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ECONOMIC EFFICIENCY AND TECHNIQUES

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***Abstract*:** Present paper studies the Economic Efficiency and Gain technologies. Most of the literature related to the measurement of economic efficiency has based its analysis either on parametric or on non-parametric Gain methods. This Article thus argues that, while Technique economy tends to be a powerful force, it is possible for concerns of Economic efficiency. The aim of this paper is to provide a critical and detailed review of both core Gain methods. In our opinion, no approach is strictly preferable to any other. Moreover, careful consideration of their main advantages and disadvantages, of the data set utilized, and of the intrinsic characteristics of the framework under analysis will help us in the correct implementation of these techniques. Recent developments in Gain techniques and economic efficiency measurement such as Bayesian techniques, bootstrapping, duality theory and the analysis of sampling asymptotic properties are also considered in this paper.

Index Terms- Economic Efficiency, CRR, MPEP Techniques, Multiple Input & output models

Introduction

The measurement of economic efficiency has been intimately linked to the use of frontier functions. The modern literature in both fields begins with the same seminal paper, namely Farrell (1957). Michael J. Farrell, greatly influenced by Koopmans (1951)'s formal definition and Debreu (1951)'s measure of technical efficiency1 introduced a method to decompose the overall efficiency of a production unit into its technical and allocate components. Farrell characterized the different ways in which a productive unit can be inefficient either by obtaining less than the maximum output available from a determined group of inputs (technically inefficient) or by not purchasing the best package of inputs given their prices and marginal productivities. These efficiency measurement techniques may be classified in different ways. Our criterion has been to distinguish between parametric and non-parametric methods. A vast literature has treated the measurement of economic efficiency by means of both parametric and non-parametric approaches. In our opinion, and the above empirical studies seem to confirm it, no approach is strictly preferable to any other. As has been shown throughout this survey, each of them has its own advantages and disadvantages. A careful consideration of them, of the data set utilized, and of the intrinsic characteristics of the industry under analysis will help us in the correct implementation of these techniques. The technical efficiency of public education is using both parametric and non parametric methods. They define an educational production function for 40 school districts in Utah with a single output, a set of school inputs associated with the instructional and no instructional activities under the control of the school management, and non school inputs including status of the students and other environmental factors that may influence student productivity. The stochastic specification assumes half and exponential distributions for the inefficiency error term while the deterministic specification uses a two-stage DEA model in which efficiency levels from an output-oriented DEA using controllable school inputs only are regressed on the non school inputs using to bit regression model.

Literature Review

There is a considerable dearth of literature on this topic, with one notable exception, which is discussed starting in the following paragraph. The other references to the topic are found, in the main, in media reports, campus publications, and Web publications. A sample of these references is also referenced below. The research in this area, however, tends to emphasize either direct labor displacement effects without considering the changes in the nature of work (for example Ayres and Miller, 1983). The modern literature in both fields begins with the same seminal paper, namely Farrell (1957). Michael J. Farrell, greatly influenced by Koopmans (1951)'s formal definition and Debreu (1951)'s measure of technical efficiency1 introduced a method to decompose the overall efficiency of a production unit into its technical and allocate components. Farrell characterized the different ways in which a productive unit can be inefficient either by obtaining less than the maximum output available from a determined group of inputs (technically inefficient) or by not purchasing the best package of inputs given their prices and marginal productivities.

Models Analysis

Parametric models analysis

The Basic Model 1.1

The method developed in Charnes, Cooper and Rhodes (1981) named the method introduced in Charnes, Cooper and Rhodes (1978) Data Envelopment Analysis. They also described the duality relations and the computational power that Charnes, Cooper and Rhodes (1978) made available. This technique was initially born in operations research for measuring and comparing the relative efficiency of a set of decision-making units (DMUs). Since that seminal paper, numerous theoretical improvements and empirical applications of this technique have appeared in the productive efficiency literature. The aim of this non-parametric approach4 to the measurement of productive efficiency is to define a frontier envelopment surface for all sample observations. This surface is determined by those units that lie on it, that is the efficient DMUs. On the other hand, units that do not lie on that surface can be considered as inefficient and an individual inefficiency score will be calculated for each one of them. In terms of a cross-sectional production function, a parametric frontier can be represented as:-

$$Yi = f\,(Xi;\,\beta).\ TEi$$

Where i=l. . .l indexes the producers, Y is the scalar output, X represents a vectors of inputs and f(.) is the production Gain techniques efficiency which depends on inputs parameter vector β, Finally, TEi indicates the output-oriented technical efficiency of producer. I defined as the ratio of the observed output to maximum feasible output.

$$TEi = \frac{Yi}{f\,(Xi,\,\beta)}$$

Farrell (1957) assumed what later literature has termed a deterministic frontier function. In terms of this specification, equation 3.1.1 can be rewritten as:-

$$Yi = f\,(Xi;\,\beta).\exp\,(\mu i)\quad \mu i \geq 0$$

where ui represents the shortfall of output from the frontier (technical inefficiency) for each producer. The additional restriction imposed on μi (μi≥ 0) guarantees that TEi_1, which is consistent with equation 3.1.2. Next, assuming that the productive technology adopts a log-linear Cobb-Douglas form,17 the deterministic frontier production function becomes:-

$$\ln Yi = \beta o+\sum_{N=1}^{n}\beta n\ \ln Xni\ \_\ ui$$

Once the production structure has been parameterized, both goal programming and econometric techniques can be applied to either calculate or estimate the parameter vector and also to obtain estimates of ui and so of TEi. Goal programming techniques calculate the technology parameter vector by solving deterministic optimization problems. The main drawback of these approaches is that the parameters are not estimated in any statistical sense but calculated using mathematical programming techniques. This complicates statistical inference concerning the calculated parameters, and precludes any hypothesis testing. It is at this stage when econometric analysis of frontier functions comes into its
own. In an attempt to accommodate econometric techniques to the underlying economic theory,18 a wide and challenging literature related to the estimation of frontier functions has proliferated over the last three decades. These attempts can be classified into two main groups according to the specification of the error term, namely deterministic and stochastic econometric approaches.

Non-parametric Model Analysis

The Basic Model 1.2

The method developed in Farrell (1957) for the measurement of productive efficiency is based on a production possibility set consisting of the convex hull of input-output vectors. This production possibility set was represented by means of a frontier unit-isoquant. According to that specification and the fact that
Farrell's efficiency measures are completely data-based, no specific functional form needed to be predefined. The single-input/output efficiency measure of Farrell is generalized to the multiple inputs/ output case and reformulated as a mathematical programming problem by Charnes, Cooper and Rhodes (1978). Charnes, Cooper and Rhodes (1981) named the method introduced in Charnes, Cooper and Rhodes (1978) Data Envelopment Analysis. They also described the duality relations and the computational power that Charnes, Cooper and Rhodes (1978) made available. This technique was initially born in operations research for measuring and comparing the relative efficiency of a set of decision-making units (DMUs). Since that seminal paper, numerous theoretical improvements and empirical applications of this technique have appeared in the productive efficiency. The aim of this non-parametric approach4 to the measurement of productive efficiency is to define a frontier envelopment surface for all sample observations. This surface is determined by those units that lie on it, that is the efficient DMUs. On the other hand, units that do not lie on that surface can be considered as inefficient and an individual inefficiency score will be calculated for each one of them. Unlike stochastic frontier techniques, Data Envelopment Analysis has no accommodation for noise, and therefore can be initially considered as a non statistical technique where the inefficiency scores and the envelopment surface are 'calculated' rather than estimated. The model developed in Charnes, Cooper and Rhodes (1978), known as the CCR model, imposes three restrictions on the frontier technology: Constant returns

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to scale, convexity of the set of feasible input-output combinations; and strong disposability of inputs and outputs. The CCR model is next interpreted through a simple example on the basis of Figure 1.1.

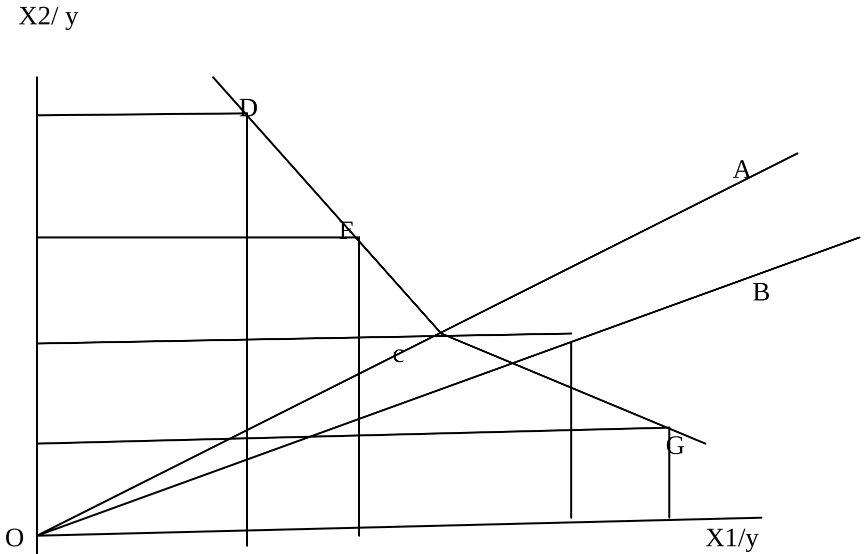

Figure:-1.1 CC R model

Here A, B, C, D, E and G are six DMUs that produce output Y with two inputs; X1 and X2. The line DG in Figure 2.1.1 represents the frontier unit iso-quant derived by DEA techniques from data on the population of five DMUs,5 each one utilizing different amounts of two inputs to produce various amounts of a single output. The level of inefficiency of each unit is determined by comparison to a single referent DMU or a convex combination of other referent units lying on the frontier iso-quant line and utilizing the same proportions of inputs. Therefore, the technical efficiency of A would be represented by the ratio OA*/OA where A* is a linear combination of referents B and C ('peer group') that utilizes the inputs in the same proportions as A, since both A and A* lie on the same ray. The efficiency of E could be directly measured by comparison with C, which is located on the efficient iso-quant and on the same ray as C. The ratio OC/OE determines the technical efficiency of E. Finally, although unit G is situated on the efficient frontier, it cannot be considered as technically efficient in a Pareto sense, since it is using the same amount of input X2 as B, but more input X1, to produce the same level of output. The main attributes of Data Envelopment Analysis techniques are their flexibility and adaptability. Indeed, this adaptability has led to the development of a large number of extensions to the initial CCR model and of applications in recent years. We next briefly review some of the most relevant contributions. The CRS specification given by Charnes Cooper and Rhodes (1978) yields misleading measures of technical efficiency in the sense that technical efficiency scores reported under that set of constraints are biased by scale efficiencies. This important shortcoming is corrected by Fare, Gross kop and Lovell (1983), Byrnes, Fare and Gross kop (1984) and Banker, Charnes and Cooper (1984)10 who extended DEA to the case of Variable Returns to Scale (VRS). Variable Returns to Scale are modeled by adding the convexity constraint to the model formulated in (1.1). This final constraint simply guarantees that each DMU is only compared to others of similar size. This mode of operation avoids the damaging effect of scale efficiency on the technical efficiency scores. That efficiency score can be calculated by means of the following mathematical programming formulation,

TECRS ¼ min μ Ω 0

S.T.

$$\sum_{J=1}^{n} \mu j\ Xij \le \Omega^{o}\ Xi \qquad I=1\ \ldots m$$

$$\sum_{J=1}^{N} \mu jyrj \ge Y^{o}r \qquad r=1\ldots\ldots s$$

The solution of this linear program reports the peer group that for each DMU analyzed, yields at least the same level of output (second constraint) but consuming just a proportion ( ) of each of the inputs used by the DMU (first constraint). The final objective is therefore to determine the linear combination of referents that for each DMU minimizes the value of . The technical efficiency scores will be determined by the formula. The econometric literature of 'average' functions has developed several alternative methods to estimate the structure of the production set coherent with the main insights of duality theory developed by Nerlove (1963) estimates the parameters of a single cost function by OLS. This technique is attractive from the point of view of its simplicity but it ignores the additional information that cost share equations can introduce into the estimation process. Berndt and Wood (1975) estimate those cost shares as a multivariate regression system. This approach also presents some deficiencies. Finally Christensen and Greene (1976) introduced the joint estimation of the cost share equations and the cost function. This procedure allows for the estimation of all relevant parameters that define the production structure. Dual econometric Gain approaches have also evolved from the estimation of single cost functions38 to multiple equation systems.39 However, as we shall next see, serious specification and estimation problems arise as one moves far from the traditional, well-behaved, and self-dual Cobb-Douglas functional forms. With respect to the specification problem, the work of Schmidt and Lovell (1979) can be regarded as the first attempt to analyze the duality between stochastic production and cost functions. They exploit the self-duality of the Cobb-Douglas functional form to provide estimates of input-oriented technical inefficiency and input a locative in efficiency.

Summary

We have analyzed a wide range of different techniques dedicated to the measurement of economic efficiency. The main issue throughout was to determine an efficient frontier function or envelopment surface, in order to compare the performance of different units with the one that characterizes the efficient geometric site. These efficiency measurement techniques may be classified in different ways. Our criterion has been to distinguish between parametric and non-parametric methods. A vast literature has treated the measurement of economic efficiency by means of both parametric and non-parametric approaches. In our opinion, and the above empirical studies seem to confirm it, no approach is strictly preferable to any other. As has been shown throughout this survey, each of them has its own advantages and disadvantages. A careful consideration of them, of the data set utilized, and of the intrinsic characteristics of the industry under analysis will help us in the correct implementation of these techniques. In any case, the present survey calls for more research. The implementation of comparative analysis between parametric and non parametric frontier techniques – such as the ones described in previous section – the integration of the two types of approaches through two-step models like the one used in Sen Gupta (1995), further research on misspecification problems (e.g. Smith, 1997) and on the quality (e.g. Pedraja, Salinas and Smith, 1999) of Data Envelopment Analysis, and extra investigation on the measurement of economic efficiency in a dynamic context as the one presented in Sen Gupta (1999 and 2000) might constitute the basis for future theoretical and applied research. In summary, it would be desirable to introduce more flexibility into the parametric frontier approach, as well as to go more deeply into the analysis of stochastic non-parametric methods and their statistical properties. In this respect, some new routes are explored in Kumbhakar and Lovell (2000), Fernandez, Koop and Steel (2002,a 2002b), or Sickles, Good and Getachew (2002) regarding the former, and in Sen Gupta (2000a), Simar and Wilson (2000a, 2000b) and Huang and Li (2001) concerning the latter. These studies constitute a set of alternative, complementary and challenging attempts to achieve better and more reliable efficiency measures. The lunch is served.

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