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Evaluation of environmental energy efficiency and its influencing factors: a prefecture-level analysis of Japanese manufacturing industries

Masayuki Shimizu¹ and Oscar Tiku^{2*}

*Correspondence:
otiku@tmu.ac.jp

¹ Faculty of Global and Regional Studies, University of the Ryukyus, 1 Senbaru, Nishihara-cho, Nakagami-gun, Okinawa 903-0213, Japan

² Graduate School of Urban Environmental Sciences, Tokyo Metropolitan University, 1-1 Minami-Osawa, Hachioji-shi, Tokyo 192-0397, Japan

Abstract

This study evaluates the progress of efficient energy use and the control of carbon dioxide (CO₂) emissions in Japan between 1990 and 2012. A new indicator of energy performance is presented called environmental energy efficiency (EEE). The EEE of manufacturing industries was measured by each prefecture in Japan. We estimated the influencing factors of EEE for each industry by applying the pooled mean group (PMG) method. Our findings are as follows: First, the Japanese manufacturing industry has not been in line with the EEE improvement goals since the adoption of the Kyoto Protocol. However, the progress of each industry was relatively consistent by region. Second, EEE tends to improve and then deteriorate or monotonically increase as economic development progresses. Third, EEE is raised by expanding industry share. Finally, EEE, which focuses on energy reduction, is likely to increase with the progress of energy-saving technology.

Keywords: Cleaner production, Data envelopment analysis, Environmental energy efficiency, Manufacturing industry, Pooled mean group

JEL Classification: C33, Q43, Q48, R11

1 Introduction

Since the adoption of the Kyoto Protocol in 1997, Japan has promoted efforts to reduce greenhouse gas emissions to mitigate global warming. The Protocol imposed an obligation on Japan to reduce greenhouse gas emissions by 6% by 2012 compared to its 1990 level. This reduction target, however, was not achieved by that deadline. Energy-related carbon dioxide (CO₂) emissions increased from 1068 million tons in 1990 to 1227 million tons in 2012, and the manufacturing sector, which is the main source of emissions, accounted for 25–33% of these emissions during this period.¹

¹ The unit of emissions is CO₂ equivalent. The manufacturing sector does not include the energy industries, such as oil refinery. We obtained CO₂ emissions and calculated the manufacturing share using the data provided by the Greenhouse Gas Inventory Office of Japan, National Institute for Environmental Studies (<https://www.nies.go.jp/gio/en/about/ghg/index.html>).

Cooperation with manufacturing companies is indispensable to cut CO₂ emissions, and environmental operations are inevitable because they are expected to address the issue of global warming as part of their corporate social responsibility (Managi and Kuriyama 2017, pp. 164–170).

Introducing cleaner production approaches can help decrease CO₂ emissions. Cleaner production aims to reduce the burden on the environment in all production processes, from the input of raw materials to the output and disposal of products (Managi and Kuriyama 2017, pp. 206–207). Since the enforcement of the Protocol, the approach has become more widespread in Japanese firms. As a result, manufacturing companies may have promoted a review of energy use, such as using clean energy, adopting energy-saving technology, and recycling energy.

Companies have an inherent incentive to improve energy performance, which is defined as energy use per unit of production, even in a situation that has not introduced cleaner production approaches. This is because it has the potential to reduce production costs through energy savings. However, in a situation where cleaner production is required to reduce CO₂ emissions, energy performance may not improve as expected immediately. This is due to the possibility that all production methods are reviewed considering long-term investments. Ideally, it is desirable for the companies that energy use remains the most efficient in either situation, considering it with and without pollution abatement.

The first objective of our study is to apply a new indicator of energy performance, considering the aforementioned situations in subnational (prefectural) scope. We refer to this new indicator as environmental energy efficiency (EEE), which has been employed at a multinational but regional level to date (Zhou and Ang 2008; Rakshit and Mandal 2020). Besides, our EEE takes a ratio to create an EEE index; this is different from previous studies. This indicator is an application of environmental efficiency proposed by Färe et al. (1996) and Kumar and Khanna (2009), which is measured by data envelopment analysis (DEA) using a distance function approach. For the period between 1990 and 2012, which was the framework for the Kyoto Protocol, we evaluate whether efficient use of energy and CO₂ emissions control has progressed by measuring the EEE of each prefecture in Japan. We focus on measuring the EEE of manufacturing industries because they are the main sources of CO₂ emissions. This study extracts seven industries from the manufacturing sector, in addition to the entire manufacturing industry, and provides policymakers with detailed information about industry-wise trends of energy performance in Japan.

Further, it is necessary to analyze the influencing factors of EEE to derive useful policy guidelines. The second objective of our study is to estimate EEE factors using a panel data analysis for the period of 1990–2012. We demonstrate that there is a significant relationship between EEE and three factors: economic development, industrial structure, and technological progress. This study investigates the influencing factors using a pooled mean group (PMG) estimator based on the autoregressive distributed lag (ARDL) approach of Pesaran et al. (1999) while simultaneously considering the

problems of cross-sectional dependence, unit roots, and cointegration in the panels. We ultimately propose appropriate environmental energy strategies for policymakers.

The remainder of this paper is organized as follows. “[Literature review](#)” Section presents a brief literature review and the contributions of our study. “[Measuring environmental energy efficiency](#)” Section provides the measurement method of EEE, including the data used and the measurement results. “[Panel data analysis](#)” Section explains our panel data models, applied panel data, and reports the estimation results. “[Conclusion](#)” Section summarizes our empirical results and suggests directions for environmental energy policies in Japan.

2 Literature review

Energy input plays a pivotal role in the production of products. However, it generates undesirable byproducts, such as greenhouse gas emissions, which raises environmental concerns. The concept of energy efficiency is associated with controlling the adverse environmental effect and has become increasingly crucial. It refers to the minimized use of energy in the production process without compromising the same level of output.

The DEA method has been increasingly used in the past decades to investigate the nexus of environment and energy efficiency (Mardani et al. 2017). The DEA models primarily apply radial or non-radial measures, while our EEE is constructed using the radial model. Previous studies on environment and energy efficiency included a wide range of analysis targets from a multi-country perspective as examples of radial measures (Zhou and Ang 2008; Rakshit and Mandal 2020). Most empirical studies were focused on China (Wu et al. 2012) and India (Mandal 2010) because they are the world’s top energy consumers and CO₂ emitters among developing countries. However, other prior studies focus on Japan (Sueyoshi and Goto 2011; Fukuyama et al. 2020). We examine the empirical results of previous studies based on the radial model that serve as benchmarks for this study.

In previous research targeting Japan, the topic of energy efficiency has been researched sequentially since Hu and Wang (2006) proposed the index of total-factor energy efficiency (TFEE) using a DEA. Honma and Hu (2008) divide energy input into 11 sources between 1993 and 2003 in earlier applications of the region-wise TFEE assessment by Japanese prefectures. They found that, unlike most efficient inland and coastal (along the Sea of Japan) regions, Niigata and other prefectures (especially Chiba, Wakayama, and Yamaguchi) located in the Pacific Belt Zone, where energy-intensive industries have developed, were less energy efficient in the use of heavy oil and coal.

Moreover, Honma and Hu (2014b, 2018) supported these results. They estimated the effects of manufacturing share on the TFEE using panel data of the Japanese prefecture from 1996–2008.² The results showed that increased shares of the manufacturing industry (especially energy-intensive industry) are associated with a decline in energy efficiency.

² Their TFEE were mainly measured by stochastic frontier analysis (SFA) using a parametric approach.

Additionally, the sector-wise TFEE in the period of 1998–2005 was examined by the work of Honma and Hu (2013). In the Japanese manufacturing sector, they confirmed that as opposed to machinery industries (i.e., general, electric, and transportation machinery), energy-intensive industries (i.e., pulp and paper, chemical, cement and ceramics, and primary metal) have worse inefficiency on energy use in all studied years. However, according to Honma and Hu (2014a), whose study measured the country-wise TFEE for seven industries comparing Japan and another 13 developed countries in the period of 1995–2005, the results indicated that the industrial energy efficiency of Japan is at a higher level among developed countries through international comparison.

Honma and Hu have mainly focused on energy efficiency, not simultaneously accounting for environmental efficiency, which measures how much pollution emissions can be reduced in a production process. Although several prior studies investigated environmental efficiency in Japanese prefectures, such as Honma and Hu (2009) and Eguchi (2017), energy input was not incorporated into their DEA applications. Consequently, this study has three differences or contributions compared to previous studies. First, the current study proposes the EEE indicator, which simultaneously accounts for energy and environmental efficiency. Second, the study focuses on the manufacturing sector, including its seven subsectors, in Japanese prefectures. Third, it investigates the influencing factors of EEE in each industry using a PMG method. Thus, our study applies prefecture- and industry-level data in the Japanese manufacturing sector, where the level of industrial development differs among prefectures, and scrutinizes the movements of environmental energy performance in Japan.

3 Measuring environmental energy efficiency

3.1 Methodology and data

To present EEE, this study uses environmental or regulated technology, which is assumed for the joint production of desirable and undesirable outputs, and traditional or unregulated technology without simultaneously accounting for undesirable outputs (Färe et al. 2007). In the regulated technology, three inputs, including labor (l), capital stock (k), and energy (e), are used for producing the added value (y), which is a desirable output, while CO_2 (c) is an undesirable output. The unregulated technology does not consider CO_2 emissions in our approach. The regulated technology can then be represented as follows:

$$T = \{(l, k, e, y, c) : (l, k, e) \text{ can produce } (y, c)\} \quad (1)$$

The technology that handles finite inputs and outputs is assumed to satisfy the standard properties: T is compact, while inputs and desirable outputs are strongly or freely disposable, as described by Färe and Grosskopf (2003). To show that it is a regulated technology, T is assumed to incorporate two additional conditions: null-jointness and weak disposability of outputs. Null-jointness is expressed as follows:

$$\text{if } (l, k, e, y, c) \in T \text{ and } c = 0 \text{ then } y = 0 \quad (2)$$

This means that CO_2 is emitted to generate an added value. The weak disposability of the outputs is as follows:

$$\text{if } (l, k, e, y, c) \in T \text{ and } 0 \leq \varphi \leq 1 \text{ then } (l, k, e, \varphi y, \varphi c) \in T \tag{3}$$

This implies that if CO₂ emissions are reduced at the rate of φ , the added value simultaneously decreases at the same rate when the inputs are kept constant.³ This assumes that it is necessary to continue to divert some of the inputs in order to continuously reduce undesirable outputs, resulting in a proportionate decrease in desirable outputs under a given production technology. This assumption is introduced by Färe et al. (1989) and shows that it is usually necessary to incur regulatory costs to control emissions. However, the unregulated technology does not incorporate CO₂ emissions in T and is represented as follows:

$$\widehat{T} = \{(l, k, e, y) : (l, k, e) \text{ can produce } y\} \tag{4}$$

\widehat{T} assumes free disposability of undesirable outputs; that is, there is no regulatory cost to control CO₂ emissions.

Let $i = (1, \dots, I)$ index be represented by the observations of inputs and outputs, $(l_i, k_i, e_i, y_i, c_i)$ for $i = 1, \dots, I$; the regulated DEA technology of T consists of the following:

$$T = \{(l, k, e, y, c) : \sum_{i=1}^I z_i y_i \geq y, \sum_{i=1}^I z_i c_i = c, \sum_{i=1}^I z_i l_i \leq l, \sum_{i=1}^I z_i k_i \leq k, \sum_{i=1}^I z_i e_i \leq e, \sum_{i=1}^I z_i = 1, z_i \geq 0, i = 1, \dots, I\} \tag{5}$$

In Eq. (5), the second constraint sets strict equality and imposes weak disposability on the undesirable output. Null-jointness is assumed to satisfy the condition $\sum_{i=1}^I c_i > 0$. z_i as an intensity variable, while the sixth constraint is assumed to impose variable returns to scale (VRS) on the technology. The unregulated DEA technology of \widehat{T} is established by excluding CO₂ emissions and dropping the second constraint in Eq. (5).

In this study, we propose two types of EEE by applying a distance function approach. To derive the first EEE, this study adopts the input distance function, accounting for both the reduction of energy use and CO₂ emissions, which applies Tyteca’s (1997) input-undesirable output model.⁴ The input distance function is defined as follows:

$$D_c(l, k, e, y, c) = \sup\{\beta : (l, k, e/\beta, y, c/\beta) \in T\} \tag{6}$$

This distance function is a modification of the Shephard carbon distance function defined by Zhou et al. (2010).⁵ The value of β indicates how much energy use and CO₂ emissions can be simultaneously reduced. We assume that the input distance function is separable in desirable and undesirable outputs, following Kumar and Khanna (2009).⁶ Equation (6) can be rewritten as:

³ This is a standard approach that imposes on technology, which clarifies the relationship between desirable and undesirable outputs. See Fig. 1 and the description on page 163 in Färe et al. (1996).

⁴ The model of Tyteca (1997) is simultaneously considered for the reduction of all inputs and undesirable outputs.

⁵ The distance function of Zhou et al. (2010) focuses only on reducing CO₂ emissions.

⁶ It is adopted in this study for the assumption of separability because its effectiveness is recognized in Färe et al. (1995). However, Kumar and Khanna (2009) employed the directional output distance function, which is simultaneously accounted for the increase in GDP and the reduction in CO₂ emissions.

$$D_c(l, k, e, y, c) = C(c)\widehat{D}_c(l, k, e, y) \tag{7}$$

where

$$\widehat{D}_c(l, k, e, y) = \sup\{\lambda : (l, k, e/\lambda, y) \in \widehat{T}\} \tag{8}$$

Equation (8) is the energy-oriented input distance function without considering CO₂ emissions. The value of λ indicates the extent to which energy use can be reduced, not considering CO₂ emissions.

However, this study also presents the second EEE using the input distance function, which only accounts for the reduction in energy use. The input distance function is defined as follows:

$$D_e(l, k, e, y, c) = \sup\{\theta : (l, k, e/\theta, y, c) \in T\} \tag{9}$$

This distance function is the Shephard energy distance function defined by Wu et al. (2012). The value of θ indicates the extent to which energy use can be reduced, considering CO₂ emissions. Based on Färe et al. (1996), we can assume that the input distance function is separable in desirable and undesirable outputs.⁷ Equation (9) can be rewritten as:

$$D_e(l, k, e, y, c) = C(c)\widehat{D}_e(l, k, e, y) \tag{10}$$

where $\widehat{D}_e(l, k, e, y) = \widehat{D}_c(l, k, e, y)$.

According to Färe et al. (1996) and Kumar and Khanna (2009), Eqs. (7) and (10) are decomposed into the terms that reveal the impact of CO₂ emissions, $C(c)$, and the term that captures the effect of energy efficiency, $\widehat{D}_c(l, k, e, y)$ and $\widehat{D}_e(l, k, e, y)$. Consequently, EEE1 and EEE2 were obtained as follows:

$$EEE1 = C(c) = \frac{D_c(l, k, e, y, c)}{\widehat{D}(l, k, e, y)} \tag{11}$$

and

$$EEE2 = C(c) = \frac{D_e(l, k, e, y, c)}{\widehat{D}(l, k, e, y)} \tag{12}$$

where $\widehat{D}(l, k, e, y) = \widehat{D}_c(l, k, e, y) = \widehat{D}_e(l, k, e, y)$. If the EEE1 and EEE2 equal 1, it can be concluded that the observation is considered environmentally energy efficient. However, if the EEE1 and EEE2 is less than 1, the observation is regarded as environmentally energy inefficient in this study.

As three input distance functions need to be computed, this study solves the following linear programming problems:

⁷ See Note 5 for the separability assumption. However, the distance function of Färe et al. (1996) is considered for the reduction of all inputs.

$$\begin{aligned}
 & [D_c(l'_i, k'_i, e'_i, y'_i, c'_i)]^{-1} = \min \beta \\
 \text{s.t. } & \sum_{i=1}^I z_i y_i \geq y'_i \\
 & \sum_{i=1}^I z_i c_i = \beta c'_i \\
 & \sum_{i=1}^I z_i l_i \leq l'_i \\
 & \sum_{i=1}^I z_i k_i \leq k'_i \\
 & \sum_{i=1}^I z_i e_i \leq \beta e'_i \\
 & \sum_{i=1}^I z_i = 1 \\
 & z_i \geq 0, i = 1, \dots, I
 \end{aligned}
 \tag{13}$$

$$\begin{aligned}
 & [D_e(l'_i, k'_i, e'_i, y'_i, c'_i)]^{-1} = \min \theta \\
 \text{s.t. } & \sum_{i=1}^I z_i y_i \geq y'_i \\
 & \sum_{i=1}^I z_i c_i = c'_i \\
 & \sum_{i=1}^I z_i l_i \leq l'_i \\
 & \sum_{i=1}^I z_i k_i \leq k'_i \\
 & \sum_{i=1}^I z_i e_i \leq \theta e'_i \\
 & \sum_{i=1}^I z_i = 1 \\
 & z_i \geq 0, i = 1, \dots, I
 \end{aligned}
 \tag{14}$$

$$\begin{aligned}
& \left[\widehat{D}(l'_i, k'_i, e'_i, y_i) \right]^{-1} = \min \lambda \\
& \text{s.t. } \sum_{i=1}^I z_i y_i \geq y'_i \\
& \quad \sum_{i=1}^I z_i l_i \leq l'_i \\
& \quad \sum_{i=1}^I z_i k_i \leq k'_i \\
& \quad \sum_{i=1}^I z_i e_i \leq \lambda e'_i \\
& \quad \sum_{i=1}^I z_i = 1 \\
& \quad z_i \geq 0, i = 1, \dots, I
\end{aligned} \tag{15}$$

To measure the EEE, this study uses one desirable and undesirable output each, and three inputs in the Japanese manufacturing industry covering 47 prefectures from 1990 to 2012. This study extracts seven industries from the manufacturing sector: (1) food, beverages, and tobacco; (2) textile; (3) pulp and paper; (4) chemical, oil, and coal; (5) ceramic, stone, and clay; (6) iron and steel; and (7) machinery, while simultaneously analyzing the manufacturing industry as a whole. Thus, because our study applies prefecture- and industry-level data in the Japanese manufacturing sector with a focus on energy use, we selected variables for which data can be obtained consistently. The variables used in this study are as follows:

- Desirable output: real added value (y).
- Undesirable output: CO₂ emissions (c).
- Inputs: employed people (l), real capital stock (k), and energy use (e).⁸

Real added value, employed people, and real capital stock are sourced from the Regional-Level Japan Industrial Productivity (R-JIP) Database 2017.⁹ The data on CO₂ emissions and energy use were sourced from the Energy Consumption Statistics by Prefecture (ECSP).¹⁰ This study uses CO₂ emitted from the combustion of fossil fuels (coal, coal products, oil, oil products, natural gas, and town gas), excluding non-energy utilization, while energy use is based on total energy consumption.¹¹ Finally, for the above

⁸ We only selected energy use as the intermediate goods data because other data have rarely been included in previous studies and are difficult to obtain at the prefecture- and industry-level in the Japanese manufacturing sector.

⁹ The R-JIP 2017 is provided by the Research Institute of Economy, Trade and Industry (RIETI) in Japan (<https://www.rieti.go.jp/jp/database/R-JIP2017/index.html>). The unit of added value and capital stock are million yen at 2000 constant prices.

¹⁰ The ECSP is provided by Agency for Natural Resources and Energy in Japan (https://www.enecho.meti.go.jp/statistics/energy_consumption/ec002/).

¹¹ Since the ECSP is available for the data of the carbon unit, we obtain CO₂ emissions by multiplying carbon output by 44/12, which is the ratio of molecular weight CO₂ to atomic weight of carbon. The unit of CO₂ emissions and energy use are thousand tons of CO₂ equivalent and terajoule, respectively.

Table 1 Summary statistics of variables

Variables	Units	Mean	Median	Maximum	Minimum	Std. dev
Food, beverages, and tobacco						
Real added value (y)	Million yen (2000 prices)	332314	212359	1278313	25831	284742
CO ₂ emissions (c)	Thousand tons of CO ₂ equivalent	568	366	2068	60	466
Employed people (l)	People	31453	22192	121441	5852	24502
Real capital stock (k)	Million yen (2000 prices)	372827	231899	1305731	28347	318060
Energy consumption (e)	Terajoule	11333	7052	41814	1303	9549
Textile						
Real added value (y)	Million yen (2000 prices)	63905	37304	617463	1943	77630
CO ₂ emissions (c)	Thousand tons of CO ₂ equivalent	232	56	2086	3	373
Employed people (l)	People	19650	13537	148538	983	20548
Real capital stock (k)	Million yen (2000 prices)	154139	94663	1210220	3123	176079
Energy consumption (e)	Terajoule	3922	1130	31522	44	5710
Pulp and paper						
Real added value (y)	Million yen (2000 prices)	59981	32758	360166	− 1727	69733
CO ₂ emissions (c)	Thousand tons of CO ₂ equivalent	575	198	5762	2	1055
Employed people (l)	People	6810	4046	42291	388	7845
Real capital stock (k)	Million yen (2000 prices)	141531	73247	945025	2874	163386
Energy consumption (e)	Terajoule	12800	5501	93408	37	20170
Chemical, oil, and coal						
Real added value (y)	Million yen (2000 prices)	292767	141987	2185619	1396	404161
CO ₂ emissions (c)	Thousand tons of CO ₂ equivalent	1917	480	18667	1	3289
Employed people (l)	People	10810	5714	102438	207	15603
Real capital stock (k)	Million yen (2000 prices)	604649	317784	3525714	2552	712295
Energy consumption (e)	Terajoule	81467	11043	977492	79	160293
Ceramic, stone, and clay						
Real added value (y)	Million yen (2000 prices)	74901	48263	457617	1036	71782
CO ₂ emissions (c)	Thousand tons of CO ₂ equivalent	842	333	10334	5	1341
Employed people (l)	People	9318	6425	61756	502	8712
Real capital stock (k)	Million yen (2000 prices)	126777	85970	616370	9249	115114
Energy consumption (e)	Terajoule	12278	4412	125699	68	17528
Iron and steel						
Real added value (y)	Million yen (2000 prices)	235456	132046	1533589	9837	275306
CO ₂ emissions (c)	Thousand tons of CO ₂ equivalent	3636	368	26,694	5	6553
Employed people (l)	People	32590	18042	217713	2496	37726
Real capital stock (k)	Million yen (2000 prices)	713576	356811	3637058	20743	849554
Energy consumption (e)	Terajoule	49672	8413	346362	88	82447
Machinery						
Real added value (y)	Million yen (2000 prices)	1184930	654098	11356088	1628	1506677
CO ₂ emissions (c)	Thousand tons of CO ₂ equivalent	341	206	3121	0	449
Employed people (l)	People	102478	55467	600038	819	118072
Real capital stock (k)	Million yen (2000 prices)	2033531	1151843	17620662	4018	2589019
Energy consumption (e)	Terajoule	11984	7891	107622	3	13465
Manufacturing						
Real added value (y)	Million yen (2000 prices)	2557873	1728268	15588344	188825	2641022

Table 1 (continued)

Variables	Units	Mean	Median	Maximum	Minimum	Std. dev
CO ₂ emissions (c)	Thousand tons of CO ₂ equivalent	8327	3405	46,151	343	9788
Employed people (l)	People	263881	162009	1711006	26901	274299
Real capital stock (k)	Million yen (2000 prices)	4671860	3198756	28087757	266401	4726436
Energy consumption (e)	Terajoule	189580	71222	1358883	11283	239233

seven manufacturing industries, we selected them by extracting only those industries for which data can be obtained consistently from the R-JIP 2017 and the ECSP.¹² The summary statistics for variables are shown in Table 1.

3.2 Measuring results

Figure 1 shows the changes in EEE1 and EEE2 for the manufacturing sector in 1990–2012, where the scores of EEE1 are significantly higher than those of EEE2 (EEE1 > EEE2). Thus, incorporating CO₂ emission reduction with energy use reduction such as of EEE1 yields a higher index than its EEE2 counterpart which only considers the reduction of energy use. Moreover, the results of EEE2 clearly show that the EEE had shifted from an upward to a downward trend since the end of the 1990s, especially following the Asian Crisis (1997–1998) and the Financial Crisis (2007–2008). In particular, the EEE plunged after 2008, owing to declining added value and subsequent energy efficiency. This phenomenon was observed not only in Japan but also in other high-income countries (Rakshit and Mandal 2020).

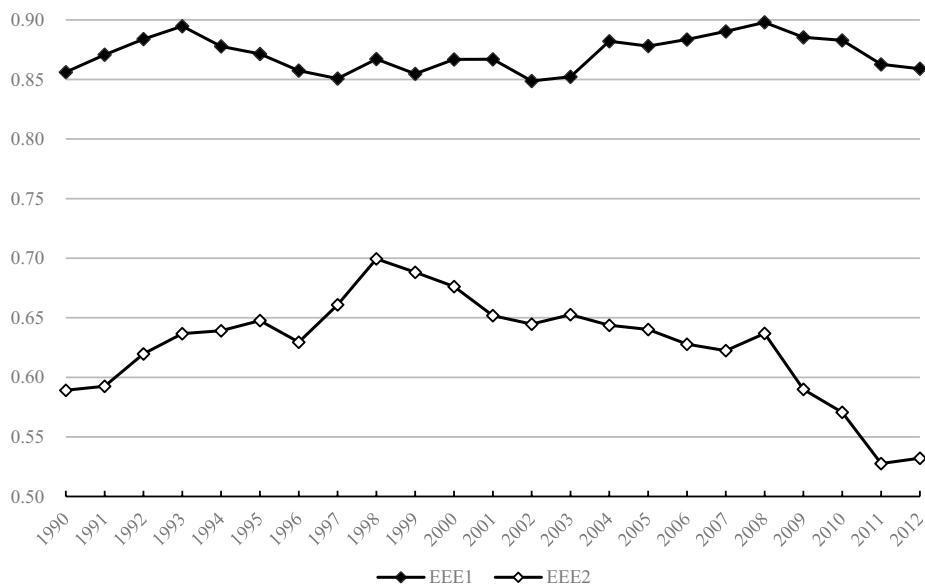


Fig. 1 Changes in EEE1 and EEE2 for the manufacturing sector (1990–2012). The values in the figure are the arithmetic mean based on the measurement results by prefecture

¹² In this study, we categorized the industries based on the SNA (System of National Accounts) classification.

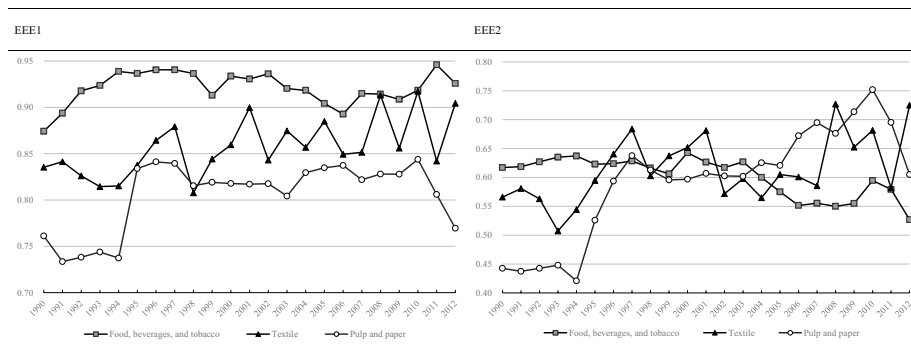


Fig. 2 Changes in EEE1 and EEE2 by light industry (1990–2012). The values in the figure are the arithmetic mean of each industry based on the measurement results by prefecture

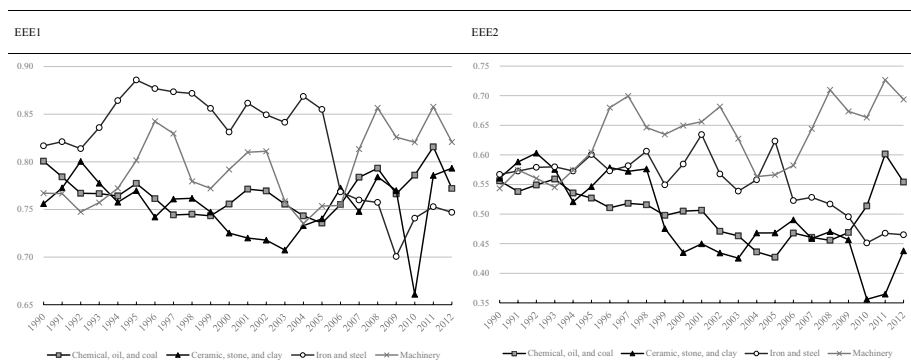


Fig. 3 Changes in EEE1 and EEE2 by heavy industry (1990–2012). The values in the figure are the arithmetic mean of each industry based on the measurement results by prefecture

Figure 2 shows the changes in EEE1 and EEE2 by light industry. Considering the EEE1 measurement for the light industry between 1990 and 2012, higher scores are observed in “food, beverages, and tobacco” followed by “textile” and “pulp and paper” consecutively, whose annual trends are almost strictly untangled. In the industry of “pulp and paper,” a noteworthy improvement was discovered between 1994 and 1995, while a notable decline occurred between 2010 and 2012. Meanwhile, in the EEE2 measurement, annual trends between 1990 and 2012 for “textile” and “pulp and paper” showed a tendency of improvement albeit inconsistent, where its conspicuous advancement is observed between 1993 and 1997, and 1994 and 1997, respectively. However, a decline occurred in “pulp and paper” between 2010 and 2012. In the industry of “food, beverages, and tobacco,” despite relative stability in the studied period, its score was gradually reduced between 1990 and 2012. Therefore, these results indicate that the light industry had failed to improve the EEE continuously since the end of the 1990s.

Figure 3 shows the changes in EEE1 and EEE2 by heavy industry, which have a fluctuating trend than light industries. Although the scores of “iron and steel” were higher

among others between 1990 and 2005, they had reduced significantly since the late 2000s. This downtrend had also occurred with “ceramic, stone, and clay” at the end of the 2000s, which was the rock-bottom for the whole heavy industry. Meanwhile, “machinery” had led as the best frontier. Likewise, an increasing trend was observed with “chemical, oil, and coal” since the late 2000s. Therefore, these results indicate that “ceramic, stone, and clay” and “iron and steel” had tended to deteriorate the EEE since the late 2000s albeit rather inconsistent for “ceramic, stone, and clay,” as opposed to “chemical, oil, and coal” and “machinery.” These results are consistent with the findings of a previous study that higher energy efficiency in machinery industries was also found by Honma and Hu (2013).

However, Table 2 shows the annual mean of EEE1 and EEE2 for the manufacturing sector by prefecture. The scores vary by prefecture, with ranges being 0.150–1.000 and 0.142–1.000, respectively. Regardless of the type of EEE, Tokyo, Aichi, and Okinawa lead as the frontier prefectures, whereas Hokkaido, Hiroshima, and Fukuoka are among the least efficient prefectures. In comparison to previous studies focusing on the results of EEE2, which is the indicator considered for energy reduction, Hokkaido is the prefecture with the lowest score, as well as Niigata, Ehime, and other prefectures located in the Pacific Belt Zone (i.e., Ibaraki, Okayama, Hiroshima, and Fukuoka) tend to be more inefficient. These results are consistent with the findings of Honma and Hu (2008, 2009) on the lowest environmental efficiency in Hokkaido and lower energy efficiency in some regions within Pacific Belt Zone.

Figures 4 and 5 show the annual mean of EEE1 and EEE2 in seven manufacturing industries by region. Compared to Figs. 4 and 5, the scores of EEE2 vary widely across regions than those of EEE1. To grasp trends between regions, focusing on the results of EEE1, the results present a significant variation in scores among industries in the Hokkaido and Tohoku, Chugoku and Shikoku, and Kyushu and Okinawa regions. Meanwhile, more efficient industries are comparatively concentrated in the Kanto, Chubu, and Kinki regions, which include a major metropolitan area. Therefore, intensive improvement in local regions might be essential.

4 Panel data analysis

4.1 Models and data

To investigate the influencing factors of EEE, this study estimates the following panel data models for EEE1 and EEE2:

[Model 1]

$$EEE1_{i,t} = \beta_1 GDPC_{i,t} + \beta_2 (GDPC_{i,t})^2 + \beta_3 IS_{i,t} + \beta_4 EI_{i,t} + \beta_5 \mu_t + \eta_i + \varepsilon_{i,t} \quad (16)$$

and

[Model 2]

$$EEE2_{i,t} = \beta_1 GDPC_{i,t} + \beta_2 IS_{i,t} + \beta_3 EI_{i,t} + \beta_4 \mu_t + \eta_i + \varepsilon_{i,t} \quad (17)$$

where the subscripts i and t represent the prefecture and year, respectively. The dependent variables EEE1 and EEE2 are measured in the previous section. For the explanatory

Table 2 Annual mean of EEE1 and EEE2 for the manufacturing sector by prefecture (1990–2012)

Prefecture	EEE1	EEE2
Hokkaido	0.653	0.142
Aomori	0.804	0.294
Iwate	0.705	0.423
Miyagi	0.932	0.344
Akita	0.857	0.780
Yamagata	0.981	0.797
Fukushima	0.773	0.583
Ibaraki	0.915	0.288
Tochigi	0.957	0.852
Gunma	0.964	0.769
Saitama	0.808	0.571
Chiba	0.957	0.674
Tokyo	1.000	1.000
Kanagawa	0.936	0.763
Niigata	0.811	0.284
Toyama	0.944	0.510
Ishikawa	0.936	0.802
Fukui	0.728	0.473
Yamanashi	0.987	0.945
Nagano	0.928	0.911
Gifu	0.889	0.437
Shizuoka	0.982	0.889
Aichi	1.000	1.000
Mie	0.763	0.503
Shiga	0.994	0.923
Kyoto	0.938	0.845
Osaka	0.726	0.493
Hyogo	0.554	0.501
Nara	0.998	0.998
Wakayama	0.908	0.443
Tottori	0.972	0.972
Shimane	0.966	0.954
Okayama	0.897	0.174
Hiroshima	0.150	0.150
Yamaguchi	0.937	0.622
Tokushima	0.971	0.778
Kagawa	0.893	0.441
Ehime	0.945	0.191
Kochi	0.772	0.772
Fukuoka	0.425	0.159
Saga	0.961	0.808
Nagasaki	0.984	0.952
Kumamoto	0.910	0.550
Oita	0.931	0.524
Miyazaki	0.962	0.383
Kagoshima	0.949	0.800
Okinawa	1.000	1.000

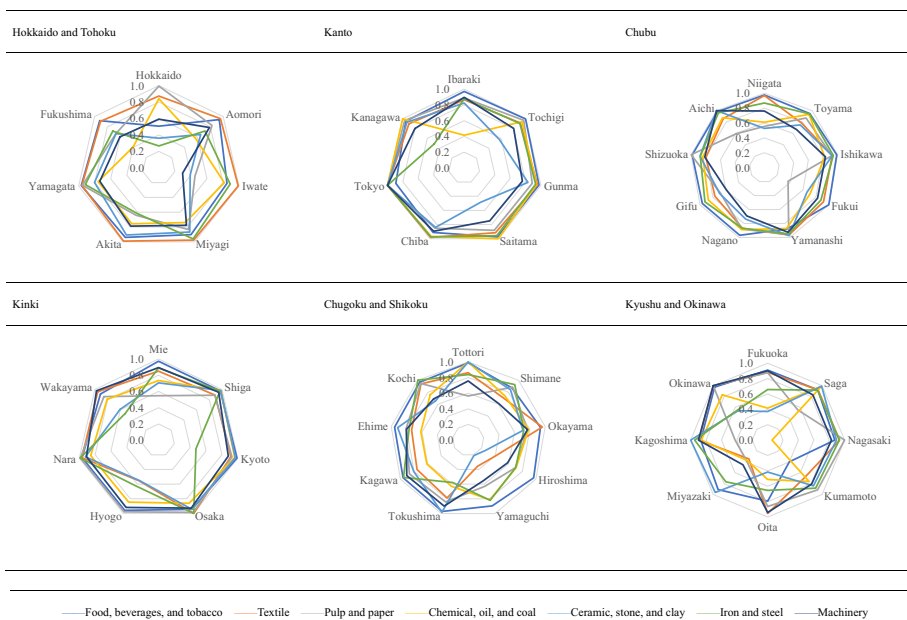


Fig. 4 Annual mean of the EEE in seven manufacturing industries by region (1990–2012). The regional classification is partially modified and integrated based on the Ministry of Economy, Trade and Industry (METI) of Japan

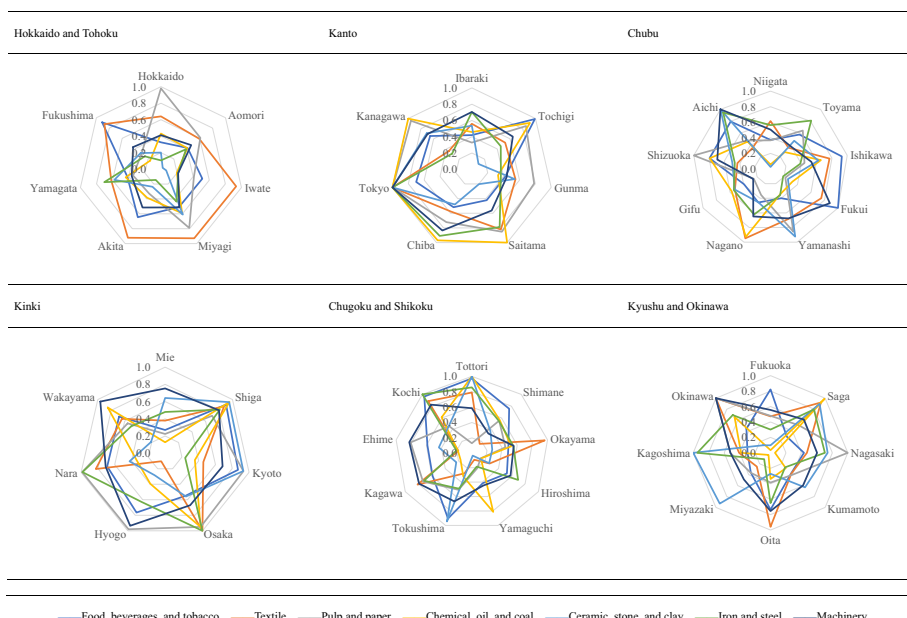


Fig. 5 Annual mean of the EEE in seven manufacturing industries by region (1990–2012). The regional classification is partially modified and integrated based on the Ministry of Economy, Trade and Industry (METI) of Japan

variables, *GDP* stands for gross domestic product (GDP) per capita, *IS* is the industry share, and *EI* is the energy intensity. η_i is the unobservable fixed effect by prefecture, μ_t is the linear trend showing a common time effect, and ε is an error term.

Following Kumar and Khanna (2009), who conducted a panel data analysis, our model includes the EEE factors associated with development level, industry structure, and technology progress. In this research, our panel data are constructed for each industry and analyzed empirically for the period 1990–2012.

GDP is the proxy for the level of economic development and is shown by the real GDP divided by population. Equation (16) shows a U-shaped relationship between *EEE1* and GDP per capita, which is intended to investigate the environmental Kuznets curve (EKC) hypothesis. This is because *EEE1* considers not only saving energy but also reducing CO₂. Therefore, the estimated parameters of the *GDP* are expected to satisfy $\beta_1 < 0$ and $\beta_2 > 0$. The turning point of GDP per capita was calculated as $(-\beta_1/2\beta_2)$. However, Eq. (17) examines if there is a linear relationship between *EEE2* and GDP per capita, and the estimated parameter is expected to be positive. This is because there is always an incentive to improve energy efficiency, and *EEE2* only focuses on saving energy without considering CO₂ reduction. Therefore, the model is not incorporated into testing the EKC hypothesis. The real GDP at 2000 constant prices (million yen) and the total population are sourced from the R-JIP 2017.

IS is the proxy for the change in industrial structure and is represented by the ratio of each industry to manufacturing total, which is calculated using the nominal added value.¹³ As industry share reflects the degree of industrial concentration, the EEE is expected to improve as its power increases. Thus, the estimated parameter of *IS* is expected to be positive. The nominal added value was sourced from the R-JIP 2017.

EI is a proxy for the progress of energy-saving technology and is used as energy intensity, which is measured by the total energy consumption divided by the real added value, for each industry. Given that the EEE is expected to improve as technology advances, the estimated parameter of *EI* is expected to be negative. The real added value at 2000 constant prices (million yen) and total energy consumption (terajoule) were sourced from the R-JIP 2017 and the ECSP, respectively. The descriptive statistics of variables are summarized in Table 3.

To examine the influencing factors, this study adopts the error correction model of the ARDL approach presented by Pesaran et al. (1999). There are three advantages to employing the model, considering the use of long-term panel data in our study. First, if there are data with unit roots, the long-term panel data are likely to be exposed to risk of non-stationary effects. However, the model can simultaneously incorporate stationary and non-stationary variables. Second, if the slope parameters are not homogeneous across cross-sectional units, slope heterogeneity could bias the estimation results (Pesaran and Smith 1995). However, this model allows parameter heterogeneity. Third, the model can be divided into a long-run effect and a short-run effect on the dependent variable. It is important to clarify the long-run relationship to provide policymakers with practical information.

In this study, our panel data models are estimated using the PMG estimator developed by Pesaran et al. (1999), which has been applied to empirical studies related to CO₂ emissions, such as Martínez-Zarzoso and Bengochea-Morancho (2004) and Iwata et al. (2011). The estimator assumes that the long-run coefficients are homogeneous across cross-sectional

¹³ When estimating a model for the entire manufacturing industry, the variable is measured by the ratio of nominal added value in the manufacturing sector to nominal GDP.

Table 3 Descriptive statistics of variables

Variables	Abbrev	Mean	Median	Maximum	Minimum	Std. dev
GDP per capita	GDPC	3.401368	3.289773	7.140661	2.149718	0.738384
Food, beverages, and tobacco						
Environmental energy efficiency	EEE1	0.920810	0.968887	1.000000	0.226224	0.135005
	EEE2	0.601457	0.532118	1.000000	0.173755	0.243965
Industry share	IS	0.172521	0.152269	0.502555	0.037058	0.091954
Energy intensity	EI	0.039409	0.038534	0.090207	0.010942	0.015266
Textile						
Environmental energy efficiency	EEE1	0.857266	0.939910	1.000000	0.010504	0.204961
	EEE2	0.615083	0.657794	1.000000	0.002600	0.338428
Industry share	IS	0.037548	0.025726	0.295093	0.002131	0.037052
Energy intensity	EI	0.074382	0.035895	1.108141	0.000979	0.113393
Pulp and paper						
Environmental energy efficiency	EEE1	0.805133	0.920144	1.000000	0.115519	0.229445
	EEE2	0.592195	0.563822	1.000000	0.020474	0.346233
Industry share	IS	0.032359	0.021934	0.233324	−0.007815	0.032804
Energy intensity	EI	0.244605	0.134847	13.62567	−6.084518	0.564507
Chemical, oil, and coal						
Environmental energy efficiency	EEE1	0.767697	0.831976	1.000000	0.026864	0.239972
	EEE2	0.506038	0.411533	1.000000	0.008014	0.365214
Industry share	IS	0.117862	0.080769	0.575739	0.005159	0.114533
Energy intensity	EI	0.217801	0.101229	2.143574	0.005064	0.288506
Ceramic, stone, and clay						
Environmental energy efficiency	EEE1	0.752341	0.832878	1.000000	0.011854	0.256517
	EEE2	0.491862	0.411994	1.000000	0.006638	0.355140
Industry share	IS	0.040689	0.033703	0.152767	0.003670	0.025904
Energy intensity	EI	0.165686	0.092359	1.983216	0.002552	0.218453
Iron and steel						
Environmental energy efficiency	EEE1	0.819577	0.921584	1.000000	0.010287	0.249648
	EEE2	0.553741	0.511257	1.000000	0.010287	0.351589
Industry share	IS	0.114141	0.093053	0.571246	0.014973	0.068371
Energy intensity	EI	0.173685	0.075748	2.228091	0.002938	0.232465
Machinery						
Environmental energy efficiency	EEE1	0.793271	0.834861	1.000000	0.057321	0.203275
	EEE2	0.630397	0.619217	1.000000	0.106591	0.252684
Industry share	IS	0.367686	0.372048	0.693636	0.007203	0.136465
Energy intensity	EI	0.014879	0.012336	0.336516	0.000417	0.016248
Manufacturing						
Environmental energy efficiency	EEE1	0.871366	0.943024	1.000000	0.077966	0.181047
	EEE2	0.626923	0.663879	1.000000	0.027070	0.316362
Industry share	IS	0.248252	0.248623	0.518462	0.054886	0.087724
Energy intensity	EI	0.082775	0.051131	0.414106	0.006202	0.080733

units, while the short-run coefficients are heterogeneous, as are the intercepts and the error correction coefficients. The PMG method is established by the ARDL approach, and Eqs. (16) and (17) are built into an ARDL (p, q) model as follows:

$$EEE_{i,t} = \sum_{j=1}^p \lambda_{i,j} EEE_{i,t-j} + \sum_{j=0}^q \delta'_{i,j} X_{i,t-j} + \gamma_i \mu_t + \eta_i + \varepsilon_{i,t} \tag{18}$$

where $X_{i,t}$ is the $K \times 1$ vector of explanatory variables, $\delta_{i,j}$ is the $K \times 1$ coefficient vector, $\lambda_{i,j}$ is the coefficient of the lagged dependent variables, and γ_i is the coefficient of the linear trend. Equation (18) can be rewritten as the following error correction model:

$$\begin{aligned} \Delta EEE_{i,t} = & \phi_i (EEE_{i,t-1} - \theta'_i X_{i,t}) + \sum_{j=1}^{p-1} \lambda_{ij}^* \Delta EEE_{i,t-j} \\ & + \sum_{j=0}^{q-1} \delta_{ij}^* \Delta X_{i,t-j} + \gamma_i \mu_t + \eta_i + \varepsilon_{i,t} \end{aligned} \tag{19}$$

where

$$\phi_i = - \left(1 - \sum_{j=1}^p \lambda_{i,j} \right),$$

$$\theta_i = - \frac{\sum_{j=0}^q \delta_{i,j}}{\phi_i},$$

$$\lambda_{i,j}^* = - \sum_{m=j+1}^p \lambda_{i,m},$$

$$\delta_{i,j}^* = - \sum_{m=j+1}^q \delta_{i,m}$$

In Eq. (19), the parenthesis is the error correction term, and ϕ_i is its coefficient, which is expected to be significantly negative to exist a long-run relationship. In the PMG estimation, the short-run coefficient vector is $\delta_{i,j}^*$. The long-run coefficient vector is θ_i , which is assumed to be homogeneous (that is, $\theta_i = \theta$ for all i) and is estimated using the maximum likelihood method (Pesaran et al. 1999).

This study uses the following four procedures to estimate the EEE factors.¹⁴ First, to examine the independence among cross-sectional units in the panels, the cross-section dependence (CD) tests are implemented by a variety of tests: the Lagrange multiplier (LM) test of Breusch and Pagan (1980), the scaled LM and CD tests of Pesaran (2004), and the bias-corrected scaled LM test of Baltagi et al. (2012). Second, if there is cross-sectional dependence, to investigate the stationarity of the panels, the panel unit root test is selected for the cross-sectionally augmented Im, Pesaran, and Shin (CIPS) test as done by Pesaran (2007). The CIPS panel unit root test can control the problem of cross-sectional dependence and then identify whether each variable is integrated with order zero or one, that is, $I(0)$ or $I(1)$. Third, if there are unit roots in the panels, the panel cointegration tests of Pedroni (1999, 2004) are conducted to confirm a cointegration relationship among the variables. Finally, the PMG estimation is carried out based

¹⁴ This study uses EViews 12 to carry forward the procedures.

Table 4 Cross-section dependence (CD) tests

Variables	Breusch-Pagan LM	Pesaran scaled LM	Bias-corrected scaled LM	Pesaran CD
GDPC	18389.50***	372.2473***	371.1791***	133.5894***
(GDPC) ²	18241.00***	369.0536***	367.9854***	133.0527***
Food, beverages, and tobacco				
EEE1	2197.673***	24.01586***	22.94767***	7.771195***
EEE2	6475.707***	116.0219***	114.9537***	12.48474***
IS	7431.661***	136.5813***	135.5131***	35.91282***
EI	6973.332***	126.7241***	125.6560***	25.01527***
Textile				
EEE1	2176.865***	23.56835***	22.50017***	6.903700***
EEE2	4172.194***	66.48113***	65.41295***	8.339922***
IS	20616.37***	420.1397***	419.0716***	136.3134***
EI	15420.77***	308.4001***	307.3319***	109.2848***
Pulp and paper				
EEE1	4003.710***	62.85761***	61.78943***	6.478504***
EEE2	3915.745***	60.96579***	59.89760***	23.17551***
IS	4069.906***	64.28127***	63.21309***	22.34278***
EI	4222.092***	67.55427***	66.48609***	8.143726***
Chemical, oil, and coal				
EEE1	2658.673***	33.93040***	32.86222***	0.945503
EEE2	3871.829***	60.02130***	58.95312***	13.73676***
IS	6639.121***	119.5364***	118.4682***	11.67073***
EI	4970.827***	83.65703***	82.58884***	5.456965***
Ceramic, stone, and clay				
EEE1	5275.150***	90.20198***	89.13380***	5.839171***
EEE2	3688.423***	56.07685***	55.00867***	25.32286***
IS	9095.209***	172.3585***	171.2904***	55.84299***
EI	5660.663***	98.49307***	97.42489***	11.66218***
Iron and steel				
EEE1	2961.432***	40.44174***	39.37356***	6.172025***
EEE2	3841.769***	59.37481***	58.30662***	1.358466
IS	5090.303***	86.22656***	85.15838***	28.29789***
EI	6670.311***	120.2072***	119.1390***	38.67571***
Machinery				
EEE1	3623.707***	54.68504***	53.61685***	9.014001***
EEE2	4221.871***	67.54952***	66.48134***	21.49952***
IS	7532.853***	138.7575***	137.6894***	41.93699***
EI	15417.91***	308.3384***	307.2703***	118.6359***
Manufacturing				
EEE1	2898.726***	39.09313***	38.02495***	3.117450***
EEE2	4979.578***	83.84523***	82.77705***	8.190819***
IS	9386.530***	178.6239***	177.5557***	75.65815***
EI	13290.18***	262.5782***	261.5100***	93.76585***

*** $p < 0.01$

Table 5 CIPS panel unit root tests

Variables	Levels		First differences		Order
	Constant	Constant and trend	Constant	Constant and trend	
GDP	-2.17864**	-2.40279	-	-	I(0)
(GDP) ²	-2.21616**	-2.42996	-	-	I(0)
Food, beverages, and tobacco					
EEE1	-2.29363***	-2.86753***	-	-	I(0)
EEE2	-1.77151	-2.48939	-3.18313***	-3.29856***	I(1)
IS	-1.10926	-2.25906	-3.19999***	-3.47456***	I(1)
EI	-1.50784	-2.18971	-2.90571***	-3.00765***	I(1)
Textile					
EEE1	-2.08487*	-2.05518	-	-	I(0)
EEE2	-1.34609	-1.85256	-3.64690***	-3.80476***	I(1)
IS	-2.97759***	-3.40605***	-	-	I(0)
EI	-1.46702	-1.67085	-3.09253***	-4.53639***	I(1)
Pulp and paper					
EEE1	-1.98447	-2.33212	-3.66913***	-3.66226***	I(1)
EEE2	-1.79496	-1.92754	-3.30750***	-3.33836***	I(1)
IS	-1.58663	-2.03860	-2.99590***	-3.04617***	I(1)
EI	-1.76187	-2.29168	-3.17031***	-3.30207***	I(1)
Chemical, oil, and coal					
EEE1	-1.69694	-2.08245	-3.44084***	-3.54160***	I(1)
EEE2	-2.05526*	-2.39509	-	-	I(0)
IS	-1.61122	-2.31463	-3.43646***	-3.56194***	I(1)
EI	-2.11258*	-2.13129	-	-	I(0)
Ceramic, stone, and clay					
EEE1	-1.68040	-2.00372	-3.19011***	-3.38972***	I(1)
EEE2	-1.99514	-2.14758	-3.61700***	-3.66830***	I(1)
IS	-2.11295*	-2.40269	-	-	I(0)
EI	-1.08257	-1.77552	-2.68741***	-2.91127***	I(1)
Iron and steel					
EEE1	-2.17211**	-2.46971	-	-	I(0)
EEE2	-1.78588	-1.96017	-3.09790***	-3.20276***	I(1)
IS	-1.68238	-2.48940	-3.40149***	-3.64857***	I(1)
EI	-1.71261	-2.13523	-3.16079***	-3.15379***	I(1)
Machinery					
EEE1	-1.36732	-1.98537	-3.29687***	-3.45063***	I(1)
EEE2	-1.50001	-2.23085	-3.37202***	-3.51415***	I(1)
IS	-2.25187**	-2.28157	-	-	I(0)
EI	-2.66379***	-3.21616***	-	-	I(0)
Manufacturing					
EEE1	-1.84003	-2.65923**	-	-	I(0)
EEE2	-1.43372	-2.44986	-3.73975***	-3.80389***	I(1)
IS	-1.61702	-2.20335	-3.47426***	-3.78557***	I(1)
EI	-1.54173	-2.50029	-3.16545***	-3.17359***	I(1)

The tests in the table select a single lag for the ADF (augmented Dickey–Fuller) regression and report the truncated CIPS statistic. The constants and trends are deterministic terms included in the tests

* $p < 0.1$

** $p < 0.05$

*** $p < 0.01$

Table 6 Pedroni panel cointegration tests

	Panel v-statistic	Panel rho-statistic	Panel PP-statistic	Panel ADF-statistic	Group rho-statistic	Group PP-statistic	Group ADF-statistic
Food, beverages, and tobacco							
Model 1	-0.633522	1.186253	-11.06104***	-9.342591***	3.191868	-14.42343***	-12.47216***
Model 2	0.524228	3.071354	-1.858378**	-3.083415***	3.074340	-8.121298***	-8.188508***
Textile							
Model 1	-3.260886	0.331943	-13.47186***	-13.51722***	3.627371	-14.75801***	-11.75723***
Model 2	-1.268942	-0.247425	-9.276928***	-9.091001***	0.936795	-12.41171***	-10.86444***
Pulp and paper							
Model 1	-1.116840	2.353719	-5.272305***	-5.810947***	4.186269	-11.65780***	-11.00601***
Model 2	-2.275577	1.352191	-5.458742***	-6.423706***	3.049061	-10.56902***	-10.60219***
Chemical, oil, and coal							
Model 1	-3.351159	1.727338	-8.860695***	-9.665512***	3.502405	-12.61057***	-10.21496***
Model 2	0.810342	-0.998458	-10.84296***	-10.16332***	2.123284	-12.58159***	-11.40520***
Ceramic, stone, and clay							
Model 1	-1.877550	2.779795	-9.887294***	-11.13769***	4.744119	-15.68208***	-14.48236***
Model 2	-0.211758	1.340087	-8.980306***	-11.52403***	4.450108	-9.940711***	-13.07724***
Iron and steel							
Model 1	-1.818146	3.258006	-4.952851***	-7.471220***	4.731502	-9.845332***	-9.396072***
Model 2	-3.388243	0.599767	-6.475321***	-8.831578***	2.740432	-8.065791***	-9.920696***
Machinery							
Model 1	-3.343544	4.425752	-2.744002***	-4.061561***	5.724367	-4.840543***	-5.351731***
Model 2	-2.486851	2.123776	-3.672093***	-5.515955***	5.406364	-1.050780	-3.824743***
Manufacturing							
Model 1	-3.998727	1.696246	-9.030381***	-9.066138***	4.470256	-14.07822***	-11.55655***
Model 2	-0.687899	0.269362	-9.502857***	-11.78776***	4.996930	-3.893301***	-7.458334***

The test of the table selects the lag length based on the SIC and uses the nonparametric Bartlett kernel as well as the bandwidth based on the Newey–West method. The constants and trends are deterministic terms included in the tests

** $p < 0.05$

*** $p < 0.01$

on the ARDL (1, 1) model by setting $p = q = 1$ in Eq. (19), which has been broadly used in empirical studies such as Li et al. (2016) and Salahuddin et al. (2016).¹⁵ However, the cross-sectional dependence, which is often caused by unobservable common factors, is modeled by including a linear trend.

4.2 Estimation results

Table 4 presents the results of the CD tests. The null hypothesis of no cross-section correlation was mostly rejected at 1% for all the variables. This result indicates that there is a cross-sectional dependence in each variable, and consequently, it is appropriate to choose the CIPS panel unit root test. Table 5 presents the results of the CIPS test, which is the null hypothesis of the unit root. The results show a mixed order of integration in our variables, and consequently, the PMG estimation is adequate in our panel data. Moreover, we examine whether there is a cointegrating relationship among the variables using the Pedroni panel cointegration tests. Table 6 presents the results of the Pedroni test. In all the models, the null hypothesis of no cointegration is rejected at 5% for four

¹⁵ Additionally, if we limit the lag length to a maximum of 3, considering the number of years of data used, our model essentially selects ARDL (1, 1) based on the SIC (Schwarz information criterion).

Table 7 Pooled mean group (PMG) estimation results in the EEE1

Variable	Food, beverages, and tobacco	Textile	Pulp and paper	Chemical, oil, and coal	Ceramic, stone, and clay	Iron and steel	Machinery	Manufacturing
Long-run coefficients								
GDP	0.147360*** (0.044047)	0.119176** (0.050132)	0.287689** (0.114281)	0.065143 (0.069830)	0.317358*** (0.101730)	0.000987 (0.050811)	0.770468*** (0.181140)	0.124310*** (0.038482)
(GDP) ²	- 0.013150*** (0.004949)	- 0.016931** (0.006778)	- 0.053956*** (0.015034)	- 0.002060 (0.008642)	- 0.040417*** (0.012120)	0.000275 (0.005466)	- 0.084354*** (0.021488)	- 0.014479*** (0.004587)
IS	0.636207*** (0.068811)	0.800343*** (0.262021)	- 1.182101*** (0.325306)	2.050849*** (0.309755)	1.584145*** (0.393550)	0.897043*** (0.175925)	0.696221*** (0.191261)	0.123055** (0.056312)
EI	2.619090*** (0.270163)	0.125938* (0.072922)	- 0.549127*** (0.086130)	0.065448 (0.072448)	- 0.526078*** (0.144798)	0.215417** (0.093065)	0.168755 (1.502901)	0.236930** (0.110316)
Error correction coefficient	- 0.579107*** (0.060363)	- 0.604490*** (0.058340)	- 0.417961*** (0.043413)	- 0.467912*** (0.067305)	- 0.559152*** (0.057536)	- 0.442013*** (0.049781)	- 0.397703*** (0.043114)	- 0.557076*** (0.054241)
Short-run coefficients								
ΔGDP	0.872251 (0.875910)	0.735941 (0.867530)	- 0.160085 (0.578635)	- 2.424064** (1.164258)	2.684560* (1.550172)	- 0.755117 (0.972145)	- 1.121660 (1.027743)	- 0.514275 (0.600495)
Δ(GDP) ²	- 0.156977 (0.130263)	- 0.074715 (0.127341)	0.034954 (0.088492)	0.428707* (0.227241)	- 0.472959* (0.250677)	0.091305 (0.174097)	0.179237 (0.161293)	0.093136 (0.106981)
ΔIS	0.670795 (0.456197)	- 1.067714 (2.008301)	5.170944* (2.672574)	0.405509 (1.176597)	1.391207 (2.227386)	0.546000 (0.506880)	0.275745 (0.235868)	- 0.289220 (0.219094)
ΔEI	- 0.535951 (1.176269)	0.150601 (0.283678)	- 0.111445 (0.248756)	0.266835 (0.655872)	- 0.244567 (0.559241)	- 1.106138 (0.771286)	0.406767 (2.395601)	- 3.527508*** (1.013906)
Constant	0.252151*** (0.034445)	0.332681*** (0.045070)	0.232160*** (0.031294)	0.109252** (0.043195)	0.087599*** (0.025015)	0.338307*** (0.041906)	- 0.391421*** (0.046563)	0.325640*** (0.037055)
Trend	- 0.002542*** (0.000857)	0.002464** (0.001164)	0.001951** (0.000876)	- 0.000346 (0.001094)	0.000467 (0.001169)	- 0.002797** (0.001297)	- 0.002589** (0.001219)	- 0.000800 (0.000648)
Observations	1034	1034	1034	1034	1034	1034	1034	1034
Turning point (million yen)	5.60	3.52	2.67	-	3.93	-	4.57	4.29

The values in parentheses are standard errors. The turning points are GDP per capita at 2000 constant prices

- * $p < 0.1$
- ** $p < 0.05$
- *** $p < 0.01$

of the seven statistics, excluding Model 2 for machinery. Hence, it is difficult to analyze whether the variables can be assumed to have a cointegrating relationship.

However, Tables 7 and 8 report the estimation results of the PMG for EEE1 and EEE2, respectively. In both tables, the error correction coefficients are significantly estimated at the 1% level and are confirmed to be negative in all the models. This means that the models have a long-run equilibrium relationship among the variables.

In the long-run coefficients of Table 7, the parameters of *GDPC* and its square are significant at the 5% level, excluding “chemical, oil, and coal” and “iron and steel.” The estimated parameters reflect an inverted U-shaped relationship between EEE1 and GDP per capita, while the turning point of GDP per capita falls within the collected data. This result indicates that there is no EKC pattern, contrary to our expectations. However, in the long-run coefficients of Table 8, the parameters of *GDPC* are significantly estimated to be positive at 5% level, excluding “food, beverages, and tobacco” and “textile.” As

Table 8 Pooled mean group (PMG) estimation results in the EEE2

Variable	Food, beverages, and tobacco	Textile	Pulp and paper	Chemical, oil, and coal	Ceramic, stone, and clay	Iron and steel	Machinery	Manufacturing
Long-run coefficients								
GDPC	0.005622 (0.006755)	- 0.006704 (0.016468)	0.364428** (0.035822)	0.224758*** (0.028553)	0.154350*** (0.039514)	0.184207*** (0.016771)	0.543159*** (0.070102)	0.041063** (0.019532)
IS	0.708107*** (0.079123)	1.949296*** (0.484480)	- 2.496876*** (0.675998)	5.289212*** (0.392801)	4.336182*** (1.421131)	2.163486*** (0.220376)	1.649937*** (0.241856)	0.047003 (0.152928)
EI	- 3.831770*** (0.348233)	- 5.070280*** (0.131664)	- 1.476130*** (0.145054)	0.522816*** (0.112337)	- 3.047312*** (0.388735)	- 0.139239 (0.121722)	- 10.23583*** (1.731946)	- 0.556327** (0.224435)
Error correction coefficient	- 0.527979*** (0.036298)	- 0.473689*** (0.052093)	- 0.219589*** (0.047404)	- 0.363852*** (0.051905)	- 0.361466*** (0.051190)	- 0.429399*** (0.044712)	- 0.295468*** (0.037209)	- 0.341524*** (0.032822)
Short-run coefficients								
ΔGDPC	0.168953*** (0.029022)	0.017391 (0.044485)	0.072457 (0.045325)	0.020243 (0.053235)	- 0.161638*** (0.049730)	- 0.061902 (0.060066)	- 0.150832*** (0.039647)	- 0.165019*** (0.042273)
ΔIS	1.921214*** (0.741870)	17.36910** (6.829242)	10.01702*** (2.961131)	3.314192*** (0.693949)	3.090692 (2.583565)	2.944536*** (0.693743)	0.626998** (0.245373)	1.508088** (0.705934)
ΔEI	- 3.456692*** (1.319924)	1.989232*** (0.308873)	- 1.569114*** (0.457523)	- 0.121598 (0.502892)	- 3.95033*** (0.907851)	- 2.338647*** (0.796632)	- 3.789504 (2.664045)	- 6.366505*** (1.436127)
Constant	0.319057*** (0.029306)	0.316795*** (0.046785)	0.004025 (0.030581)	- 0.339447*** (0.062929)	0.112356*** (0.031647)	- 0.074982** (0.031271)	- 0.356596*** (0.045152)	0.220408*** (0.029064)
Trend	- 0.001520** (0.000671)	0.011687*** (0.001792)	-	- 0.007135*** (0.002408)	- 0.003524*** (0.001153)	- 0.005454*** (0.001409)	- 0.009763*** (0.001397)	- 0.003527*** (0.001050)
Observations	1034	1034	1034	1034	1034	1034	1034	1034

The values in parentheses are standard errors. Since the model is suspected of having multicollinearity, the trend variable is dropped in Model 2 for pulp and paper

** $p < 0.05$

*** $p < 0.01$

expected, the estimated parameters show a linear relationship between EEE_2 and GDP per capita. Therefore, the EEE in the Japanese manufacturing industry tends to improve and then deteriorate or monotonically increase as economic development progresses.

Likewise, the estimation results of the other variables are also meaningful. The parameters of IS are significantly estimated to be positive at 5% level in Tables 7 and 8, or both, excluding “pulp and paper,” as expected. This result means that the EEE in the Japanese manufacturing industry is raised by expanding the industry share. This finding suggests that the EEE is likely to improve as industry concentration increases. For the industry of “pulp and paper,” which is significantly estimated to be negative, the results should be carefully interpreted and seem to be influenced by the consolidation of companies. However, it should be reconsidered in subsequent analysis.

Meanwhile, although the parameters of EI are significantly estimated in Tables 7 and 8, or both, the sign of the coefficients is mixed. However, in the results of EEE_2 , which is the indicator focused on energy reduction, the parameters are estimated to be significantly negative at the 5% level (Table 8), excluding “chemical, oil, and coal” and “iron and steel,” which is consistent with our expectations. This result suggests that the progress of energy-saving technology could lead to an increase in EEE through energy reduction in the Japanese manufacturing industry. In this regard, it is too early to draw any conclusions from the result. This is because most industries in Table 7 are significantly estimated to be positive, contrary to our expectations. The findings suggest that manufacturing companies have pushed for a review of energy use, such as alternatives to clean energy, despite little progress in reducing energy consumption. Therefore, it can be analyzed in future studies whether EI is appropriate as a proxy for the progress of energy-saving technology, as it has been typically used in empirical studies (Kumar and Khanna 2009).

5 Conclusion

This section summarizes the empirical results and derives the policy implications. For changes in the energy performance of Japan, some practical information was confirmed from the measurement results of the EEE in the manufacturing industry. The EEE of the entire manufacturing industry was at almost the same level or on a downward trend from late 1990 to 2012. However, the changes in the EEE have different movements by individual industries. Notably, the EEE had improved in “chemical, oil, and coal” and “machinery,” although it had deteriorated in “iron and steel” since the late 2000s. This finding indicates that the Japanese manufacturing industry had not been keeping in step with the improvement of EEE since the adoption of the Kyoto Protocol.

Meanwhile, the EEE of the entire manufacturing industry has different trends by each prefecture during the studied period. Tokyo, Aichi, and Okinawa were the most efficient prefectures, whereas Hokkaido, Hiroshima, and Fukuoka were inefficient. However, more efficient industries tended to have comparatively concentrated in the Kanto, Chubu, and Kinki regions. Consequently, this finding suggests that the progress of each industry was relatively consistent by region.

Furthermore, some interesting results were obtained from the panel data analysis. First, the EEE was likely to improve and then deteriorate or monotonically increase with economic development between 1990 and 2012. This implies that the improvement phase can occur because more advanced systems, skilled labor, and sophisticated facilities are

prepared as development increases. Therefore, policymakers should consider creating an institutional environment that encourages investment in human and physical capital in the environmental energy fields. Moreover, the EEE was raised by expanding the industry share during the study period. This indicates that strengthening industrial concentration on specific industries within the manufacturing industry is an improvement factor. It is necessary to promote the selection and concentration of industries as a part of the environmental energy policy. Finally, the EEE, focusing on energy reduction, was likely to increase with the progress of energy-saving technology during that period. This suggests that efforts to conserve energy could be another improvement factor. It might be important to support the innovation of energy-saving technologies as part of the environmental energy strategy.

However, it should be noted that some analytical challenges remain in our research.

Although the study period is limited to 1990–2012 due to data constraints, it would be valuable to extend the period and include the impact of the Paris Agreement in future research.¹⁶ In this study, it would be more beneficial to subdivide the manufacturing industry more than it is classified in the current survey. In addition, it would be desirable to verify the industry-wise trend and its influencing factors of the EEE using micro-level firm data. If the study can resolve these challenges, it will be possible to provide policymakers with more detailed information and solid evidence to help implement an effective environmentally friendly energy policy in Japan.

Abbreviations

ADF	Augmented Dickey–Fuller
ARDL	Autoregressive distributed lag
CD	Cross-section dependence
CIPS	Cross-sectionally augmented Im, Pesaran, and Shin
CO ₂	Carbon dioxide
DEA	Data envelopment analysis
ECSP	Energy consumption statistics by prefecture
EEE	Environmental energy efficiency
EKC	Environmental Kuznets curve
GDP	Gross domestic product
LM	Lagrange multiplier
METI	Ministry of Economy, Trade and Industry
PMG	Pooled mean group
RIETI	Research Institute of Economy, Trade and Industry
R-JIP	Regional-Level Japan Industrial Productivity
SIC	Schwarz information criterion
SFA	Stochastic frontier analysis
SNA	System of National Accounts
TFEE	Total-factor energy efficiency
VRS	Variable returns to scale

Acknowledgements

The Article Processing Charge was covered by the funds of PAPAIOS and JSPS (KAKENHI Grant Number JP 21HP2002). We are grateful to the anonymous reviewers for their accurate and helpful comments.

Author contributions

OT analyzed the environmental energy efficiency in the Japanese manufacturing industries. MS estimated the influencing factor of the environmental energy efficiency by industry and was a major contributor in writing as well as editing the manuscript. All authors read and approved the final manuscript.

Funding

Not applicable.

¹⁶ Although the latest version of R-JIP 2021 and the ECSP provide data available through 2018, this study focuses on the 1990–2012 period, which was the framework for the Kyoto Protocol. This is because the data for R-JIP 2021 is only available from 1994. From the perspective of the current study, however, we believe that it is meaningful to evaluate the achievements of the Kyoto Protocol by making comparisons from 1990, which was the target year.

Availability of data and materials

The data supporting this study's findings are available from the corresponding author upon reasonable request.

Declarations**Competing interests**

There are no conflicts of interest to declare.

Received: 28 March 2022 Revised: 1 March 2023 Accepted: 3 March 2023

Published online: 17 April 2023

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