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Design of experiments applied to environmental variables analysis in electricity utilities efficiency: The Brazilian case

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ABSTRACT

Benchmarking plays a central role in the regulatory scene. Regulators set tariffs according to a performance standard and, if the companies can outperform such a standard, they can retain the gains observed by such outperformance. Efficiency performance is usually assessed by comparison (or a benchmark) against either other companies or the company's own historical performance. This paper discusses the impact of environmental variables on the efficiency performance of electricity distribution companies. Indeed, such variables, which are argued to be unmanageable, may affect the electricity utilities' performance. Thus, this paper proposes a simulation methodology based on design of experiment philosophy for statistically testing environmental variables and the interactions among them, enabling regulators to build the best suited semi-parametric two-stage model of electricity utility benchmarking analysis. To demonstrate the power of the proposed approach, experimental simulations are carried out using real data published by Brazil's regulator. The results show that environmental variables may impact efficiency performance linearly and nonlinearly.

1. Introduction

When competition is feasible, the market determines the optimal combination of price and quality. A market automatically converges, economists believe, to prices that reflect efficient costs for suitable products. In natural monopolies, however, which are what electricity distribution networks are, competition is not feasible. Here optimal cost efficiency and quality standards are determined by the hand of the regulator.

Initially, the regulator makes sure that a utility's costs are all recovered and supplemented by a reasonable return. This approach, known as rate-of-return, sets prices based on observed costs; it offers a company no stimulus and no incentive, to be efficient. It is the regulator's duty, however, to not only ensure non-discriminatory access charges but to also design charges that reflect efficient costs.

Thus, regulators around the world have investigated and implemented numerous efficiency-based regulatory approaches by benchmarking electricity utilities (see Jamasb and Pollitt, 2001). Benchmarking analysis is usually integrated into a *RPI-X* mechanism, a mechanism that refers to incentive regulation (Brophy Haney and Pollitt, 2009; Evans and Guthrie, 2006; Joskow, 2008). Such a regulation model adjusts tariffs based on the rate of inflation — the Retail Price Index (*RPI*) — and on the Distribution System Operators' (DSOs) efficiency compared to that of the reference company, and efficiency is known as the expected efficiency savings, or *X-factors*.

The most widely used of the benchmark techniques are Corrected Ordinary Least Squares (COLS), Stochastic Frontier Analysis (SFA), and Data Envelopment Analysis (DEA). The first two select an equation that defines the relationship between the explanatory and dependent variables. As dependent variables are usually considered the costs and the explanatory variables are usually the services to be analyzed. Such approaches are defined as parametric. Then, the efficiency gap to be closed is defined by the error between the selected equation and the actual value of costs. The third benchmark technique, DEA, was first proposed by Charnes et al. (1978), and it is a non-parametric technique. DEA uses linear programming to define an envelope around observations. The frontier is defined by the envelope that efficient firms form around less efficient ones. The distance separating the two defines the efficiency gap. Shuttleworth (2005) pointed out that DEA used on

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electricity distribution business has limitations regarding the small sample size and statistical inferences. Jamasb and Pollitt (2003), however, have shown that to deal with the sample size problem regulators can use cross-country benchmarking. These limitations may also be overcome using bootstrap techniques (see Odeck, 2009), robust solutions of linear programming problems contaminated with uncertain data (see Sadjadi and Omrani, 2008), or Bayesian inferences (see Tsionas and Papadakis, 2010).

Nevertheless, other issues arise when DSO results are influenced by certain contextual factors. In the utility business, these contextual factors are also known as environmental variables. Businessmen argue that unmanageable environmental variables usually affect a firm's costs and quality efficiency performance. Weather conditions, for example, have been shown to be highly correlated to the reliability of a distribution network (Billinton and Allan, 1984; Coelho et al., 2003; Domijan et al., 2003; Wang and Billington, 2002). It may be argued, on the other hand, that utilities adapt their operations and investment to mitigate the environment's adverse effects. Indeed, Yu et al. (2009), who studied the effects of weather conditions in the cost and quality performance of UK DSOs, concluded that on average the impact is small. The authors argued that considering one or another output in the efficiency analysis might internalize the effect of the contextual factors.

In most countries, contextual factors are summed up as weather conditions. However, in an expansive country like Brazil, the environmental variables may also include the regions' disparate conditions such as salary and population density. Indeed, as further discussed, besides a wide area country, Brazil has a large heterogeneity that characterizes the Brazilian utility industry. For instance, some DSOs are responsible for just a single town with high consumption density, whereas others are responsible to deliver energy in large states. Other discrepancies are discussed in a recent study by Brazil's regulator, who suggested that four environmental variables could explain DSOs' inefficiency (ANEEL, 2010, 2011), as further discussed.

In analyzing environmental variables, two drawbacks arise: first, one must use a mathematical model which measures the influence of environmental variables on efficiency score with a reasonable degree of confidence; second, one must choose a set of environmental variable and test their significance on the mathematical model as well as the interactions among them.

For the first drawback, the semi-parametric two-stage approach has been gaining great attention in the literature (Chilingerian and Sherman, 2004; Ray, 2004; Ruggiero, 2004). Such approach regresses the efficiency estimated using traditional DEA (first stage) on environmental variables (second stage), which is also known as two-stage DEA. In exploring semi-parametric two-stage approach, Simar and Wilson (2007) thus proposed a data-generating process consistent with non-parametric efficiency estimates, avoiding problems with serially correlated data. In the approach proposed by Simar and Wilson (2007), the bootstrap technique makes model inference possible and feasible. Such approach is used in this paper to model the environmental variables' impact in efficiency scores. As for the second drawback, despite several applications in the literature, no straightforward way exists to identify regressors; the applications require different statistical techniques and often end up being a process of trial and error.

In this sense, this paper presents an alternative approach based on design of experiments (DOE). DOE is a collection of statistical techniques capable of generating and analyzing experimental designs in which several factors are varied simultaneously. These experimental design methods, introduced by Fisher (1966), are widely used in production and operation management, as well as manufacturing and quality control (Montgomery, 2009). The methodology seeks to plan an experimental design so that appropriate data can be obtained that lead to good conclusions, by using a minimal number of experiment runs. Thus, in analyzing environmental variables, the DOE technique may help evaluate the significance of each factor in estimating efficiency, as well as it is also useful in assessing the statistical significance of interaction among variables. The regulator is then able to assess the impact of environmental variables on DSO inefficiency by using the two-stage DEA model.

Recently, DOE has been used extensively in applications related to simulation analysis (see Kleijnen, 2005). Balestrassi et al. (2009), for instance, used the fractional and full factorial designs to better determine the parameters of an artificial neural network (ANN), bypassing the trial-and-error technique. Sun and Li (2013), in turn, have used designed simulation experiments in optimizing operating room scheduling. In the same way, Oliveira et al. (2011) presented a novel approach, using mixture design of experiments, to adjust the conditional value at risk metric for a mix of contracts on the energy market.

Importantly, this paper has no ambition of constructing a new benchmark model. It intends rather to propose, with the help of DOE, a simulation approach for environmental variable analysis. Its major contribution resides in the proposing of a simulation methodology for statistically testing environmental variables and the interactions among them, enabling analysts to build the best suited second stage model to electricity utility benchmarking analysis, when two-stage semi-parametric approach is considered. To demonstrate the power of the proposed approach, experimental simulations are carried out using real data published by Brazil's regulator. The results show that environmental variables may impact efficiency performance linearly or nonlinearly, so that the approach proposed in this paper may avoid a misspecified model.

The remainder of this paper is organized as follows: Section 2 briefly reviews some incentive regulation concept and Brazil's network regulation background; Section 3 presents the semi-parametric two-stage DEA used in this paper; Section 4 discusses the features of DOE philosophy and lays out the methodology adopted; and Section 5 presents the results and a discussion of the experimental simulated dataset. Finally, Section 6 presents our conclusions.

2. Regulation of electricity distribution network in Brazil

When dealing with utility regulation, regulators may consider two incentive mechanisms: revenue cap and price cap. The revenue cap limits the predetermined level of annual revenue that a DSO can collect from its consumers. The price cap defines, based on the prices of different products (access, energy, demand, etc.), the annual permitted revenue. In these regulatory scenarios, prices are decoupled from observed costs.

The annual permitted revenue in incentive regulation consists of setting tariffs according to a performance standard and, if the companies can outperform such a standard, they can retain the gains observed by such outperformance. Hence, the DSO is motivated to operate efficiently and thereby cut down on costs to increase the shareholders' profits. Under such mechanism, benchmarking plays a central role. In fact, regulators' measure of the performance standard is usually assessed by comparing it against the company's own historical performance and/or against other companies. Thus, based on each DSO's performance analysis, the regulator sets its initial annual permitted revenue P_0. Once the permitted income is so defined, the cost allocation establishes how to collect it from the end-users (Steele Santos et al., 2012).

Nevertheless, when a capital-intensive industry (like that of an electricity utility) adopts an efficiency-based regulatory approach it can lead to a degradation in service quality, so one must consider the *X-factors*. By establishing *X-factors the* regulator considers a benchmark model for efficiency and quality; it uses *X-factors* to close any eventual inefficiency gaps. The benchmark is usually set by the identification of the most efficient practice in the sector. Jamasb and Pollitt (2003) presented some approaches for efficiency benchmark models. Also, Ajodhia and Hakvoort (2005) discussed quality regulation approaches.

Eq. (1) describes the usual framework of the incentive regulation mechanism: each company faced with a permitted annual revenue P_0, which is kept for the subsequent period, say a year, adjusted only to a