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Output-specific energy efficiency assessment: A data envelopment analysis approach

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HIGHLIGHTS

- Alternative output-specific energy efficiency measures are developed.
- Joint inputs and sub-joints inputs are taken into DEA models.
- Outputs are characterized in their own production technologies.
- The proposed method provides an alternative way of dealing with undesirable output.
- The novel method is more capable of identifying inefficient production behavior.

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ABSTRACT

Past decade has seen numerous data envelopment analysis (DEA)-based energy efficiency studies, which usually treat the production process as a "black box" and ignore the internal production information. This paper takes into account the joint inputs and sub-joint inputs to reveal the specific information on how inputs are allocated to outputs. To this end, we first propose an extended output-specific production technology based on which two novel energy efficiency measures are developed. We also present an empirical study on 32 countries to demonstrate the novelty and the usefulness of our method. We find that our output-specific energy efficiency measures provide a more straightforward way of dealing with undesirable output and are better capable of identifying inefficient production behavior.

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1. Introduction

Energy efficiency analysis has become an important topic in various disciplines such as energy economics and operations research. The aim of energy efficiency analysis is to evaluate a decision making unit's (DMU's) efficiency in terms of energy input by comparing its energy consumption to its peers in a similar production environment, which in turn leads to possible actions for energy efficiency improvement and provides analysis foundation for energy and environmental decision making. Amongst various energy efficiency assessment techniques, data envelopment analysis (DEA) has received much popularity worldwide as revealed by Zhou et al. [1] and Liu et al. [2].

Many studies have contributed to the energy efficiency assessment by developing various DEA models. For example, Hu and Wang [3] first constructed a total-factor energy efficiency (TFEE) index through DEA. Under the TFEE framework, Wang et al. [4] developed a non-radial directional distance function method to measure the scenario-based energy efficiency of China. Wang et al. [5,6] respectively proposed a multi-directional and a range-adjusted approach for energy efficiency assessment. Wang et al. [7] built a meta-frontier DEA approach in order to account for the technology heterogeneity. Recently, Zhou et al. [8] developed a procedure to measure energy efficiency when production technology shows evidence of congestion. Duan et al. [9] proposed a bootstrapped directional distance function approach to correct the energy efficiency estimate bias. A common feature of these studies is that they treat the production system as a "black box" and the structure information on the production process is not incorporated into modeling. The efficiency models in the absence of internal structure information may lack discriminating power as pointed out by Lewis and Sexton [10]. Recently, some network DEA models aiming at opening the "black box" of energy efficiency

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assessment have been proposed. For example, Liu and Wang [11] addressed the different properties of energy consumption processes and built an adjusted network DEA method. Wu et al. [12] constructed a two-stage network DEA model in which the undesirable outputs produced in the energy utilization stage were reused as inputs in the pollution treatment stage.

In this paper, we develop two alternative output-specific energy efficiency measures which contribute to opening the "black box" of energy efficiency analysis in a way of particularly characterizing joint inputs and sub-joint inputs in DEA models. The idea of accounting for (sub-) joint inputs in the DEA methodology was first proposed by Cherchye et al. [13] and has been applied to cost efficiency, coordination efficiency, profit efficiency and technical efficiency analysis [13–16]. It is found that these jointly used inputs give rise to economies of scope and are commonly used in multi-output production processes. Despite the merits, none of earlier TFEE studies have taken them into consideration.[1] In contrast, by incorporating such allocation information, our energy efficiency measures can closely relate to economies of scope and hence establish themselves as desirable methods for modeling multi-output production process at firm level, sector level, and even country level.

Another appealing feature of our energy efficiency measures is that they are based on an output-specific production technology. The output-specific production technology, developed by Cherchye et al. [13], characterizes each individual output in its own production technology and is found to provide a natural way of dealing with undesirable output [17]. Different from previous undesirable output treatments in energy efficiency studies [4,12,18–26], we employ the output-specific production technology to provide some new insights into the ways of dealing with undesirable output. To this end, we first make some extensions to the original work of Cherchye et al. [13] to illustrate how to construct an extended output-specific production technology when the practitioners have acquired some clear information about the production technology. Based on the extended output-specific production technology, some novel DEA models for energy efficiency assessment are proposed. Since no extra non-verifiable assumptions are imposed on undesirable output, the energy efficiency bias caused by model misspecification can be avoided. As such, our energy efficiency measures could be particularly attractive in the energy efficiency studies with joint production of both desirable output and undesirable output.

In the literature, there are a large number of empirical studies focusing on the developed economies' energy efficiency [18,23,24,27–30]. However, it is arguably necessary to also examine the energy efficiency performance of developing countries [31–33]. We therefore apply our novel method to an empirical study on both developed and developing countries to demonstrate its novelty and usefulness. A comparison with some traditional energy efficiency measures is also proposed. The results show that our method for energy efficiency assessment is more capable of identifying inefficient production behavior.

The rest of this paper is organized as follows. In Section 2, we introduce the extended output-specific production technology based on which several DEA models are proposed to develop two alternative output-specific energy efficiency measures. In Section 3, we present the data used in the empirical study and conduct a country-level energy efficiency analysis. Some discussions based on the empirical results are further proposed to provide some implications. Concluding remarks are presented in Section 4.

[1] Note that the shared input in Liu and Wang [11] can be proportionally allocated to specific outputs. It is therefore not a joint input defined in this paper.

2. Methodology

2.1. Extended output-specific production technology

To illustrate our extended output-specific production technology, we shall first introduce the original output-specific production technology proposed by Cherchye et al. [13]. Consider a production process which uses N inputs, captured by the vector $X = (x^1, x^2, \ldots, x^n)' \in R_+^N$ to produce M outputs, captured by the vector $Y = (y^1, y^2, \ldots, y^m)' \in R_+^M$. The output-specific production technology T which allows us to characterize each output m by its own production technology can be expressed as

$$T = I^m(y^m) = \left\{X^m \in R_+^N | X^m \text{ can produce } y^m\right\} \tag{1}$$

where X^m represents the input vector used for the production of output m, and y^m represents the quantity of output m. The input requirement set $I^m(y^m)$ is used to capture all the inputs combinations that can produce y^m. The true set $I^m(y^m)$ cannot be observed directly in practice, but it can be estimated after imposing several standard production axioms [13]. First of all, the inputs and outputs are strongly or freely disposable. That is, more input never reduces the outputs and if X^m can produce y^m, then it can also produce less output. Second, the input requirement set is convex, which means if two input vectors can produce the output, then any convex combination of the two input vectors can also produce the same output. Finally, all observed input–output combinations are certainly feasible. Suppose we observe a dataset for I DMUs, and each DMU i $(i = 1, 2, \ldots, I)$ uses input vector X_i which can be decomposed into $(X_i^1, X_i^2, \ldots, X_i^m)$ to produce output vector Y_i. A standard form of the output-specific production technology based on the above minimum necessary assumptions can be expressed within a DEA framework as follows:

$$T = \left(X^m \middle| \sum_{s \in D_t^m} \lambda_s^m X_s^m \leqslant X^m, \sum_{s \in D_t^m} \lambda_s^m = 1, \lambda_s^m \geqslant 0\right) \tag{2}$$

where the set D_t^m is used to capture all the DMUs that produce at least the estimated DMU t's output y_t^m, i.e. $D_t^m = \{s | y_t^m \leqslant y_s^m\}$. The variables λ_s^m provide the weights of DMU s $(s \in D_t^m)$ for constructing the technical feasibility set associated with output y_t^m. The different λ_s^m for different output m indicate that the outputs are characterized using their own production technologies. The equality constraint related to λ_s^m indicates that the production technology is based on the variable returns to scale (VRS) assumption.

It is worth noticing that the output-specific production technology allows invoking different technology assumptions for different outputs. This feature makes the practitioners capable of constructing more realistic DEA models especially when they have acquired clear information about the production technology. In what follows, we will especially focus on a joint production of both desirable output and undesirable output and introduce how to construct an extended output-specific production technology when the outputs exhibit some specific production technologies.

In production, it is generally assumed that the rate of increase in economic output is related to the associated increase in the inputs, showing a returns-to-scale property. Another property concerning the economic output is convexity which indicates that if one input vector could produce two different output levels, then it can also produce any convex combination of the two output levels. In energy efficiency studies, the imposition of constant return to scale (CRS) and output convexity assumptions on the desirable output has become a common practice. We could therefore integrate them within Eq. (2). Regarding the undesirable output, previous energy efficiency studies have developed several ways of dealing with it. The dominant one is to integrate weak disposability assumption

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