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Total-factor energy productivity growth of regions in Japan

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A B S T R A C T

This article computes the energy productivity changes of regions in Japan using total-factor frameworks based on data envelopment analysis (DEA). Since the traditional DEA-Malmquist index cannot analyze changes in single-factor productivity changes under the total-factor framework, we apply a new index proposed by Hu and Chang [2009. Total-factor energy productivity growth of regions in China. Energy Policy, submitted for publication]: a total-factor energy productivity change index (TFEPI) that integrates the concept of the total-factor energy efficiency index into the Malmquist productivity index (MPI). Moreover, we separate TFEPI into change in relative energy efficiency, or the 'catching up effect,' and shift in the technology of energy use, or the 'innovation effect.' The data from 47 prefectures during the period of 1993–2003 are used to compute the TFEPI and its components for 4 kinds of energy. The TFEPI of electric power for commercial and industrial use changes −0.6% annually, which can be separated into a total-factor energy efficiency change of 0.2% and a technical change of −0.8%. The TFEPI for coal deteriorates by 1.0%/year, which is mostly caused by a decrease in relative energy efficiency change. We define and identify 'innovators' who cause the frontier to shift. Most regions identified as frontier shifters are located outside of Japan's four major industrial areas.

1. Introduction

The first oil crisis hit the Japanese economy in 1973 and led to a drive for efficient energy use in Japan. As a result, Japan has achieved one of the highest levels of energy efficiency in the world. Energy conservation policy has been a crucial concern for Japan as a resource-poor country without a stable supply of energy. Moreover, Japan ratified the Kyoto protocol and must, by 2012, decrease its greenhouse gas emissions by 6% from its 1990 level. The Ministry of Environment (MOE) of Japan has proposed a carbon tax to mitigate carbon dioxide emissions since 2003. The proposed tax rate in 2003 was 3400 yen (approximately 29 US$ at the day's exchange rate) per ton of carbon contained in fossil fuel emissions, and, since 2004, it has been reduced to 2400 yen (approximately 22 US$ at the day's exchange rate). However, because of opposition from business interests, the MOE has failed to institute the carbon tax. Japan's carbon dioxide emissions from energy use have remained above the 1990 baseline and, in 2007, increased 15.0% above it. As Kasahara et al. (2007) suggested, a climate change tax combined with international emission trading might be a rational choice for Japan; however, in reality a climate change tax has been and will continue to be politically unacceptable. The Japanese government's plan depends on voluntary action to reduce energy use in industrial, commercial, and residential sectors, which seems to be unrealistic. In addition to Japan's obligation to implement the Kyoto mechanism including the international emission trading, improving energy efficiency or energy productivity *per se* has been the key issue for Japan's energy-environmental policy. However, the energy efficiency-enhancing policy may have two unintended consequences: First, improvements in energy efficiency may result in lower energy prices and in turn increased energy consumption. This is called the rebound effect which was first suggested by W.S. Jevons in 1865; however, this effect still remains debatable (recently, e.g., Hanley et al., 2009). Second, energy efficiency measures may not necessarily lead to reducing carbon emissions when Japan participates in international emissions trading schemes. In that case, the social cost of reducing carbon dioxide as well as the cap amount of carbon emissions will be different if Japan does not participate in these schemes.[1]

Two well-known indicators are commonly used to study whether energy inputs are efficiently used. The first is energy intensity, which measures the amount of energy consumption for economic output produced in the economy. According to this kind

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[1] Söderholm and Pettersson (2008) show that the social cost of power generation depends upon whether or not the country participates in international emissions trading in the Swedish case.

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of indicator, Japan is one of the world's leading countries in energy use. For example, if Japan's primary energy consumption (on a crude oil equivalent basis) per real GDP is taken as 1 in 2005, then that of the United States is 2.00, that of the United Kingdom is 1.35, that of France is 1.82, and that of Germany is 1.65.[2] For example, at the industry level, if energy consumption per unit of production in the Japanese iron and steel industry is taken as 1, that of the United States is 1.25, that of the United Kingdom is 1.22, and that of Germany is 1.17.[3] Moreover, if energy consumption per cement clinker in Japan is taken as 1, that of the United States is 1.77 and that of Western Europe is 1.30. The second indicator is energy efficiency (or energy productivity), defined as the economic output divided by the energy input (e.g., Berndt, 1990; Patterson, 1996; Han et al., 2007). Notice that although each indicator represents identical measures from different perspectives, we focus only on the application of energy efficiency and productivity in this paper.

The conventional energy efficiency index introduced in Patterson (1996) is partial-factor energy productivity because it disregards the substitution among energy consumption and other factors (e.g., labor and capital stock). If energy consumption is evaluated in terms of partial-factor energy productivity, the end result is a misleading estimate (Hu and Wang, 2006; Hu and Kao, 2007; Han et al., 2007; Honma and Hu, 2008). For this reason, even though of the above international comparisons, it does not follow that energy efficiency in Japan is higher than in other developed countries. For example, Hu and Kao (2007) show that Japan is not the best performer in the APEC economy in 1991–2000 using a total-factor framework.

This article evaluates the energy productivity change of regions in Japan with a total-factor framework. Under the traditional DEA-Malmquist index, one cannot evaluate the change in single-factor productivity under the total-factor framework. As a result, we use a new index, the total-factor energy productivity change index (TFEPI), which was proposed in Hu and Chang (2009). Following Hu and Chang (2009), we extend the work of Honma and Hu (2008) on total-factor energy efficiency (TFEE) to introduce a total-factor energy productivity index that integrates the concept of the total-factor energy efficiency index into the Malmquist productivity index (MPI). The MPI was first introduced by Caves et al. (1982) to measure total-factor productivity change by the ratio of the distance functions. Färe et al. (1994) broke down the MPI into efficiency change and technical change. They used data envelopment analysis (DEA), which is a nonparametric, linear programming method. To evaluate the TFEPI, we also use DEA. Moreover, we can decompose TFEPI into changes in relative energy efficiency (the catching up effect) and shifts in the technology of energy use (the innovation effect) under the total-factor framework. This study extends the panel dataset of Honma and Hu (2008) and analyzes prefecture-level data from 1993 to 2003. There are a single, aggregate output (real GDP) and 14 inputs in our DEA model, including 3 production factors (labor employment and real private and real public capital stocks), and 11 energy sources. To the best of our knowledge, no studies have attempted to assess changes in energy productivity for regions in Japan using a total-factor framework.[4] The revised energy conservation law evaluates energy efficiency with respect to each apparatus, factory, and building from April 2009. Our results shed new light on Japan's energy productivity changes by examining those changes by region and energy type.

The remainder of this paper is organized as follows: Section 2 introduces the proposed total-factor energy productivity index using the DEA approach. Section 3 interprets the data sources and describes the variables involved. Section 4 presents and discusses the empirical results in the case of Japan. Finally, Section 5 concludes the paper.

2. Total-factor energy productivity index

Hu and Chang (2009) propose the TFEPI, which combines the concepts of TFEE and MPI to investigate the energy productivity changes in regions of China. Because TFEE examines the optimal energy input level with the input-oriented constant returns to scale (CRS) DEA model, our TFEPI also follows an input-oriented model. Additionally, MPI, which is usually computed by an output-oriented DEA approach, is applied using an input-oriented framework in this study. In the following subsection, we first introduce the input-oriented MPI and proceed with TFEE. Finally, the TFEPI is presented with a discussion of how MPI and TFEE are integrated.

2.1. Input-oriented Malmquist productivity index

First, we assume that the production technology $\mathbf{S}^t$ models the transformation of multiple inputs, $\mathbf{x}^t \in R_+^K$, into multiple outputs, $\mathbf{y}^t \in R_+^M$, for each time period t, where

$$\mathbf{S}^t = \{(\mathbf{x}^t, \mathbf{y}^t) : \mathbf{x}^t \text{can produce } \mathbf{y}^t\} \tag{1}$$

The computation of input-oriented MPI relies on input-based distance functions. Following Färe et al. (1985) and Boussemart et al. (2003), the input distance function can be defined at t as

$$D_i^t(\mathbf{x}^t, \mathbf{y}^t) = \sup\{\delta : (\mathbf{x}^t/\delta, \mathbf{y}^t) \in \mathbf{S}^t\} = (\inf\{\delta : (\delta\mathbf{x}^t, \mathbf{y}^t) \in \mathbf{S}^t\})^{-1} \tag{2}$$

where distance function (2) is based upon the reciprocal of the maximum proportional reduction of the input vector by a scalar δ to catch up to the production frontier. It is notable that $D_i^t(\mathbf{x}^t, \mathbf{y}^t) \geqslant 1$ and $D_i^t(\mathbf{x}^t, \mathbf{y}^t) = 1$ if and only if $(\mathbf{x}^t, \mathbf{y}^t)$ is on the production frontier. Therefore, input-oriented MPI can be measure as follows:

$$\begin{aligned} M_i(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{x}^t, \mathbf{y}^t) &= \left[\left(\frac{D_i^t(\mathbf{x}^t, \mathbf{y}^t)}{D_i^t(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})} \right) \left(\frac{D_i^{t+1}(\mathbf{x}^t, \mathbf{y}^t)}{D_i^{t+1}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})} \right) \right]^{1/2} \\ &= \frac{D_i^t(\mathbf{x}^t, \mathbf{y}^t)}{D_i^{t+1}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})} \left[\left(\frac{D_i^{t+1}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})}{D_i^t(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})} \right) \left(\frac{D_i^{t+1}(\mathbf{x}^t, \mathbf{y}^t)}{D_i^t(\mathbf{x}^t, \mathbf{y}^t)} \right) \right]^{1/2} \end{aligned} \tag{3}$$

2.2. Total-factor energy efficiency

In order to pursue overall technical efficiency with energy inputs, our study adopts the CRS DEA model (Charnes et al., 1978). Let us first define some mathematical notations. There are K inputs and M outputs for each of N objects. The ith object is represented by the column vectors $\mathbf{x}_i$ and $\mathbf{y}_i$, respectively. The $K \times N$ input matrix $\mathbf{X}$ and the $M \times N$ output matrix $\mathbf{Y}$ represent the data for all N objects. The input-oriented CRS DEA model then solves the following linear programming problem for object I in each year:

$$\begin{aligned} &\text{Min}_{\theta,\lambda}\ \theta \\ &\text{s.t.}\ -\mathbf{y}_i + \mathbf{Y}\lambda \geqslant 0 \\ &\theta\mathbf{x}_i - \mathbf{X}\lambda \geqslant 0 \\ &\lambda \geqslant 0 \end{aligned} \tag{4}$$

[2] The above figures are based on OECD (2007).

[3] Japan Business Federation (2008).

[4] On the productivity change of Japanese prefectures, Nemoto and Goto (2005) compute the total-factor productivity change for 1981–2000, and Miyara and Fukushige (2008) compute it for 1976–1997. However, these two models do not include energy as an input; their inputs are only capital stocks and labor.