Dynamics and regional heterogeneity in power generation efficiency of PV power plants in Japan focusing on new market entrants

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Abstract

In order to achieve the reduction target of GHG emissions, the Japanese government aims at securing 33.6-35.3 TWh of electricity generation from renewable energy sources by 2030 and photovoltaic (PV) power generation is expected to account for a large share of electricity generation. Actually, recently there has been numbers of new entrants in the PV power generation business in Japan. This study applies the data envelopment analysis (DEA) and metafrontier global malmquist index (MGMI) to the unbalanced panel data on PV power generation activity from fiscal 2016 to 2020 in Japan and investigates the static and dynamic power generation efficiency for the PV power plants considering new entrants and regional heterogeneity. The results of static analysis indicate that the west region shows the most outstanding performance. On the other hand, the results of MGMI indicate that the east region experienced the largest growth in MGMI and the main driver of the increase in MGMI is technology innovation within the same region. In addition, this study also identifies the innovative PV power plants which contributed to the progress in regional and global frontier technology and the results imply that policymakers should encourage technology spillover between the innovative power plants and the others by coordinating interactions among them.

1. Introduction

According to The Sixth Strategic Energy Plan in Japan, the Japanese government plans to further promote the energy saving to address the growing energy demand induced by economic development and increase in the rate of electrification (Ministry of Economy, Trade and Industry: METI, 2021). As a result, the electricity demand is expected to be 86.4 TWh in 2030, which will be reduced by 13% compared to that in 2013 (METI, 2021). In order to achieve the reduction target of GHG emissions (46% reduction compared to 2013 level), the Japanese government aims at securing 33.6-35.3 TWh of electricity generation from renewable energy sources, which will account for 36-38% of the total electricity generation in Japan in 2030. The installation capacity of photovoltaic (PV) power generation systems is 72 GW in Japan, the third largest installation capacity in the world, in 2020 (International Energy Agency: IEA, 2021). Furthermore, at most 26.2 GW of newly installation in PV power generation systems is expected by 2030 (METI, 2021).

On the other hand, high rate of production improvement resulted from incremental innovation has been leading to the dramatic cost reduction in the products such as light bulbs, aircraft (e.g., DC-3), passenger car (e.g., the Model T Ford), computer core memory and TV (OECD, 2018: Abernathy and Utterback, 1978). In the near future, PV power generation systems will be added to these model cases. Actually, the global weighted-average levelized cost of electricity (LCOE) for the commercial PV power generation systems decreased by as large as 85% from 2010 to 2020 (International Renewable Energy Agency: IRENA, 2021).

When focusing on Japan, the LCOE value drastically decreased from 0.339 USD/kWh in 2012 to 0.132 USD/kWh in 2020 (IRENA, 2021) and it has been lowering the entry wall in the PV power generation business. Moreover, recently there has been a growing attention to the carbon neutrality in Japan and it has been attracting numbers of new entrants in the PV power generation business (METI, 2022). Specifically, after the introduction of feed-in tariff (FIT) system in 2012, newly approved installation capacity in PV power generation systems (with the inverter rated capacity over 10 KW and not for residential) reached approximately 67.7 GW in total as of the end of December 2021 (Agency for Natural Resources and Energy, 2022). On the other hand, when we look at the share of newly approved installation capacity in PV power generation systems by region, it varies from region to region (North: 6.5%, East: 51.0%, West: 42.5%) (Agency for Natural Resources and Energy, 2022). This fact means that there is a difference in the levels of vitalization of new entrants in PV power generation business among the regions.

Baily et al. (1992) and Foster et al. (2001) pointed out that the growth rate of total factor productivity (TFP) increases when a company with cutting-edge technology and advanced business model newly enters into the market or when a company with deteriorated productivity due to reasons such as technology obsolescence leaves from the market. Although the innovation has been confirmed in terms of cost in the PV power generation business, it has not been cleared yet that the technology innovation resulted from the new entrants pointed out by Baily et al. (1992) and Foster et al. (2001) has been promoted.

For evaluating the levels of technology innovation, a combined analytical framework of data envelopment analysis (DEA) and Malmquist productivity index (MPI) has been widely utilized (Cooper et al., 2007). DEA is a nonparametric method first developed by Charnes et al.

(1978) to evaluate the performance of decision-making units (DMUs) simultaneously considering multiple inputs and outputs without any assumption for the type of production function. In DEA, efficiency scores are estimated based on the relative distance between the inefficient DMUs and the production possibility frontier (Cooper et al., 2007). On the other hand, conventional MPI decomposes the productivity change into two terms of frontier-shift effect (i.e., innovation effect) and catch-up effect (Cooper et al., 2007; Färe et al., 1994). However, conventional MPI has two shortcomings. First, the MPI is calculated on the basis of geometric mean and thus is not circular and its adjacent period components can provide different measures of productivity change (Pastor and Lovell, 2005). Second, the MPI overlooks the innovation effect within the group (e.g., regional and industrial groups) (Oh and Lee, 2010).

To address these shortcomings, Oh and Lee (2010) proposed the metafrontier global Malmquist index (MGMI) assuming the contemporaneous and intertemporal frontier technologies as well as the global frontier technology. The MGMI is circular and can shed light on the technology innovation at group levels. Furthermore, Zhang and Choi (2013) proposed the method for identifying the 'innovator'[1] by utilizing the framework of MGMI. Zhang and Choi (2013) found that fossil fuel power plant companies owned by the central government in China lacked technological innovation and technological leadership, while several companies owned by the local government contributed to the progress in local group frontier and global frontier technologies during the study period.

In the light of these research background and acquired knowledge from the previous

[1] In Zhang and Choi (2013), 'innovators' are defined as the DMUs which contribute to the progress in global or group frontier technologies.

studies, this study applies the DEA and MGMI to the unbalanced panel data consist of pooled 750 observations for PV power generation activity from fiscal 2016 to 2020 in Japan to address the following research questions;

- Have the new entrants in the PV power generation business been promoting the technology innovation in this field?
- In that case, how much difference in the levels of technology innovation would be existing between the regions?
- What are the characteristics of the 'innovators'?

To the best our knowledge, most previous DEA studies only considered the existing companies and ignored new entrants. In this paper, we investigate the dynamics in technology innovation in the field of PV power generation systems in Japan in detail and discuss the issues for the substantial new installation of them in the future.

The remainder of this paper is organized as follows. In Section 2, the proposed research framework is described. The data used in this study are explained in Section 3, the results and policy discussion are presented in Section 4, and concluding remarks are given in Section 5.

2. Methodology

2.1 Output-oriented slacks-based measure (SBM) model

This study employs output-oriented SBM model to evaluate power generation efficiency of PV power plants in Japan. Following Tone (2001), we can calculate power generation efficiency of n'-th power plant by solving the following fractional programming problem:

$$\text{min.} \qquad D_{n'}(x,y) = \frac{1-\frac{1}{J}\sum_{j=1}^{J}\frac{s_{jn'}^{-}}{x_{jn'}}}{1+\frac{1}{K}\sum_{k=1}^{K}\frac{s_{kn'}^{+}}{y_{kn'}}}$$

$$\text{subject to} \qquad 1+\frac{1}{K}\sum_{k=1}^{K}\frac{s_{kn'}^{+}}{y_{kn'}} = 1$$

$$x_{jn'} - s_{jn'}^{-} = \sum_{n=1}^{N}\lambda_n x_{jn} \qquad (j = 1,\dots,J)$$

$$y_{kn'} + s_{kn'}^{+} = \sum_{n=1}^{N}\lambda_n y_{kn} \qquad (k = 1,\dots,K)$$

$$\sum_{n=1}^{N}\lambda_n = 1$$

$$\lambda_n \geq 0, s_{jn'}^{-} \geq 0, s_{kn'}^{+} \geq 0 \qquad (1)$$

where λ_n is an intensity variable for constructing the production possibility set by a convex combination, $s_{jn'}^{-}$ is slack of j-th input for plant n', and $s_{kn'}^{+}$ is slack of k-th output for plant n'. J, K, and N denote the number of inputs, outputs, and observations, respectively. We consider three inputs (solar irradiation, temperature, and inverter rated capacity) and one output (actual electricity generation) in this study. Thus, the number of inputs and outputs are three and one, respectively (i.e., $J = 3$ and $K = 1$). $D_{n'}(x,y)$ is the efficiency score and power plant with $D_{n'}(x,y) = 1$ can be regarded as efficient. The fractional programming problem (1) can be transformed into a linear program using the Charnes-Cooper transformation (See Tone, 2001).

2.2 Metafrontier Global Malmquist Index (MGMI)

Following Oh and Lee (2010) and Zhang *et al*. (2013), this study calculates MGMI and decomposes it into three components: efficiency change (EC), best practice gap change (BPGC), and technological gap change (TGC). PV power generation performance is closely related to latitude and weather; thus, there is regional heterogeneity in PV power generation technology. To deal with the heterogeneity, we employ metafrontier DEA framework (O'Donnell, 2008; Eguchi *et al*., 2021). This study divides all PV power plants into three regional groups: north, east, and west.

The MGMI can be calculated and decomposed by solving three types of DEA model: global model, intertemporal model, and contemporaneous model. In the global model, power generation efficiency of n'-th power plant in year t' (i.e., global efficiency) is calculated by referring to the global production technology constructed by all regions in all years as follows:

$$\text{min.} \qquad D_{n'}^{G}(x_{t'}, y_{t'}) = \frac{1 - \frac{1}{J}\sum_{j=1}^{J} \frac{s_{jn't'}^{-}}{x_{jn't'}}}{1 + \frac{1}{K}\sum_{k=1}^{K} \frac{s_{kn't'}^{+}}{y_{kn't'}}}$$

subject to $1+\frac{1}{K}\sum_{k=1}^{K}\frac{s^{+}_{kn't'}}{y_{kn't'}}=1$

$$x_{jn't'}-s^{-}_{jn't'}=\sum_{n=1}^{N}\sum_{t=1}^{T}\lambda_{nt}x_{jnt} \qquad (j=1,\ldots,J)$$

$$y_{kn't'}+s^{+}_{kn't'}=\sum_{n=1}^{N}\sum_{t=1}^{T}\lambda_{nt}y_{knt} \qquad (k=1,\ldots,K)$$

$$\sum_{n=1}^{N}\sum_{t=1}^{T}\lambda_{nt}=1$$

$$\lambda_{nt}\geq 0, s^{-}_{jn't'}\geq 0, s^{+}_{kn't'}\geq 0 \qquad (2)$$

where N and T denote the number of observations and years, respectively. The study period of this study is between fiscal 2016 and 2020, and there were 750 observations during the period (i.e., $N=750$ and $T=5$).

In the intertemporal model, power generation efficiency of n'-th power plant in year t' (i.e., intertemporal efficiency) is calculated by referring to the intertemporal production technology constructed by each region in all years as follows:

$$\text{min.} \qquad D^{I}_{n'}(x_{t'},y_{t'})=\frac{1-\frac{1}{J}\sum_{j=1}^{J}\frac{s^{-}_{jn't'}}{x_{jn't'}}}{1+\frac{1}{K}\sum_{k=1}^{K}\frac{s^{+}_{kn't'}}{y_{kn't'}}}$$

subject to $1+\frac{1}{K}\sum_{k=1}^{K}\frac{s^{+}_{kn't'}}{y_{kn't'}}=1$

$$x_{jn't'}-s^{-}_{jn't'}=\sum_{n=1}^{N^{R}}\sum_{t=1}^{T}\lambda_{nt}x_{jnt} \qquad (j=1,\ldots,J)$$

$$y_{kn't'}+s^{+}_{kn't'}=\sum_{n=1}^{N^{R}}\sum_{t=1}^{T}\lambda_{nt}y_{knt} \qquad (k=1,\ldots,K)$$

$$\sum_{n=1}^{N}\sum_{t=1}^{T}\lambda_{nt} = 1$$

$$\lambda_{nt} \geq 0, s_{jn't'}^{-} \geq 0, s_{kn't'}^{+} \geq 0 \qquad (3)$$

where N^R denotes number of observations classified as group R ($R =$ north, east, and west). The number of observations in north, east, and west regions is 263, 192, and 300, respectively. Thus, $N^{\text{north}} = 263$, $N^{\text{east}} = 192$, and $N^{\text{west}} = 300$.

In the contemporaneous model, power generation efficiency of n'-th power plant in year t' (i.e., contemporaneous efficiency) is calculated by referring to the contemporaneous production technology constructed by each region in each year as follows:

$$\text{min.} \qquad D_{n'}^{C}(x_{t'}, y_{t'}) = \frac{1-\frac{1}{J}\sum_{j=1}^{J}\frac{s_{jn't'}^{-}}{x_{jn't'}}}{1+\frac{1}{K}\sum_{k=1}^{K}\frac{s_{kn't'}^{+}}{y_{kn't'}}}$$

$$\text{subject to} \qquad 1+\frac{1}{K}\sum_{k=1}^{K}\frac{s_{kn't'}^{+}}{y_{kn't'}} = 1$$

$$x_{jn't'} - s_{jn't'}^{-} = \sum_{n=1}^{N^{R}{}_{t'}}\lambda_{nt'}x_{jnt'} \qquad (j = 1, \dots, J)$$

$$y_{kn't'} + s_{kn't'}^{+} = \sum_{n=1}^{N^{R}{}_{t'}}\lambda_{nt'}y_{knt'} \qquad (k = 1, \dots, K)$$

$$\sum_{n=1}^{N}\sum_{t=1}^{T}\lambda_{nt} = 1$$

$$\lambda_{nt} \geq 0, s_{jn't'}^{-} \geq 0, s_{kn't'}^{+} \geq 0 \qquad (4)$$

where $N^{R_{t'}}$ denotes number of observations classified as group R ($R =$ north, east, and west) in year t'. The number of observations in each region and each year is presented in Table 1 in Section 3. The illustration of the global, intertemporal, and contemporaneous frontiers is described in Figure 1.

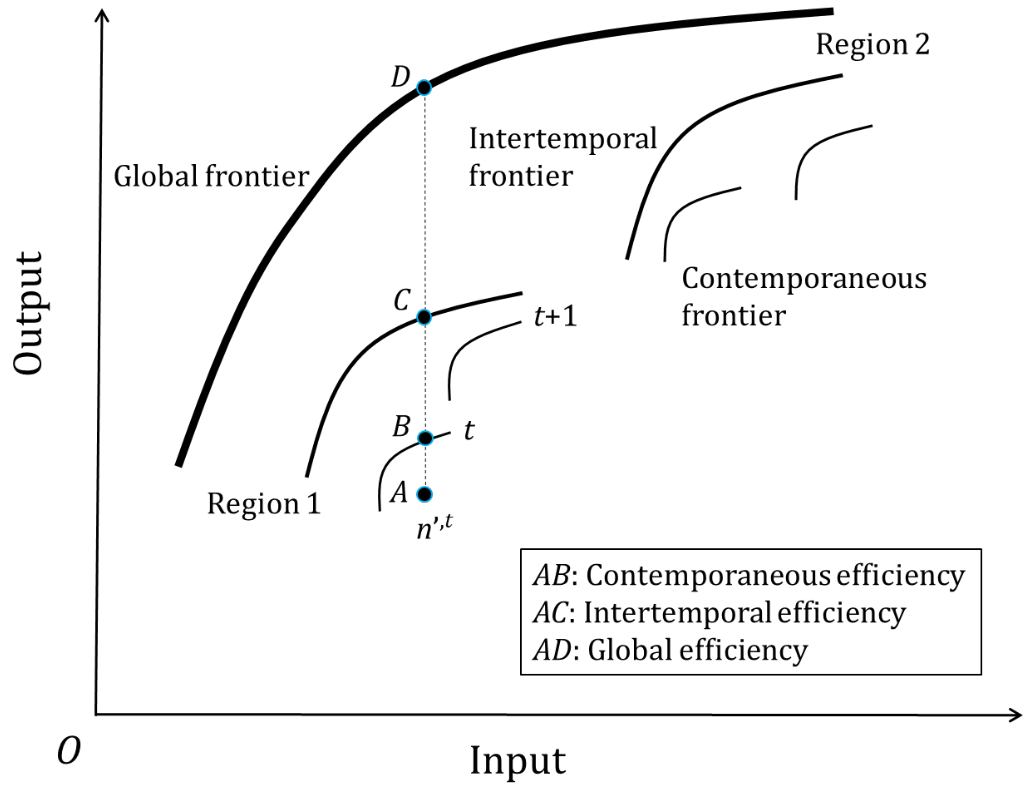


Figure1. Illustration of the proposed research framework

Solving the above three models, we can calculate and decompose MGMI. The calculation and decomposition process of MGMI are as follows:

$$
\begin{aligned}
MGMI_{n'} &= \frac{D_{n'}^{G}(x_{t'+1}, y_{t'+1})}{D_{n'}^{G}(x_{t'}, y_{t'})} \\
&= \left\{\frac{D_{n'}^{C}(x_{t'+1}, y_{t'+1})}{D_{n'}^{C}(x_{t'}, y_{t'})}\right\} \times \left\{\frac{\left\{\frac{D_{n'}^{I}(x_{t'+1}, y_{t'+1})}{D_{n'}^{C}(x_{t'+1}, y_{t'+1})}\right\}}{\left\{\frac{D_{n'}^{I}(x_{t'}, y_{t'})}{D_{n'}^{C}(x_{t'}, y_{t'})}\right\}}\right\} \times \left\{\frac{\left\{\frac{D_{n'}^{G}(x_{t'+1}, y_{t'+1})}{D_{n'}^{I}(x_{t'+1}, y_{t'+1})}\right\}}{\left\{\frac{D_{n'}^{G}(x_{t'}, y_{t'+1})}{D_{n'}^{I}(x_{t'}, y_{t'})}\right\}}\right\} \\
&= \frac{TE_{n',t'+1}}{TE_{n',t'}} \times \frac{BPG_{n',t'+1}}{BPG_{n',t'}} \times \frac{TGR_{n',t'+1}}{TGR_{n',t'}} \\
&= EC_{n'} \times BPGC_{n'} \times TGC_{n'} \qquad (5)
\end{aligned}
$$

where TE_i^t denotes technical efficiency, BPG_i^t denotes best practice gap, and TGR_i^t denotes technology gap ratio of i-th plant in year t. In addition, EC denotes efficiency change, $BPGC$ denotes best practice gap change, and TGC denotes technology gap change. The EC term is a measure of the catch-up effect within the same region, and EC captures how close a plant moves toward the contemporaneous production technology. Here, $EC > 1$ means an efficiency gain within the same regional group. The BPGC term measures changes in best-practice gap ratio between contemporaneous production technology and intertemporal production technology during two periods. Here, $BPGC > 1$ means that contemporaneous technology frontier shifts toward the intertemporal technology frontier. The TGC term is a measure of changes in the technology gap ratio between intertemporal production technology and global production technology during two periods. Here, $TGC > 1$ indicates a decrease in the technology gap between the intertemporal production technology for a specific regional group and the global production technology. See Oh and Lee (2010) and Zhang et al. (2013) for more details.

2.3 Identifying the innovators

Finally, we identify the innovative power plants which contributed to the progress in global or group frontier technologies (i.e., innovators) during the study period following Zhang and Choi (2013). Group innovators are the power plants with outstanding technology growth rate within a regional group and global innovators are the innovative power plants in terms of global production technology. Group innovators can be identified by the following three conditions (Zhang and Choi, 2013):

$$BPGC > 1 \quad (6a)$$

$$\vec{D}^{t}\left(x^{t+1}, y^{t+1}\right) > 1 \quad (6b)$$

$$\vec{D}^{t+1}\left(x^{t+1}, y^{t+1}\right) = 1 \quad (6c)$$

Eq. (6a) indicates that the contemporaneous frontier around an innovative power plant should shift toward the intertemporal frontier between year *t* and *t*+1. Eq. (6b) suggests that the production activity of an innovative power plant in year *t*+1 should be outside the contemporaneous frontier in year *t*. Eq. (6c) means that an innovative power plant should be located on the contemporaneous frontier in year *t*+1.

Global innovators can also be identified as follows (Zhang and Choi, 2013).

$$TGC > 1 \quad (7a)$$

$$\vec{D}^{G}\left(x^{t+1}, y^{t+1}\right) = 1 \quad (7b)$$

Eq. (7a) indicates that a global innovative power plants should be among technologically leading power plants, reducing the technology gap between the intertemporal production technology for a specific regional group and the global production technology between year *t* and *t*+1. Eq. (7b) means that a global innovative power plant should be located on the global frontier in year *t*+1.

3. Data

This study considers three inputs and one output to evaluate the power generation efficiency of the PV power plants in Japan. As the inputs, we consider solar irradiation (MJ/m^2), temperature (*degree*)[2] and inverter rated capacity (*Mw*). As the output, actual electricity generation (*Gwh*) is utilized. Increasing solar irradiation and inverter rated capacity leads to the increment in electricity generation. However, increase in the temperature would deteriorate the power generation efficiency (Dubey et al., 2013). Therefore, we utilize the inverse of temperature as an input. In this study, annual input and output data for each PV power plant are considered as individual observations. We constructed the annual dataset by summing up the monthly data for solar irradiation, inverter rated capacity and actual electricity generation when the PV power plants were under operation, while we utilized the average value for the temperature as an input. The data for the inverter rated capacity and actual electricity generation were obtained from METI (2022) and solar irradiation and temperature were from JMA (2022). The research period is from fiscal 2016 to 2020.

Table 1 shows the average values for each input and output and the number of observations by regional groups. Following JMA (2022), each PV power plant is classified into three regional groups (i.e., north, east, west) based on the location. It should be noted that number of observations varies from year to year because we utilize the pooled data to investigate the impact of new entrants on the frontier technology of PV power plants. In the north, east and west regions, number of observations is increased by 3.64, 3.65 and 2.10 times from 2016 to 2020, respectively. In the east and west regions during the study period, inverter rated capacity and actual electricity generation increase by annual rate of approximately 7-8%. Conversely, in the north region, inverter rated capacity and actual electricity generation decrease by annual rate of 1.8% and 3.2%, respectively.

[2] We utilized the data on solar irradiation and temperature observed at the nearest seat of a prefectural government for each PV power plant.

Table 1. Average values for each input and output and number of observations by regional groups

		2016	2017	2018	2019	2020
North	Number of observations	25	35	45	62	91
	Solar irradiation (*MJ/m²*)	130.00	130.41	133.08	139.92	127.67
	Temperature (*degree*)	6.70	7.62	9.47	5.63	9.55
	Inverter rated capacity (*Mw*)	267.63	261.44	251.44	249.72	249.02
	Actual electricity generation (*Gwh*)	31.49	30.97	29.27	30.66	27.91
East	Number of observations	17	30	28	55	62
	Solar irradiation (*MJ/m²*)	140.68	148.92	169.14	145.57	151.44
	Temperature (*degree*)	13.00	11.13	16.08	14.36	14.38
	Inverter rated capacity (*Mw*)	177.92	199.33	216.83	229.07	241.83
	Actual electricity generation (*Gwh*)	21.14	24.63	25.53	28.10	29.93
West	Number of observations	40	46	57	73	84
	Solar irradiation (*MJ/m²*)	141.27	167.46	152.91	147.73	162.77
	Temperature (*degree*)	14.84	16.34	15.93	16.12	16.18
	Inverter rated capacity (*Mw*)	236.76	262.84	294.18	287.13	322.23
	Actual electricity generation (*Gwh*)	28.95	34.33	36.64	34.96	40.70

4. Result

4.1 Static efficiency

Figure 2 provides the comparison of average value of the three static efficiency scores during the whole study period, which are measured based on the contemporaneous, intertemporal and global models. For all three efficiency scores, the west region shows the highest performance. Specifically, when focusing on the gap in three efficiency scores in the west region, the gap is smaller than the other two regions, meaning that relative distance between the contemporaneous, intertemporal and global frontiers in this region is very close. In Japan, west region is the area with sufficient solar irradiation (Table 1) and it would contribute to this result.

The gap in global, intertemporal and contemporaneous efficiency scores between the west and north regions is 0.214, 0.219 and 0.066, respectively. These results indicate that, although the static efficiency gap within the same region is marginal, efficiency gap between the regions and years is very remarkable.

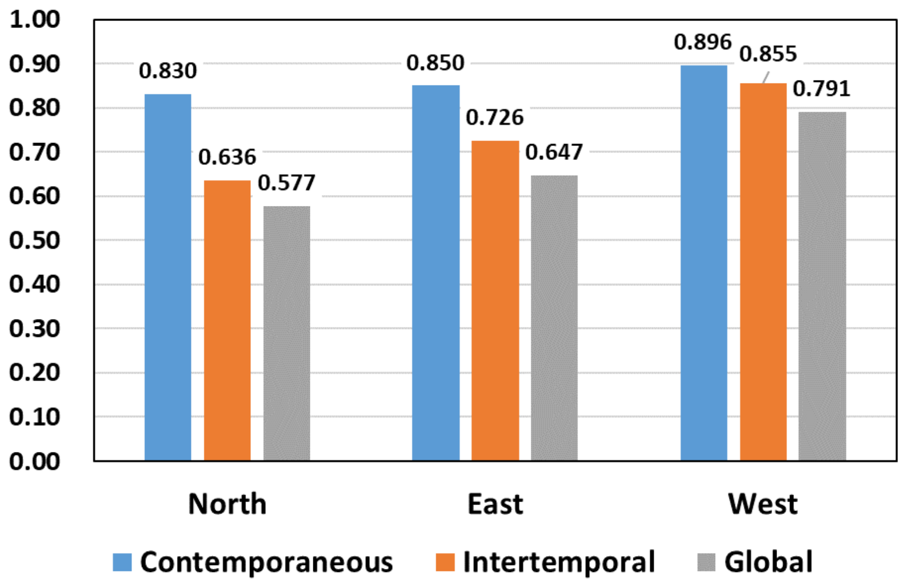


Figure 2. Comparison of the three static efficiency scores (average)

4.2 Dynamic efficiency and its drivers

Figure 3 and Table 2 represent the cumulative and annual changes in average MGMI for each region between 2016 and 2020, respectively. According to Figure 3, all three regions experienced the consistent growth in MGMI during the study period except for the north region between 2019 and 2020. As one of the possible reasons for the decline in MGMI in the north region between 2019 and 2020, the amount of solar irradiation was the smallest in 2020 during the whole study period and it would have lowered the electricity generation. Figure 3 also indicates that the east region shows the most substantial growth in MGMI among the three regions and it increased by 33.2% between 2016 and 2020. Annual change rate of MGMI for the north, east and west regions is 2.4%, 7.5% and 5.6%, respectively (Table 2).

Considering the obtained results in Figures 2 and 3, the west region shows the highest static efficiency scores among the three regions, while the east region experienced the largest growth in MGMI. Next we identify the drivers of the dynamic efficiency change by investigating the components of MGMI.

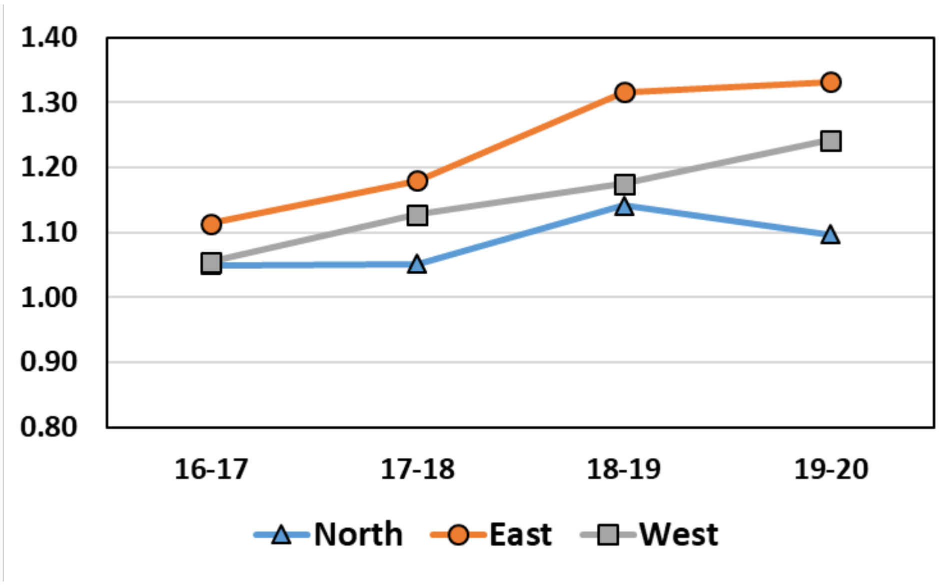


Figure 3. Cumulative change in MGMI

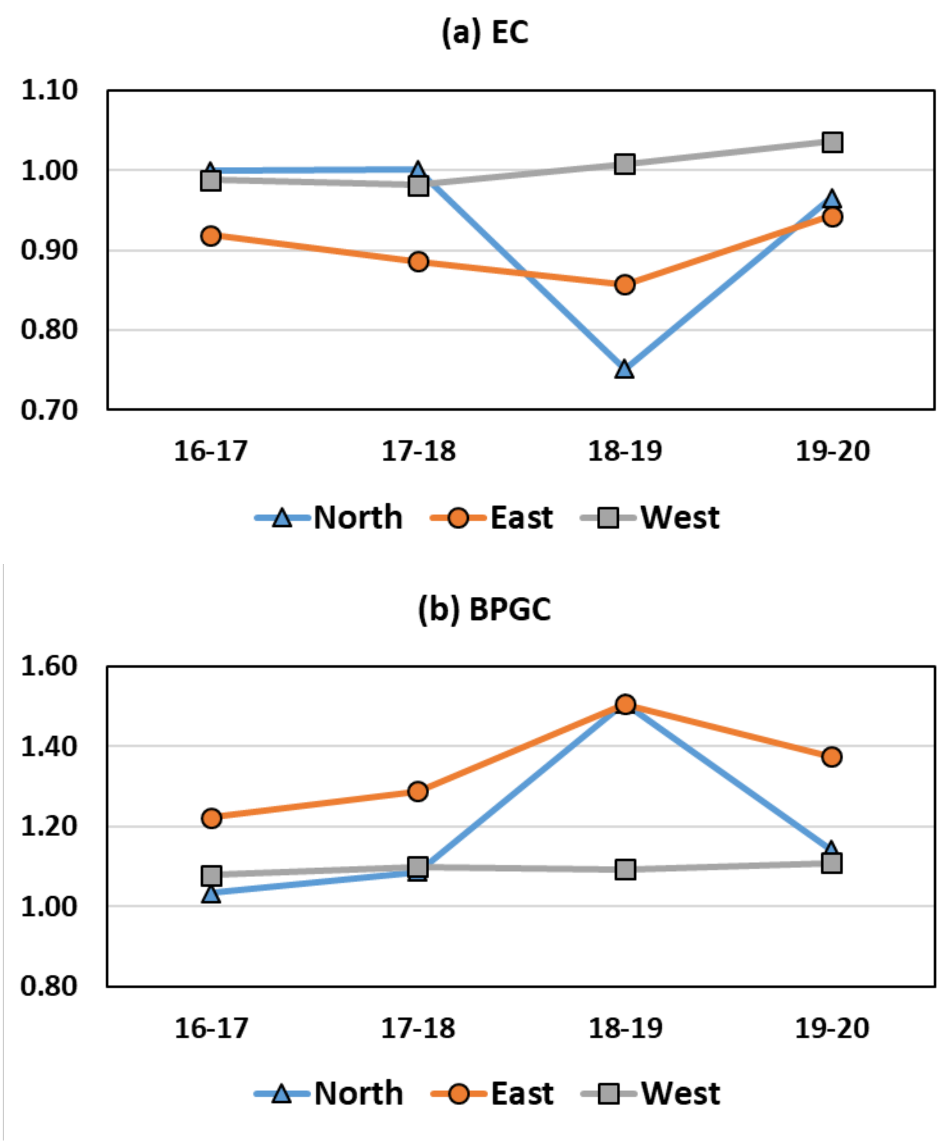
Table 2. Annual change rate of MGMI

	16-17	17-18	18-19	19-20	Average
North	1.050	1.002	1.085	0.961	1.024
East	1.114	1.059	1.115	1.012	1.075
West	1.054	1.069	1.042	1.058	1.056

Figure 4 and Table 3 represent the cumulative and annual changes in EC, BPGC, and TGC, respectively. When focusing on the average annual change rate of the three indicators provided in Table 3, BPGC is dominant in all three regions. This result demonstrates that the increase in BPGC, technology innovation within the same region (i.e., narrowed relative distance between the contemporaneous and intertemporal frontiers), is the main driver of the increasing power generation efficiency of PV power plants in all three regions.

On the other hand, when we look at the change in EC (Figure 4(a) and Table 3), it has the negative impact on MGMI in the east region, while the east region shows the highest average annual growth rate of BPGC and TGC among the three regions. These results imply that, although the innovative PV power plants in the east region substantially progressed the contemporaneous and intertemporal frontier during the study period, catch-up by the other PV power plants was not promoted enough.

Focusing on the annual change rate of each indicator for the west region, TGC overcomes BPGC during the periods of 2017-18 and 2018-19 (Table 3). This result indicates that the technology innovation in this region more progressed the intertemporal frontier technology rather than the contemporaneous frontier technology in these periods. In next section, we identify the innovative PV power plants which contribute to the progress in contemporaneous and intertemporal frontiers.



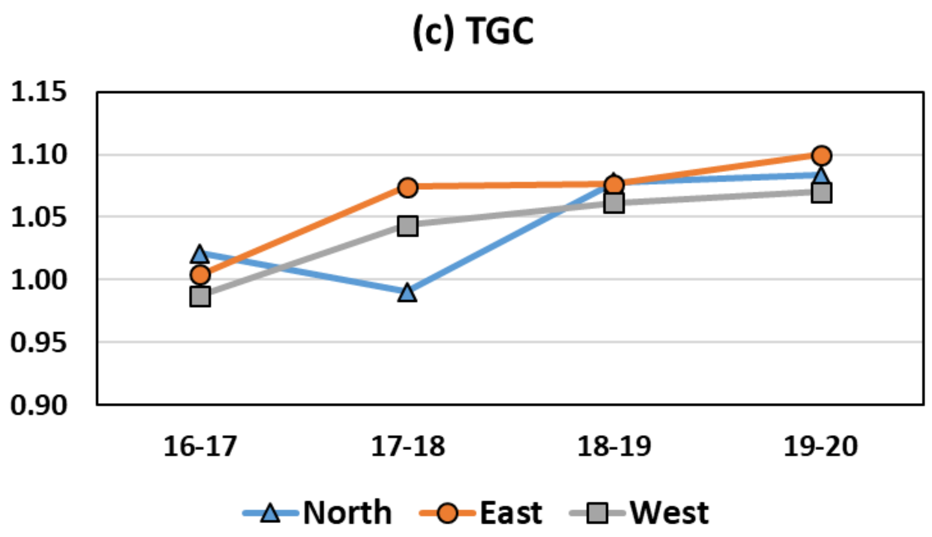


Figure 4. Cumulative changes in EC, BPGC and TGC

Table 3. Annual change rate of EC, BPGC and TGC

		16-17	17-18	18-19	19-20	Average
EC	North	0.999	1.002	0.751	1.285	1.009
	East	0.919	0.964	0.968	1.099	0.988
	West	0.988	0.993	1.027	1.028	1.009
		16-17	17-18	18-19	19-20	Average
BPGC	North	1.034	1.051	1.388	0.756	1.057
	East	1.222	1.054	1.168	0.913	1.089
	West	1.079	1.020	0.994	1.015	1.027
		16-17	17-18	18-19	19-20	Average
TGC	North	1.021	0.970	1.088	1.005	1.021
	East	1.004	1.070	1.002	1.022	1.024
	West	0.987	1.057	1.017	1.008	1.017

4.3 Identifying group and global innovators

In this section, we identify the innovative PV power plants by using Eqs. (6a)-(7b). Table 4 provides the list of innovative PV power plants for contemporaneous and global frontiers[3]. Group innovator represents the PV power plants which contributed to the progress in contemporaneous frontier technology and narrowing the distance between contemporaneous and intertemporal frontiers. Global frontier innovator represents the PV power plants which contributed to the progress in intertemporal frontier technology and narrowing the distance between intertemporal and global frontiers.

Table 4 indicates that, in all three regions, a lot of innovative power plants contributed to the progress in contemporaneous frontier technology between 2017 and 2018. However, after 2018, the number of group innovators drastically decreased in the north and east regions. This result means that large increase in BPGC in the east region between 2018 and 2019 (Table 3) was led by only power plant #5 (Table 4). On the other hand, in the west region, a lot of PV power plants still contributed to the progress in contemporaneous frontier technology after 2018. Furthermore, several group and global innovators started the operation after 2017. This result proves that technology innovation has been induced by the new entrants in the field of PV power generation.

Interestingly, several PV power plants were identified as group innovator multiple times (i.e., North: #92, East: #5, #46, #84, West: #175, #179, #185, #190, #218, #229). Other plant managers and policymakers should refer to the facilities and management of these PV power plants in their region for improving the power generation efficiency. In addition, power plants #92, #93, and #94 in the north region and power plants #208 and #210 in the west region are operated by the same company. The expertise of this company would be useful for the

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[3] We were not able to make use of the data before 2016. Therefore, the PV power plants whose initial year of operation is 2016 might be started operating before 2016.

technology improvement for the other PV power plants. Moreover, the PV array rated capacity of innovators rages from 5 MW to 235.4 MW. Thus, plant managers can refer to the suitable innovator with production capacity close to their own power plants.

Finally, most of the global frontier innovators are concentrated in the west region. This result would indicate that technology innovation has been actively advancing in the west region. On the other hand, it might be possible that distinctive characteristics of the west region (e.g., large amount of solar irradiation) has also been boosting the innovation. Conventional Malmquist index would overlook the innovation in the group frontiers. We made use of metafrontier global Malmquist index to shed light on the group innovators to provide the useful information of the technology spillover and knowledge sharing for the effective operation of PV power generation systems in Japan. In addition, we consider the impact of new entrants on the technology innovation, whereas most previous studies ignore it. These are the main novelty of this study.

Table 4. Innovative PV power plants for contemporaneous and global frontiers

Period	Group innovator		
	North	East	West
2016-17	#92 (Fukushima, 2016, 12.2MW),	#46 (Choshi, 2016, 27MW), #84 (Shizuoka, 2016, 32MW)	#123 (Hikone, 2016, 35MW), #179 (Takamatsu, 2016, 25.3MW), #191 (Osaka, 2016, 19.7MW), #208 (Osaka, 2016, 10MW), #210 (Osaka, 2016, 10.5MW)
2017-18	#16 (Fukushima, 2017, 55.6MW), #92 (Fukushima, 2016, 12.2kW), #93 (Fukushima, 2016, 5.0kW), #94 (Aomori, 2016, 148.0MW), #108 (Fukushima, 2017, 29.9MW)	#4 (Choshi, 2016, 20MW), #5 (Toyama, 2016, 5.3MW), #31 (Tsukuba, 2017, 20.5MW), #46 (Choshi, 2016, 27MW), #84 (Shizuoka, 2016, 32MW), #99 (Nagoya, 2016, 10.5MW) #110 (Nagoya, 2016, 27.7MW)	#172 (Fukuoka, 2017, 11MW), #175 (Kagoshima, 2016, 70MW), #185 (Kagoshima, 2016, 12.6MW), #192 (Kumamoto, 2016, 22.4MW), #194 (Miyazaki, 2017, 96.2MW), #218 (Kagoshima, 2017, 32.3MW)
2018-19	#50 (Muroran, 2016, 111.0MW), #108 (Fukushima, 2017, 29.9MW)	#5 (Toyama, 2016, 5.3MW)	#175 (Kagoshima, 2016, 70MW), #185 (Kagoshima, 2016, 12.6MW), #190 (Matsue, 2016, 42.9MW), #208 (Osaka, 2016, 10MW), #218 (Kagoshima, 2017, 32.3MW), #229 (Hiroshima, 2017, 235.4MW)
2019-20	–	–	#179 (Takamatsu, 2016, 34.0MW), #185 (Kagoshima, 2016, 12.6MW), #190 (Matsue, 2016, 42.9MW), #191 (Osaka, 2016, 15MW) #214 (Miyazaki, 2016, 24.5MW), #229 (Hiroshima, 2017, 235.4MW)
Period	Global frontier innovator		
	North	East	West
2016-17	–	–	–
2017-18	–	#84 (Shizuoka, 2016, 32MW)	#218 (Kagoshima, 2017, 32.3MW)
2018-19	#108 (Fukushima, 2017, 29.9MW)	–	#185 (Kagoshima, 2016, 12.6MW), #208 (Osaka, 2016, 10MW)
2019-20	–	–	#214 (Miyazaki, 2016, 24.5MW)

*Information in the parentheses represents location of PV power plant, initial year of operation and PV array rated capacity, respectively.

5. Conclusion

This study applied the DEA and MGMI to the unbalanced panel data for PV power generation activity from fiscal 2016 to 2020 in Japan and investigated the static and dynamic power generation efficiency for the PV power plants. The results of static analysis indicate that the east region shows the most outstanding performance and efficiency gap between the regions and years is very remarkable. On the other hand, the results of MGMI indicate that, although the MGMI increased in all three regions, the east region experienced the largest growth in MGMI.

Investigating the components of MGMI indicates that BPGC, technology innovation within the same region, is the main driver of increasing MGMI in all three regions. However, EC has the negative impact on MGMI in the north and east region, implying that, although the technology innovation within the same region was promoted by several innovative power plants, catch-up by the other PV power plants was not enough. In order to increase the EC effect, policymakers should encourage technology spillover between the innovative power plants and the others by coordinating interactions among them.

At the presentation of the IIOA conference in Langkawi, we further discuss the future direction of PV power generation in Japan.

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