Reducing the Asymmetry of Information Through the Comparison of the Relative Efficiency of Several Regional Monopolies

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Abstract: Following the process initiated by Chile in the early 1980s, most countries in South America have undergone deep transformations in their electric industries. In this new playing field, the comparison of the relative efficiency of several regional monopolies seems to be a potentially valuable tool to reduce the asymmetry of information that is involved in the regulator-firm relationship. However, to be useful in the regulatory process, productive frontier estimates require a broad set of comparable firms and detailed information about them. This availability of data, although a necessary condition, is far from sufficient. One must also count on adequate techniques. In this paper we carry out an efficiency analysis in the electricity distribution sector in South America using different techniques, stating the conditions under which they become a useful tool in crafting an efficient regulation of the firms in that sector. Despite the particular results found here, the paper underscores the importance of conducting a consistency analysis whenever using efficiency measures in applied regulation.

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I. INTRODUCTION

Following the process initiated by Chile in the early 1980s, most countries in South America have undergone deep transformations in their electric industries, which include both restructuring and privatization of the prevailing public monopolies. As a result of these processes, a strong change in the role of government has occurred, leaving its producer and firm owner roles to become a regulator of those activities that constitute natural monopolies (namely transmission and distribution).

In this new regulatory role, the comparison of the relative efficiency of several regional monopolies seems to be a potentially valuable tool to reduce the asymmetry of information that is involved in the regulator-firm relationship. This fact has been recognized in many of the reform processes in which horizontal break-up of transmission and distribution firms was an important ingredient of the transformations.

In this context, the productive frontier estimates can be helpful to the regulators as a tool in the setting of the X factor in a price cap regime of the form RPI-X. This X factor reflects the expected price falls due to efficiency gains the firms can achieve during the duration of the price cap. These efficiency gains are basically of two types: shifts of the frontier and efficiency gains due to catching up. The first of these terms must be included in the X factor of all the firms in the sector. That is, if it is expected a productivity growth of 1% per year, all the firms must have this rate incorporated in the X factor. However, firms that are not on the frontier can reduce their costs (and increase their efficiency) in a magnitude equal to their current inefficiency. The X factor will include, for each firm, the shift of the frontier plus an additional term that will have the purpose of eliminating the differences between the firm and the frontier.

However, to be useful in the regulatory process the productive frontier estimates need two conditions to be satisfied. On the one hand, they require a broad set of comparable firms and detailed information about them. In this respect CIER's[1] effort to build up a regional database is a fundamental contribution to the development of an efficient regulation of electric utilities. But, on the other hand, this availability of data, although a necessary condition, is far from sufficient. One must also count on adequate techniques that allow an exhaustive analysis of the available data with reference to an appropriate conceptual framework.

The main goal of this paper fits into that criterion. We carry out an efficiency analysis in the electricity sector under different approaches[2], stating the conditions under which they become a useful tool in crafting an efficient regulation of the firms in that sector.

The paper outline is as follows. Section II enumerates the consistency conditions and how to apply them in a regulatory setting. In Section III, the theoretical model is formulated and then estimated, and the different models found in the literature are reviewed. Section IV analyses the consistency conditions explained in Section II. Finally, in Section V, conclusions to this work are made.

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[1] CIER accounts for "Comisión de Integración Eléctrica Regional" (Commission of Regional Electricity Integration).

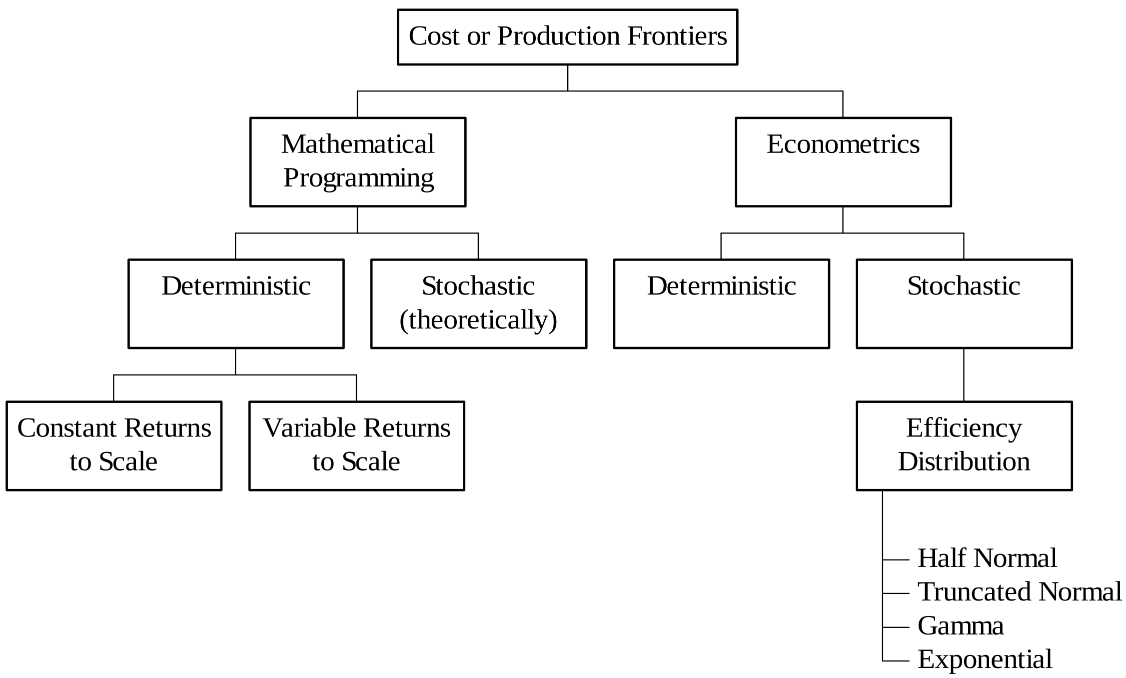
[2] The technicalities of the different approaches are discussed at length in Rodriguez Pardina et al. (1999).

II. CONSISTENCY CONDITIONS

A problem faced by regulators willing to apply frontier studies consists in the number of methods available for efficiency measurement of individual firms. The following figure shows the most common options available to the regulator for efficiency measurement.

The problem is far more serious if the different approaches give mutually inconsistent results. The question then arises at whether are efficiency studies are empirically useful.

Figure 1



In an attempt to answer this question, Bauer et al. (1998) propose a set of consistency conditions which must be met by the efficiency measures obtained from the different methodologies for them to be of some use to regulatory authorities.

These measures ought to be consistent in their efficiency levels, rankings and identification of the best and the worst firms, they also ought to be consistent over time and with the conditions under which the industry evolves, and they should be consistent with other performance measures employed by the regulators. Specifically, the consistency conditions are:

(i) The efficiency measures generated by the different approaches should have similar means and standard deviations;

(ii) the different approaches should rank firms in a similar order;

(iii) the different approaches should identify, in general, the same firms as the "best" and the "worst";

(iv) the efficiency measures should be reasonably consistent with other performance measures;

(v) individual efficiency measures should be rather stable over time, i.e. should not vary significantly from one year to the other; and

(vi) the different measures should be reasonably consistent with the expected results from the industry, given the conditions under which it operates. In the particular case of regulated firms, for example, it is expected that those firms regulated under a price cap mechanism will be more efficient than those regulated under rate-of-return regulation.

Broadly speaking, the first three conditions determine the degree to which the different approaches are mutually consistent, whereas the remaining conditions establish the degree to which the different efficiency measures are consistent with reality. So the last three conditions would be like an "external criterion" for the evaluation of the different approaches. In other words, the first three conditions say if the different approaches will give the same answers to the regulators, while the last three conditions say if it is likely that these answers are correct.

Using efficiency measures in the practice of regulation

One of the main changes of the last decade in the practice of regulation has been the adoption by a large number of regulators of some form of price cap regimes. 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 reduction in costs—typically within 3-5 years after a regulatory review of improvements in the efficiency in the regulated sector. 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 side show 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 is 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.

The next regulatory challenge is to understand that efficiency gains of a firm can come from two main sources, which require some idea on the part of the regulator of where the cost frontier lies. Indeed, gains can come from shifts in the frontier reflecting efficiency gains at the sectoral level. Efficiency gains at the firm level can also reflect a catching up effect. These are the gains to be made by firms not yet on the frontier. These firms should be able to achieve not only the industry gain but also specific gains offsetting firm specific inefficiencies (that explain why the firm is not on the frontier). This is why it is so important for a regulator to be able to use all the information provided by frontier based measures in the firm specific tariff revision.

This can be done by recognizing that efficiency indicators are by construction index numbers varying from 0 to 1, where 1 reflects the fact that a firm is totally efficient and 0 that it is completely inefficient (i.e. as far as possible from the sector frontier). For instance, if a firm has an efficiency index of 0.8, 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.[3]

The implementation of this mechanism, however, requires that at the minimum the first consistency condition is met (consistency in efficiency levels). If this is not meet, this mechanism should not be applied since the individual efficiency measures would be somewhat subjective and hence unreliable.

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. Indeed, identifying the rough ordering of which the firms are more efficient than others is usually more important for regulatory policy decisions than measuring the level of efficiency (Bauer et al., 1998). For example, identifying the ranking would help to discriminate the X factor among the firms in the sector.

If nor the first nor the second consistency condition is met, but the third consistency rule does (consistency in identifying best and worse performers), it would still be possible to use a third approach: to publish the results. This approach is used in the UK in the water and electricity sectors. The idea is to inform the users and allow them to compare prices and services across regions and give them a reason to put pressure on their own operator if it is not performing well.

III. THE SPECIFICATION OF THE MODEL

Sometimes regulated companies differ from one another either because of geographical or topological characteristics, factors which difficult the effective employment of yardstick competition. However, as Burns and Estache (1998) state, when these differences can be unambiguously identified, the regulator still has a potent tool: it may simply adjust the prices for each business by the extent of the costs which are outside their control. In terms of the construction of the model that means that apart from the standard explanatory variables (inputs, in a production function model; output/s and input prices, in a cost function model), the model must include a number of additional variables. These additional variables are called environmental variables, and their role is to capture external

[3] In some cost function applications the efficiency measures are defined as equal or greater than one. In those cases, an efficiency measure of 1.2 would be showing that the firm's expenditure is 20% higher than it could be.

factors not directly controllable by the firms, that might influence their performance. Some examples of environmental variables include (see Fried, Schmidt and Yaisawarng, 1995):

- ownership differences, such as public/private;
- location characteristics;
- labor union power; and
- regulatory regime.

However, care should be taken as regards the selection of environmental variables to be included in the model. In the case of ownership, for example, its inclusion as an explanatory variable gives information on the differences in efficiency for each ownership type. A set of dummy variables that measure these differences should not be included in a model intended for yardstick competition, for ownership effects would be netted out from the efficiency measures, thus punishing the firms belonging to the most efficient ownership type. If yardstick comparisons are to be made, the model should be estimated without dummy variables, and then the results (the relative efficiency measures) should be cross-checked with ownership information.

Geographical characteristics, on the other hand, are the kind of variables that should in general be included in the model, especially if the location of the firm is given by the concession contract (as is the usual case with regional monopolies). Because the firms cannot control their geographical environment, the efficiency measures should take into account that constraint. Efficiency scores should also incorporate every variable over which the firms have no control (climate, labor unions power, etc.).

Of course, it is clear that yardstick competition requires the regulator to have complete information on all those external factors that can affect costs (or the productive process). In other cases the possibility exists for the firm to engage in strategic behavior by explaining away firm specific inefficiencies as a state of nature (CRI, 1995): if an econometric approach were chosen, a firm could always find a variable that only it possessed, which, in statistical terms, would work as a dummy variable in the regressions, explaining away all the firm's inefficiency (thus rendering it efficient –or more efficient); if, on the other hand, a DEA methodology were employed, a firm could make itself appear as more efficient by including additional environmental variables, because it would be difficult to find comparable firms in the set when an increasing number of dimensions is considered in the analysis (and not because it is actually efficient).

Special attention must be taken in relation to the inclusion or not of quality related variables. If quality standards do not exist, then the omission of quality variables in the model might cause some firms to appear with lower cost not because they are more efficient but because they provide a good or service of inferior quality. In these cases, it might be convenient to include quality variables in the specification of the model. However, the regulator must have in mind that quality levels above reasonable standards should be passed to the consumers through higher tariffs. If quality standards do exist, the optimal outcome results if the amount of potential fines is included in the computed costs.

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. If they are indeed making the best effort to minimize cost, they should have enough information under their exclusive control to show that they are doing so and they should provide it to the regulator. This information should then be incorporated in any future work the regulators would use to compare companies, and become a component of standard informational requirements imposed on all companies (Crampes et al., 1997).

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. In this sense, yardstick competition can be viewed as a "learning by doing" process in which both firms and regulators learn while playing the game (Rossi and Ruzzier, 2000).

Previous models found in the applied literature

Econometrics

(1) Neuberg (1977) describes four related but distinguishable activities in electricity distribution. Firstly, distribution properly which includes maintenance of equipment and installations to users and load dispatch. Secondly, meter reading and billing. Thirdly, sales including related activities such as publicity and fourthly administration. Neuberg suggests four variables as main cost drivers in electricity distribution: number of customers served, total kWh sold, km. of distribution lines and km^2 of distribution area.

The main conceptual problem is to identify within this set of variables which one or ones are the output. Neuberg discards the possibility of treating distribution companies as multiproduct firms given that the different variables cannot be separately sold and/or priced. For example, once the number of clients is identified as the product (with a price equal to average annual revenue per customer of the firm), energy sales in kWh cannot be sold separately. Given that the remaining variables cannot be considered outputs (nor inputs for which a price is paid) they can be introduced in the model as specific characteristics of the firms to allow for comparisons among them.

Summing up, Neuberg estimates a Cobb-Douglas cost function as follows:

$$C = f(Y, Z, P_l, P_k, D),$$

where C is the total distribution cost, Y is the output (number of customers served), Z is a vector of environmental variables (MWh sold to final customers, miles of overhead distribution lines, square miles of service area), P_l is the price of labour, P_k is the price of capital, and D is dummy variable which distinguishes between public and privately owned firms.

Neuberg analyses a cross section sample for distribution firms in USA in 1972; defining an electricity distribution firm as the one which has nonzero distribution and maintenance costs and has at least one residential customer.

The following are the main results of the paper:

- None of the models generates any empirical evidence to support the claim that the privately owned firms are more cost efficient than publicly owned firms.

- There is evidence of increasing returns to scale, though not over the entire existing output range.
- All the variables are statistically significant at the usual levels of confidence.

(2) Burns and Weyman-Jones (1996), and Burns et al. (1994) add some additional variables when compared with Neuberg's (1977) paper: maximum demand (which determines system configuration and size), transform capacity (which affects losses) and demand structure (which determines load factors at different moments of the day).

Summing up, Burns and Weyman-Jones estimate two production functions, one assuming a Cobb-Douglas technology (as Neuberg) and the other assuming a more flexible translog technology, which is similar as the Cobb-Douglas but includes the second order terms.

The final model estimated with ordinary least squares is as follows:

$$C = f(Y, Z, P_l, P_k, D),$$

where C are the operative costs, Y are the customers, Pl and Pk are the prices of labour and capital respectively, and Z is a vector of environmental variables (kilometres of distribution network, population density, maximum demand, kWh sold, and transformer capacity). The variable market structure was excluded from the final model because it was not significant.

The authors estimate the same model but using generalised least squares (a panel data model with random effects), finding that the variables kWh sold, transformer capacity, kilometres of distribution network and population density turn into not significant.

The following are the main results of the paper:

- estimation by GLS results in a number of variables becoming statistically insignificant. This illustrates the important differences between cross section and panel estimates;
- there are significant scale economies in electricity distribution;
- most companies' rankings do not change dramatically with the different approaches;
- there is a small but significant positive effect on cost efficiency in the post privatisation years.

(3) Pollitt estimates the following cost function (the author's notation is followed):

$$DAC = \alpha + \beta_1 \log SALESC + \beta_2 (\log SALESC)^2 + \beta_3 MAXRAT + \beta_4 (MAXRAT)^2 + \beta_5 CUST + \beta_6 RESID + \beta_7 OGKMC + \beta_8 UGKMC + \beta_9 TRANSC + \beta_{10} WC + \beta_{11} AREA + \beta_{12} ODUM + \beta_{13} CDUM$$

where *DAC* is distribution cost in 1000s of US dollars per million kWh, *SALESC* is sales per customer in million kWh, *MAXRAT* is the ratio of maximum to average demand, *CUST* is number of customers, *RESID* is the share of residential sales in total sales, *OGKMC* is overground distribution circuit km per customer, *UGKMC* is underground distribution circuit km per customer, *TRANSC* is transformer capacity (in MVA) per customer, *WC* is wage cost in 1000s of US dollars per employee, *AREA* is service area in square kilometers, *ODUM* is a dummy variable related to ownership (public=1 or private=0), and *CDUM* is another dummy variable that adopts a value of unity when the firm is from UK, and a value of zero otherwise. Including the last dummy variable, Pollitt seeks an international comparison, though somewhat limited (for he only includes in his sample firm data for two countries: UK and USA[4]), of the productive efficiency.

Pollit uses a sample of 145 electricity distribution firms in the accounting year ending in 1990. This dataset includes 136 firms from the United States and 9 firms from United Kingdom (119 of them were privately owned and 26 were publicly owned).

The following are the main results of the paper:

- The regression explains only 62% of the variation in distribution costs. The F test indicates that the regression is significant at 0.1%.
- The estimated function indicates the significance of sales per customer, sales per customer squared, number of customers, overground circuit km per customer and labour costs in explaining the variation in average operation and maintenance costs in distribution.
- The negative coefficient on the ownership dummy indicates lower costs in public firms. However, this coefficient is not significant.
- The coefficients on the UK country dummy variable is not significant.

(4) Huettner and Landon (1977), in turn, estimate the following cost function:

$$DAC = \alpha + \beta_1 \log TCAP + \beta_2 (\log TCAP)^2 + \beta_3\, UTCAP + \beta_4 (UTCAP)^2$$
$$+ \beta_5\, NTRANSC + \beta_6\, RESIDC + \beta_7\, COMMC + \beta_8\, INDC + \beta_9\, WC$$
$$+ \beta_{10}\, GDUMs + \beta_{11}\, HDUMs$$

where *DAC* is distribution cost per kWh, *TCAP* is total capacity in MW, *UTCAP* is average demand as a ratio of maximum capacity, *NTRANSC* is number of line transformers per customer, *RESIDC* is residential sales per customer in MWh, *COMMC* is commercial sales per customer in MWh, *INDC* is industrial sales per customer in MWh, *WC* is the company wage cost in $/hour, the *GDUMs* are geographical dummy variables, and the *HDUMs* are holding company dummy variables (related to ownership).

Huettner and Landon work with a sample of 74 firms and the following are the main results of their paper:

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[4] To the authors' knowledge, Pollitt's (1995) work is the first to attempt an international comparison in the electricity distribution sector.

- The reported R^2 for the ordinary least squares regression is 0.60.
- The long run average variable cost curve is U-shaped.

(5) Scarsi (1999) analyzes the relative efficiency of the electricity distribution firms in Italy for the period 1994-96. The author estimates a cost function with two outputs, three inputs and a set of environmental variables. The explained variable is the total distribution costs. The input prices considered in the paper are those of materials, capital and labor. Two outputs are considered as regressors: GWh sold and number of customers. The environmental variables used are: customer density in the service area, market structure (% of energy sold to industrial customers), percentage of third-party services, percentage of overhead low-voltage lines on total lines, percentage of primary substations on total transforming substations, and a set of dummy variables: landscape features (which takes a value of 1 if the local zone is made up of more than 50% mountains higher than 770m), coastal areas (which takes a value of 1 if the zone includes coastal areas), geographical peculiarities (which takes a value of 1 if the distribution zone is located in Southern Italy), metropolitan areas (which takes a value of 1 if the zone is serving a metropolitan area), political borderline (which might capture externalities coming form interconnected neighbouring countries), industrial district (a dummy that takes the value 1 if the zone is in the neighbourhood of a municipal distributor to which expensive connection has to be granted), and generation plants (which takes a value of 1 if the zone also includes some generating plants).

The following are the main results of the paper:

- consumer density was found to be beneficial in terms of total cost minimization;
- industrial output (as a percentage of total energy delivered) also contributed to lower distribution costs, the same as third-party works;
- overhead cables in low-voltage distribution are more expensive than standard underground connections;
- primary substations raise costs;
- the territorial North-South dummy was not statistically significant;
- there were not statistically significant differences between privately and publicly owned firms;
- All coefficients of the variables coastal areas, political borderline, landscape effects, metropolitan areas, and industrial district turned out to be statistically insignificant.

(6) Thompson (1997) estimates a translog cost function for the period 1977-92, in the United States. Thompson works with 83 firms with data for the years 1977 and 1982, and 85 firms for the years 1987 and 1992 (he works with data from only these four years).

The explained variable in the translog cost function is the total power procurement and delivery cost. As regressors, the author included the prices of capital and labour, the output (low-voltage service volumes), and environmental variables (number of customers and service territory characteristics).

The findings of the study suggest that attempts to estimate the costs of the individual stages of production of vertically integrated electric utilities could produce biased results for some purposes.

(7) Kumbhakar and Hjalmarsson (1998) analyze the productive efficiency of the electricity distribution sector in Sweden for the period 1970-1990, using a hedonic pricing approach.

The following are the main results of the paper:

- The privately owned firms are relatively more efficient than the publicly owned ones.
- There is evidence of increasing returns to scale.
- There is evidence of technical progress in the period 1970-1990.

Data Envelopment Analysis

(1) Weyman-Jones (1992) uses a DEA model to measure the efficiency of a sample of 12 Area Electricity Boards of England and Wales during the period 1970-1 to 1988-9. The purpose of this study is to examine the possibility of implementing relative performance measures for non-competitive firms, thus facilitating yardstick competition. Weyman-Jones presents two different models:

Model W-J (1992) 1

Inputs:	*Outputs:*
1. Manpower	1. Domestic sales (kWh)
2. Network size (km)	2. Commercial sales (kWh)
3. Transformers	3. Industrial sales (kWh)
	4. Maximum demand (kW)

Model W-J (1992) 2

Inputs:	*Outputs:*
1. Manpower	1. Number of customers
Environmental variables:	
1. Network size (km)	
2. Transformers	
3. Total sales (kWh)	
4. Maximum demand (kW)	
5. Population density	
6. Industrial/total sales (%)	

In the first model, the choice of inputs and outputs follows well-established conventions in the empirical literature on electricity distribution. The different demand categories reflect differences in load (duration of peak, voltage). The input choices represent traditional input categories (labor, capital). This model's objective is to measure the technical efficiency of the Area Boards, allowing for variable returns to scale. The second model draws on suggestions made by Neuberg (1977), who argued that distribution companies are interested in delivering a service to customers; hence total customers should be the relevant output. The role of environmental variables is to allow for the measurement of productive efficiency in a way that explicitly takes into account the differences in the operating environment of the companies. The purpose of this second model is to measure overall productive efficiency (including allocative efficiency).

Weyman-Jones (1992) found that:

- Inefficiency has been a characteristic of the Area Boards prior to privatization.
- Different Boards moved on to and off the efficient frontier in different years.
- Boards should be compared at similar points in their regional economic cycle, rather than at the same point in time.
- Efficiency improved with the move towards privatization.
- The variance of efficiency reduced as the industry approached privatization.

(2) A paper by Hjalmarsson and Veiderpass (1992) examines productive efficiency and ownership in the Swedish electricity distribution industry, for 285 firms operating in 1985. They estimate the following DEA model:

Model H+V

Inputs:	*Outputs:*
1. Labor (hours)	1. High voltage output (MWh)
2. High voltage lines (km)	2. Low voltage output (MWh)
3. Low voltage lines (km)	3. High voltage customers (numbers)
4. Transformer capacity (kVA)	4. Low voltage customers (numbers)

Hjalmarsson and Veiderpass also estimate a second model in which they eliminate outputs 3 and 4, and a third model with only outputs 3 and 4.

Their results show that:

- Average technical efficiency is low.
- Rural distribution companies are relatively scale inefficient.
- Ownership, economic organization and service area do not appear to affect efficiency scores in a significant way.

(3) Pollitt (1995) examines technical efficiency and ownership in a sample of 145 distribution firms from the USA (136) and the UK (9) in the accounting year ending in 1990. The dataset includes information on 119 private firms and 26 publicly owned companies, and it is divided in three subsamples on the basis of calculated labor employed. Pollitt characterizes the distribution function as follows:

Model P

Inputs:	*Outputs:*
1. Number of employees	1. Number of customers
2. Transformers (MVA)	2. Residential sales (MWh)
3. Circuit km.	3. Non-residential sales (MWh)
	4. Service area (km^2)
	5. Maximum demand (MW)

Inputs 2 and 3 represent the capital input, and input 1, the labor input. On the output side, 1 captures the number of nodes to be supplied, and together with 4 it captures density effects; 5 captures a load profile; and 2-3 distinguish voltage effects. In another section of his work, Pollitt computes four additional measures of efficiency, assuming that (i) input 3 and output 4, (ii) the former plus output 5, (iii) all of the preceding variables plus input 2, and (iv) every variable except input 1 and output 1, are environmental variables.

The results from the analysis if the distribution sample shows that:

- Publicly owned firms outperform their private counterparts, though the null hypothesis of no difference between ownership types cannot be rejected
- 54% of the large firms exhibit increasing returns to scale.
- The differences in average efficiency for public and private firms are usually of the order of 5% or less.

(4) In a 1998 paper, Kumbhakar and Hjalmarsson attempt to examine whether ownership or organization of the distribution companies in Sweden has any systematic impact on economies of scale, technological change and relative efficiency in labor use, and whether there is any evidence that yardstick competition enhances efficiency. The data used contains information on a very large number of electricity retail distributors over the period 1970-1990, divided into private companies, municipal companies, municipal utilities and mixed ownership firms. Kumbhakar and Hjalmarsson explore two different DEA models (under variable returns to scale):

Model K+H 1

Inputs:	*Outputs:*
1. Low voltage power lines (km)	1. Low voltage electricity (MWh)
2. High voltage power lines (km)	2. High voltage electricity (MWh)
3. Number of employees	3. Low voltage customers
4. Total transformer capacity (kVA)	4. High voltage customers

Model K+H 2

Inputs:	*Outputs:*
1. Number of employees	1. Low voltage electricity (MWh)
2. Total transformer capacity (kVA)	2. High voltage electricity (MWh)
	3. Low voltage customers
	4. High voltage customers
	5. Low voltage power lines (km)
	6. High voltage power lines (km)

The empirical results found in this study are:

- The results are sensitive to variable specification.
- There is trend of declining inefficiency across ownership types.
- Privately owned firms are relatively more efficient.
- Increasing returns to scale are observed most years.
- The persistent differences in efficiency scores between private and public firms are interpreted to be due to the impact of yardstick regulation.

(5) Weyman-Jones (1991) applies linear programming to the calculation of the technical efficiency of the twelve area electricity boards of England and Wales, for the year 1986/87. The model adopted displays two inputs, capital and labor, and three outputs. Labor input is measured as number of employees because no dissagregated measure was available. Two different measures of the capital input were considered (giving rise to two different models shown below): (i) total value of assets, and (ii) circuit kilometers of mains distributions.

Model W-J (1991) 1

Inputs:	*Outputs:*
1. Number of employees	1. Sales to domestic consumers (kWh/year)
2. Valuation of assets (£)	2. Sales to commercial consumers (kWh/year)
	3. Sales to industrial consumers (kWh/year)

Model W-J (1991) 2

Inputs:	*Outputs:*
1. Number of employees	1. Sales to domestic consumers (kWh/year)
2. Mains distribution in service (km)	2. Sales to commercial consumers (kWh/year)
	3. Sales to industrial consumers (kWh/year)

The main findings of this work are:

- The boards differ significantly in efficiency.
- The valuation basis of capital services is less able to discriminate between efficient and inefficient firms than the physical capital measure.
- Only five out of twelve boards operate on the frontier, and two of them dominate the reference sets for the seven inefficient firms.
- Most of the efficient boards derive relatively little of their efficiency from the unregulated commercial and industrial sectors, suggesting that the regulation might be too narrowly focused on the domestic segment.

(6) Grifell-Tatjé and Lovell (2000) benchmark the actual performance of the existing distribution network in Spain not against "best practice" standards but against the potential performance of an ideal network designed by engineers employed by an international consultancy. They measure performance in terms of the cost differential incurred in meeting electricity demand and decompose this measure to identify the sources of the differences. Their data set describes the 1996 actual performance of Spanish electricity distributors and the engineering standards, obtained by aggregation of the detailed information generated by the consultancy. Their model is as follows:

Model G-T+L

Inputs:

1. Low voltage lines (km)

2. Medium voltage lines (km)

3. High voltage lines (km)

4. Substation transformer capacity from high to high & medium voltage, and from medium to medium voltage (MVA)

5. Substation transformer capacity from medium to low voltage (MVA)

Outputs:

1. Low voltage customers (#)

2. Medium & high voltage customers (#)

3. Service territory area (km2)

4. Low, medium & high voltage electricity distributed (GWh)

5. Service reliability [low & medium voltage electricity distributed (MVh) / low & medium voltage electricity lost to unplanned interruptions (MVh)]

The empirical findings of this work are:

- The existing distribution network operates at a cost that is nearly 40% higher than the cost of operating the ideal network.
- Over half of the cost saving of operating the consultancy's ideal network is attributable to lower input prices proposed by the consultancy.
- The ideal network is not as cost efficient as the existing network.
- The source of the superior cost efficiency of the existing network is the superior allocative efficiency.

(7) The Netherlands Electricity Regulatory Service (DTe, 2000), in the process of introducing price controls for the Dutch electricity sector, analyzed the availability of data and the choice of models for benchmarking. Given data limitations, DTe recommended that a DEA model be used. DTe modeled the distribution and retail businesses as follows, and computed DEA models under both constant and variable returns to scale specifications:

Model DTe 1	
Input:	*Outputs:*
1. Operating expenditures (OPEX)	1. Units distributed
	2. Customer numbers

Model DTe 2	
Input:	*Outputs:*
1. Operating expenditures (OPEX)	1. Units distributed
	2. Small customer numbers
	3. Large customer numbers

Model DTe 3	
Input:	*Outputs:*
1. Operating expenditures (OPEX)	1. Units distributed
	2. Small customer numbers
	3. Large customer numbers
	4. Network length
	5. Transformer numbers

Model DTe 4

Input:	*Outputs:*
1. Operating expenditures (OPEX)	1. Units distributed
	2. Small customer numbers
	3. Large customer numbers
	4. Network length
	5. Transformer numbers
	6. Network density

Model DTe 5

Input:	*Outputs:*
1. OPEX plus tangible depreciation	1. Units distributed
	2. Customer numbers

Model DTe1 includes only two key outputs, whereas Model DTe2 attempts to capture differences in the composition of each company's customer base. The third model adds variables that proxy the dispersion of the customer base and the complexity of the network, and Model DTe4 further incorporates network density (network length per customer) as a proxy for network dispersion. The last model is similar to the first one, but uses an extended input concept.

The results of the study reveal that:

- There is a considerable spread of relative inefficiency among the companies.
- There is scope for efficiency improvement, particularly among larger companies.
- Constant returns to scale models are more appropriate than variable returns to scale models.

(8) Kittelsen (1999) examines the theoretical and practical possibilities and problems in using yardstick competition based on cost information from the DEA methodology. The author uses a stepwise procedure to select the specification of variables in the model for the Norwegian Electricity Distribution Utilities:

Model K

Inputs:	*Outputs:*
1. Labor	1. Energy delivered
2. Energy loss	2. Number of customers
3. Transformers	3. Line length 1-24 kV
4. Lines	
5. Goods and services	

The variables that were eliminated included corrosion index, climatic index, maximum power and disaggregation of energy by institutional customer groups. The main findings of the analysis are:

- Mean technical efficiency: 0.93
- Mean technical productivity: 0.90
- Mean cost efficiency: 0.81
- Mean total efficiency: 0.77
- Mean Malmquist Productivity change: 1.9% p.a. 1983-1989.

(9) Scarsi (1999) analyses the technical efficiency of local electricity distribution in Italy by means of econometric and linear programming (DEA) tools. A pooled sample of 76 firms (37 municipal firms and 39 ENEL –the Italian electricity monopolist- zones) for the years 1994, 1996 was built, and DEA was used to cross-check the results obtained with a stochastic frontier (econometric) approach. DEA computations were made under an output orientation (maximization of outputs with fixed inputs). This orientation was chosen because Italian firms are not strictly compelled to provide customers with whatever electricity they desire at given (regulated) prices, and because inputs are assumed to be moderately fixed in the short run. Scarsi estimates three different models, assuming variable returns to scale, which are shown below.

Model S 1	
Inputs:	*Outputs:*
1. Employees	1. Energy delivered (GWh/year) to final customers
2. Km. of distribution lines	2. Number of customers
Model S 2	
Inputs:	*Outputs:*
1. Employees	1. Number of customers
2. Km. of distribution lines	
Model S 3	
Inputs:	*Outputs:*
1. Employees	1. Energy delivered (GWh/year) to final customers
2. Km. of distribution lines	

Energy delivered to final customers include sales to industrial customers, publicly-owned enterprises and residential (both urban and rural) users. Employees stands for the number of full-time employees (end-year average). Scarsi found that:

- Pooled analysis failed to spot any systematic superiority of ENEL units over municipalities.

- Statistical testing showed limited agreement between both econometric and DEA approaches on efficiency outcomes.

(10) Burns and Weyman-Jones (1994) use mathematical programming techniques to construct measures of relative efficiency and productivity growth in a multiple input, multiple output model of UK electricity distribution before and after privatization. The 12 Regional Electricity Companies of England and Wales are compared over the years 1971-1993. The choice of inputs and outputs in this study is as follows:

Model B+W	
Inputs:	*Outputs:*
1. Number of full time employees	1. Number of customers
2. Distribution network (circuit km)	2. Units delivered to domestic consumers (kWh)
3. Transformer capacity (MVA)	3. Units delivered to commercial consumers (kWh)
	4. Units delivered to industrial consumers (kWh)
	5. Maximum demand (kW)
Environmental variables:	
1. Customer density (number of customers per square km. of company territory)	
2. Market structure (share of industrial energy delivered in total)	

The authors found that:

- The null hypothesis that productivity growth before and after privatization has been the same cannot be rejected.
- The industry is performing more efficiently since privatization, but this effect is solely due to secular technical progress, with no incremental efficiency gain.
- There is a wider diversity of performance amongst the companies compared with their performance under state ownership.

Summary of previous models

In the following table we summarize every previous works we have mentioned here, highlighting the specification used (cost vs. production, econometrics vs. mathematical programming), the output/s, the inputs and the environmental variables chosen. In Appendix 1, we survey other utilities sectors (gas distribution, water services and electricity transmission).

Table 1
Electricity Distribution

Author/s	Specification /Estimation	Output/s	Inputs	Environmental Variables
Neuberg, 1977	Cost function, Econometrics	Customers	Capital, labor	MWh sold, KM of distribution line, area of service
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
Weyman-Jones, 1991	Production approach, DEA	Domestic, commercial and industrial sales	Labor, mains distribution	
Weyman-Jones, 1992	Production approach, DEA	Domestic, commercial and industrial sales, maximum demand	Manpower, network size, transformers	
Weyman-Jones, 1992	Production approach, DEA	Customers	Manpower	Network size, transformers, total sales, maximum demand, density, industrial share
Hjalmarsson and Veiderpass, 1992	Production approach, DEA	High and low voltage output (MWh), high and low voltage customers	Labor, high and low voltage lines, transformer capacity	
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, transformers, circuit kilometers	
Burns and Weyman-Jones, 1996	Cost function, Econometrics	Customers	Labor, capital	Maximum demand, area of service, consumer density, kWh sold, market structure, kilometers of mains line, transformer capacity
Thompson, 1997	Cost function	High and low voltage sales	Labor (transmission and distribution), power, capital (transmission and	Area of service, Number of customers

			distribution plants)	
Kumbhakar and Hjalmarsson, 1998	Production approach, DEA and Econometrics	High and low voltage customers	Labor, transformer capacity, kilometers of low and high voltage lines	
Scarsi, 1999	Production approach, DEA	Energy delivered to final customers, number of customers	Employees, kilometers of distribution lines	
Scarsi, 1999	Production approach, DEA	Number of customers	Employees, kilometers of distribution lines	
Scarsi, 1999	Production approach, DEA	Energy delivered to final customers	Employees, kilometers of distribution lines	
Scarsi, 1999	Cost function, Econometrics	GWh sold, customers	Capital, labor, materials	Customer density, market 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, customer numbers	Operating expenditures	
DTe, 2000	Cost efficiency, DEA	Units distributed, small customer numbers, large customer numbers	Operating expenditures	
DTe, 2000	Cost efficiency, DEA	Units distributed, small customer numbers, large customer numbers, network length, transformer numbers	Operating expenditures	
DTe, 2000	Cost efficiency, DEA	Units distributed, small customer numbers, large customer numbers, network length, transformer numbers, network density	Operating expenditures	
DTe, 2000	Cost efficiency, DEA	Units distributed, customer numbers	Operating expenditures plus tangible depreciation	
Grifell-Tatjé	DEA	Low, medium	Low, medium and high	

and Knox Lovell, 2000		and high voltage customers, area, low, medium and high voltage sales, service reliability	voltage lines, substation transformer capacity	

In Appendix 2 we make a more detailed description of those variables that, in our belief, need such a description.

Our econometric model

Since we are attempting an international comparison, and since in many of the analyzed countries the electricity firms are publicly owned, in this paper we estimate a production frontier.[5] The stochastic production function model (Cobb-Douglas[6]) with panel data is written as:

$$Y_{it} = \beta_0 + X'_{it}\,\beta + \varepsilon_{it},$$

where Y_{it} is the natural logarithm of the output of firm i (i=1, 2,...,N) at time t (t=1,2,...,T), X_{it} is the corresponding matrix of k inputs (and environmental variables, also in logs) and β is a $k\times1$ vector of unknown parameters to be estimated. The error term is specified as

$$\varepsilon_{it} = v_{it} - u_{it}.$$

The v_{it} are statistical noise and are assumed to be independently and identically distributed, while u_{it} are non-negative random variables which represent technical efficiency. The v_{it} represent those effects that cannot be controlled by the firm, such as measurement errors, omitted variables and weather conditions. Technical inefficiency, on the other hand, accounts for those factors that can be controlled by the firm, and can be defined as the discrepancy between a firm's actual and potential outputs.

Since it is not convenient in empirical applications to impose to the model an a priori distribution of the inefficiency term, we use the more flexible truncated normal distribution proposed by Stevenson (1980). This distribution is obtained by truncating at zero a normal distribution with median μ and variance σ^2. Setting μ to zero reduces to the traditional half-normal model. To represent the temporal evolution of the inefficiency term we use the model proposed by Battese and Coelli (1992).

An important advantage of this model is its great flexibility, which allows the testing of different specifications in order to choose the one that best fits the data. In this paper we

[5] The estimation of cost frontiers involves the utilization of variables measured in monetary units (data on costs as well as on input prices is needed), 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 homogeneous). Additionally, whenever there is public ownership the firms, in general, would not seek profit maximization as their main goal. As Pestieu and Tulkens (1990) argue, public enterprises do not share the same objectives and constraints that their private counterparts do, so their relative performance should only be compared on the basis of technical efficiency. Besides, in public firms, prices may be neither available nor reliable (Charnes, Cooper and Rhodes, 1978).

[6] We did not estimate a translog cost function, which is a more flexible form, because the inclusion of the second order and cross terms would leave the model with very few degrees of freedom.

test the hypothesis that the inefficiency term has a half-normal distribution (H_0: μ=0) vis a vis the more flexible truncated (at zero) normal. We also contrast the hypothesis that the inefficiency is time invariant (H_0: η=0), and the null that there is no technical change in the analyzed period.

The next important decision we have to make is the choice of the variables to include in the model. Neuberg (1977) describes four related but distinguishable activities in electricity distribution. First, distribution properly which includes maintenance of equipment and installations to users and load dispatch. Second, meter reading and billing. Third, sales including related activities such as publicity, and fourth, administration. Neuberg suggests four variables as main cost drivers in electricity distribution: number of customers served, total kWh sold, Km of distribution lines and Km^2 of distribution area. Burns et al. (1994) add some additional variables: maximum demand (which determines system configuration and size), transformer capacity (which affects losses) and demand structure (which determines load factors at different moments of the day).

The main conceptual problem is to identify within this set of variables which one or ones are the output. Neuberg discards the possibility of treating distribution companies as multiproduct firms given that the different variables cannot be separately sold and/or priced. For example, once the number of clients is identified as the product (with a price equal to average annual revenue per customer of the firm), energy sales in (kWh) cannot be sold separately. This is the road we follow in the estimations, taking number of customers as the (single) output in our production function. Given that the remaining variables cannot be considered outputs (nor inputs for which a price is paid) they can be introduced in the model as specific characteristics of the firms to allow for comparisons among them.

The initial estimated production function is therefore:

$$\text{Ln CUSTOMER} = \beta_0 + \beta_1 \text{ Ln KMNET} + \beta_2 \text{ Ln EMPLOYEE} + \beta_3 \text{ Ln TRANSF}$$
$$+ \beta_4 \text{ Ln AREA} + \beta_5 \text{ Ln STRUCT} + \beta_6 \text{ TIME}$$

where Ln stands for natural logarithm. The dependent variable is the number of customers (CUSTOMER), and the regressors are: distribution lines (KMNET, in km), number of employees in distribution (EMPLOYEE), service area (AREA, in km^2), transformer capacity (TRANSF, in kV), and proportion of sales to residential customers (a proxy of market structure, STRUCT). We include a time trend (TIME) in the model to account for technical change.

The data

The raw data used in this work has been obtained from the Secretaría General de la Comisión de Integración Eléctrica Regional (CIER) reports, “Datos Estadísticos. Empresas Eléctricas. Año 1994”, and “Datos Estadísticos. Empresas Eléctricas. Años 1995-1996-1997”. The database includes information about a large number of variables for the following countries: Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay and Venezuela. After cleaning the database we obtained an unbalanced panel with

99 observations for a total of 35 firms in the period 1994-97. The summary statistics of the sample of 35 firms are presented in Table 2.

Table 2
Basic Statistics

Variable	Sample Size	Mean	Standard Deviation
Number of Customers	99	520688	854816
Residential/Total Sales (%)	99	41	15
Mains of Distribution (km)	99	107244	326034
Transformer Capacity (kVA)	99	1236911	1876080
Concession Area (km^2)	99	76704	164473
Sales (MWh)	99	3421278	6524999
Number of Employees in Distribution	99	716	1539

We start our estimates with a flexible model and then we test different specifications using a LR test, which requires the estimation of the model under both the null and the alternative hypotheses. The statistic is calculated as

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

where L_R is the log-likelihood of the restricted model (i.e., the half-normal specification) and L_U is the log-likelihood of the unrestricted model. The LR statistic has a chi-square distribution with degrees of freedom equal to the number of restrictions involved (in this instance one).

In a first step we test the null hypothesis that there are no technical inefficiency effects in the model. Comparing the log-likelihood of the ML and OLS model (not shown) we found that there are significant differences between them.[7] Since the LR statistic is greater than the critical value (one degree of freedom), the null that there are no technical inefficiency effects in the sample can be rejected.[8]

The next step is to test the half-normal model versus the alternative truncated normal. The log likelihood function of the unrestricted model is not significantly different from the log likelihood of the restricted (μ=0) model. Since we cannot reject the null, in the final model the efficiency component is assumed to have a half-normal distribution.

Finally, we test the time invariant inefficiency effect hypothesis. We do so by running two models, one with the parameter η and another without it. The log likelihood of the unrestricted model is 58.2, which is not significatively greater than the log likelihood of the restricted (57.2, when η=0) model. Since the LR test cannot reject the null H_0: η=0, we do not include η in the model. The ML estimates are presented in column A of table 3. Since

[7] Some difficulties arise in testing the null Ho: γ=0 because γ=0 lies on the boundary of the parameter space for γ. In this case, if the null is correct the LR statistic has asymptotic distribution, which is mixture of chi-square distributions. The rule of thumb for a test of size α is: "Reject Ho if LR exceeds the chi-square value for a size 2α" (Coelli et al., 1998).

[8] The ML estimate of γ is 0.997, value, which reinforces the conclusion above.

we cannot reject the time invariant efficiency hypothesis, we also estimate a deterministic frontier with GLS (a random effects model). The GLS estimates are presented in column B.

Table 3
Econometric Models[9]

Variable	**Column A: ML**	**Column B: GLS**
Intercept	5.565 (4.501)	5.629 (10.017)
Ln EMPLOYEES	0.199 (4.124)	0.172 (4.114)
Ln KMNET	0.256 (4.261)	0.232 (6.657)
Ln TRANSF	0.315 (12.67)	0.238 (7.177)
Ln AREA	0.015 (0.459)	0.061 (2.048)
Ln STRUCT	0.019 (0.339)	0.010 (0.207)
TIME	0.024 (3.123)	0.029 (4.754)

The dependent variable is Ln CUSTOMER. The t statistics are in parentheses.

In both the ML and GLS models all the inputs have the right sign and are significant at the usual levels of confidence. In both models AREA has an unexpected sign, though in the ML model it is not significant. The sign of AREA is a problem from a regulatory perspective, since it says that, ceteris paribus, the model demands more output from a firm that has a larger concession area. The only not significant variable (in both models) is STRUCT.

Technical change can be analyzed through the coefficients of the variable TIME.[10] The total rate of technical change is obtained as the first derivative of the natural logarithm of the production function with respect to time, dLnCUSTOMER/dTIME, which in this particular case is equal to β_6. In the ML model $\beta_6 = 0.024$ and in the GLS model $\beta_6 = 0.029$. These values can be interpreted as constant annual growth rates and shows a positive shift in the technical frontier of the electricity distribution sector as a hole in South America.

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 non-parametric estimation, i.e. we have a model with only one output[11] (number of customers), three inputs (labor, km of distribution lines, and transformer capacity in kV), and two environmental variables (concession area and a proxy

[9] For the ML estimates, we use FRONTIER 4.1, written by Coelli (1996). For the GLS estimates we use EVIEWS.

[10] In this case it has no sense to construct a Malmquist Index since there is not a catching up effect (the efficiency is time invariant).

[11] Though DEA is suitable for multi-output environments, as stated above. The need to compare, however, prevails.

for market structure). The orientation chosen is to the proportional reduction in inputs achievable by a firm while maintaining the level of output. We considered 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:

$$\min \lambda$$

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

This problem gives as a solution the proportion (λ) in which the observed inputs of the firm being analyzed could be reduced if they were used efficiently. 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):

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

As shown in Coelli et al. (1998), the technical efficiency scores obtained from DEA-C can be decomposed into pure technical inefficiency and scale inefficiency, which measures the average product of the firm under consideration relative to the average product of a point of optimal scale. Table 4 shows these three measures for every firm in the sample.

Table 4
DEA Efficiency Scores

Firm	DEA-C Technical Efficiency	DEA-V Technical Efficiency	Scale Efficiency
EMSA	0.390	0.394	0.990
EDET	0.693	0.700	0.991
EDENOR	1.000	1.000	1.000
CRE	0.419	0.428	0.979
CEB	0.449	0.451	0.996
CELG	0.981	0.982	0.999
CEMAT	1.000	1.000	1.000
CEMIG	1.000	1.000	1.000
CESP	0.907	0.916	0.991
COPEL	1.000	1.000	1.000
CONAFE	1.000	1.000	1.000

EDELMAG	1.000	1.000	1.000
CHEC	1.000	1.000	1.000
EEPPM	0.940	0.980	0.959
ENERCALI	0.993	0.993	1.000
EPSA	0.901	1.000	0.901
ESSA	0.687	0.694	0.991
EEQSA	0.783	0.785	0.997
EERCSCA	0.615	0.621	0.990
EERSSA	0.916	0.934	0.981
ELEPCOSA	0.993	1.000	0.993
EMELMANABI	0.671	0.678	0.990
ANDE	0.461	0.504	0.915
ELC	1.000	1.000	1.000
ELECTRO SUR	0.701	0.742	0.945
LUZ DEL SUR	0.841	0.843	0.997
SEAL	0.934	0.940	0.994
UTE	0.483	0.523	0.924
CALEV	0.999	1.000	0.999
CALEY	1.000	1.000	1.000
ELECAR	0.988	0.999	0.989
ELEGGUA	1.000	1.000	1.000
ELEVAL	0.975	0.977	0.998
ENELCO	0.585	0.628	0.932
ENELVEN	0.647	0.757	0.855

In the results it would be expected to find that the efficiency measures are lower for the DEA-C case than for the DEA-V case (fewer firms are found efficient in the former); and it should also be found that firms labeled efficient in the first model are also considered efficient in the second. Both expectations are confirmed by the results. The mean of the efficiency measures was .827 and .842 for DEA-C and DEA-V respectively.

IV. CONSISTENCY CONDITIONS ANALYSIS

Results of previous studies

Although there is a vast literature on efficiency measurement in the utilities sector, few studies try to compare the efficiency measures obtained with different approaches. Among them, there are the works of Pollitt (1995), Ray and Murkherjee (1995), and Burns and Weyman-Jones (1996). The first two studies compare parametric and non-parametric measures, while the latter compares only parametric measures.

Ray and Murkherjee (1995) apply the DEA methodology to a sample consisting of 123 electricity firms, the same sample used by Greene (1990), though this author applies the stochastic frontier approach (under different assumptions about the distribution of the inefficiency term). From the comparison of both studies it is concluded that DEA results are consistent with those of SPF whenever the inefficiency term has a gamma or half-normal distribution. The consistency result is weaker for other distributions of the inefficiency term.

Burns and Weyman-Jones (1996), in turn, compare the efficiency rankings stemming from DFA-R and SPF methodologies. Correlation between both rankings turned out to be 0.395, rejecting the hypothesis of zero correlation at the 95% significance level. In support of the consistency between the models, the authors show that both approaches identify the same firms as the most or least efficient.

Pollitt (1995) compares the DEA, DPF and SPF approaches in the case of electric power plants, finding correlations ranging from 0.57 to 0.95. According to the author, the results of the application of the different methodologies reveal a relatively high correlation between the rankings derived from the various techniques, specially a very high correlation between both parametric approaches. However, when the same exercise is performed in the case of base load power plants, lower correlations than in the former case obtains.

Finally, Rodríguez Pardina et al. (1999) made an international comparison of the relative efficiency of the firms in the electricity distribution sector and found that, broadly speaking, the different approaches are consistent in their means, rankings and identification of the same firms as the "best" and the "worst" (internal consistency). Moreover, they found that there exists a positive (but close to zero) correlation between the diverse efficiency measures and the partial productivity indices usually used to measure firms' performances (this is the only external condition tested by the authors).

The literature is far more extensive in sectors other than electricity, and the results are diverse (see Bauer et al., 1998, for a discussion of these results in the financial sector). A detailed analysis of the consistency conditions, however, has not yet been attempted in the utilities sector.

An interesting conclusion reached by Drake and Weyman-Jones (1996) is that the non-parametric and stochastic approaches provide the lower and upper bounds respectively for the efficiency measures, though unfortunately the range between both bounds is often too large.

Our results

In this paper, four different approaches have been used to estimate the efficiency measures: DEA with constant returns to scale (DEA-C), DEA with variable returns to scale (DEA-V), stochastic parametric approach estimated with panel data and maximum likelihood (DFA-ML) and deterministic parametric frontier estimated with GLS (DPF-GLS). To ensure comparability, the four techniques use the same efficiency concept (technical efficiency), the same sample of firms (unbalanced panel of 35 firms for the period 1994-1997, 99 observations), equal specifications of inputs (employees, kilometers of net and transformer capacity), environmental variables (concession area and market structure) and output (customers), and (for parametric methods) the same functional form (Cobb-Douglas production function). The consistency conditions sketched in Section II will be now analyzed.

(i) Comparison of the distribution of the efficiency measures across the different approaches

Table 5 presents the efficiency measures and the respective ranking for all the firms in the sample for the four approaches.

Table 5
Efficiency measures and rankings by approach

Firm	DEA-C		DEA-V		DPF-GLS		DFA-ML	
	Measure	Ranking	Measure	Ranking	Measure	Ranking	Measure	Ranking
EMSA	0.390	35	0.394	35	0.1478	35	0.217	35
EDET	0.693	25	0.700	26	0.2809	20	0.394	20
EDENOR	1.000	1	1.000	1	1.0000	1	0.972	1
CRE	0.419	34	0.428	34	0.1874	32	0.272	33
CEB	0.449	33	0.451	33	0.3136	16	0.366	22
CELG	0.981	15	0.982	16	0.4685	7	0.635	4
CEMAT	1.000	1	1.000	1	0.5403	3	0.932	3
CEMIG	1.000	1	1.000	1	0.4661	8	0.514	10
CESP	0.907	20	0.916	21	0.3538	14	0.421	17
COPEL	1.000	1	1.000	1	0.5353	4	0.603	5
CONAFE	1.000	1	1.000	1	0.3593	13	0.517	8
EDELMAG	1.000	1	1.000	1	0.2570	23	0.359	24
CHEC	1.000	1	1.000	1	0.3701	11	0.511	11
EEPPM	0.940	17	0.980	17	0.4777	6	0.497	13
ENERCALI	0.993	12	0.993	15	0.5012	5	0.567	6
EPSA	0.901	21	1.000	1	0.3107	17	0.442	15
ESSA	0.687	26	0.694	27	0.2373	26	0.316	28
EEQSA	0.783	23	0.785	23	0.3639	12	0.459	14
EERCSCA	0.615	29	0.621	30	0.2090	29	0.298	32
EERSSA	0.916	19	0.934	20	0.1879	31	0.321	27
ELEPCOSA	0.993	13	1.000	13	0.2441	24	0.408	18
EMELMANABI	0.671	27	0.678	28	0.2245	27	0.336	25
ANDE	0.461	32	0.504	32	0.2791	21	0.379	21
ELC	1.000	1	1.000	1	0.2967	19	0.515	9
ELECTRO SUR	0.701	24	0.742	25	0.1793	33	0.312	29
LUZ DEL SUR	0.841	22	0.843	22	0.4545	9	0.524	7
SEAL	0.934	18	0.940	19	0.3038	18	0.510	12
UTE	0.483	31	0.523	31	0.3312	15	0.403	19
CALEV	0.999	11	1.000	1	0.5479	2	0.949	2
CALEY	1.000	1	1.000	1	0.2184	28	0.360	23
ELECAR	0.988	14	0.999	14	0.4055	10	0.435	16
ELEGGUA	1.000	1	1.000	1	0.1902	30	0.307	30
ELEVAL	0.975	16	0.977	18	0.2645	22	0.321	26
ENELCO	0.585	30	0.628	29	0.1621	34	0.224	34
ENELVEN	0.647	28	0.757	24	0.2379	25	0.303	31

Table 6 presents the main characteristics of the distributions generated by the four methodologies employed.

Table 6
Consistency Condition (i)

Approach	DEA-C	DEA-V	DPF-GLS	DFA-ML
Mean	0.827	0.842	0.340	0.454
Median	0.934	0.977	0.304	0.408
Deviation	0.208	0.201	0.164	0.186
Maximum	1.000	1.000	1.000	0.972
Minimum	0.390	0.394	0.148	0.217
Sample	35	35	35	35

As it was expected, average efficiency is higher in the stochastic approach than in the parametric deterministic methodology. The comparison between the parametric and non-parametric approaches concludes that the latter show a higher mean, probably reflecting the bias of having two many variables relative to the number of observations or that the firms are very heterogeneous (remember that a necessary condition was a broad set of *comparable* firms).

The Kruskal-Wallis (non-parametric) test was carried out to test the null hypothesis that the four populations from where the samples came have identical population medians, and we cannot reject the null.

(ii) Correlation between rankings

Table 7 contains the coefficients of Spearman's ranking correlations, which show the existing relationship between each ranking and the others. All the correlations are positive, and significantly different from zero at the usual levels of confidence. According to these results, consistency condition (ii) would be met among the different approaches.

Table 7
Consistency Condition (ii)

Approach	DEA-C	DEA-V	DPF-GLS	DFA-ML
DEA-C	1.000	0.925**	0.375*	0.512**
DEA-V		1.000	0.348*	0.489**
DPF-GLS			1.000	0.930**
DFA-ML				1.000

* correlation significatively distinct from zero at a 5% level, two tails.
** correlation significatively distinct from zero at a 1% level, two tails.

(iii) Identification of the same firms as "best" and "worst"

The upper triangle of the matrix displayed in Table 8 shows, for each pair of approaches, the fraction of firms that both approaches simultaneously classified in the upper third (12 firms). The lower triangle of the matrix shows the same for the case of the lower third (12 firms, also, leaving 11 firms in the middle third). It is worth mentioning that if the fraction were purely random, it would be expected to be around 33.3%.

Table 8
Consistency Condition (iii)

Approach	DEA-C	DEA-V	DPF-GLS	DFA-ML
DEA-C		0.916	0.583	0.750
DEA-V	1.000		0.500	0.666
DPF-GLS	0.666	0.666		0.750
DFA-ML	0.666	0.666	0.833	

These results appear to imply that condition (iii) is being met. The advantage of knowing if the different approaches are consistent relative to the identification of firms as the "best" or the "worst" is that, even in the case of no fulfillment of the first two consistency conditions, it would be possible to use a mechanism like the one employed by OFWAT, which publishes the efficiency rankings in the media as a reward or a punishment to the firms.

(iv) Consistency with other performance measures

Partial productivity measures, though theoretically inferior to efficiency frontiers, are used as a complement to frontier analysis.[12] This external condition requires the efficiency measures generated by the different approaches to be positively correlated with the partial productivity measures, although the correlations must be far away from unity (Bauer et al., 1998). Table 9 shows the performance measure used in checking condition (iv):

Table 9
Partial Productivity Measures

Measure	Mean	Deviation	Sample	Maximum	Minimum
Customers/ Employee	1252	1268	35	6884	397
Sales/ Employee	6277	6390	35	29123	1244

Table 10 displays the correlations between the partial productivity measure and the efficiency measures obtained with the four methodologies.

[12] These partial productivity measures fail mainly because they do not take into account the possibility of input substitution. Moreover, they do not recognize the existence of variables beyond the firm's control. However, they are widely used as complements to efficiency frontier estimations. One of the reasons for their usefulness may be that they can point out measurement errors in the data (e.g. an implausible value in an output/input ratio).

Table 10
Consistency Condition (iv)

Approach	Sales/Employee	Customers/Employee
DEA-C	0.117	0.230
DEA-V	0.150	0.225
DPF-GLS	0.262	0.294
DFA-ML	0.385	0.468

According to Table 10, condition (iv) would be met because all the correlations are positive and far from unity. Moreover, it can be observed that the correlations tend to be higher when customers are used as output in the construction of partial productivity indices (the same choice as in frontier estimation).

(v) Individual efficiency measures should be rather stable over time

As discussed above, to be useful for regulatory purposes, it is important that the efficiency measures be reasonably stable over time. Though some firms may marginally improve or worsen their performance over short periods of time, it is unlikely that a very efficient firm in one year would become very inefficient in the next, only to return to high efficiency in the following year (Bauer et al., 1998). We now determine the year-to-year stability of DEA-C and DEA-V efficiency estimates over time. We do not include both parametric approaches (DPF and DFA) because we were not able to reject the null hypothesis that the efficiency was constant over time (so we already know that the measures generated by DPF and DFA are stable). We calculated the correlations for each of the two time-varying efficiency measures between each pair of years. That is, we computed the correlation between DEA-C efficiency measures in year i, i=1994, ..., 1997, and DEA-C efficiency scores in year j, j=1995, 1996, 1997, with j>i to avoid redundancy, and then repeated this process for the DEA-V approach. Table 11 presents the average correlations by the number of years apart. In general, the n-year apart figures are averages of the 4-n correlations between efficiencies that are n years away from each other.

Table 11
Consistency Condition (v)

Approach	1 year apart	2 year apart	3 year apart
DEA-C	0.901	0.925	0.865
DEA-V	0.899	0.941	0.886

The correlations are high and statistically significant over all the available lags for both methods examined, suggesting that the non-parametric efficiency scores are stable over time and giving support to the results obtained in the parametric estimates.

(vi) The different measures should be reasonably consistent with the expected results from the industry, given the conditions under which it operates

At the end of 1997, several of the countries in South America (Argentina, Bolivia, Chile, Colombia and Peru) had undergone a restructuring process in their electricity sectors. The reforms included 15 firms out of 35 in our sample (leaving 20 firms in non-reforming countries).

One of the main objectives of all these restructuring processes was productive efficiency, so one would expect to find that the relative efficiency of the firms in the reforming countries is higher than that of the other firms. To test this hypothesis, we used the Kruskal-Wallis non-parametric test (as in condition (i)), and found that the null hypothesis of no differences between both groups can be rejected at the usual levels of significance. Therefore, the results are consistent with the a priori expectations, and condition (vi) is met.[13]

V. CONCLUSIONS

The present work made an international comparison of the relative efficiency of the firms in the electricity distribution sector. To achieve such a goal, it used different methodologies that allowed the construction of several efficiency rankings, on which a consistency analysis was performed. That analysis showed that, broadly, the different approaches are consistent in their means, rankings and identification of the same firms as the "best" and the "worst" (internal consistency). Moreover, the external consistency conditions are also met.

Despite the particular results found here on the consistency conditions, the paper underscores the importance of conducting a consistency analysis whenever using efficiency measures in applied regulation.

Thinking about the future, this kind of work highlights the importance of having homogeneous databases in the different countries in order to make the comparisons. In this sense, it is important to note the work of the Comisión de Integración Eléctrica Regional (CIER), source of the information on which this study was based.

[13] A similar result is found in Rodríguez Pardina and Rossi (1999), but using a different methodology.

APPENDIX 1

Table A-1
Previous Studies: Electricity Transmission

Author/s	Specification/ Estimation	Output/s	Input/s	Environmental Variables
Huettner and Landon, 1977	Cost function, Econometrics	Total capacity, utilization of total capacity (%)	Labor	Underground circuit miles/1000 customers, structure miles/1000 customers, commercial sales (% of total), industrial sales (% of total), utility-muni sales (% of total), and a set of regional dummy variables and of holding companies dummy variables
Pollit, 1995	Cost function, Econometrics	Circuit km*voltage level, ratio of maximum to average demand,	Labor	Percentage of residential sales in total, lenght of underground circuits (km), lenght of overhead circuits (km), transformer capacity (MVA), and a dummy variable for ownership
Pollit, 1995	Production approach, DEA	Number of employees, circuit km*capacity (kV), electric energy losses	Electric energy delivered, maximum system demand, route km	
Pollit, 1995	Production approach, DEA	Number of employees, circuit km*voltage level (kV), transformer capacity (MVA)	Electric energy entered, maximum system demand, circuit km	
Pollit, 1995	Production approach, DEA	Number of employees, transformer capacity (MVA)	Electric energy entered, maximum system demand	Circuit km*voltage level (kV), circuit km
Pollit, 1995	Production approach, DEA	Number of employees, transformer capacity (MVA)	Electric energy entered	Circuit km*voltage level (kV), circuit km, maximum system demand
Pollit, 1995	Production approach, DEA	Number of employees	Electric energy entered	Circuit km*voltage level (kV), circuit km, maximum system demand, transformer capacity (MVA)
DTe, 2000	Cost efficiency, DEA	Units transmitted (GWh/a), maximum demand (MW), generation capacity connected (MW), quality of service	Costs of transmission	Area, population density, mains length (km), transformer numbers, share of underground cables (%)

Table A-2
Previous Studies: Water

Author/s	Specification /Estimation	Output/s	Inputs	Environmental Variables
Fox and Hofler, 1986	Production approach, Econometrics	Water produced, miles of distribution pipeline	Man-hours, maximum treatment capacity	% of water distributed to nonresidents
Byrnes et al., 1986	Production approach, DEA	Water distributed	Ground water, surface water, purchased water, miles of pipeline, part-time labor, full-time labor, storage capacity	
Stewart, 1993	Cost function, Econometrics	Volume of water delivered		Length of mains, % of sales to non-households, Average pumping head, % of distribution input from groundwater
Bhattacharyya et al., 1995	Production function, Econometrics	Water supplied	Energy, labor, materials	Water input, population density, capital[14], % of metered connections, distribution pipe length, system water loss, and a set of dummy variables[15]
Crampes et al., 1997	Cost function, Econometrics	Water produced[16]	Labor, Capital	Number of connections, number of connections per employee, the ratio of billed water to produced water
Estache and Rossi, 1999	Cost function, Econometrics	Customers	Labor	Population density, number of connections, number of hours of water availability, % of residential sales, and a dummy concessionaire firm

Table A-3
Previous Studies: Gas Distribution

Author/s	Specification /Estimation	Output/s	Inputs	Environmental Variables
Burns and Weyman-Jones, 1998	Cost function, Econometrics	Domestic and non-domestic customers served	Labor, capital	[17]
Rodríguez Pardina and Rossi, 1999	Cost function, Econometrics	Number of customers	Labor	Kilometers of pipes, concession area, % or residential sales, total sales, maximum demand
Rossi, 2000	Production function, Econometrics	Number of customers	Kilometers of network, employees	Concession area, maximum demand, % of residential sales

[14] Capital is defined as the current value of the water utilities' assets.
[15] These are: Firms treating water, firms with surface water, firms with groundwater, firms with water and sewer.
[16] In a second model the authors also include water volume billed.
[17] Though the authors include control variables, they do not explicit them.

APPENDIX 2: DEFINITIONS OF THE VARIABLES

Here we make a more detailed description of those variables that, in our belief, need such a description.

Burns and Weyman-Jones (1994)

Customer density: number of customers per square kilometer of company territory.

Market structure: the share of industrial energy delivered in total energy delivered.

Labor: number of full time equivalent employees.

Capital 1: size of the distribution network in circuit kilometers.

Capital 2: size of network reinforcement by transformer capacity (megavoltamps).

Pollitt (1995)

Labor costs: Average salary in 1000s of US dollars in the utility. This is total wages and salaries divided by the number of full-time employees plus half the number of part-time employees. UK data has been converted to US dollars using a Purchasing Power Parity exchange rate of 0.609.

Operation and Maintenance Costs: Operation and maintenance costs in distribution in 1000s US dollars. This figure includes rent but not depreciation. UK data has been converted to US dollars using a Purchasing Power Parity exchange rate of 0.609. UK data include operation and maintenance costs of 132 and 66 kV lines, which are not counted as part of the distribution system. This implies UK labor and average cost data are biased upwards when compared to US data.

Labor: Number of employees in the distribution function. This figure is derived by dividing operation and maintenance costs in distribution by the labor cost. This gives a labor equivalent operation and maintenance cost.

Peak Output: Maximum demand on the system in MW.

Scarsi (1999)

Total Distribution Costs: It is made up of capital and labor costs, plus materials (goods and services supplied by third parties), which are seen as residual cost components.

Price of Labor: Obtained as the ratio between labor cost and average number of employees, without including part-time jobs.[18]

Price of Capital: Computed as the ratio between capital costs and the length of distribution lines. As the author says, this is clearly a proxy value for the user cost of capital.

Within a cross-sectional analysis, no correction for either depreciation or real interest rates is needed. The unit cost of capital should be calculated as (KCOST $(r+\delta)$)/K, where

[18] The author states that part-time jobs are not common in Italian electricity sector.

KCOST is the historic cost of capital, r is the real interest rate, δ is the depreciation charge for each period, and K is the quantity of capital in physical terms. This formula intends to represent the rental price of capital, which includes an arbitrary depreciation charge.

Price of materials: Computed as the ration between total cost of third-party deliveries and the number of transformers. The idea is that since materials are especially used in specific plants such as substations and capacitors, the materials price can be expressed in terms of transforming units (substations).

Burns and Weyman-Jones (1996)

Cost: Is the audited cost data. A fundamental point about this source of cost data is that the shareholder accounts and the regulatory accounts are important instruments to the firm as a way of sending strategic signals to shareholders and regulators.

Cost of Capital: User cost of capital in manufacturing from the NIESR macroeconomic model (see Young, 1992, for a description of its construction).

Cost of Labor: User cost of labor in manufacturing from the Bank of England macroeconomic model.

Thompson (1997)

Capital Service Prices and Costs: are determining using the methods developed by Christensen and Jorgenson (1969) (see also Scarsi, 1999).

Neuberg (1977)

Price of Labor: Is obtained by dividing total wages and salaries for each firm by 2000 x its number of full-time equivalent employees.[19]

Price of Capital: Is set equal for all firms and thus collapsed in the intercept parameter.

DTe (2000)

Network Dispersion: network length per customer.

Operating Expenditures: include materials, services, wage costs and other costs.

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[19] Notice that 2000 hours = (40 hours/week) x 50 weeks. Thus the author is implicitly assuming that each full-time equivalent employee of a firm works 50 40-hour weeks in a year. Part-time employees were counted as halt-time employees.

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