Environmental efficiency of Japanese regions before and after the Great East Japan Earthquake

Honma, Satoshi and Ushifusa, Yoshiaki and Taghizadeh-Hesary, Farhad and Okamura, Soyoka and Vandercammee, Lilu

Tokai University

15 May 2024

Environmental efficiency of Japanese regions before and after the Great East Japan Earthquake

Satoshi Honma[a*], Yoshiaki Ushifusa[b], Farhad Taghizadeh-Hesary[c], Soyoka Okamura[d], and Lilu Vandercamme[e]

[a] School of Political Science and Economics, Tokai University, Japan
[b] Faculty of Economics and Business Administration
The University of Kitakyushu, Japan
[c] School of Global Studies, Tokai University, Japan
[d] Faculty School of Agriculture, Kyoto University, Japan
[e] Faculty of Economics, Keio University, Japan

Abstract. This study measured the environmental and energy efficiency of 47 regions in Japan for the period 2005–2017, which was before and after the Great East Japan Earthquake (GEJE) in March 2011, using the slacks-based measure data envelopment analysis model. Our model had comprehensive inputs and outputs: seven inputs (labor, capital, coal, oil, gas, renewables, and electricity), one desirable output (gross regional product), and four undesirable outputs (CO_2, SO_x, NO_x, and dust). In our results, before GEJE, the mean environmental efficiency deteriorated from 0.529 in 2005, 0.518 in 2008, 0.501 in 2011, and 0.464 in 2014 but improved to 0.527 in 2017. Iwate, Miyagi, and Fukushima in the Tohoku region were severely damaged by the earthquake, but these areas were inefficient even before the disaster. Tokyo's environmental efficiency deteriorated from unity in 2005 and 2008 to 0.839 in 2008 and 0.698 in 2011 and then improved back to unity in 2017. We also presented potential reduction ratios for energy and undesirable outputs. To examine the determinants of efficiency, we regressed the efficiency on influencing factors using the panel Tobit model. Gross regional product per capita and tertiary industry share were positively correlated with environmental efficiency.

---

* Corresponding author. Tel.: +81-463-58-1211; Fax: +81-463-58-2025. E-mail address: honmasatoshi@tokai.ac.jp (S. Honma). The authors gratefully acknowledge financial support from the Japan Society for the Promotion of Science (JSPS) KAKENHI Grant Number 22H03816.

This implies that the development of the service sector is more helpful for transitioning to a sustainable society compared with other sectors.

Keywords: Environmental efficiency; Data envelopment analysis; Fukushima nuclear disaster; Japan

1 Introduction

Historically, economies have faced frequently unanticipated events, such as natural disasters, financial crises, and pandemics. For instance, COVID-19 recently had an irregular and profound impact on the economy. Thus, examining how unanticipated events affect environmental performance is crucial to achieving the goals of the Paris Agreement in an uncertain world.

The Great East Japan Earthquake (GEJE) that occurred in March 2011 had a much larger scope and scale of damage than those of past large-scale disasters. Furthermore, the disaster had a tremendous impact on the Japanese economy, including secondary effects such as power supply constraints. Fig.1 shows epicenter of GEJE and ten regions in Japan.

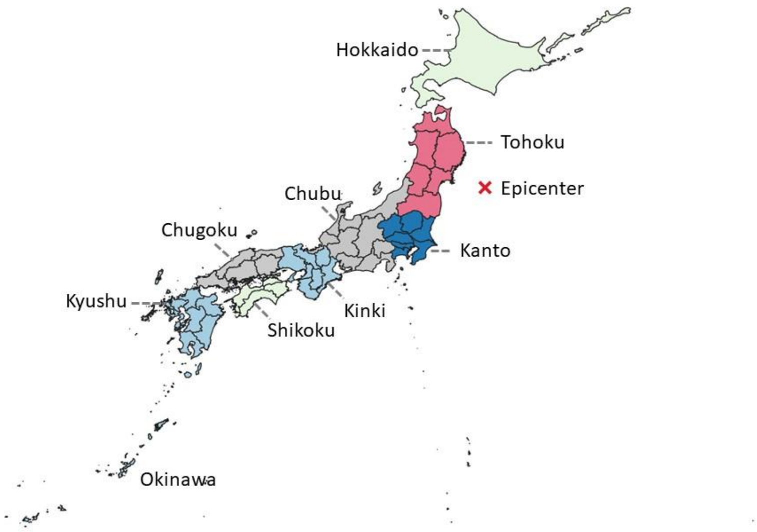


Fig. 1 Epicenter of GEJE and ten regions in Japan

The first characteristics of this disaster were the size of the affected area and the magnitude of the damage. In addition to the damage caused by the massive magnitude 9.0 earthquake, the massive tsunami it triggered caused extensive and widespread damage.

The second is that the economic impact of the earthquake was widespread beyond the affected areas because of power supply constraints and supply chain disruptions. The tsunami damaged nuclear power plants and other facilities, significantly reducing the electricity supply capacity not only in the affected areas but also in a wide area of eastern Japan. These power supply constraints have made it impossible for households and businesses to meet their electricity needs as in the past, which has naturally led to a decline in economic activity.

The third is that supplies have become increasingly fragmented and interdependent because of the optimization of company locations and inventory management in recent years. The earthquake caused factories located in the affected areas to shut down; thus, the supply of certain products was disrupted, leading to the shutdown of factories in Japan and some overseas locations. This may have reduced the emissions of hazardous substances and improved the environment.

The impacts of GEJE on the economy–environment nexus should be examined to prepare for future natural disasters. Therefore, this paper attempts to quantitatively evaluate the impact of an earthquake on the environment using environment-related data from before and after the disaster. The last one is the impact of the earthquake on environmental aspects. The earthquake caused a slowdown in economic activity and a decrease in the use of energy and resources. Meanwhile, the shutdown of nuclear power plants has increased the share of thermal power generation. Our research questions are as follows:

1. How did environmental efficiencies in Japanese regions change before and after GEJE?
2. How did GEJE impact environmental efficiencies in the affected regions?
3. How did GEJE impact environmental efficiencies in areas outside the affected regions through direct and indirect economic influences?
4. How did potential reductions in energy consumption and pollutants in the affected areas vary between predisaster and postdisaster periods?
5. What were the determinants of environmental efficiency?

To examine the above questions, we employed a slacks-based measure (SBM) data envelopment analysis (DEA) model with undesirable outputs to evaluate the environmental efficiency of 47 prefectures in Japan. To comprehensively understand environmental impacts, we incorporated seven inputs (labor, capital, coal, oil, gas, renewables, and electricity), one desirable output (gross regional product [GRP]), and four undesirable outputs (CO_2, SO_x, NO_x, and dust).

The rest of the paper is organized as follows. Section 2 provides a review of the related empirical literature. Section 3 provides the theoretical foundation of our study. Section 4 describes the research methodology and data. Section 5 presents the research findings and a discussion of the main results. Section 6 presents the conclusion.

2 Literature review

The economic and human damage caused by natural disasters and their relevance have long been studied (Noy, 2009; Hosoya, 2016, 2019; Evgenidis et al., 2021; Taghizadeh-Hesary et al., 2021). Earlier studies, such as that of Taghizadeh-Hesary et al. (2021), assessed the economic impacts of natural disasters and ways to enhance resilience in the face of damage. The relationship between disasters and economic performance has been studied from various perspectives, including shock spillovers, disaster resilience, and reconstruction. However, unlike previous studies, this study examines economic performance with environmental considerations.

GEJE has been investigated from various aspects, including resilience (Oliva and Lazzeretti, 2018), carbon emissions (Cho et al., 2016; Long et al., 2021), and economic impacts (Tokui et al., 2017; Carvalho et al., 2021). Tokui et al. (2017) indicated that production losses due to supply chain disruptions were 0.35% of Japan's GDP using a unique interregional input–output table. Meanwhile, Carvalho et al. (2021) studied the disruptions of GEJE and found that it resulted in a 0.47% decline in Japan's real GDP growth.

The Fukushima Daiichi Nuclear Power Plant accident and the subsequent power plant shutdown contributed significantly to the restructuring of Japan's energy infrastructure through the increased use of thermal power to compensate for shortages. Additionally, the introduction of the Feed-in-Tariff Policy helped bolster the promotion of renewable energy sources. Consequently, GEJE has had a profound impact on Japan's energy landscape. The total fossil fuel use in Fukushima Prefecture increased mainly because of changes in electricity generation (Cong et al., 2022). Japan's power generation sector faced supply shortages in the immediate aftermath of GEJE and the challenge of fossil fuel dependence in the medium term (Huenteler et al., 2012).

The environmental impacts of GEJE and their economic impacts have been examined. For instance, Cho et al. (2016) predicted that GEJE caused 4.3 million metric tons (0.26% higher) of additional CO_2 emissions in 2011, where a 23.8-million-metric-ton increase in CO_2 emissions (1.43% higher) due to the substitution of fossil fuels for nuclear power was partially offset by a 19.5-million-metric-ton decrease in CO_2 emissions (1.17% lower) due to lower electricity consumption. Meanwhile, Long et al. (2021) showed that the driver of carbon emissions varied across regions using the logarithmic mean Divisia index. They found that the main driver was the expanding coal use in the Kyushu, Kansai, and Chubu regions, whereas it was the changing industrial structures in the Kansai and Kanto regions.

The earthquake also had a major impact on energy security of Japan and world (Hayashi and Hughes, 2013ab; Hong et al., 2013). Hong et al. (2013) evaluated Japan's energy options using multicriteria decision-making analysis and concluded that "a nuclear-free pathway for Japan is the worst option to pursue." However, beyond the scope of this paper, restarting nuclear power plants is politically difficult. Considering current circumstances, improving environmental and energy efficiency is a crucial policy concern for Japan to not only enhance the ecology but also bolster energy security.

What is needed to achieve a sustainable society is to produce more output with fewer negative externalities and less polluting emissions. In this regard, DEA has been widely used to measure the environmental performance of countries, regions, and firms (Chung et al., 1997; Zaim and Taskin, 2000; Zaim, 2004; Honma and Hu, 2008, 2009; Halkos and Tzeremes, 2009; Zhang et al., 2016; Matsumoto et al., 2020). In particular, the undesirable outputs SBM DEA models have been widely applied for measuring environment- and energy-related efficiency in various countries, regions, and firms (Bi et al., 2014, 2015; Chang et al., 2013; Chin and Low, 2010; Choi et al., 2012; Iram et al., 2020; Li and Hu, 2012; Song et al.,2015; Taleb, 2023; Zhang and Choi, 2023; Zhang et al., 2015). Table 1 summarizes relevant previous studies on Japan. For instance, Goto et al. (2014) proposed three types of efficiency measures: operational efficiency, unified efficiency under natural disposability, and unified efficiency under natural and managerial disposability. They evaluated the manufacturing and nonmanufacturing industries of 47 prefectures in Japan in 2002, 2005, and 2008. The desirable and undesirable outputs used in their model were the same as ours; however, their sampling period was before GEJE. They found that the Porter hypothesis was valid in Japanese industrial sectors; that is, environmental regulations contribute to improving the performance of Japanese industrial sectors. Furthermore, they showed that the main cause of inefficiency was the emission of greenhouse gases in both industries. Meanwhile, Fukuyama et al. (2020) also measured the energy and environmental efficiency of 47 prefectures from 2001 to 2014, incorporating aggregate well-being. They showed that network capacity utilization inefficiency increased from 2013 to 2014 because of GEJE. Honma et al. (2023) measured the total factor CO_2 emission performance of the metal industry, which consisted of iron and steel, nonferrous metal, and metal processing industries, in 39 Japanese prefectures from 2008 to 2019. Otsuka (2023) measured the efficiency of industrial electricity consumption for a period using stochastic frontier analysis. He found that GEJE had a structural effect on improving the efficiency of electricity consumption. This result could be attributed to the power-saving behavior of companies due to power shortages after GEJE.

GEJE also influenced the efficiency of aspects other than the local economy. Suzuki et al. (2015) demonstrated that all ten major power generation companies in the area experienced a decline in efficiency from 2010 to 2011. This was due to increased fuel costs, which were compensated for by the electricity shortage caused by the shutdown of nuclear power plants.

Disasters not only impact the local economy but also produce significant quantities of waste. In this regard, Sasao (2016) investigated the cost and efficiency of disaster waste disposal caused by GEJE in 22 damaged municipalities. The number of temporary incinerators and secondary waste stock served as enhancing factors for disaster waste disposal efficiency. However, the disposal of materials was a deteriorating factor for efficiency. The efficiency impact of the disaster was not analyzed; however, a greater amount of sediment resulting from a tsunami reduced the average disposal cost.

As mentioned, disasters have significant impacts on both the environment and the economy of each region. Goto et al. (2014), like us, comprehensively studied not only CO_2 but also other pollutants, but their analysis period was before GEJE. To the best of our knowledge, no study has comprehensively analyzed the environmental efficiency of the 47 prefectures before and after GEJE. Our study fills this gap by measuring environmental efficiency for the period and examining the impact of the disaster on efficiency and potential reductions in energy consumption and pollutants.

Table 1 Literature review summary

Authors	Entities/year	Main Inputs	Main Desirable outputs/ undesirable outputs	Impact of GEJE on efficiency	Method
Goto et al. (2014)	47 prefectures/ 2002, 2005, and 2008	*K*, *L*, and *E*	*Y*/ CO_2, SO_x, NO_x, and dust	Not analyzed	DEA
Suzuki et al. (2015)	10 electrical power companies/ 2010–2011	Expenditure	Electricity generated/ CO_2	−	DEA
Sasao (2016)	22 municipalities	Cost, *L*	Four types of waste	Not analyzed	DEA
Fukuyama et al. (2020)	47 prefectures/ 2001 and 2014	*K*, *L*, and *E*	*Y*/ CO_2 and ICWI	−	DEA
Honma et al. (2023)	39 prefectures/ 2008 to 2019	*K*, *L*, and *E*	*Y*/ CO_2	−	SFA
Otsuka (2023)	1990 to 2015	Electricity consumption	*Y*	+	SFA

Note: *K*, capital; *L*, labor; *E*, energy; *Y*, gross regional product; ICWI, integrated composite well-being indicator; CO_2, carbon emissions; +, improved efficiency; −, deteriorated efficiency; DEA, data envelopment analysis; SFA, stochastic frontier analysis. The four types of waste in Sasao (2016) were tsunami sediments, recycled sediments, disaster waste, and recycled waste.

3 Theoretical foundation

We constructed a simple theoretical model to conceptually present how disasters affect environmental efficiency.

We assumed the following production function:

$$Y = F(K, L, E, N) \tag{1}$$

where Y is the industry's total production, K is the capital input, L is the labor input,

E is the fossil energy, and N is the nonfossil energy, which typically comprises renewable and nuclear electricity. We assumed $F_I > 0$ and $F_{II} < 0$ for all $I = K, L, E, N$ as a usual manner. The industry's profit is given by

$$\text{Max } \Pi = P^Y Y - rK - wL - (P^E + t)E - P^N N \tag{2}$$

where Π denotes the industry's profit, P^Y is the price of the product, r is the rental price of capital, w is the wage rate, P^E is the price of fossil energy, t is the carbon tax rate for fossil energy, and P^N is the price of nonfossil energy. A representative household has utility, which is a function of good consumption Y and leisure $S = \bar{L} - L$. For simplicity, the number of households was assumed to be unity. Hence, the household solves the following constrained maximization problem, where environmental damage $D = g(E)$ is as given:

$$\begin{gathered}\text{Max } U(Y, \bar{L} - L) - D \\ \text{s.t. } PY = wL + tE\end{gathered} \tag{3}$$

where $\bar{L}$ denotes the endowment of labor. We assumed $U_J > 0$ and $U_{JJ} < 0$ for $J = Y, S$ as a usual manner. Assuming the number of households as unity, the carbon tax revenue returned to the household is simply reduced to tE. Assuming interior solutions, there exists the factor demand $(K(t), L(t), E(t), N(t))$, labor supply $L^S(t)$, and output given by $Y(t) = F(K(t), L(t), E(t), N(t)$ at the equilibrium for a given t[1]. Hence, the corresponding profit $\Pi(t)$ and indirect utility $V(t)$ are obtained.

The government maximizes the following social welfare:

$$\max_t W(t) = \Pi(\mathrm{t}) + V(t). \tag{4}$$

Assuming an interior solution, the optimal tax rate t^* stipulates the optimal production factors $(K^*, L^*, E^*, N^*) = (K(t^*), L(t^*), E(t^*), N(t^*))$, and the optimal output is given

[1] We omit describing the price mechanisms in the factor markets.

by $Y^* = F(K^*, L^*, E^*, N^*)$.

If a natural disaster occurs, resource constraints of production factors arise, and the production factors then deviate from the optimum.

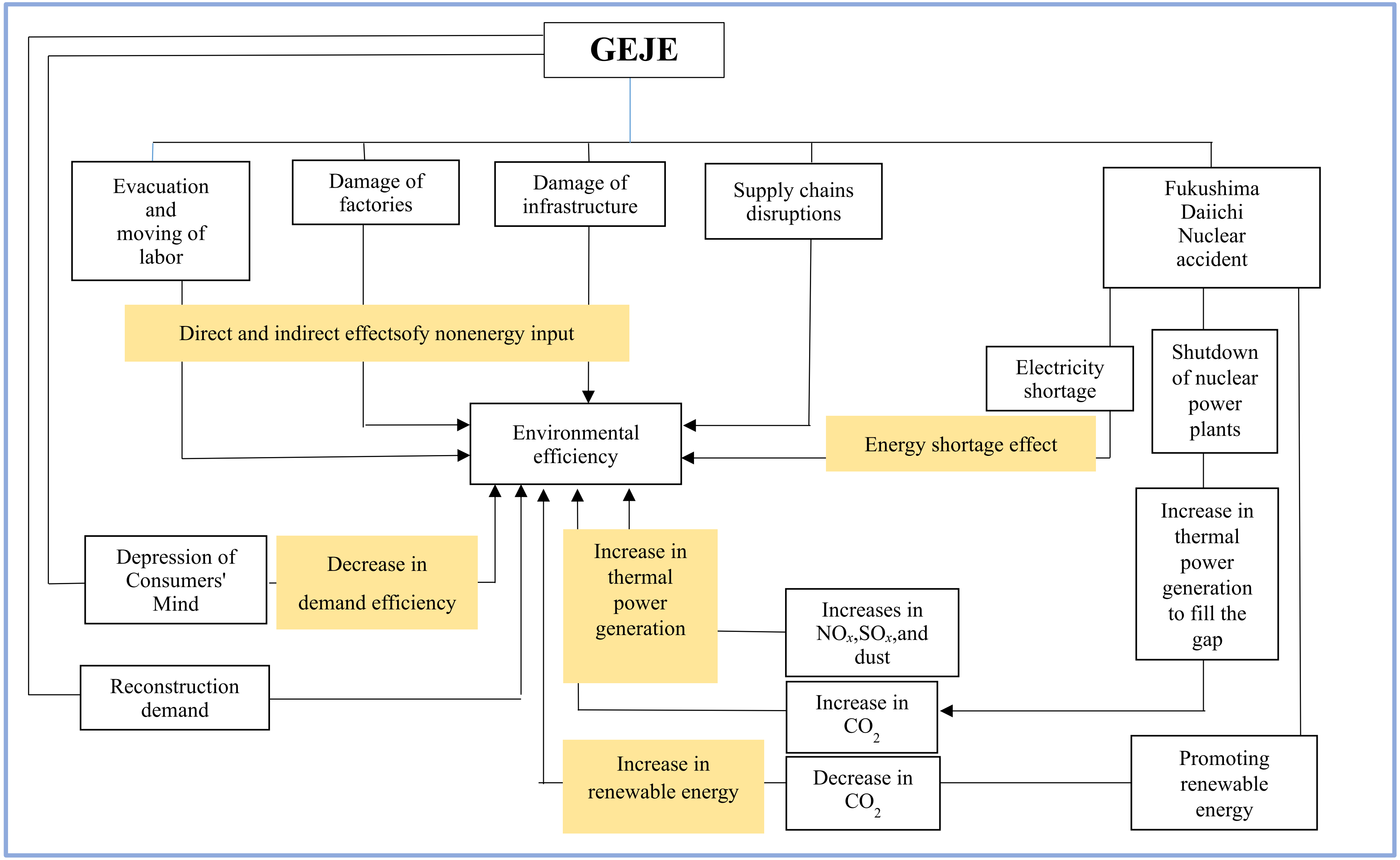
Fig. 2 illustrates the impact of the earthquake on the economy through various channels. As the nuclear power plant was shut down in GEJE, suppose that the nonfossil energy was reduced by $\Delta N < 0$, where Δ denotes the change in the variable. Substituting fossil and nonfossil energies, fossil energy should increase and be put at $\Delta E > 0$. Assuming that the carbon tax rate was fixed, the change in social welfare could be decomposed into the following:

$$\Delta W = \underbrace{(F_K \Delta K + F_L \Delta L)}_{\text{Direct and indirect effects of nonenergy input fluctuation}} + \underbrace{F_N \Delta N}_{\text{Energy shortage effect}} + \underbrace{(F_E - D'(E))\Delta E}_{\text{Increase in thermal power generation}} + \underbrace{U_Y \Delta Y}_{\text{Decrease in the consumption effect}} - \underbrace{U_L \Delta L}_{\text{Decrease in the labor supply effect}} \tag{5}$$

Except for $U_L \Delta L$, which is less important for our study, all terms on the right-hand side of (5) are negative. For the direct and indirect effects of nonenergy input fluctuation $F_K \Delta K + F_L \Delta L$ the earthquake brought about both direct and indirect impacts, leading to a loss of capital and human suffering, affecting the supply chain, and rendering intermediate goods unavailable. Note that such impacts can extend beyond the Tohoku and Kanto areas. The energy shortage effect $F_N \Delta N$ means electricity shortage due to the shutdown of nuclear power plants. The increase in the thermal power generation effect $\left(F_E - D'(E)\right)\Delta E$ would take a large negative value. This effect would be somewhat mitigated by the increase in renewable energy due to the introduction of the FIT in the year following the earthquake. The decrease in consumption effect $U_Y \Delta Y$ and the decrease in labor supply effect $U_L \varDelta L$ are also caused by disasters; however, they are beyond our concern.

The impact of the disaster can be expressed as the ratio $\varDelta W/W(t^*)$. The DEA technique provides the deteriorated efficiency value $1 - \varDelta W/W(t^*)$ caused by the disaster.

Fig. 2 Channels of the impact of GEJE



4 Methodology and data

4.1 Methodology

In this study, we evaluated the environmental efficiency of 47 prefectures in Japan using the SBM model with undesirable outputs proposed by Cooper et al. (2007). The inputs and desirable and undesirable outputs of a decision-making unit (DMU) i are given by $\boldsymbol{x}_i = (x_{1i,}\ldots x_{ni,})^T$, $\boldsymbol{y}_i^g = (y_{1i}^g, \cdots, y_{mi}^g)^T$, and $\boldsymbol{y}_i^b = (y_{1i}^b, \cdots, y_{ki}^b)^T$. The input, desirable outputs, and undesirable output matrices are given by $\boldsymbol{X} = \{x_{ji}\} \in \boldsymbol{R}^{n\times I}$, $\boldsymbol{Y}^g = \{y_{ji}^g\} \in \boldsymbol{R}^{m\times I}$, and $\boldsymbol{Y}^b = \{y_{ji}^b\} \in \boldsymbol{R}^{k\times I}$, respectively. We assumed $\boldsymbol{X} > 0$, $\boldsymbol{Y}^g > 0$, and $\boldsymbol{Y}^b > 0$.

The production possibility set is defined as

$$P = \{\boldsymbol{x}, \boldsymbol{y}^g, \boldsymbol{y}^b | \boldsymbol{x} \geq X\boldsymbol{\lambda}, \boldsymbol{y}^g \leq Y^g\boldsymbol{\lambda}, \boldsymbol{y}^b \geq Y^b\boldsymbol{\lambda}, L \leq \boldsymbol{e\lambda} \leq U, \boldsymbol{\lambda} \geq \boldsymbol{0}\} \qquad (6)$$

where $\boldsymbol{e} = (1, \cdots, 1)$, $L(0 \leq L \leq 1)$ and $U(U \geq 1)$. We assumed that a variable returns to scale technology, so $L = U = 1$.

The fractional programming problem solved by the SBM DEA model with undesirable outputs is as follows:

$$\min\ \rho_i = \frac{1 - \frac{1}{n}\sum_{j=1}^{n}\frac{s_j^-}{x_{ji}}}{1 + \frac{1}{m+k}\left(\sum_{j=1}^{m}\frac{s_j^g}{y_{ji}^g} + \sum_{j=1}^{k}\frac{s_j^b}{y_{ji}^b}\right)}$$

$$\text{s.t.}\ \boldsymbol{x}_i = X\boldsymbol{\lambda} + \boldsymbol{s}^-$$

$$\boldsymbol{y}_i^g = Y^g\boldsymbol{\lambda} - \boldsymbol{s}^g$$

$$\boldsymbol{y}_i^b = Y^b\boldsymbol{\lambda} + \boldsymbol{s}^b$$

$$\boldsymbol{e\lambda} = \boldsymbol{1}$$

$$\boldsymbol{s}^-, \boldsymbol{s}^g, \boldsymbol{s}^b, \boldsymbol{\lambda} \geq \boldsymbol{0}$$

(7)

where $\boldsymbol{s}^{-} \in R^{n}$, $\boldsymbol{s}^{g} \in R^{m}$, and $\boldsymbol{s}^{b} \in R^{k}$ are slacks for excess input, shortage of desirable outputs, and excess of undesirable outputs, respectively. We also calculated the economic efficiency without undesirable outputs (Tone, 2001).

$$
\begin{aligned}
\min\ \sigma_i = {} & \frac{1-\frac{1}{n}\sum_{j=1}^{n}\frac{s_j^{-}}{x_{ji}}}{1+\frac{1}{m}\sum_{j=1}^{m}\frac{s_j^{g}}{y_{ji}^{g}}} \\
\text{s.t. } & \boldsymbol{x}_i = X\boldsymbol{\lambda} + \boldsymbol{s}^{-} \\
& \boldsymbol{y}_i^{g} = Y^{g}\boldsymbol{\lambda} - \boldsymbol{s}^{g} \\
& \boldsymbol{e\lambda} = \mathbf{1} \\
& \boldsymbol{s}^{-}, \boldsymbol{s}^{g}, \boldsymbol{\lambda} \geq \mathbf{0}.
\end{aligned} \tag{8}
$$

The efficiency change before and after GEJE is crucial for our study. To measure the efficiency of cross-sectional and time-varying data, we applied the window analysis technique introduced by Charnes and Cooper (1984). We chose a window width of three, that is, for our triennial data sets, 2005, 2008, 2011, 2014, and 2017, region *i* of 2005 was evaluated in the 2005–2008 set, region *i* of 2008 was evaluated in the 2005–2008–2011 set, and region *i* of 2017 DMU was evaluated in the 2014–2017 set. The Malmquist productivity index was also applied to panel data. However, it could not fully capture technological progress because desirable and undesirable outputs include technical heterogeneity (Wu et al., 2020). Hence, window analysis is widely used as a stable technique in efficiency studies (Halkos and Tzeremes, 2009; Zhang et al., 2011; Yang et al., 2018a, 2018b; Zhu et al., 2019; Wu et al., 2020).

To examine the determinants of efficiency, we regressed the environmental efficiency using the panel Tobit model:

$$\rho_{it} = \boldsymbol{\beta Z} + \epsilon_{it} \quad (9)$$

where Z indicates the vector of the efficiency determinants, i indicates the prefecture ID, and t indicates the year.

4.2 Data

Data on real GRP and labor were taken from the Prefectural Economic Accounts. Capital Stock, R-JIP2021 corrected the capital stock from the calendar year presentation to the year presentation at $0.75K_t + 0.25K_{t+1}$ at the 2011 prices in million yen. CO_2 emissions were obtained from the Ministry of the Environment. For consistency with the economic and air pollution data, totals for the industrial, commercial, and freight transportation sectors were used (excluding the residential sector). Data on NO_x, SO_x, and soot were obtained from the Ministry of the Environment's Comprehensive Survey of Air Pollutant Emissions. This survey is conducted every 3 years and covers air pollution from fixed emission sources, such as factories and thermal power plants (mobile emission sources are not covered).

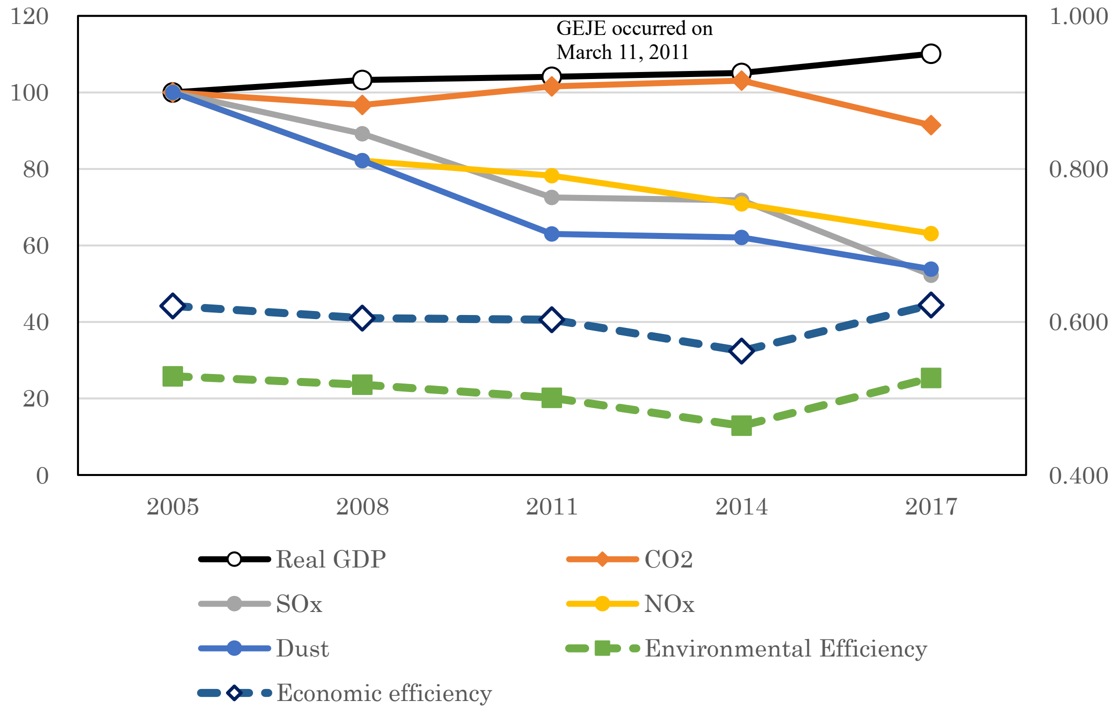
5 Empirical results

5.1 Environmental and economic efficiency results

Fig. 3 presents the changes in GDP, CO_2, SO_x, NO_x, dust, and environmental and economic efficiencies in the sample period. Note that the global financial crisis occurred in 2007–2008 and GEJE occurred on March 11, 2011. The national GDP slightly increased from 2014 to 2017 partly due to reconstruction demand; however, CO_2 decreased partly due to the diffusion of renewable energy through feed-in tariffs

(Kharecha and Sato, 2019). Note that the emission numbers of the three air pollutants, SO_x, NO_x, and dust, showed downward trends. This may have also contributed to improving environmental efficiency.

The environmental and economic efficiencies decreased in 2014 and then increased in 2017. Before GEJE, the mean environmental efficiency deteriorated from 0.529 in 2005, 0.518 in 2008, 0.501 in 2011, and 0.464 in 2014 but improved to 0.527 in 2017. The economic efficiency showed the same trend as 0.621 in 2005, 0.605 in 2008, 0.603 in 2011, 0.562 in 2014, and 0.622 in 2017.



Note: Except for environmental and economic efficiencies, FY2005 = 100.

Fig. 3 Changes in GDP, CO_2, SO_x, NO_x, dust, and environmental and economic efficiencies

Fig. 4 shows the scatter plot of the environmental and economic efficiencies in 2005, 2008, 2011, 2014, and 2017. The two efficiencies were highly correlated, with a correlation coefficient of 0.982. Some prefectures achieved environmental efficiency but were economically inefficient in some years.

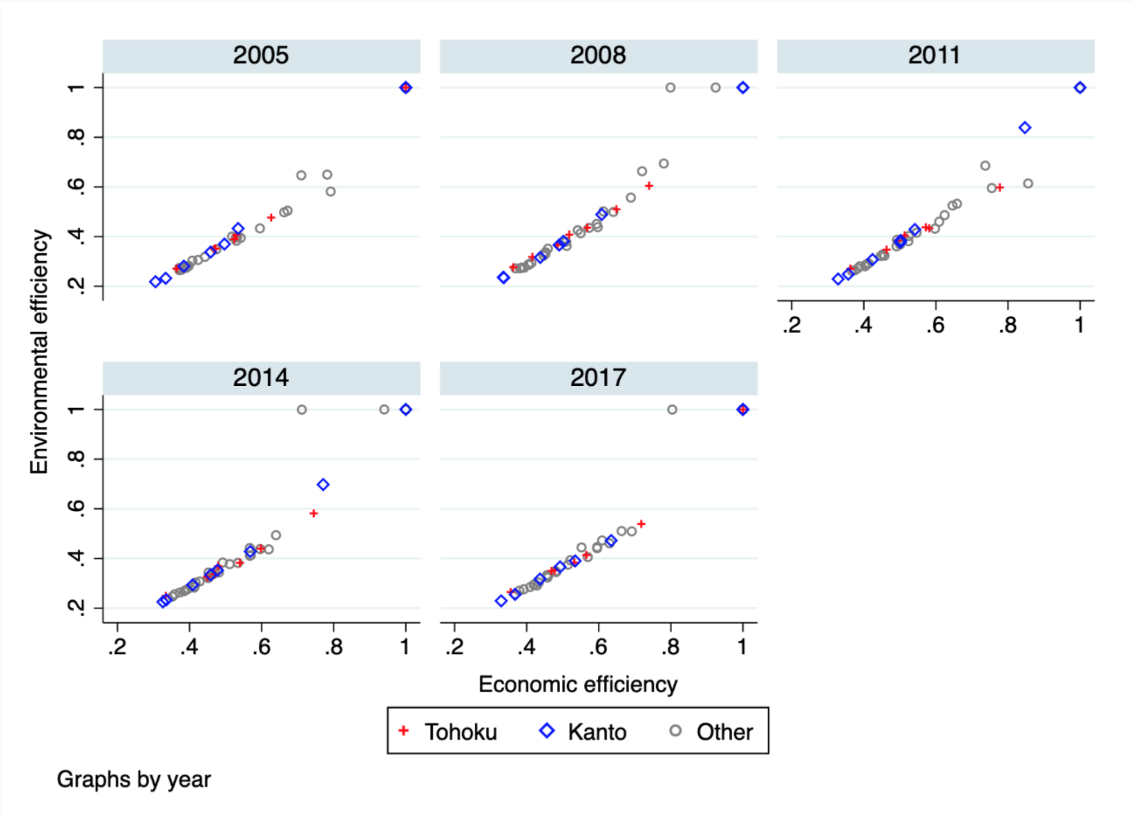


Fig. 4 Scatter plot of environmental and economic efficiencies in 2005, 2008, 2011, 2014, and 2017

Fig. 5 presents the environmental and economic efficiencies of 47 Japanese prefectures during the sample period. For almost all prefectures, both efficiencies showed the same pattern. Iwate (03), Miyagi (04), and Fukushima (07) in the Tohoku region were severely damaged by the earthquake, but these areas were inefficient even before the disaster. Yamanashi (19), Nara,(29), Tottori (31), Shimane (32), Tokushima (36), Kouchi (39), and Okinawa (47) were almost consistently highly efficient with respect to both environmental and economic efficiencies. Tokyo's 13) environmental efficiency deteriorated from unity in 2005 and 2008 to 0.839 in 2008 and 0.698 in 2011 and then improved back to unity in 2017.See the Appendix for potential reduction rates for each fossil fuel and pollutant.

To investigate the determinants of environmental efficiency, we regressed them on GRP per capita, tertiary industry share, and population density using the panel Tobit model. Table 2 presents the estimation results. Among the three variables, GRP per capita and tertiary industry share were statistically significant in models 4 and 7, implying that they positively correlated with environmental efficiency. In the fixed effects model, a 1% increase in per capita income and tertiary industry share increases environmental efficiency by 0.894% and 1.153%, respectively.This implies that economic growth and development of the service industry lead to a sustainable society. The negative coefficients of the 2011 and 2014-year dummies suggest that GEJE and its aftermath deteriorated Japan's environmental performance during those periods.

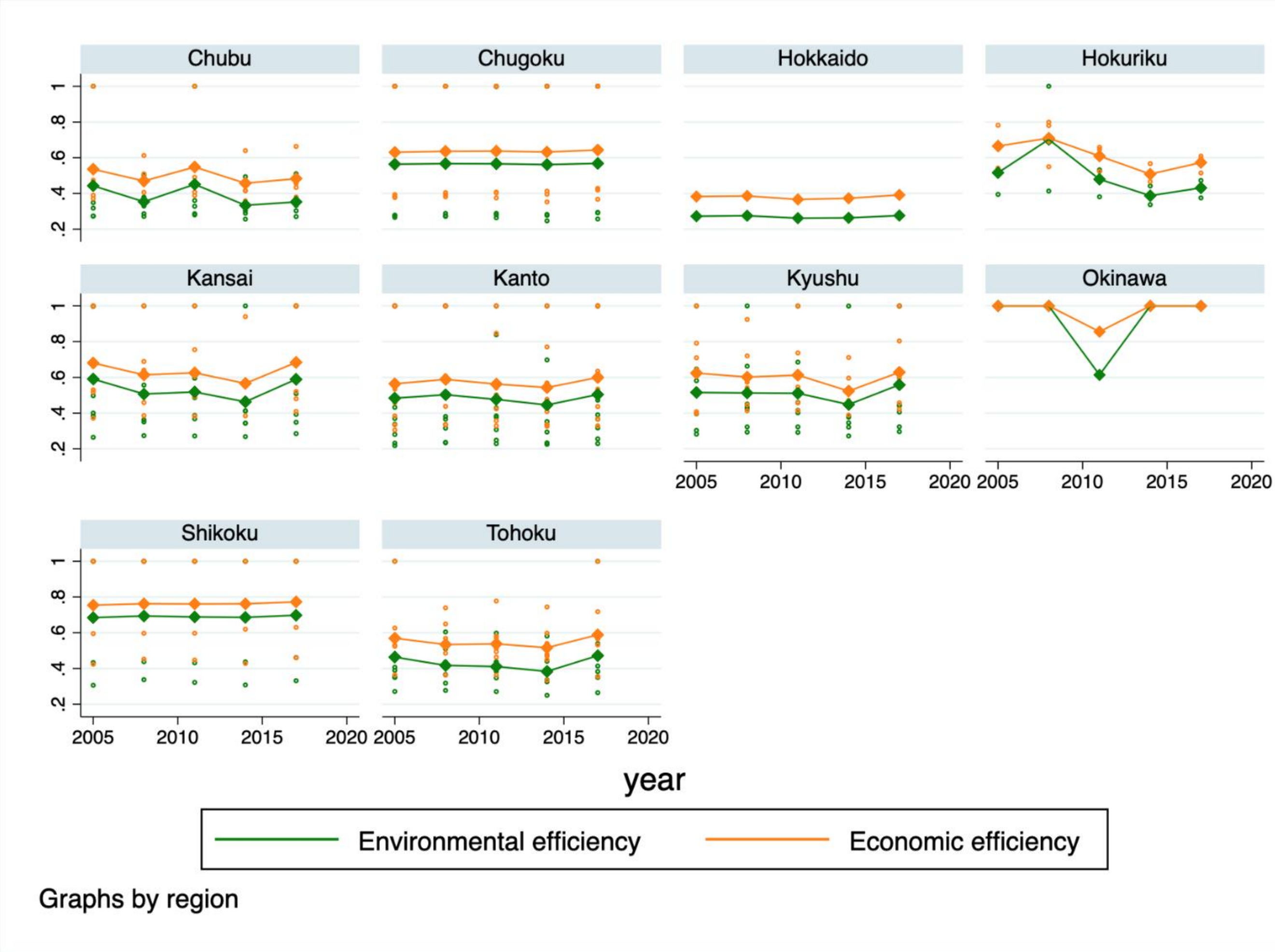


Fig. 5 Environmental and economic efficiencies of ten regions in 2005, 2008, 2011, 2014, and 2017.

Table 2 Empirical results of environmental efficiency determinants

Model	Panel Tobit	Fixed effects	Random effects
Log of GRP per capita	0.506	0.894**	0.435*
	[0.335]	[0.355]	[0.231]
Tertiary industry share	1.101	1.153*	1.006**
	[0.699]	[0.687]	[0.454]
Log of population density	−0.087	0.158	−0.074
	[0.063]	[0.365]	[0.055]
Constant	−3.776	−8.688**	−3.260*
	[2.891]	[4.317]	[1.875]
2008Dummy	0.025	0.026	0.027
	[0.037]	[0.036]	[0.032]
2011Dummy	−0.003	0	0.007
	[0.036]	[0.032]	[0.026]
2014Dummy	−0.044	−0.045	−0.033
	[0.044]	[0.038]	[0.035]
2017Dummy	0.011	−0.021	0.013
	[0.036]	[0.036]	[0.027]
Log-likelihood	55.942		
R^2			
N	235	235	235

Note: Standard errors for the panel Tobit model were estimated from bootstrapping with 50 replications.

6 Concluding remarks

Natural disasters considerably affect not only economic activities but also environmental performance. From the viewpoint of resilience, the extent to which catastrophes disrupt and restore the relationship between the economy and the environment is a question to be explored.

In this study, we measured the environmental efficiency of 47 regions in Japan for the period 2005–2017, which was before and after GEJE in March 2011, using the SBM DEA model. One of the features of our model was that it included comprehensive inputs and outputs: seven inputs (labor, capital, coal, oil, gas, renewables, and electricity), one desirable output (GRP), and four undesirable outputs (CO_2, SO_x, NO_x, and dust). Our empirical results showed that the mean environmental efficiency deteriorated from 0.529 in 2005 to 0.464 in 2014 after GEJE in 2011 but improved to 0.527 in 2017. Iwate, Miyagi, and Fukushima in the Tohoku region were severely damaged by the earthquake, but these areas were inefficient even before the disaster. Tokyo's environmental efficiency deteriorated from unity in 2005 and 2008 to 0.839 in 2008 and 0.698 in 2011 and then improved back to unity in 2017. We also presented PRRs for energy and undesirable outputs.

To examine the determinants of efficiency, we regressed the efficiency on influencing factors using the panel Tobit model. GRP per capita and tertiary industry share were positively correlated with environmental efficiency. This implies that economic growth and development of the service industry lead to a sustainable society.

Acknowledgement

This work was supported by the Japan Society for the Promotion of Science (JSPS) KAKENHI under grant no. 22H03816.

References

Bi, G. B., Song, W., Zhou, P., & Liang, L. (2014). Does environmental regulation affect energy efficiency in China's thermal power generation? Empirical evidence from a slacks-based DEA model. Energy Policy, 66, 537-546.

Bi, G., Luo, Y., Ding, J., & Liang, L. (2015). Environmental performance analysis of Chinese industry from a slacks-based perspective. Annals of Operations Research, 228, 65-80.

Carvalho, V. M., Nirei, M., Saito, Y. U., & Tahbaz-Salehi, A. (2021). Supply chain disruptions: Evidence from the great east japan earthquake. The Quarterly Journal of Economics, 136(2), 1255-1321.

Chang, Y. T., Zhang, N., Danao, D., & Zhang, N. (2013). Environmental efficiency analysis of transportation system in China: A non-radial DEA approach. Energy Policy, 58, 277-283.

Charnes, A., & Cooper, W. W. (1984). Preface to topics in data envelopment analysis. Annals of Operations Research, 2(1), 59-94.

Chin, A. T., & Low, J. M. (2010). Port performance in Asia: Does production efficiency imply environmental efficiency? Transportation Research Part D: Transport and Environment, 15(8), 483-488.

Choi, Y., Zhang, N., & Zhou, P. (2012). Efficiency and abatement costs of energy-related CO2 emissions in China: A slacks-based efficiency measure. Applied Energy, 98, 198-208.

Cho, S. H., Tanaka, K., Wu, J., Robert, R. K., & Kim, T. (2016). Effects of nuclear power plant shutdowns on electricity consumption and greenhouse gas emissions after the Tohoku earthquake. Energy Economics, 55, 223-233.

Chung, Y. H., Färe, R., & Grosskopf, S. (1997). Productivity and undesirable outputs: A directional distance function approach. Journal of Environmental Management, 51(3), 229-240.

Cong, R., Gomi, K., Togawa, T., Hirano, Y., & Oba, M. (2022). How and why did fossil fuel use change in Fukushima Prefecture before and after the great East Japan earthquake? Energy Reports, 8, 1159-1173.

Cooper, W. W., Seiford, L. M., & Tone, K. (2007). Data envelopment analysis: A comprehensive text with models, applications, references and DEA-solver software (Vol. 2, p. 489). New York: Springer.

Evgenidis, A., Hamano, M., & Vermeulen, W. N. (2021). Economic consequences of follow-up disasters: Lessons from the 2011 great East Japan earthquake. Energy Economics, 104, 105559.

Fukuyama, H., Hashimoto, A., & Weber, W. L. (2020). Environmental efficiency, energy efficiency and aggregate well-being of Japanese prefectures. Journal of Cleaner Production, 271, 122810.

Goto, M., Otsuka, A., & Sueyoshi, T. (2014). DEA (Data envelopment analysis) assessment of operational and environmental efficiencies on Japanese regional industries. Energy, 66, 535-549.

Halkos, G. E., & Tzeremes, N. G. (2009). Exploring the existence of Kuznets curve in countries' environmental efficiency using DEA window analysis. Ecological Economics, 68(7), 2168-2176.

Hayashi, M., and Hughes, L. (2013a). The policy responses to the Fukushima nuclear accident and their effect on Japanese energy security. Energy Policy, 59, 86-101.

Hayashi, M., and Hughes, L. (2013b). The Fukushima nuclear accident and its effect on global energy security. Energy policy, 59, 102-111.

Hong, S., Bradshaw, C. J., & Brook, B. W. (2013). Evaluating options for the future energy mix of Japan after the Fukushima nuclear crisis. Energy Policy, 56, 418-424.

Honma, S., & Hu, J. L. (2008). Total-factor energy efficiency of regions in Japan. Energy Policy, 36(2), 821-833.

Honma, S., & Hu, J. L. (2009). Efficient waste and pollution abatements for regions in Japan. International Journal of Sustainable Development and World Ecology, 16(4), 270-285.

Hosoya, K. (2016). Recovery from natural disaster: A numerical investigation based on the convergence approach. Economic Modelling, 55, 410-420.

Hosoya, K. (2019). Importance of a victim-oriented recovery policy after major disasters. Economic Modelling, 78, 1-10.

Huenteler, J., Schmidt, T. S., & Kanie, N. (2012). Japan's post-Fukushima challenge–implications from the German experience on renewable energy policy. Energy policy, 45, 6-11.

Iram, R., Zhang, J., Erdogan, S., Abbas, Q., & Mohsin, M. (2020). Economics of energy and environmental efficiency: Evidence from OECD countries. Environmental Science and Pollution Research International, 27(4), 3858-3870.

Kharecha, P. A., & Sato, M. (2019). Implications of energy and CO_2 emission changes in Japan and Germany after the Fukushima accident. Energy Policy, 132, 647-653.

Li, L. B., & Hu, J. L. (2012). Ecological total-factor energy efficiency of regions in China. Energy Policy, 46, 216-224.

Long, Y., Yoshida, Y., Liu, Q., Guan, D., Zheng, H., Li, Y., & Gasparatos, A. (2021). Japanese carbon emissions patterns shifted following the 2008 financial crisis and the

2011 Tohoku earthquake. Communications Earth & Environment, 2(1), 1-12.

Matsumoto, K. I., Makridou, G., & Doumpos, M. (2020). Evaluating environmental performance using data envelopment analysis: The case of European countries. Journal of Cleaner Production, 272, 122637.

Noy, I. (2009). The macroeconomic consequences of disasters. Journal of Development Economics, 88(2), 221-231.

Oliva, S., & Lazzeretti, L. (2018). Measuring the economic resilience of natural disasters: An analysis of major earthquakes in Japan. City, Culture and Society, 15, 53-59.

Otsuka, A. (2023). Industrial electricity consumption efficiency and energy policy in Japan. Utilities Policy, 81, 101519.

Sasao, T. (2016). Cost and efficiency of disaster waste disposal: A case study of the Great East Japan Earthquake. Waste management, 58, 3-13.

Song, M., Wang, S., & Cen, L. (2015). Comprehensive efficiency evaluation of coal enterprises from production and pollution treatment process. Journal of Cleaner Production, 104, 374-379.

Suzuki, S., Nijkamp, P., & Rietveld, P. (2015). A target-oriented data envelopment analysis for energy-environment efficiency improvement in Japan. Energy Efficiency, 8, 433-446.

Taghizadeh-Hesary, F., Sarker, T., Yoshino, N., Mortha, A., & Vo, X. V. (2021). Quality infrastructure and natural disaster resiliency: A panel analysis of Asia and the Pacific. Economic Analysis and Policy, 69, 394-406.

Taleb, M. (2023). Modelling environmental energy efficiency in the presence of carbon emissions: Modified oriented efficiency measures under polluting technology of data envelopment analysis. Journal of Cleaner Production, 414, 137743.

Tokui, J., Kawasaki, K., & Miyagawa, T. (2017). The economic impact of supply chain disruptions from the Great East-Japan earthquake. Japan and the World Economy, 41, 59-70.

Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. European Journal of Operational Research, 130(3), 498-509.

Wu, D., Wang, Y., & Qian, W. (2020). Efficiency evaluation and dynamic evolution of China's regional green economy: A method based on the super-PEBM model and DEA window analysis. Journal of Cleaner Production, 264, 121630.

Yang, T., Chen, W., Zhou, K., & Ren, M. (2018a). Regional energy efficiency evaluation in China: A super efficiency slack-based measure model with undesirable outputs. Journal of Cleaner Production, 198, 859-866.

Yang, L., Wang, K. L., & Geng, J. C. (2018b). China's regional ecological energy efficiency and energy saving and pollution abatement potentials: An empirical analysis using epsilon-based measure model. Journal of Cleaner Production, 194, 300-308.

Zaim, O., & Taskin, F. (2000). A Kuznets curve in environmental efficiency: An application on OECD countries. Environmental and Resource Economics, 17(1), 21-36.

Zaim, O. (2004). Measuring environmental performance of state manufacturing through changes in pollution intensities: A DEA framework. Ecological Economics, 48(1), 37-47.

Zhang, N., & Choi, Y. (2013). Environmental energy efficiency of China's regional economies: A non-oriented slacks-based measure analysis. The Social Science Journal, 50(2), 225-234.

Zhang, N., Kong, F., & Yu, Y. (2015). Measuring ecological total-factor energy efficiency incorporating regional heterogeneities in China. Ecological Indicators, 51, 165-172.

Zhang, S., Lundgren, T., & Zhou, W. (2016). Energy efficiency in Swedish industry: A firm-level data envelopment. Energy Economics, 55, 42-51.

Zhang, X. P., Cheng, X. M., Yuan, J. H., & Gao, X. J. (2011). Total-factor energy efficiency in developing countries. Energy Policy, 39(2), 644-650.

Zhou, P. A. B. W., Ang, B. W., & Poh, K. L. (2006). Slacks-based efficiency measures for modeling environmental performance. Ecological Economics, 60(1), 111-118.

Zhou, S., & Xu, Z. (2022). Energy efficiency assessment of RCEP member states: A three-stage slack based measurement DEA with undesirable outputs. Energy, 253, 124170.

Zhu, W., Xu, L., Tang, L., & Xiang, X. (2019). Eco-efficiency of the Western Taiwan Straits Economic Zone: An evaluation based on a novel eco-efficiency model and empirical analysis of influencing factors. Journal of Cleaner Production, 234, 638-652.