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The economic meaning of Data Envelopment Analysis: A 'behavioral' perspective

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ABSTRACT

We reconsider the motivation of Data Envelopment Analysis (DEA), the non-parametric technique that is widely employed for analyzing productive efficiency in academia, the private sector and the public sector. We first argue that the conventional engineering motivation of DEA can be problematic since it often builds on unverifiable production axioms. We then provide a dual viewpoint and highlight the 'behavioral' interpretation of DEA models. We start from a specification of the production objectives while imposing minimal structure on the production possibilities, and construct tools to meaningfully quantify deviations of observed producer behavior from optimizing behavior. This brings to light the economic meaning of DEA, provides guidelines for selecting the appropriate model in practical research settings, and prepares the ground for instituting new DEA models. We also provide an empirical application that demonstrates the practical relevance of our arguments. We hope that our insights will contribute to the further dissemination of DEA, and stimulate public sector applications of DEA that build on its behavioral interpretation.

1. Introduction

The public sector is increasingly interested in the productive efficiency of its entities. For instance [15], extensively discuss the relevance of efficiency evaluations for regulated sectors. More generally, the growing number of empirical applications suggests that productive efficiency analysis is of key interest for many sectors such as academia, the business community and government institutions; see, e.g. Refs. [29] and [22] for overviews. This observation calls for well-established empirical tools that are specially tailored for testing consistency of observed behavior with (theoretical) optimizing behavior, and for quantifying deviations from optimization (or 'inefficiencies').

Afriat [1], Hanoch and Rothschild [31], Diewert and Parkan [21] and Varian [38]; among others, have advocated a 'behavioral' non-parametric approach to analyzing producer behavior. This approach starts from a behavioral model of optimizing/efficient behavior and allows for testing implications of micro-economic theory directly on the data. That is, one does not need a functional representation of the production technology, and so one can minimize the risk of erroneously rejecting optimizing producer behavior due to an erroneous parametric specification of the (typically unknown) technology. This is particularly convenient, since economic theory does in general not imply a particular functional form and reliable specification tests are not available in many cases.

Non-parametric efficiency analysis is increasingly applied for measuring the degree of 'efficiency' of observed producer behavior, most commonly under the label 'Data Envelopment Analysis' (DEA; after Charnes et al. [7]).[1] DEA models are conventionally motivated from 'engineering' information, e.g. pertaining to the prevalent returns-to-scale or the marginal rates of input substitution/output transformation. Still, such engineering information is mostly difficult to verify in practice. In fact, imposing production properties that cannot be justified in a convincing way seems to conflict directly with the very nature of non-parametric analysis, which is often credited for imposing minimal structure on the research setting under investigation. This consideration is particularly relevant for DEA evaluations of the public sector, which are usually characterized by minimal information on the nature of production possibilities.

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[1] See Refs. [17,25,28,16] for extensive surveys of DEA models.

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In this paper, we adopt an 'economic' (as opposed to 'engineering') perspective on DEA: we start from a clear specification of the production-behavioral models and use minimal (non-verifiable) engineering information. Our insights re-interpret DEA efficiency measures as measures for violations of economically optimizing behavior. To keep our exposition simple, we mainly focus on profit maximizing and cost minimizing behavior. However, as we will indicate, our insights readily extend towards alternative production-behavioral models. By making explicit this economic motivation of DEA, we hope to contribute to its further dissemination and to stimulate public sector applications of DEA that build on its behavioral interpretation.

We note at the outset that our discussion bears some analogy to that in Refs. [3,39,24]; where a similar interpretation of DEA efficiency measures is (implicitly) advocated.[2] Unfortunately, although these ideas have some clear advantages, they are only minimally used in the applied DEA literature; see, e.g. Refs. [8–10], for some applications that demonstrate the advantages of the behavioral perspective of DEA. If only for that reason, it seems useful to set out methodological guidelines for economically meaningful applications of DEA. Furthermore, our discussion includes a number of insights that have not yet been articulated in the literature, and prepares the ground for instituting new DEA models depending on the production-behavioral model that is subject to testing.

The remainder of this paper unfolds as follows. In Section 2 we briefly review the conventional 'axiomatic' DEA approach for reconstructing production possibilities. Section 3 is concerned with non-parametric economic efficiency analysis, following the perspective of Afriat [1], Hanoch and Rothschild [31], Diewert and Parkan [21] and Varian [38]. Section 4 bridges the gap between the seemingly distinct viewpoints adopted in Sections 2 and 3, and brings to light the economic meaning of DEA. Section 5 presents an empirical application on efficiency in academia and illustrates the relevance of choosing an appropriate DEA model. Section 6, finally, reproduces the main insights and provides some concluding discussion.

2. Reconstructing production possibilities: an axiomatic approach

A producer creates outputs from various combinations of inputs (factors of production). To study producer choices we need a convenient way to summarize the production possibilities, i.e. which inputs and outputs are *technologically feasible*. The set of all technologically feasible input–output combinations is called the *production possibility set*.

To formally represent that set, we denote by $z = (z^1, \ldots, z^q) \in \mathbb{R}^q$ a (non-zero) netput vector with z^j the value of netput commodity j. Positive components of z represent outputs and negative components represent inputs. Throughout we assume that the vector z captures at least one input and at least one output, and that all producers use the same commodities as inputs and produce the same outputs. The production technology is represented by the (non-empty and closed) production possibility set

$$T = \{z \in \mathbb{R}^q | \text{netput } z \text{ is technically feasible}\}. \tag{1}$$

If we make the explicit distinction between input and output vectors, we use $z = (-x, y)$ with $x \in \mathbb{R}^l_+$ the input vector and $y \in \mathbb{R}^m_+$ the output vector ($q = l + m$). Then, the set T can be decomposed into input requirement sets

$$L_T(y) = \left\{ x \in \mathbb{R}^l_+ \middle| (-x, y) \in T \right\}, \tag{2}$$

which contain all input vectors x that can produce the output vector y.

2.1. Production axioms

The true production possibility set T (or the input requirement set $L_T(\cdot)$) is usually not observed. Therefore the DEA-type axiomatic approach typically approximates the unobserved set T by an empirical production set that is constructed from a set of observed producers. We represent each observed producer s by the netput vector $z_s = (-x_s, y_s)$, with $s \in S = \{1, \ldots, |S|\}$, for S the set of observed producers. To construct the empirical approximation of T, we will consider the production axioms **A1**–**A4**.[3]

A1 (inclusion of observations): $\forall s \in S : (-x_s, y_s) \in T$.

This axiom says that all observed netput vectors are technologically feasible and thus that they should belong to the (unobserved) production set T. This is really an empirical postulate rather than a production postulate. It makes that we exclude empirical phenomena such as measurement error or outlier behavior.[4]

A2 (monotonicity): if $z \in T$ and $z' \leq z$ then $z' \in T$.

Monotonicity, sometimes also referred to as 'strong (or free) disposability' of inputs and outputs, implies that the producer can always costlessly dispose unwanted inputs and/or outputs. That is, more inputs cannot lead to producing less outputs and producing less outputs cannot lead to using more inputs. It implies that marginal rates of substitution/transformation (between inputs, between outputs and between inputs and outputs) are nowhere negative or, in other words, there is no congestion.

A3 (convexity in netput space): if $z \in T$ and $z' \in T$, then $\lambda z + (1 - \lambda) z' \in T$ for all $\lambda \in [0,1]$.
A4 (convexity in input space): if $x \in L_T(y)$ and $x' \in L_T(y)$, then $\lambda x + (1 - \lambda) x' \in L_T(y)$ for all $\lambda \in [0,1]$.

Convexity in netput space entails that marginal rates of substitution/transformation (between inputs, between outputs and between inputs and outputs) are nowhere increasing. Convexity in input space, finally, is a weaker version of **A3** and entails non-decreasing marginal rates of input substitution.

Apart from these specific production axioms, the (axiomatic) DEA approach typically builds on a 'minimal extrapolation' requirement, which says that the production set approximation should be the minimal set that is consistent with the axioms adopted; see Ref. [2].

2.2. Production set approximations

Different production set approximations are obtained from different sets of axioms. First, if we impose axioms **A1** and **A2**, then

[2] Actually, some of the ideas that we develop here were already implicit in the seminal DEA paper of Banker, Charnes and Cooper [2].

[3] In a theoretical framework, Ref. [36] provides a comprehensive list of production axioms (including ours), which we do not intend to fully review. Other axioms presented in the DEA literature (see, e.g. Ref. [25]), are not considered because they are not instrumental to our following discussion.

[4] See, e.g. Ref. [30], for extensions of DEA that weaken this assumption.