Energy 76 (2014) 884–890

Contents lists available at ScienceDirect

Energy

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

Measuring energy efficiency under heterogeneous technologies using a latent class stochastic frontier approach: An application to Chinese energy economy

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A R T I C L E I N F O

Article history:
Received 20 April 2014
Received in revised form
9 August 2014
Accepted 31 August 2014
Available online 26 September 2014

Keywords:
Latent class analysis
Stochastic frontier analysis
Energy efficiency
Technology heterogeneity

A B S T R A C T

The importance of technology heterogeneity in estimating economy-wide energy efficiency has been emphasized by recent literature. Some studies use the metafrontier analysis approach to estimate energy efficiency. However, for such studies, some reliable priori information is needed to divide the sample observations properly, which causes a difficulty in unbiased estimation of energy efficiency. Moreover, separately estimating group-specific frontiers might lose some common information across different groups. In order to overcome these weaknesses, this paper introduces a latent class stochastic frontier approach to measure energy efficiency under heterogeneous technologies. An application of the proposed model to Chinese energy economy is presented. Results show that the overall energy efficiency of China's provinces is not high, with an average score of 0.632 during the period from 1997 to 2010.

1. Introduction

In recent years, the impact of climate change became increasingly severe. It has been commonly recognized that the growing emissions of greenhouse gas caused by fossil fuels consumption take the most responsibility for the climate change. Improving energy efficiency is regarded as one of the most cost-effective ways to fight against climate change (Ang et al. [1]). As such, evaluating economy-wide energy efficiency performance has attracted much attention, and the number of studies about this topic has grown over the years.

In literature, conceptually speaking, there are two categories of energy efficiency indicators: PFEE (partial factor energy efficiency) indicators and TFEE (total factor energy efficiency) indicators. PFEE indicators are defined by the ratio relations between energy input and output. There are two well-known PFEE indicators: energy intensity (the ratio of energy input to output) and energy productivity (the ratio of output to energy input). A variety of researchers (e.g., Choi et al. [2], Ang and Zhang [3], Ang and Liu [4], and Wang [5]) have devoted to developing analysis tools of investigating the mechanisms of PFEE changes. Due to the ease of use, PFEE indicators are widely used in practice. For instance, Lin and Moubarak [6] and Lin and Wang [7] employed cointegration method to analyze the influencing factors of energy intensity changes in China's paper industry and iron and steel sector, respectively. However, PFEE indicators do not take into account the roles of other input factors (labor and capital), which is not in line with the real production activity, thus being criticized by some recent studies. See, for example, Boyd [8], Hu and Wang [9], and Stern [10].

Different from PFEE indicators, TFEE indicators are defined as a ratio of the optimal-to-actual energy input in a multi-factor framework. Conceptually, TFEE indicators are built on the neoclassical production theory. There are mainly two approaches for estimating the TFEE indicators: DEA (data envelopment analysis) and SFA (stochastic frontier analysis).

DEA is a nonparametric approach which uses linear programming techniques to estimate the frontier so that the imposition of a function form on the frontier is not needed. Using DEA to estimate energy efficiency is computationally convenient and can avoid the possible misspecification of the model. In this sense, DEA has been popular in energy efficiency analysis. Examples of such studies

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http://dx.doi.org/10.1016/j.energy.2014.08.089
0360-5442/

include Wei et al. [11], Zhou and Ang [12], Khoshnevisan et al. [13], Zhao et al. [14], Wu et al. [15], and Cui et al. [16].

Although the advantages of DEA are distinct, it does not take into account the influence of statistical noises. Thus, it is often criticized that results of empirical studies using DEA models are very sensitive to outliers, especially when data include measurement error (Simar [17]). For this reason, recently researchers advocated SFA for estimating TFEE. For instance, Buck and Young [18] applied a stochastic frontier approach to analyze the potential for energy efficiency gains in the Canadian commercial building sector. Zhou et al. [19] measured the economy-wide energy efficiency through the Shephard energy distance function and developed a SFA approach for estimation. Lin and Wang [20] employed Zhou et al. [19]'s model to explore energy efficiency in China's iron and steel industry. Based on the SFA model, Rahman and Hasan [21] estimated productivity and energy efficiency of wheat farming in Bangladesh.

In terms of TFEE indicators, previous studies typically assume that the underlying production technology is shared by all the DMUs (decision-making units). However, in practice this assumption is very strong and unrealistic. Different DMUs might use different types of production technologies because of their variations in resources endowment, institutional environment and development stage of economy. In this case, estimating energy efficiency based on the common technology would be biased. Because the estimated technology parts from the true technology and unobserved heterogeneity in technologies might be inappropriately interpreted as energy inefficiency.

Despite the importance of technology heterogeneity, to our awareness, there are only two studies regarding the estimation of energy efficiency attempted to take this factor into consideration. Lin and Du [22] proposed a parameter metafrontier approach to estimate China's regional energy efficiency and technology gap. Wang et al. [23] developed a metafrontier DEA approach to analyze the energy efficiency of China's provinces.

Technically, metafrontier analysis is carried out in two stages. The first stage is to divide all the DMUs into subgroups with different technologies (Technologies of DMUs within the group are assumed to be homogeneous while those across groups are assumed to be heterogeneous). For example, Wang et al. [23] divided 29 provinces of China into three groups according to their geographical locations. Lin and Du [22] employed cluster analysis for the index of energy intensity to segment China's 30 provinces into three groups. These ways of sample separation are based on some priori information (e.g., economic development, energy intensity, and geographical location). However, such priori information might not be reliable as technology at economy-wide level which cannot be observed directly and is determined by many factors. Consequently, dividing the sample observations according to arbitrary and ad hoc criteria might bring risks of inconsistent results and inference. The second stage of the metafrontier analysis is estimating the group-specific frontier and constructing the metafrontier. Thus, another drawback of the metafrontier analysis is that separately estimating the frontier for each group may lose the common information of DMUs across different groups (Alvarez and Del Corral [24]).

In order to address the shortcomings of the existing studies, this paper introduces a latent class stochastic frontier approach, which was first proposed by Greene [25] and further developed by Greene [26] and Orea and Kumbhakar [27], to measure energy efficiency under heterogeneous technologies. Our proposed approach integrates the model of Zhou et al. [18] with latent class analysis which is a single-stage approach allowing for classifying the DMUs through endogenous sample separation information. Compared with the metafrontier analysis, the latent class stochastic frontier approach can reduce the likelihood of misspecification regarding the sample splitting.

The rest of our paper is structured as follows. Section 2 describes the methodology in detail. Section 3 presents an application study to the Chinese energy economy. Section 4 concludes the paper.

2. Methodology

Technically, TFEE is usually measured through the Shephard distance function. In this regard, choosing the reference technology is essential to calculate the Shephard distance function. However, production technologies cannot be observed directly (at least for the econometrician). Therefore, it is difficult to construct the appropriate frontier for the DMUs (decision-making units) under heterogeneous technologies. To address this problem, this paper uses latent class analysis.

Assume that all the DMUs (the number of DMUs is denoted by N) can be divided into J subgroups according to their production technologies. The technologies of the DMUs within a group are assumed to be the same while those across groups are varied. The group specific technology is used as the basis of evaluating the energy efficiency performances for its group members.

Consider a neoclassic production framework where DMUs use capital (K), labor (L), and energy (E) to generate output (Y). The production possible set for group j can be described as:

$$T_j = \{(K, L, E, Y|\omega_j) : (K, L, E) \text{ can produce } Y \text{ with technology } \omega_j\}, j = 1, \ldots, J \quad (1)$$

where ω_j is group specific parameter describing technological heterogeneity among groups. Following Lin and Du [22], the Shephard energy distance function relative to the group specific technology is defined as:

$$D_{E|j}\left(K, L, E, Y\right) = \sup\left\{\beta : \left(K, L, E/\beta, Y\right) \in T_j\right\}, j = 1, \ldots, J \quad (2)$$

where β denotes the scale of energy reduction.

The Shephard energy distance function describes the maximum reduction of energy input while keeping other inputs and output unchanged given the group-specific technology. The idea can be depicted by Fig. 1. The curve represents the production isoquant. Point A is the assessed DMU. It can be seen that the DMU is departure from the frontier, indicating that it use excess energy. For reaching the frontier, the most energy-saving way is moving the DMU from A to B, which means reducing its current level of energy input from E_1 to E_0. Thus, the value of the Shephard energy distance function can be calculated as AD/AB.

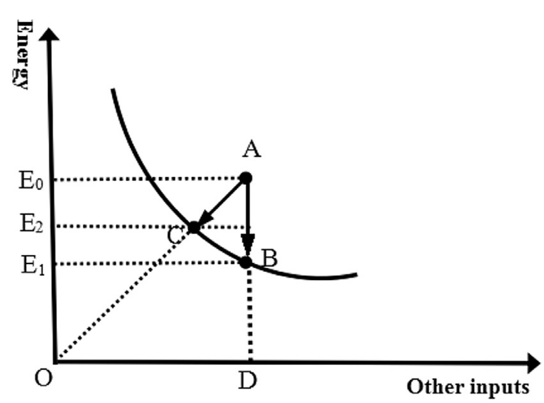

Fig. 1. A graphical illustration of the Shephard energy distance function.