ON THE REGULATORY CHOICE OF RETURNS TO SCALE IN DEA MODELS: AN APPLICATION TO THE ARGENTINE ELECTRICITY DISTRIBUTION SECTOR

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ABSTRACT

In the distribution activity, "High-power" regulatory regimes were adopted in most of the reformed electricity sectors. In particular, in a price cap regime with a RPI-X rule, it is commonly used a benchmarking exercise based on efficiency frontier estimations. DEA is a widely used tool to accomplish this objective. Given that DEA efficiency scores are affected by the assumption about returns to scale, it is relevant for regulators to test that assumption. In this sense, the aim of this study is to determine if there is any evidence that the scale of production is constant in the electricity distribution activity. To achieve this objective, we construct efficiency frontiers using data from Argentine distribution firms in order to use them to statistically evaluate hypotheses about characteristics of production and factors affecting productivity. We find evidence of the presence of constant returns to scale in the Argentina electricity distribution.

INTRODUCTION

This study describes the application of Data envelopment Analysis (DEA) tools to the measurements of efficiency of electricity distribution sector in Argentina. The objective of this study is to determine if there is any evidence that the level and scale of production condition is constant in the electricity distribution activity. We construct efficiency frontiers, based on both a cost function and a production function, applying DEA methodology in order to use them to statistically evaluate hypotheses about characteristics of production and factors affecting productivity.

In a regulatory context, it is particularly relevant for regulators to have some idea about the plausibility of the assumptions on returns to scale (RTS) needed to calculate relative efficiency using DEA. The choice of the envelopment surface (constant or variable returns to scale) is one of the regulatory choices included in the regulator task of measuring efficiency [7]. This paper is aimed to tackle this issue. Hence, we present a simple testing process to justify the utilization of determined returns to scale assumption.

BACKGROUND

Given the empirical nature of our objective, it is important to remark some aspects of the regulatory environment in Argentina. Baldwin and Cave [8] identify a number of conditions for a successful implementation of a benchmarking methodology: a considerable number of comparable firms, a common regulator, and enough data for all the firms. The number of firms and the information available is long enough. Even though there is not a common regulator for all of them, local legislations are not so different, making them comparable. Most of the firms are regulated with a price cap regime with a service obligation condition, but some public firms remain.

EMPIRICAL ANALYSIS OF DATA

A successful DEA analysis depends crucially on the quality of the data. Also, for the understanding and interpretation of results, we think that is important to get a real feel for the data.

Sample Population and description of variables

The data consist of annual observations of outputs and inputs from all type and size of electricity distribution companies (plant-level observations), which was obtained from ADEERA (Argentine Distribution of Electricity Association) and firm's financial statements. The time period is 1993 to 2001. The accounting data cover total costs extracted from each firm's financial statements. Total costs include operating, administrative and marketing expenses, as well as energy purchases. Besides, we consider including others variables which could be important for the performance of the study: energy sales are in physical units (GWh), employment (include permanent and temporary employees), total number of clients, area of operation (Km^2) and lines (low, medium and high-tension). Moreover, we enclose some additional ratios like: density (number of customers to area), structure of demand (proportion of residential sales to total sales).

Data Analysis

DEA introduces an alternative principle for extracting information about a population of observations.

In the context of DEA with panel data, some options are available. One is to construct a frontier for each year and estimate the relative efficiency of each firm for the annual frontier. Another possibility is to treat each observation as independent and construct a single frontier for all period. The last one is the option chosen in this paper.

The following Table 1 presents the descriptive statistics of each of the variables of the estimation.

Table 1: *Argentina, Electricity Distribution 1993-2001.*

Descriptive statistics

Variable	*Mean*	*Std. Dev.*	*Min*	*Max*
Sales (GWh/year)	1936.0	2786.4	217.8	10600.0
Clients (Thousands)	457.4	629.8	360.1	2275.1
Area (Km2)	80295	56026	3309	203000
Employment	1202	1308	75	5051
Lines (Km)	13432	11151	3000	46865
Total Costs (Million $)	245,8	303,1	29,3	963,8
Total Wage ($)	31041	9353,2	14900	69500
Structure of demand /Residential sales / Total sales)	0,42	0,11	0,11	0,61
Density (Clients/Km^2)	73,1	180,6	0,38	637,2

Source: own elaboration

DEA MODEL AND STATISTICAL TESTS

DEA Methodology

Data Envelopment Analysis involves the use of linear programming methods to construct a non-parametric piece-wise surface over the data. It means, optimizes on each individual observation with and objective of calculating a piece-wise frontier determined by the set of Pareto-efficient DMUs (Decision Making Units) [1].

For the selection of the model, we use the results of Margaretic and Romero [9] where econometrics techniques have been used in order to reach a robust specification. The basic linear (envelopment) programme solved for the estimation of efficient frontiers is the following:

$$\min_{\phi,\lambda} \hat{\phi}$$

subject to

$$\lambda X \le \phi x_j$$
$$\lambda Z \le z_j$$
$$Y\lambda \ge y_j$$
$$\lambda \in R + J$$

($\hat{\phi}$ is the DEA estimator of ϕ).

Where Y is a N×r matrix of outputs (N: number of firms; r: number of outputs); X stands for a N×m matrix of inputs (m: number of inputs); Z represents a N×s matrix with information about s environmental variables; ϕ is a scalar and λ is a Nx1 vector of constants. The value of $\hat{\phi}$ obtained will be the efficiency score for the ith DMU. It will satisfy $\hat{\phi}$ < 1, with a value of 1 indicating a point on the frontier and hence a technically efficient Decision Making Unit, according to the Farrell definition [2]. The linear programming problem must be solved N times, once for each DMU in the sample. A value of $\hat{\phi}$ is then obtained for each DMU, see [3].

The CRS (Constant Returns to Scale) assumption is only appropriate when all DMU's are operating at an optimal scale. Imperfect competition or constraints on finance, among others, may cause a DMU to be not operating at optimal scale. Banker, Charnes and Cooper (BCC) [4] suggested an extension of the CRS DEA model to account for variable returns to scale (VRS) situations. The use of the CRS specification when not all DMU's are operating at the optimal scale, will result in measures of total efficiency. The CRS linear programming problem can be easily modified to account for VRS by adding the convexity constraint: $\sum_j \lambda_j = 1$ to the previous problem. One shortcoming of this measure of efficiency is that the value does not indicate whether the DMU is operating in an area of increasing or decreasing returns to scale. This may be determined by running an additional DEA problem with a non-increasing returns to scale (NIRS) assumption. Although this is not prove in this study it is important to keep in mind.

Statistical Foundation for DEA (Tests of Constant Returns to Scale)

In empirical applications of DEA, the efficiency variable ϕ is not observed and needs to be estimated from output and input data, so the following linear program is used to estimate efficiency:

$$\min_{\phi,\lambda} \hat{\phi}$$

subject to

$$\lambda X \le \phi x_j$$
$$\lambda Z \le z_j$$
$$Y\lambda \ge y_j$$
$$\sum_j \lambda_j = 1$$
$$\lambda \in R + J$$

Consider the efficiency $\hat{\phi}^c$ estimated using the Charnes, Cooper and Rhodes model (CCR) [5] obtained from the BCC linear program in the above equation by deleting the constraint $\sum_j \lambda_j = 1$.

By constructing $\hat{\phi}^c \ge \hat{\phi}$. All observations in the sample are scale efficient if and only if the sample data could be rationalized by a production set exhibiting constant returns to scale [6].

The null hypothesis of scale efficiency (or equivalently, constant returns to scale) in the sample can be evaluated by constructing the following test statistics (developed by Banker and Natarajan [6]), after taking the natural logarithm of the true efficiency ($\hat{\phi}$):

1. If $\hat{\phi}$ is distributed as half-normal over [0,∞), the test statistics is calculated as $\sum\left[\ln(\hat{\phi}^c)\right]^2 / \sum\left[\ln(\hat{\phi})\right]^2$ which is evaluated relative to the half-F distribution $|F_{N,N}|$, with N,N degrees of freedom over the range [1,∞).

2. If $\hat{\phi}$ is distributed as exponential over [0,∞), the test statistics is calculated as $\sum \ln(\hat{\phi}^c) / \sum \ln(\hat{\phi})$ which is evaluated relative to the half-F distribution $|F_{2N,2N}|$, with 2N,2N degrees of freedom over the range [1,∞), since by construction the test is never less than 1.
3. If there are not any assumptions maintained about the probability distribution of $\hat{\phi}$, a non-parametric Kolmogorov-Smirnov´s test statistic given by the maximum vertical distance between $F^c \lfloor \ln(\hat{\phi}^c) \rfloor / F \lfloor \ln(\hat{\phi}) \rfloor$ is used. This statistics takes values over the range [0,1] and a high value indicates the existence of significant scale efficiency in the sample.

EMPIRICAL RESULTS

Calculating Efficiencies

The purpose of this section is to illustrate the different efficiency measures obtained by the following two models: (1) *Productive efficiency (PE)*, which reflects the ability of a firm to use the inputs in optimal proportions, given their respective prices and the production technology; (2) *Technical efficiency (TE)*, which reflects the ability of a firm to obtain maximal output from a given set of inputs.
The first model estimated (**PRO-(EV)-CRS**) which is considered as the original one assumes CRS and includes the number of clients as output, total costs as inputs and two environmental variables: density and structure of demand. Additionally, the next model estimated (**TEC-(EV)-CRS**) includes the same output and environmental variables, but two different inputs: employees and lines.
Regarding the inclusion of environmental variables, we estimate some variations to both original models (PRO-(EV)-CRS / TEC-(EV)-CRS). The first alternative specification does not include any environmental variable (**PRO-CRS** and **TEC-CRS**). In this case, the omission of any variable that might capture the effect of the environment makes the firms of the set appear as relatively inefficient. It penalizes the relative efficiency measurement for the majority of firms. After that, we consider again PRO-(EV)-CRS, TEC-(EV)-CRS (adding PRO-CRS and TEC-CRS) but now assuming that the returns are variable (**PRO-(EV)-VRS** / **TEC-(EV)-VRS / PRO-VRS** / **TEC-VRS**).
Moreover, considering the number of clients, we create different samples for each of the models calculated in order to identify whether the whole sector present CRS or a specified interval of firms. The different samples created were the following: **Sample A** considers the entirety of the data (all firms), **Sample B** is Sample A without the biggest firms (these firms withdrawal were EDENOR and EDESUR), **Sample C** considers the interval 100.000 – 450.000 clients and **Sample D** contains the interval 100.000 – 300.000 clients. We include these last two sample because of we are interested in testing the robustness of the measures.
Table 2 and

Table 3 show the results of *Productive Efficiency* and *Technical Efficiency* estimations*, respectively*.

Table 2: *Productive Efficiency Measures*

Productive Efficiency (*)	*PRO-CRS*	*PRO-VRS*	*PRO-(EV)-CRS*	*PRO-(EV)-VRS*
Sample A	*0,598* (0,130)	*0,662* (0,158)	*0,842* (0,158)	*0,845* (0,160)
Sample B	*0,583* (0,135)	*0,660* (0,164)	*0,822* (0,163)	*0,825* (0,165)
Sample C	*0,608* (0,147)	*0,675* (0,160)	*0,847* (0,160)	*0,856* (0,161)
Sample D	*0,618* (0,155)	*0,681* (0,173)	*0,882* (0,144)	*0,885* (0,145)

Source: own elaboration

Table 3: *Technical Efficiency Measures*

Technical Efficiency (**)	*TEC- CRS*	*TEC-VRS*	*TEC-(EV)-CRS*	*TEC-(EV)-VRS*
Sample A	*0,313* (0,207)	*0,322* (0,230)	*0,748* (0,226)	*0,753* (0,231)
Sample B	*0,464* (0,192)	*0,506* (0,228)	*0,728* (0,229)	*0,732* (0,232)
Sample C	*0,501* (0,210)	*0,503* (0,214)	*0,771* (0,180)	*0,776* (0,184)
Sample D	*0,463* (0,189)	*0,471* (0,205)	*0,841* (0,139)	*0,856* (0,145)

Source: own elaboration

Note: In italics, averages. In brackets (), standard deviations.
(*) PRO-(EV)-CRS: number of clients as output, total costs as input and two environmental variables: density and structure of demand. **PRO-CRS:** PRO-(EV)-CRS without environmental variables. **PRO-(EV)-VRS:** stand for PRO-(EV)-CRS with different assumptions regarding variable returns to scale. **PRO-VRS:** stand for PRO-CRS with different assumptions regarding variable returns to scale.
(**) TEC-(EV)-CRS: number of clients as output, lines and number of employees as inputs and two environmental variables: density and structure of demand. **TEC-CRS:** TEC-(EV)-CRS without environmental variables. **TEC-(EV)-VRS:** stand for TEC-(EV)-CRS with different assumptions regarding variable returns to scale. **TEC-VRS:** stand for TEC-CRS with different assumptions regarding variable returns to scale.
Each model has been calculated for different samples: **A:** Until 2 millions clients (all firms), **B:** A without EDENOR and EDESUR (biggest firms), **C:** From 100.000 to 450.000 clients, **D:** From 100.000 to 300.000 clients.

Looking at the efficiency measures predicted by both models, we can notice that, independently of the sample, the measures related to PE are higher than the measures related to TE, however, all the measures of TE except one have bigger standard deviations.
Finally, we choose the models without environmental variables to prove our hypotheses in this paper due to the higher ratio VRS to CRS (stronger efficiency effects), although there are not habitual among the literature.

Evaluating Constant Returns to Scale using Statistical Tests

The starting point was the establishment of the null hypothesis. In this case, we would like to test scale efficiency or constant returns to scale for each of the samples created. Once calculated all the efficiency scores, we begin the statistical testing with a Kolmogorov-Smirnov non-parametric test. The results obtained are the no rejection in all the cases of the null hypothesis with a level of significance of 5%, except in two cases, PRO B and PRO C. This finding supports the assumprion of CRS in the electricity distribution sector (see Table 4).

Table 4: *Kolmogorov-Smirnov Statistical Test (*)*

Variable	*Statistic Value*	*P-value*	*Corrected*	*H_0 Condition*
Productive Efficiency				
PRO A	0,1744	0,146	0,111	Not Rejected
PRO B	0,2676	0,012	0,008	Rejected
PRO C	0,2917	0,034	0,021	Rejected
PRO D	0,2051	0,385	0,302	Not Rejected
Technical Efficiency				
TEC A	0,0522	0,993	0,990	Not Rejected
TEC B	0,1441	0,173	0,137	Not Rejected
TEC C	0,0274	1,00	1,00	Not Rejected
TEC D	0,0635	1,00	1,00	Not Rejected

Source: Own elaboration.
Note: *Level of significance 5%, (*) No assumptions maintained about the probability distribution.*

Nevertheless, we consider some F-tests in order to check the outcomes of the above test, but this time supposing certain distributions: **Alternative 1**, Exponential and **Alternative 2,** Half-normal.

Table 5: *Other Statistical Tests (Half-F distribution)*

Variable	*Statistic Value*	*Critic Value*	*H_0 Condition*
Alternative 1 – Efficiency is distributed as expoenential			
Technical Efficiency			
TEC A	1,0086	1,2230	Not Rejected
TEC B	1,0847	1,2393	Not Rejected
TEC C	1,0025	1,3141	Not Rejected
TEC D	1,0114	1,3420	Not Rejected
Productive Efficiency			
PRO A	1,2202	1,2860	Not Rejected
PRO B	1,2715	1,3192	Not Rejected
PRO C	1,2533	1,4013	Not Rejected
PRO D	1,2347	1,4547	Not Rejected
Alternative 2 – Efficiency is distributed as Half-Normal			
Technical Efficiency			
TEC A	1,0019	1,3300	Not Rejected
TEC B	1,0773	1,3553	Not Rejected
TEC C	1,0005	1,4734	Not Rejected
TEC D	1,0049	1,5183	Not Rejected
Productive Efficiency			
PRO A	1,3430	1,4286	Not Rejected
PRO B	1,4370	1,4815	Not Rejected
PRO C	1,4508	1,6154	Not Rejected
PRO D	1,3961	1,7045	Not Rejected

Source: Own elaboration.
Note: *Level of significance 5 %,*

In Table 5, we observe that the entirely set of tests do not reject the null hypothesis. Besides, we have done all these tests but including the environmental variables and the results are exactly the same, although these outcomes are not showed in this paper.

CONCLUDING REMARKS

In this paper we applied DEA methodology for the efficiency measurement in a regulatory context by the construction of an efficiency frontier. From the results obtained, it appears that DEA is appropriately for the estimation of the relative efficiency and at the same time it allows us to increase the information that a regulator has, which contributes to alleviate the problem of imperfect information, typical of this kind of sectors.
After analysing the scores obtained by each of the models specified, we show the existence of CRS in the Argentine electric distribution using different statistical test. This finding has an important regulatory result: it gives a justification to be a "tough" regulator at the time to choose the envelopment surface.

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