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Industrial electricity consumption efficiency and energy policy in Japan

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A B S T R A C T

This study analyzes the potential for energy savings by identifying inefficiencies in electricity use and their determinants in the Japanese industrial sector. Specifically, we used stochastic frontier analysis to estimate inefficiencies in electricity consumption based on data obtained from electric power companies. We identified significant determinants of electricity consumption efficiency and that changes in national energy policy following the Great East Japan Earthquake changed electricity consumption behavior. The contribution of this study is that its findings can be used to improve the cost-effectiveness of policies aimed at improving energy efficiency.

1. Introduction

The International Energy Agency (IEA) projects that, with current policies, global primary energy consumption in 2040 will be about 1.19 times higher than that in 2018, which is well over what would be realized if all decarbonization policies were implemented (IEA, 2020). Therefore, improving energy efficiency has become a primary political goal for numerous countries to mitigate greenhouse gas (GHG) emissions. In Japan, the Strategic Energy Plan, which outlines this country's energy supply plan, was revised in 2021 to achieve its carbon neutrality goal by 2050 (METI, 2021). It was decided that renewable energy would be the nation's primary energy source and that the use of fossil fuels would be reduced. To develop cost-effective strategies to ensure energy saving, estimating the energy-saving potential of different societal sectors is helpful. If a given sector has considerable energy-saving potential, the strategic issue is how its energy efficiency can be increased.

This study thus aimed to identify inefficiencies in electrical use and their determinants in the Japanese industrial sector's electricity consumption. Stochastic frontier analysis (SFA) techniques are often used to estimate electricity usage inefficiency. SFA is an analytical tool that helps identify the most efficient level of electricity consumption based on electricity consumption data. Utilizing this analytical approach can give insight into the impact of socioeconomic characteristics on the efficiency level of this sector's electricity consumption. Relevant information obtained can then be used within targeted regional industrial policies as this information would outline the socioeconomic factors most likely to increase efficiency and reduce energy consumption. This approach could lead to more cost-effective policies and reduced GHG emissions (Allcott and Greenstone, 2012; Gillingham et al., 2018; Malinauskaite et al., 2020).

Econometric methods for estimating efficiency can be broadly classified into parametric and non-parametric approaches (Andor and Hesse, 2014; Andor et al., 2019; Parmeter and Zelenyuk, 2019). Data envelopment analysis (DEA) is the most widely applied non-parametric approach within the field of efficiency analysis (Charnes et al., 1978). This approach is flexible but does not consider statistical noise in its standard form. Stochastic frontier analysis (SFA), on the other hand, considers statistical noise and generally requires assumptions on the functional form of the frontier and the error term distribution (Aigner et al., 1977; Meeusen and van den Broeck, 1977). Therefore, SFA is often preferable to DEA because it can deal with statistical noise (Zhou et al., 2012). Furthermore, Filippini and Hunt (2011, 2012), Stern (2012), Zhou et al. (2012), Lin and Du (2013, 2014, 2015), and Filippini et al. (2014) support the application of SFA, a parametric frontier approach, as an energy efficiency measurement.

SFA utilizes production theory based on the idea that the frontier function provides the maximum output or minimum cost level that an economic agent can achieve. In the case of the cost function, the frontier represents the minimum cost that can be achieved for a given output. This same concept can be applied to an electricity consumption function. The difference between the observed and minimized electricity consumption for a given production output is its inefficiency. For an

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aggregate electricity consumption function, the frontier function provides the minimum electricity required by a production activity to achieve a given output. In other words, estimating the electricity demand frontier function makes it possible to estimate the baseline electricity consumption, which reflects the regions that efficiently manage energy use in their production activities. Therefore, SFA makes it possible to determine whether a region is on the frontier. If a region is not on the frontier, its distance from the frontier indicates the portion of its electricity consumption that exceeds the baseline usage, which can be viewed as electricity-usage inefficiency.

Energy efficiency indicators using SFA have been applied in several countries (Otsuka and Goto, 2015). For example, Filippini and Hunt (2011), Evans et al. (2013), and Zhou et al. (2012) measured economy-wide energy efficiency indicators in various OECD countries. Further, both Borozan (2018) and Filippini et al. (2014) measured efficiency levels among European countries. At a more regional level, Wei et al. (2009) and Filippini and Zhang (2016) measured energy efficiency in Chinese provinces, while Filippini and Hunt (2012) and Orea et al. (2015) measured energy efficiency among states in the United States (US). Additionally, Honma and Hu (2014), Otsuka and Goto (2015), and Otsuka (2017a, 2018a, 2018b, 2020) analyzed the determinants of energy efficiency among various Japanese prefectures. Finally, Boyd (2008), Alberini and Filippini (2018), and Andor et al. (2021) analyzed the efficiency of electricity use via microdata for the US.

This study contributes scientifically by identifying the determinants of inefficiency in electricity consumption. Such information will likely help policymakers consider more targeted ways to improve energy efficiency. Simple awareness that industrial electricity consumption is inefficient does not provide insights into how to reduce it. Hence, it is crucial to identify the socioeconomic factors determining this inefficiency. For example, Blasch et al. (2017), Boogen (2017), Broadstock et al. (2016), Weyman-Jones et al. (2015), Andor et al. (2021), and Brodny and Tutak (2022) consider the role of determinants of energy efficiency for the household and industrial sectors. Understanding the impact of local characteristics on inefficient energy consumption is likely to provide valuable information to regional policymakers. Local governments interested in reducing GHG emissions may then develop regional policies that are more compatible with a decarbonized society, such as promoting competitive markets. Specifically, providing more knowledge to local governments could reduce overall energy policy costs.

Section 2 describes our methodology for analyzing the industrial sector's electricity consumption efficiency. This section presents the empirical model and the data used in the analyses. In Section 3, we evaluate the efficiency of electricity consumption and analyze its efficiency in the region. Finally, Section 4 presents our conclusions, policy implications, and future directions based on our findings.

2. Methodology and data

2.1. Empirical model

The theoretical foundation of SFA was developed by Meeusen and van den Broeck (1977) and Aigner et al. (1977). Based on this theoretical foundation, various SFA models have been proposed by other researchers to measure the efficiency of economic activities (Kumbhakar and Lovell, 2000). SFA models can be used to measure efficiency indicators specific to economic agents. Further, SFA can also be used to identify several factors that determine measured efficiency indicators. Furthermore, panel dataset use can take into account any unobserved heterogeneity.

Among the SFA models proposed by prior researchers, this study used the energy demand frontier model presented by Filippini and Hunt (2011, 2012). This model applies Battese and Coelli's (1995) SFA approach to the energy demand function. Traditional analytical SFA methods originally applied a two-stage approach to estimate the relationship between efficiency and its determinants. The frontier function was estimated in the first stage, with the efficiency values then being measured. In the second stage, a factor analysis was conducted on the efficiency values measured in the first stage. However, this two-stage approach does raise an inconsistency in the assumption of the error term between the first and second stages. Battese and Coelli's single-stage regression method solves this inconsistency problem caused by the assumption of the independence of inefficiencies.

First, we assumed that the following industrial electricity demand frontier function (Equation (1)) holds:

$$\ln E_{jt} = \alpha + \alpha_P \ln P_{jt} + \alpha_Y \ln Y_{jt} + \alpha_{CDD} \ln CDD_{jt} + \alpha_{HDD} \ln HDD_{jt} + v_{jt} + u_{jt}, \tag{1}$$

wherein j is the region ($j = 1, \ldots, J$); t is time ($t = 1, \ldots, T$); E is the electricity; P is the electricity price; Y is the production value; CDD and HDD are the cooling and heating degree days, respectively (representing temperature components); while α is an estimated parameter. The error term ($v_{jt} + u_{jt}$) consists of two parts: the random error term v_{jt} and the error term for inefficiency u_{jt}. A random error term v_{jt} with a distribution of $N(0, \sigma^2)$ is assumed to be independent of u_{jt} and all other explanatory variables. Further, u_{jt} is a non-negative random variable that is assumed to have a distribution of $N(\mu, \sigma_u^2)$.

Given equation (1), the efficiency of electricity consumption EF_{jt} was then estimated using the conditional expectation of the efficiency term $E(u_{jt} | v_{jt} + u_{jt})$ (Jondrow et al., 1982); that is, EF_{jt} is measured using the ratio of the estimated electricity demand frontier E_{jt}^F relative to the observed electricity consumption. In other words:

$$EF_{jt} \equiv E_{jt}^F \Big/ E_{jt} = e^{-u_{jt}}, 0 < EF_{jt} \leq 1.$$

In this study, the average inefficiency of electricity consumption μ was formulated in Equation (2) as follows:

$$\mu_{jt} = \beta_0 + \beta_{CDD} \ln CDD_{jt} + \beta_{HDD} \ln HDD_{jt} + \beta_{SCL} \ln SCL_{jt} + \beta_{PLT} \ln PLT_{jt} + \beta_{DS} \ln DS_{jt} + \beta_{CMP} \ln CMP_{jt}, \tag{2}$$

wherein β is the estimated parameter. If an element of the inefficiency term improves the overall efficiency, then β will be negative. Herein, we considered temperature factors, such as cooling degree days (*CDD*) and heating degree days (*HDD*), average establishment size (*SCL*), plant ratio (*PLT*), establishment density (*DS*), and market competitiveness (*CMP*) as factors that cause inefficiency in electricity consumption in the industrial sector.

Furthermore, factories and offices located in regions with harsh climates have relatively high heating and cooling demand. These heating and cooling demands primarily involve electric air conditioning. Thus, firms in regions with more severe climates are more likely to be incentivized to operate cost-effectively because they face the relatively high electricity costs associated with air conditioning. As such, firms in regions with more severe weather conditions are more likely to be incentivized to use electricity more efficiently and, hence, are more likely to be efficient in their electricity usage. In other words, regions with higher *CDD* and *HDD* tend to have higher efficiency. Hence, β_{CDD} and β_{HDD} values were expected to be negative therein.

Furthermore, larger establishments require more numerous and generally larger workspaces, reducing the frequency with which power is shared among their employees. For example, an organization with numerous employees per establishment would require larger offices with more compartments. Office automation equipment is then needed in proportion to the number of employees, which means that more electricity will be required. The introduction of electronic devices in proportion to the number of employees would also increase per-unit power demand, thus reducing the efficiency of their electricity consumption. In other words, the inefficiency of electricity consumption is higher in regions with larger average establishment sizes.

However, one recent study confirmed that workplace electrification could increase the efficiency of electricity consumption (Otsuka, 2018b). For example, introducing a Building and Energy Management System (BEMS) for commercial buildings can help to manage and reduce their energy consumption. Furthermore, a Factory Energy Management System (FEMS) could also make energy consumption more efficient by electrifying factories. The FEMS works with power generation, power storage, and energy-saving equipment to enable energy savings that could not otherwise be achieved in more traditional industries. As such, the FEMS is a method that can save energy in various ways. However, Kimura and Ofuji (2014) found that Japanese factories are not fully electrified and tend to have lower energy-saving rates than offices. Hence, regions in Japan with large numbers of factories may have higher electricity consumption inefficiencies than those with large concentrations of offices. If our assumptions are correct, both β_{SCL} and β_{PLT} will be positive.

The spatial agglomeration of firms also affects their electricity consumption efficiency. Spatial agglomeration has been described as an external economy in agglomeration economies (Marshall, 1890). An agglomeration economy refers to the cost savings and productivity gains from the spatial agglomeration of firms, the effects of which have been confirmed by several empirical studies (Combes and Gobillon, 2015; Otsuka, 2017b). This increase in productivity has been linked to improvements in energy efficiency; for example, Porter and Van der Linde (1995) outline how efforts to improve productivity throughout the production process, under appropriate environmental regulations, can increase energy use efficiency. Further, the studies by Boyd and Pang (2000) and Otsuka et al. (2014) show that energy efficiency guides productivity improvement. Based on these studies, areas with a higher business density may have higher productivity and lower electricity consumption inefficiencies. If our assumptions are correct, β_{DS} would then have a negative sign.

The spatial agglomeration of industries contributes not only to the productivity of firms but also to the region's competitiveness. As the scale of production in a region expands due to industrial agglomeration, a new regional market is created where related firms can locate. The location of new service industries targeting the local market allows firms to strengthen the efficient division of labor. This strategy not only increases the cost competitiveness of firms in the agglomeration but also creates a base for multiple firms to locate in various industrial sectors, resulting in increased competition within the region. This intra-regional competitive pressure incentivizes firms to operate more efficiently, reduce production costs, and engage in innovation activities. Therefore, firms within competitive markets are often more cost-conscious and are, thus, incentivized to use electricity more efficiently. As such, firms in areas involving more competitive markets are likely to be more efficient in electricity consumption. The relative number of firms can then be used to measure whether a regional market is competitive or monopolistic (Glaeser et al., 1992). The measure of the competitiveness of a regional market, *CMP*, is defined using the following equation:

$$CMP_j \equiv \frac{N_j/L_j}{\sum_j N_j / \sum_j L_j},$$

wherein N_j is the number of establishments in region j, while L_j is the number of employees in region j. When this indicator exceeds 1, the ratio of the number of establishments to the region's size, as measured by the number of employees, is relatively high compared with the national average, implying that this particular regional market is competitive. If our assumptions are correct, we would expect β_{CMP} to be negative.

2.2. Data

This study analyzes industrial electricity consumption using regional panel data from ten electric power companies from 1990 to 2015. Fig. 1 shows the electricity supply regions in Japan that were used in this analysis.

The primary data sources comprised the "Electricity Utilities Handbook" of Japan's Ministry of Economy, Trade, and Industry and the "Social and Demographic Statistics System" of the Ministry of Internal Affairs and Communications.

Industrial electricity consumption (E) is derived from the "Electricity Utilities Handbook data." This value is obtained by dividing the amount of electricity consumption by the number of establishments listed in the Economic Census (Ministry of Internal Affairs and Communications). The electricity price (P) is then the total unit price. The total unit price is obtained by dividing the number of electricity sales stated in the annual securities reports of electric power companies by the amount of electricity consumption. This value is then deflated using the corporate goods price index published by the Bank of Japan. Production value (Y) is the real gross prefectural product per establishment. *CDDs* and *HDDs* are derived from data from prefectural capitals and weather stations. *CDDs* are the sum of the difference between the average temperature on days when the temperature exceeds 24 °C and 22 °C. *HDDs* are determined as the sum of the difference between the average temperature on days when the temperature is below 14 °C and 14 °C. The establishment size (*SCL*) is the number of employees divided by the number of establishments. The plant ratio (*PLT*) is the ratio of the number of plants to the number of establishments. The density of establishments (*DS*) is the ratio of the number of establishments to the total inhabitable land area. Finally, we calculated *CMP* based on the abovementioned indices. These data are calculated based on data from the "Social and Demographic Statistics System."

Table 1 presents the descriptive statistics of the study data. Electricity consumption per establishment consistently increased from the

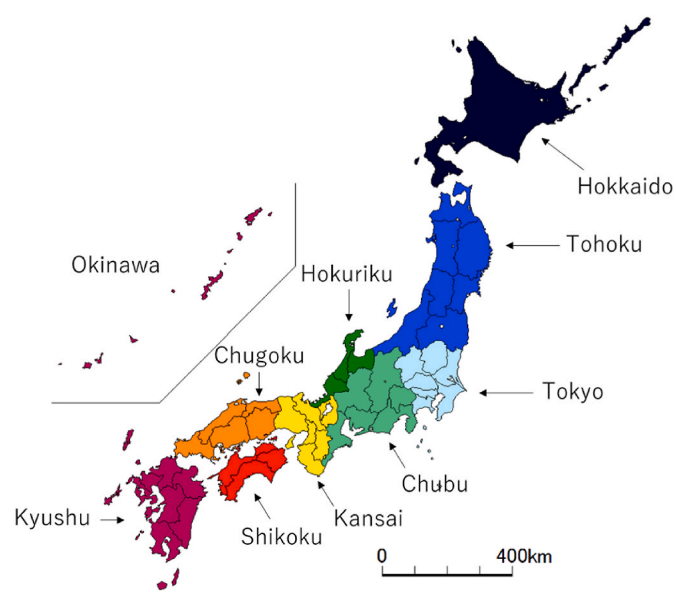

Fig. 1. Regional classification of Japan's power supply
Note: The regional classification is structured as follows: Hokkaido (Hokkaido); Tohoku (Aomori, Iwate, Miyagi, Akita, Yamagata, Fukushima, and Niigata); Tokyo (Saitama, Chiba, Tokyo, Kanagawa, Ibaraki, Tochigi, Gunma, and Yamanashi); Hokuriku (Toyama, 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 1
Descriptive statistics.

		Electricity consumption per business establishment	Electricity price for industry	Real gross regional product per business establishment	Cooling degree days	Heating degree days	Average scale of business establishment	Plant ratio	The density of business establishments	Competition index
		(kWh)	(2010 = 100)	(Million JPY)			(Labor per establishment)	(%)	(Establishment per km^2)	
		E	*P*	*Y*	*CDD*	*HDD*	*SCL*	*PLT*	*DS*	*CMP*
Mean	1990–2000	71,671	120	3.76	400	1042	8.58	5.33	61.82	0.94
Standard Deviation	1990–2000	15,610	9	0.78	246	615	0.93	1.82	34.89	0.10
Maximum	1990–2000	97,514	140	5.16	1190	2687	10.56	9.01	140.40	1.13
Minimum	1990–2000	40,688	102	2.30	5	0	6.46	1.91	12.74	0.73
Mean	2000–2010	90,926	106	3.30	429	1041	9.19	4.25	55.65	0.93
Standard Deviation	2000–2010	16,658	6	0.64	248	622	0.94	1.36	30.74	0.09
Maximum	2000–2010	121,533	122	4.41	1021	2707	11.79	7.37	126.33	1.13
Minimum	2000–2010	43,165	96	2.18	0	0	6.57	1.83	11.50	0.73
Mean	2010–2015	94,471	114	2.92	457	1081	9.92	3.54	52.50	0.93
Standard Deviation	2010–2015	15,614	12	0.56	231	626	0.94	1.07	29.66	0.09
Maximum	2010–2015	120,309	143	3.84	994	2613	12.41	5.69	115.04	1.14
Minimum	2010–2015	64,650	100	2.10	40	1	8.40	1.73	10.93	0.80
Mean	1990–2015	84,338	113	3.39	424	1051	9.12	4.50	57.30	0.93
Standard Deviation	1990–2015	18,901	11	0.75	243	618	1.07	1.66	32.27	0.09
Maximum	1990–2015	121,533	143	5.16	1190	2707	12.41	9.01	140.40	1.14
Minimum	1990–2015	40,688	96	2.10	0	0	6.46	1.73	10.93	0.73

1990s to the 2010s. Further, the standard deviation barely changed during this observation period, with the overall power demand increasing nationwide.

Electricity prices, the key explanatory variable for the electricity consumption function, declined significantly from the 1990s to the 2000s. Subsequently, electricity prices increased slightly from the 2000s to the 2010s. Furthermore, the production scale of firms consistently increased from the 1990s to the 2010s. This continuous increase in the scale of firms' production is likely to have impacted the observed increase in electricity consumption. The *CDD* demonstrated an upward trend throughout the observation period, while the *HDD* revealed no significant changes.

Establishment size, the explanatory variable for the electricity consumption efficiency function, consistently increased throughout the observation period, meaning that the number of employees per establishment increased. Such an increase in employees requires a larger workspace, likely increasing electricity waste. The factory ratio declined consistently throughout the observation period. Further, many domestic factories transferred to overseas production sites during this period. The density of business establishments also consistently declined throughout the observation period. Accelerated decentralization of business locations may have hindered the efficient use of electricity. Finally, the competitiveness index changed little throughout the observation period.

It should be noted that two structural changes occurred in Japan's electricity supply system during the observation period. One was the deregulation of the electricity supply system. In postwar Japan, each electric power company had a monopoly on supplying power to its area; however, after 2000, electricity deregulation began, targeting the industrial sector. Large factories, department stores, and office buildings that use high-voltage electricity could then freely choose where to purchase their electricity from among existing power companies. Furthermore, electricity could also be purchased by power companies entering the electricity market. In 2016, the electricity market was fully liberalized, eliminating the voltage categories subject to deregulation. As a result, the initial regional monopoly of electric power companies was dissolved. This study examined whether this liberalization had any structural impact on firms' electricity consumption (i.e., the efficiency of electricity use since 2001, when the full liberalization of the electricity market began). It needs to be noted that electricity prices were on a downward trend from 2000 until the Great East Japan Earthquake in 2011. This trend was due to competition in the electricity market and lower fuel costs.

The second structural change in Japan's electricity supply involves alterations in the national energy policy following the Great East Japan Earthquake that occurred in Tohoku in 2011. This disaster increased the unit cost of electricity generation, leading to higher electricity prices. The Great East Japan Earthquake also halted the operation of nuclear power generation, which was replaced with thermal power (IEE, 2013; Otsuka, 2019, 2023a). As a result, there were significant constraints on the electricity supply, with energy conservation being promoted nationwide. Japan's Basic Energy Plan was also revised to address global warming, with the Japanese government building an electricity supply system centered on renewable energy sources. This study also examined whether these energy policy changes affected the efficiency of electricity consumption in the industrial sector.

3. Results and discussion

3.1. Estimation results

Model A in Table 2 shows Equations (1) and (2) estimation results. The value for the electricity price was negative, while that for the production value was positive, which is consistent with economic theory. Because electricity is a necessary good, price and production elasticity should be small, according to economic theory. The values in this Table show that both price and production elasticities were less than 1,

Table 2
Estimation results for the electricity demand frontier function.

	Estimation for 1990–2015		Robustness estimation for 1990–2010	
	(A)		(B)	
Frontier function				
Constant (α_0)	10.220	**	10.239	**
	(0.313)		(0.509)	
α_P	−0.621	**	−0.723	**
	(0.052)		(0.081)	
α_Y	0.559	**	0.589	**
	(0.030)		(0.038)	
α_{CDD}	0.191	**	0.217	**
	(0.008)		(0.019)	
α_{HDD}	0.075	**	0.101	**
	(0.004)		(0.008)	
Inefficiency function				
Constant (β_0)	−3.241	**	−2.995	**
	(0.177)		(0.354)	
β_{CDD}	−0.165	**	−0.207	**
	(0.007)		(0.019)	
β_{HDD}	−0.077	**	−0.118	**
	(0.005)		(0.012)	
β_{SCL}	1.904	**	1.986	**
	(0.071)		(0.171)	
β_{PLT}	0.432	**	0.500	**
	(0.019)		(0.043)	
β_{DS}	−0.054	**	−0.068	**
	(0.014)		(0.032)	
β_{CMP}	−2.324	**	−2.636	**
	(0.106)		(0.196)	
σ^2	0.005	**	0.005	**
	(0.000)		(0.000)	
γ	0.045	**	0.166	**
	(0.003)		(0.047)	
Log-likelihood	325.47		271.85	
Observations	260		210	

Notes: 1) ** and * indicate significance at the 1% and 5% levels, respectively.
2) The values in parentheses indicate standard errors.
3) The software used for the estimation was Frontier 4.1 (Coelli, 1996).

which is also consistent with economic theory. The values for the *CDD* and *HDD* were both positive. This finding means that electricity consumption was higher for heating and cooling applications in factories and offices in cold and warm regions.

Further, the regression coefficient for the *CDD* exceeded that for the *HDD*. Cooling demand primarily revolves around electric air conditioners. In contrast, heating demand is often met by electricity-based devices like air conditioners and devices that use other fuels, such as gas and oil. Therefore, the impact of *CDD* on electricity consumption exceeded that of *HDD*.

Next, we evaluated the estimation results on the inefficiency term. The sigma and gamma values were statistically significant, with the estimation results being stable. First, the *CDD* and *HDD* had negative and statistically significant values. Warm and cold regions have a high demand for heating and cooling systems, which will likely be a cost burden for the affected firms. Therefore, firms in these regions may be more cost-conscious and have a higher incentive to use electricity more efficiently.

The business establishment size and factory ratio values were positive and statistically significant. The larger the number of employees in a factory or office, the larger the workspace required. Because larger workspaces require larger air-conditioning equipment, there is a high probability that their electricity use will be increasingly wasteful. Furthermore, as mentioned earlier, a prior Japanese study reported that factories have lower electricity-saving rates than offices (Kimura and Ofuji, 2014). Therefore, if there are more factories in a given location than offices, there is likely to be a higher wastage of electricity.

The value for establishment density was both negative and statistically significant. Office buildings in Japan have well-developed BEMS; thus, increasing their business density leads to more efficient electricity use. In factories, the efficient production of electricity from waste heat is also increasing among industrial complexes and factory parks. Therefore, the more geographically concentrated a production site becomes, its electricity use might be cost-saving and enhance productivity.

Finally, the value for the competitiveness index was negative and statistically significant. Increased competition in local markets increases the cost consciousness of economic agents and provides incentives to use electricity more efficiently. In other words, firms in highly competitive regions tend to use electricity more efficiently. Further, the competitiveness index has the most significant impact on the efficient use of electricity because of the magnitude of its regression coefficient. Creating an environment conducive to market competition thus maximizes efficient energy use.

These results satisfied all the assumed sign conditions. To check their robustness, we limited the estimation period and evaluated the stability of these results. Model B (Table 2) presents these findings. In Japan, the Great East Japan Earthquake of 2011 changed the composition of power sources and caused electricity prices to soar nationwide. Therefore, we set the estimation period from 1990 to 2010 (i.e., the period before the earthquake) to determine whether there was a significant difference in the estimated parameters. The analysis confirmed no significant differences in the estimated parameters, even when the estimation period was shortened. In other words, our estimation results were both stable and reliable.

3.2. Evaluation of structural changes

We also evaluated possible structural changes affecting the efficiency of industrial electricity consumption. First, we examined whether the retail electricity deregulation implemented in 2000 affected firms' electricity-saving behaviors. Deregulating the retail electricity market has led to intense competition among electric power companies. Using a dummy variable, we evaluated whether firms' electricity consumption was affected by the increased competition among electric power companies. Model C (Table 3) presents these results. The dummy variable was set to 1 for 2001–2015 (i.e., since the deregulation of electricity) and was set to 0 for all other years. If the dummy variable is statistically significant, then electricity deregulation will be shown to affect firms' electricity-saving behaviors. This analysis revealed that the dummy variable β_{dummy_0115} was both positive and statistically significant. In other words, it appeared that the deregulation of retail electricity did not improve firms' economic behavior in terms of their electricity consumption but rather reduced their overall efficiency. Since electricity prices continued to decline from 2000 until the advent of the Great East Japan Earthquake, this decline can be associated with government policy changes that likely increased firms' electricity consumption inefficiency.

Next, we examined the possibility that the Great East Japan Earthquake affected firms' electricity-saving behaviors using dummy variables. Model D in Table 3 shows these results. The effects of the Great East Japan Earthquake were immediately apparent; thus, the dummy variable was set to 1 for 2011–2015 and 0 for all other years. If the dummy variable is statistically significant, this will indicate that the Great East Japan Earthquake affected firms' electricity-saving behaviors. The results showed that the null hypothesis that the regression coefficient would be zero could be rejected as the value on the parameter of the dummy variable β_{dummy_1115} was negative. This finding indicated that the earthquake had a structural effect on the efficiency of electricity consumption. After the Great East Japan Earthquake, Japanese firms faced increased power-saving needs due to the resulting electricity shortage. The results of this study are thus consistent with these experiences.

Table 3
Test results for the structural changes in electricity consumption efficiency.

	Test for structural changes from 2001		Test for structural changes from 2011	
	(C)		(D)	
Frontier function				
Constant (α_0)	10.012	**	10.018	**
	(0.397)		(0.299)	
α_P	−0.510	**	−0.551	**
	(0.073)		(0.055)	
α_Y	0.571	**	0.553	**
	(0.034)		(0.027)	
α_{CDD}	0.159	**	0.183	**
	(0.017)		(0.020)	
α_{HDD}	0.045	**	0.061	**
	(0.008)		(0.004)	
Inefficiency function				
Constant (β_0)	−2.158	**	−3.484	**
	(0.279)		(0.217)	
β_{CDD}	−0.134	**	−0.148	**
	(0.021)		(0.022)	
β_{HDD}	−0.045	**	−0.063	**
	(0.009)		(0.004)	
β_{SCL}	1.191	**	1.956	**
	(0.138)		(0.115)	
β_{PLT}	0.441	**	0.407	**
	(0.027)		(0.021)	
β_{DS}	−0.041	**	−0.049	**
	(0.018)		(0.013)	
β_{CMP}	−1.755	**	−2.301	**
	(0.153)		(0.112)	
β_{dummy_0115}	0.143	**		
	(0.016)			
β_{dummy_1115}			−0.041	**
			(0.016)	
σ^2	0.006	**	0.005	**
	(0.000)		(0.000)	
γ	0.088	**	0.014	**
	(0.027)		(0.004)	
Log-likelihood	320.27		323.42	
Observations	260		260	

Notes: 1) ** and * indicate significance at the 1% and 5% levels, respectively.
2) The values in parentheses indicate standard errors.
3) The software used for the estimation was Frontier 4.1 (Coelli, 1996).

Table 4
Regional average of the electricity consumption efficiency levels.

	Mean level for the entire sample period	Mean level for the 1990s	Mean level for the 2000s	Mean level for the 2010s
Hokkaido	0.755	0.795	0.692	0.792
Tohoku	0.774	0.793	0.759	0.768
Tokyo	0.995	0.993	0.996	0.997
Chubu	0.852	0.871	0.857	0.811
Hokuriku	0.782	0.797	0.788	0.746
Kansai	0.964	0.982	0.970	0.925
Chugoku	0.955	0.984	0.963	0.894
Shikoku	0.943	0.965	0.958	0.884
Kyushu	0.990	0.998	0.995	0.968
Okinawa	0.927	0.969	0.939	0.835

Note: The regional classification is structured 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).

3.3. Efficiency evaluations by region

Furthermore, we evaluated the efficiency level of each region in Japan and explored their electricity-saving potential. Table 4 presents the estimated efficiency values for each region. The regions with the highest power efficiency included Tokyo, Kansai, Chugoku, Shikoku, Kyushu, and Okinawa. Each region's value was close to 1, indicating a high efficiency in electricity use. Tokyo and Kansai are large metropolitan areas with relatively high competitiveness indices. Chugoku, Shikoku, Kyushu, and Okinawa have smaller average establishment sizes and lower factory ratios. Hence, their efficiency values were high. These regions were thus sufficiently efficient in electricity consumption, with the potential for further power savings likely to be insignificant.

Conversely, the values for Hokkaido, Tohoku, and Hokuriku deviated significantly from 1, indicating a low efficiency in electricity use. The density of business establishments in these regions was found to be remarkably low. Thus, this low density and the dispersed location of factories in these regions are likely to explain the low efficiency of electricity use. Therefore, it is likely that these regions could increase their efficiency by encouraging a concentration of business establishments. As such, these areas have a sizeable power-saving potential.

The time-series changes in the estimated efficiency values showed that these values declined in numerous regions from the 1990s to the 2010s. As shown in Table 5, the factory ratio declined nationwide during the observation period as companies moved their factories overseas. Specifically, the factory ratio declined in Tokyo and Chubu, which may have resulted in a higher office demand for electricity and higher electricity use efficiency. Furthermore, during this period, the decentralized location of business offices increased, which may have worsened efficiency. Furthermore, since the competitiveness index was higher in Tokyo and showed an upward trend, market competition in Tokyo was likely to have increased the efficiency of electricity use in that region.

3.4. Discussion

In this discussion, we evaluate the results of the analysis of this study in comparison with the results of previous studies. Otsuka (2023b) applied SFA to the residential sector in Japan to evaluate the efficiency of electricity consumption in the residential sector. The same analysis period as this study was employed, and efficiency was evaluated based on data from electric power companies. Policymakers can obtain valuable suggestions by comparing the results obtained concerning the industrial sector in this study with those concerning the residential sector in previous studies.

However, the results obtained for the industrial and residential sectors have similarities and differences. The common finding was that cooling demand affects the efficiency of electricity consumption. In both sectors, an increase in cooling demand increased the efficiency of electricity consumption. In warmer climates, the cost-consciousness of economic agents is more likely to be activated because electricity costs rise when cooling demand increases. In other words, a high number of CDDs provides an incentive for the efficient use of electricity.

However, the impact of heating demand on the efficiency of electricity consumption differed between the industrial and residential sectors. In cold regions, kerosene and gas are available as substitutes for electricity. In other words, when alternative energy sources exist to power heating demand and their use weights are high, an increase in heating demand does not necessarily lead to electricity-conserving behavior by economic agents. In this sense, it can be inferred that the industrial sector is less likely to generate substitution effects than the residential sector because of the higher weight of electricity used for heating purposes.

Furthermore, a common feature in both sectors is that efficiency deteriorated in many regions during the 1990s and 2000s. This period was a period of continuous decline in electricity prices. Therefore, it is highly likely that the decline in electricity prices reduced cost-

Table 5
Regional average of determinant variables for electricity consumption efficiency.

	Average scale of business establishment (SCL)		Plant ratio (PLT)		The density of business establishment (DS)		Competition index (CMP)	
	Mean level for the entire sample period	Δ (2015–1990)	Mean level for the entire sample period	Δ (2015–1990)	Mean level for the entire sample period	Δ (2015–1990)	Mean level for the entire sample period	Δ (2015–1990)
Hokkaido	9.57	1.09	2.91	−1.12	12.2	−2.42	0.982	−0.070
Tohoku	8.78	1.41	4.64	−2.12	25.5	−5.49	0.901	−0.026
Tokyo	11.01	2.05	4.51	−3.41	100.2	−9.74	1.128	0.000
Chubu	9.65	1.87	6.85	−3.80	68.3	−11.65	0.988	0.005
Hokuriku	8.62	1.68	6.31	−2.72	43.5	−10.41	0.883	0.006
Kansai	9.62	1.74	5.54	−3.43	124.2	−28.40	0.985	−0.004
Chugoku	9.22	1.46	4.56	−2.18	46.7	−9.30	0.945	−0.028
Shikoku	8.22	1.67	4.44	−2.33	46.3	−11.34	0.842	0.014
Kyushu	8.96	1.81	3.35	−1.23	42.9	−6.53	0.917	0.015
Okinawa	7.55	2.38	1.91	−0.28	63.2	−5.29	0.772	0.097

Note: The regional classification is structured 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).

consciousness about electricity use and diminished the power-saving awareness of economic agents. In contrast, some regions showed efficiency improvements from the 2000s to the 2010s, when electricity prices rose sharply. It is highly likely that the rise in electricity prices increased the cost-consciousness of economic agents and encouraged them to become more efficient in their electricity use.

Finally, a significant difference between the two sectors was found with regard to the impact of the change in Japan's energy policy following the Great East Japan Earthquake in 2011 on electricity consumption behavior. Otsuka (2023b) shows that, in the residential sector, the energy policy shift had no statistically significant impact on the efficiency concerning electricity consumption, which indicated that no structural change had occurred in the efficiency concerning electricity consumption in the residential sector during the observation period. In contrast, in the industrial sector analyzed in this study, it was found that the energy policy shift significantly impacted the electricity consumption behavior of economic agents, with increased efficiency concerning electricity consumption in the industrial sector.

4. Conclusion and policy implications

Improving energy efficiency is an international policy priority to prevent global warming. A vital step in optimally reducing energy consumption is identifying the energy-saving potential across different societal sectors and the best strategies to increase their overall efficiency. Therefore, this study analyzed the potential for energy saving by identifying the degree of inefficiency in electricity use in the industrial sector and its determinants. Specifically, we used SFA to estimate the electricity demand frontier function and related inefficiency from a regional science perspective. Based on these methods, the following results were obtained.

First, we found that local climatic conditions negatively impact electricity consumption inefficiency. The demand for air conditioning is high in regions with a more severe climate. Therefore, the cost of electricity consumption for air conditioning is higher in these regions, with firms being incentivized to behave in a cost-saving manner. Thus, in regions with a harsher climate, electricity consumption inefficiencies are likely lower, and electricity use is less wasteful.

Second, we found that the average establishment size positively affected electricity consumption inefficiency. Firms with more employees per establishment require more workspaces and electronic devices to accommodate their increased number of employees. Increasing the number of office rooms and using individual office automation devices means fewer opportunities for employees to share power, which generates increased wastage in power use. Hence, policies focusing on improving energy efficiency in large establishments are needed.

Third, we found that the ratio of factories in a region positively affected the inefficiency of its electricity consumption. Factories in Japan are relatively less electrified than offices. Therefore, if a region has numerous factories that are not electrified, energy is not likely to be used efficiently.

Fourth, establishment density was found to affect electricity consumption inefficiency negatively. The spatial concentration of establishments increases their productivity via agglomeration economies. This finding accords with previous studies showing that increased productivity is associated with increased energy efficiency, which suggests that encouraging firm agglomeration is an effective means of improving energy efficiency.

Fifth, we found that the competitive nature of the local market negatively affects electricity consumption inefficiency. When competition is more active in a given local market, local firms are incentivized to behave more cost-effectively. Firms will use electricity more efficiently, resulting in less waste. Therefore, promoting competition in local markets and increasing firms' cost consciousness are effective policy measures for increasing energy efficiency.

Furthermore, this study analyzed whether changes in Japan's national energy policy affected electricity consumption efficiency. The results showed that changes in energy policy following the Great East Japan Earthquake improved the efficiency of electricity consumption. The Great East Japan Earthquake led to the shutdown of most of Japan's nuclear power generation, resulting in a sharp increase in electricity prices. Furthermore, this revised energy policy then set the direction for renewable energy to be the primary source of electricity in Japan, with electricity prices likely to continue to rise in the future. These changes in the national energy policy may make firms more cost-conscious and less wasteful in their electricity use.

The results of this study can be used to improve the cost-effectiveness of regional policies aimed at increasing energy efficiency. Specifically, the findings guide local governments in creating an external environment that stimulates firms' cost consciousness to increase electricity consumption efficiency.

This study has some limitations. First, this study only used a single-method analysis and regional aggregate data. To further verify this study's conclusions, additional assessment is needed using multiple analyses, which could be undertaken using two possible approaches. One approach could be a non-parametric approach using DEA; however, as noted, there is an issue concerning the non-consideration of statistical noise, although several methods have been proposed to resolve this issue (Olesen and Petersen, 2016). Another approach could be to use micro-data based on macro data. A more detailed analysis of firm characteristics obtained from macro data could help verify the validity of the analytical results. However, data availability constraints remain an issue in effectively addressing this limitation.

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Compliance with ethical standards

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

References

Aigner, D.J., Lovell, C.A.K., Schmidt, P., 1977. Formulation and estimation of stochastic frontier production function models. J. Econ. 6, 21–37.
Alberini, A., Filippini, M., 2018. Transient and persistent energy efficiency in the US residential sector: evidence from household-level data. Energy Eff. 11, 589–601.
Allcott, H., Greenstone, M., 2012. Is there an energy efficiency gap? J. Econ. Perspect. 26, 3–28.
Andor, M.A., Bernstein, D.H., Sommer, S., 2021. Determining the efficiency of residential electricity consumption. Empir. Econ. 60, 2897–2923.
Andor, M.A., Hesse, F., 2014. The StoNED age: the departure into a new era of efficiency analysis? A Monte Carlo comparison of StoNED and the "oldies" (SFA and DEA). J. Prod. Anal. 41, 85–109.
Andor, M.A., Parmeter, C., Sommer, S., 2019. Combining uncertainty with uncertainty to get certainty? Efficiency analysis for regulation purposes. Eur. J. Oper. Res. 274, 240–252.
Battese, G.E., Coelli, T.J., 1995. A model for technical inefficiency effects in a stochastic frontier production function for panel data. Empir. Econ. 20, 325–332.
Blasch, J., Boogen, N., Filippini, M., Kumar, N., 2017. Explaining electricity demand and the role of energy and investment literacy on end-use efficiency of Swiss households. Energy Econ. 68, 89–102.
Boogen, N., 2017. Estimating the potential for electricity savings in households. Energy Econ. 63, 288–300.
Borozan, D., 2018. Technical and total factor energy efficiency of European regions: a two-stage approach. Energy 152, 521–532.
Boyd, G.A., 2008. Estimating plant level energy efficiency with a stochastic frontier. Energy J. 29, 23–43.
Boyd, G.A., Pang, J.X., 2000. Estimating the linkage between energy efficiency and productivity. Energy Pol. 28, 289–296.
Broadstock, D.C., Li, J., Zhang, D., 2016. Efficiency snakes and energy ladders: a (meta-) frontier demand analysis of electricity consumption efficiency in Chinese households. Energy Pol. 91, 383–396.
Brodny, J., Tutak, M., 2022. Analysis of the efficiency and structure of energy consumption in the industrial sector in the European Union countries between 1995 and 2019. Sci. Total Environ. 808, 152052.
Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision making units. Eur. J. Oper. Res. 2, 429–444.
Coelli, T.J., 1996. A Guide to Frontier, Version 4.1: A Computer Program for Stochastic Frontier Production and Cost Function Estimation. CEPA Working Papers No. 96/07. University of New England, Australia, NSW.
Combes, P.P., Gobillon, L., 2015. The empirics of agglomeration economies. In: Duranton, G., Henderson, J.V., Strange, W. (Eds.), Handbook of Regional and Urban Economics, Volume 5a. Elsevier, Amsterdam, pp. 247–348.
Evans, J., Filippini, M., Hunt, L.C., 2013. The Contribution of Energy Efficiency towards Meeting CO2 Targets. Edward Elgar Publishing, Cheltenham, Handbook on energy and climate change.
Filippini, M., Hunt, L.C., 2011. Energy demand and energy efficiency in the OECD Countries: a stochastic demand frontier approach. Energy J. 32, 59–79.
Filippini, M., Hunt, L.C., 2012. US residential energy demand and energy efficiency: a stochastic demand frontier approach. Energy Econ. 34, 1484–1491.
Filippini, M., Hunt, L.C., Zorić, J., 2014. Impact of energy policy instruments on the estimated level of underlying energy efficiency in the EU residential sector. Energy Pol. 69, 73–81.
Filippini, M., Zhang, L., 2016. Estimation of the energy efficiency in Chinese provinces. Energy Eff. 9, 1315–1328.
Gillingham, K., Keyes, A., Palmer, K., 2018. Advances in evaluating energy efficiency policies and programs. Annu. Rev. Resour. Econ. 10, 511–532.
Glaeser, E.L., Kallal, H.D., Scheinkman, J.A., Shleifer, A., 1992. Growth in cities. J. Polit. Econ. 100, 1126–1152.
Honma, S., Hu, J.L., 2014. Industry-level total-factor energy efficiency in developed countries: a Japan-centered analysis. Appl. Energy 119, 67–78.
IEA, 2020. World Energy Outlook 2020. International Energy Agency, Paris.
IEE, 2013. Energy Policy in Japan: Challenges after Fukushima (access 20220720). https://eneken.ieej.or.jp/data/4700.pdf.
Jondrow, J., Lovell, K., , C.A., Materov, I.S., Schmidt, P., 1982. On the estimation of technical inefficiency in the stochastic frontier production function model. J. Econ. 19, 233–238.
Kimura, O., Ofuji, K., 2014. 2014. Persistency of electricity savings in commercial and industrial sectors after the great East Japan earthquake Update. CRIEPI (Cent. Res. Inst. Electr. Power Ind.) Rep. Y14013 (in Japanese).
Kumbhakar, S.C., Lovell, C.A.K., 2000. Stochastic Frontier Analysis. Cambridge University Press, Cambridge.
Lin, B., Du, K., 2013. Technology gap and China's regional energy efficiency: a parametric metafrontier approach. Energy Econ. 40, 529–536.
Lin, B., Du, K., 2014. Measuring energy efficiency under heterogeneous technologies using a latent class stochastic frontier approach: an application to Chinese energy economy. Energy 76, 884–890.
Lin, B., Du, K., 2015. Modeling the dynamics of carbon emission performance in China: a parametric Malmquist index approach. Energy Econ. 49, 550–557.
Malinauskaite, J., Jouhara, H., Egilegor, B., Al-Mansour, F., Ahmad, L., Pusnik, M., 2020. Energy efficiency in the industrial sector in the EU, Slovenia, and Spain. Energy 208, 118398.
Marshall, A., 1890. Principles of Economics. MacMillan, London.
Meeusen, W., van den Broeck, J., 1977. Efficiency estimation from Cobb-Douglas production functions with composed error. Int. Econ. Rev. 18, 435–444.
METI, 2021. Outline of Strategic Energy Plan. Agency for Natural Resources and Energy (access 20220720). https://www.enecho.meti.go.jp/en/category/others/basic_plan/pdf/6th_outline.pdf.
Olesen, O.B., Petersen, N.C., 2016. Stochastic data envelopment analysis - a review. Eur. J. Oper. Res. 251, 2–21.
Orea, L., Llorca, M., Filippini, M., 2015. A new approach to measuring the rebound effect associated to energy efficiency improvements: an application to the US residential energy demand. Energy Econ. 49, 599–609.
Otsuka, A., 2017a. Regional Energy Demand and Energy Efficiency in Japan. Springer, Switzerland.
Otsuka, A., 2017b. A New Perspective on Agglomeration Economies in Japan. Springer, Singapore.
Otsuka, A., 2018a. Regional determinants of energy efficiency: residential energy demand in Japan. Energies 11, 1557.
Otsuka, A., 2018b. Determinants of energy demand efficiency: evidence from Japan's industrial sector. In: Intech Open. Energy Policy. https://doi.org/10.5772/intechopen.81482.
Otsuka, A., 2019. Natural disasters and electricity consumption behavior: a case study of the 2011 Great East Japan Earthquake. Asia-Pac. J. Reg. Sci. 3, 887–910.
Otsuka, A., 2020. How do population agglomeration and interregional networks improve energy efficiency? Asia-Pac. J. Reg. Sci. 4, 1–25.
Otsuka, A., 2023a. Lessons from regional electricity demand change following natural disasters in Japan. Reg. Sci. Pol. Pract. https://doi.org/10.1111/rsp3.12631.
Otsuka, A., 2023b. Stochastic demand frontier analysis of residential electricity demands in Japan. Asia-Pac J. Reg. Sci. 7, 179–195.
Otsuka, A., Goto, M., 2015. Estimation and determinants of energy efficiency in Japanese regional economies. Reg. Sci. Pol. Pract. 7, 89–101.
Otsuka, A., Goto, M., Sueyoshi, T., 2014. Energy efficiency and agglomeration economies: the case of Japanese manufacturing industries. Reg. Sci. Pol. Pract. 6, 195–212.
Parmeter, C.F., Zelenyuk, V., 2019. Combining the virtues of stochastic frontier and data envelopment analysis. Oper. Res. 67, 1628–1658.
Porter, M.E., Van der Linde, C., 1995. Toward a new conception of the environment-competitiveness relationship. J. Econ. Perspect. 9, 97–118.
Stern, D.I., 2012. Modeling international trends in energy efficiency. Energy Econ. 34, 2200–2208.
Wei, C., Ni, J., Shen, M., 2009. Empirical analysis of provincial energy efficiency in China. China World Econ. 17, 88–103.
Weyman-Jones, T., Boucinha, J.M., Inácio, C.F., 2015. Measuring electric energy efficiency in Portuguese households: a tool for energy policy. Manag. Environ. Qual. 26, 407–422.
Zhou, P., Ang, B.W., Zhou, D.Q., 2012. Measuring economy-wide energy efficiency performance: a parametric frontier approach. Appl. Energy 90, 196–200.