Chapter

Determinants of Energy Demand Efficiency: Evidence from Japan's Industrial Sector

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Abstract

With the growing demand for energy, improving energy efficiency has become a key policy issue in Japan. Therefore, this study estimates the energy demand function of Japan's industrial sector using a stochastic frontier model and analyzes the level of energy efficiency and its determinants. An empirical analysis based on the data of 47 Japanese prefectures presents three main findings. First, installment in large production facilities deteriorates energy efficiency and second, it is effective in increasing the electrification rate to improve energy efficiency. Finally, improving productivity leads to an increase in the electrification rate. These results suggest that policies aimed at increasing electrification by enhancing the productivity of factories and offices significantly contribute to improving energy efficiency.

Keywords: energy efficiency, industrial sector, electrification rate, stochastic frontier analysis, Japan

1. Introduction

Technological modernization is one of the key elements of success in improving productivity and environmental management [1]. It has advanced in power plants and as a result, energy efficiency has increased. Regarding plant efficiency, there are numerous findings from the engineering viewpoint [2, 3]. Research on fuel cells is also active, Taner [4] measuring the energy efficiency of the proton exchange membrane fuel cell. Based on these technical studies, this chapter focuses on the efficiency of the overall energy demand in a country and region, not the individual efficiencies of plants and technology unit. In other words, this study analyzes the energy consumption efficiency from an economic viewpoint. Energy consumption is primary and secondary, or final energy consumption. The focus of this study is final energy demand efficiency.

Energy consumption is mainly affected by energy efficiency. Given the current trend in Japan, the energy saving in the manufacturing sector as a subsector of the industrial sector has strengthened, given the drastic improvements in the energy efficiency of factory facilities. However, in the commercial sector as another subsector of the industrial sector, energy saving has deteriorated and this, in turn, has increased energy consumption. Japan's industrial sector accounts for a large proportion of the nation's energy consumption, and thus, increasing the energy efficiency of this sector has become a key policy issue.

There is no clear and accepted definition of energy efficiency, but according to Bhattacharyya [5], most definitions are based on a simple ratio of "useful output of a process/energy input into a process." Additionally, Patterson [6] shows several ways to quantify the output and input of this ratio. One of the ratios most frequently used in energy analysis at the macro level is the energy-GDP ratio, called energy intensity, which is in fact the reciprocal of the economic-thermodynamic index of energy efficiency identified by Patterson [6]. Energy intensity has been traditionally used as an indicator of energy efficiency. However, this approach has been disputed by the claims that energy intensity may not reflect the specific factors that enable energy intensity to accurately approximate energy efficiency [7–9]. An Energy Information Administration (EIA) [7] report first highlighted that energy intensity and efficiency are often used interchangeably and discussed the use of energy intensity as a measure of energy efficiency. Energy intensity is thus susceptible to socioeconomic factors other than energy efficiency, such as energy price, income, and production environment. Given this energy intensity problem, we need to control other important factors to obtain a pure measure of energy efficiency. Therefore, numerous studies attempted to measure the energy efficiency indices by conducting stochastic frontier analysis (SFA) and data envelopment analysis (DEA).

For instance, Huntington [10] discusses the relationship between energy and production efficiency using the framework of production theory. Feijoo et al. [11] conduct SFA to measure the energy efficiency of Spanish industries and Buck and Young [12] to estimate the energy efficiency of commercial buildings in Canada. Similarly, Boyd [13] analyzes the energy efficiency of wet corn milling plants and highlights the advantage of not having to define the problem of energy intensity in an SFA. Further, Zhou and Ang [14] measure the energy efficiency of 21 OECD countries using DEA. On the other hand, Filippini and Hunt measure the energy efficiency of 29 OECD countries [15] and calculate the energy efficiency of the US household sector using SFA [16]. The authors show that the energy efficiency level measured by conducting an SFA is not correlated with energy intensity, thus concluding that energy intensity is not a suitable proxy for energy efficiency. Carvalho [17] follows a time frame similar to that of Filippini and Hunt [15] and covers a series of non-OECD countries. Aranda-Uson et al. [18] perform an SFA to measure the energy efficiency for Spain's grocery and tobacco manufacturing, textile, chemical, and nonferrous metal product manufacturing industries. China-based studies have also applied SFA to measure the energy efficiency of the thermal power [19], iron and steel, and chemical industries [20, 21]. Lin and Du [22] and Filippini and Lin [23] compare energy efficiency levels across Chinese provinces using various econometric models, including SFA.

In sum, numerous studies support the use of an SFA instead of energy intensity as an indicator of energy efficiency. Moreover, SFA is a parametric approach that can tackle statistical noise and thus, is more desirable than DEA, a nonparametric approach. To this effect, Zhou et al. [24] evaluate the energy efficiency index using both approaches and show SFA is more desirable than DEA. A large body of research focuses on measuring energy efficiency values using SFA, whereas few studies explore the individual factors determining energy efficiency levels, such as the empirical works by Otsuka [25, 26]. These studies analyze the energy consumption trends of households and reveal that resident characteristics determine energy and electricity efficiency. However, to the best of the author's knowledge, there is a scarcity of research on economic production sectors. Particularly, how mechanization and electrification affect the energy efficiency have not been clarified.

This study thus measures the level of energy efficiency by using SFA and clarifies the determinants of the improvements in energy efficiency for Japan's industrial

sector. Specifically, it focuses on two factors influencing the energy efficiency of the industrial sector. The first is the capital-labor ratio, that is, "mechanization," wherein installing large intensive machinery equipment deteriorates energy efficiency. Conversely, the installation of compact and dispersed production facilities is expected to increase the energy efficiency. The second factor is the electrification rate. Advancing the electrification of factories and offices is directly linked to greater operational productivity and thus, the possibility of increasing energy efficiency.

Porter and van der Linde [27] highlight that improving productivity throughout the production process under appropriate environmental regulations could relatively reduce energy usage and, consequently, increase the energy efficiency. Boyd and Pang [28] and Otsuka et al. [29] also empirically demonstrate that productivity gain improves energy efficiency, that is, energy efficiency serves as a guidepost for improving productivity. Drawing on these works, this study verifies the hypothesis that productivity improvements under environmental constraints are compatible with those in energy efficiency.

The remainder of this study is organized as follows. Section 2 describes the empirical analysis framework, as well as the models and data. Section 3 presents the empirical results, followed by an analysis of the findings. Section 4 concludes the study.

2. Materials and methods

2.1 Econometric model for energy efficiency

This study assumes the following aggregated energy demand function, f, exists at the Japanese prefectural level. That is,

$$E_{jt} = f\left(P_t, Y_{jt}, KL_{jt}, IK_{jt}, CDD_{jt}, HDD_{jt}, EF_{jt}\right) \quad (1)$$

where j denotes a region (j = 1, ..., J), t is time (t = 1, ..., T) and E is the final energy consumption for the industrial sector. P is the energy price index for the sector and Y income. KL is the capital-labor ratio and represents the degree of mechanization in a factory or office. Thompson and Taylor [30] show that capital and energy both have short- and long-term relationships. IK is the proportion of investment in capital stock and represents the degree of vintage. CDD and HDD are the cooling and heating degree days and represent temperature. In regions with severe temperatures, energy consumption is more likely to be associated with air conditioning. Previous studies have shown that CDD and HDD, as indicators of cooling and heating, are related to energy consumption [31, 32]. EF is the level of energy efficiency in a region.

It is necessary to estimate energy efficiency, particularly because it is not directly observable in an economic system. Therefore, this study estimates energy efficiency using a stochastic frontier energy demand function. Stochastic frontier functions generally measure the economic performance of production and operation processes and have therefore been applied to production or cost theory using an econometric approach. This approach is based on the notion that frontier functions produce the maximum output or minimum cost levels achievable by a producer. In a production function, the frontier represents the maximum production level for a given input. In a cost function, the frontier is the minimum cost for a given output. An energy demand function can thus be considered similar to a cost function. In other words, the difference between observed energy demand and minimized demand is the technical inefficiency observed when the output for a production activity is given. In an aggregate energy demand function, the frontier denotes the

minimum energy level needed for the production activities in a region to achieve a given production level. In other words, by estimating an energy demand frontier function, it is possible to determine the baseline energy demand that reflects the energy demand in a region that is efficiently managing energy use through its production and operational processes. Additionally, it allows us to ascertain whether a region is on the frontier. If a region is not on the frontier, the distance from the frontier indicates the rate of energy consumption exceeding baseline demand (i.e., energy inefficiency) [33].

The panel SFA in this study follows the premise of Aigner et al. [34]. Further, this study adopts the one-step approach of Battese and Coelli [35]. It thus estimates the energy frontier function and the determinants of the energy inefficiency term simultaneously. Traditionally, a two-step estimation method is adopted, in which inefficiency is obtained by estimating the stochastic frontier function, and the value is regressed by determinants. In this case, a contradiction arises between the assumption of the distribution on the inefficiency term of the frontier function and the regression analyzing the inefficiency determinant. As such, the consistency of the estimation result is not guaranteed [36]. By adopting the one-step approach, we can avoid this problem. An SFA model using this approach approximates an economy's energy efficiency level based on a one-sided non-negative error term. That is, this study assumes the log-log function type in Eq. (1) can be specified as follows:

$$\begin{aligned} \ln E_{jt} &= \alpha + \alpha_P \ln P_t + \alpha_Y \ln Y_{jt} + \alpha_{KL} \ln KL_{jt} + \alpha_{IK} \ln IK_{jt} \\ &\quad + \alpha_{CDD} \ln CDD_{jt} + \alpha_{HDD} \ln HDD_{jt} + v_{jt} + u_{jt}, \end{aligned} \tag{2}$$

where α is an estimated parameter. The error term $(v_{jt} + u_{jt})$ consists of two parts, a random error term v_{jt} and an error term for inefficiency, u_{jt}. It is assumed that v_{jt} has a distribution $N(0, \sigma^2)$ and is independent of u_{jt} and all explanatory variables. u_{jt} is a non-negative random variable and follows the distribution $N(\mu, \sigma_u^2)$. u_{jt} indicates that the efficiency energy level EF in Eq. (1) is an energy inefficiency index. Given Eq. (2), the energy efficiency level EF_{jt} is estimated using the conditional expectation $E(u_{jt}|v_{jt} + u_{jt})$ for the efficiency term [37]. Specifically, the energy efficiency level EF_{jt} is measured by the ratio of the estimated energy demand frontier E_{jt}^F to the observed energy demand E_{jt}. In other words, $EF_{jt} \equiv E_{jt}^F / E_{jt} = e^{-u_{jt}}$, $0 < EF_{jt} \leq 1$.

Improvements in energy efficiency can be achieved through social innovation in the production and consumption processes of energy services, as well as the technical and organizational factors of energy demand. Average energy efficiency in this study is formulated as:

$$\mu_{jt} = \beta + \beta_{KL} \ln KL_{jt} + \beta_{ER} \ln ER_{jt}, \tag{3}$$

where β is an estimated parameter, KL is the capital-labor ratio, and ER is the electrification rate for the industrial sector. If the factor of the inefficiency term improves the efficiency, the sign of β is negative.

Factories and offices with large-scale facilities have high energy consumption and low energy efficiency in production. For example, a petrochemical complex, the paper pulp manufacturing industry, and the steel industry have large-scale production facilities. Therefore, the energy efficiency levels of these industries are low. Meanwhile, labor-intensive factories and offices have compact-scale production facilities, thus low energy consumption and high energy efficiency. For example, labor-intensive process-assembled industries are more energy efficient than material-based industries [38]. To control the differences in local production

industries, this study considers capital-labor ratio. The coefficient values for *KL* are expected to be positive.

Regions that use coal and kerosene tend to report higher carbon dioxide emissions than those using electricity. Further, areas with a low electrification rate are considered wasteful in terms of energy use. Electrification of factories and offices enables an efficient use of energy. For example, a factory energy management system (FEMS) can be introduced to electrify a factory. A FEMS functions in coordination with power generation, power storage, and energy saving devices, allowing for energy saving that industries have been unable to hitherto realize. Furthermore, the implementation of a building energy management system (BEMS) for commercial buildings could reduce energy consumption and control energy-related facilities. Consequently, energy efficiency could increase with a rise in electricity usage through promoting electrification. Therefore, the coefficient values for *ER* are expected to be negative.

2.2 Determinant model for the electrification rate

Electrification can significantly influence the improvement of energy efficiency in a region. Therefore, this study conducts a quantitative analysis as an additional regression that account for the characteristics of factories and offices that may be electrification determinants.

The variables in the following equation are assumed to be determinants of a region's electrification rate:

$$\begin{aligned} \ln ER_{jt} &= \delta_{LN} \ln LN_{jt} + \delta_{OR} \ln OR_{jt} + \delta_{TFP} \ln TFP_{jt} + \delta_{CDD} \ln CDD_{jt} \\ &+ \delta_{HDD} \ln HDD_{jt} + \delta_j + \varepsilon_{jt}, \end{aligned} \tag{4}$$

where *j* is a region (j = 1, …, J), *t* is the time (t = 1, …, T), *ER* is the electrification rate in the industrial sector, and *LN is* the number of employees per establishment, comprising offices and factories, and denotes the scale of an establishment. *OR* is the ratio of the number of offices to that of establishments; *TFP* is the total factor productivity and represents an establishment's productivity level; *CDD* and *HDD* are cooling and heating degree days, respectively; and δ is an estimated parameter. Since this study uses panel data, δj denotes the fixed effect. In estimation of (4), it is necessary to consider endogeneity between the productivity and the electrification rate. It would be possible that a higher electrification rate also influences productivity. Although these endogeneity effects can be treated with a fixed effect model, it is not sufficient. To obtain robust results, this study calculates the estimates by panel GMM using instrumental variables in addition to the fixed effect model.

2.3 Data

The data used for the analysis are 1990–2010 panel data for 47 prefectures. Data on the final energy consumption (*E*) of the sectors of each prefecture are taken from the Energy Consumption Statistics by Prefecture (Ministry of Economy, Trade, and Industry). The energy price index (*P*) is estimated using the real energy price index for the respective sector by the International Energy Agency (IEA). Income (*Y*) is a real gross regional expenditure, data for which are available in the Annual Report on Prefectural Accounts (Cabinet Office). The capital-labor ratio (*KL*) is the ratio of capital stock to the number of employees, and data for the number of employed persons are available in the Annual Report on Prefectural Accounts

Description	Variable	Mean	Std. dev.	Maximum	Minimum
Final energy consumption (TJ)	E	199,829	214,836	1,181,999	24,530
Energy price index (2010 = 100)	P	86.5	8.9	111.5	77.7
Income (JPY, millions)	Y	10,422,755	14,063,661	100,931,767	1,865,830
Capital-labor ratio	KL	15.48	3.51	26.19	7.27
Vintage	IK	0.061	0.016	0.118	0.035
Cooling degree day	CDD	367.0	175.6	1186.1	0.0
Heating degree day	HDD	1106.3	470.9	2769.2	0.2
Electrification rate (%)	ER	36.18	12.08	59.29	8.55
Establishment size (person)	LN	9.34	0.87	12.12	7.08
Office ratio (%)	OR	94.92	1.62	98.20	89.67
TFP index	TFP	0.185	0.112	0.662	−0.055

Sources: For final energy consumption, see Energy Consumption Statistics by Prefecture (Ministry of Economy, Trade and Industry: http://www.enecho.meti.go.jp/statistics/energy_consumption/ec002/); for energy price index, see International Energy Agency databases; for income, see Annual Report on Prefectural Accounts (Cabinet Office: http://www.esri.cao.go.jp/jp/sna/sonota/kenmin/kenmin_top.html); for capital-labor ratio, see Central Research Institute of Electric Power Industry databases; for vintage, see Central Research Institute of Electric Power Industry databases; for electrification rate, see Energy Consumption Statistics by Prefecture (Ministry of Economy, Trade and Industry: http://www.enecho.meti.go.jp/statistics/energy_consumption/ec002/); for establishment size and office ratio, see Economic Census (Statistics Bureau, Ministry of Internal Affairs and Communications: http://www.stat.go.jp/data/e-census/index.html); and for TFP index, see Otsuka and Goto [29]: https://link.springer.com/article/10.1007/s00168-016-0745-x.

Table 1.
Descriptive statistics.

Panel A							
	Final energy consumption (TJ)	**Energy price index (2010 = 100)**	**Income (JPY, millions)**	**Capital-labor ratio**	**Vintage**	**Cooling degree day**	**Heating degree day**
Region	**E**	**P**	**Y**	**KL**	**IK**	**CDD**	**HDD**
Hokkaido	322,771	100.00	19,199,451	15.09	0.035	124.0	2591.2
Tohoku	84,446	100.00	5,948,899	18.69	0.042	315.4	1907.7
Kita-Kanto	170,132	100.00	7,908,596	19.67	0.046	450.4	1407.0
Greater Tokyo area	613,806	100.00	41,983,820	19.21	0.046	492.5	1060.9
Chubu	234,453	100.00	14,956,162	21.40	0.046	511.0	1270.3
Hokuriku	55,461	100.00	4,209,377	20.81	0.043	476.2	1522.8
Kansai	211,767	100.00	13,566,039	20.86	0.047	556.5	1116.0
Chugoku	269,740	100.00	5,900,042	20.52	0.045	539.2	1194.3
Shikoku	75,918	100.00	3,549,752	19.05	0.046	572.4	910.6
Kyushu	138,517	100.00	6,618,666	18.32	0.047	545.1	911.8
Okinawa	38,462	100.00	3,850,416	12.97	0.052	909.0	122.2

Panel B				
	Electrification rate (%)	**Establishment size (person)**	**Office ratio (%)**	**TFP index**
Region	**ER**	**LN**	**OR**	**TFP**
Hokkaido	34.69	9.84	97.67	0.25
Tohoku	44.58	9.27	96.33	0.15
Kita-Kanto	46.78	9.53	95.23	0.27
Greater Tokyo area	30.67	11.08	96.82	0.40
Chubu	44.25	9.70	94.77	0.26
Hokuriku	51.66	8.84	95.00	0.22
Kansai	40.63	9.34	95.82	0.32
Chugoku	28.35	9.53	96.47	0.19
Shikoku	38.06	8.55	96.59	0.21
Kyushu	38.78	9.53	97.13	0.15
Okinawa	49.24	8.24	98.20	0.14

Notes: the regional classification is as follows: Hokkaido (Hokkaido), Tohoku (Aomori, Iwate, Miyagi, Akita, Yamagata, Fukushima, and Niigata), Tokyo (Saitama, Chiba, Tokyo, Kanagawa, Ibaraki, Tochigi, Gunma, and Yamanashi), Hokuriku (Toyama, Ishikawa, and Fukui), Chubu (Nagano, Gifu, Shizuoka, Aichi, and Mie), Kansai (Shiga, Kyoto, Osaka, Hyogo, Nara, and Wakayama), Chugoku (Tottori, Shimane, Okayama, Hiroshima, and Yamaguchi), Shikoku (Tokushima, Kagawa, Ehime, and Kochi), Kyushu (Fukuoka, Saga, Nagasaki, Kumamoto, Oita, Miyazaki, and Kagoshima), and Okinawa (Okinawa).

Table 2.
Regional characteristics for Japan (as of 2010).

(Cabinet Office). Capital vintage (*IK*) is the ratio of capital investment to capital stock. Data on capital investment and stock are based on the data published by the Central Research Institute of Electric Power Industry. Data on *CDD* and *HDD* are from the prefectural government's location and weather station—cooling degree day is the sum of the difference between average temperature on the days exceeding 24 and 22°C, while heating degree day is the sum of the difference between average temperatures below 14°C and above 14°C. The *ER* is estimated from the data in the Energy Consumption Statistics by Prefecture (Ministry of Economy, Trade, and Industry). The estimation for the percentage of offices for all establishments (*OR*) is based on the number of business establishments listed by the Economic Census (Ministry of Economy, Trade, and Industry). Data for productivity (*TFP*) are the total factor productivity calculated by Otsuka and Goto [39]. **Table 1** presents the descriptive statistics.

Table 2 presents the regional characteristics for Japan as of 2010. Particularly, large metropolitan areas, such as the Greater Tokyo Area, Kansai, and Chubu, report high energy consumption. Moreover, the income scale is large and vintage is high in these areas. The capital-labor ratio is relatively high because the manufacturing industry is concentrated in the Chubu and Hokuriku regions. The degree of air conditioning usage is significant in the warm western Japan, and the number of heating days is high in eastern Japan. Further, the Greater Tokyo Area, Kansai, and Chubu have several large-scale business establishments and productivity tends to be high here.

3. Results and discussion

Table 3 presents the estimation results for the energy demand frontier function. Model A shows the estimation results of (2) and (3). Model B shows the estimation result of the model considering a nonlinear effect in the inefficiency determinant.

First, let us consider the results of Model A. The estimated coefficients show the expected signs, and all variables are statistically significant. Since each variable is a logarithmic variable, the estimated parameter can be interpreted as elasticity. Estimated price elasticity is 0.046 and income elasticity 0.707, indicating that income elasticity significantly exceeds price elasticity. Price elasticity is inelastic and denotes the nature of energy goods as essential goods. The capital-labor ratio and the coefficient on vintage are positive and have reasonable signs. This suggests that there is more energy demand in areas where industries for which mechanization is progressing are located. It also shows that capital investment increases energy demand. The coefficients for cooling degree day are slightly significant, but their magnitude is small. Additionally, the coefficients for heating degree day are not significant. These results show that temperature is a weak determinant of energy demand in the industrial sector.

Next, this study evaluates the estimation results for the factors determining energy efficiency. The capital-labor ratio is positive and reports the expected sign. This indicates that energy efficiency deteriorates with an increase in mechanization. In other words, energy efficiency is lower in regions where numerous industries with large-scale facilities are located. The electrification rate is negative, reporting the expected sign. The results show that an increase in the electrification rate enhances energy efficiency. The coefficient value for the electrification rate is considerably larger than that for the capital-labor ratio. That is, the positive impact

	Model A		**Model B**	
	Coefficient	**Standard error**	**Coefficient**	**Standard error**
Constant (α)	−0.584**	(0.038)	−0.571**	(0.040)
α_P	−0.046**	(0.009)	−0.039**	(0.009)
α_Y	0.707**	(0.010)	0.705**	(0.010)
α_{KL}	0.10 **	(0.023)	0.109**	(0.021)
α_{IK}	0.065**	(0.010)	0.073**	(0.011)
α_{CDD}	−0.021*	(0.009)	−0.021*	(0.009)
α_{HDD}	−0.005	(0.007)	−0.006	(0.007)
Constant (β)	0.534**	(0.043)	0.556**	(0.047)
β_{KL}	0.093**	(0.025)	0.096**	(0.024)
β_{KL}^2			−0.028**	(0.009)
β_{ER}	−0.522**	(0.011)	−0.556**	(0.026)
β_{ER}^2			−0.019	(0.011)
$\sigma_u^2 + \sigma_v^2$	0.062**	(0.004)	0.063**	(0.004)
$\sigma_u^2/(\sigma_u^2 + \sigma_v^2)$	0.692**	(0.096)	0.690**	(0.092)
Number of observations	987		987	

*Note: ** and * denote significance at the 1 and 5% levels, respectively.*

Table 3.
Estimation results for 1980–2010.

of installing power facilities and an increase in the electrification rate from office automation are more significant than the negative impact of installing large productive capital equipment.

Due to these effects, this study estimates Model B, which account for the nonlinear effects of determinants. Statistically, significant values are obtained for the quadratic term of the capital-labor ratio. The sign of the quadratic term is negative. This shows there is a threshold for the impact of the capital-labor ratio on energy efficiency. Specifically, the increase in mechanization improves energy efficiency, but it exacerbates energy efficiency when it exceeds a threshold value. On the other hand, the quadratic terms for electrification are not statistically significant, and the nonlinear effects of electrification are not recognizable.

During the observation period (1990–2010), there was financial crisis in 2008. As the economic depression spreads worldwide from the US, Japan's economic growth rate fell greatly in 2008. This economic downturn had a significant influence on the production system of the regional industry. Hence, when considering result stability, this influence must be considered. Therefore, the analysis period is reset from 1990 to 2007, and Model A and Model B reestimated. **Table 4** shows the reestimation results. Model C represents the result of reestimation of Model A and Model D of Model B. There is no significant difference in the regression coefficients in **Table 4**. Therefore, the results in **Table 3** can be judged as robust.

Table 5 presents the descriptive statistics for the energy efficiency values of each prefecture, obtained from the estimation results (Model A). An efficiency value of 1 denotes the highest efficiency, while a value below 1 indicates lower energy efficiency. The average energy efficiency value is 0.617 and the median value 0.685. More importantly, a maximum value of 0.950 and a minimum of

	Model C		**Model D**	
	Coefficient	**Standard error**	**Coefficient**	**Standard error**
Constant (α)	−0.577**	(0.044)	−0.576**	(0.049)
α_P	−0.063**	(0.014)	−0.056**	(0.014)
α_Y	0.709**	(0.011)	0.706 **	(0.011)
α_{KL}	0.121**	(0.027)	0.118**	(0.027)
α_{IK}	0.073**	(0.012)	0.079**	(0.012)
α_{CDD}	−0.018	(0.009)	−0.018	(0.009)
α_{HDD}	−0.006	(0.008)	−0.008	(0.007)
Constant (β)	0.520**	(0.051)	0.552**	(0.058)
β_{KL}	0.094**	(0.029)	0.091**	(0.029)
β_{KL}^2			−0.028*	(0.010)
β_{ER}	−0.522**	(0.012)	−0.543**	(0.028)
β_{ER}^2			−0.012	(0.012)
$\sigma_u^2 + \sigma_v^2$	0.062 **	(0.004)	0.063**	(0.004)
$\sigma_u^2/(\sigma_u^2 + \sigma_v^2)$	0.648**	(0.111)	0.667**	(0.106)
Number of observations	846		846	

*Note: ** and * denote significance at the 1 and 5% levels, respectively.*

Table 4.
Estimation results for 1980–2007.

Mean	0.617
Std. dev.	0.234
Minimum	0.114
Maximum	0.950
Median	0.685

Note: The energy efficiency scores in the table are calculated using the estimation results for Model A.

Table 5.
Descriptive statistics of energy efficiency scores.

0.114 point to a significant difference in energy efficiency levels among regions. **Figure 1** shows the time-series transition of the national average energy efficiency scores. The average energy efficiency score of Japan's industrial sector has been consistently increasing until 2007, after declining from 1990 to 1994. Energy conservation progressed from the latter half of the 1990s to the 2000s, and energy efficiency thus improved. However, in 2008, energy efficiency worsened and then increased slightly.

Table 6 presents the average energy efficiency scores for each prefecture and ranks them accordingly. Nara, Tokyo, Yamanashi, Ishikawa, Saga, and Yamagata are among the high-ranking areas. The factories and offices located in these areas are likely to report an increasing rate of electrification. On the other hand, Oita has the lowest energy efficiency. Okayama, Chiba, and Yamaguchi have petrochemical complexes and, thus, low energy efficiency, because petrochemical complexes have large-scale production facilities and are lagging in electrification, given the large demands for coal, kerosene, and gas for production.

Table 6 also shows the change rate of the average scores for the energy efficiency between the 1990s and the 2000s. The table highlights two key characteristics. First, Mie, Wakayama, and Fukuoka report improved average scores. Specifically, Mie has the highest improvement score, and its energy efficiency value shows an annual improvement of 1.87%. Wakayama and Fukuoka's scores improve by 1.36 and 1.12%

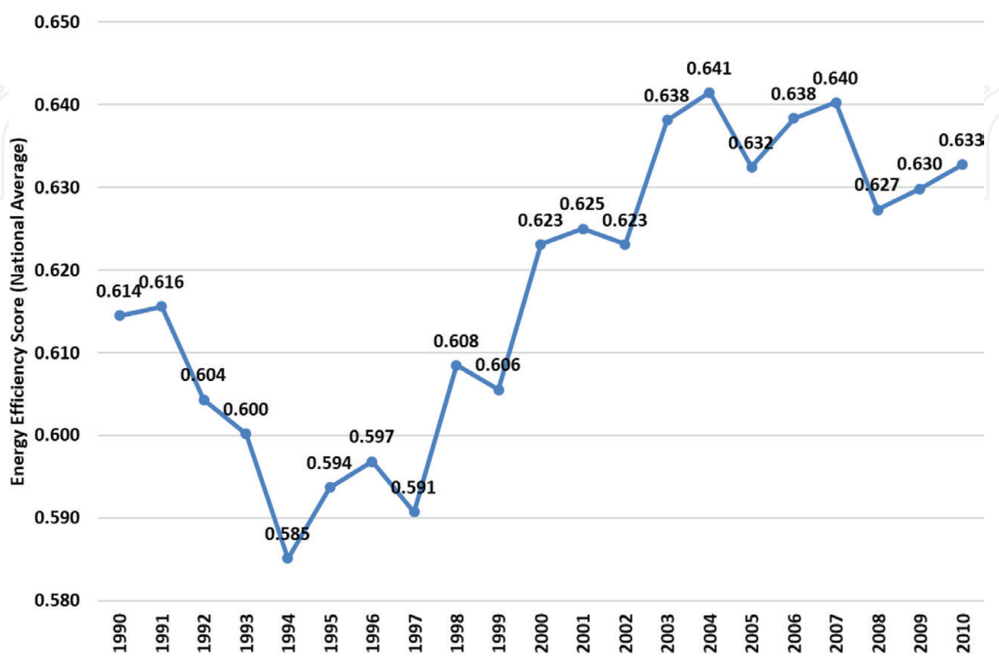

Figure 1.
Time trend of national average energy efficiency scores.

Rank	Prefecture	Average efficiency score	Change rate of score
1	Nara	0.93	−0.22
2	Tokyo	0.92	−0.10
3	Yamanashi	0.91	−0.10
4	Ishikawa	0.90	−0.20
5	Saga	0.87	−0.06
6	Yamagata	0.86	−0.01
7	Nagano	0.86	0.17
8	Kyoto	0.85	−0.19
9	Okinawa	0.84	−0.07
10	Gunma	0.84	0.00
11	Akita	0.84	−0.46
12	Fukui	0.83	−0.01
13	Kumamoto	0.79	−0.38
14	Fukushima	0.79	0.73
15	Shiga	0.77	0.81
16	Shimane	0.77	0.61
17	Tochigi	0.77	−0.18
18	Nagasaki	0.76	0.79
19	Gifu	0.72	−0.13
20	Saitama	0.72	−0.14
21	Kagoshima	0.72	−0.29
22	Tottori	0.71	−1.07
23	Miyagi	0.71	−0.59
24	Iwate	0.68	0.15
25	Toyama	0.67	0.51
26	Shizuoka	0.65	0.81
27	Tokushima	0.64	1.39
28	Miyazaki	0.63	0.82
29	Osaka	0.61	0.16
30	Niigata	0.60	0.11
31	Aichi	0.53	0.23
32	Aomori	0.53	0.38
33	Hokkaido	0.51	0.10
34	Kochi	0.49	0.43
35	Kagawa	0.47	0.77
36	Hyogo	0.42	0.35
37	Fukuoka	0.42	1.12
38	Ehime	0.40	0.15
39	Kanagawa	0.37	−0.58
40	Wakayama	0.31	1.36
41	Hiroshima	0.29	0.53

Rank	Prefecture	Average efficiency score	Change rate of score
42	Mie	0.28	1.83
43	Ibaraki	0.25	−0.26
44	Yamaguchi	0.20	−0.25
45	Chiba	0.15	−0.32
46	Okayama	0.14	0.49
47	Oita	0.13	0.95

Note: The energy efficiency scores in the table are calculated using the estimation results for Model A.

Table 6.
Average energy efficiency scores and change rate of the score.

Rank correlation method	Rank correlation coefficient	P-value
Kendall's tau	−0.2396	0.0175
Spearman	−0.3207	0.0280

Table 7.
Results of rank correlation.

annual rates. These prefectures rank low in average energy efficiency. Therefore, it is highly likely these regions have several electrical machineries and equipment manufacturing units, and their machinery industry has progressive electrification rates, thus contributing to the improvement of energy efficiency. Second, energy efficiency is deteriorating in regions with high energy efficiency levels, including Nara, Tokyo, Yamanashi, Ishikawa, and Saga. This suggests that the regional disparities in energy efficiency are decreasing.

This study verifies the possibility of reducing regional disparities in energy efficiency by calculating the rank correlation coefficient between the average energy efficiency score and its change rate. **Table 7** shows the results of the rank correlation coefficient. The Kendall rank correlation coefficient is −0.2396, which is statistically significant. Spearman's rank correlation coefficient is −0.3207, also being statistically significant. The sign of any rank correlation coefficient is negative, and the improvement in energy efficiency is progressing in the region with a low energy efficiency.

The energy efficiency level is highly related to electrification. **Figure 2** is a cross-sectional plot of the average values for the electrification rate and energy efficiency. The figure clearly illustrates an upward trend. In other words, regions with advanced electrification have high energy efficiency levels. Specifically, regions where offices are concentrated (e.g., Tokyo) are located in the upper right corner, while those with petrochemical complexes (e.g., Oita, Okayama, and Chiba) are in the lower right.

Furthermore, it is also highly possible that energy efficiency improvements have progressed to electrification. **Figure 3** plots the time-series relationship between the electrification rate and energy efficiency and shows an upward trend. In other words, it is highly likely that advanced electrification contributes to energy efficiency improvements. As described above, Mie is likely to report improved energy efficiency, given its progress in electrification. On the other hand, Chiba has lower energy efficiency, given the low energy efficiency of petrochemical complexes.

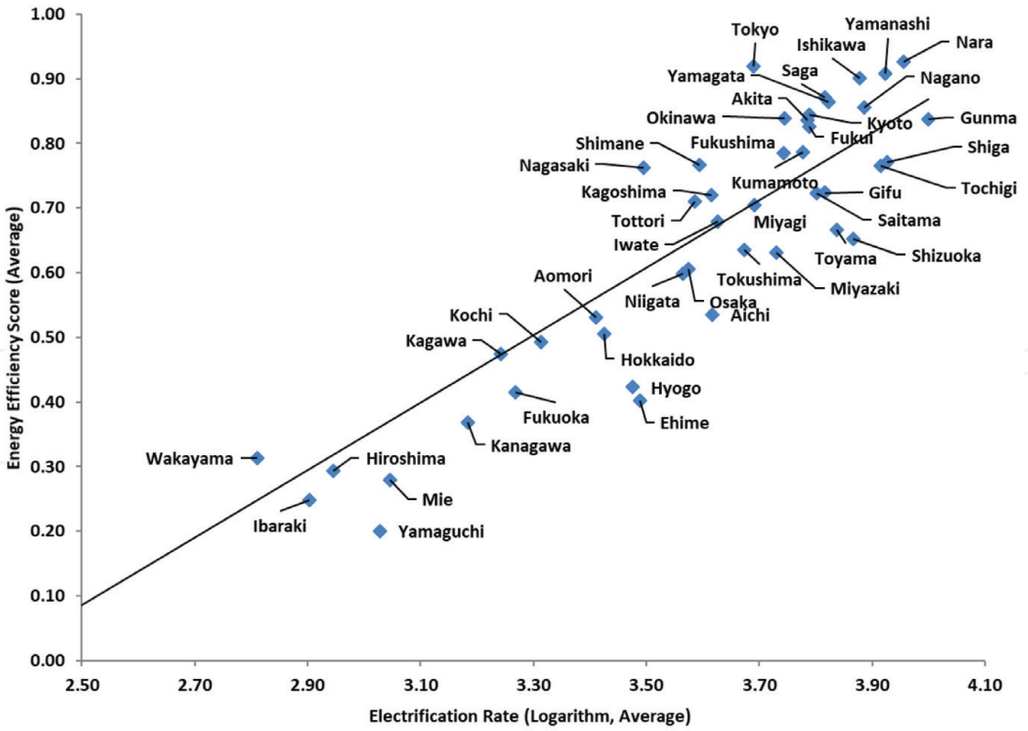

Figure 2.
Static relationship between energy efficiency score and electrification rate.

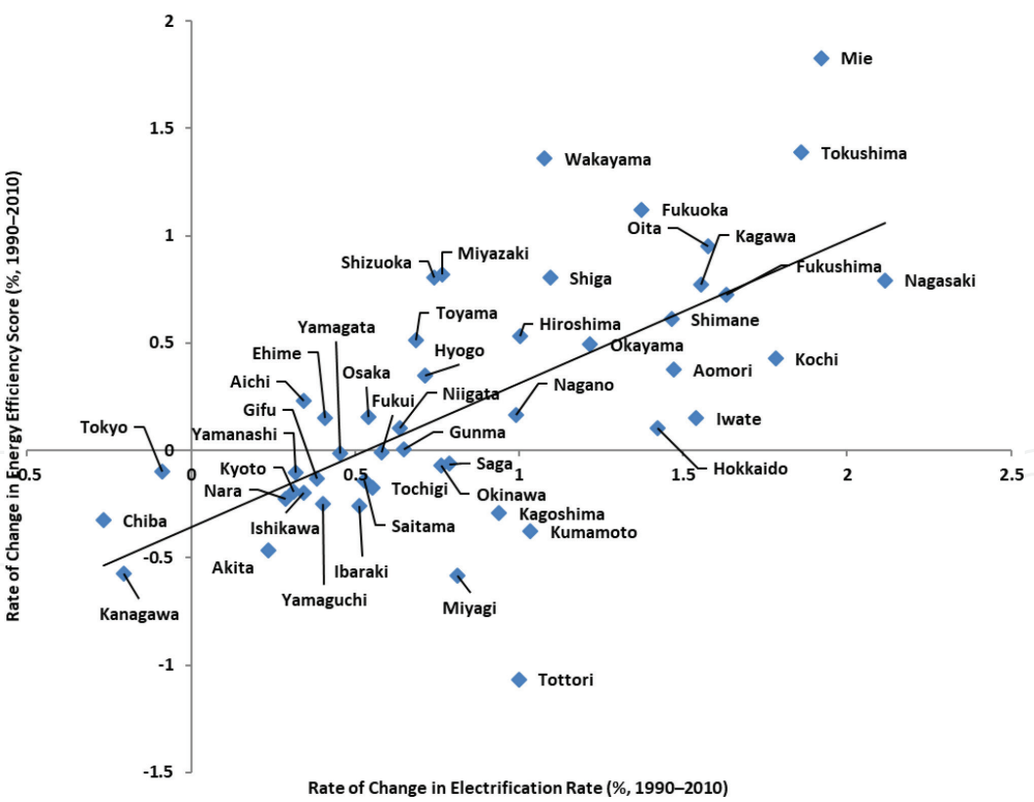

Figure 3.
Dynamic relationship between energy efficiency score and electrification rate.

Finally, this study analyzes the determinants of the electrification rate, which is one of the key factors to improve energy efficiency. **Table 8** presents the estimation results for Eq. (4). First, the F-test checks for fixed effects and rejects the null hypothesis that there is no fixed effect at the 1% significance level. Additionally, the Hausman test rejects the null hypothesis that the fixed effect is a random effect

Method	EF		Panel GMM	
	Coefficient	Standard error	Coefficient	Standard error
Constant (δ)	−0.434**	(0.196)	0.240	(0.264)
δ_{LN}	0.215**	(0.080)	0.331**	(0.084)
δ_{OR}	3.751**	(0.328)	4.781**	(0.368)
δ_{TFP}	0.707**	(0.008)	0.550**	(0.037)
δ_{CDD}	0.001	(0.003)	0.000	(0.003)
δ_{HDD}	0.000	(0.008)	0.001	(0.008)
Number of observations	987		940	
Adjusted R-squared	0.9850		0.9840	
Hausman test	17.086**			
Prob (Hausman)	[0.0043]			
J-statistic			0.0122	
Prob(J-statistic)			[0.9119]	
Instrument			TFP(−1)	

*Note: 1. ** and * indicate significance at the 1 and 5% levels, respectively. 2. The values between parentheses are p-values.*

Table 8.
Panel estimation results on determinants of the electrification rate.

at the 1% significance level. Therefore, the fixed effect model is appropriate for the panel regression analysis. Further, to test the validity of the panel GMM estimation, this study performs a Sargan-Hansen test for the exogeneity of the instrumental variables. From Hansen J's statistical results, the number of instrumental variables is appropriate and satisfies the condition of heteroskedasticity.

The signs for all the variables are consistent under both models. The sign for the establishment size is positive, meaning establishments with a larger number of employees have a higher electrification rate. Further, the higher the proportion of offices, the greater the electrification rate. It is also noteworthy that the sign of an establishment's productivity is positive. This indicates that an increase in the establishment's productivity is proportional to that in the electrification rate. The magnitude of the coefficient on productivity is between 0.475 and 0.676, and it significantly influences the electrification rate. Neither cooling nor heating degree days are statistically significant.

In sum, the establishment scale and productivity are closely related to the electrification rate, which may influence energy efficiency. That is, productivity improves energy efficiency through an increase in electrification at factories and business establishments. Therefore, the efforts to increase the office productivity could improve energy efficiency.

4. Conclusions and policy implications

This study analyzed the energy efficiency levels and their determinants in Japan's industrial sector using an energy demand frontier function. To the best of the author's knowledge, this is the first attempt to do so. Energy intensity has been traditionally used as a proxy for energy efficiency and depends on economic

variables such as price and income. However, this study specified energy demand and controlled for price, income, production environment, and climate factors, thus rendering energy efficiency a more accurate index.

This study focused on compact mechanization and electrification as the two main determinants of the improvements in the energy efficiency of the industrial sector. The analysis presented three key findings. First, an installment in large capital facilities deteriorates energy efficiency. Therefore, policies aimed at promoting small- or medium-sized production facility installments lead to improvements in energy efficiency. Second, an increase in the electrification rate of a given region can improve its energy efficiency. Finally, it is necessary to increase the productivity and also the electrification rate, that is, raising the productivity of factories and offices promotes electrification, which considerably contributes to increased energy efficiency. This finding highlights the relationship between increasing productivity and improvements in energy efficiency, suggesting the possibility of the Porter hypothesis being established.

It can be concluded that the energy efficiency of the industrial sector can be improved by developing an appropriately competitive environment and encouraging electrification in each region's energy market. Additionally, electrification increases environmental efficiency by reducing carbon dioxide emissions. Therefore, the promotion of electrification is critical to the achievement of not only energy efficiency but also improving environmental efficiency. Nevertheless, further research is needed to verify whether this trend also applies to other countries to ensure the effectiveness of electrification.

The future research agenda relates to both the micro and macro viewpoints. The former indicates that future studies should examine the energy efficiency of electric power as an energy source from a more diversified viewpoint, including power saving. An important factor that warrants consideration in power consumption efficiency is an appropriate way to account for the efficiency of plant facilities and performance of air conditioning. Since this research could not account for the performance of each device, quantitatively examining this factor warrants further research.

The research agenda from the macro viewpoint clarifies how the increase in urban population density affects energy efficiency, as discussed in Otsuka and Goto [40] and Otsuka [41]. In developed countries, urban compactification is being promoted from the viewpoint of city sustainability. The rise in urban population density exacerbates energy efficiency by causing a heat island phenomenon. Meanwhile, population concentration in cities has the merit of promoting the use of public transportation. Further, cities have more dwelling units than detached houses, and apartments have high thermal insulation and energy efficiency. As such, living in the city center may increase the energy efficiency. It seems that clarifying these problems would deepen the understanding of energy efficiency.

Acknowledgements

This study was funded by the Japan Society for the Promotion of Science (grant no. 18K01614).

Conflict of interest

The author declares no conflict of interest. The funders had no role in the design of the study; the collection, analyses, or interpretation of data; the writing of the manuscript, or the decision to publish the results.

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References

[1] Yang Q, Kaneko S, Fujii H, Yoshida Y. Do exogenous shocks better leverage the benefits of technological change in the staged elimination of differential environmental regulations? Evidence from China's cement industry before and after the 2008 great Sichuan earthquake. Journal of Cleaner Production. 2017;**164**:1167-1179. DOI: 10.1016/j.jclepro. 2017.06.210

[2] Taner T, Sivrioglu M. A techno-economic & cost analysis of a turbine power plant: A case study for sugar plant. Renewable and Sustainable Energy Reviews. 2017;**78**:722-730. DOI: 10.1016/j.rser.2017.04.104

[3] Taner T. Economic analysis of a wind power plant: A case study for the Cappadocia region. Journal of Mechanical Science and Technology. 2018;**32**:1379-1389. DOI: 10.1007/s12206-018-0241-6

[4] Taner T. Energy and exergy analyze of PEM fuel cell: A case study of modeling and simulations. Energy. 2018;**143**:284-294. DOI: 10.1016/j.energy.2017.10.102

[5] Bhattacharyya SC. Energy Economics Concepts, Issues. Markets and Governance. London: Springer-Verlag; 2011

[6] Patterson MG. What is energy efficiency? Concepts, indicators and methodological issues. Energy Policy. 1996;**24**:377-390. DOI: 10.1016/0301-4215(96)00017-1

[7] Energy Information Administration (EIA). Measuring Energy Efficiency in the United States' Economy: A Beginning. US DOE/EIA-0555(95)/2. Washington, DC, USA; 1995

[8] Energy Information Administration (EIA). International Energy Outlook 2013. U.S. Energy Information Administration; 2013

[9] International Energy Agency (IEA). Progress with Implementing Energy Efficiency Policies in the G8. International Energy Agency Paper; 2009

[10] Huntington HG. Been top down so long it looks like bottom up to me. Energy Policy. 1994;**22**:833-838. DOI: 10.1016/0301-4215(94)90142-2

[11] Feijoo ML, Franco JF, Hernández JM. Global warming and the energy efficiency of Spanish industry. Energy Economics. 2002;**24**:405-423. DOI: 10.1016/S0140-9883(02)00013-0

[12] Buck J, Young D. The potential for energy efficiency gains in the Canadian commercial building sector. Energy. 2007;**32**:1769-1780. DOI: 10.1016/j.energy.2006.11.008

[13] Boyd GA. Estimating plant level energy efficiency with a stochastic frontier. Energy Journal. 2008;**29**:23-43. https://www.jstor.org/stable/41323155

[14] Zhou P, Ang BW. Linear programming models for measuring economy-wide energy efficiency performance. Energy Policy. 2008;**36**:2911-2916. DOI: 10.1016/j.enpol.2008.03.041

[15] Filippini M, Hunt LC. Energy demand and energy efficiency in the OECD countries: A stochastic demand frontier approach. Energy Journal. 2011;**32**:59-79. DOI: 10.5547/ISSN0195-6574-EJ-Vol32-No2-3

[16] Filippini M, Hunt LC. US residential energy demand and energy efficiency: A stochastic demand frontier approach. Energy Economics. 2012;**34**:1484-1491. DOI: 10.1016/j.eneco.2012.06.013

[17] Carvalho A. Energy efficiency in transition economies. The Economics of Transition. 2018;**26**:553-578. DOI: 10.1111/ecot.12152

[18] Aranda-Uson A, Ferreira G, Mainar-Toledo MD, Scarpellini S, Liera E. Energy consumption analysis of Spanish food and drink, textile, chemical and non-metallic mineral products sectors. Energy. 2012;**42**:477-485. DOI: 10.1016/j.energy.2012.03.021

[19] Lin B, Yang LS. The potential estimation and factor analysis of China's energy conservation on thermal power industry. Energy Policy. 2013;**62**:354-362. DOI: 10.1016/j.enpol.2013.07.079

[20] Lin B, Wang X. Exploring energy efficiency in China's iron and steel industry: A stochastic frontier approach. Energy Policy. 2014;**72**:87-96. DOI: 10.1016/j.enpol.2014.04.043

[21] Lin B, Long HA. Stochastic frontier analysis of energy efficiency of China's chemical industry. Journal of Cleaner Production. 2015;**87**:235-244. DOI: 10.1016/j.jclepro.2014.08.104

[22] Lin BQ, Du KR. Technology gap and China's regional energy efficiency: A parametric meta frontier approach. Energy Economics. 2013;**40**:529-536. DOI: 10.1016/j.eneco.2013.08.013

[23] Filippini M, Lin B. Estimation of the energy efficiency in Chinese provinces. Energy Efficiency. 2016;**9**:1315-1328. DOI: 10.1007/s12053-016-9425-z

[24] Zhou P, Ang BW, Zhou DQ. Measuring economy-wide energy efficiency performance: A parametric frontier approach. Applied Energy. 2012;**90**:196-200. DOI: 10.1016/j.apenergy.2011.02.025

[25] Otsuka A. Determinants of efficiency in residential electricity demand: Evidence from Japan. Energy, Sustainability and Society. 2017;**7**:1-10. DOI: 10.1186/s13705-017-0135-y

[26] Otsuka A. Regional determinants of energy efficiency: Residential energy demand in Japan. Energies. 2018;**11**: 1-14. DOI: 10.3390/en11061557

[27] Porter ME, Van der Linde C. Toward a new conception of the environment competitiveness relationship. Journal of Economic Perspectives. 1995;**9**:97-118. https://www.jstor.org/stable/2138392

[28] Boyd GA, Pang JX. Estimating the linkage between energy efficiency and productivity. Energy Policy. 2000;**28**:289-296. DOI: 10.1016/S0301-4215(00)00016-1

[29] Otsuka A, Goto M, Sueyoshi T. Energy efficiency and agglomeration economies: The case of Japanese manufacturing industries. Regional Science Policy and Practice. 2014;**6**: 195-212. DOI: 10.1111/rsp3.12039

[30] Thompson P, Taylor TG. The capital-energy substitutability debate. The Review of Economics and Statistics. 1995;**77**:565-569. https://www.jstor.org/stable/2109916

[31] Metcalf GE, Hassett KA. Measuring the energy savings from home improvement investment: Evidence from monthly billing data. The Review of Economics and Statistics. 1999;**81**:516-528. https://www.jstor.org/stable/2646774

[32] Reiss PC, White MW. What changes energy consumption? Prices and public pressures. RAND Journal of Economics. 2008;**39**:636-663. https://www.jstor.org/stable/25474390

[33] Otsuka A, Goto M. Estimation and determinants of energy efficiency in Japanese regional economies. Regional Science Policy and Practice. 2015;**7**: 89-101. DOI: 10.1111/rsp3.12058

[34] Aigner DJ, Lovell CAK, Schmidt P. Formulation and estimation of stochastic frontier production function model. Journal of Econometrics. 1977;**6**:21-37. DOI: 10.1016/0304-4076(77)90052-5

[35] Battese GE, Coelli TJA. A model for technical inefficiency effects in a stochastic frontier production function for panel data. Empirical Economics. 1995;**20**:325-332. DOI: 10.1007/BF01205442

[36] Coelli TJ. Recent development in frontier modeling and efficiency measurement. Australian Journal of Agricultural Economics. 1995;**39**:219-245. DOI: 10.1111/j.1467-8489.1995.tb00552.x

[37] Jondrow J, Knox Lovell CA, Materov IS, Schmidt P. On the estimation of technical inefficiency in the stochastic frontier production function model. Journal of Economics. 1982;**19**:233-238. DOI: 10.1016/0304-4076(82)90004-5

[38] Otsuka A. Regional Energy Demand and Energy Efficiency in Japan. Switzerland: Springer; 2017. DOI: 10.1007/978-3-319-47566-0

[39] Otsuka A, Goto M. Total factor productivity and the convergence of disparities in Japanese regions. The Annals of Regional Science. 2016;**56**:419-432. DOI: 10.1007/s00168-016-0745-x

[40] Otsuka A, Goto M. Regional determinants of energy intensity in Japan: The impact of population density. Asia-Pacific Journal of Regional Science. 2018;**2**:257-278. DOI: 10.1007/s41685-017-0045-1

[41] Otsuka A. Population agglomeration and residential energy consumption: Evidence from Japan. Sustainability. 2018;**10**:1-12. DOI: 10.3390/su10020469