



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



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ABSTRACT

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the country's thermal power plants, including some plants that were inactive before the Fukushima disaster because of outdated technology, and efforts by firms and households to save energy, serious electricity shortages remain.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 Gutiérrez [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 (CO₂) efficiency (which is defined as the ratio of the CO₂ frontier to actual emissions) for more than 170 countries. Refs. [27] and [29] employed a stochastic cost function in which energy or CO₂ 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.

Because the distance function is homogeneous to one degree in the energy input, the above equation can be rearranged as

$$\ln D_E(K_{it}, L_{it}, E_{it}, Y_{it}) = \ln E_{it} + \beta_0 + \beta_K \ln K_{it} + \beta_L \ln L_{it} + \beta_E \ln 1 + \beta_Y \ln Y_{it} + v_{it}, \quad (2)$$

which can be rewritten as

$$-\ln E_{it} = \beta_0 + \beta_K \ln K_{it} + \beta_L \ln L_{it} + \beta_E \ln 1 + \beta_Y \ln Y_{it} + v_{it} - \ln D_E(K_{it}, L_{it}, E_{it}, Y_{it}). \quad (3)$$

Thus,

$$\ln(1/E_{it}) = \beta_0 + \beta_K \ln K_{it} + \beta_L \ln L_{it} + \beta_Y \ln Y_{it} + v_{it} - u_{it}, \quad (4)$$

where u_{it} is the inefficiency term, which follows a non-negative distribution, and $v_{it} - u_{it}$ is the error component term of a stochastic production frontier. Eq. (4) is consistent with the panel data stochastic frontier model proposed by Battese and Coelli [35]. The free software Frontier Version 4.1, which was kindly provided by Professor Coelli [37], can be used to estimate Eq. (4). The TFEE of region i at time t is then

$$TFEE_{it} = \exp(-u_{it}). \quad (5)$$

Therefore, we can apply the panel data stochastic production frontier approach to estimate the TFEE, but we are limited to use of the input-oriented DEA suggested by Refs. [12,13]. Moreover, if we use disaggregated energy inputs, we can change the logged inverse energy inputs on the left-hand side of Eq. (4) and keep the other logged inputs on the right-hand side fixed, thereby obtaining the TFEE scores for different energy inputs.

Battese and Coelli [35] added the following inefficiency equation for performing simultaneous estimates with a stochastic frontier in the form of Eq. (4):

$$u_{it} = \delta_0 + \delta_1 z_{it}^1 + \dots + \delta_H z_{it}^H + \varepsilon_{it}, \quad (6)$$

where the z^1, \dots, z^H are environmental variables and ε_{it} is white noise, which is normally distributed. Consequently, we can simultaneously estimate Eqs. (4) and (6) by applying the approaches of [35,36].

2.2. DEA

DEA is a linear programming method that is used to assess the comparative efficiency of DMUs (decision-making units), such as countries, regions, firms, and other organizations. There are K inputs and M outputs for each of the N regions. Because the SFA model finds a frontier with curvature, we assume VRS (variable returns to scale) in the DEA model. The VRS envelopment of the i -th region can be derived using the following linear programming problem, which was proposed by Banker et al. [38]:

$$\begin{aligned} & \text{Min}_{\theta, \lambda} \theta \\ & \text{s.t. } -y_i + Y\lambda \geq 0 \\ & \theta x_i - X\lambda \geq 0 \\ & e\lambda = 1 \\ & \lambda \geq 0, \end{aligned} \quad (7)$$

where θ is a scalar that represents the efficiency score of the i -th DMU, e is a $1 \times N$ vector of ones, λ is an $N \times 1$ vector of constants, y_i is the $M \times 1$ output vector of DMU i , Y is the $M \times N$ output matrix that is composed of all of the output vectors of the N DMUs, x_i is the $K \times 1$ input vector of DMU i , and X is the $K \times N$ input matrix that is composed of all of the input vectors of the N DMUs.

The efficiency score satisfies $0 \leq \theta \leq 1$, which is a radial contraction coefficient for the inputs. If $\theta = 1$, DMU i operates on the efficiency frontier and is technically efficient. This is an input-oriented model in which the radial adjustment coefficient, θ , multiplies the input vector of DMU i . Following literature studies that have used DEA, such as [12–14], the TFEE score of DMU i at time t can be found by dividing its target energy input (which is determined by the DEA model) by its actual energy input:

$$TFEE_{it} = \text{Target Energy Input}_{it} / \text{Actual Energy Input}_{it}. \quad (8)$$

To control the annual environment, all efficiency scores and input targets for region i in year t are determined by comparing them with the regional efficiency frontier in year t . Note that the VRS-DEA model in this study uses regional observations from the same year.

In the second-stage regression, the determinants of inefficiency are estimated using the following equation:

$$-\ln(TFEE_{it}) = \gamma_0 + \gamma_1 z_{it}^1 + \dots + \gamma_H z_{it}^H + \varepsilon_{it}, \quad (9)$$

where ε is normally distributed white noise. Because $TFEE_{it}^{SFA} = \exp(-u_{it})$ in the SFA model, for consistency, we take the corresponding inefficiency term in the DEA, $u_{it} = -\ln(TFEE_{it}^{DEA})$, as the dependent variable in the second-stage regression. Because the dependent variable $-\ln(TFEE_{it}^{DEA})$ is censored at zero when $TFEE_{it} = 1$, we use Tobit regression left censored at zero.

2.3. Data and variables

In our SFA model, we assume that the reciprocal of energy consumption is based on regional real GDP (million yen), labor (person), and capital stock (million yen). These data are taken from Refs. [39], in which all monetary values are given in million yen based on the year 2000 and labor is represented by the number of employees.

Data on energy regarding are taken from Ref. [40], where in which aggregated energy consumption is the sum of oil, gas, coal, electricity, and industrial heat presented in terms of thermal units (tera joules [TJ]). In contrast with previous studies that take considered regional/national energy consumption as a whole as one input [12–14,17,31], our aggregated energy consumption data do not include residential and transportation sectors or non-energy use. Residential energy consumption, such as cooking, heating, and hot water supply systems, generates no added value and are hence excluded from the aggregated energy consumption data. For the same reason, energy consumption by private vehicles is also excluded. Data regarding energy consumption in the business transportation sector are unavailable because fuel consumed outside regional borders cannot be accurately allocated by region. Using the selected energy consumption data allows more precise measurement of energy efficiency than was previously possible.

We employ industry shares as the environmental variables in two technical inefficiency effects models. The first model (whose efficiency score is hereafter referred to as $TFEE_{it}^{SFA,M}$) includes as environmental variables the regional GDP shares of the manufacturing industry, service activities, and both wholesale and retail trade. The second model (hereafter $TFEE_{it}^{SFA,E}$) replaces the manufacturing share with shares of the following five energy-intensive industries: chemicals; iron and steel; non-ferrous metals; non-metallic mineral products; and pulp, paper, and paper products.

Data regarding industry shares are taken from Ref. [41]. The data about each energy-intensive industry's shares exclude Okinawa

Prefecture because such data are unavailable for this prefecture, which comprises several small islands. All data are annual, and as mentioned above, the sample period spans the years 1996–2008. Table 1 summarizes the input, output, and environmental variable statistics.

3. Results

3.1. TFEE scores

The ML estimates of the TFEE scores are given in Table 2 together with the DEA TFEE are presented in Table 2. The estimates of the SFA TFEE scores are calculated using the Frontier 4.1 software package provided by Coelli [37]. (For more details, see Coelli et al. [42]). Space limitations allow us to show present only the mean TFEE scores and rankings of the four TFEE scores for the years 1996–2008. The TFEE scores of each region are stable during the sample period. Following Refs. [31] and [32], $TFEE^{SFA,O}$ represents the estimated TFEE scores without the environmental variables, whereas following [12–14], $TFEE^{DEA}$ represents the DEA TFEE scores under VRS assumptions. $TFEE^{SFA,O}$ and $TFEE^{DEA}$ are mainly presented here as comparisons with $TFEE^{SFA,M}$ and $TFEE^{SFA,E}$.

It should be emphasized that the rankings are similar; nevertheless, the TFEE scores differ among the four methods. The maximum value of the DEA TFEE scores reaches unity because they do not take into account statistical noise. Tokyo, Nara, and Tottori achieve unity scores for $TFEE^{DEA}$ throughout the sample period.

In comparing the four TFEEs, we observe that the rankings between $TFEE^{SFA,M}$ and $TFEE^{SFA,E}$ are similar, while those among others are not. There may be several explanations for why some regions experience different rankings between $TFEE^{SFA,O}$ and $TFEE^{SFA,M}$ and between $TFEE^{SFA,O}$ and $TFEE^{SFA,E}$. Because the expected mean inefficiency terms in $TFEE^{SFA,M}$ and $TFEE^{SFA,E}$ vary across regions depending on their individual environmental variables, regions located in a more-advantageous environments are relatively more efficient. Tottori, Shiga, and Tokyo vary widely across the ranks of the TFEEs. Tottori is ranked first on in terms of $TFEE^{DEA}$ but 10th, 21st, and 19th in terms of on $TFEE^{SFA,O}$, $TFEE^{SFA,M}$, and $TFEE^{SFA,E}$, respectively. Shiga is ranked 8th in terms of on $TFEE^{DEA}$ but 33rd in terms of on $TFEE^{SFA,M}$ and 32nd in terms of on $TFEE^{SFA,E}$. Tokyo is ranked 1st in terms of on $TFEE^{DEA}$ but 25th in terms of on $TFEE^{SFA,O}$. This result likely reflects whether statistical noise is considered. In addition, we assume that if a regional economy is far from average size, the estimated TFEE score is less accurate.

Next, we examine individual TFEE scores by region. The top three—Yamagata, Tokyo, and Nagasaki—exhibit similar relationships between $TFEE^{SFA,M}$ and $TFEE^{SFA,E}$. These regions have very high TFEE scores (exceeding 0.95), except for Tokyo's $TFEE^{SFA,E}$. This

result indicates that these regions have little potential to further reduce energy consumption (less than 5%). Observing Tokyo's results, a significant divergence exists between the $TFEE^{SFA,O}$ and each of the $TFEE^{SFA,M}$ and $TFEE^{SFA,E}$ scores. This result may reflect Tokyo's more-advantageous environment for the variables included in $TFEE^{SFA,M}$ and $TFEE^{SFA,E}$. Chiba, Okayama, and Oita are the bottom three regions for all TFEE scores and also exhibit similar rankings between them. Their TFEE scores for all four models are very low (<0.2), which implies that the potential energy savings are great (>80%) for all three regions. We discuss possible improvements that can be implemented in regions that have very low TFEE scores in Section 4.2.

Table 3 shows the correlation coefficients for the four TFEE scores. Pearson correlation coefficients are presented below the diagonal, and Spearman rank correlation coefficients are presented above the diagonal. The four TFEE scores are highly correlated with one another. Whereas the correlation coefficients between the three SFA TFEE scores are greater than 0.9, those between the SFA TFEE scores and DEA TFEE are approximately 0.8. All correlations presented in Table 3 are significant at the one percent level.

Fig. 1a–d presents histograms of the four TFEEs during the years 1996–2008. In the histogram of $TFEE^{SFA,O}$, two peaks, which are located in the ranges of 0.5–0.6 and 0.9–1.0, are observed, and the frequency decreases in the 0.8–0.9 range (Fig. 1a). Only the histograms of $TFEE^{SFA,M}$ and $TFEE^{SFA,E}$ are very similar. In these histograms also, two peaks are observed but in the ranges of 0.6–0.7 and 0.8–0.9 (Fig. 1b and c). In the histogram of $TFEE^{DEA}$, the peak is located in the range of 0.9–1.0 (Fig. 1d).

3.2. Simultaneous estimates of determinants of inefficiency by SFA

Table 4 presents the estimated coefficients and determinants of inefficiency in the SFA TFEE scores. Except for the coefficients of log regional GDP in $TFEE^{SFA,O}$ and $TFEE^{SFA,E}$, the coefficients for the log regional GDP, log labor, and log capital stock are significant. However, the coefficients of GDP are not directly interpretable. For example, the coefficient of log GDP in $TFEE^{SFA,M}$ (0.306) means indicates that a 1% increase in GDP reduces energy consumption by 0.306%. This finding is inconsistent with the standard production theory. We note that these implausible results may stem from the underlying assumption that attributing inefficiencies regarding in outputs and inputs can be attributed to energy use.

In the ML estimates, the variances of v and u , σ_v^2 and σ_u^2 , are reparameterized as $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2/\sigma^2$, respectively. The parameter γ must lie between 0 and 1, and it indicates the relative contributions of u to the error components. The large values of γ (0.999, 0.999, and 0.994) for the three SFA TFEE scores imply that the variance in the error components is almost explained by technical inefficiency.

Table 1
Statistical summary of inputs, outputs, and environmental variables.

Variable	Unit	Mean	SD	Min	Max	Obs
Regional GDP	million yen	11,267,620	14,899,507	2,070,534	100,982,870	611
Labor	person	1,358,697	1,437,445	300,652	8,746,255	611
Capital stock	million yen	36,051,479	34,440,744	7,662,999	230,327,688	611
Energy	TJ	203,883	221,225	28,331	1,181,999	611
Manufacturing industry share	proportion	0.21239	0.07702	0.04031	0.43107	611
Chemical industry share	proportion	0.01798	0.01867	0.00021	0.10745	598
Iron and steel industry share	proportion	0.01395	0.01466	0.00044	0.10167	598
Non-ferrous metals industry share	proportion	0.01359	0.00945	0.00198	0.09322	598
Non-metallic mineral products industry share	proportion	0.00854	0.00588	0.00124	0.03798	598
Pulp, paper, and paper products industry share	proportion	0.00575	0.00591	0.00006	0.04200	598
Service activities share	proportion	0.19281	0.02771	0.11619	0.29261	611
Wholesale and retail trade industry share	proportion	0.11268	0.03134	0.05782	0.21673	611

Table 2
Mean TFEЕ scores and rankings by region in Japan (1996–2008).

Region	TFEE ^{SFA,O}	TFEE ^{SFA,M}	TFEE ^{SFA,E}	TFEE ^{DEA}
Hokkaido	0.406 (33)	0.641 (25)	0.607 (25)	0.488 (33)
Aomori	0.528 (29)	0.574 (30)	0.567 (30)	0.526 (31)
Iwate	0.770 (14)	0.845 (14)	0.838 (13)	0.727 (22)
Miyagi	0.584 (23)	0.674 (22)	0.676 (21)	0.626 (28)
Akita	0.877 (9)	0.888 (9)	0.886 (10)	0.867 (12)
Yamagata	0.971 (3)	0.966 (1)	0.967 (1)	0.884 (11)
Fukushima	0.689 (17)	0.802 (16)	0.793 (15)	0.799 (16)
Ibaraki	0.181 (43)	0.225 (43)	0.223 (42)	0.243 (43)
Tochigi	0.564 (24)	0.614 (26)	0.623 (24)	0.664 (26)
Gunma	0.663 (18)	0.750 (17)	0.754 (16)	0.704 (23)
Saitama	0.53 0 (28)	0.727 (19)	0.731 (18)	0.577 (29)
Chiba	0.105 (47)	0.146 (45)	0.144 (44)	0.128 (47)
Tokyo	0.562 (25)	0.951 (3)	0.949 (3)	1.000 (1)
Kanagawa	0.233 (40)	0.345 (39)	0.344 (38)	0.311 (41)
Niigata	0.513 (30)	0.656 (24)	0.637 (23)	0.671 (25)
Toyama	0.530 (27)	0.533 (32)	0.532 (31)	0.809 (14)
Ishikawa	0.920 (8)	0.889 (8)	0.907 (8)	0.943 (9)
Fukui	0.785 (11)	0.747 (18)	0.745 (17)	0.959 (7)
Yamanashi	0.964 (6)	0.881 (12)	0.900 (9)	0.987 (5)
Nagano	0.777 (13)	0.914 (7)	0.914 (7)	0.780 (17)
Gifu	0.617 (22)	0.704 (20)	0.701 (20)	0.659 (27)
Shizuoka	0.434 (32)	0.585 (29)	0.58 (28)	0.501 (32)
Aichi	0.305 (38)	0.479 (34)	0.469 (33)	0.414 (36)
Mie	0.207 (42)	0.229 (42)	0.230 (41)	0.312 (40)
Shiga	0.543 (26)	0.514 (33)	0.527 (32)	0.953 (8)
Kyoto	0.734 (16)	0.814 (15)	0.835 (14)	0.778 (18)
Osaka	0.375 (34)	0.599 (28)	0.589 (27)	0.481 (34)
Hyogo	0.254 (39)	0.352 (38)	0.347 (37)	0.337 (39)
Nara	0.982 (2)	0.887 (10)	0.916 (6)	1.000 (1)
Wakayama	0.349 (35)	0.341 (40)	0.338 (39)	0.464 (35)
Tottori	0.800 (10)	0.690 (21)	0.704 (19)	1.000 (1)
Shimane	0.987 (1)	0.924 (5)	0.920 (4)	0.990 (4)
Okayama	0.111 (46)	0.125 (46)	0.125 (45)	0.162 (46)
Hiroshima	0.219 (41)	0.269 (41)	0.268 (40)	0.290 (42)
Yamaguchi	0.137 (44)	0.148 (44)	0.146 (43)	0.211 (44)
Tokushima	0.634 (20)	0.571 (31)	0.578 (29)	0.802 (15)
Kagawa	0.477 (31)	0.447 (36)	0.456 (34)	0.536 (30)
Ehime	0.337 (36)	0.363 (37)	0.361 (36)	0.389 (37)
Kochi	0.632 (21)	0.602 (27)	0.598 (26)	0.748 (19)
Fukuoka	0.328 (37)	0.452 (35)	0.448 (35)	0.345 (38)
Saga	0.967 (5)	0.919 (6)	0.917 (5)	0.964 (6)
Nagasaki	0.935 (7)	0.958 (2)	0.961 (2)	0.830 (13)
Kumamoto	0.785 (12)	0.882 (11)	0.881 (11)	0.736 (21)
Oita	0.117 (45)	0.115 (47)	0.116 (46)	0.168 (45)
Miyazaki	0.660 (19)	0.665 (23)	0.669 (22)	0.682 (24)
Kagoshima	0.758 (15)	0.853 (13)	0.844 (12)	0.739 (20)
Okinawa	0.970 (4)	0.938 (4)	na	0.919 (10)
Mean	0.570	0.621	0.614	0.640
SD	0.270	0.257	0.258	0.265
Max	0.987	0.988	0.988	1.000
Min	0.104	0.104	0.105	0.107

Note: Figures indicate the mean TFEЕ scores, and parentheses indicate rankings in each column.

The trend of the time-varying inefficiency parameter, η , (Battese and Coelli, [43]) is also estimated in TFEЕ^{SFA,O} instead of the share variables. A positive (negative) η implies that efficiency decreases (increases) over time. For TFEЕ^{SFA,O}, η is slightly positive (0.001) but insignificant.

The determinants of inefficiency are simultaneously estimated for TFEЕ^{SFA,M} and TFEЕ^{SFA,E} using the technical inefficiency model

Table 3
Pearson (below diagonal) and Spearman rank (above diagonal) correlation coefficients between the TFEЕ scores by model.

	TFEE ^{SFA,O}	TFEE ^{SFA,M}	TFEE ^{SFA,E}	TFEE ^{DEA}
TFEE ^{SFA,O}	1	0.912	0.921	0.826
TFEE ^{SFA,M}	0.931	1	0.998	0.761
TFEE ^{SFA,E}	0.937	0.999	1	0.770
TFEE ^{DEA}	0.843	0.808	0.814	1

[35]. Note that a positive (negative) coefficient for an industry's share implies an inefficiency-reducing (inefficiency-inducing) factor. For TFEЕ^{SFA,M}, the estimated coefficients for the shares of manufacturing and the wholesale and retail trade, 15.531 and 11.332, respectively, are highly significant, but that for the service industry is insignificant. We find that higher shares of manufacturing and wholesale and retail trade correspond to lower efficiency. The estimates of TFEЕ^{SFA,E} in Column 3 provide a more comprehensive analysis of the determinants of inefficiency. With the exception of the non-ferrous metals industry, which has a negative coefficient, the other four energy-intensive industries—chemicals; iron and steel; non-metallic mineral products; and pulp, paper, and paper products—are highly significant in reducing efficiency. The wholesale and retail trade industry share continues to affect inefficiency levels, but its coefficient decreases to a lower value in TFEЕ^{SFA,E} than in TFEЕ^{SFA,M}.

Generalized likelihood ratio tests of various null hypotheses for the three SFA TFEЕ models are presented in Table 5. The generalized likelihood-ratio test statistic, $\lambda = -2(\log \text{likelihood}(H_0) - \log \text{likelihood}(H_1))$, has an approximately chi-square or mixed chi-square distribution for which the parameter is the number of parameters set to be zero in the null hypothesis, H_0 . All null hypotheses are rejected at the 1% level. The hypothesis $H_0: \gamma = 0$, which specifies that the regions are fully technically efficient, is rejected for each case. In particular, for TFEЕ^{SFA,M} and TFEЕ^{SFA,E}, the null hypothesis that all of the coefficients associated with various industry share variables (and the constant term) are zero is rejected.

3.3. Second-stage estimates of the determinants of inefficiency by DEA

To compare the simultaneous estimates of the determinants of inefficiency of TFEЕ^{SFA,M} and TFEЕ^{SFA,E} with those of TFEЕ^{DEA}, we regress the inefficiency of TFEЕ^{DEA} on industry shares using the Tobit model. As in the previous subsection, we exclusively use the manufacturing industry share and the five energy-intensive industry shares.

Table 6 presents the results for the second-stage regression of the inefficiency of TFEЕ^{DEA} on the environmental variables. Note that in the inefficiency equation of the SFA model, the inefficiency term is related to the efficiency score as $TFEE_{it}^{SFA} = \exp(-u_{it})$ for region i at time t . For consistency in the second-stage regression, the inefficiency term under DEA is obtained by the transformation as $u_{it} = -\ln(TFEЕ_{it}^{DEA})$ for region i at time t . Column 1 in Table 6 presents the estimation results that involve the manufacturing industry share, which is significantly positive in Column 1. A higher manufacturing industry share corresponds to less-efficient energy use. Note that a coefficient of Tobit regression is generally not comparable with that of another model on account of the distortion to the distribution due to the censored data. However, in our model, the marginal effects computed are similar to the coefficients presented in Table 6. Regarding the manufacturing share, the coefficient of TFEЕ^{SFA,M}, 15.531, in Table 4 are greater than the corresponding coefficient for TFEЕ^{DEA}, 3.083, in Table 6. We hypothesize that this occurs mainly because the inefficiency terms in TFEЕ^{SFA,M} depend upon the industry shares as the environmental variables in Eq. (6), whereas the efficiency measurement of TFEЕ^{DEA} does not use industry shares. The signs for the shares of service activities and the wholesale and retail trade industry are positive, but the sign is significant only for the latter.

Column 2 of Table 6 presents the estimation results for involving the shares of the five energy-intensive industries. All coefficients of these industry shares are significant at the 1% level. Among them, energy-intensive industries, except for the non-ferrous metals industry, are highly significant in reducing TFEЕ.

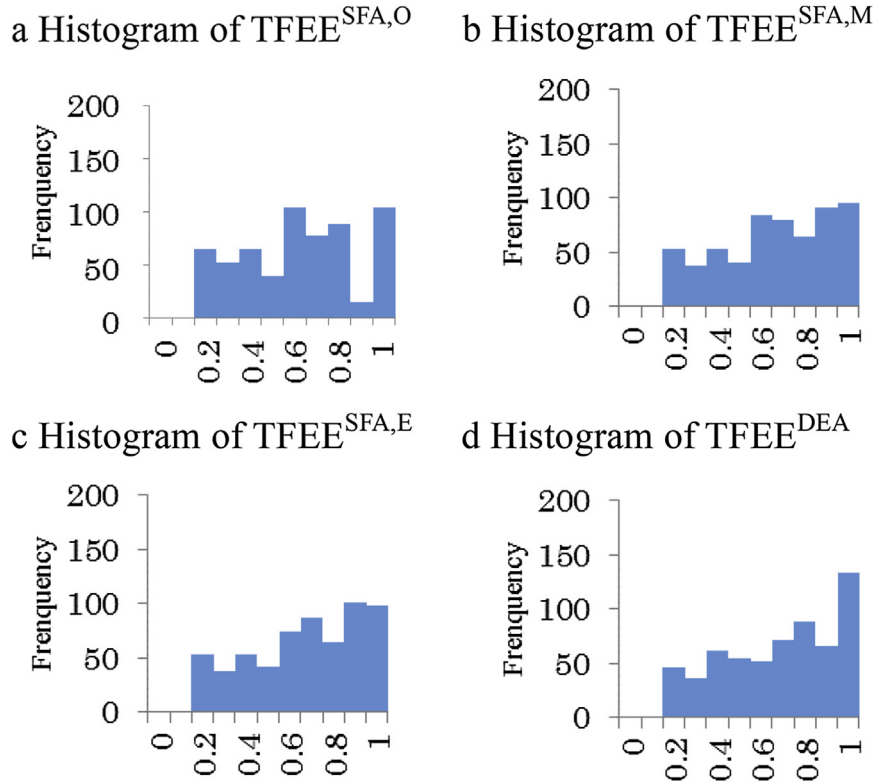


Fig. 1. Histograms of the TFEEs.

Table 4
ML estimates of the stochastic frontier function parameters for the Japanese regions.

Variable	Inefficiency of TFEESFA,O	Inefficiency of TFEESFA,M	Inefficiency of TFEESFA,E
Constant (β_0)	-0.530 (-0.458)	3.491*** (6.940)	2.912*** (6.804)
Log regional GDP	-0.069 (-1.271)	0.306* (1.861)	0.181 (1.451)
Log labor	-0.576*** (-6.410)	-0.971*** (-7.492)	-0.928*** (-9.109)
Log capital stock	-0.084*** (-2.827)	-0.354*** (-3.735)	-0.239*** (-2.907)
Constant (δ_0)		-5.369*** (-2.389)	-1.640*** (-3.866)
Manufacturing industry share (δ_1)		15.531*** (4.187)	
Chemical industry share (δ_2)			18.872*** (11.527)
Iron and steel industry share (δ_3)			35.694*** (15.276)
Non-ferrous metals industry share (δ_4)			-8.696** (-2.517)
Non-metallic mineral products industry share (δ_5)			41.388*** (7.098)
Pulp, paper, and paper products industry share (δ_6)			24.243*** (4.925)
Service activities share (δ_7)		-4.120 (-0.610)	-0.785 (-0.453)
Wholesale and retail trade industry share (δ_8)		11.332** (2.504)	7.359*** (6.392)
$\sigma^2 = \sigma_u^2 + \sigma_v^2$	2.311 (0.986)	1.397*** (3.982)	0.254*** (9.846)
$\gamma = \sigma_u^2/\sigma^2$	0.999*** (1292.201)	0.999*** (1646.483)	0.994*** (353.468)
μ	-1.961 (-0.623)		
η	0.001 (0.956)		
Log likelihood	901.151	-287.998	-122.431
Number of observations	611	611	598
Number of regions	47	47	46

Note: t-values are in parentheses. Statistical significance at the one-, five-, and ten-percent levels are indicated by ***, **, and *, respectively.

Only the coefficient of the non-ferrous metals industry share is positive. These results are consistent with those for TFEESFA,E. Each (absolute) value of the coefficients for TFEESFA,E is smaller less than that of the corresponding coefficients for TFEESFA,E in Table 4. This result can be attributed to the same reason as that given above.

4. Discussion

4.1. Importance of incorporating the environmental variables

In this subsection, we discuss the advantage of energy efficiency estimation using a stochastic model with environmental variables

Table 5
Generalized likelihood-ratio tests of hypotheses of parameters of the stochastic frontier and technical energy inefficiency.

Null hypothesis	Log-likelihood value	Test statistic (λ)	Critical value	Decision
Given TFEESFA,O				
$H_0: \gamma = 0$	-505.410	2813.121	10.50	Reject H_0
$H_0: \eta = 0$	261.466	1279.369	6.63	Reject H_0
$H_0: \mu = 0$	654.311	493.679	6.63	Reject H_0
Given TFEESFA,M				
$H_0: \gamma = \delta_0 = \delta_1 = \delta_7 = \delta_8 = 0$	-505.410	434.824	14.33	Reject H_0
$H_0: \delta_0 = \delta_1 = \delta_7 = \delta_8 = 0$	-363.874	151.754	13.28	Reject H_0
$H_0: \delta_1 = \delta_7 = \delta_8 = 0$	-338.729	101.462	11.34	Reject H_0
Given TFEESFA,E				
$H_0: \gamma = \delta_0 = \delta_2 = \delta_7 = 0$	-498.232	751.603	20.97	Reject H_0
$H_0: \delta_0 = \delta_2 = \dots = \delta_8 = 0$	-362.442	480.022	20.09	Reject H_0
$H_0: \delta_2 = \dots = \delta_8 = 0$	-341.182	437.502	18.48	Reject H_0

Note: All test statistics are statistically significant at the $p < 0.01$ level. The correct critical values for the hypotheses that involve $\gamma = 0$ are obtained from Table 1 of Kodde and Palm [44].

Table 6
Second-stage estimates of the determinants of inefficiency.

Variable	Inefficiency of TFEEDEA	
Constant	-0.872*** (-2.746)	-0.536*** (-2.808)
Manufacturing industry share	3.083*** (7.478)	
Chemical industry share		10.571*** (10.284)
Iron and steel industry share		22.117*** (8.398)
Non-ferrous metals industry share		-10.245*** (-8.142)
Non-metallic mineral products industry share		13.114*** (3.432)
Pulp, paper, and paper products industry share		7.453*** (2.831)
Service activities share	1.251 (1.105)	-0.014 (-0.017)
Wholesale and retail trade industry share	4.514*** (6.402)	5.092*** (8.712)
Sigma	0.556*** (26.417)	0.4203*** (22.440)
Number of observations	611	598
Number of regions	47	46
Log likelihood	-520.207	-359.426

Note: Robust t-values are in parentheses. Statistical significance at the one-, five-, and ten-percent levels are indicated by ***, **, and *, respectively.

instead of one without environmental variables. The coefficients of labor and capital of TFEESFA,O and TFEESFA,E differ considerably from one of TFEESFA,O in Table 4. Incorporating the environmental variables allows us to estimate a more-adequate stochastic frontier. Thus, the estimated frontier may be an imprecise curvature without the environmental variables, and the resulting efficiency values would provide a misleading evaluation. As for our sample, TFEESFA,O underestimates TFEES for much of the inefficient regions (Fig. 2).¹

4.2. Policy implications of the TFEES scores

How should policy makers consider the values of the various TFEES scores? In what follows, we discuss the policy implications of our TFEES results. It is ideal but implausible for all regions to achieve scores that are near unity. As previously stated, inefficiency is successfully explained by industry shares, which cannot be radically changed. In addition, regions that specialize in energy-intensive industries supply energy-intensive goods to regions that barely produce them. In fact, industry composition should be considered as fixed to some extent.

¹ Because the scatter plot of TFEESFA,E against TFEESFA,O is almost the same, we omit it here.

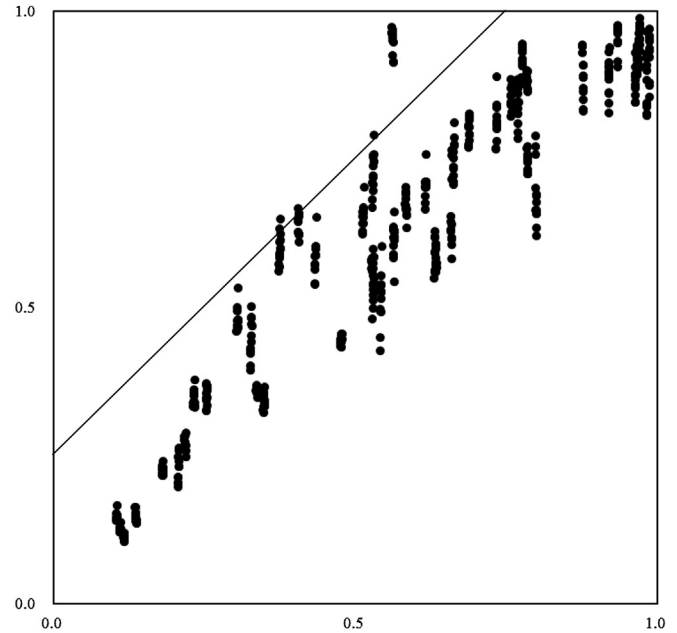


Fig. 2. Scatter plot of TFEESFA,M against TFEESFA,O. Note: The vertical and horizontal axes correspond to TFEESFA,M and TFEESFA,O, respectively.

Policy makers in an inefficient region may target a minimum efficiency level that could be achieved given the region's industry composition. This target can be set by comparing with regions that have similar industry compositions.

4.3. Simultaneous estimation versus second-step estimation

In Eq. (3) of the stochastic approach, all regions have the same intercept, β_0 . This value can vary by region if unobserved heterogeneity exists. Greene [45,46] proposes the true fixed-effects and true random-effects models to estimate unit-specific constants. This line of research should be explored in energy efficiency research. However, unobserved heterogeneity in the parameter estimates is beyond the scope of this study, in which our plain panel results serve as the benchmark.

5. Concluding remarks

This study parametrically and non-parametrically estimates the TFEES scores for 47 regions in Japan and the determinants of inefficiency for the years 1996–2008. We extend the SFA approach employed by Zhou et al. [31] and Hu [32] and incorporate the technical inefficiency effects model proposed by Battese and Coelli [35]. Our two technical inefficiency effects models exclusively include the manufacturing industry share and the five energy-intensive industry shares as environmental variables that influence inefficiency, the scores of which are referred to as TFEESFA,M and TFEESFA,E, respectively. For comparison, a stochastic TFEES without environmental variables, TFEESFA,O, is also computed. In addition, we use the DEA technique to measure a non-parametric TFEES score under VRS, TFEEDEA.

The four TFEES scores are highly correlated with one another, especially TFEESFA,O, TFEESFA,M, and TFEESFA,E. The trend of the mean TFEES scores suggests that energy efficiency improved during the sample period. However, there is considerable potential for further savings on reductions in energy consumption in the Japanese regions. For the bottom three regions—Chiba, Okayama, and Oita—the TFEES scores in all four models are very low (<0.2). This

result suggests the possibility of conserving reducing energy consumption by more than 80% in all three regions.

We compare not only the TFEE scores but also the determinants of inefficiency between SFA and DEA. In SFA, the determinants are estimated simultaneously with inefficiency. This simultaneous estimation suitably incorporates influences from environmental variables into inefficiency. This is SFA's advantage over the two-step estimation performed in DEA. However, in the SFA estimation, we must introduce additional assumptions regarding the functional form of the frontier and the distributions of the inefficiency and error terms compared to with the DEA. In contrast, the inefficiency of the DEA TFEE scores is regressed on environmental factors via a Tobit approach. The signs of the Tobit model are consistent with those of the SFA estimation. For both SFA and DEA, the results that include the manufacturing industry share indicate that higher manufacturing and wholesale and retail trade shares correspond to lower energy efficiencies. The results that include shares from energy-intensive industries – chemicals; iron and steel; non-metallic mineral products; and pulp, paper, and paper products – indicate that higher shares of energy-intensive industries correspond to significantly lower levels of efficiency.

Our study has two limitations. First, in our SFA model, all inefficiencies are attributed to energy input. This may lead to overestimating energy inefficiency. On this point, DEA is superior to SFA because the DEA TFEE takes into account both radial and non-radial slack with respect to energy inputs. The second limitation is that the estimates do not consider unobserved heterogeneity.

Our approach can be extended in various directions. First, the environmental variables that affect energy efficiency should be further explored. It is important not only to measure efficiency but also to examine the determinants of inefficiency. Second, the functional form can be easily changed from the Cobb–Douglas function to more general functional forms, such as a translog function. Third, replacing energy input with undesirable outputs or natural resources would allow us to estimate environmental efficiency using the total-factor framework. Fourth, our model can be applied to other regions for a cross-country comparison. If so, environmental variables should be explored.

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