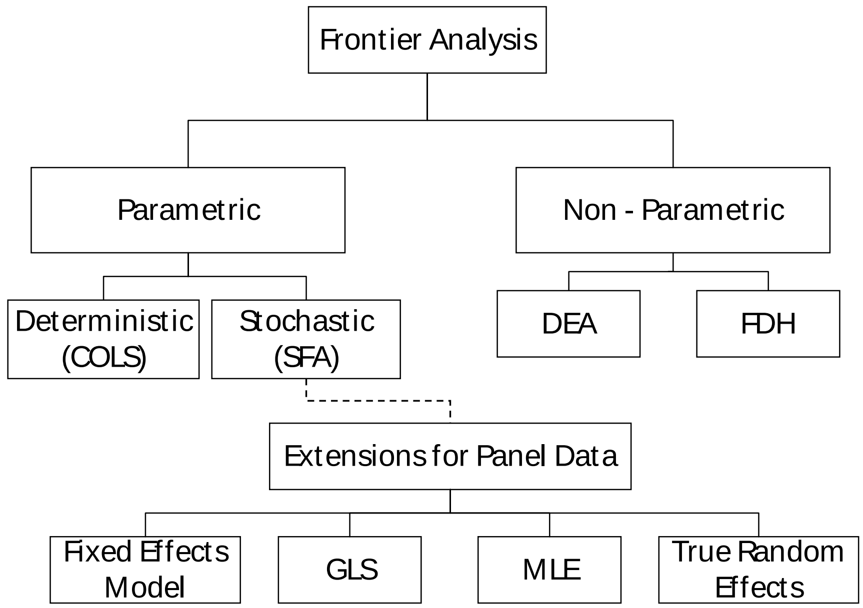
[14] Production frontier represents the maximum output produced by a given set of inputs, whereas cost frontier defines the minimum costs of producing an output level with given input prices.

[15] The only way to disentangle allocative and technical inefficiencies in a cost-frontier framework is through input factor demand equations. Because of the complexity of the resulting error structure, a satisfactory econometric solution remains to be developed (Kumbhakar and Lovell, 2000; Greene, 1997).

[16] See Murillo-Zamorano (2004) for a general presentation of different methodologies.

form is imposed.[17] Moreover, non-parametric approaches are generally easier to estimate and can be implemented on small datasets.

Figure 1. Efficiency measurement methods



A simple case of DEA, one of the most commonly used method in benchmarking, can be summarized as follows: 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:

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

where w_i and x_i are k×1 vectors respectively representing input prices and quantities for firm i (i= 1, 2, ..., N); y_i is an m×x1 vector representing the given output bundle; X and Y are

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

respectively input and output matrices namely, a $k \times N$ and a $m \times N$ matrix consisting of the observed input and output bundles for all the companies in the sample; **N** is an $N \times 1$ vector of ones; and λ is an $N \times 1$ 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*.

Another important group of frontier methods are parametric approaches, which assume a parametric form for the cost/production frontier. Apart from a few exceptions, all these methods have a stochastic element in their frontier function. Thus, this group of methods is also 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 the entire stochastic term is considered as inefficiency, the frontier remains deterministic.

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. In the stochastic frontier model the error term is divided into 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 random 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.[18] A basic 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: $Eff_i = \exp(u_i)$.

SFA models allow for a random unobserved heterogeneity among different firms (as represented by v_i) 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

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

inference on the effect 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.[19]

The complete analysis of the comparative advantages and drawbacks of the parametric and non-parametric approaches is beyond the scope of this study.[20] Although neither of the two approaches has emerged as a dominant method in the scientific community, the DEA method is the most commonly used approach in benchmarking practice in electricity industry. This can be explained by the relative simplicity of DEA models and the possibility of their implementation in a small data set. Stochastic frontier methods on the other hand require several choices, mainly on the functional form and distribution assumptions, which many practitioners might find difficult to explain.

It is important to note that even within each approach there exist several models that can be used and the choice of model is not usually straightforward. Several studies have reported discrepancies in efficiency estimates between different approaches and model specifications. For instance, using a cross section of 63 power distribution utilities in Europe, Jamasb and Pollit (2003) show that there are substantial variations in estimated efficiency scores and rank orders across different approaches (parametric and non-parametric) and among different econometric models. Similarly, using data from South America, Estache et al. (2004) provide evidence of "weak consistency" between parametric and non-parametric methods.[21] These results are supported by two other studies (Farsi and Filippini, 2004; 2005) that show that the efficiency ranking of the companies can differ significantly across econometric models and across different approaches. Such discrepancies are partly due to methodological sensitivity

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[19] 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.

[20] See Murillo-Zamorano (2004) and Coelli et al. (2003) for further discussion.

[21] 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.

in the estimation of individual efficiency scores and are not limited to a specific network industry.[22] The regulated companies operate in different regions with various environmental and network characteristics that are only partially observed. Given that the unobserved factors are considered differently in each method,[23] the resulting estimates could vary across methods. One can expect that the magnitude of variation depends on the importance of the unobserved factors, which might change from one case to another.

In most cases, there is no clear criterion for the choice of the model and approach. Thus, it is assumed that the results are valid if they are independently obtained from several models. For instance, Bauer et al. (1998) have proposed a series of criteria that can be used to evaluate if the efficiency estimates from different methods are mutually "consistent", that is, lead to comparable scores and ranks. However, the empirical results suggest that these criteria are not satisfied in many cases in network industries. The significant uncertainties in efficiency estimates could have important undesired consequences especially because in many cases the estimated efficiency scores are directly used to reward/punish individual companies through regulation schemes such as price-cap formulas.

Given the above problems, it is not surprising that the benchmarking models used in electricity networks have been frequently criticized.[24] In the next section, we discuss the ways that panel data can be used with parametric methods to overcome some of these shortcomings and provide more attractive instruments to use in regulation.[25] In particular, we focus on two possibilities: First, a better control for the firm- or network-specific unobserved heterogeneity, which is a source of discrepancy across different benchmarking methods; and

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[22] 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. The former paper shows that such problems persist in a panel data set with six periods.

[23] While the econometric approach uses additive stochastic terms, the linear programming method allows heterogeneity in production by relaxing the restrictions imposed by a specific functional form.

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

[25] Some of these alternative models have been used in a few recent studies (Alvarez et al., 2004; Greene, 2005; Farsi and Filippini, 2004; Farsi, Filippini and Greene, 2006).

secondly, the possibility of moving from point estimates for efficiencies to confidence intervals for predicted costs. Both improvements rely on repeated observations over several periods namely, panel data. The use of panel data models is especially interesting as data for several years have become available to an increasing number of regulators in many countries.

4. ALTERNATIVE APPROACHES USING PANEL DATA

The stochastic frontier literature provides a variety of panel data models. These models have been explained elsewhere.[26] There are several ways of classifying these models. Some of the main categories are given in Figure 1. Here, for the sake of our analysis we consider two groups that we label as "conventional" and "true" panel models. By conventional we refer to all the panel data models that deduce the efficiency estimates from the individual firm-specific effects, which can be fixed or random. These include original models like Pitt and Lee (1981) and Schmidt and Sickles (1984) that interpreted the individual effects as time-invariant (in)efficiency as well as the extensions like Cornwell, Schmidt and Sickles (1990) and Battese and Coelli (1992) that incorporate the variation of efficiency over time as a deterministic function that is similar across firms.[27] The main restriction of these models is that the unobserved factors are random over time and across firms, which implies that the unobserved network and environmental characteristics that are usually time-invariant are not considered as heterogeneity. Moreover, with a few recent exceptions such as Sickles (2005), the variation of efficiency over time is deterministic and/or follows a same functional form for all firms. Given that sources of inefficiency depend on technology shocks and other

[26] See Kumbhakar and Lovell (2000) for a survey of conventional models and Dorfman and Koop (2005) for an overview of recent developments. A brief discussion of a selection of models is also given in Farsi, Filippini and Kuenzle (2005).

[27] In the model proposed by Cornwell, Schmidt and Sickles the parameters of the time function can vary across firms. Recent developments such as Han et al. (2005) and Sickles (2005) consider more general temporal variation.

variations in the input markets and the managers' abilities to cope with them, it can be argued that inefficiencies are random over time.[28]

The "true" panel models extend the original stochastic frontier model (Aigner, Lovell and Schmidt, 1977) to panel data by adding an individual time-invariant effect. These models (Kumbhakar, 1991; Polachek and Yoon, 1996; and more recently Greene, 2005) include two stochastic terms for unobserved heterogeneity, one for the time-variant factors and one for the firm-specific constant characteristics. Assuming that network and environmental characteristics and their effects on production do not vary considerably over time and that the inefficiency is time-variant, these models help separate these unobserved effects from efficiency estimates.

To illustrate the differences between conventional and "true" panel models, here we summarize the results reported in Farsi, Filippini and Greene (2006). That paper applies three models to a panel of 59 Swiss electricity utilities to estimate a total cost function. The models include GLS (Schmidt and Sickles, 1984), MLE (Pitt and Lee, 1981), and the true random effects (TRE) model (Greene, 2005).[29] A descriptive summary of the efficiency estimates from different models and their correlation matrix are given in Table 2. As indicated in the table, while GLS and MLE models give similar results (12 to 15 percent excess costs), the TRE model predicts a much higher average efficiency rate, implying only about 4 percent excess in costs. The results also suggest a high correlation between GLS and MLE estimates whereas the TRE estimates show a weak correlation with the conventional models. 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 might overestimate the inefficiency. This conclusion is valid to the extent that inefficiencies do not

[28] Alvarez et al. (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 because it depends on a host of time-variant factors that have an interacting effect with the manager's skills.

remain constant over time and unobserved network effects remain constant.[30] However, one should bear in mind that these relatively new models can only give a partial solution to the sensitivity problems.

Table 2. Efficiency scores of Swiss distribution utilities (***Farsi, Filippini and Greene, 2006***)

	GLS	MLE	TRE
Average	.868	.887	.957
Minimum	.723	.735	.861
Maximum	1	.993	.996
Correlation Coefficients:			
with GLS	1	.970	.042
with MLE	.970	1	.055

When panel data is available, the regulators have also the possibility of using some panel data parametric methods for the prediction of intervals for companies' costs. The predicted intervals can consequently be used in the application of yardstick competition (Schleifer, 1985) among companies or to assess if the costs reported by the companies and used, for instance in ROR regulation, are reasonable. In these cases, the regulated companies are required to contain the costs within the interval imposed by the regulator, or have to justify any costs beyond the predicted range. A similar approach has been used in the water supply regulation in Italy.[31] Though in principle this approach is also possible in cross-sectional data, in panel data, the repeated observations of same companies are used to identify part of their unobserved time-invariant characteristics and adjust the predictions accordingly. As Farsi and Filippini (2004) show in an example, panel data frontier models allow a reasonably low prediction error.

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[29] The adopted specification of the cost frontier is a single-output Cobb-Douglas cost function with three input factors and several output characteristics such as load factor, number of customers and the service area size.

[30] If instead it is assumed that inefficiencies are persistent and do not change considerably over time, then the results obtained from conventional panel models provide better estimates of the inefficiencies. For a discussion of this issue see Farsi, Filippini and Greene (2006).

To this date the use of panel data parametric methods has been generally limited to academic research. However, as we have discussed above, these methods although being short of a perfect solution to all sensitivity problems, can provide the regulators with useful information. Given that in many cases panel data are increasingly available, the number of applications of these methods in regulatory practice should increase in the future.

5. CONCLUDING REMARKS

As efficiency has become a main concern in electricity networks, benchmarking analysis of the companies' inefficiency levels is increasingly used as an instrument to monitor the companies and induce cost-saving incentives. Benchmarking can be used in various forms in regulation schemes. For instance, the efficiency estimates of different firms can be used to adjust their X-factor in price cap regulation to differentiate maximum prices across companies.[32] Benchmarking can also be used to reduce the information disadvantage of the regulator regarding the companies' expenditures. For instance, parametric frontier methods can be used to predict costs in order to assess if the reported company's costs used in ROR regulation are "reasonable".

This paper's survey of different regulatory practices in a selected set of OECD countries shows that in many countries the regulators are moving toward a performance-based regulation system that uses the results of benchmarking analysis in one way or another. In some countries the regulators use these results in an explicit and rather "mechanical" way, while in others benchmarking results are used only as an additional instrument for regulatory decisions. .

[31] See Antonioli and Filippini (2001) for more details.
[32] See also Carrington et al. (2004) for an application in gas distribution networks.

As shown in several studies and laid out in this paper, the empirical evidence suggests that the results obtained from benchmarking analysis are sensitive to the adopted methods. In this paper, we discuss the ways that panel data can be used with specific parametric frontier models to overcome some of these shortcomings and provide more effective instruments to use in regulation. However, it should be noted that the individual efficiency estimates could remain sensitive to the assumptions regarding the adopted approach and model specification. The results reported in this paper also suggest that these panel data models can be used in an effective way to predict costs within an interval.

From this discussion and the empirical analysis available in previous studies, we can draw several implications for the regulators. First, the results obtained from benchmarking analysis on efficiency should not be used in a mechanical way in the implementation of price cap regulation. Rather, such results should be used as an additional instrument for regulatory decisions. Secondly, panel data parametric frontier models could be used to estimate confidence intervals for one-year-ahead costs. The predicted intervals can be then used to implement a yardstick regulation framework in line with Schleifer (1985), or as an alternative to judge if the costs reported by the companies and used, for instance in ROR regulation, are adequate. In this latter case predicted cost intervals could be used to reduce the regulator's information disadvantage in assessing reasonable costs for each firm.[33] We contend that this is the right role of benchmarking analysis in regulation. Third, any benchmarking analysis should be flexible and open to legitimate modifications for instance including additional variables and network characteristics requested by the companies. Therefore, the interaction between the regulator and companies and the possibility of iterative analysis are important factors that can improve the benchmarking practice in electricity networks.

[33] See Joskow (2006) for other applications of yardstick model for reducing information asymmetry.

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