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A panel data parametric frontier technique for measuring total-factor energy efficiency: An application to Japanese regions

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A B S T R A C T

Using the stochastic frontier analysis model, we estimate TFEE (total-factor energy efficiency) scores for 47 regions across Japan during the years 1996–2008. We extend the cross-sectional stochastic frontier model proposed by Zhou et al. (2012) to panel data models and add environmental variables. The results provide not only the TFEE scores, in which statistical noise is taken into account, but also the determinants of inefficiency. The three stochastic TFEE scores are compared with a TFEE score derived using data envelopment analysis. The four TFEE scores are highly correlated with one another. For the inefficiency estimates, higher manufacturing industry shares and wholesale and retail trade shares correspond to lower TFEE scores.

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1. Introduction

After the Fukushima Daiichi nuclear disaster on March 11, 2011, energy conservation has become an urgent issue in Japan. All 54 nuclear reactors in Japan were shut down following the accident. The resulting shortages in electricity supply made "Setstuden," which means "saving electricity" in English, into a mantra throughout Japan. In July 2012, the Japanese government decided to reactivate reactors #3 and #4 of the Oi nuclear power plant in response to the electricity shortages experienced in the Kansai Electric Power Company's jurisdiction in summer 2012. Both reactors, however, were shut down again in September 2012 following a periodic check.

Although a new feed-in tariff to promote renewable energy was introduced in July 2012, it cannot fully compensate for the shortfall in energy that has resulted from the cessation of nuclear power generation. Despite the full-capacity operation of the country's thermal power plants, including some plants that were inactive before the Fukushima disaster because of outdated technology, and efforts by firms and households to save energy, serious electricity shortages remain. Vivoda [1] asserted that nuclear reactors should be restarted as soon as possible because Japan is facing an energy security predicament. However, this option is politically difficult because of the growing anti-nuclear public sentiment.

Severe energy constraints in Japan cause the following four serious problems [2]. First, dependence on fossil fuels for electricity generation amounted to 88% in 2012, which is greater than the dependence during the first oil crisis, 76%. Second, Japan loses approximately 3.6 trillion yen (3.5 million US dollars) per year in international trade related to importing additional fossil fuels after the Fukushima disaster; this amounts to approximately 30 thousand yen (290 US dollars) per capita. Third, electricity prices are higher now than before the Fukushima disaster, with a standard family facing an average appreciation rate of 20%. Fourth, general electric utilities have increased carbon dioxide emissions by 110 million tons, which corresponds to 9% of the nation's emissions in 2010. We believe that improving energy efficiency is one feasible solution to the problems listed above. Morikawa [3] surveyed more than 3000 firms and determined that 45% of Japanese firms have been directly or indirectly affected by rolling blackouts and regulation of electricity usage.

Japan has pursued an energy conservation policy since the first oil crisis in 1973. The Energy Conservation Law was enacted in 1979 and has since been revised eight times. We should examine whether such revisions have exerted a significant effect on Japan's energy situation. Therefore, we require a more accurate measurement of regional energy efficiency.

Energy is a fundamental factor from the viewpoints of both national security and the economy, and many empirical studies

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have examined energy efficiency. In this section, we classify these studies into three approaches.

The first approach is based on energy intensity, which is defined as energy consumption per unit of output, such as GDP (gross domestic product), or energy productivity (the reciprocal of energy intensity). This approach is considered the traditional energy efficiency index because it is easily calculated and has been widely used to compare countries [4–8] and to investigate particular countries or industries [e.g., [9,10]]. However, this approach combines energy with other inputs, such as labor and capital stock. Therefore, because it is a partial-factor framework, energy intensity has limited utility for measuring energy efficiency [11,12].

The second approach DEA (data envelopment analysis), which is a non-parametric linear programming methodology that is used to measure the efficiency of multiple decision-making units. Hu and Wang [12] and Hu and Kao [13] incorporated the TFEE (total-factor energy efficiency) index into the DEA model, thereby resulting in creating an approach method that was subsequently applied to Japan by Honma and Hu [14,15], to China by Zhao et al. [16], to Taiwan by Hu et al. [17], and to OECD (Organisation for Economic Co-operation and Development) countries by Honma and Hu [18]. Moreover, Sözen and Alp [19] compared Turkey's energy efficiency with that of the EU (European Union) countries by incorporating energy consumption, greenhouse gas emissions, and local pollutants into the DEA model. Lozano and Gutiérreza [20] proposed DEA models with undesirable outputs to estimate the maximum GDP (minimum greenhouse gas, or GHG, emissions) compatible with given levels of population, energy intensity, and carbonization intensity (levels of population, GDP, energy intensity, or carbonization index). Mukherjee [21] evaluated the energy efficiency of six sectors and found that the highest energy consumption occurs in the United States. Recently, Goto et al. [22] proposed a new DEA approach with three efficiency concepts that separates inputs into two categories and applied the approach to the manufacturing and non-manufacturing industries of Japan's 47 regions. Although DEA has been widely applied in energy efficiency studies, its drawback is that its efficiency analysis suffers from statistical noise. The third approach uses SFA (stochastic frontier analysis), which was developed by Aigner et al. [23] and Meeusen and van den Broeck [24] (For a comparison of DEA and SFA, see Refs. [25,26]). To overcome the statistical noise problem, several authors applied the SFA approach to measure energy efficiency. Filippini and Hunt [27] measured economy-wide energy efficiency in OECD countries. Stern [28] computed energy efficiency by applying SFA to 85 countries and examining the determinants of inefficiency. Herrala and Goel [29] investigated global carbon dioxide (CO_2) efficiency (which is defined as the ratio of the CO_2 frontier to actual emissions) for more than 170 countries. Refs. [27] and [29] employed a stochastic cost function in which energy or CO_2 was the cost, GDP was a main explanatory output variable, and neither labor nor capital stock data were used. In contrast [28], used labor and capital stock data, but energy intensity was an explained variable. Recently, Menegaki [30] employed SFA models to renewable energy management and economic growth in European countries.

Unlike the aforementioned studies, we measure energy efficiency on the basis of a standard Cobb–Douglas production function within the SFA approach. The study that is most closely related to ours is Zhou et al. [31], who proposed a parametric frontier approach by using the Shephard energy distance function. Their approach essentially uses a single-output production frontier model. One feature of their estimation technique is that it deems the reciprocal of energy consumption to be an output that is produced using labor, capital stock, and GDP as inputs. This methodology enables us to parametrically estimate energy efficiency, taking into account the statistical noise involved. Hu [32] expanded the cross-sectional model presented by Ref. [31] to a panel data model to measure the energy efficiency of regions in Taiwan. Recently, Lin and Du [33], using the metafrontier procedure of Battese et al. [34], also expanded the work of [31] to conduct a panel data SFA estimation of the first stage of Chinese regional energy efficiency. However, their model does not include environmental variables.

The purpose of the present study is threefold. The first goal is to expand the cross-sectional SFA model proposed by Zhou et al. [31] to a panel data model and simultaneously estimate the determinants of inefficiency. The second purpose is to estimate the TFEE scores for 47 administrative regions in Japan during the years 1996–2008 and examine the effects of Japan's energy-saving policies over that period. The third goal is to compare the SFA results with those from DEA with respect to not only efficiency but also its determinants.

In our SFA model, efficiency measurements are based on the Shephard energy distance function, which is assumed to take the Cobb–Douglas functional form. Following Ref. [31], we also assume that the reciprocal of energy consumption is produced by GDP, labor, and capital stock. The ML (maximum likelihood) estimator is used to estimate the parameters, including the inefficiency component.

In a departure from the studies conducted by Refs. [31–33], we simultaneously estimate the determinants of inefficiency by employing the technical inefficiency effects model proposed by Battese and Coelli [35]. Before Ref. [35], a two-stage approach was employed in which efficiency was estimated in the first stage; then, this estimated efficiency was regressed against the determinants in the second stage. This two-stage approach has been criticized because both stages suffer from serious biases [[36],p. [39]].

In contrast, the potential determinants of inefficiency can be estimated using the two-stage DEA model. However, this model exhibits two problems [36]. One problem is the possible correlation between the input–output variables and the efficiency-determinant factors. The other problem arises from the fact that the interdependency of the DEA efficiency scores violates the basic assumption of independence within the sample. Instead of a non-parametric DEA approach, our parametric approach provides an alternative method to estimate efficiency and its underlying factors.

The remainder of this study is organized as follows. Section 2 describes our methodology and data. Section 3 presents the TFEE results and the determinants of inefficiency for both the SFA and DEA models. Section 4 discusses the results' implications. Section 5 concludes with a brief summary of the study.

2. Methodology and data

2.1. SFA model for input efficiency

Zhou et al. [31] applied the single-equation, output-oriented SFA model to estimate the TFEE. Their cross-sectional SFA model was used to analyze 21 OECD countries in 2001. Combining the studies of Zhou et al. [31] and Battese and Coelli [35], this study expands the panel data SFA model further by estimating the TFEE.

Following Ref. [31], we assume that the stochastic frontier distance function is included in the Cobb–Douglas function as

$$\ln D_E (K_{it}, L_{it}, E_{it}, Y_{it}) = \beta_0 + \beta_K \ln K_{it} + \beta_L \ln L_{it} + \beta_E \ln E_{it} + \beta_Y \ln Y_{it} + v_{it}, \quad (1)$$

where $D_E(\cdot)$ is the distance function, K_{it} is the amount of capital stock, L_{it} is labor employment, E_{it} is the energy input, Y_{it} is the real economic output, i indicates the region, t indicates the time, and v_{it} is the statistical noise, which is assumed to be normally distributed.

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