Centre for Energy Policy and Economics
Swiss Federal Institutes of Technology

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CEPE Working Paper Nr. 39
July 2005

Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich
École Polytechnique Fédérale de Lausanne
Paul Scherrer Institut

CEPE
ETH Zurich
Zürichbergstrasse 18 (ZUE E)
CH-8032 Zürich
www.cepe.ethz.ch

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

Mehdi Farsi[†] Massimo Filippini[†] William Greene[‡]

[†] Department of Management, Technology and Economics
Swiss Federal Institute of Technology
Zürichbergstr. 18, CH-8032 Zurich, Switzerland
and
Department of Economics, University of Lugano
Via Maderno 24, 6900 Lugano, Switzerland

[‡] Department of Economics, Stern School of Business
New York University
44 West 4th St., New York, NY 10012, USA
[†] Center for Energy Policy and Economics

June 2005

Correspondence: Massimo Filippini, CEPE, ETH, Zürichbergstr. 18, CH-8032, Zurich, Switzerland

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

* The authors are grateful to the Swiss Federal Office for Education and Science for their financial support. They also wish to thank Aurelio Fetz for his assistance.

ABSTRACT

This paper explores the application of several panel data models in measuring productive efficiency of the electricity distribution sector. Stochastic Frontier Analysis has been used to estimate the cost-efficiency of 59 distribution utilities operating over a nine-year period in Switzerland. The estimated coefficients and inefficiency scores are compared across three different panel data models. The results indicate that individual efficiency estimates are sensitive to the econometric specification of unobserved firm-specific heterogeneity. When these factors are considered as a separate stochastic term, the efficiency estimates are substantially higher indicating that conventional models could confound efficiency differences with other unobserved variations among companies. The results suggest that alternative panel models such as the “true” random effects model proposed by Greene (2005) could be used to evaluate the possible impacts of unobserved factors such as network effects on efficiency estimates.

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/or cost efficiency, against a reference performance.[2]

There exist a variety of methods for efficiency measurement.[3] As pointed out in Jamasb and Pollit (2003), Estache et al. (2004) and Farsi and Filippini (2005), different methods could lead to significantly different individual efficiency estimates.[4] This problem is

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

[2] Other measures of performance such as quality and productivity are not considered here.This paper focuses on productive (in)efficiency, which can be decomposed into technical and allocative (in)efficiencies (cf. Kumbhakar and Lovell, 2000). Another source of inefficiency is related to the size (scale) of the production unit (cf. Chambers, 1988). However, scale inefficiency is usually beyond the firm's control, thus generally not considered in benchmarking.

[3] See Kumbhakar and Lovell (2000) and Coelli et al. (1998) for extensive discussion of these methods.

[4] Jamasb and Pollit (2003) report substantial variations in estimated efficiency scores and rank orders across different approaches (parametric and non-parametric) and among different econometric models applied to a cross sectional sample of European power distribution utilities. Similar results are reported by Farsi and Filippini (2004, 2005) in a sample from Switzerland. Estache et al. (2004) provide more or less similar discrepancies between parametric and non-parametric methods applied to a sample of power distributors from South America. Other authors like Horrace and Schmidt (1996), Street (2003) and Jensen (2000) reported substantial errors and

especially important for in most cases, there is no clearly defined criterion for choosing a unique method among several legitimate models. Moreover, the inefficiency estimates 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. For instance, 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. However, in many cases because of a considerable discrepancy, these criteria are not satisfied. This can be considered as an improvement over the benchmarking models commonly used in electricity networks, which have been frequently criticized.[5]

In the literature we can distinguish two main approaches to measure efficiency – the econometric (parametric) approach and the linear programming (non-parametric) method.[6] Although the latter category, particularly Data Envelopment Analysis, has become popular among electricity regulators, both approaches have advocates in the scientific community. The purpose of this paper is not to stress the advantages and disadvantages of these two different approaches, but to present how some limitations of frontier models can be overcome if panel data are available.[7] This paper focuses on econometric methods as they can be relatively easily adapted to panel data. Productive efficiency can also be estimated using production or cost frontiers. In this paper we focus on the latter category that can be readily used to estimate cost-efficiency.

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inconsistency problems in the estimation of individual efficiency scores in cross sectional data from other industries.

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

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

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

As opposed to cross-sectional data, panels provide information on same companies over several periods. Repeated observation of the same company over time allows an estimation of unobserved firm-specific factors, which might affect costs but are not under the firm's control. Individual companies operate in different regions with various environmental and network characteristics that are only partially observed, it is crucial for the regulator to distinguish between inefficiency and such exogenous heterogeneity. Several recently developed models such as Greene (2005, 2004), Alvarez, Arias and Greene (2004) and Tsionas (2002) have addressed this issue using alternative panel data models. Some of these models have proved a certain success in other applications such as public transportation networks in that they give more plausible efficiency estimates.[8] These results raise an important question as to whether (or to what extent) the sensitivity problems can be solved by using panel data and the adapted frontier models. This question is especially important in the electricity sector, in which the application of benchmarking has been frequently criticized based on reliability of efficiency estimates.[9] Moreover, given that in many countries the regulatory reforms have been in effect for several years, an increasing number of regulators have access to panel data. However, the number of empirical studies is still insufficient to provide a general answer to this question. This paper studies the performance of an alternative panel data econometric frontier model to distinguish unobserved firm-specific heterogeneity from inefficiency in the context of electricity distribution networks.

The results of this paper suggest that the alternative panel data models can separate part of the unobserved heterogeneity from inefficiency estimates, thus can be considered as a promising complement to other regulatory instruments such as cost prediction (as proposed in Farsi and Filippini, 2004) and case-by-case analyses. The rest of the paper proceeds as

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

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

follows: Section 2 discusses the application of stochastic frontier models in panel data. The model specification and the adopted econometric methods are described in Section 3. Following a brief description of the data, the estimation results are presented and discussed in Section 4. And Section 5 summarizes the main conclusions.

2. PANEL DATA AND STOCHASTIC FRONTIER MODELS

The first use of panel data models in stochastic frontier models goes back to Pitt and Lee (1981) who interpreted the panel data random effects as inefficiency rather than heterogeneity.[10] 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

[10] 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

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 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.[11] Polachek and Yoon (1996) attempted to

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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.

[11] 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.

estimate a panel data frontier model with firm dummies using a one-step procedure. Greene (2002a) discussed the numerical obstacles that have apparently delayed such a development.

As shown by Greene (2002a), assuming that the inefficiency term follows a distributional form, both models with random and fixed effects can be estimated using maximum likelihood estimation methods. These models are referred to as “true frontier models” in that they are a 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, 2005).

3. MODEL SPECIFICATION

To illustrate the differences across models, we focus on three panel data models: GLS model in line with Schmidt and Sickles (1984), MLE model as in Pitt and Lee (1981), and the True Random Effects (TRE) model as proposed by Greene (2005, 2004). These methods have been applied to a panel of 59 Swiss distribution utilities.[12] 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.[13] 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

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

[13] 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.

firm's employees. For those companies that produce part of their power the average price of input electricity is assumed to be equal to the price of purchased power.

The costs of distribution utilities consist of two main parts: the costs of the purchased power and the network costs including labor and capital costs. There are therefore two alternatives for measuring cost efficiency in power distribution utilities: total costs approach and network costs approach. The network costs approach has a practical advantage in that the estimated average costs can be directly used in a price-cap formula.[14] 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:

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

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

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

characteristics. Moreover, given the purpose of this study, we want to use a simple 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.[15] 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 (α_i) being time-invariant (firm-specific) and the other (ε_{it}) varying across observations. Table 2 summarizes the econometric specification of the models used in this study. The table also provides the estimation procedure for the efficiency scores. These scores are relative

[15] 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).[16]

Table 2. Econometric specifications of the stochastic cost frontier

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

4. DATA AND ESTIMATION RESULTS

The data consist of an unbalanced panel of 59 Switzerland's distribution utilities over a 9-year period from 1988 to 1996. The sample includes 380 observations with a minimum of four observations per company. From about 900 power distribution companies in Switzerland, the companies included in the sample deliver about a third of Switzerland's electricity consumption, thus can be considered as representative of relatively large distribution utilities in the country.[17] The descriptive statistics are given in Table 3.

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

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

Table 3. Descriptive statistics (380 observations)

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

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

The estimated parameters of the cost frontier are listed in Table 4. This table shows that almost all the coefficients are highly significant and have the expected signs. The results are more or less similar across different models. It should be noted that the three models are similar in the sense that they all have a firm-specific and a time-variant stochastic term, but differ in the distribution of these terms. Moreover, in all the models it is assumed that the firm-specific term is uncorrelated with the time-variant one.[18]

[18] 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
lnCU	.150*	.033	.145*	.048	.185*	.004
lnAS	.052*	.009	.046*	.014	.056*	.001
lnLF	-.234*	.038	-.211*	.022	-.155*	.007
lnP_L	.044*	.013	.044*	.014	.033*	.003
lnP_K	.173*	.009	.166*	.005	.164*	.002
HGRID	.074*	.026	.108*	.047	.066*	.003
DOT	.049*	.021	.033	.032	.032*	.002
Constant	-.854*	.360	-.870*	.355	-.345*	.058
σ_α	-	-	-	-	.083*	.001
σ_u (half-normal)	-	-	.146*	.022	.063*	.001
σ_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 distribution utilities presented in the literature point to sensitivity problems in the benchmarking methods commonly used in the regulation practice. The discrepancy appears to be high when the efficiency scores or ranks are considered for individual companies, whereas the efficiency of the whole sector or large groups of utilities prove to be more or less robust. This general result applies to both parametric and non-parametric methods. A possible explanation of this inconsistency problem can be related to the difficulty of benchmarking models in accounting for unobserved heterogeneity in environmental and network characteristics across companies. Parametric panel data models could be helpful to 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.[19]. 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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