Productivity growth in electric energy commercialization in Colombia. A bootstrapped Malmquist indices approach*

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August 24, 2011

Abstract

This paper offers a productivity growth estimate for electric energy commercialization firms in Colombia, using a non-parametric Malmquist bootstrap methodology. The estimation and methodology serve two main purposes. First, in Colombia commercialization firms are subject to a price-cap regulation scheme, a non-common arrangement in the international experience for this part of the industry. Therefore the paper's result suggest an estimate of the productivity factor to be used by the regulator, not only in Colombia but in other countries where commercialization is a growing part of the industry (renewable energy, for instance). Second, because of poor data collection from regulators and firms themselves, regulation based on a single estimation of productivity seems inappropriate and error-prone. The non-parametric Malmquist bootstrap estimation allows an assessment of the result in contrast to a single one estimation. This would open an opportunity for the regulator to adopt a narrower and more accurate productivity estimation or override an implausible result and impose a productivity factor in the price-cap to foster the development of the industry.

JEL codes:

Key words: DEA, Malmquist, Productivity growth, Bootstrap, Electricity commercialization, Colombia.

*Many thanks to

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1 Introduction

Colombia's 1994 electric energy regulatory reform split a vertically integrated and state owned electricity industry into four activities: generation, transmission, distribution and commercialization. While nation wide transmission and local distribution function as natural monopolies, generation and commercialization are meant to engage into competitive behavior in order to increase welfare and quality of service to intermediate and final users. This paper offers a productivity growth estimate for electric energy commercialization (or retailing) firms in Colombia, using a non-parametric Malmquist bootstrap methodology.

The estimation and methodology serve two purposes. First, Colombia's commercialization firms are subject to a price-cap regulation scheme. Therefore the paper's result offers an estimate of the productivity offset or the X-factor to be used by the regulator. The productivity estimate as well as the discussion of energy commercialization objectives, inputs and outputs, can be used for further estimations in other countries or other industries.

Second, part of the success of price-cap regulation lies on an appropriately estimated productivity component. The estimation should capture the long term trend of the industry, must be resilient to the estimation method and to exogenous shocks. Besides, when information is poor (in length of time, number of units under evaluation or quality of data) such estimation can be inaccurate and error-prone. The non-parametric Malmquist bootstrap methodology allows an assessment of the productivity estimate in contrast to a single estimation via non-parametric Malmquist or other non-parametric or parametric method. This assessment opens an opportunity for the regulator to adopt a narrower and more precise productivity estimation or override an implausible result and use the productivity factor as a tool to foster the development of the industry in its early stages.

Non-parametric Malmquist productivity indices (or Data Envelopment Analysis (DEA) - Malmquist) have been used to evaluate productivity growth in different industries or policy change settings.[1] As reported in Jamasb and Pollitt (2001) it has also been used in single and cross-country studies for the assessment of performance and productivity in transmission and distribution. Jamasb and Pollitt also report the use of DEA in translating efficiency and productivity estimation into the price-setting process by the regulator. Several countries do so, however two warnings are in order. First, in a fully liberalized power sector, distribution and retailing are separated, however this is not the usual prac-

[1]There are plenty of studies gathered in Emrouznejad et al. (2008) compilation of efficiency and productivity studies using DEA.

tice and in most cases both activities function under the same umbrella. Therefore the productivity offset is the same for both activities. And second, "Frontier approaches are susceptible to shocks and errors in data. This is specially the case when cross-sectional data is used and there is no allowance for errors (...) [and] [f]irm specific efficiency scores are sensitive to the specification and assignment of the outputs, inputs and environmental variables" Jamasb and Pollitt (P. 28, 2001).

Both warnings are addressed in this paper. First, the productivity estimation is restricted to data available for energy commercialization firms in Colombia. Second, via bootstrapping the Malmquist estimation, an assessment of the productivity estimate is possible on statistical grounds.

Bootstrapping Malmquist indices was proposed more than a decade ago by Simar and Wilson (1999, 2000a). However, few empirical studies are available, and those are in disperse research fields, i.e., Hoff (2006); Balcombe et al. (2008); Latruffe et al. (2008) and Odeck (2009) in agricultural economics; Tortosa-Ausina et al. (2008) and Murillo-Melchor et al. (2010) in banking; and Assaf (2011) in airport services. However, neither there are studies touching the electricity industry, nor energy commercialization services. In all, the contribution of the paper is to scrutinize the energy commercialization service using a suitable case study and a methodological approach unfairly not used more often.[2].

Firm specific productivity growth results suggest high volatility and no clear trend on productivity growth from 2006 to 2009. In most of the cases, the estimated confidence intervals for Malmquist productivity, efficiency and technical change suggest that indices growth are not different from unity. These results suggest no statistically differentiable progress in performance in energy commercialization throughout the last five year. From a regulatory point of view, the results suggest the need to select a productivity offset factor in view of the development of the industry and not strictly to simulate market competition conditions.

The paper proceeds as follows. Section 2 briefly outlines the functioning of retail or commercialization firms. Section 3 discusses bootstrapping DEA and Malmquist indices. Section 4 presents the energy commercialization service in Colombia. Section 5 presents the data and estimation results. Section 6 concludes.

2 The commercialization of electric energy in a DEA and Malmquist productivity analysis

The commercialization of electric energy (also called energy –and related services– retailing or customer sales) links generation, transmission and distribution of power with final customers. This is the entity that power consumers take as the "electric company"

[2]Colombia's electricity industry has been well documented in previous studies, see: Pombo (2001); Garcia and Arbelaez (2002); Larsen et al. (2004), and Pombo and Taborda (2006)

forgetting the supply chain behind it (Philipson and Willis, 1999). In a fully de-regulated electric industry Philipson and Willis (1999) presents energy retailing as "(...) the most powerful player in the industry (...) for two reasons." First it controls the money flow from customers to the rest of the supply chain, and second it is involved in all levels of the industry.

In a fully (less) liberalized and developed power industry, commercialization is usually split (joined) from (with) distribution. When a pool market exists, commercialization firms are strongly active and visible; working with large customers willing to engage in buying electricity at better prices and setting long term contracts with generators. For small customers (for example: residential users) commercialization firms are not as visible and blend with the distribution service. In all, electric energy commercialization provides an homogeneous good at a given price, where the only differentiation among retailers is the supply of alternative / complementary energy services. Therefore those services, mainly focused on customer satisfaction, are the source of higher income and profit maximization.

Under several possible settings and institutional arrangements, some of the tasks (among many others) undertaken by a commercialization firm are:

- Be an agent in the pool market.
- Follow up connection (and disconnection) of customers to the distribution grid.
- Account of customers consumption. Including reading, metering and billing.
- Managing unpaid bills (Debtors).
- Ensure quality of service to customers.
- Supply of backup power or uninterrupted service.
- Supply automation, control and efficiency consumption options to customers.
- Product distinction and energy use plans.
- Selling other form s of energy (gas, propane, etc.).

The development of electric energy commercialization highly depends on existing regulation on ease of entry and use of technologies that can assure final users that changing provider neither represent an extra cost for the commercialization and distribution industry nor for the final customer. Commercialization firms then, provide an intermediation service and function as any other profit maximizing firm. Its functioning and characterization for the DEA and Malmquist productivity estimation can be summarized in the use of the following inputs and outputs:

Inputs: Assets; employment; costs.

Outputs: Queries, complaints and appeals (QCA); debtors; customers; electricity consumption.

The proposed list of inputs proxies some of the variables that can be taken as inputs in the functioning of an energy commercialization firm. Assets are proposed as a proxy of capital, employment of labor, and costs as a decision variable susceptible of being used to increase efficiency and therefore productivity. Within the domain of outputs, QCA proxies the quality of service, the lower the number of QCA the higher firm's efficiency. Management and size of debtors shows the financial health of the firm; lower debts to the company show better management practices. The number of customers and electricity consumption both capture the purpose to increase output.

3 Bootstrapping DEA and Malmquist indices

Based on the concepts developed in Simar and Wilson (1998) and Simar and Wilson (2000a) to bootstrap nonparametric efficiency scores, Simar and Wilson (1999) introduced a bootstrapping algorithm for Malmquist indices (see also Simar and Wilson, 2000b). Their presentation is clear and thoroughly, following their notation this section restricts to present basic concepts and the logic of the bootstrapping in search for an appropriate characterization of the Data Generating Process (DGP) $\mathcal{P}$ behind nonparametric efficiency estimation.

3.1 The Farrell theoretical world

Abstracting from the estimation method (DEA or Free Disposal Hull (FDH)) the input-oriented Farrell (1957)'s frontier model can be defined by a production set Ψ

$$\Psi = \left\{ (x, y) \in \mathbb{R}_{+}^{p+q} | x \text{ can produce } y \right\} \tag{1}$$

where x is a column vector of p inputs, y is a column vector of q inputs of different Decision Making Units (DMUs). The input requirement set (or the minimum inputs needed to produce y given a technology) is defined $\forall y \in \Psi$

$$X(y) = \left\{ x \in \mathbb{R}_{+}^{p} | \, (x, y) \in \Psi \right\} \tag{2}$$

the Farrell efficiency frontier is the subset of $X(y)$ denoted by $\partial X(y)$:

$$\partial X(y) = \{ x | x \in X(y), \; \theta x \notin X(y) \quad \forall \, 0 < \theta < 1 \} \tag{3}$$

the Farrell input measure of efficiency for a combinations of input and output $(x, y) \in \Psi$ is defined as a measure of the distance from (x, y) to the efficient frontier $\partial X(y)$:

$$\theta(x, y) = \inf \{ \theta | \theta \in X(y) \} \tag{4}$$

the inverse is the Shepard input distance function:

$$\delta(x, y) = (\theta(x, y))^{-1} = \sup \left\{ \delta \left| \frac{x}{\delta} \in X(y) \right. \right\} \tag{5}$$

function δ is the radial measure of efficiency giving the maximum feasible, proportionate reduction of inputs for a firm to operate at $(x, y) \in \Psi$. The intersection between $\partial X(y)$ and $(\theta x, y)$ is the efficient level of input corresponding to the output y:

$$x^{\partial}(y) = \frac{x}{\delta(x, y)} \tag{6}$$

in practice Ψ, $X(y)$, $\partial X(y)$ and $\delta(x, y)$ are unknown and DEA provides an estimate.

3.2 The DEA world

From a sample of input-output combinations, $\mathcal{X} = \{(x_i, y_i), \quad i = 1, \ldots, n\}$, equations 1 and 2 are denoted $\hat{\Psi}$ and $\partial \hat{X}(y)$ and 5 is solved via linear programming:

$$\begin{aligned} \left(\hat{\delta}(x, y)\right)^{-1} = \min \{\theta > 0 \quad | & \\ & y \leq \sum_{i=1}^{n} \gamma_i y_i, \\ & \theta x \geq \sum_{i=1}^{n} \gamma_i x_i, \\ & \sum_{i=1}^{n} \gamma_i = 1, \\ & \gamma_i \geq 0, \\ & i = 1, \ldots, n\} \end{aligned} \tag{7}$$

the efficient level of inputs is:

$$\hat{x}^{\partial}(y) = \frac{x}{\hat{\delta}(x, y)} \tag{8}$$

Figure 1 shows graphically the discussion above.

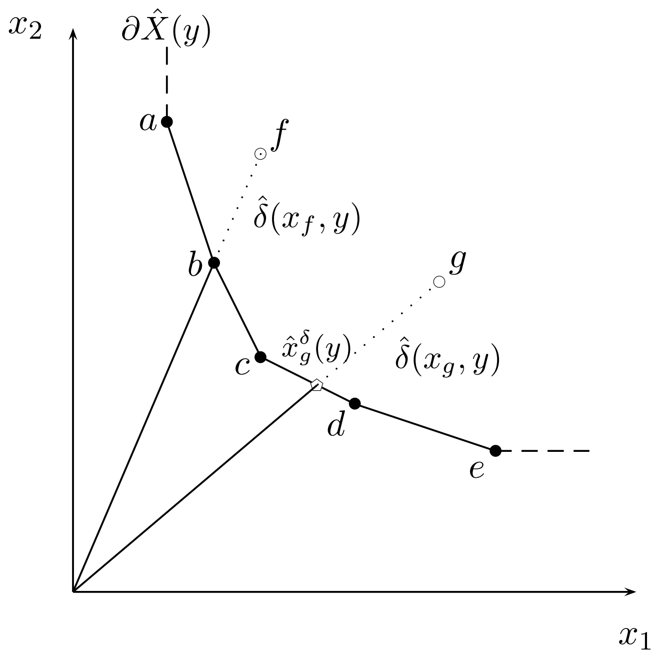


Figure 1. Basic DEA setup.
Note: a to g are different DMUs, $\hat{x}_g^{\delta}(y)$, $\hat{\delta}(x_g, y)$, and $\partial\hat{X}(y)$ are defined in section 3.2.
Source: Author's diagram

3.3 The DEA-bootstrap world

From a new sample of input-output combinations $\mathcal{X}^\star = \{(x_i^\star, y_i), \quad i = 1, \ldots, n\}$, drawn from the DGP $\hat{\mathcal{P}}$, equations 1 and 2 are denoted $\hat{\Psi}^\star$ and $\partial\hat{X}^\star(y)$ and 5 is solved via linear programming:

$$\begin{aligned}
\left(\hat{\delta}^\star(x, y)\right)^{-1} = \min \{\theta > 0 \quad | \\
& y \leq \sum_{i=1}^{n} \gamma_i y_i, \\
& \theta x \geq \sum_{i=1}^{n} \gamma_i x_i^\star, \\
& \sum_{i=1}^{n} \gamma_i = 1, \\
& \gamma_i \geq 0, \\
& i = 1, \ldots, n\}
\end{aligned} \tag{9}$$

the efficient level of inputs is:

$$\hat{x}^{\star\partial}(y) = \frac{x}{\hat{\delta}^\star(x, y)} \tag{10}$$

From $\hat{\mathcal{P}}$, B samples $\mathcal{X}_b^\star$ can be obtained via Monte Carlo Methods generating B pseduo efficiency estimates $\delta_b^\star(x, y)$. Two key elements of the bootstrap are: the generation of the pseudo sample $(x_i^\star, y_i)$ and how to obtain $\mathcal{X}_b^\star$.

First, to generate $x_i^\star$ select randomly with replacement $\delta_i^\star$ from $\hat{\delta}_i$ (equation 7) where:

$$\delta_1^\star, \ldots, \delta_n^\star \sim \text{i.i.d } \hat{F} \tag{11}$$

replace 8 in 10

$$\frac{\hat{\delta}(x,y)}{\hat{\delta}^\star(x,y)}\hat{x}^\partial = \hat{x}^{\star\partial}(y) = x_i^\star \tag{12}$$

in this way $x_i^\star$ is formed by taking a random deviation from the input vector right on the frontier.

Simar and Wilson (1998) and Simar and Wilson (2000a) show how $\hat{F}$ in 11 has a positive mass at $\delta = 1$ therefore in the sampling of efficiency scores to generate $x_i^\star$ would be biased. The problem is summarized as the fact that in cases of high number of efficient units, $\hat{F}$ would be a poor estimate of the true distribution of δ being too close to the upper efficiency bound 1. The solution is a smoothed bootstrap from a kernel density estimate of $\hat{F}$.

When the bootstrap is founded in the random selection of (in)efficiency measurements and its use in the generation of a new pseudo sample $x_i^\star$ this is analogous to the bootstrap on residuals in regression analysis. Note that efficiency measures are relative to an estimate of the frontier, therefore there is uncertainty because the sampling variation, and the DGP can be reduced to understand the variation in efficiency. In Simar and Wilson words "Basing the bootstrap on the $[\hat{\delta}]$ will account for the fact that hte observed inefficiencies are conditional on the observed outputs as well as the observed frontier $[\partial\hat{X}(y)]$."(Simar and Wilson, 1998, p. 54)

3.4 The Malmquist-bootstrap world

Efficiency based Malmquist indices were proposed by Färe et al. (1992). The estimation implies having at least two time periods of input-output data and requires four different estimations of Farrell efficiencies as in 5:

$$\delta_i^{t_1|t_2} = \sup\left\{\delta \,\middle|\, \frac{x_{it_1}}{\delta} \in X^{t_2}(y_{it_1})\right\} \tag{13}$$

and Färe et al.'s Malmquist productivity index is:

$$\mathcal{M}_i(t_1,t_2) = \frac{\delta_i^{t_2|t_2}}{\delta_i^{t_1|t_1}} \times \left(\frac{\delta_i^{t_2|t_1}}{\delta_i^{t_2|t_2}} \times \frac{\delta_i^{t_1|t_1}}{\delta_i^{t_1|t_2}}\right)^{\frac{1}{2}} \tag{14}$$

$\mathcal{M}_i(t_1,t_2)$ can be interpreted as an index of total factor productivity under the assumption of constant returns to scale (Caves et al., 1982). The index would show growth (reduction) in productivity from time t_1 to t_2 when (in the input-oriented case) less (more) than 1. The change in technical efficiency is equal to the first ratio of 14, and the remainder raised to the square root is the growth in technical change.

Since the estimation of 13 is the same as in 7 the use of DEA and the bootstrapping applies in the same way as discussed above. Firms deviate from the true frontier and the distance function suggests this random deviation as inefficiency. This is the DGP that supports the bootstrap and sensitivity analysis.

4 Colombia's energy commercialization services

The structure of Colombia's energy retail is similar to the discussed in section 2 with an highly but not completely liberalized energy industry. From the rigid and monolithic structure the industry moved into a fully disintegrated industry into generation, transmission, distribution and commercialization services. Besides the progress on the macro-arrangement of the industry, progress in the commercialization service is far from the picture presented in Philipson and Willis (1999, chapter 12).

In many cases, commercialization firms never split completely from the distribution business and the apparently joint structure does not let to distinguish who provides what service. A second failure of the liberalization is the poor deepening of business. There are no energy related services provided by these firms as some of the ones listed in section 2. Services such as quality of service, backup power, supply automation, efficiency consumption, product differentiation via consumption plans, power from alternative energy sources (e.g.: solar or wind).

In summary, although the liberalization of electricity services did provide benefits, in particular regarding generation backup alternatives (non hydrological sources of power generation during draught times), deepening of each new section of the industry has not been encouraging. Services are provided in very much the same way as done in pre-liberalization times.

The regulatory structure of energy and gas services at all levels is on the hands of Comisión de Regulación de Energía y Gas (CREG). CREG deals mainly with tariff structure and long term sustainability of power supply. However, CREG has no penalizing means upon firms that do not comply with quality and end-users complaints. Instead, Superintendencia de Servicios Públicos Domiciliarios (SSPD) is the government agency whose responsibility is to track the operation of all public utilities (water, gas, power, garbage collection). SSPD does have the ability to penalize utilities, however the performance on this regards is still poor.

5 Data and empirical results

Data on commercialization services of power in colombia is obtained from Sistema Único de Información (SUI), SSPD's utilities information database. The variables extracted from this database provide information on financial and quality of service performance. Variable extraction was done in line with the functions pursued by a power retail firm as in section 2. The estimation was performed using 18 commercialization firms for which information from 2005 to 2009 was available and complete. The bootstrap was done with 3,000 repetitions using the FEAR package (Wilson, 2008, 2010) in R (R Development Core Team, 2011) and further manipulations in STATA (StataCorp, 2009).

The bootstrapping Malmquist indices (and the underlying DEA) was done with the following input-output variables.

Inputs: Assets; employment; costs.

Outputs: Queries, complaints and appeals; arrears, customers; electricity consumption.

Variables are defined as:

Assets: Long term assets, taken from accounting practices refers to value of assets the firm declared the corresponding year. (Million of Colombian pesos, year base 2005).

Employment: Number of employees hired by the firm.

Costs: Annual operational costs. (Million of Colombian pesos, year base 2005).

Queries, complaints and appeals: Number of recorded queries or complaints filled by customers.

Arrears: Customers' unpaid bills.

Customers: Number of customers served.

Electricity consumption: Electricity consumption in kwh.

Results for the Malmquist productivity, technical efficiency and technical change are presented in figures 2, 3 and 4, with 95% confidence intervals for the 18 retail firms studied. All indexes are expressed as the reciprocal of the respective (input - oriented) estimated index. Given the construction of the Malmquist index, to infer productivity growth, the index should be compared against a value of 1, for instance a value of 1.05 implies a 5% productivity growth. Efficiency and productivity improvements appear when the indices are bigger than unity and reduction if less than unity.

A first finding for the Malmquist productivity index (figure 2) is volatility through time. No firm shows a steady productivity growth, and two (firm 157 and 194) show a decreasing productivity trend. When confidence intervals include a value of one, no productivity change can be attributed to the firm. This result is observed 10 out of 72 (4 years $\times$ 18 firms) productivity measures. 35 out of 72 measures of productivity suggest a significant increase in productivity, and 27 out of 72 a significant reductions of productivity.

Looking at the decomposition of the Malmquist index into efficiency and technical change, four firms (labeled 174, 180, 190 and 194) show absolute no change in efficiency, leaving all productivity effect to technical change. Confidence intervals are a lot wider here than in the Malmquist estimates. In 8 out of 18 retail firms, although non-bootstrapped estimation suggest efficiency change (growth or reduction), confidence intervals are wide enough to include unity, making any statement about efficiency unreliable for all period of study. There are only a few cases of efficiency change that can be assessed as significantly different from one.

Confidence interval for technology changes include unity in 15 out of 18 firms (for all the time period studied), although the point Malmquist estimates suggests growth or reduction. This result is in line with the finding of high non-significant change in efficiency.

Concluding, the results on productivity, efficiency and technical change figures, along with the confidence intervals, suggest that the volatility and uncertainty should refrain the regulator to use a single DEA - Malmquist estimation for regulatory purposes upon single firms. Once a single estimation of productivity is used in a price-cap formula or remuneration formula for single production units, the chances of obtaining a different estimate of productivity growth are high. This is confirmed in the following set of results for the industry.

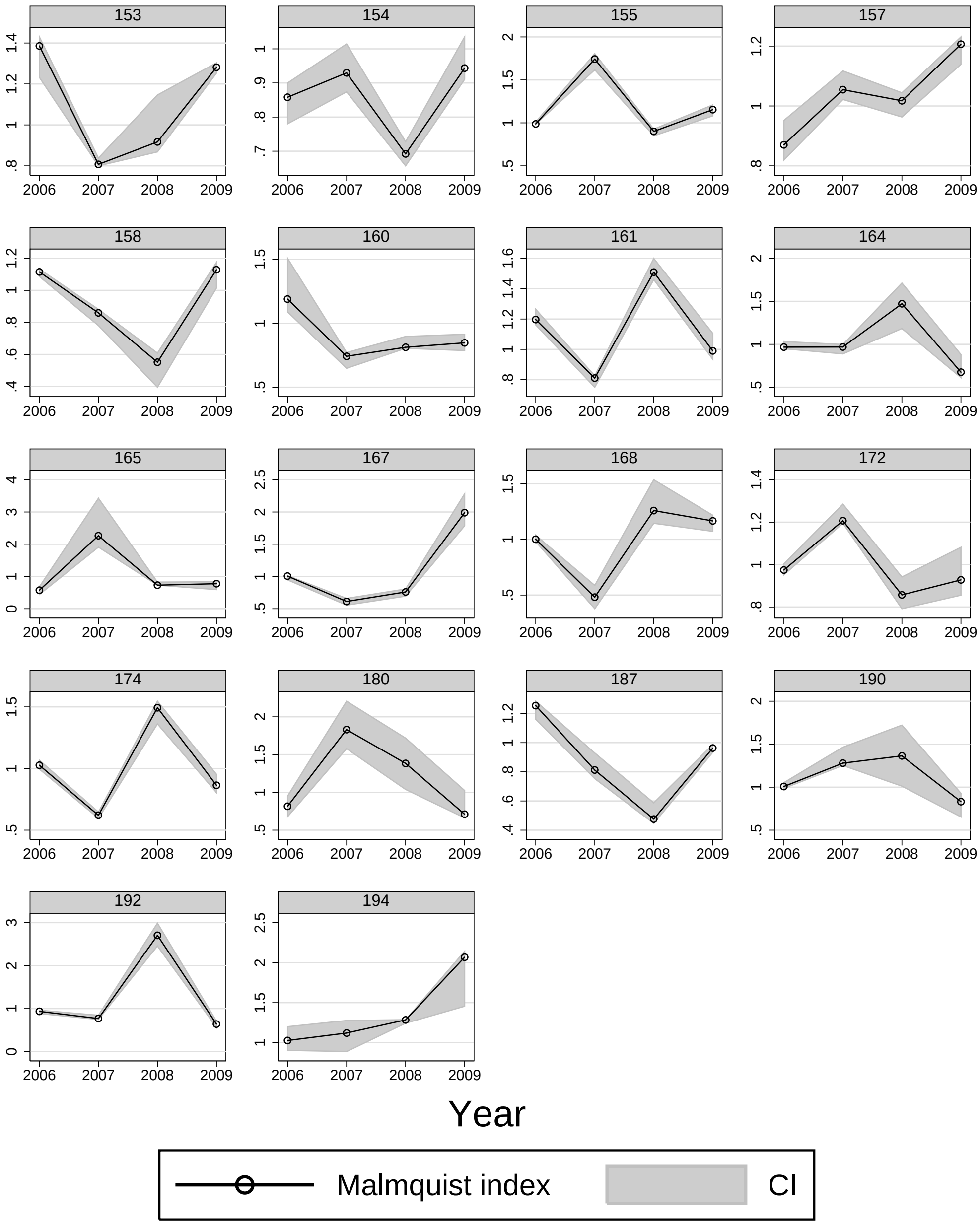


Figure 2. Malmquist productivity and 95% confidence intervals.
Note: Malmquist productivity index.
Source: Author's calculation.

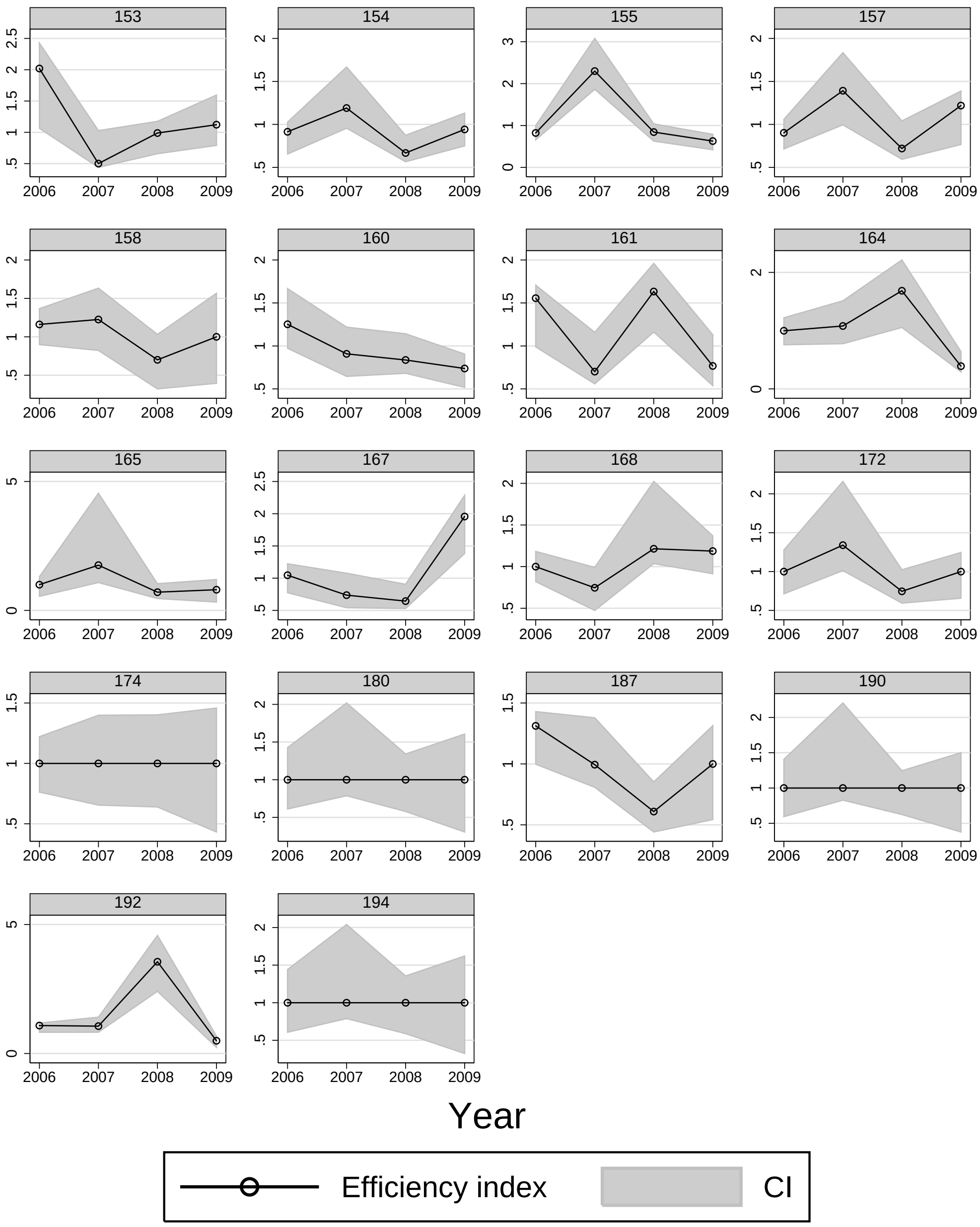


Figure 3. Efficiency and 95% confidence intervals.
Note: Efficiency.
Source: Author's calculation.

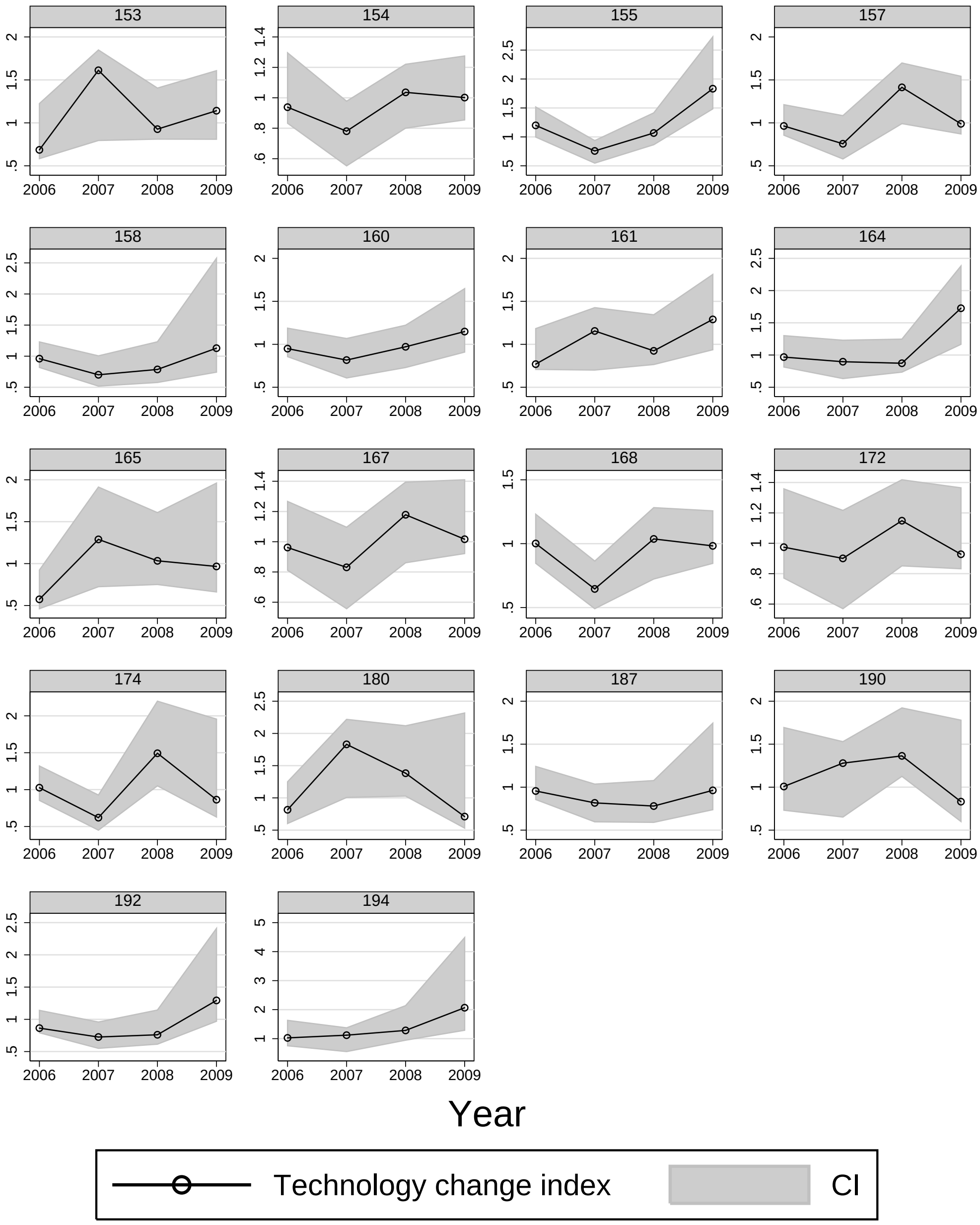


Figure 4. Technical change and 95% confidence intervals.
Note: Technical change.
Source: Author's calculation.

5.1 Industry wide results

An option for the regulator is to estimate the average productivity, efficiency or technological change results up to the industry level and use this result in the price-cap formula. Table 1 shows the mean and median of Malmquist, efficiency and technical change from a single Malmquist estimation and the 3,000 bootstrapped 3000. Figure 5 in a box plot shows basic distributional characteristics of the results.

Table 1 use the average and median to summarize the point estimates of productivity, efficiency and technical change and the bootstrapped estimation. The box plot summarizes the distributional characteristics of the productivity results. The box is bounded by the 75% and 25% percentiles, the 50% percentile is the horizontal line inside the box and whiskers the minimum and maximum.

All the aggregate estimations suggest growth in the Malmquist productivity index, ranging from 2.48% in 2006 to 10% in 2007 for the point estimation results (2.58% to 11.38% in the bootstrapped estimation). Average efficiency growth is high for the bootstrapped estimation (31%) offset by the technology reduction of 14%.

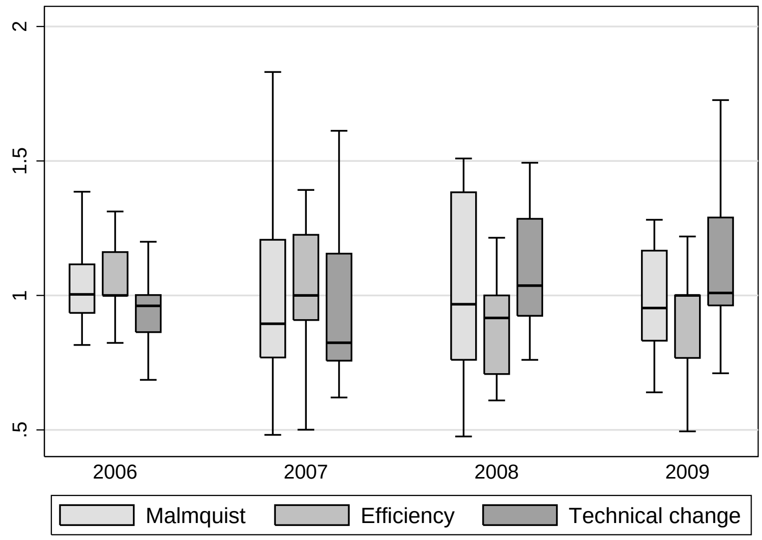
Table 1. Malmquist, efficiency and technical change (mean and median)

Point Malmquist estimation						
Year	Malmquist	Efficiency Mean	Technology	Malmquist	Efficiency Median	Technology
2006	1.0248	0.9364	1.1108	0.9962	1	1.0402
2007	1.1086	1.0122	1.1246	1.1194	1	1.2136
2008	1.0572	1.1087	0.9647	1.0366	1.0982	0.9647
2009	1.0371	1.1774	0.9287	1.0492	1	0.9909

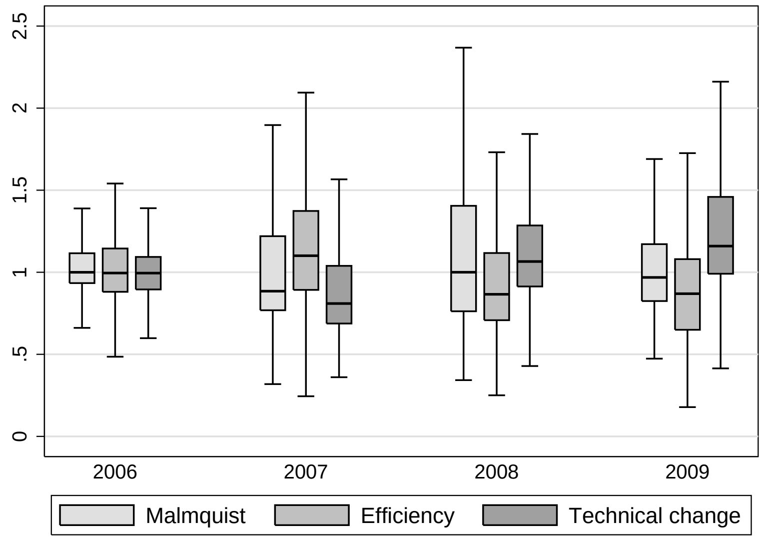
Bootstrapped Malmquist estimation						
Year	Malmquist	Efficiency Mean	Technology	Malmquist	Efficiency Median	Technology
2006	1.0258	1.0056	1.0466	1.0001	1.0046	1.0051
2007	1.1138	0.9498	1.2168	1.1301	0.9084	1.2351
2008	1.0605	1.1443	0.9526	0.9998	1.155	0.9385
2009	1.0329	1.3165	0.8606	1.0325	1.1501	0.8625

Note: Industry's Malmquist, efficiency and technical change (mean and median) from bootstrapped DEA - Malmquist estimation.

Source: Author's calculation.



a. Point Malmquist estimation



b. Bootstrapped Malmquist estimation

Figure 5. Single and Bootstrapped Malmquist productivity, efficiency and technological change.
Note: Point and bootstrapped industry's Malmquist productivity, efficiency and technological change.
Source: Author's calculation.

6 Conclusion

This paper has estimated Malmquist productivity, efficiency and technical change indices for commercialization or retail services in Colombia's electric energy industry from 2005 to 2009. The estimation has been performed bootstrapping the underlying DEA estimation following Simar and Wilson (1998, 1999, 2000a). The benefit of this approach is to be able to assess the significance of the estimated indices upon the statistical properties of the bootstrap methodology. In particular, to see if the indices are significantly different from unity, in other words if the a point estimation showing productivity growth or reduction can be regarded as non-significant.

The empirical results confirm that firm specific Malmquist productivity indices are not significant in 10 out of 72 estimations. Efficiency and technical change show a lower performance, most of the estimations bounded by the 95% confidence intervals include unity. Therefore any assessment of catch-up effect or technology growth can be disregarded. Albeit the disparate results at firm level, the aggregate productivity figures wander around values of 1 with great variance and high probability of being statistically not different from unity.

From the empirical analysis of Colombia's retail firms, two main messages can be drawn. First, productivity figures from the DEA-Malmquist methodology are downgraded by the firms under scrutiny when results are not favorable, claiming its deterministic approach and the inability to be tested on statistical grounds. Under such criticism bootstrapping surges as a plausible alternative. As in this case study, results are not only framed into a statistics framework but can show no productivity, efficiency or technological change at all.

On the other hand, when regulators require a productivity measure for the offset factor the message is to be ready to find nil productivity changes and to use his discretionary power to determine an "X" factor in order to promote growth and deeper competitive-like environment to increase welfare and profit in the industry.

Acronyms

CREG Comisión de Regulación de Energía y Gas (Colombia's power and gas utilities regulator.)

DEA Data Envelopment Analysis

DGP Data Generating Process

DMU Decision Making Unit

FDH Free Disposal Hull

QCA Queries, complaints and appeals

SSPD Superintendencia de Servicios Públicos Domiciliarios (Colombia's governmental utilities quality and service body)

SUI Sistema Único de Información (SSPD's utilities information system)

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