Energy Policy 39 (2011) 644–650

Contents lists available at ScienceDirect

Energy Policy

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

Total-factor energy efficiency in developing countries

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ARTICLE INFO

Article history:
Received 5 May 2010
Accepted 27 October 2010
Available online 13 November 2010

Keywords:
DEA window analysis
Total-factor energy efficiency
Tobit model

ABSTRACT

This paper uses a total-factor framework to investigate energy efficiency in 23 developing countries during the period of 1980–2005. We explore the total-factor energy efficiency and change trends by applying data envelopment analysis (DEA) window, which is capable of measuring efficiency in cross-sectional and time-varying data. The empirical results indicate that Botswana, Mexico and Panama perform the best in terms of energy efficiency, whereas Kenya, Sri Lanka, Syria and the Philippines perform the worst during the entire research period. Seven countries show little change in energy efficiency over time. Eleven countries experienced continuous decreases in energy efficiency. Among five countries witnessing continuous increase in total-factor energy efficiency, China experienced the most rapid rise. Practice in China indicates that effective energy policies play a crucial role in improving energy efficiency. Tobit regression analysis indicates that a U-shaped relationship exists between total-factor energy efficiency and income per capita.

1. Introduction

Global warming is one of the world's most important environmental problems. The problem is largely attributable to the greenhouse gas carbon dioxide, which is released by the burning of fossil fuels. Because of this, a growing body of research has focused on improving energy efficiency, which is a crucial approach to alleviating global warming. During the past several decades, some appropriate methods have been developed to monitor energy-efficiency trends and compare energy efficiency performance across countries. These methods are generally classified as parametric and non-parametric methods (Sadjadi and Omrani, 2008). Parametric methods such as stochastic frontier analysis estimate a cost or production function. Therefore, deviations in the function form affect the results of such models. In contrast, it is not necessary to estimate the cost or production function when using non-parametric methods. Data envelopment analysis (DEA) is a non-parametric method that is capable of handling multiple inputs and multiple outputs.

Energy intensity and energy efficiency are the two well-known energy-efficiency indicators that are commonly used in macro-level policy analysis. Energy intensity is defined as the energy consumption divided by the economic output, and energy efficiency is the reciprocal of energy intensity. These traditional energy-efficiency indicators take energy consumption into account as a single input that produces an economic output; therefore, some other key inputs are ignored, such as capital and labor. Energy consumption must be combined with other inputs to produce an economic output, and substitution effects exist between energy and other input factors (e.g., labor and capital stock). If energy consumption is evaluated in terms of partial-factor energy efficiency, the result is a misleading estimate (Hu and Wang, 2006; Honma and Hu, 2009). Boyd and Pang (2000) indicated that energy-efficiency improvement relies on total-factor productivity improvement. To overcome the disadvantage of partial-factor energy efficiency, an increasing number of researchers have devoted themselves to analyzing total-factor energy efficiency using DEA.

There are essentially two research strands in the literature analyzing total-factor energy efficiency using DEA. The first strand focuses on measuring total-factor productivity change based on the DEA–Malmquist index, which was first introduced by Caves et al. (1982). For example, Forsund and Kittelsen (1998) applied DEA efficiency scores to calculate the Malmquist productivity index in Norwegian electricity distribution companies. Edvardsen and Fbrsund (2003) applied an input-oriented DEA model and the Malmquist productivity index to analyze the performance of 122 electricity distributors in Denmark, Finland, Norway, Sweden and the Netherlands. Wei et al. (2007) applied this approach to investigate changes in the energy efficiency of China's iron and steel sectors. The index of total-factor productivity takes only radial adjustment into account and disregards the non-radial slack; it is therefore unable to measure single-factor efficiency under a total-factor framework (Honma and Hu, 2009).

The second strand utilizes the index of total-factor energy efficiency (TFEE) first proposed by Hu and Wang (2006). TFEE is defined as the target energy input divided by the actual energy input. Taking non-radial slack into account, the TFEE is capable of measuring single-factor efficiency in a total-factor framework. Following Hu and Wang (2006), Honma and Hu (2008) measured

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doi:10.1016/j.enpol.2010.10.037

the TFEE of 47 regions in Japan for the period 1993–2003. Integrating the concept of TFEE with the Malmquist productivity index, Hu and Chang (2009) proposed the total-factor energy productivity index (TFEPI) to investigate energy productivity changes in regions of China. Honma and Hu (2009) extended their previous work (Honma and Hu, 2008) by applying TFEPI.

Following Hu and Wang (2006) and Honma and Hu (2008), we use DEA theory to investigate the total-factor energy efficiency of developing countries. This paper extends the contributions of these earlier studies in three ways. First, this study investigates the total-factor energy efficiency of 23 developing countries. The Kyoto Protocol is severely criticized for not including emission reduction obligations for developing countries because many developing countries have become major carbon dioxide emitters. For example, China is the second largest energy-related CO_2 emitter and India ranks fourth in the world. Therefore, the choice to study developing countries is motivated by the rising importance of their contribution to global warming. Secondly, we use the DEA window analysis introduced by Charnes and Cooper (1985) for the first time to develop total-factor energy-efficiency measures for the 23 developing countries during the period of 1980–2005. This approach can indicate efficiency trends over a specified period of time while simultaneously examining stability and other properties of the efficiency evaluations within the specified windows (Hartman and Storbeck, 1996; Webb, 2003). Third, we use dynamic Tobit model to investigate the relationship between total-factor energy efficiency and income for 23 developing countries over the period 1980–2005.

The remainder of this paper is organized as follows: The next section describes the methods used in the study; Section 3 presents the data; Section 4 presents the empirical results; and Section 5 concludes the paper.

2. Method

2.1. Total-factor energy efficiency based on DEA

Hu and Wang (2006) proposed the TFEE, which is defined as the target energy input divided by the actual energy input, and also utilized what is known as the constant returns to scale (CRS) DEA model. It is universally known that the assumption of the CRS model is appropriate only when all decision-making units (DMUs) are operating at an optimal scale. However, some factors, such as imperfect competition and constraints on finance, may cause a DMU not to operate at an optimal scale. If it is likely that the size of the DMUs under investigation will influence their ability to create outputs efficiently, then the assumption of CRS is inappropriate (Halkos and Tzeremes, 2009). Banker et al. (1984) suggested an extension of the CRS model to account for variable returns to scale (VRS) situations. The less restrictive VRS frontier allows the best practice level of outputs to inputs to vary with the size of the countries (Halkos and Tzeremes, 2009). Because the 23 developing countries in this study have different sizes, we use the VRS model. The VRS model could be obtained by adding the convexity constraint based on the CRS model (Charnes et al., 1978).

The model employs the following mathematical notation: For each of N DMUs, there are K inputs and M outputs. For the ith DMU, the inputs and outputs are represented by the column vectors x_i and y_i, respectively. The input-oriented VRS model solves the following linear programming problem for DMU_t^o:

$$
\begin{aligned}
&\text{Min} \quad \theta \\
&\text{s.t.} \quad \sum_{j=1}^{N} \lambda_j y_j - s^+ = y^o \\
&\sum_{j=1}^{N} \lambda_j x_j + s^- = \theta x^o \\
&\sum_{j=1}^{N} \lambda_j = 1 \\
&\lambda_j \geq 0, \quad j = 1, 2, \ldots, N
\end{aligned} \tag{1}
$$

where θ is a scalar with $0 \leq \theta \leq 1$, λ is a $N \times 1$ vector of constants that form a convex combination of observed inputs and outputs and s represents the non-radial slack.

DEA identifies the most efficient point on the frontier as a target for those inefficient DMUs to achieve through a sequence of linear programming computation (Coelli, 1996). The value of θ represents the technically efficient score for the ith DMU. $(1-\theta)x_i$ is called radial adjustments. The ith DMU is the most efficient point on the frontier and is technically efficient if $\theta = 1$ and the slack equals zero; if $\theta = 1$ and the slack is larger than zero, the ith DMU is weakly technically efficient; $\theta < 1$ indicates that the ith DMU is technically inefficient. The sum of the radial and non-radial adjustments is called the total adjustments, which can be reduced to reach optimal technical efficiency without decreasing the output levels. The total adjustments for the technically efficient DMUs equal zero, but are larger than zero for the other DMUs. The target energy input (TEI) in this study is therefore actual energy input (AEI) minus the total adjustments (TA), which represents a practical minimum level of energy input to be taken as a target to perform at the optimal energy consumption efficiency. Hence, the TFEE index of DMU i at time t can be measured as (Hu and Wang, 2006)

$$TFEE(i,t) = \frac{TEI(i,t)}{AEI(i,t)} = \frac{AEI(i,t) - TA(i,t)}{AEI(i,t)} \tag{2}$$

The total adjustments are not less than zero according to model (1). Total adjustments of zero indicate that the actual energy input is indeed the target energy input, so TFEE is unity and the energy is used at the optimal efficiency. TFEE is lower than unity if the total adjustments are larger than zero. This implies there is redundant energy input, which should be reduced without decreasing the output. Therefore, the index of TFEE is always between zero and unity. The greater the value of TFEE, the more efficient the energy consumed.

2.2. Total-factor energy efficiency based on DEA window analysis

DEA window analysis, which was introduced by Charnes and Cooper (1985), is a variation of the traditional DEA that can handle cross-sectional and time-varying data to allow for dynamic effects. DEA window analysis operates on the principle of moving averages (Charnes et al., 1994a; Yue, 1992) and establishes efficiency measures by treating each DMU in different years as a separate unit. The performance of a DMU in a period can be contrasted with its own performance in other periods as well as to the performance of other DMUs (Asmild et al., 2004). Therefore, DEA window analysis can explore the evolution of performance through a sequence of overlapping windows. Moreover, the number of data points is increased several times over in DEA window analysis, which is very useful when dealing with small sample sizes.

A brief DEA window analysis review is presented here. A window with $N \times w$ observations is denoted starting at time $t (1 \leq t \leq T)$ with window width w $(1 \leq w \leq T-t)$. The matrix of inputs for this window is

$$\mathbf{X}_{tw} = (x_t^1, x_t^2, \ldots, x_t^N, x_{t+1}^1, x_{t+1}^2, \ldots, x_{t+1}^N, \ldots, x_{t+w}^1, x_{t+w}^2, \ldots, x_{t+w}^N)$$

and the matrix of outputs is given by

$$\mathbf{Y}_{tw} = (y_t^1, y_t^2, \ldots, y_t^N, y_{t+1}^1, y_{t+1}^2, \ldots, y_{t+1}^N, \ldots, y_{t+w}^1, y_{t+w}^2, \ldots, y_{t+w}^N)$$