Measuring the Effect of the Rules and Regulations on Global Malmquist Index

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ABSTRACT

The circle-type or global Malmquist index, which is based on Data Envelopment Analysis (DEA) models, is an important index that is widely used for measuring the relative productivity change of decision-making units (DMUs) in multiple time periods. This index, similar to the standard approach of measuring the productivity change using the standard Malmquist index, breaks down into various components, which can then be used to measure the impact of the efficiency, technology, and scale on productivity changes over time. However, empirical studies show that there are some rules and regulations that can affect the result of the productivity changes. Therefore, this paper presents new insight into the global Malmquist index for measuring the effect of the rules and regulations on productivity changes that come from imposing some trade-offs to the production possibility set of the problem, and provides a new decomposition of this index.

Keywords: Data Envelopment Analysis, Decision-Making Units, Global Malmquist Index, Regulation Efficiency Change, Trade-Off

INTRODUCTION

Data envelopment analysis (DEA) is a mathematical optimization-based method that measures the productive efficiency of similar decision-making units (DMUs) with multiple inputs and outputs without recourse to a-priori weights and without requiring explicit specification of functional forms between inputs and outputs. In fact, it makes a piecewise frontier (efficient frontier) with calculation of a maximal productivity measure for each DMU relative to all other observed measures. Charnes et al. (1978) first proposed DEA as an evaluation tool to measure and compare DMUs’ relative efficiency. Their model assumed constant returns to scale (CRS model). It was developed for variable returns to scale (VRS model) by Banker et al. (1984). Now, DEA is an area in operational research that has many tools for evaluating the performance of DMUs (Charnes et al., 1997; Cooper et al., 2000).

In the basic DEA models, the efficiency of DMUs is the ratio of the weighted sum of outputs to the weighted sum of inputs. In addition, the weights are allowed to vary freely, and this flexibility makes each DMU appear

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at its best in the relative efficiency. Hence, the weight flexibility in evaluating each DMU is one of the most significant advantages of DEA in comparison with other methods that are ultimately enforced to assign fixed weights to similar factors in all DMUs (Alirezaee & Afsharian, 2007b).

In spite of these positive effects, however, this complete flexibility may cause a number of problems, as well. For instance, it may ignore some inputs and/or outputs in the efficiency assessment in the presence of zero or negligible weights. In other words, in the DEA literature, all DMUs are supposed to be homogenous and comparable, but this assumption is, obviously, not valid when some extraordinary DMUs exist. Therefore, this situation imposes zero or a small constant as a weight for inputs and outputs of almost all DMUs (Alirezaee & Afsharian, 2007b). Another problem is related to the discrimination between the performances of DMUs. In fact, basic DEA models often provide poor discrimination between the efficiencies of DMUs. This is especially the case when the user has relatively few DMUs to assess while their activities require the use of many input-output variables in order to be reflected adequately. Hence, this can make the performance assessment process of DMUs inefficient. However, these problems are reduced by using some advanced tools such as selective proportionality, unobserved DMUs, weight restrictions, and trade-offs (Podinovski, 2004).

Weight restrictions, especially the direct form such as assurance regions type I, assurance regions type II, and absolute weight restrictions, are most commonly used by decision-makers because they can provide more discrimination between DMUs. Moreover, they can consider some important rules and regulations imposing the relative importance of the weights as well. In other words, mathematically, weight restrictions are commonly based upon judgments about the importance of individual inputs and outputs, and depending on the rules and regulations, the model could be more realistic considering the relative importance of the weights (Allen et al., 1997; Dyson et al., 1998).

The incorporation of any trade-offs is mathematically equivalent to the use of weight restrictions, so we can view trade-offs as the dual form of weight restrictions; however, trade-offs allow us to incorporate technology judgments explicitly in the DEA models. From the mathematics point of view, when we use trade-offs as some rules and regulations in our models, the original technology expands to include the new area. Podinovski (2004) showed that the production possibility set (PPS) generated by the traditional DEA axioms may not include all of the producible production points; the PPS made by the DEA models is only the subset of PPS with trade-offs. Podinovski also described the theatrical development of trade-offs and demonstrated that trade-offs can improve the traditional meaning of efficiency as a radial improvement factor for inputs or outputs (Podinovski, 2007).

The classic Malmquist index is the most important index, which is parametrically (Kumbhakar & Lovell, 2004) or non-parametrically (Fare et al., 1994) estimated in various situations for measuring the relative productivity change of DMUs in multiple time periods. First, Caves, Christensen, and Dievert (1982) introduced the earliest type of the Malmquist index, and then Fare, Grosskopf, Lindgren, and Roos (1992) applied DEA to measuring the Malmquist index (FGLR model). In fact, they assumed constant returns to scale and identified the technological change and the change of technical efficiency as two components of productivity changes over time. Subsequently, Fare, Grosskopf, Norris, and Zhang (1994) considered the variable return to scale and offered an extended decomposition of the Malmquist index, adding another important factor capturing changes in scale efficiency (FGNZ model).

The Malmquist index components in this approach use DEA models with different technologies for computing their distance functions. However, each DEA model makes an efficient frontier with the calculation of a maximal efficiency measure for each DMU relative to other observed measures. Therefore, all components are measured based on these constructed effi-
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