Socio-Economic Planning Sciences 48 (2014) 89–103

Contents lists available at ScienceDirect

Socio-Economic Planning Sciences

journal homepage: www.elsevier.com/locate/seps

Structural and behavioral robustness in applied best-practice regulation☆

Per J. Agrell[a,*], Pooria Niknazar[b]

[a] Louvain School of Management and CORE, Université catholique de Louvain, B-1348 Louvain-la-Neuve, Belgium
[b] École Polytechnique de Montréal, Department of Mathematics and Industrial Engineering, P.O.B. 6079, Station Centre-Ville, Montréal, Québec H3C 3A7, Canada

ARTICLE INFO

Article history:
Available online 25 December 2013

Keywords:
DEA
Regulation
Energy networks
Outlier detection

ABSTRACT

Benchmarking methods, primarily non-parametric techniques such as Data Envelopment Analysis, have become well-established and informative tools for economic regulation, in particular in energy infrastructure regulation. The axiomatic features of the non-parametric methods correspond closely to the procedural and economic criteria for good practice network regulation. However, critique has been voiced against the robustness of best-practice regulation in presence of uncertainty regarding model specification, data definition and collection. Incorrect data may result from structural sources, such as heterogeneous technologies; deterministic approaches applied to stochastic data generation processes or poorly defined scope of activity. Specifically within regulation, reporting may also be biased through individual gaming or collusive behavior, including the intentional provision of absurd data in order to stall or perturb regulatory process (here called maverick reporting). We review three families of outlier detection methods in terms of their function and application using a data set from Swedish electricity distribution, illustrating the different types of outliers, contrasting with the actual analysis *ex post*. This paper investigates the foundation of the critique both conceptually and by describing the actual state-of-the-art used in energy network regulation using frontier analysis models in Sweden (2000–2003) and in Germany (2007-). Finally, the paper concludes on the role of outlier detection as a mean to implement regulation with higher robustness.

1. Introduction

One of the more prominent applications of state-of-the-art benchmarking is in the regulation of natural monopolies in general and for electricity and gas networks, in particular. Benchmarking studies applied to inform such regulation have considerable economic impact on firms and consumers alike. The theoretical and intuitive appeal of using best-practice rather than average-practice cost norms in the regulation is undisputed. Still, economic regulation affecting private and public firms deploying large investments for essential infrastructure provision to the society must fulfill the highest criteria with respect to feasibility and regulatory robustness. In this paper, we will review some of the critique voiced against frontier-based regulation. In particular, we will relate the conjectures of various sources to the actual practice of energy network regulation with respect to the systematic use of outlier detection techniques. Specifically, we aim at addressing three research questions: (i) what are the specific requirements for structural and behavioral robustness in regulatory applications? (ii) what are the effects of using multi-stage outlier detection, theoretically and in real data sets? (iii) what is the final impact on regulatory robustness of the application of outlier detection methods?

The paper makes three contributions to the literature. First, it provides a conceptual view on the importance, specific requirements and classification of outlier detection and treatment for DEA applications to regulation. Given the prevalence of such applications in practice and their practical and economic importance, the paper fills an important gap in the current literature on frontier regulation. Second, although there is some work on suggested applications of DEA and SFA to energy network regulation, there are no scientific papers documenting how the regulators actually assure robustness in DEA modelling, calculation and interpretation. This paper thus provides empirical evidence that can be used as

☆ This text presents research results of the P7/36 PAI project COMEX, part of the Belgian Program on Interuniversity Poles of Attraction initiated by the Belgian State, Prime Minister Office, Science Policy Programming.

* Corresponding author. Tel.: +32 10 47 43 05; fax: +32 10 47 43 01.
E-mail address: per.agrell@uclouvain.be (P.J. Agrell).

0038-0121/$ – see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.seps.2013.12.004

factual reference for researchers working with methodological development. Third, the paper as such provides a response to some of the published critique raised against frontier analysis applications in regulation. More generally, it contributes to the scientific discourse on the role and limitations of Data Envelopment Analysis in the public sector.

The outline of the paper is as follows: In Section 2 we offer a review of frontier analysis methods and regulatory regimes, followed by the model notation for DEA. In Section 3 we discuss the criteria and challenges of using frontier analysis in regulatory applications. Section 4 provides a classification of the outlier detection approaches in statistics and regulatory economics, as well as a review of existing approaches for outlier detection in DEA. The actual practice in frontier analysis is documented through the short case studies of the electricity network regulation in Sweden (2000–2003) in Section 5 and in Germany (from 2007) in Section 6. Section 7 is devoted to a comparative analysis of the outlier detection methods in section 4 applied to real data for the Swedish case. The paper is closed with conclusions and a final discussion in Section 8.

2. Literature review

2.1. Frontier analysis methods

Best practice or *frontier analysis methods* model the frontier of the technology and identify a subset of the reference set to form the peers, the performance of which is to be emulated by the others. The use of frontier models in regulation has practical as well as methodological advantages. The absence of *a priori* assumptions on the functional form and the foundation on a limited subset of identifiable best practice peers, make the frontier methods well adjusted to judicially implementable incentive regulation. Moreover, the behavioral effects defining attainable, yet evolving and demanding, performance targets are also well established in practice.

The *frontier* is defined as the edge of the empirical production possibility set. In frontier analysis, each firm is being seen as a decision Making Unit (DMU) which uses some inputs to produce some outputs, services or goods. The projection of the individual firm's position onto the efficient frontier determines the scope and areas for necessary performance improvements in order to achieve best practice [1]. The frontier analysis informs both *static* and *dynamic* efficiency assessments, i.e. the incumbent efficiency differences for a given year and the productivity improvements over time relative to technological progress. Generally, there are two main approaches for modelling and estimating the frontier; parametric and non-parametric, as well as two fundamental paradigms related to the data generation process, i.e. deterministic and stochastic models.

Parametric models are defined *a priori* except for a finite set of unknown parameters, estimated from the data. Parametric stochastic models consider the possible random noise and efficiency distributions in the data. Stochastic Frontier Analysis (SFA) is a family of methods in this category developed by Aigner et al. [2] and Meeusen and van Den Broeck [3], cf. Khumbakhar and Lovell [69]. Deterministic parametric models do not consider the noise in the data and any variation in data is considered to be information about the shape of the production possibility set and, by extension, about firm efficiency. Modified Ordinary Least Squares (MOLS)[1] [4], estimating a deterministic frontier using OLS is the main method of this type.

Non-parametric models relax the assumption of a known functional form. Of more limited attention in the regulation literature concerning stochastic nonparametric models we find the Stochastic Data Envelopment Analysis (SDEA) [5]. SDEA essentially relaxes the strict inclusion of all observations in the empirical production set in favor of a 'fuzzy' stochastic frontier [6]. A recent addition to the family of estimation techniques used for energy regulation came in 2011 for Finland, where the regulator proposed to use the Stochastic Nonsmooth Envelopment of Data (StoNED) method [7,8]. The StoNED model is basically a combination of a semi-nonparametric estimation of a monotonous and convex production frontier and an SFA-type estimation of a decomposed error term into stochastic inefficiency and idiosyncratic noise. A piece-wise linear estimation of the frontier as in Convex Nonparametric Least Squares Regression, Hildreth [9] resembles the DEA framework, but the treatment of the error term leads to quite different estimates of the productive inefficiency. For the deterministic case, finally, Data Envelopment Analysis (DEA) constructs a piece-wise linear hull (envelope) around the empirical production set, based on linear programming. In the following section, we explain the DEA model in detail.

2.2. DEA

Expanding early work in Farrell [10], the name Data Envelopment Analysis (DEA) and the popularity of the approach were launched with the classical work in Charnes et al. [11] and Banker et al. [12]. Below we make a condensed overview over relevant models and notation for our presentation, for a general description of the various DEA models, see texts such as Cooper [13] or Bogetoft and Otto [14].

The bearing principle of DEA is to construct a piecewise linear approximation of the best practice production set T from the observations using linear programming without requiring any imposed functional relationship between inputs and outputs. Following the convention, the observations are denoted Decision Making Units (DMU). DEA estimates the technology set T from the observed data on actual production activities based on the *minimal extrapolation principle*. The efficiency measure used in conventional DEA is a radial projection from the DMU to the efficient (best practice) frontier, either over inputs or outputs. Accordingly, the *efficiency frontier* is composed of those DMU classified as fully efficient.

To formalize the above, we assume that each of n DMUs, say DMU^i transform m_x controllable inputs x^i and m_z non-controllable categorical inputs z^i into m_y outputs y^i. The prices, if existing, on the controllable inputs are $w^i \in \mathbb{R}_+^{m_x}$.

We assume that the technological possibilities are the same for all DMUs' (except for the differences captured by the non-controllable variables). Specifically, these possibilities may be thought of as the set T of feasible input–output combinations

$$T = \{(x,z,y) | (x,z) \text{can produce } y\} \tag{1}$$

We shall generally assume that T satisfy.

Condition 1. *Free disposability:* $(x,z,y) \in T, x' \geq x, z' \geq z, 0 \leq y' \leq y \Rightarrow (x',z',y') \in T$.

Condition 2. *Convexity: T is convex.*

Condition 3. *r returns to scale,* $(x,z,y) \in T \Rightarrow (qx,z,qy) \in T,\ \forall q \in K(r)$, *where* $r =$ *"crs", "drs" or "vrs" and* $K(\text{crs}) = \Re_0, K(\text{drs}) = [0,1]$ *and* $K(vrs) = \{1\}$*, respectively.*

The production frontier can be estimated using only the first condition with the Free Disposability Hull (FDH) by Deprins et al.

[1] MOLS is a generalization of the Corrected OLS, where the regression line is transposed to form a lower bound for the dataset.