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# BENCHMARKING ANALYSIS IN ELECTRICITY DISTRIBUTION

MASSIMO FILIPPINI, MEHDI FARSI, AURELIO FETZ

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# BENCHMARKING ANALYSIS

# IN ELECTRICITY DISTRIBUTION *


Massimo Filippini Mehdi Farsi Aurelio Fetz

Center for Energy Policy and Economics

Department of Management, Technology and Economics

Swiss Federal Institute of Technology

ETH Zentrum, WEC, 8092 Zurich, Switzerland

*Correspondence:* Prof. Massimo Filippini, CEPE, ETH Zentrum, CH-8092, Zurich, Switzerland

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



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**ABSTRACT**

As competition is introduced into electricity generation, incentive regulation of distribution utilities has become more common. Most of the regulation schemes used in practice are based on *benchmarking* that is, measuring a company's efficiency against a reference performance. In benchmarking applications the regulator is generally interested in obtaining a measure of firms' efficiency in order to reward (or punish) companies accordingly. The reliability of efficiency scores is therefore crucial for an effective implementation of the incentive mechanism. There are a wide variety of methods to measure efficiency. These methods can be classified into two main categories: non-parametric or linear programming methods such as data envelopment analysis, and parametric or econometric methods such as stochastic frontier analysis. A main problem faced by regulators is the choice of the benchmarking method (parametric and non-parametric) and within each method the choice among several legitimate models, especially as different models usually produce different results. Part of this discrepancy is related to the unobserved heterogeneity across firms namely those related to network characteristics and other external differences that are beyond the firm's control. In the context of parametric methods, panel data could be helpful to distinguish efficiency differences from unobserved heterogeneity. This paper studies how panel data models can be used for this purpose. After a brief overview of the different methods for estimating efficiency and the regulatory practice in Europe, several stochastic frontier models have been applied to a panel of 59 Swiss distribution utilities operating over a nine-year period. The estimated coefficients and inefficiency scores are compared across different specifications. This paper also discusses an alternative approach to conventional benchmarking that uses panel data models for predicting the expected costs rather than efficiencies. This method can be used as an alternative regulation instrument in order to narrow the information gap between the regulator and the regulated companies. Generally, the study concludes that benchmarking analysis should be used to support rather than to determine regulatory decisions, for instance the value of the price cap. With this respect, the use of econometric models to predict the expected costs appears to be an interesting instrument.

## 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-based schemes on the other hand, are designed to provide incentive for productive efficiency by compensating the company with its savings. A variety of methods have been 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 most of the models used in practice, are based on 'benchmarking' that is, measuring a company's productive efficiency, i.e. technical and cost efficiency, against a reference performance.

Since these companies operate in different regions with various environmental and network characteristics that are only partially observed, it is crucial for the regulator to distinguish between inefficiency and exogenous heterogeneity that influences the costs. Therefore, it is important that the benchmarking methods used by the regulators distinguish the cost difference due to unobserved heterogeneity in external factors from the excess costs due to the company's inefficiency. Moreover, the inefficiency estimates

[1] See Joskow and Schmalensee (1986) for a review of regulation models.

can have great financial consequences for the firms and therefore, their reliability is crucial for an effective regulation system. In particular, if the estimated inefficiency scores are sensitive to the benchmarking methods, a more detailed analysis to justify the adopted approach is required. Bauer et al. (1998) have proposed a series of criteria that can be used to evaluate if the results in terms of inefficiency level obtained from different approaches and models are mutually “consistent”, that is, lead to comparable inefficiency scores and ranks.

In the literature we can distinguish two principal types of approaches to measure efficiency – the *econometric (parametric) approach* and the *linear programming (non-parametric)* approach.[2] The empirical evidence in the electricity sector suggests that the results in term of efficiency are sensitive to the approach used. 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.[3] These results are supported by two other studies by Farsi and Filippini (2004, 2005). These authors using a data set on 59 power distribution utilities in Switzerland show that the efficiency ranking of the companies varies significantly across econometric models and across different approaches. Such discrepancies may suggest 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.

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

Both approaches – *econometric* and *linear programming* – have advocates and at least in the scientific community neither one has emerged as dominant. However, it has to be noted that the programming approaches such as DEA have became a popular methodology among electricity regulators. The purpose of this paper is not to stress the advantages and disadvantages of these two different approaches, but to present how some limitations of econometric frontier models can be overcome if panel data are available.[4] Especially, we are interested to analyze the ability of alternative panel data econometric frontier models to distinguish unobserved firm-specific heterogeneity from inefficiency.[5] Such models have proved a certain success in other applications such as public transportation networks in that they give more plausible efficiency estimates.[6] These results raise an important question as to whether (or to what extent) the sensitivity problems such as those reported by Jamasb and Pollitt (2003), Estache et al. (2004) and Farsi and Filippini (2004) can be solved by alternative cost frontier models that are better adapted to panel data. The number of empirical studies is still insufficient to provide a general answer to this question. However, it is clear that the alternative models can separate part of the unobserved heterogeneity from inefficiency estimates. This can be considered as an improvement over the benchmarking models commonly used in electricity networks, which have been frequently criticized.[7]

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[3] 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.

[4] In contrast with cross-sectional data, panels provide information on same companies over several periods.

[5] See for instance, Greene (2005, 2004), Alvarez, Arias and Greene (2003) and Tsionas (2002).

[6] See Farsi, Filippini and Kuenzle (2004) and Farsi, Filippini and Greene (2004) for applications in bus and railway transports respectively.

[7] For instance see Shuttlewoth (2003) and Irastorza (2003) for criticisms of benchmarking approaches in electricity industry.

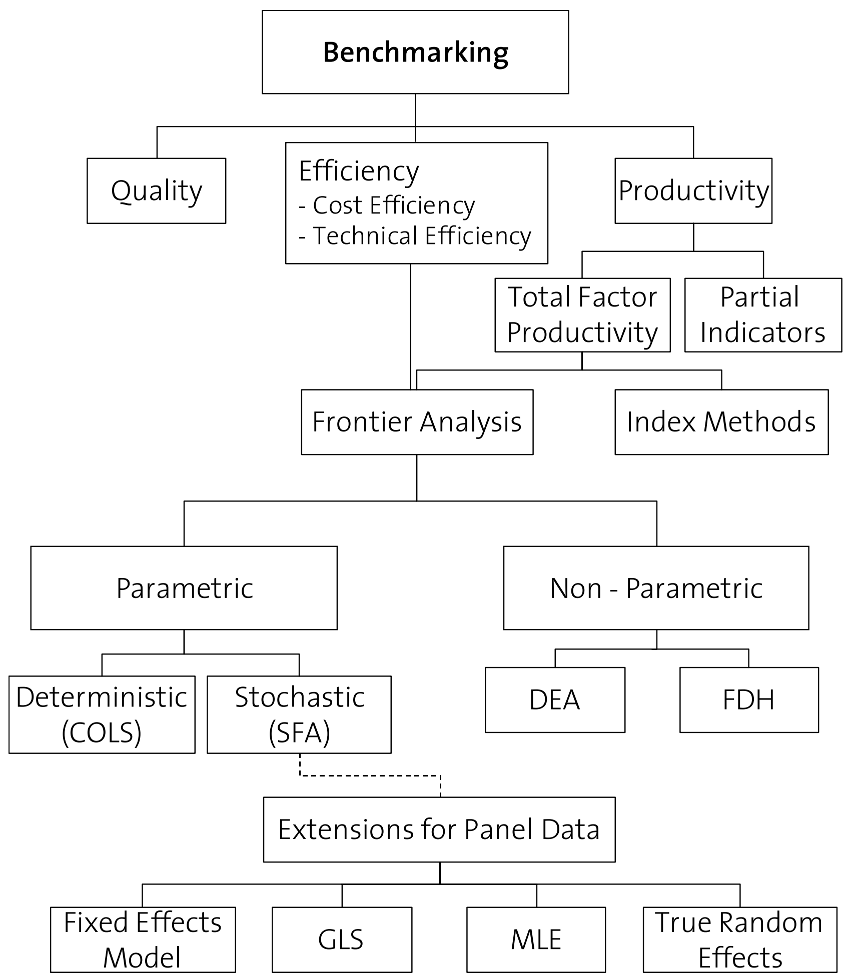
As shown by Farsi and Filippini (2004) another potential use of panel data models is in forecasting costs. The results reported by these authors suggest that the panel data models can predict individual companies' total costs with a rather reasonable precision. Therefore, the regulator could use these models to predict a confidence interval for the costs of each one of the firms. Acceptable intervals for revenue and price caps can be calculated accordingly. Using such predictions along with other monitoring instruments, the regulator can hold the companies within a reasonably well-predicted range of cost-efficiency.

The rest of the paper proceeds as follows: Section 2 provides a discussion of the concepts of cost and technical efficiencies. A general picture of alternative benchmarking methods and an overview of benchmarking practice in Europe is presented in Section 3. Section 4 discusses the application of stochastic frontier models in panel data. An example of cost efficiency estimation using panel data models is presented in Section 5. Section 6 concludes the paper.

## 2. BENCHMARKING: DIFFERENT APPROACHES AND THE EUROPEAN PRACTICE

Benchmarking can be defined as a process of comparison of some measure of actual performance against a reference or benchmark performance. Figure 1 illustrates a general classification of benchmarking types. The performance of a company can be regarded in three main aspects: efficiency, productivity and quality. Efficiency and productivity are the most commonly used measure of performance in electricity sector. Quality benchmarking is an important issue in the regulation but is not addressed in this paper.[8] The concept of productivity is equivalent to that of technical efficiency, thus can be considered as a special case of efficiency. However, the estimation methodology is different for productivity indexes. These indexes are subject of a great body of literature that has been developed independently of the efficiency literature.[9]

**Figure 1. Benchmarking**




[8] See Giannakis et al. (2004) for a discussion on quality benchmarking.
[9] See Coelli et al. (1998) for an introduction to this literature.

Productivity indexes are based on the ratios of measures of output to measures of input. These indexes can be classified into partial indexes and Total Factor Productivity (TFP) measures. Both measures are usually estimated as a relative difference over a given period of time resulting in measures of productivity growth. However, they can also be calculated as a relative difference compared to a benchmark company, measuring relative productivity. A summary of these methods is provided in Coelli et al. (2003) and C.E.P.A. (2003). Tornqvist and Malmquist indexes are the most commonly known TFP measures. The TFP measures can also be estimated using frontier analysis. In particular, the frontier methods can help decompose the TFP growth into separate components of scale-efficiency, technical efficiency and technological progress.[10]

The focus of this paper is on efficiency. Efficiency is mainly estimated using frontier methods.[11] Cost efficiency and technical efficiency are two main measures of a firm's performance. Overall inefficiency of a given company is the sum of these two inefficiencies.[12]

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

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[10] An example of such decomposition of the Malmquist index is given in Giannakis et al. (2004). See also Coelli et al. (2003, section 3) for decomposition of TFP growth using cost frontier analysis.

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

[12] Another source of inefficiency is related to the size of the production unit. The optimal size of a company can be defined as the output level that minimizes the average costs (cf. Chambers, 1988). Companies that operate at an output level lower than the optimal size can benefit from scale economies by increasing their output.

production unit is measured as its distance form a frontier (envelope) that is the locus of the optimal production plans. Such distances are measured by distance functions defined in the space of output(s) or input(s), resulting respectively in output-oriented and input-oriented measures of inefficiency.[13]

The methods used for measuring inefficiency are commonly referred to as frontier approaches. These methods can also be classified into two categories: cost frontiers which defines the minimum costs of producing a given output with given input prices and production frontiers that define the maximum output produced by a given set of inputs. A common measure of inefficiency is the distance, measured in the output space, to the production frontier. This measure only represents only the technical inefficiency and does not include allocative inefficiency. In fact as the inputs are given, the potential savings by reallocating inputs are not considered. Another common measure of inefficiency is the distance from the cost frontier, which directly measures the excess costs compared to an efficient production. This measure commonly referred to as cost inefficiency, can be considered as an input-oriented measure. Cost-inefficiency is a measure of overall inefficiency, which includes both technical and allocative inefficiencies. Each of the above-mentioned measures has their own advantages and problems. The first measure (technical inefficiency) does not require any financial data related to costs and prices, which might be difficult to obtain. However, this measure provides information only on the production technology and not on cost minimization process, which is more appealing form an economic point of view. The cost-inefficiency measure includes both allocative and technical inefficiencies but does not provide an easy way to separate these two

[13] See Kumbhakar and Lovell (2000) for an extensive discussion of inefficiency measures.

sources of inefficiency.[14] Moreover, it requires information about input factor prices. However, a main advantage of the cost efficiency approach is that it treats the output as given, an assumption that is more consistent with the decision making in a regulated firm. In most regulated industries, the level of output is set by the regulator or determined by the demand factors, which firms cannot influence.

***Efficiency measurement methods***

There are two principal types of approaches to measure efficiency – the *econometric (parametric) approaches* and the *linear programming (non-parametric) approaches*.[15] The econometric approaches require the specification of a production, cost, revenue, or profit function as well as assumptions about the error term(s). Depending on the approach, any deviation from the frontier is then attributed to inefficiency or to a combination of inefficiency and random error. These approaches can be classified into deterministic frontier method of Corrected (ordinary) Least Squares (COLS) and Stochastic Frontier Analysis (SFA). In the COLS method 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. In the 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. Therefore, in the SFA, the cost/production frontier varies across production

[14] The only way to disentangle allocative inefficiency from technical inefficiency in a cost-frontier framework is through additional input factor demand equations in a stochastic cost frontier model. Because of the complexity of the resulting error structure, a satisfactory econometric specification remains to be developed. See Kumbhakar and Lovell (2000) and Greene (1997) for a detailed discussion of this issue.
[15] See Murillo-Zamorano (2004) for a general presentation of the different methodologies.

units. This approach is due to Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977).

The primary advantages of the econometric approaches are as follows: a) allow for the separation of the inefficiency effect from the statistical noise due to data errors, omitted variables, random unobserved heterogeneity etc. b) allow statistical inference on the significance of the variables included in the model, using standard statistical tests.; c) environmental variables are easier to consider in the model specification; d) outliers are easier to identify; e) especially with panel data at hand, the unobserved heterogeneity can be better identified because the time-invariant elements of heterogeneity can be separately specified by firm-specific effects. On the other side, the econometric approaches suffer from the following drawbacks:  a) is vulnerable to errors in the specification of the functional form; b) the specification of the decomposition of the error term(s) is imposed a priori; c) the estimation of the econometric models requires large sample size, which may not be available.[16]

The non-parametric approaches such as Data Envelopment Analysis (DEA) and Free Disposal Hull (FDH) use linear programming to determine a company's efficiency frontier, which is assumed to be deterministic.[17] The primary advantages of the non-parametric approaches are as follows: a) no specific functional form is imposed; b) are generally easier to estimate and can be implemented on small datasets; c) are transparent methods and easily understandable. The main drawbacks: a) any departure from the frontier is measured as inefficiency, i.e., the method does not allow for stochastic factors, measurement errors and unobserved heterogeneity; b) as more variables are included in

[16] See Murillo-Zamorano (2004) for a discussion on advantages and disadvantages of the different methodologies

the model, the number of firms on the frontier increases; c) statistical inference requires elaborate and sensitive re-sampling methods like bootstrap techniques.[18]

DEA method is the most commonly used approach in practice. This can be explained by the simplicity of this method and the possibility to implement it with a small data set. Stochastic frontier methods on the other hand require several choices, mainly on the functional form and distribution assumptions, which both parties might find difficult to understand and communicate.

In panel data, when a company is observed over several periods, the SFA models have an additional flexibility in that they allow an account of unobserved firm-specific heterogeneity, such as environmental and network characteristics. We contend that a main source of discrepancy across different benchmarking approaches is related to the unobserved differences across companies. Therefore, controlling for such heterogeneity is critical for a reliable estimation of efficiencies. Panel data can be helpful to account for some of these, to the extent that they are constant over time. The use of panel data models is especially interesting as data for several years become available to an increasing number of regulators throughout Europe. The extensions of SFA approach for panel data will be discussed in the next section.

### *Benchmarking methods applied in European countries*

Jamasb and Pollitt (2001) provide an overview of the different benchmarking methods applied in OECD countries. The regulatory approaches show an important variation across countries. Table 1 shows an updated summary of the regulatory

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

approaches and benchmarking practices for a selection of European countries. This selection includes mainly those countries that use the incentive regulation schemes. The regulation methods can be classified into three main groups: rate of return (ROR) regulation, price/revenue cap regulation and Yardstick competition. All these methods have been practiced in Europe. Although it is still being used in many European countries, the ROR approach does not provide incentive for efficient production.[19]

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.[20] 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.[21]

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

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[18] 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.

[19] According to Eurelectric (2004), Belgium, Denmark, Finland, Sweden, Greece, Ireland, Portugal, Germany and Romania use ROR method. Some of these countries like Finland and Sweden combine the conventional ROR method with other incentive regulation approaches.

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

[21] See Eurelectric (2004) for more details. See also table 1 for more references about the regulation in Finland and Sweden.

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 (see table 1). This practice has faced a court's objection in a lawsuit in Netherlands (cf. DTe, 2003 and Riechmann, 2003), but has become commonplace in other countries like Norway (see Ajodhia et al., 2003).

In general, there exist two approaches concerning the use of benchmarking results. Regulators in many European countries like Norway, the UK and the Netherlands use the efficiency results as an explicit part of the regulation process. In a few other countries like Finland the benchmarking analysis is used as an additional instrument for regulatory decisions. As for methods 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.

## Table1: Characteristics of regulatory practices in a selection of European countries

| Country | Regulation method | Ex ante/ ex post | Benchmarking method | Variables | | Efficiency scores | Explicit use of benchmarking |
|---|---|---|---|---|---|---|---|
| | | | | Input | Output | | |
| **Finland** [a] | Expenditure -cap & Rate of Return | Ex post | DEA | Opex | Delivered energy<br># of customers<br>Network length<br>Interruption period | Generic | No |
| **Netherlands** | Yardstick | Ex ante | DEA | Opex and capex | Delivered energy<br># of small/ large customers<br>Peak demand low/ high voltage<br>Network length<br># of transformers | Generic and individual | Yes |
| **Norway** | Revenue-cap | Ex ante | DEA | Working hours<br>Network losses<br>Capital stock<br>Goods & Services | Delivered Energy<br># of customers<br>Network length | Generic and individual | Yes |
| **Sweden** [b] | Yardstick | Ex post | DEA<br>Performance assessment model (engineering analysis) | Opex<br>capex and Grid losses[b] | Delivered energy<br># of customers<br>Network length<br>Maximum power<br>Climate factor<br># of substations divided by total installed capacity | Individual | Yes |
| **United Kingdom** | Price-cap | Ex ante | COLS<br>Bottom-up Engineering Analysis | Opex | Composite variable (delivered energy, # of customers, network length) | Generic and individual | Yes |

[a] Planning for the use of individual efficiency scores starting from 2008.
[b] Several specifications are used for benchmarking.The included output and input variables vary across specifications.

References: **Finland**: Honkapuro et al. (2004), Energiamarkkinavirasto (2002, 2004); **Netherlands**: DTe (2000, 2002, 2003), 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**: C.E.P.A. (2003), Irastorza (2003), Giannakis, Jamasb and Pollitt (2004).

## 3. PANEL DATA AND STOCHASTIC FRONTIER MODELS

The first use of panel data models in stochastic frontier models goes back to Pitt and Lee (1981) who interpreted the panel data random effects as inefficiency rather than heterogeneity.[22] This tradition continued with Schmidt and Sickles (1984) who used a similar interpretation applied to a panel data model with fixed effects. Both models have been extensively used in the literature. A main shortcoming of these models is that any unobserved, time-invariant, firm-specific heterogeneity is considered as inefficiency. In more recent papers the random effects model has been extended to include time-variant inefficiency. Cornwell, Schmidt and Sickles (1990) and Battese and Coelli (1992) are two important contributions in this regard. In particular the former paper proposes a flexible function of time with parameters varying among firms. However, in both these models the variation of efficiency with time is considered as a deterministic function that is commonly defined for all firms. We contend that the time variation of inefficiency may be different across firms. Even within a given firm, these variations could depend on unobserved factors thus can be assumed as a stochastic term rather than a deterministic function of time.

As shown by Alvarez, Arias and Greene (2003), even in cases where inefficiency is due to time-invariant factors such as constant managers' capability, the resulting cost inefficiencies can vary over time. These authors assume that the management skills are one of the inputs that can interact with other time-variant input factors thus, create time-variant cost inefficiency. This result is consistent with the economic theory in that a firm's inefficiency is a dynamic phenomenon and cannot be constant. Firms constantly face new events and technologies, which they gradually learn how to deal with and apply. As the learning process

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

continues, inefficiency with regards to the existing technologies decrease but other new events and technologies appear. Therefore the overall inefficiency of a firm depends on not only the managers' efforts but on the effect of new technologies and events on the production process. Based on this argument, the inefficiency can best be modeled as a time-variant stochastic term. On the other hand a major part of the unobserved heterogeneity such as network and location-related factors can be considered as constant over time.

The discrepancy in efficiency estimates in conventional panel data models has been shown in Horrace and Schmidt (1996) and Farsi and Filippini (2004). A common feature of all these models is that they do not fully separate the sources of heterogeneity and inefficiency at the firm level. In fact, the time-variant error term in these models could include a major part of inefficiencies whereas the firm-specific effects that are interpreted as inefficiency could be mainly due to time-invariant heterogeneity.

An alternative approach is to consider an additional stochastic term for cost efficiency. Theoretically, a stochastic frontier model in its original form (Aigner, Lovell and Schmidt, 1977) can be extended to panel data models, by adding a fixed or random effect in the model. There are however few papers that have explored this possibility. The first development can be attributed to Kumbhakar (1991) who proposed a three-stage estimation procedure to solve the model with time- and firm-specific effects.[23] Polachek and Yoon (1996) attempted to estimate a panel data frontier model with firm dummies using a one-step procedure. Greene (2002a) discussed the numerical obstacles that have apparently delayed such a development.

As shown by Greene (2002a), assuming that the inefficiency term follows a distributional form, both models with random and fixed effects can be estimated using maximum likelihood estimation methods. These models are referred to as "true frontier

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

models” in that they are a straightforward extension of original frontier framework (in line with Aigner et al., 1977) to panel data. He proposed numerical solutions for both models, which he respectively refers to as ‘true’ fixed and random effects models (see also Greene, 2005). In particular, Greene’s true random effects model has proved useful in efficiency measurement of network industries (Farsi, Filippini and Greene, 2004).

## 4. AN APPLIACTION OF PANEL DATA MODELS

To illustrate the differences across models, we focus on three panel data models: GLS model in line with Schmidt and Sickles (1984), MLE model as in Pitt and Lee (1981), and the True Random Effects (TRE) model as proposed by Greene (2005, 2004). These methods have been applied to a panel of 59 Swiss distribution utilities.[24]

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.[25] 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.

[23] See also Heshmati and Kumbhakar (1994) and Kumbhakar and Hjalmarsson (1995) for two applications of this model. Note that in the latter paper, it is assumed that both time- and firm- specific effects are part of inefficiency.

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

[25] 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.

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.[26] However, this approach neglects the potential inefficiencies in the choice of the generator and also in the possibilities of substitution between capital and input energy. In this paper we use the first approach based on the total costs.

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

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

where $C$ represents total cost; $Y$ is the output in kWh; $P_K$, $P_L$ and $P_P$ are respectively the prices of capital, labor and input power; $LF$ is the 'load factor' defined as the ratio of utility's average load on its peak load; $CU$ is the number of customers; and $AS$ the size of the service area served by the distribution utility. $HGRID$ is a binary indicator to distinguish the utilities that operate a high-voltage transmission network in addition to their distribution network and $DOT$ is a dummy variable representing the utilities whose share of auxiliary revenues is more than 25 percent of total revenues.

The specification of the cost frontier used in this analysis is similar to the one used in the previous section. Here, we included two additional variables. A Cobb-Douglas functional form has been adopted. We excluded the flexible forms like translog to avoid the potential risk of multicollinearity among second order terms due to strong correlation between output characteristics. Moreover, given the purpose of this study, we want to use a simple

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

specification and avoid an excessive number of parameters required in the flexible functional forms.

After imposing the linear homogeneity in input prices the adopted cost function can be written as:

$$\ln\left(\frac{C}{P_P}\right)_{it} = \beta_0 + \beta_Y \ln Y_{it} + \beta_K \ln\left(\frac{P_K}{P_P}\right)_{it} + \beta_L \ln\left(\frac{P_L}{P_P}\right)_{it} + \gamma_1 \ln LF_{it}$$
$$+\gamma_2 \ln AS_{it} + \gamma_3 \ln CU_{it} + \delta_1 HGRID_{it} + \delta_2 DOT_{it} + r_{it} \qquad (2),$$
$$\text{with} \quad i = 1, 2, \ldots, N \ \text{ and } \ t = 1, 2, \ldots, T_i$$

This specification is similar to that used in Farsi and Filippini (2004) with the only difference that here we excluded two explanatory variables whose effects proved to be statistically insignificant.[27] Subscripts $i$ and $t$ denote the company and year respectively and $r_{it}$ is the stochastic term.

Quality of service usually measured by the number of interruptions is among the excluded variables. Given that in Switzerland, practically there has been no outage cases, we can assume that all the utilities operate at a sufficient level of quality reinforced by a tight regulation system. Therefore, we contend that the quality differences are not significant. Another excluded variable is the network length. In our model, this variable is proxied by the service area.

All the three models are based on the specification given in (2). The differences are in the specification of the residuals ($r_{it}$). This term is composed of two components, one of which ($\alpha_i$) being time-invariant (firm-specific) and the other ($\varepsilon_{it}$) varying across observations. Table 2 summarizes the econometric specification of the models used in this study. The table also provides the estimation procedure for the efficiency scores. These scores are relative

[27] The excluded variables are the linear trend and the dummy variable representing the forested areas.

efficiencies on a scale of 0 to 1 against the best practice. The conditional expectations are estimated using the procedure proposed by Jondrow et al. (1982).[28]

**Table 2. Econometric specifications of the stochastic cost frontier**

| $r_{it} = \alpha_i + \varepsilon_{it}$ | *Model I*<br>**GLS** | *Model II*<br>**MLE** | *Model III*<br>**True RE** |
|---|---|---|---|
| Firm-specific component $\alpha_i$ | $iid\ (0, \sigma_\alpha^2)$ | Half-normal<br>$N^+ (0, \sigma_\alpha^2)$ | $N (0, \sigma_\alpha^2)$ |
| Time-variant component $\varepsilon_{it}$ | $iid\ (0, \sigma_\varepsilon^2)$ | $N (0, \sigma_\varepsilon^2)$ | $\varepsilon_{it} = u_{it} + v_{it}$<br>$u_{it} \sim N^+ (0, \sigma_u^2)$<br>$v_{it} \sim N (0, \sigma_v^2)$ |
| Inefficiency | $\hat{\alpha}_i - \min\{\hat{\alpha}_i\}$ | $\mathrm{E}\left[u_i \middle| \hat{r}_{i1}, \hat{r}_{i2}, .., \hat{r}_{iT}\right]$ | $\mathrm{E}\left[u_{it} \middle| \hat{r}_{it}\right]$ |
| Relative efficiency (0-1) | $e^{-(\hat{\alpha}_i - \min\{\hat{\alpha}_i\})}$ | $\mathrm{E}\left[e^{-u_i} \middle| \hat{r}_{i1}, \hat{r}_{i2}, .., \hat{r}_{iT}\right]$ | $\mathrm{E}\left[e^{-u_{it}} \middle| \hat{r}_{it}\right]$ |

The data consist of an unbalanced panel of 59 Switzerland's distribution utilities over a 9-year period from 1988 to 1996. The sample includes 380 observations with a minimum of four observations per company. From about 900 power distribution companies in Switzerland, the companies included in the sample deliver about a third of Switzerland's electricity consumption, thus can be considered as representative of relatively large distribution utilities in the country.[29] The descriptive statistics are given in Table 3. All money values are converted to 1996 Swiss Francs using the global consumer price index.

The estimated parameters of the cost frontier are listed in Table 4. This table shows that almost all the coefficients are highly significant and have the expected signs. The results are more or less similar across different models. It should be noted that the three models are similar in the sense that they all have a firm-specific and a time-variant stochastic term, but

[28] See also Greene (2002b) and Battese and Coelli (1992).

differ in the distribution of these terms. Moreover, in all the models it is assumed that the firm-specific term is uncorrelated with the time-variant one.[30]

**Table 3. Descriptive statistics (380 observations)**

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

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

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

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

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

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

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

A descriptive summary of the efficiency estimates from different models is given in Table 5. The results indicate quite similar estimates for the GLS and MLE models, with a difference of about .02 in the median and average values. This can be explained by the fact that these models have a similar interpretation of inefficiency as a time-invariant factor. The True RE model predicts on the other hand, a much higher average efficiency rate. According to this model, the companies are on average 96% efficient. Noting that this model assumes a time-variant inefficiency term and a separate stochastic term for firm-specific unobserved heterogeneity, these results suggest that the other models overestimate the inefficiency. This conclusion is valid to the extent that inefficiencies do not remain constant over time.

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

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

The correlation coefficients between the efficiency estimates from different models are listed in Table 6. As expected these results indicate a high correlation between the GLS and MLE estimates. However, the True RE estimates are only weakly correlated with those of the two other models. The correlation between efficiency ranks shows a similar pattern, thus excluded from the paper. These results suggest that the assumption about the inefficiency term is crucial for the estimations. The assumption that inefficiencies are random over time is more realistic than considering constant inefficiency. In fact, the regulated firms cannot sustain a constant level of inefficiency for a long period of time. Not only are they presumably induced to improve their efficiency they constantly face new technological and organizational problems. On the other hand there are a host of parameters such as network characteristics and location related factors that remain more or less constant. Therefore, the assumptions of the True RE model appear to be more consistent with the real world. The results in Table 6 indicate that if the model does not separate unobserved heterogeneity from inefficiency, the efficiency estimates could be misleading.

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

| | **GLS** | **MLE** | **True RE** |
|---|---|---|---|
| **GLS** | 1 | .970 | .042 |
| **MLE** | .970 | 1 | .055 |

## 5. CONCLUSION

The results of frontier analyses of electricity utilities presented in the literature point to sensitivity problems in the benchmarking methods commonly used in the regulation practice. The discrepancy appears to be high when the efficiency scores or ranks are considered for individual companies, whereas the efficiency of the whole sector or large groups of utilities prove to be more or less robust. This general result applies to both parametric and non-parametric methods. A possible explanation of this inconsistency problem can be related to the difficulty of benchmarking models in accounting for unobserved heterogeneity in environmental and network characteristics across companies. Parametric panel data models could be helpful to solve at least partially this heterogeneity problem. In this paper we applied several stochastic frontier models to a panel of Swiss distribution utilities. Consistent with previous research, the results suggest that the panel data models cannot completely solve the problem. However, the alternative models like the 'true' random effect model (cf. Greene, 2005) can be helpful to disentangle unobserved heterogeneity from inefficiency estimates. This study along with the previous empirical literature suggests that the estimation errors for individual efficiency scores are rather high. Given these possible errors, the direct use of benchmarking results in regulation could have significant financial consequences for the companies. Therefore, the benchmarking results should not be directly applied to discriminate companies through different individual X-factors. Such differentiations require a complementary study of individual cases. However, the results can be used as an instrument to minimize the information asymmetry between the regulator and the regulated companies. For instance benchmarking can be used as a guide to classify the companies into several efficiency groups.

An interesting feature of parametric methods is that they can be used to predict the costs/revenues for each company within a confidence interval. Therefore, such methods can be employed to implement a yardstick regulation framework in line with Schleifer (1985). The prediction power of these models can be considerably improved by using panel data. For instance, Farsi and Filippini (2004) show that panel data models can have a reasonably low out-of-sample prediction error.[31]. This method could be used as an alternative to conventional use of benchmarking methods. In practice this regulation approach implies that the regulator predicts a confidence interval of the expected costs of a given utility accounting for its unobserved characteristics and considering a level of efficiency. The utilities are then required to justify any costs in excess of the predicted range.

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

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

## 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.

Ajodhia, V., K. Petrov and G. C. Scarsi (2003) 'Benchmark and its Application', Zeitschrift für Energiewirtschaft 27 (4): 261-274.

Alvarez, A., C. Arias, and W. H. Greene (2003) 'Fixed Management and Time-Invariant Technical Efficiency in a Random Coefficients Model', *Working Paper*, Department of Economics, Stern School of Business, New York University.

Antonioli, B., and M. Filippini (2001) 'The Use of a Variable Cost Function in the Regulation of the Italian Water Industry', *Utilities Policy*, 10 (3-4): 181-187.

Battese, G. E., and T. 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, P. W., A. N. Berger, G. D. Ferrier, and D. 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.

C. E. P. A. (2003) '*Background to work on assessing efficiency for the 2005 distribution price control review'*, Scoping study, Final report, Prepared for The UK Office of Gas and Electricity Markets (Ofgem), Cambridge Economic Policy Associates, available at: www.ofgem.gov.uk.

Chambers, R. G. (1988) '*Applied Production Analysis: A Dual Approach'*, Cambridge University Press.

Coelli, T., A. Estache, S. Perelman and L. Trujillo (2003) '*A Primer on Efficiency Measurement for Utilities and Transport Regulators'*, World Bank Institute Development studies, The World Bank, Washington DC.

Coelli, T., D. S. P. Rao, and G. E. Battese (1998) '*An Introduction to Efficiency and Productivity Analysis'*, Norwell, MA: Kluwer Academic Publishers.

DTe (2000) 'Guidelines for price cap regulation of the Dutch electricity sector in the period from 2000 to 2003'.

DTe (2002) 'Yardstick Competition – Regional Electricity Network Companies, Second Regulatory Period", Information and consultation document, 20 November 2002.

DTe (2003) 'New Price-cap for electricity grid managers'. Press release, available at: www.dte.nl.

Energiamarkkinavirasto (2002) 'Consideration of efficiency in the assessment of the reasonableness of electricity distribution pricing', Helsinki, available at: www.energiamarkkinavirasto.fi.

Energiamarkkinavirasto (2004) 'Guidelines for assessing reasonableness in pricing of electricity distribution network operations for 2005-2007', Helsinki, available at: www.energiamarkkinavirasto.fi.

Estache, A., M. A. Rossi and C. A. Ruzzier (2004) 'The case for international coordination of electricity regulation: evidence from the measurement of efficiency in South America', *Journal of Regulatory Economics*, 25 (3): 271-295.

Eurelectric (2004) '*Eurelectric report on Regulatory Models in a Liberalised European Electricity Market*', Brussels, Eurelectric.

Farsi, M. and M. Filippini (2004) 'Regulation and Measuring Cost Efficiency with Panel Data Models Application to Electricity Distribution Utilities', *Review of Industrial Organization*, 25 (1): 1-19.

Farsi, M. and M. Filippini (2005) 'A Benchmarking analysis of electricity distribution utilities in Switzerland', Mimeo, Centre for Energy Policy and Economics, Swiss Federal Institute of Technology, Zurich, Switzerland.

Farsi, M., M. Filippini and W. H. Greene (2004) 'Efficiency Measurement in Network Industries: Application to the Swiss railway Companies', *Working Paper* 32, Centre for Energy Policy and Economics, Swiss Federal Institute of Technology, Zurich, Switzerland.

Farsi, M., M. Filippini and M. Kuenzle (2004) 'Cost efficiency in regional bus companies: An application of new stochastic frontier models', *Working Paper* 33, Centre for Energy Policy and Economics, Swiss Federal Institute of Technology, Zurich, Switzerland.

Filippini, M., J. Wild, et al. (2001) 'Regulierung der Verteilnetzpreise zu Beginn der Marktöffnung', CEPE.

Giannakis, D., T. Jamasb and M. Pollitt (2004) 'Benchmarking and incentive regulation of quality of service: an application to the UK electricity distribution utilities', *Cambridge Working Papers in Economics 2004*.

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, W. H. (2005) 'Reconsidering Heterogeneity in Panel Data Estimators of the Stochastic Frontier Model', *Journal of Econometrics*, forthcoming.

Greene, W. H. (2004) 'Distinguishing between heterogeneity and inefficiency: Stochastic frontier analysis of the World Health Organization's panel data on national health care systems', *Health Economics*, 13: 959-980.

Greene, W. H. (2002a) 'Fixed and random effects in stochastic frontier models', Working paper, Stern School of Business, New York University (October 2002).

Greene, W. H. (2002b) ‘Alternative panel data estimators for stochastic frontier models’, Working paper, Stern School of Business, New York University (September 2002).

Greene, W. H. (1997) ‘Frontier Production Functions’ in *Handbook of Applied Econometrics, Vol. II: Microeconomics*, Editors: M. H. Pesaran and P. Schmidt, chapter 3, pp. 81-166.

Greene, W. H. (1980) ‘Maximum Likelihood Estimation of Econometric Frontier Functions’, *Journal of Econometrics*, 13: 27-56.

Heshmati, A. and S. C. Kumbhakar (1994) ‘Farm heterogeneity and technical efficiency: some results from Swedish dairy farms’, *Journal of Productivity Analysis*, 5 (1): 45-61.

Honkapuro, S., J. Lassila, et al. (2004) ‘Effects of benchmarking of electricity distribution companies in nordic countries - comparison between different benchmarking methods’. Nordic Distribution and Asset Management Conference.

Horrace, W. C., and P. Schmidt (1996) ‘Confidence Statements For Efficiency Estimates From Stochastic Frontier Models’, *Journal of Productivity Analysis*, 7: 257-282.

Irastorza, V. (2003) ‘Benchmarking for Distribution Utilities: A Problematic Approach to Defining Efficiency’, *The Electricity Journal*, 16 (10): 30-38.

Jamasb, T., and M. Pollitt (2003) ‘International Benchmarking and Regulation: An Application to European Electricity Distribution Utilities’, *Energy Policy*, 31 (2003): 1609-1622.

Jamasb, T., and M. Pollitt (2001) ‘Benchmarking and Regulation: International Electricity Experience’, *Utilities Policy*, 9 (3): 107-130.

Jensen, U. (2000) ‘Is it Efficient to Analyse Efficiency Rankings?’, *Empirical Economics*, 25, 189-208.

Joskow, P. J., and R. Schmalensee (1986) ‘Incentive Regulation for Electric Utilities’, *Yale Journal of Regulation*, 4 (1): 1-49.

Kinnunen, K. (2005) ‘Pricing of electricity distribution: an empirical efficiency study in Finland, Norway and Sweden’, *Utilities Policy*, 13 (1): 15-25.

Kumbhakar, S. C. (1991) ‘Estimation of technical inefficiency in panel data models with firm- and time-specific effects’, *Economics Letters*, 36 (1991): 43-48.

Kumbhakar, S. C. and L. Hjalmarsson (1995) ‘Estimation of technical inefficiency in panel data models with firm- and time-specific effects’, *Journal of Applied Econometrics*, 10: 33-47.

Kumbhakar, S. C., and C. A. K. Lovell (2000) ‘*Stochastic Frontier Analysis’*, Cambridge: Cambridge University Press.

Meeusen, W., and J. van den Broeck (1977)  ‘Efficiency Estimation From Cobb-Douglas Production Functions With Composed Error’, *International Economic Review*, 18 (2): 435-444.

Murillo-Zamorano, L. R. (2004)  ‘Economic Efficiency and Frontier Techniques’, *Journal of Economic Surveys,* 18 (1): 33-77.

Nillesen, P. H. L., and M. G. Pollitt (2004)  ‘The Consequences for Consumer Welfare of the 2001-2003 Electricity Distribution Price Review in the Netherlands’, *Cambridge Working Papers in Economics 2004*.

Pitt, M., and L. Lee (1981)  ‘The Measurement and Sources of Technical Inefficiency in Indonesian Weaving Industry’, *Journal of Development Economics*, 9: 43-64.

Polachek, S., and B. Yoon (1996)  ‘Panel estimates of a two-tiered earnings frontier’, *Journal of Applied Econometrics*, 11: 169-178.

Plaut (2002)  ’Norwegische Elektrizitätsmarktöffnung: Kostenrechnung- und Preisbildungsfragen der Netzgesellschaften’, Bern, Bundesamt für Energie (BFE).

Riechmann, C. (2003)  ’Regulierung von Energiemärkten - Aufsicht über Netztarife im internationalen Vergleich’, *e/m/w*, 4: 19-23.

Sand, K. and D. E. Nordgard (2004)  ‘Comparison of Nordic Benchmarking Methods’, Nordic Distribution and Asset Management Conference 2004.

Schleifer, A. (1985)  ‘A Theory of Yardstick Competition’, *Rand Journal of Economics,* 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. (2003)  ‘Detecting Outliers in Frontier Models: A simple approach’, *Journal of Productivity Analysis,* 20: 391-424.

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.

Simar, L., and P. W. Wilson (2000)  ‘Statistical Inference in Nonparametric Frontier Models: The State of the Art’, *Journal of Productivity Analysis*, 13, 49-78

Shuttleworth, G. (2003)  ‘Firm-Specific Productive Efficiency: A Response’, *The Electricity Journal*, 16 (3), 42-50.

Street, A. (2003) 'How Much Confidence Should We Place in Efficiency Estimates?', *Health Economics*, 12 (11): 895-907.

Tsionas, E. G. (2002) 'Stochastic Frontier Models With Random Coefficients', *Journal of Applied Econometrics*, 17, 127-147.

Viljainen, S., K. Tahavanainen, et al. (2004) 'Regulation of electricity distribution business', Nordic Distribution and Asset Management Conference 2004.

Wals, A. F., E. Cross, and E. J. W. van Sambeek (2003) 'Review of current electricity policy and regulation', Energy research Centre of the Netherlands (ECN).