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Best-practice benchmarking using clustering methods: Application to energy regulation

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ABSTRACT

Data envelopment analysis (DEA) is widely used as a benchmarking tool for improving productive performance of decision making units (DMUs). The benchmarks produced by DEA are obtained as a side-product of computing efficiency scores. As a result, the benchmark units may differ from the evaluated DMU in terms of their input–output profiles and the scale size. Moreover, the DEA benchmarks may operate in a more favorable environment than the evaluated DMU. Further, DEA is sensitive to stochastic noise, which can affect the benchmarking exercise. In this paper we propose a new approach to benchmarking that combines the frontier estimation techniques with clustering methods. More specifically, we propose to apply some clustering methods to identify groups of DMUs that are similar in terms of their input–output profiles or other observed characteristics. We then rank DMUs in the descending order of efficiency within each cluster. The cluster-specific efficiency rankings enable the management to identify not only the most efficient benchmark, but also other peers that operate more efficiently within the same cluster. The proposed approach is flexible to combine any clustering method with any frontier estimation technique. The inputs of clustering and efficiency analysis are user-specified and can be multi-dimensional. We present a real world application to the regulation of electricity distribution networks in Finland, where the regulator uses the semi-nonparametric StoNED method (stochastic non-parametric envelopment of data). StoNED can be seen as a stochastic extension of DEA that takes the noise term explicitly into account. We find that the cluster-specific efficiency rankings provide more meaningful benchmarks than the conventional approach of using the intensity weights obtained as a side-product of efficiency analysis.

1. Introduction

The purpose of benchmarking is to help the management of a decision making unit (DMU) to improve performance and productivity. The process of the best practice benchmarking involves the identification of the best firms in an industry or a sector, comparison of the specific performance metrics or indicators (e.g., unit cost, productivity, or efficiency), and learning from the peers how the business processes could be improved. The benchmarking process can be repeated continuously to allow DMUs improve their practices over time.

Data Envelopment Analysis (DEA) [1,2] has been widely applied for efficiency estimation and benchmarking (see, e.g., Section 3.9 of [3], and the recent surveys of DEA applications [4,5]). Technically, DEA is mainly geared towards efficiency estimation, applying input–output weights that maximize the efficiency score of the evaluated DMU. The conventional benchmarks provided by DEA can be seen as a side-product of the envelopment problem where the frontier is constructed as a convex hull of the observed data points using the so-called intensity weights (reference DMUs that have strictly positive intensity weights are identified as benchmarks, see Section 3.9 of [3]), while the benchmarks are widely considered as an appealing feature of DEA, to our knowledge, there is little evidence about the usefulness of the intensity weights for benchmarking (let alone their optimality). In the recent DEA literature (see [3] for an excellent survey), it is well recognized that units identified as benchmarks can differ from the evaluated DMU in terms of the input profile (e.g., capital intensity) or the output structure (economies of specialization versus scope). Further, the benchmarks can operate at different scale sizes than the evaluated DMU, particularly when constant returns to scale (CRS) is assumed. Indeed, if the benchmarks are located far away

Abbreviation: NMM, normal mixture model; StoNED, stochastic non-smooth envelopment of data; DEA, data envelopment analysis; DMU, decision making unit; SFA, stochastic frontier analysis; CNLS, Non-parametric methods including convex non-parametric least squares; CRS, constant returns to scale; VRS, variable returns to scale.

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from the evaluated DMU in the input–output space, the benefits of the benchmarking exercise may be questionable.

The benchmark selection has attracted growing interest in the recent DEA literature: there is a growing stream of DEA studies on the identification of closest targets, axiomatic characterization of benchmarks, and the use of preference information and interactive procedures (see, e.g., Refs. [6–11] and Section 3.9 of [3] for further discussion). To our knowledge, however, these recent developments restrict to the deterministic DEA framework that assumes away noise. It is well recognized that DEA can be sensitive to random noise and heterogeneity of DMUs and their operating environments. In a stochastic environment, some DMUs may appear more efficient than others due to more favorable operational conditions or just pure luck (consider, e.g., external demand factors or weather conditions), while DEA can identify successful units, it may be difficult to transfer the success recipes to inefficient DMUs if the success is due to external conditions or just good fortune.

The motivation of this paper stems from a real-world application to the regulation of electricity distribution networks, which is one of the most significant application areas of DEA and efficiency analysis. Traditionally, regulators in many countries have applied DEA to estimate the efficient frontier to serve as the best practice benchmark in the regulatory framework. In the past decade, several countries have adopted stochastic frontier analysis (SFA [12,13]) models to complement DEA. The main advantage of SFA is that it models the random noise term explicitly in a probabilistic manner. However, the SFA imposes more restrictive parametric functional form assumptions than DEA. Recently, the Finnish regulator (Energiamarkkinavirasto EMV) replaced the conventional DEA and SFA by the new StoNED method (stochastic nonparametric envelopment of data [14,15]). The StoNED method combines the appealing features of both DEA and SFA, melding the axiomatic DEA-style non-parametric frontier with the probabilistic SFA-style treatment of noise. The StoNED method differs from the semi-parametric extensions of SFA in that it does not make any assumptions about the functional form or its smoothness (see [14] for a more detailed discussion). Rather, StoNED builds directly on the axioms of production theory (such as free disposability and convexity), similar to DEA. Compared to DEA, the StoNED method differs in its probabilistic treatment of inefficiency and noise, while the DEA frontier is typically spanned by a small number of influential observations, which makes it sensitive to outliers and noise, the StoNED method uses information of all observations in the data set to estimate the frontier. The StoNED method can also be applied to panel data (see [14]) and the observed heterogeneity of units and their operating environments can be explicitly modeled as an integral part of the estimation (see [16,17]).

Benchmarking forms an integral part of the frontier based regulatory regimes. As inefficient energy companies are required to reduce their total costs, it is necessary to indicate companies that provide comparable service in a similar environment with a lower cost. Of course, the conventional approach is to identify benchmarks based on the intensity weights, and this could be used equally well in DEA and StoNED. In the present application, however, many energy companies find the conventional benchmarks inappropriate. Finland is a sparsely populated country with a relatively large land area covered by forest and lakes. As a result, the Finnish electricity distribution sector consists of a very heterogenous group of firms. Some firms operate in larger cities such as Helsinki, where underground cables form a large proportion of the electricity grid. A majority of firms operates in rural areas, using overhead cables. There are also some small firms which are specialized to supply power to industrial users. The main problem with the conventional DEA benchmarks is that often urban network companies are identified as benchmarks for rural network firms, and vice versa. It is necessary to take the heterogeneity of firms explicitly into account in the benchmarking procedure.

To identify more appropriate benchmarks, in this paper we propose a novel approach based on the clustering methods, which applies equally well to the conventional DEA and SFA as well as to the recently introduced StoNED method. The proposed approach can be briefly described as follows. We apply a certain clustering method to identify a number of mutually exclusive groups from the original input–output data, or from the input–output vectors that are first projected to the estimated frontier. In each cluster, we rank the DMUs in the descending order of efficiency. These cluster-specific rankings allow managers to identify not only the best performing DMUs within each group, but also a range of DMUs that performs better within the same cluster. The full range of efficiency scores within a cluster can provide managerial insights into why some DMUs are more efficient than others within the same cluster, and help the managers to identify the most appropriate benchmarks, both in the short run and long run.

We must recognize that clustering methods have been used in the context of efficiency analysis before. For example, the latent class SFA models identify groups of DMUs which are interpreted to operate with different technologies (see, e.g., [18]). O'Donnell et al. suggested using clustering methods to identify latent classes in the context of meta-frontier estimation [19]. In the DEA literature, Po et al. proposed to apply DEA as a clustering technique [20]. Triantis et al. presented a two-stage strategy for efficiency performance analysis [21]. Fallah-Fini et al. proposed a bootstrapped nonparametric meta-frontier approach to measure the efficiency of highway maintenance contracting strategies [22]. To summarize, the previous studies that combine clustering approaches with efficiency analysis restrict to specific clustering method or to particular applications. To our knowledge, this paper is the first one to apply clustering methods specifically for benchmarking purposes.

The general approach to benchmarking proposed in this paper is highly flexible. It applies to any frontier estimation method, including DEA, SFA, and StoNED. Further, any appropriate clustering technique may be applied. Since there exists a large literature of clustering methods, we present a concise survey of methods, classified as hierarchical, partitioning, and model-based clustering methods. The approach is also flexible in terms of the clustering criteria. One can use the input–output variables, some functions thereof, or some other observed characteristics of the firm as input data to clustering. One can apply different techniques or combinations thereof to gain better understanding of which DMUs are similar to the evaluated unit, and which criteria can best characterize similarity. The choice of the criteria and the clustering method can be conducted interactively with the management to ensure the maximum relevance for the decision makers.

The rest of the paper is organized as ‘theory’, ‘application’ and ‘conclusion’. In the next section we introduce the frontier production model, briefly review the DEA and StoNED approaches, summarize the widely used clustering methods, and elaborate our proposal for the benchmarking framework. Section 3 presents the real world application for the regulation of electricity distribution networks in Finland, and discusses some implementation issues. Finally, Section 4 concludes.

2. Theory

The proposed clustering based benchmarking framework incorporates frontier estimation and clustering methods into a unified flexible framework. As the two main steps in the framework for