Energy Economics 38 (2013) 146–152

Contents lists available at SciVerse ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneco

A critique of non-parametric efficiency analysis in energy economics studies

Chien-Ming Chen *

Nanyang Business School, Nanyang Technological University, 50 Nanyang Avenue, Singapore 639798, Singapore

ARTICLE INFO

Article history:
Received 10 October 2012
Received in revised form 9 March 2013
Accepted 19 March 2013
Available online 29 March 2013

JEL classification:
C52
C61
D24
Q49

Keywords:
Non-parametric production models
Undesirable outputs
Environmental efficiencies

ABSTRACT

The paper reexamines non-additive environmental efficiency models with weakly-disposable undesirable outputs appeared in the literature of energy economics. These efficiency models are used in numerous studies published in this journal and other energy-related outlets. Recent studies, however, have found key limitations of the weak-disposability assumption in its application to environmental efficiency analysis. It is found that efficiency scores obtained from non-additive efficiency models can be non-monotonic in pollution quantities under the weak-disposability assumption — which is against common intuition and the principle of environmental economics. In this paper, I present taxonomy of efficiency models found in the energy economics literature and illustrate the above limitations and discuss implications of monotonicity from a practical viewpoint. Finally, I review the formulations for a variable returns-to-scale technology with weakly-disposable undesirable outputs, which has been misused in a number of papers in the energy economics literature. An application to evaluating the energy efficiencies of 23 European Union states is presented to illustrate the problem.

1. Introduction

The energy-generation process can result in long-term environmental impact, if not well-managed. In terms of greenhouse effect, for example, activities related to energy supply alone accounts for 26% of the global greenhouse gas (GHG) emissions (IPCC, 2007). Meanwhile, the demand for energy in both developing and developed countries has been steadily increasing. The world's total energy supply is predicted to increase to 33% above of the 2010 level by 2035.[1] Therefore, management of energy generation and consumption relies critically on a systematic approach to weight the energy (and economic) outputs against the concomitant environmental impacts associated with the economic entity under consideration (from the regional, country-wide level, down to the firm and even plant level). In this regard, the non-parametric efficiency model provides a convenient tool for policymaker to incorporate undesirable outputs into the assessment of relative environmental efficiencies of different energy generation units.

The energy economics literature has witnessed a rapid growth in the number of papers that utilize the nonparametric efficiency models; see Zhou et al. (2008a,b) for a comprehensive bibliographical survey. The popularity of the efficiency models stems primarily from the difficulty to estimate the social value of environmental externalities from industrial pollution (or greenhouse gas emissions for the matter of climate change). Hence it becomes a major challenge to assess a firm's or a country's relative efficiency while considering their multiple inputs and desirable and undesirable outputs. Non-parametric efficiency analysis bypasses the requirement of a priori weight specification and the potential bias therein — each observation is allowed to select the input and output weights that maximize its technical efficiency. The non-parametric efficiency models can calculate an efficiency score for each producer in sample, by which we can compare the producer's overall performance against the best-practice producers in the sample.

At the core of environmental efficiency models lies the regularity condition of environmental by-products in the production function. Regarding this, Shephard's production model has been the classic model in the literature (Shephard, 1970). In Shephard's model, undesirable outputs are assumed to be *weakly disposable* in the production possibility set. Under this technological assumption, firms can only reduce undesirable outputs by forgoing desirable outputs in proportion to the % decrease in undesirable outputs. The weak-disposability assumption is adopted in several well-cited environmental efficiency models; most notably, the directional distance function (DDF) with undesirable outputs (Chung et al., 1997).

Recent studies, however, have found that non-additive efficiency models (including DDF and others) are non-monotonic in pollution quantities under the weak-disposability assumption (Chen, 2012; Chen and Delmas, 2012). A direct consequence of this non-monotonicity is that a strongly output-dominated observation may be indicated as efficient, and an observation's efficiency may improve upon increasing its pollution to a threshold value (ceteris paribus) and vice versa. The non-monotonicity then casts severe doubt on the face validity of

* Corresponding author. Tel.: +65 67906248; fax: +65 67922313.
E-mail address: cmchen@ntu.edu.sg.

[1] Source: 2012 Key World Energy Statistics, International Energy Agency (http://www.iea.org).

0140-9883/$ – see front matter © 2013 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.eneco.2013.03.009

non-parametric efficiency models and therefore we must question whether findings from the energy economics studies building on these models require further reexamination.

The purpose of this paper is to highlight the above issues the existing energy economics literature. Based on the way that efficiency scores are calculated, I categorize extant applications of non-additive models in publications from the three major journal outputs: Energy Economics, Energy Policy, and Resource and Energy Economics. Drawing on the 2009 data from 23 European Union states, I show that these models under both constant and variable returns-to-scale assumptions exhibit non-monotonic responses to increase in CO_2 emissions. In light of a growing number of papers adopting the model at issue, this paper provides a timely input on a commonly used methodology in the analysis of the efficiency of energy systems. It is hoped that through this paper, researchers can be made aware of these important limitations when conducting future research work.

2. Weak disposability in a non-parametric production model

The use of weak-disposability assumption in non-parametric production model has been subject to a contentious debate; see, e.g., the in-depth discussion in Sueyoshi and Goto (2012a,b), Yang and Pollitt (2010), and Kuosmanen and Podinovski (2009). Despite this debate, most of the recent studies still impose the classical weak-disposability assumption in their analysis (Shephard, 1970). The current paper is not intended to take position in the ongoing debate about the way in which weak disposability can be best formulated, but to underline the methodological consequences of imposing the classical weak-disposability assumption, especially in the context of *non-additive efficiency models* (Chen and Delmas, 2012).

I begin this section by introducing the mathematical formulation of the non-parametric production model and the related directional distance function (DDF). Then, I will use DDF as an example to illustrate that efficiency scores in a nonparametric production model with weakly disposable undesirable outputs are not monotonic in environmental outputs. Finally, I will introduce five other types of non-parametric models commonly used in the literature of energy-policy analysis.

2.1. Directional distance function

Suppose we observe a sample of n homogeneous entities. Entity j uses inputs $X_j = (x_{j1}, \ldots, x_{jm}) \in \Re^m_{++}$ and produces desirable outputs $Y_j = \left(y_{j1}, \ldots, y_{js}\right) \in \Re^s_{++}$, along with undesirable outputs $B_j = (b_{j1}, \ldots, b_{ju}) \in \Re^u_{++}$. The production possibility set under the weak-disposability and constant returns-to-scale assumptions can be formulated as a linear system (Shephard, 1970):

$$
\begin{aligned}
P(X) = \{(Y,U) : & \textstyle\sum_{j=1}^{n} \lambda_j x_{ji} \le x_i \;\; for\ i = 1, \ldots, m \\
& \textstyle\sum_{j=1}^{n} \lambda_j y_{jr} \ge y_r \;\; for\ r = 1, \ldots, s \\
& \textstyle\sum_{j=1}^{n} \lambda_j b_{jt} = b_r \;\; for\ t = 1, \ldots, u \\
& \lambda_j \ge 0 \; for\ j = 1, \ldots, n\}.
\end{aligned}
\tag{1}
$$

Model (1) satisfies the axiomatic condition that a decrease in undesirable outputs must be accompanied by a proportional decrease in desirable outputs; namely, $(Y,B) \in P(X)$ and $\theta \in [0,1]$ imply $(\theta Y, \theta B) \in P(X)$.

The directional distance function defined based on Eq. (1) is the maximal ratio of the non-negative directional vector (d_t^b, d_r^y) by which the evaluated entity (k) can progress while still remains in P (X):

$$
\begin{aligned}
& Max\,\theta \\
s.t.\;\; & \textstyle\sum_{j=1}^{n} \lambda_j x_{ji} \le x_{ik} \;\; for\ i = 1, \ldots, m \\
& \textstyle\sum_{j=1}^{n} \lambda_j y_{jr} \ge y_{kr} + \theta d_r^y \;\; for\ r = 1, \ldots, s \\
& \textstyle\sum_{j=1}^{n} \lambda_j b_{jt} = b_{kt} - \theta d_t^b \;\; for\ t = 1, \ldots, u \\
& \lambda_j \ge 0 \;\; for\ j = 1, \ldots, n.
\end{aligned}
\tag{2}
$$

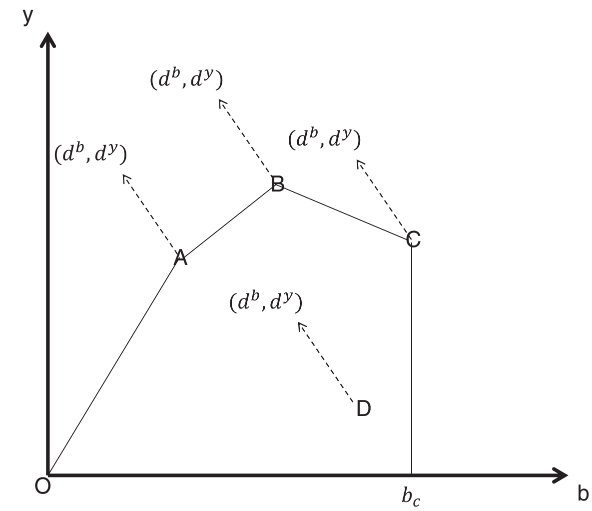

Fig. 1. Directional distance function.

I use a simple example to illustrates Model (2) at work and its non-monotonicity in undesirable outputs. For more general analytical results, readers are referred to Chen and Delmas (2012) and Chen (2012). The example in Fig. 1 consists of four observations (A, B, C, and D) that use the same amount of inputs to produce one desirable output and one undesirable output. The production possibility set under the weak-disposability assumption is the area enclosed by "OABCb_c." Suppose the directional vector at use is the $\left(d^b, d^y\right) \in \Re_+ \times \Re_+$ in the figure.

In this example, observations A, B, and C will obtain a DDF score of zero (i.e., the optimal value of Model (2)), while the DDF score of D will be positive. The results indicate that observations A, B, and C are efficient under the directional vector, while D can improve its output performance (i.e., increasing y while decreasing b) along (d^b, d^y). This example highlights two important issues. First, C is dominated by B in both y and b, but the zero DDF score would indicate that C is efficient. Second, D at its current output level is inefficient because it produces less in y but more in b than its efficient output level on the efficiency frontier. However, if D increases its undesirable output to more than b_c, D's DDF score would become zero and D would attain an efficiency status. In other words, this means that D's relative efficiency status will *improve* after D increases its pollution to more than a threshold value (in this example, when D reaches a pollution level such that (d^b, d^y) emanating from D does not intersect the strongly efficient frontier $\overline{AB}$ and $\overline{BC}$). Moreover, if D increases its pollution to a level that exceeds the lower-right extension of $\overline{BC}$, C will become inefficient — this would look as if C and D can compete for efficiency by increasing production of undesirable outputs or pollution.[2]

Since most empirical applications of Model (2) involve multiple inputs and outputs, our judgment on which observations are the best-practice units in our sample would depend entirely on the efficiency scores obtained from the efficiency model, and a graphic analysis such as Fig. 1 is not applicable when the input–output data have more than three dimensions. In fact, a problem with a higher dimension may increase the number of observations that are misclassified as efficient such as C in Fig. 1 (Chen, 2012).

Note that although C in the above example can move horizontally to reach the efficiency frontier (or more generally speaking, reducing only the undesirable outputs of an observation), but for a more general problem, where multiple undesirable outputs (such as CO_2, SO_2, and NO_x) are considered and there are more than one dominated observation

[2] Note that although the illustrative example shown later in this section is created based on DDF, the results apply to other non-additive models in Table 2 as well.