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Estimating the technical efficiency of health care systems: A cross-country comparison using the directional distance function

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ABSTRACT

Economic activity produces not only desirable outputs but also undesirable outputs. Undesirable outputs are usually omitted from efficiency assessments (i.e., applications of Data Envelopment Analysis) which fail to express the true production process. The directional distance function model has been used for handling asymmetrically both desirable and undesirable outputs in the assessment process. In the present paper, we apply a generalized directional distance function to measure the efficiency of the health systems of 171 countries. We incorporate both desirable and undesirable outputs into the efficiency assessment without transforming the latter type of outputs into inputs or into their inverse form, as is done in most of the extant studies that deal with the measurement of health efficiency. The methodology that we apply introduces a modified definition of the efficiency score which yields results consistent with those obtained from radial DEA models. In addition, our results are independent of the length of the direction vector.

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1. Introduction

Data Envelopment Analysis (DEA) is a nonparametric methodology for evaluating the production process of operational units, or, as they are usually called in DEA literature, decision making units (DMUs). Drawing on the seminal paper of Charnes, Cooper, and Rhodes (1978), the scope of DEA is the comparative efficiency assessment of DMUs defining the minimum inputs engaged or the maximum outputs produced. At that study, outputs were regarded as a non-homogeneous entity with a unitary (positive) impact for every DMU.

Nowadays, becoming more sensitive to the negative impact of human activity (e.g., pollution, health system inequalities, medical complications, negative effects of policy making), a distinction between good and bad outputs should not be neglected, if such is present. Characteristically, in recent years, because of the growing interest in incorporating both desirable and undesirable outputs in performance measurements, an increased number of scholars in the DEA literature are engaged with the development of methods for handling asymmetrically the two types of outputs (Chung, Färe, & Grosskopf, 1997; Färe, Grosskopf, Lovell, & Pasurka, 1989; Scheel, 2001; Seiford & Zhu, 2002; Tone, 2004). In the presence of undesirable outputs, their omission from the evaluation process is regarded as a misspecification error which yields misleading results (Färe et al., 1989; Lozano & Gutierrez, 2011; Yang & Pollitt, 2009; Yu, Hsu, Chang, & Lee, 2008).

The methods that deal with good and bad outputs in the DEA literature can be classified into three groups according to their methodological framework. Each group introduces the following: (a) transformations of conventional DEA models (i.e., hyperbolic efficiency measure (Färe et al., 1989), separating measures for good and bad outputs (Scheel, 2001), linear monotone decreasing transformation of the bad outputs (Seiford & Zhu, 2002), and handling of the bad outputs as inputs (Yang & Pollitt, 2009); (b) modifications on the slacks-based measure (SBM) (Lozano & Gutierrez, 2011; Tone, 2004); and (c) modifications on the directional distance function (Chung et al., 1997). In practice, the directional distance function (DDF) is applied mostly for handling desirable and undesirable outputs (Lozano & Gutierrez, 2011; Podinovski & Kuosmanen, 2011).

In most of the studies that deal with the measurement of efficiency in health, undesirable outputs are either treated as inputs (Prior, 2006; Retzlaff-Roberts, Chang, & Rubin, 2004) or transformed into desirable outputs (e.g., survival rate (desirable) = 1 − mortality rate (undesirable)) (Afonso & St Aubyn, 2005; Alexander, Busch, & Stringer, 2003). Grosskopf, Self, and Zaim (2006) use the inverse of a bad output (i.e., infant mortality)

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in the assessment of healthcare efficiency. Furthermore, Hollingsworth and Wildman (2003) select an undesirable output (i.e., morbidity) together with desirable outputs to compose an aggregate health index that stands for a proxy of life expectancy. This index is treated as a desirable output in the assessment of health efficiency.

After a review of the extant literature, we identified only a few studies that evaluate health efficiency by applying DDF, such as Arocena and Garcia-Prado (2007), Bisel and Davutyan (2011), Ferrier, Leleu, and Valdmanis (2009), and Dervaux, Ferrier, Leleu, and Valdmanis (2004). The first two works also incorporate undesirable outputs into their analysis. Arocena and Garcia-Prado (2007) apply a generalized DDF that was originally put forth by Chavas and Cox (1999) (Appendix A). The limitation of the applied model is that the obtained efficiency scores depend upon an arbitrarily user-defined variable (i.e., α). The model that Bisel and Davutyan (2011) use is a traditional expression of the directional distance function.

In addition, we should note that the majority of the published works neglect to introduce bad outputs, either with their original negative impact or with a transformed positive magnitude, to the measurement of health efficiency (Blank & Valdmanis, 2005; Butler & Li, 2005; Chang, Cheng, & Das, 2004; Grosskopf, Margaritis, & Valdmanis, 2004; Kirigia, Emrouznejad, & Sambo, 2002; Martinussen & Midttun, 2004).

Our study incorporates both desirable and undesirable outputs in the measurement of health efficiency acknowledging the significance of the latter variables in the assessment of health production processes. We utilize a generalized directional distance function (GDDF) that introduces a modified definition of the efficiency score. This generalized expression yields results that are consistent with those obtained from radial DEA models. In addition, the applied GDDF produces efficiency scores that are independent of the length of the direction vector. Moreover, the defined inefficiency scores always lie within the interval null and unity without violating the restrictions applied to traditional directional distance function-based measures.

Given that the purpose of this study is the measurement of efficiency and ranking of health systems, we apply our GDDF in conjunction with super-efficiency DEA. Similarly, Ray (2008) applied a super-efficiency DDF to airlines data.

This paper is organized as follows. Section 2 presents the foundations of the directional distance function, and discusses a limitation of this methodology. Section 3 analyzes a generalized efficiency measure in the directional distance function. In Section 4, the new efficiency measure is applied to real-world data from the national health system of 171 countries. The scope of this section is the measurement of efficiency in the presence of both desirable and undesirable outputs, the ranking of the evaluated DMUs, the determination of optimal input and output levels, and the comparative analysis between the GDDF and the radial DEA, DDF and SBM models. Section 5 concludes.

2. The directional distance function

The DDF can be seen as a generalized form of the radial model

$$\begin{aligned} \max \quad & \beta \\ s.t. \quad & X\lambda + \beta g_x \leqslant x_0 \\ & Y\lambda - \beta g_y \geqslant y_0 \\ & \lambda \geqslant 0 \\ & g_x \geqslant 0, \quad g_y \geqslant 0 \end{aligned} \tag{1}$$

which is formulated appropriately when undesirable outputs exist

$$\begin{aligned} \max \quad & \beta \\ s.t. \quad & X\lambda + \beta g_x \leqslant x_0 \\ & Y\lambda - \beta g_y \geqslant y_0 \\ & B\lambda - \beta g_b = b_0 \\ & \lambda \geqslant 0 \\ & g_x \geqslant 0, \quad g_y \geqslant 0, \quad g_b \leqslant 0 \end{aligned} \tag{2}$$

In model (1), g_x and g_y denote the direction vectors associated with inputs (x) and outputs (y), respectively, and β is the measure of inefficiency. Model (2) differs from model (1) in that it introduces a distinction between good outputs, denoted by y, and bad outputs, expressed by b. Accordingly, an additional direction vector (g_b) is incorporated that refers to bad outputs (b).

Note that the direction vector that refers to bad outputs, namely, g_b in expression (2), should be non-positive, which indicates that the undesirable outputs are reduced in order to reach the frontier. In addition, the equality that is used instead of inequality in the third constraint of model (2) indicates the weak disposability of the undesirable outputs.

One drawback of the DDF is that although β stands for a measure of inefficiency, it is not compatible with the inefficiency measures yielded by the radial and SBM models because β can be greater than unity. This incompatibility is eliminated only when $g_x = x_0$, $g_y = y_0$ and $g_b = b_0$. In practice, when the direction vectors are considered equal to the observed inputs and outputs, the DDF is equivalent to a radial model. Assuming that bad outputs are not present, the DDF is equivalent to the input-oriented radial model if $g_x = x_0$ and $g_y = 0$; if $g_x = 0$ and $g_y = y_0$, the DDF is equivalent to the output-oriented radial model (Chambers, Chung, & Färe, 1998).

3. A generalized efficiency measure in directional distance function

In this section, we develop a generalized definition of the efficiency score for the DDF even if no simplification in the direction vectors is applied.

By assuming that no undesirable outputs are present, the GDDF can be defined as:

$$\begin{aligned} \min \quad & \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \beta g_i / x_{i0}}{1 + \frac{1}{s}\sum_{r=1}^{s} \beta g_r / y_{r0}} \\ s.t. \quad & X\lambda + \beta g_x \leqslant x_0 \\ & Y\lambda - \beta g_y \geqslant y_0 \\ & \lambda \geqslant 0, \quad x_{i0} \neq 0, \quad y_{r0} \neq 0 \\ & g_x \geqslant 0, \quad g_y \geqslant 0 \end{aligned} \tag{3}$$

and when undesirable outputs are produced by the production process, model (3) is rewritten as:

$$\begin{aligned} \min \quad & \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \beta g_i / x_{i0}}{1 + \frac{1}{s+p}\left(\sum_{r=1}^{s} \beta g_r / y_{r0} + \sum_{t=1}^{p} \beta g_t / b_{t0}\right)} \\ s.t. \quad & X\lambda + \beta g_x \leqslant x_0 \\ & Y\lambda - \beta g_y \geqslant y_0 \\ & B\lambda - \beta g_b = b_0 \\ & \lambda \geqslant 0 \\ & g_x \geqslant 0, \quad g_y \geqslant 0, \quad g_b \leqslant 0 \end{aligned} \tag{4}$$

where s denotes the number of good outputs and p the number of bad outputs. The ratio $\beta g_i/x_{i0}$ indicates the proportion of the inputs' decrease. Accordingly, the ratios $\beta g_r/y_{r0}$ and $\beta g_t/b_{t0}$ express the proportion of the good outputs' increase and the proportion of the bad outputs' decrease, respectively.

The proposed model (4) can be combined with the super-efficiency DEA model in order to increase its discriminatory power

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