The Case for International Coordination of Electricity Regulation: Evidence from the Measurement of Efficiency in South America*

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ABSTRACT

A decade long experience shows that the monitoring of the performance of public and private monopolies in South America is proving to be the hard part of the reform. The operators control most of the specific information needed for regulatory purposes and have little interest in volunteering their dissemination unless they have an incentive to do so. This paper argues that, in spite of, and maybe because of, a much weaker information base and governance structure, Latin America's electricity sector could rely on an approach that relies on performance rankings based on comparative efficiency measures. The paper shows that with the rather modest data currently available publicly, such an approach could already yield useful results. It provides estimates of efficiency levels in South America's main distribution companies between 1994 and 2000. Moreover, it illustrates how relatively simple tests can be used by regulators to check the robustness of their results and strengthen their position at regulatory hearings.

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INTRODUCTION

Following the process initiated by Chile about 20 years ago, many South American countries have transformed their electricity sector. The changes started with a restructuring to increase competition *in* and *for* the markets. They entailed an unbundling of electricity generation, transmission and distribution and resulted in generally competitive generation markets but maintained monopolies for transmission and distribution which were generally auctioned to private operators. Whenever possible, reformers also broke up horizontally the former national distribution companies into several regional monopolies to reduce the strength of the residual monopolies. In most countries, these changes were associated with the creation of new regulatory agencies responsible for the monitoring of the performance of the residual public and private monopolies.

A decade long experience shows that this monitoring is proving to be the hard part of the reform. The private operators control most of the specific information needed for regulatory purposes and have little interest in volunteering their dissemination unless they have an incentive to do so. Most of the regulators have tried to mandate the publication of information. Many have also relied on public audiences to promote public debates of relevant information. The results of these approaches to reducing the information asymmetry between regulators and operators have been mixed at best.[1]

This paper argues that in spite of, and maybe because of, a much weaker information base and governance structure, Latin America's electricity sector could, thanks to a much more effective cross-country coordination, reduce the information asymmetry by relying on performance rankings based on comparative efficiency measures, as achieved with some success by various regulators in England and recently by the Dutch electricity regulator. While never spelled out quite in the specific terms adopted here, what the approach essentially achieves is a shift of the burden of proof for justification of bad performance from the regulator to the operators by relying on competition between markets more systematically.[2] The authorized levels of recoverable costs or the performance levels recognized by the regulators to assess the share of efficiency gains to be passed on to consumers can be estimated from best practice benchmarks obtained by comparing performance across markets. Unless the operators can prove with the appropriate information that their performance is sub-par for specific reasons they will have to comply with the regulatory assessment of their performance based on the approaches suggested here.

Coordination is needed because this benchmarking approach to regulation, which further promotes competition *between markets*, requires the best possible assessments of cost or production frontiers across countries and this in turn requires a minimum of coordination in terms of the definition and measurement of the indicators to be used in the process. As large as possible a number of operators must be monitored over 3-4 years at least to maximize the quality of the data available.

The paper shows that with the rather modest data currently available publicly, such an approach could already yield useful results. It provides estimates of efficiency levels in South

[1] A theoretical approach to this regulatory problem, in terms of principal-agent games, can be found in Bogetoft (1997), where the selection of a efficiency measurement procedure appears as the Nash equilibrium of a regulatory game.

[2] This approach has also been advocated for the Mexican Port sector by Estache, Gonzalez and Trujillo (2002), for instance, and more generally in Coelli, Estache, Perelman and Trujillo (2002).

America's main distribution companies between 1994 and 2000. Moreover, it illustrates how relatively simple tests can be used by regulators to check the robustness of their results and strengthen their position at regulatory hearings. This is important since efficiency estimates used by regulators to shift the burden of proof on the operators are likely to be contested routinely by unhappy operators. The quality of the regulatory assessments should be such that improvements in efficiency measures would only come from additional information provided by the operators trying to make their case rather than from improvements in the use of the existing information.

The paper is organized as follows. Section 1 specifies the model which could be used by coordinated regulators and argues for a production function rather than a cost function. Section 2 discusses the data currently available to test the chosen model and presents the main characteristics of the 39 distribution companies covered by the data sample. Section 3 covers the various estimation procedures among which to pick. Section 4 explains the test used to check the robustness of the results and discusses the various levels of confidence with which the regulators can argue their case. In particular, this section makes the case for at least a mild form of international yardstick competition between electricity distribution companies in South America. Section 5 concludes.

1. THE SPECIFICATION OF THE MODEL

The main challenge for any regulator is to make the most of the information available. This basic, quite obvious, observation has already been internalized by most applied economists working on efficiency measures for electricity companies. This means that pragmatism will often rule over strict theory. While the theory would argue for a detailed structural model accounting for all possible factors, pragmatism implies that the best one can hope to achieve in practice is to estimate a single equation production function.

The estimation of a cost function (a valid alternative[3]) involves an assumption about firms' behavior, namely profit maximization. However, whenever there is public ownership, the firms, in general, will not seek profit maximization as their main goal. As Pestieau and Tulkens (1990) argue, public enterprises do not share the same objectives and constraints as their private counterparts, so their relative performance should only be compared on the basis of a production relationship which serves as a common ground. Moreover, the estimation of cost frontiers involves the utilization of variables measured in monetary units, which could be a serious problem if one wishes to make international comparisons. Production functions, instead, only require variables measured in physical units (i.e. homogeneous among countries –or at least much more homogeneous). Given that we are estimating an international frontier and that the sample includes private and public firms as well, we choose to estimate a production function.

Having decided upon the relationship to be estimated, we still have to make a decision over the variables that should be included in the analysis. What are the outputs of the industry? What are the inputs? Are there variables beyond the firms' control?

The first issue is to decide which output to focus on. According to Neuberg (1977), both number of customers served and total energy sold qualify as potential outputs in this sector. In order to decide between them, some regulatory insights must be taken into account. In particular, it is important to note that energy delivered to final customers is not really exogenous, especially in non-regulated public utilities. That is, the utility is not always compelled to provide its customers with whatever quantities they desire at given prices. Number of customers, on the other hand, cannot be controlled by utilities since in general everybody has the right to be connected to the local distributor. Therefore, energy delivered is a better output measure for the production function specification.

[3] Just to name to two most common relationships that are estimated.

The next challenge is identifying the inputs. The number of employees is the standard labor input and is easily obtained. As for the capital inputs, the options are more complex. Transformer capacity is widely accepted as a required variable. However, kilometers of distribution lines, which measures the amount of capital in the form of network, can be misleading since it can reflect geographical dispersion of consumers rather than differences in productive efficiency (Kumbhakar and Hjalmarsson, 1998). Therefore, in a study of relative efficiency differences, network capital can either be treated as an output or as input but only after controlling for geographical dispersion. In this paper we adopt the second position and hence correct appropriately by accounting for consumer density.

Regarding the environmental variables (variables beyond the firms' control) to be included in the model[4], service area is unambiguously an exogenous operating characteristic of the firm's environment. As we argue above, the number of customers served and their distribution is also exogenous, so we include not only service area as a control variable, but also customer density. The idea is that customer density should capture the effect of demographic features, in the sense that higher values of this variable can be expected to enable a firm to deliver more output per unit of input. For similar reasons, we need to measure the effect of delivering energy at different voltages required by different customers, and therefore we include the proportion of total energy delivered that is distributed to residential customers as an additional operating characteristic. Finally, the variable GNP per capita is included to control for differences in the socio-economic environment in which firms operate in each country.

[4] Introducing environmental variables in the production function specification assumes that these variables affect technology rather than computed efficiency scores, and generates net efficiency measures. See the discussion in Section 3.

The particular choice of variables made here follows the general consensus found in the current literature. We review this literature in the Appendix. Although comparison of some alternative modeling could yield additional insights, we believe that the model chosen is reasonably general in terms of the current literature and that the motivation for the choice of variables is rather convincing.

In many cases there are good reasons why some firms do not follow an efficient pattern, but once the regulators have done this initial sorting out, the burden of proof should be on the regulated companies. That is to say, the initial model used as a yardstick is not so determinant, since the firms can impugn the proposed model until every part (firms and regulators) agree about the final model –involving themselves in a "learning by doing" iterative process in which both firms and regulators learn while playing the game (see Burns and Estache (1998), Rossi and Ruzzier, (2000), Coelli, Estache, Perelman and Trijillo (2002)).

Following the discussion above and the availability of data, the initial model for the production function will be:

Initial Model

Output:	*Inputs:*	*Environmental variables:*
1. Total sales	1. Number of employees	1. Service area
	2. Distribution network	2. Customer density
	3. Transformer capacity	3. Demand structure
		4. GNP per capita

The final model will be obtained after testing the statistical significance of the environmental variables. The idea is that a frontier model has two parts: the "core" of the model and the environmental variables (Rossi and Ruzzier, 2000). In a production function approach the (theoretically determined) core is formed by the inputs, whereas the set of environmental variables includes those factors that might influence the firms' performance and are not directly controllable by them. The initial specification for the core of the model is subject to theoretical considerations. Environmental variables, on the other hand, are not theoretically determined and will only be included in the final model if they are statistically and economically significant.

2. THE DATABASE

The sample accounts for 39 electricity distribution companies (23 private, 16 public) spread over 10 countries. It is representative of the sector in the region and covers: Argentina (8 firms, including the two largest firms in terms of number of customers), Bolivia (2), Brazil (2), Chile (2), Colombia (2), Ecuador (4), Paraguay (1), Peru (12), Uruguay (1) and Venezuela (5), for the period 1994-2000. The only missing countries are the Guyana, French Guyana and Suriname. The Brazilian sector is probably underrepresented since we only have data on two firms, including the second largest one. Some details are provided in Table 1.

Table 1: Firms, Countries and Ownership

Country	**Number of firms covered by the sample**
Argentina	5 private, 3 public
Bolivia	1 private, 1 public
Brazil	2 public
Chile	2 private
Colombia	2 public
Ecuador	3 private, 1 public
Paraguay	1 public
Peru	8 private, 4 public
Uruguay	1 public
Venezuela	4 private, 1 public

Firm data was collected from several sources. Data for the period 1994-1999 was mostly compiled from CIER (Comisión de Integración Eléctrica Regional – Regional Electric Integration Commission) reports, “Datos Estadísticos. Empresas Eléctricas. Año 1994”, “Datos Estadísticos. Empresas Eléctricas. Años 1995-1996-1997”, “Información Económica y Técnica de Empresas Eléctricas. Datos 1998-1999”. Data for Peru was partly compiled from CTE (commission in charge of energy tariffs), and data for Argentina in the year 2000 was partly provided by ADEERA (an association of distribution companies). For the most recent data, we relied directly on firms. When possible, the data was cross-checked and completed using firms’ balance sheets (or firms’ web pages), and information provided by regulators and governmental agencies.

When a particular piece of information was missing, in order not to lose the entire observation, some algorithm was used to fill the gap. After eliminating utilities for which data quality was insufficient, we obtained an unbalanced panel with 194 observations from the 39 firms in the period 1994-2000. We only included in our panel firms for which we had at least three consecutive observations.

The following variables are going to be used in the estimations: sales (in GWh, calculated as total sales minus sales to other electric companies, in order to isolate the distribution activity in the case of integrated firms), number of employees (in vertical integrated firms we use only employees in the distribution activity, as informed by the firms), total distribution lines (in kilometers), total transformer capacity (in kVA), service area (in square kilometers), residential sales’ share (a proxy for demand structure), customer density in the service area (in customers per square kilometer), and GNP per capita (in purchasing power parity units, PPP).

The PPP estimates of GNP per capita for the period 1994-1998 were obtained from the World Development Reports 1996-2000. We used PPP figures in order to correct for international differences in relative prices (for details, see World Development Reports technical notes). The figures for the years 1999 and 2000 were calculated using the World Development Indicators database from the World Bank. The summary statistics are presented in Table 2. In all cases the sample size is equal to 194 observations.

Table 2: Summary Statistics

Variable	Sample Mean	Sample Standard Deviation	Minimum	Maximum
Sales (in GWh)	3566	6944	31	37777
Distribution Lines (in km)	21103	55404	443	316997
Number of Employees	1518	2541	26	12239
Transformer Capacity (in kVA)	1440	2207	16	9986
Service Area (in km^2)	77878	159682	59	823700
Customer Density (in customers per km^2)	117	203	0.31	677
Residential Sales / Sales (in %)	42	9	17	63
GNP per capita (in PPP units)	6568	2590	2400	13091

3. THE ESTIMATION PROCEDURES

To provide a full assessment of the potential value of the information available, we cover as wide a spectrum of approaches regulators could adopt with the data available as possible. We present both econometric and Data Envelopment Analysis (DEA) estimates to assess the efficiency performance of South America's electricity distribution companies. More specifically, we test two parametric models, a stochastic frontier estimated by Maximum Likelihood (ML) and a random effects model estimated by Feasible Generalized Least Squares (FGLS), and two non-parametric DEA (one with variable returns to scale and another with constant returns to scale).

3.1. The econometric models

We define the general stochastic frontier production function model by

$$\ln Y_{it} = f(X_{it}, t; b) + e_{it},$$

where Y_{it} denotes output, X_{it} is a matrix of inputs, t represents time, b are technological parameters to be estimated, and f is some appropriate functional form. The error term is

$e_{it} = v_{it} - u_{it}$, where v_{it} are assumed independent and identically distributed random errors which have normal distribution with mean zero and unknown variance, s_n^2, and u_{it} are non-negative random variables which represent technical inefficiency. The Battese and Coelli (1992) representation $(u_{it} = \exp[-h\ (t-T)]u_i)$ is used for the technical inefficiency term.

The time term is included to account for technical change. Representing technical change by including a time term in the production frontier may seem relatively innocuous but it is in fact a very strong assumption and is not always realistic. Many innovations and developments that one would like to subsume under the rubric of technical change are not consistent with this formulation, which assumes that technical change does not require new inputs and further that the production frontier maintains the same basic form as time elapses. However, as many authors point out, including a time term in production frontiers may not be perfect, but it is a workable alternative with some definitive advantages (i.e., analytical and econometric tractability) over some other approaches.[5]

The translogarithmic (or translog) and the Cobb-Douglas production functions are the two most common functional forms which have been used in empirical studies on production, including frontier analyses. The translog is a flexible function, since it is a second-order Taylor approximation (in logarithms) to any smooth, continuous function. The Cobb-Douglas production frontier is a special case of the translog in which the coefficients of the second order terms are zero.

[5] Different null hypothesis associated with technical change are analyzed in Rossi (2002). The results show that non neutral technical change models or models with quadratic time trend do not differ significantly from the more parsimonious model present here. Therefore, in our preferred model we include only a linear time trend.

In this paper the most general functional form for the stochastic frontier for electricity distribution in South America is a translog production function:

$$\ln Y_{it} = b_0 + X_{1it} b_1 + X_{2it} b_2 + X_{3it} b_3 + X_{1it}^2 b_{11} + X_{2it}^2 b_{22} + X_{3it}^2 b_{33} + X_{1it} X_{2it} b_{12} + X_{1it} X_{3it} b_{13} + X_{2it} X_{3it} b_{23} + t b_t + n_{it} - u_i \tag{1}$$

where Y indicates sales, X_1 is the natural logarithm of the number of permanent employees, X_2 is the natural logarithm of distribution network, and X_3 is the natural logarithm of transformer capacity.

The production function above does not include environmental variables. Coelli, Perelman and Romano (1999) suggest that the literature offers two alternative approaches to their inclusion. One assumes that the environmental factors influence the shape of the technology and hence that these factors should be included directly into the production functions as regressors, while the other assumes that they directly influence the degree of technical inefficiency. In this study we adopt the position of including them as regressors in order to get efficiency measures that are net of environmental influences. As pointed out by Coelli, Perelman and Romano (1999), measuring net efficiency is an important issue as it allows one to predict how companies would be ranked if they were able to operate in equivalent environments.

Therefore, the most general function to be estimated is as in equation (1) but including four additional environmental variables:

$$\ln Y_{it} = b_0 + X_{1it} b_1 + X_{2it} b_2 + X_{3it} b_3 + X_{1it}^2 b_{11} + X_{2it}^2 b_{22} + X_{3it}^2 b_{33} + X_{1it} X_{2it} b_{12} + X_{1it} X_{3it} b_{13} + X_{2it} X_{3it} b_{23} + t b_t + A_1 b_{A1} + A_2 b_{A2} + A_3 b_{A3} + A_4 b_{A4} + n_{it} - u_i$$

where A_1 is the natural logarithm of demand structure, A_2 is the natural logarithm of customer density, A_3 is the natural logarithm of service area, A_4 and is the natural logarithm of GNP per capita.

As it is now usual in this literature, we use the parameterization proposed by Battese and Corra (1977), which uses $\gamma = \sigma_u^2 / \left(\sigma_\nu^2 + \sigma_u^2 \right)$. The program FRONTIER 4.1, developed by T. Coelli (1996), is used for the estimations.

In this paper we take advantage of the great flexibility of this model and we test the half-normal distribution hypothesis vis a vis the more general truncated normal distribution $(H_0 : \mu = 0)$, and we also contrast the hypothesis that the efficiency is time invariant $(H_0 : \eta = 0)$. Finally, we test the null hypothesis that there are no technical inefficiency effects in the model; $H_0 : \gamma = 0$. As suggested by Coelli (1996), these alternative models are estimated and the preferred models are selected using a Likelihood Ratio (LR) test. This test is based on the Log Likelihood functions as follows:

$$LR = -2[L_R - L_U],$$

where L_R is the Log Likelihood of the restricted model and L_U is the Log Likelihood of the unrestricted model. Asymptotically, the LR statistic has a chi-square distribution with degrees of freedom equal to the number of restrictions involved.[6]

The ML estimates of the parameters in the unrestricted translog stochastic frontier production function (called Model 1) are shown in Table 4. Formal tests of hypothesis associated to Model 1 are given in Table 3. The first null hypothesis, $H_0 : \beta_{11} = \beta_{22} = \beta_{33} = \beta_{12} = \beta_{13} = \beta_{23} = 0$, that the Cobb-Douglas is an adequate representation of the technology is rejected by the data. The second hypothesis, $H_0 : \gamma = 0$, which

[6] It must be noted that in the case where the null includes the restriction that $\gamma = 0$ (a point on the boundary of the parameter space), the likelihood ratio statistics will have asymptotic distribution equal to a mixture of chi-square distributions $\frac{1}{2}\chi_0^2 + \frac{1}{2}\chi_1^2$ (Coelli 1993, Lee 1993).

specifies that firms are fully efficient is strongly rejected. The null that the inefficiency has a half-normal distribution, $H_0 : m = 0$, cannot be rejected by the data, and therefore in our preferred model we work assuming a half-normal distribution for the inefficiency terms. The null hypothesis that the technical inefficiency is time invariant, $H_0 : h = 0$, cannot be rejected. Finally we test the significance of the environmental variables. The null hypothesis $H_0 : b_{A1} = b_{A2} = b_{A3} = b_{A4} = 0$ is strongly rejected by the data, suggesting that environmental variables cannot be omitted in the estimation of production frontiers in this kind of sector. A fact which would probably argued for by most operators.

Table 3: Likelihood Ratio Tests

Null Hypothesis	Log Likelihood	$c^2_{0.99}$ value	Test statistic*
Given Model 1	**167.00**		
$H_0 : b_{11} = b_{22} = b_{33} = b_{12} = b_{13} = b_{23} = 0$	155.79	12.59	22.41*
$H_0 : g = 0$	17.40	6.25	299.21*
$H_0 : m = 0$	166.66	3.84	0.67
$H_0 : h = 0$	166.98	3.84	0.03
$H_0 : b_{A1} = b_{A2} = b_{A3} = b_{A4} = 0$	117.27	9.49	99.46*

*An asterisk on the value of the test statistic indicates that it exceeds the 99th percentile for the corresponding c^2 distribution and so the null hypothesis is rejected.

The above tests suggest that the preferred model (we call it Model 1P) is a translog stochastic production function with neutral technical change and time-invariant inefficiency, which is assumed distributed as a half-normal. The production function includes demand structure, customer density, service area and GNP per capita as environmental variables.

Since we cannot reject the hypothesis of constant technical efficiency, we can run Model 1P as a random effects model (we call it Model 1G). The ML estimates of the unrestricted model (Model 1) and the preferred model (Model 1P), and FGLS estimates of the preferred model (Model 1G) are shown in Table 4.

Table 4: Econometric Results

Variable	Model 1	Standard Errors	Model 1P	Standard Errors	Model 1G	Standard Errors
Constant	-4.861	1.393	-5.914	1.205	-5.223	1.550
Ln Employee	-0.386	0.219	-0.388	0.211	-0.346	0.240
Ln Net	0.328	0.288	0.171	0.269	0.210	0.323
Ln Capacity	0.162	0.230	0.357	0.220	0.179	0.265
(ln Employee)^2	0.029	0.025	0.043	0.023	0.014	0.026
(ln Net)^2	-0.012	0.022	0.001	0.023	-0.011	0.026
(ln Capacity)^2	0.156	0.030	0.156	0.032	0.145	0.032
Ln Employee × ln Net	0.095	0.034	0.091	0.031	0.102	0.039
Ln Employee × ln Capacity	-0.129	0.047	-0.146	0.047	-0.118	0.054
Ln Net × ln Capacity	-0.108	0.036	-0.120	0.035	-0.102	0.039
Ln Demand Structure	-0.517	0.061	-0.511	0.060	-0.536	0.064
Ln Customer Density	0.725	0.091	0.763	0.065	0.781	0.082
Ln Service Area	0.695	0.086	0.726	0.059	0.744	0.086
Ln GNP per capita	0.105	0.091	0.180	0.072	0.057	0.092
Time	0.016	0.009	0.013	0.005	0.014	0.005
g	0.982	0.013	0.987	0.005		
m	0.495	0.157				
h	-0.003	0.013				
Average Efficiency	0.578		0.657		0.564	

Since the coefficients of the translog production functions do not have any direct interpretation, we calculate the elasticities of output with respect to each of the inputs corresponding to models above

$$EL_k = \frac{\partial Y_{it}}{\partial X_k} = b_k + 2b_{kk} X_{kit} + \sum_{j \neq k} b_{kj} X_{jit}\ ,\ k = 1,2,3;\ j = 1,2,3.$$

In general, returns to scale is calculated from the sum of the input elasticities as

$$RTS = \sum_k EL_k\ .$$

However, it is sometimes noted that when the model includes environmental variables related to scale (such as service area), the scale elasticity is given by the proportionate effect on production of changes in the input variables and these environmental variables. The main point is that changing the scale of a firm would involve changing not only the inputs but also all of these characteristics (Burns and Weyman-Jones, 1994). Given customer density, demand structure and the socio-economic conditions, returns to scale should be defined as relating the change in output to a change in all inputs and service area. That is,

$$RTS = \sum_k EL_k + b_{A3}.$$

The following table shows input elasticities, service area elasticity and returns to scale for both preferred models, Model 1P and Model 1G. Input elasticities are calculated at the sample means values (the Taylor series expansion points).

Table 5: Elasticities and Returns to Scale

	Elasticity with respect to				
Model	Employees	KM of network	Transformer Capacity	Service Area	Returns to scale
Model 1P	0.08	-0.01	0.36	0.73	1.15*
Model 1G	0.02	-0.01	0.40	0.74	1.16*

*Reject the null of constant returns to scale at a 5% level.

Elasticities with respect to service area and transformer capacity are positive and quite comparable across models. However, we cannot reject the null that labor and network elasticity are equal to zero in both models. As expected, in both models returns to scale are significantly greater than one.

The estimated coefficients of the environmental variables have the expected signs. The negative influence of demand structure implies that firms with a lower proportion of residential customers benefit from a more favorable environment and hence perform better when no attempt is made to take into account this advantage. Customer density has a positive effect on output, which means that as the number of customers per square kilometer rises (ceteris paribus), energy delivered will consequently go up. Service area has also a positive sign, since given customer density it is playing an input role. Finally, the positive coefficient of GNP per capita suggests that firms operating in countries with high GNP per capita benefit from a more favorable socio-economic environment.

The annual rate of technical change is 1.3 percent in Model 1P and 1.4 percent in Model 1G. Finally, average efficiency is around 66 percent in Model 1P, and around 56 percent in Model 1G. These results suggest that there is scope for efficiency improving for the average firm in the sample.

3.2. The DEA estimates

In order to allow for the comparison of the results, we used the same model as in the last section to perform the nonparametric estimation, i.e. we have a model with only one output (total sales), three inputs (labor, km of distribution lines and transformer capacity), and four environmental variables (service area, customer density in the service area, a proxy for demand structure and GNP per capita). The orientation chosen is to the proportional augmentation in output achievable by a firm while maintaining the level of inputs, for this is consistent with the interpretation of the econometric results.

There exist basically two alternative assumptions about the returns to scale: constant returns to scale (DEA-C) and variable returns to scale (DEA-V). The theoretical specification of the DEA-C model consists in an optimization problem subject to constraints, like the following:

$$\max \; l$$

$$s.to \quad l u \leq zU, zX \leq x, zE \leq e, z \in R_{+}^{n}.$$

This problem gives as a solution the proportion (l) in which the observed outputs of the firm being analyzed could be expanded if the firm were efficient. U is a $n*r$ matrix of outputs of the firms in the sample (n denoting the number of firms and r the number of outputs). X is a $n*m$ matrix of inputs of the sample firms (m indexing considered inputs). E is a $n*s$ matrix containing all the information about s environmental variables of the n firms. u, x and e are the observed output, input and environmental variables vectors, respectively, of the firm under evaluation.

Finally, z is a vector of intensity parameters (z_1, z_2, ..., z_n) that allows for the convex combination of the observed inputs and outputs (in order to build the envelopment surface).

To obtain the second model, DEA-V, it suffices to add the following constraint to the above problem (Seiford and Thrall, 1990):

$$\sum_{i=1}^{n} z_i = 1.$$

Though model DEA-V would be a desirable choice, since it does not restrict returns to scale to be constant (hypothesis rejected in the econometric setting), we nevertheless compute also model DEA-C, given that quite often in the case of models with variable returns to scale the smallest and low-productive units (in terms of partial productivities) show up as fully efficient just because they lack comparators. We chose to model environmental variables as non-discretionary inputs (see Coelli, Prasada Rao and Battese, 1998). In this fashion, each firm is only evaluated against a hypothetical firm which has an environment (which cannot be altered by the firm) that is not better than that of the firm under evaluation. As a drawback, this modeling choice implies an a priori judgment on the direction of influence of each environmental variable upon efficiency. This judgment was made on the basis of the econometric results shown in Table 4.[7]

Since we have panel data, several possibilities arise within the context of DEA. One of them is to compute a frontier for each period (seven cross-section analyses) and to compare these cross-sectional runs. In this way, one constructs a frontier in each year and calculate the efficiency of each firm relative to the frontier in each period. Another possibility is to treat the panel as a single cross-section (each firm in each period being considered as an independent

[7] Since one variable (demand structure) has a negative impact on production, we inverted it prior to inclusion, instead of treating the variable as a non-discretionary "output". See Coelli, Prasada Rao and Battese (1998).

observation), pooling the observations altogether. Under this approach, a single frontier is computed, and the relative efficiency of each firm in each period is calculated by reference to this single frontier. An intermediate alternative would be the window analysis approach proposed by Charnes et al. (1985).[8] The choice of width for the windows poses an additional complication, since it is entirely ad hoc, and "currently determined by trial and error" (Charnes et al., 1994, p.60). In this study, we try treating the panel as a single cross-section under two different assumptions concerning returns to scale –variable (Model DEA-V) and constant (Model DEA-C), and calculate averages of the efficiency scores of each firm.[9]

4. CONSISTENCY OF THE RESULTS

To ensure comparability between the various approaches, the four techniques used the same efficiency concept (technical efficiency), the same sample of firms (unbalanced panel of 39 firms for the period 1994-2000, 194 observations), equal specifications of inputs (employees, kilometers of distribution lines and transformer capacity), environmental variables (service area, customer density, demand structure and GNP per capita) and output (total sales).

Section 3 made it clear that the main problem faced by regulators willing to apply frontier studies is the variety of options at hand. The problem is particularly serious if the different approaches give mutually inconsistent results. In an attempt to establish the conditions under which frontier methodologies are most useful to regulatory authorities, Bauer et al. (1998) propose a set of consistency conditions which, if met, would avoid the choice between

[8] The first two possibilities can be thought of as special cases of the window analysis: in the first case, window width is equal to 1, and in the second, it is equal to the total number of periods.

[9] We programmed the optimization problem in GAMS Version 1.0.4, and used the MINOS5 solver for the computations.

approaches. The efficiency measures generated by the different techniques should show internal and external consistency; they should (i) be consistent in their efficiency levels, rankings and identification of the best and the worst performers, and (ii) be consistent over time.

Broadly speaking, the first conditions determine the degree to which the different approaches are mutually consistent (internal consistency), whereas the remaining condition establishes the degree to which the different efficiency measures are consistent with reality (external consistency). The first conditions say if the different approaches will give the same answers to the regulators, while the last condition says if it is likely that these answers are correct.

To see what this means in practice, we focus on its implication in the context of price cap regulation. The main purpose of a switch from rate of return regulation to price cap regulation has been to increase the incentive for firms to minimize their costs and to ensure that eventually users will benefit from these reductions in costs—typically within 3-5 years after a regulatory review. The adoption of price cap regulation is one of the main reasons for this increase in the efforts to measure efficiency in regulated sectors. Indeed the observed cost reductions would be associated with efficiency gains, which have to be measured. Efficiency measures are no longer a sideshow as they were under rate of return regulation.

The initial regulatory challenge at the time of a price review is the following. If the productivity gain used to assess the new price cap is specific to the firm and based on gains achieved by this firm in the past, this firm will not have strong incentives to improve efficiency to cut costs because this would result in a lower price cap. An alternative for the regulator would be to measure efficiency gains by relying on factors that are not under the control of the regulated firm. But in that situation, if the regulator has very little knowledge of the past costs of the firm and bases its measure of efficiency gain on, for instance, the productivity gains in a related sector in the economy, some perverse effects may penalize the firm. This is why the suggestion to rely on yardstick competition should be so tempting for regulators. Price can be set for an industry based on the aggregate industry performance. For instance, the price cap can be based on the average unit cost in the industry rather than on the firm specific average unit cost and this gives a strong incentive to the firm to have a unit cost below average. In this context, efficiency measures are inputs in the regulatory mechanism in an even more direct way than under rate of return regulation.

If a firm has an efficiency index of 0.8 for instance, it means that it could produce the same level of output at 80% of its current costs (cost function approach) or produce the same level of output using an 80% of its current inputs (production function approach). This means that the cap should be based on 80% of current cost, not 100%. With this approach, only the firms reaching 100% of efficiency would be allowed to recover their opportunity cost of capital while the others would have lower rates of return.

The implementation of such a mechanism, however, requires that at the minimum the first consistency condition is met (consistency in efficiency levels). If this is not met, this mechanism should not be applied since the individual efficiency measures would be somewhat subjective and hence unreliable. Table 6 presents the main characteristics of the distributions generated by the four methodologies tested.

The Kruskal-Wallis (nonparametric) test was carried out to contrast the null hypothesis that the four techniques generate the same distribution of efficiency scores, and we do reject the null at a level of significance of 1%.[10] That is, this consistency condition is not met. This result is not particular to our sample, but rather general in the applied literature, and it could help in

[10] We used EViews Version 3.0 to perform the test.

explaining why regulators tend not to translate efficiency measures one-for-one into X factors or expected cost reductions.

Table 6: Comparison of the Distributions of Efficiency Measures Across Methods

Approach	**ML**	**FGLS**	**DEA-V**	**DEA-C**
Mean	0.657	0.564	0.966	0.873
Median	0.659	0.567	0.998	0.929
Deviation	0.194	0.195	0.080	0.153
Maximum	0.978	1.000	1.000	1.000
Minimum	0.327	0.258	0.594	0.490
Sample	39	39	39	39

If the levels of efficiency are not consistent across the different methods of frontier estimation, it is still possible that these methods generate similar rankings of firms by their efficiency scores. Identifying the ranking would help to discriminate the X factor among the firms in the sector.

Table 7 shows Spearman's ranking correlation between pairs of techniques.[11] All the correlations between pairs of approaches are positive and significantly different from zero at the usual levels of confidence (the null hypothesis of zero correlation is rejected). The correlations are particularly high between nonparametric models (Spearman's ranking correlation between DEA-V and DEA-C is 0.723, which is significantly different from zero at 1%) and between parametric techniques (Spearman's ranking correlation between ML and FGLS is 0.943, which is also significantly different from zero). Therefore, there is evidence that the methodologies are consistent under this condition.

Table 7: Spearman's Ranking Correlation Between Pairs of Techniques

Approach	**ML**	**FGLS**	**DEA-V**	**DEA-C**
ML	1.000	0.943	0.340	0.582
FGLS		1.000	0.345	0.539
DEA-V			1.000	0.723
DEA-C				1.000

[11] We used Intercooled Stata 7.0 for Windows 98/95/NT to compute the correlations.

If consistency in efficiency levels and rankings is not met, but consistency in identifying best and worst performers is, it would still be possible to discriminate the X factor among *groups* of firms in the sector. Indeed, identifying the rough ordering of firms is usually more important for regulatory policy decisions than measuring the level of efficiency or the efficiency rankings. The upper triangle of the matrix displayed in Table 8 shows, for each pair of techniques, the fraction of firms that both simultaneously classified in the upper quartile (10 firms). The lower triangle of the matrix shows the same for the case of the lower quartile (10 firms).[12]

Table 8: Consistency in Identifying Best and Worst Performers

Approach	ML	FGLS	DEA-V	DEA-C
ML		0.90	0.40	0.50
FGLS	0.90		0.40	0.50
DEA-V	0.50	0.50		0.80
DEA-C	0.70	0.70	0.50	

Overall, these results appear to imply that the top and bottom performers can reasonably be identified by any of the methods and hence the third condition for robustness of the results is being met. The advantage of knowing if the different approaches are consistent in identifying "best" or "worst" firms is that, even if the first two consistency test fail, a "mild" form of benchmark regulation can be relied on. This is somehow what the water regulator for England and Wales does when it publishes the efficiency rankings in the media to increase public pressure on the regulated companies. The idea is to inform the users and allow them to compare prices and services across regions and give them an instrument to put pressure on their own operator if it is not performing well.

[12] It is worth mentioning that if these fractions were purely random, they would be expected to be around 25%.

We now turn to external consistency and determine the year-to-year stability of DEA-V and DEA-C efficiency estimates over time. We do not include the econometric approaches because we tested whether efficiency was constant over time and were not able to reject this hypothesis. We calculated the correlations for the time-varying efficiency measures between each pair of years. That is, for both DEA models, we computed the correlation between DEA efficiency measures in year i, i = 1994, ..., 1999, and the efficiency scores in year j, j = 1995, …, 2000, with j > i to avoid redundancy. Table 9 presents the average correlations by the number of years apart. In general, the n-year apart figures are averages of the 7-n correlations between efficiencies that are n years away from each other.

Table 9: Correlations Between DEA Efficiency Measures

Approach	1 year apart	2 year apart	3 year apart	4 year apart	5 year apart	6 year apart
DEA-V	0.836	0.647	0.564	0.536	0.639	0.629
DEA-C	0.750	0.607	0.574	0.677	0.865	0.702

The correlations are high and statistically significant over all the available lags, suggesting that the efficiency scores of the DEA-V and DEA-C models are stable over time and giving additional support to the result of no efficiency change obtained with the parametric techniques used here.

5. CONCLUSIONS

The most important result of this paper has been to show that yardstick or benchmark competition organized around measures of technical efficiency is possible, at least in a mild form. This is not to say that the operators will not complain and question not only the results but also the methodologies. But this is normal. Regulation amounts to a game played between regulators and operators, most of the time, with the purpose of allocating the rent generated by the regulated monopolistic business between operators, users and the government. Too often in the past the game has been biased in favor of firms since they control much of the information. This implies that too often the efficiency gains actually achieved through restructuring and competition for the market have not been shared with the final users.

This approach levels the playing field by providing the regulator in each country with an instrument that reduces the information asymmetry. By allowing the regulator to propose its own estimate of the rent to be distributed based on the best practice defined by the performance of the top 5 or 10 firms, the approach proposed here forces the regulated firms unhappy with the regulator's assessment to reveal more information than it otherwise would.

A necessary condition for this form of competition to work is for regulators to coordinate with the other regulators in the region in a much more focused way than they have done in the past. For this sector and for most countries, the performance comparison can only be international. The more comparable across countries the information is, the more effective is this form of competition and the easier it is for each individual regulator to rely on useful results in its own regulatory settings.

APPENDIX

The applied literature is a good starting point in the identification of the variables to be included in the model. In the following table we summarize previous works found in the applied literature, highlighting the specification used (cost vs. production), the estimation technique (econometrics vs. mathematical programming), the outputs, the inputs and the environmental variables chosen.

Table A.1
Summary of Previous Studies

Author/s	*Specification/ Estimation*	*Output/s*	*Inputs*[13]	*Environmental Variables*
Neuberg, 1977	Cost function, Econometrics	Customers	Capital, labor	MWh sold, KM of distribution line, service area
Huettner and Landon, 1977	Cost function, Econometrics	Total capacity, average demand as a ratio of maximum capacity	Labor	Line transformers per customer, residential, commercial and industrial sales per customer, and a set of dummy variables
Roberts, 1986	Cost function, Econometrics	High and low voltage deliveries, serviced area, customers	KWh input, capital (transmission and distribution), labor	
Nelson and Primeaux, 1988	Cost function, Econometrics	Number of customers	Lines, Labor	City size, a dummy variable for the nature of the competitive environment
New Zealand Ministry of Energy, 1989	Cost function, Econometrics	Electricity distributed	Labor, capital, electricity purchased and "other"	
Weyman-Jones, 1991	Production approach, DEA	Residential, commercial and industrial sales	Labor, mains distribution	
Weyman-Jones, 1992	Production approach, DEA	Residential, commercial and industrial sales, maximum demand	Labor, network size, transformer capacity	
Weyman-Jones, 1992	Production approach, DEA	Customers	Labor	Network size, transformer capacity, total sales, maximum demand, population density, industrial share in sales
Hjalmarsson and Veiderpass,	Production approach, DEA	High and low voltage output (MWh), high and	Labor, high and low voltage lines, transformer capacity	

[13] In cost approaches, inputs prices are used in the models instead of input quantities.

Author/s	*Specification/ Estimation*	*Output/s*	*Inputs*[13]	*Environmental Variables*
1992a,b		low voltage customers		
Hougaard, 1994	DEA	Length of power lines, total power deliveries, number of customers	Labor, operating expenses, operating capital, transmission losses	
Salvanes and Tjøtta, 1994	Cost function, econometrics	GWh produced, number of customers	Labor, purchased electricity	Load factor, topography, climate, dummy rural area
Kittelsen, 1994	DEA	Length of power lines, total power deliveries, number of customers	Labor, transmission losses, external services bought	
Burns and Weyman-Jones, 1994	Production approach, DEA	Customers, domestic, commercial and industrial sales, maximum demand	Labor, distribution network, transformer capacity	Consumer density, market structure
Pollitt, 1995	Cost function, Econometrics	Sales per customer, ratio maximum to average demand, Customers	Labor	% of residential sales, overground and underground distribution circuits, transformer capacity, service area, and a set of dummy variables
Pollitt, 1995	Production approach, DEA	Customers , residential sales, non-residential sales, service area, maximum demand	Number of employees, transformer capacity, circuit kilometers	
Bagdadioglu, Waddams Price and Weyman-Jones, 1996	DEA	Customers, electricity supplied, maximum demand, service area	Labor, transformer capacity, network size, network losses, general expenses	
Burns and Weyman-Jones, 1996	Cost function, Econometrics	Customers	Labor, capital	Maximum demand, service area, consumer density, kWh sold, market structure,[14] kilometers of mains line, transformer capacity
Thompson, 1997	Cost function	High and low voltage sales	Labor (transmission and distribution), power, capital (transmission and distribution plants)	Service area, number of customers
Zhang and Bartels, 1998	DEA	Total number of customers	Transformer capacity, labor, total km of distribution lines	

[14] Market structure is defined as the share of industrial energy delivered in total energy delivered.

Author/s	*Specification/ Estimation*	*Output/s*	*Inputs*[13]	*Environmental Variables*
Førsund and Kittelsen, 1998	DEA	Distance index, customers, total energy delivered	Labor, energy loss, materials, capital	
Filippini, 1998	Cost function, econometrics	KWh delivered, number of customers	Labor, capital, purchased power	Load factor, service area
Kumbhakar and Hjalmarsson, 1998	Production approach, DEA and Econometrics	High and low voltage customers, high and low voltage energy sold	Labor, transformer capacity, kilometers of low and high voltage lines	
Scarsi, 1999	Production approach, DEA	Energy delivered to final customers, number of customers	Labor, kilometers of distribution lines	
Scarsi, 1999	Production function, econometrics	Energy delivered to final customers	Labor, kilometers of distribution lines	Customer density and a set of dummy variables
Scarsi, 1999	Cost function, Econometrics	GWh sold, customers	Capital, labor, materials	Customer density, demand structure, % of third-party services, % of overhead low-voltage lines, % of primary substations, and a set of dummy variables
Kittelsen, 1999	Cost approach, DEA	Energy delivered, customers, line length 1-24 kV	Labor, energy loss, transformers, lines, goods and services.	
DTe, 2000	Cost efficiency, DEA	Units distributed, small customer numbers, large customer numbers, network length, transformer numbers, network density	Operating expenditures	
Grifell-Tatjé and Knox Lovell, 2000	DEA	Low, medium and high voltage customers, area, low, medium and high voltage sales, service reliability	Low, medium and high voltage lines, substation transformer capacity	
Langset, 2000	DEA	Energy Supplied (high and low voltage), number of customers (high and low voltage), length of lines (by kV)	Labor, energy losses, capital, goods and services.	
Jamasb and	Econometrics	Energy delivered,	Controllable operating	Distribution losses, number

Author/s	*Specification/ Estimation*	*Output/s*	*Inputs*[13]	*Environmental Variables*
Pollitt, 2001	and DEA, cost function	number of customers (residential and non-residential), length of network (overhead and underground cables)	expenditures, capital expenditures	of transformers
Filippini and Wild, 2001	Cost function, econometrics	KWh transported on the medium-voltage grid	Labor, capital	Customer structure, load factor, customer density, average consumption, share of agricultural, forest and unproductive land, other revenues, dummy high-voltage

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