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Measuring energy performance with sectoral heterogeneity: A non-parametric frontier approach

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ABSTRACT

Evaluating economy-wide energy performance is an integral part of assessing the effectiveness of a country's energy efficiency policy. Non-parametric frontier approach has been widely used by researchers for such a purpose. This paper proposes an extended non-parametric frontier approach to studying economy-wide energy efficiency and productivity performances by accounting for sectoral heterogeneity. Relevant techniques in index number theory are incorporated to quantify the driving forces behind changes in the economy-wide energy productivity index. The proposed approach facilitates flexible modelling of different sectors' production processes, and helps to examine sectors' impact on the aggregate energy performance. A case study of China's economy-wide energy efficiency and productivity performances in its 11th five-year plan period (2006–2010) is presented. It is found that sectoral heterogeneities in terms of energy performance are significant in China. Meanwhile, China's economy-wide energy productivity increased slightly during the study period, mainly driven by the technical efficiency improvement. A number of other findings have also been reported.

1. Introduction

Improving energy efficiency is an effective way to enhance energy security and industrial competitiveness. It helps to reduce energy consumption and energy-related CO_2 emissions and therefore contributes to environmental sustainability. Many countries have implemented measures to improve energy efficiency. As a result, evaluating energy efficiency performance to support energy efficiency policy has attracted increasing attention among policy makers and researchers. In the existing literature, a number of approaches have been used for such a purpose, e.g. index decomposition analysis (IDA), the frontier approach, engineering methods and applied econometrics (Evans et al., 2013). This study focuses on the frontier approach.

The frontier approach has been widely used to assess energy and environmental efficiency at different levels of aggregation. Methodologically, it mainly consists of two branches, namely the parametric frontier approach such as stochastic frontier analysis (SFA), and the non-parametric frontier approach which is often operationalized as a data envelopment analysis (DEA) model. For a given case, SFA econometrically estimates an energy demand frontier function which contains stochastic elements. An advantage of SFA is that the inefficiency in energy use can be isolated from the statistic noise in the data, which facilitates further statistical testing on energy efficiency. Since econometric models are used, SFA can quantify impacts of various economic factors and policy measures on energy demand as well as energy efficiency. However, SFA requires prior specification of a definite functional form, rendering it vulnerable to misspecification. Examples of studies using the parametric frontier approach are Zhou et al. (2012b), Filippini and Hunt (2012, 2015), Lin and Du (2013), and Ma and Zhao (2015).

DEA aims to calculate the relative technical efficiency of a sample of entities, often called decision making units (DMUs), with respect to the best practice frontier constructed by all observations. Unlike SFA, it does not need any prior specification on the functional form of the frontier. It is able to endogenously benchmark DMUs with respect to the constructed frontier. Various DEA models have been proposed to assess energy and environmental performances (Zhou et al., 2008). For example, Hu and Wang (2006) propose a radial DEA model to build a total-factor energy efficiency index. Zhou and Ang (2008) point out the importance of accounting for undesirable outputs in measuring economy-wide energy efficiency. The directional distance function

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introduced by Chung et al. (1997) was adopted by Riccardi et al. (2012) to empirically study the impact of undesirable outputs on energy efficiency. Zhou et al. (2012a) propose the non-radial directional distance function for energy efficiency assessment, which can be calculated by a non-radial additive DEA model accounting for the slacks for all variables (Chen, 2013). The recent study by Zhou et al. (2016) shows the impact of potential congestion effect on the total-factor energy efficiency index. With the progress in methodology, different DEA models have been used to study energy and environmental performances at various sectoral and economy-wide levels. See, for example, Zhou et al. (2014) for the transport sector, Managi and Jena (2010) and Wu et al. (2012) for the industry sector, Färe et al. (2014) for power plants, Molinos-Senante et al. (2014) for waste water treatment plants, Fang et al. (2013) for the service sector, Kumar and Managi (2010) and Wang et al. (2013) for economy-wide studies.

It should be noted that the aforementioned energy efficiency index such as Hu and Wang (2006) derived from DEA models is only for a particular year. Further to the static analysis, it is worthwhile to track DMUs' energy performance trends over time. In the literature, Malmquist productivity index, originally defined as the ratio of two distance functions (Caves et al., 1982), is usually used to measure the change in DMUs' performance during a time span. Färe et al. (1994) introduce the Malmquist index in the DEA framework by exploring the relationship between distance functions and Farrell's technical efficiency measures. Chung et al. (1997) extend the Malmquist index by taking undesirable outputs into account. More recently, the Malmquist productivity index has been combined with various DEA models to assess DMUs' energy or emission performance changes, e.g. Färe et al. (2010), Zhou et al. (2010), Wang (2011, 2015) and Wang et al. (2013, 2016).

The energy consumption in a country is normally divided into several major sectors such as industry, transport, service, etc. From an energy analysis viewpoint, a sensible practice in tracking economy-wide energy performance is to analyze first by sector and then aggregate the results to generate an overall economy-wide energy efficiency index (Ang et al., 2010). The reason for using this bottom-up approach is that heterogeneity exists among energy consuming sectors (Ma, 2014). Different sectors exhibit diverse production technologies and processes, as well as energy consumption patterns. The conventional DEA approach treats the overall economy as a whole without looking into the heterogeneity issue. It may therefore lead to a biased energy efficiency index in economy-wide studies. Further, when accounting for sectoral heterogeneities, the conventional DEA approach cannot be directly used to track economy-wide energy performance trends, and it is not able to reveal the driving forces behind changes over time. Solving these two problems can help to improve the non-parametric approach to tracking the economy-wide energy performance trends. It is the purpose of this study to address these issues. We shall propose an extended DEA approach based on which the potential sectoral heterogeneity in economy-wide energy performance analysis can be accounted for. In such an extension, relevant techniques in index number theory will be incorporated. The proposed approach will be used to study China's economy-wide energy efficiency and productivity in its 11th five-year plan period (2006–2010).

The rest of this paper is organized as follows. Section 2 introduces the methodology for measuring economy-wide energy efficiency and productivity performances. Section 3 presents an empirical study on China. Section 4 concludes this study.

2. Methodology

2.1. Environmental production technology

It is known that a sector of an economy uses energy and other inputs to produce desirable and undesirable outputs. Suppose we have N sectors ($i = 1, \ldots, N$) under consideration. Let $\mathbf{E}, \mathbf{X}, \mathbf{Y}$ and $\mathbf{U}$ denote the vector for energy inputs, non-energy inputs, desirable outputs and undesirable outputs, respectively. According to production theory, the production technology for sector i can be conceptually formulated as:

$$T_i = \{(\mathbf{E}_i, \mathbf{X}_i, \mathbf{Y}_i, \mathbf{U}_i) : (\mathbf{E}_i, \mathbf{X}_i) \text{ can produce } (\mathbf{Y}_i, \mathbf{U}_i)\} \tag{1}$$

To characterize the production technology, its feature of returns to scale needs to be specified. In the literature, a number of returns to scale assumptions have been proposed and applied, e.g. constant returns to scale (CRS), non-increasing returns to scale (NIRS), variable returns to scale (VRS), etc. Of these commonly used assumptions, VRS is able to cater for various returns to scale features. Given that the objective of this study is to account for heterogeneities in evaluating energy performances, we model the production technology using the VRS assumption.[1]

Under the VRS specification, we follow Färe et al. (1989) and Zhou et al. (2008) to impose two more assumptions to further characterize the joint production of desirable and undesirable outputs, which are given as follows:

i. Null-jointness assumption: if $(\mathbf{E}_i, \mathbf{X}_i, \mathbf{Y}_i, \mathbf{U}_i) \in T_i$ and $\mathbf{U}_i \to 0$, then $\mathbf{Y}_i \to 0$
ii. Weakly disposable assumption: if $(\mathbf{E}_i, \mathbf{X}_i, \mathbf{Y}_i, \mathbf{U}_i) \in T_i$ and $0 < \theta \le 1$, then $(\mathbf{E}_i, \mathbf{X}_i, \theta\mathbf{Y}_i, \theta\mathbf{U}_i) \in T_i$

Assumption (i) implies that the undesirable output is a by-product of the production process, and the desirable output becomes infinitesimal if the undesirable output is eliminated to be infinitesimal. Assumption (ii) indicates that the reduction of undesirable output is at the cost of proportional decrease of desirable output, which could reasonably reflect the abatement cost of undesirable output. With these two assumptions, the production technology T_i can meaningfully model the joint production process of sector i in an economy, and T_i can be regarded as the environmental production technology exhibiting VRS (Färe et al., 2004; Zhou et al., 2008).

Notwithstanding, Eq. (1) cannot be directly applied in empirical studies since it does not have a specific functional form. In the literature, a common practice is to employ the non-parametric piecewise linear approach to modeling this production technology. For each sector, suppose M regions ($j = 1, \ldots, M$) are under evaluation. Following Zhou et al. (2008), the i-th sector's environmental production technology exhibiting VRS can then be formulated as:

$$T_i = \left\{ (\mathbf{E}_i, \mathbf{X}_i, \mathbf{Y}_i, \mathbf{U}_i) : \begin{array}{l} \sum_j \lambda_j E_{ij} \le E_i \\ \sum_j \lambda_j X_{ijk} \le X_{ik}, \forall k \\ \sum_j \lambda_j Y_{ijl} \ge \alpha Y_{il}, \forall l \\ \sum_j \lambda_j U_{ij} = \alpha U_{ip}, \forall p \\ \sum_j \lambda_j = 1 \\ \alpha \ge 1, \lambda_j \ge 0, j = 1, \ldots, M \end{array} \right\} \tag{2}$$

where α is an adjusting parameter, λ denotes intensity variable, k,l and p respectively denote the type of non-energy inputs, desirable outputs and undesirable outputs. Combined with an efficiency measurement, model (2) can be used to calculate the i-th sector's energy efficiency in each region.

2.2. Economy-wide energy efficiency performance index

Assuming an economy is first disaggregated into N energy consuming sectors and further into M regions, the resulting data structure is

[1] Changes to other returns to scale assumptions can be easily made, if needed. Readers may refer to Zhou et al. (2008) for more details on the modelling of CRS and NIRS assumptions using DEA.