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Chu, Ling

Takeuchi, Kenji

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# The non-operating solar projects: Examining the impact of the feed-in tariff amendment in Japan


Ling Chu[*], Kenji Takeuchi[†]

Graduate School of Economics, Kobe University

Rokko, Kobe 657-8501, Japan



[*]Ph.D. student, Graduate School of Economics, Kobe University, E-mail: chulingkoharu@gmail.com

[†]Professor, Graduate School of Economics, Kobe University, E-mail: takeuchi@econ.kobe-u.ac.jp

**Abstract**

The non-operating solar power projects indicate a large gap between the operating and approved solar capacity in Japan. The country amended the feed-in tariff (FIT) law in 2017 to address this issue. This empirical study investigates the impact of the amended FIT policy on non-operating solar projects using municipality-level panel data from 2014 to 2019. We find that the amended policy improved the relationship between the approved capacity and operating capacity of solar power projects. The impacts are heterogeneous across different sizes of solar power projects: they are more substantial in large- and mega-scale solar power projects than in small-scale ones. To explore the determinants of non-operation, we also apply a cross-sectional analysis to identify municipal characteristics related to non-operating capacity. The results indicate that non-operating projects are located in municipalities with higher construction costs. These findings shed light on how the revisions of existing policies could effectively support renewable energy and provide lessons for other countries or regions on designing a better energy policy.

Keywords: Solar power; Feed-in tariff; Japan; Non-operation; Panel data analysis

# 1 Introduction

Renewable power generation in Japan is expected to increase further because of its importance in reducing GHG emissions and attaining energy self-sufficiency after the Fukushima Daiichi accident in 2011. The Japanese government approved the 5th Basic Energy Plan[1] in July 2018; the plan emphasizes the need for renewable energy as a major power source (METI, 2018b). The draft of the 6th Basic Energy Plan sets an ambitious target according to which renewable energy will account for 36% to 38% of the energy mix in 2030 (METI, 2021a). However, as of 2019, the share of renewable energy in electric power generation in Japan was 18.1% (10.3%, if hydroelectric power is excluded) (METI, 2021b). There is still a long way to go in order to achieve the newest target for renewable energy.

Japan launched the feed-in tariff (FIT) scheme in 2012 as a policy measure to promote the deployment of renewable energy. Although FIT has increased renewable power generation, particularly by solar cells, it has encountered several challenges. The biggest challenge pertains to the non-operating solar power projects, which have created a large gap between the operating and approved solar capacity. The non-operating projects are due to the design of the initial FIT scheme. First, the scheme provides an urgent incentive for project developers to obtain earlier FIT approval. Under the scheme, the purchase price for renewable electricity is determined by the year of FIT approval. As the FIT price is expected to decline over time, obtaining earlier approval leads to a higher purchase price and revenue for selling renewable electricity. Second, the scheme also provides an incentive for project developers to install solar PV later. Since the price of solar panels is decreasing dramatically in the domestic market, it is possible to decrease the equipment cost by delaying the installation of solar PV. Moreover, there was no explicit regulation on the deadline for approved projects to start their operation. As a result, developers who obtained FIT approval in the early years can increase their revenue by delaying their start of operation. Future consumers will have to pay the higher FIT price determined by the year of approval even though the cost of operation is reduced. The country amended the FIT law in 2017 to address this issue by revising requirements to obtain project approval.

[1] The Basic Energy Plan is the government's medium- to long-term energy outlook. The Agency of Natural Resources and Energy (ANRE) of the Ministry of Economy, Trade and Industry (METI) revises the plan every three to four years.

This study empirically investigates the impact of amended FIT policies on the operation of solar power. We estimate the relationship between operating capacity and approved capacity before and after the amendment using municipality-level data of solar power capacity in Japan from 2014 to 2019. To investigate the heterogeneous effect on solar projects among different scales, we distinguish the projects according to their capacity to explore whether the policy impact differs according to project size. In addition, the study examines the characteristics of municipalities that locate non-operating solar projects.

Many studies have evaluated policy instruments to support renewable energy. Jenner et al. (2013) assess the effectiveness of FIT policies in promoting renewable energy in 26 European Union countries from 1992 to 2008. They create an indicator for policy strength that represents the return on investment provided by FIT and find that, for a 10% increase in return on investment, countries will install 3.8% more solar capacity and 2.8% more onshore wind capacity. Polzin et al. (2015) investigate the influence of different measures on subsequent investments in renewable energy capacity by institutional investors in OECD countries from 2003 to 2011. They find that FIT is more effective than subsidies for less-mature technologies such as solar. Renewable portfolio standards and emission trading systems seem to be more effective for mature technologies such as wind. Böhringer (2017) examines the impact of the German FIT on the innovation of renewable energy technologies from 1990 to 2014 and finds a positive effect of FIT on inducing innovation. However, the inducement effect of prior FITs with moderate subsidy rates is not significantly different from that of later FITs with much higher prices. Muhammad-Sukki et al. (2014) investigate the impact of Japanese FIT schemes on residential and non-residential solar power using financial analysis. They indicate that FIT rates generate a good profit, a moderate annual return on investment, and an acceptable payback period, suggesting that this would potentially attract more interest in installing solar photovoltaic (PV) systems.

Our study complements the literature that investigates the unexpected issues arising from the adverse incentives of renewable energy supporting policy. Supportive but poorly designed renewable energy policies can lead to a market bubble, distortion in resource allocation, and other undesirable consequences. Gómez et al. (2016) investigate the energy bubble in Spain from an energy planning perspective. Supply bubbles of gas combined cycle and solar technologies cause surplus investment. The authors find that appropriate energy planning could have reduced investments by 28.6 billion euro, suggesting that energy planning requires committed policy-making to succeed. Xia et al. (2020) investigate curtailment issues in the wind power sector in China from the perspective of excess capacity occurred under the FIT scheme. FIT rates were adjusted slowly while the investment costs declined quickly, thus generating a high mark-up that incentivizes excess investment. Xia et al. (2020) find that a 0.1 yuan increase in the mark-up leads to a 2% to 3% increase in the share of the curtailed wind power out of the maximum potential generation at full utilization of installed capacity. By increasing the FIT rate adjustment frequency to reflect the declining trend of wind power costs, the curtailment could be reduced by more than 43 billion kWh. This outcome indicates that the economic efficiency of FIT could be improved with a design that better reflects the generation costs. Yu et al. (2021) analyze resource misallocation in the Chinese wind power industry. They find that the FIT policy exacerbates industry-wide resource misallocation, thus lowering productivity in the wind power industry.

This study also relates to previous studies that examine the factors affecting the growth of solar PV capacity. Zhang et al. (2011) use prefecture-level data from 1996 to 2006 to analyze the factors affecting the diffusion of residential solar PV systems in Japan. They find that the regional government's policies help promote PV system adoption. Installation costs have a significant negative effect, whereas housing investment and environmental awareness have positive impacts. Tanaka et al. (2017) examine the factors determining purchasing decision time for residential solar PV using survey data in 2012 in Japan. The results show that FIT accelerates the decision-making process while subsidy schemes do not reduce the decision-making time, leading to the purchase of a PV system. FIT offers long-term benefits to PV system users by allowing them to sell surplus electricity back to the grid, contrary to subsidies that provide financial assistance only initially at the time of investment. Conversely, information obtained from other users lengthens the decision-making process regarding purchasing a PV system since consumers who sought information or who communicated with existing users were more cautious in their purchasing decisions. Using county-level data from 2005 to 2013 in the northeastern United States, Crago and Chernyakhovskiy (2017) investigate the impact of policy incentives on the commercial solar power capacity. They find that rebates, sales exemptions, and renewable portfolio standards have statistically significant and positive effects. Factors that directly affect financial viability and returns on investment, such as solar insolation and installation cost, have the most impact on capacity growth in the commercial solar

PV market.

Contrary to the existing literature, this study focuses on the non-operating capacity of solar power projects. It also sheds light on how the improvement in policy design corresponding to the changes in the market condition could alleviate the perverse impact. We examine whether the amended FIT policy alleviates the gap between the operating and approved solar capacity. Few studies have mentioned the existence of non-operating solar power. For instance, Kuramochi (2015) reviews policy measures on energy and climate change implemented in Japan and points out a large gap between the installed capacity and the approved capacity, particularly for non-residential facilities. However, no quantitative analysis was conducted in this policy review. To the best of our knowledge, our study is the first to empirically investigate the issue of non-operating solar projects by examining the effect of FIT amendments. Furthermore, in contrast to studies focusing on drivers of growth in solar PV installed capacity (Zhang et al., 2011; Crago and Chernyakhovskiy, 2017; Crago and Koegler, 2018), we examine municipal characteristics that tend to locate non-operating facilities and explore the characteristics before and after the amendment of the FIT scheme.

Although the issue of non-operating solar projects is unique to Japan, it is important for other countries or regions to explore the mechanism behind and how amendment of the program can fix the issue. They can learn from Japanese FIT how supporting policy for renewable energy is as important as the choice of particular policy instruments. To avoid the issues arising from renewable energy policy, they should pay attention to the incentives provided and how these incentives interact with the continuously changing market. For example, when policymakers decide to adopt an FIT policy, they should design the implementation rules carefully and adjust them to actual market conditions.

The remainder of this paper is organized as follows. Section 2 provides an overview of Japan's FIT policy, the issue of non-operating solar projects, and the revisions made by the amended FIT scheme. Section 3 presents the regression model and describes the dataset used in the analysis, while Section 4 discusses the empirical results. Finally, Section 5 presents the conclusions.

# 2 Policy Background

## 2.1 Feed-in Tariff Policy in Japan

To increase the share of renewable energy in the energy mix,[2] Japan launched a national FIT scheme based on the Act on Special Measures Concerning Procurement of Electricity from Renewable Energy Sources by Electricity Utilities in July 2012. Under FIT, renewable energy producers: solar PV, wind power, small hydro, geothermal, and biomass, are required to submit documents to obtain FIT approval[3] from the Japanese government. Electric utilities[4] are obliged to purchase electricity generated from renewable energy sources at a fixed price (tariff) for a specific period. Electricity generated from renewable energy sources shall be transmitted to the power grid of the electric utility and distributed to end-users. All electricity users will then pay a surcharge for renewable energy proportional to their usage to cover the expense of purchasing renewable power (METI, 2012).

Table 1 presents the purchase price under FIT from 2012 to 2020. The Japanese government adopted a nationwide but source- and size-specific price scheme. A unified FIT scheme would reduce unfavorable renewable capacity allocations, foster market competition, and reduce electricity costs but would not benefit some high-cost renewables. In contrast, setting differentiable purchase prices would encourage investment by ensuring profit margins, but would also risk increasing the economic burden on electricity consumers (Li et al., 2019). Hence, the Ministry of Economy, Trade, and Industry (METI) sets the purchase price differentiated by the category of renewable energy sources and the size of the power generation facilities. The FIT payments are also adjusted for new projects to address changes in electricity supply and generation cost over time. The purchase prices for electricity generated by solar power have continued to fall year by year while prices for other renewable sources remained relatively stable.

The FIT scheme guarantees a fixed price (tariff) for a designated period, thereby enhancing certainty and stability for FIT-eligible renewable electricity producers. The approved capacity of

[2] Japan implemented a renewable portfolio standard program from 2003 to 2011, but its impact on renewable power development was small.

[3] FIT approval refers to the application of an existing or proposed renewable energy power facility confirmed and certified by the Ministry of Economy, Trade, and Industry.

[4] Ten regional electric utility companies are Hokkaido, Tohoku, Tokyo, Hokuriku, Chubu, Kansai, Chugoku, Shikoku, Kyushu, and Okinawa.

renewable energy has been growing rapidly (it was 88,773 MW by the end of December 2016) (Ito, 2015). However, the operating capacity among them was only 33,659 MW, indicating that more than 62% of solar projects were not in operation, regardless of the FIT approval. This problem of "non-operation" was even more serious in non-residential solar power ($\geq$10 kW) projects because most of the non-operating capacities fall under this category.

The economic reason behind many non-operating solar projects is that the purchase price is determined when the METI approves the facility. Earlier approval implies a higher tariff and revenue from selling electricity. For instance, by receiving the FIT approval in 2012, the electricity producer of non-residential solar power can sell the electricity at 43.2 Japanese yen per kWh, which is 35% higher than the purchase price for solar power approved in 2014. Meanwhile, the price of a typical 10 kW solar PV system decreased from 430,000 in 2012 to 346,000 JPY/kW in 2014 (METI, 2018a), which means that by delaying installation of solar PV, one can enjoy a lower equipment cost. Moreover, there was no explicit deadline for approved projects to connect to the electricity grid and start their operation. Thus, the scheme provides solar power developers an incentive to obtain FIT approval as early as possible and delay the operation to maximize profits. In 2014, METI investigated the status of installations of non-residential facilities approved during 2012. A total of 3 GW capacity of the approved facilities had either not secured land or ordered the purchase of a solar PV system, or did not respond to the inquiry (Kuramochi, 2015).

Many FIT-approved projects should have been generating electricity already. The existence of non-operating projects implies that a substantial amount of potential electricity from renewable resources is not available despite the rapid expansion of approved capacity, suggesting that the original FIT scheme is not effective in promoting renewable electricity. Furthermore, if these non-operating projects start operations and generate electricity long after the FIT approval, they have the privilege of selling electricity with higher FIT prices. The higher purchase price would then be transferred to the future consumers, leading to their welfare loss. The unnecessary financial burden lowers the economic efficiency of the FIT scheme.

Table 1. Purchase price under Japan's FIT scheme (JPY/kWh), 2012-2020

| Energy source | Category | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | Duration(year) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Solar PV | <10kW | 42 | 38 | 37 | 35 | 33 | 30 | 28 | 26 | 21 | 10 |
| | 10kW-50kW | 40 | 36 | 32 | 27 | 24 | 21 | 18 | 14 | 13 | 20 |
| | 50kW-250kW | 40 | 36 | 32 | 27 | 24 | 21 | 18 | 14 | 12 | 20 |
| | 250kW-500kW | 40 | 36 | 32 | 27 | 24 | 21 | 18 | 14 | 10-12 | 20 |
| | 500kW-2MW | 40 | 36 | 32 | 27 | 24 | 21 | 18 | 10.5-13.99 | 10-12 | 20 |
| | $\geq$ 2MW | 40 | 36 | 32 | 27 | 24 | 17.2-21 | 14.25-15.45 | 10.5-13.99 | 10-12 | 20 |
| Wind | <20kW | 55 | 55 | 55 | 55 | 55 | 55 | 20 | 19 | 18 | 20 |
| | $\geq$ 20kW | 22 | 22 | 22 | 22 | 22 | 21 | 20 | 19 | 18 | 20 |
| | offshore | - | - | 36 | 36 | 36 | 36 | 36 | 36 | 36 | 20 |
| Geothermal | <15MW | 40 | 40 | 40 | 40 | 40 | 40 | 40 | 40 | 40 | 15 |
| | $\geq$ 15MW | 26 | 26 | 26 | 26 | 26 | 26 | 26 | 26 | 26 | 15 |
| Hydro | <200kW | 34 | 34 | 34 | 34 | 34 | 34 | 34 | 34 | 34 | 20 |
| | 200kW-1MW | 29 | 29 | 29 | 29 | 29 | 29 | 29 | 29 | 29 | 20 |
| | 1MW-5MW | 24 | 24 | 24 | 24 | 24 | 27 | 27 | 27 | 27 | 20 |
| | $\geq$5MW | - | 24 | 24 | 24 | 24 | 20-24 | 20 | 20 | 20 | 20 |
| Biomass | Manure biogas | 39 | 39 | 39 | 39 | 39 | 39 | 39 | 39 | 39 | 20 |
| | Forest residues | 32 | 32 | 32 | 32-40 | 32-40 | 32-40 | 32-40 | 32-40 | 32-40 | 20 |
| | Primary mill residues | 24 | 24 | 24 | 24 | 24 | 21-24 | 19.6-24 | 24 | 18.5-24 | 20 |
| | General waste | 17 | 17 | 17 | 17 | 17 | 17 | 17 | 17 | 17 | 20 |
| | Recycled wood | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 20 |

Source: METI (2012-2020), Dong and Shimada (2017)

Note: Duration means the period for purchasing electricity generated by each power source. The purchase prices for $<$ 10 kW solar are tax inclusive. Purchase prices for $\geq$ 2 MW solar after 2017, $\geq$ 500 kW solar after 2019, $\geq$ 250 kW solar, floating offshore wind, $\geq$ 10 MW biomass solid fuels, and biomass liquid fuels after 2020 are determined by bidding process.

## 2.2 Amended FIT Policy in Japan

To address the issue of non-operating solar projects, the Japanese government has promulgated the amendment to the FIT Act on June 2, 2016. The amendments came into effect on April 1, 2017, and made three major revisions to reduce non-operating solar projects through different channels. First, renewable power producers must conclude grid connection agreements before obtaining the approval of FIT. Regarding the approved projects, deadlines for connection agreements are set to ensure the continued validity of the applicable purchase price and purchase period. The projects lose eligibility of FIT if these deadlines are missed. The requirement of grid connection agreements can reduce the uncertainty in grid connection of FIT-approved projects and decrease non-operating solar projects caused by the lack or the delay of grid connection. Second, the amended FIT set deadlines for starting the operation of approved projects. Renewable energy developers must implement solar projects larger than 10 kW three years after the approval and smaller than 10 kW one year after approval. If they do not meet the deadlines, they will lose their FIT approval or their purchase period will be reduced. The setting of deadlines directly helps mitigate the non-operating issue. Third, a bidding system is introduced for solar projects larger than 2 MW. The main purpose of the bidding system is to lower the applicable purchase price and promote competition among developers. Because the system acts as an entry barrier for less qualified and uncontemplated projects, it reduces potential non-operating projects.

In summary, the amended FIT policy tightens the requirements for FIT approval and introduces competition to determine FIT prices. These amendments are expected to reduce non-operating solar projects. Figure 1 shows the total approved capacity and operating capacity of solar power during 2012-2019. According to METI (2017), 456,000 approved projects with a total capacity of 27.66 GW were expected to lose their FIT approval validity after the amendment. A sharp decline is observed in the cumulative capacity of approved projects from 2016 to 2017. The previous FIT policy only required information concerning facility location and the PV system specifications for approval. In contrast, the amended FIT introduced a stricter requirement on the commencement of operation, such as grid connection agreements, thus increasing the operating capacity. The figure shows that the gap between operating capacity and approved capacity decreased after 2017, suggesting that the amended FIT policy mitigated the issue of non-operating projects.

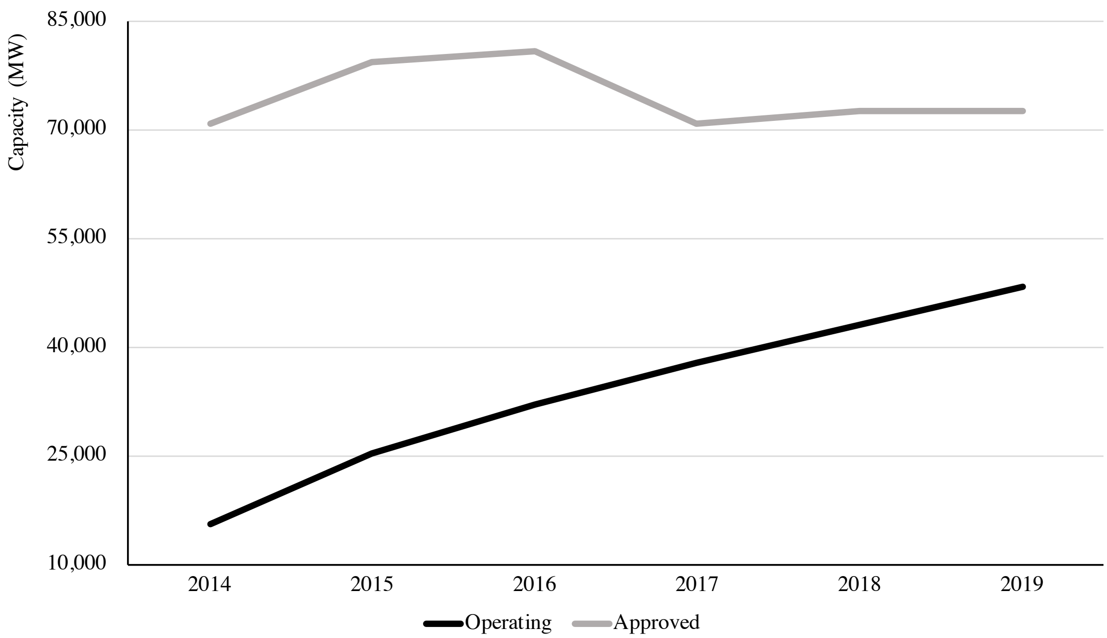


Figure 1: Time trend of FIT approved capacity and operating capacity

# 3 Empirical Strategy and Data

## 3.1 Model Specification

Our empirical analysis investigates the impact of the amended FIT policies on the operation of new solar power facilities[5] approved by FIT. We estimate the impact by examining the relationship between operating capacity and approved capacity before and after the amendment. We hypothesize that the linear relationship between operating and FIT-approved capacity changed after the amendment.

Figure 2 illustrates this hypothesis. The 45-degree dashed line implies that the operating capacity equals the approved capacity. However, in reality, because neither deadline for commencing operation nor grid connection agreements were required when approving new facilities under the previous FIT policy, the operating capacity is much lower than the approved capacity. This is shown by the flatter line in the figure. The amended FIT affects this relationship by imposing stricter requirements. Thus, the slope becomes steeper than before. This change in slope reflects the impact of the FIT amendment.

[5] In this context, new solar power facilities refer to facilities deployed after the implementation of the FIT policy.

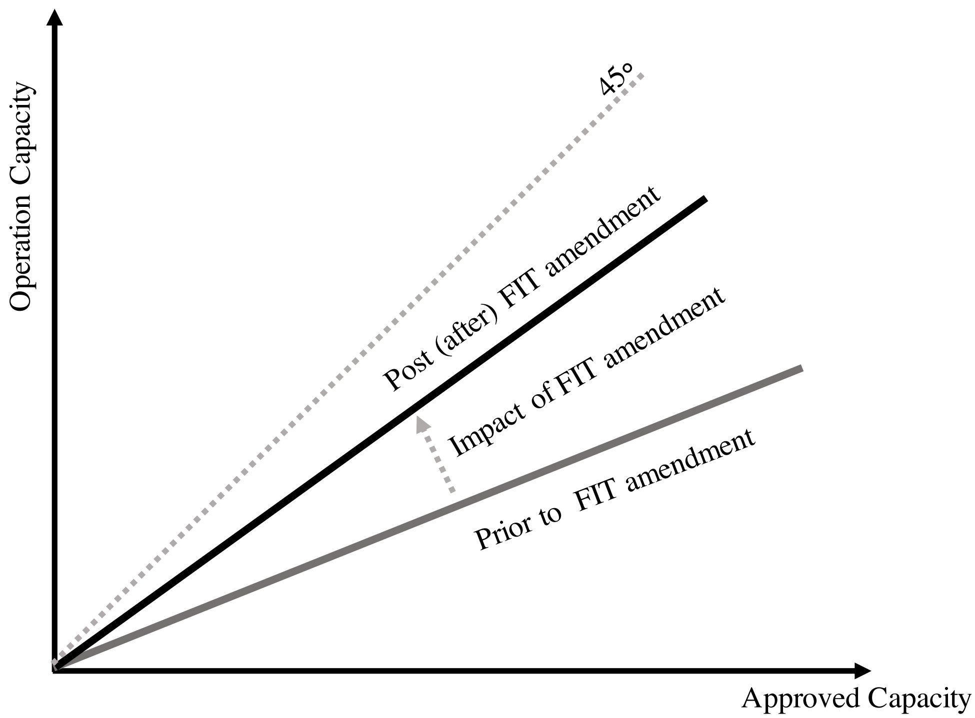


Figure 2: Hypothesis on the effect of amended FIT

A linear fixed effect regression is adopted to estimate the effect of the amended FIT. The general specification can be written as follows:

$$Y_{it} = \beta_1 A_{it} + \beta_2 A_{it} \times Post + \beta_3 E_{it} + \lambda_t + \theta_i + \epsilon_{it}$$

where $Y_{it}$ denotes the installed capacity of operating solar facilities with FIT approval in municipality $i$ by the end of year $t$. $A_{it}$ represents the FIT-approved capacity of new solar power facilities in municipality $i$ by the end of year $t$, which has not necessarily started its operation. The interaction term $A_{it} \times Post$ denotes the approved capacity after enforcement of the amended FIT. Time-varying and municipality-varying economic conditions are captured by $E$. $\lambda_t$ is the vector of the year dummy capturing the year fixed effects. It controls for unobserved factors that change over time and remain constant across municipalities. $\theta_i$ denotes the municipality fixed effects estimator, which accounts for time-invariant municipality characteristics. $\epsilon_{it}$ is the error term. The operating capacity in this study only refers to the capacity of active solar power facilities approved by FIT. In other words, it should not be larger than the approved PV capacity. Thus, the constant term is removed in the ordinary least squares (OLS) model.

In addition, to explore the determinants of the non-operating capacity of solar power across municipalities, we used a cross-sectional model. This model focuses on municipality heterogeneity by including municipality-specific variables in regressions. We run cross-sectional regressions in 2014 and 2019 to investigate changes over time. We also performed regression as a benchmark using the operating capacity as the dependent variable. The specifications of our estimation model are as follows:

$$Y_i = \alpha + \beta_1 M_i + \beta_2 E_i + \beta_3 L_i + \beta_4 D_i + \beta_5 P_i + \epsilon_i.$$

where $Y_i$ denotes the operating or non-operating capacity of solar power facilities that have received FIT approval in municipality $i$ by 2014 or 2019. The FIT-approved capacity of operating new solar power facilities is defined as the operating capacity; otherwise, it is defined as the non-operating capacity. Regarding the choice of explanatory variables, we reviewed the previous literature on solar power deployment (Crago and Chernyakhovskiy, 2017; Hughes and Podolefsky, 2015; Krasko and Doris, 2013; Kwan, 2012; and Sarzynski et al., 2012). However, the literature generally investigates the installation of residential solar power and does not provide potential determinants for large-scale solar power installation. Therefore, we select explanatory variables mostly based on theoretical validity and data availability. They can be categorized into meteorological factor ($M_i$), economic activity ($E_i$), land availability ($L_i$), electricity grid access ($D_i$), and geographic factor ($P_i$). Regarding the meteorological factor, we use solar insolation because the endowment of solar resources is directly related to the revenue of a solar power plant. It is expected that rich solar insolation leads to a larger capacity of installed solar projects. Economic activity refers to the level of economic transactions in each municipality. We use the number of new construction of dwellings that are often used as leading indicators of economic trends in Japan. Land availability could also affect solar projects' operation. Particularly, a large-scale solar power plant requires enough space to set up the PV panels. Electricity grid access is related to the construction cost of the grid connection. We expect that poor access to the electricity grid increases the non-operating capacity of solar power projects. Regarding the geographic factor, we use the terrain slope as an important determinant. Hill areas with steep slopes tend to suffer from natural disasters, such as landslides, more than flat areas. They also lead to higher construction costs and risks of a project, leading to a higher number of non-operating projects. $\epsilon_i$ denotes the disturbance term.

To explore the heterogeneity of the effect among solar power projects with different sizes, we decompose solar facilities according to their capacity. Solar power project with less than 10 kW capacity is defined as small-scale (residential) solar PV facility. When the capacity is larger than 10 kW and less than 2 MW, we define it as large-scale commercial solar power. Projects larger than or equal to 2 MW capacity are categorized into mega commercial solar.

### 3.2 Data

We construct a panel dataset of 1,741 municipalities from 2014 to 2019, and also use a sub-dataset in our cross-sectional analysis. Table 2 and Table 3 present the descriptions and summary statistics of the variables used in the empirical analysis.

Data on solar power capacity have been aggregated at the municipality level. The data were obtained from the website of the Agency for Natural Resources and Energy (ANRE) of Japan.[6] The agency collects capacity information from the application documents submitted by renewable energy project developers for FIT approval. As shown in Table 3, the average FIT approved capacity is 42.8 MW, while the average operating capacity is approximately 19.3 MW. This indicates that, on average, at the municipality level, only 45% of the solar power capacity approved by FIT is in operation. Figure **??** depicts scatter plots between the operating and approved capacity of large-scale solar power. This graphically suggests that the correlation between operating and approved capacity improved after 2017 in support of our hypothesis on the effect of the amended FIT.

Data on new housing construction are used as a proxy for economic conditions. They were collected from the Survey on Construction Statistics of the Ministry of Land, Infrastructure, Transport, and Tourism (MLIT). Data on arable land and abandoned farmland as a measure for land availability were obtained from the Statistical Survey on Crops of the Ministry of Agriculture, Forestry and Fisheries (MAFF), while data on solar insolation were obtained from the New Energy and Industrial Technology Development Organization (NEDO). Insolation is a measure of solar radiation energy received on a given surface area at a given time. It is expressed as the average irradiance in kilowatt-hours per square meter per day (kWh/$m^2$/day). Electricity grid access is

[6] The website for information disclosure of FIT in Japanese. Available at `https://www.fit-portal.go.jp/PublicInfoSummary`.

related to the construction cost of the grid connection and affects solar power plants' operation. The distance from the municipal office to the nearest electricity grid is used as an index of access to the electricity grid and measured using Geographic Information System (GIS) software.

Table 2. Description of variables

| Variable | Unit | Description |
|---|---|---|
| Operating Capacity | kW | Total installed capacity of new solar power facilities approved by FIT that have been in operation |
| Non-operating Capacity | kW | Capacity of solar power facilities approved by FIT but have not started operation |
| Approved Capacity | kW | FIT Approved capacity of new solar power facilities |
| House | house | Number of new construction starts of dwellings |
| Solar Insolation | kWh/$m^2$/day | Solar radiation energy received |
| Arable Land | hectare | Area of arable land |
| Electricity Grid Access | km | Distance from the municipal office to the nearest electricity grid |
| Slope | degree | Steepness of the land surface |

Table 3. Summary statistics

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Operating Capacity | | | | | |
| Solar | 10,446 | 19,313 | 31,879 | 0 | 497,904 |
| Small Solar | 10,446 | 2,768 | 5,441 | 0 | 86,436 |
| Large Solar | 10,446 | 13,955 | 22,701 | 0 | 372,875 |
| Mega Solar | 10,446 | 2,591 | 10,656 | 0 | 185,980 |
| Non-operating Capacity | | | | | |
| Solar | 1,741 | 13,961 | 32,326 | 0 | 440,561 |
| Small Solar | 1,741 | 156 | 323 | 0 | 4,272 |
| Large Solar | 1,741 | 5,917 | 10,705 | 0 | 90,864 |
| Mega Solar | 1,741 | 32,981 | 53,763 | 0 | 504,376 |
| Approved Capacity | | | | | |
| Solar | 10,446 | 42,810 | 72,912 | 0 | 905,690 |
| Small Solar | 10,446 | 3,044 | 5,895 | 0 | 90,207 |
| Large Solar | 10,446 | 25,409 | 40,707 | 0 | 457,453 |
| Mega Solar | 10,446 | 14,358 | 43,784 | 0 | 676,420 |
| House | 10,446 | 430 | 1,590 | 0 | 38,199 |
| Solar Insolation | 1,741 | 3.5 | 0.2 | 3 | 4.5 |
| Arable Land | 1,741 | 2,526 | 3,679 | 0 | 63,300 |
| Electricity Grid Access | 1,741 | 1.406 | 2.904 | 0 | 49.393 |
| Slope | 1,741 | 0.359 | 0.2 | 0 | 0.773 |

Note: Solar represents total solar PV facilities.

Small solar means $< 10kW$ solar power. Large solar means $10kW \sim 2MW$. Mega solar means $\geq 2MW$.

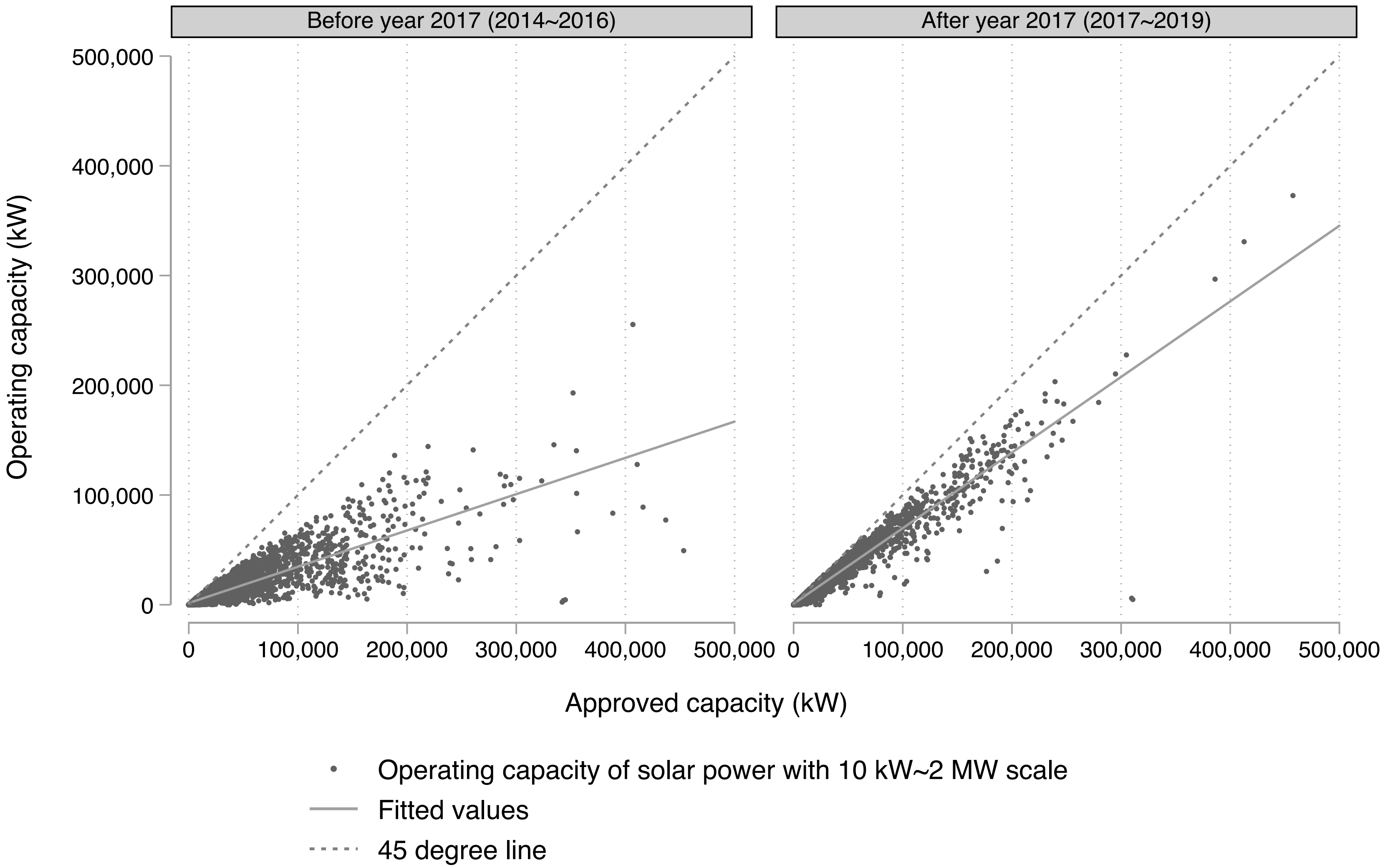


Figure 3: Scatter plots of operating and approved capacity (large-scale solar power)

# 4 Results and Discussion

## 4.1 The effect of FIT amendment

We estimate the effect of the amended FIT on the gap between the approved and operating capacity of solar power using a linear regression model. We assign solar power to three categories: residential solar (<10 kW), large commercial solar ($\geq$ 10 kW and <2 MW), and mega solar ($\geq$ 2 MW). The OLS model with time fixed effects was used as a baseline regression owing to the expected linear proportional relationship between approved capacity and operating capacity. We also use the fixed effect model to mitigate the omitted variable bias. The results of the Hausman test confirm that the fixed effect model is more preferred than the random effect model for this dataset.

Table 4 presents the main regression results on the effect of the amended FIT. The interaction term between approved capacity and post captures the effect of the amended FIT on the gap between the approved and the operating capacity. In all the model specifications, coefficients for the interaction term are statistically significant and positive. The results suggest that the amendment of the FIT increased the operation of solar power projects. The estimated coefficient in column 1 indicates that, after the amended FIT, 1 kW of added approved capacity is related to an additional 0.265 kW increase in operating solar PV capacity. When controlling for the municipality fixed effects in column 2, the estimated coefficient of interaction term decreases by 0.053.

The results from columns 3 to 8 demonstrate the heterogeneous effects across different sizes of solar power. The most substantial impact is found in large-scale solar radiation. In column 3, before the amendment, 1 kW of approved capacity was related to 0.320 kW of operating capacity. After the amendment, it was associated with 0.68 kW of operating capacity. The estimated coefficients decrease slightly when including the municipality fixed effects shown in column 4. In contrast, the change is marginal for small-scale solar. As shown in column 4, the correlation between approved and operational capacity is 0.85, even before the amendment. The amendment added 0.104, a 10% increase in the relationship. The results in column 7 show that the amended FIT has a positive impact on mega solar power. The amendment of FIT reduced the gap between operation and approved capacity by an additional 0.129 kW with regard to 1 kW approval. These results suggest that the amendment was effective for commercial facilities rather than residential facilities.

Table 4. The effect of FIT amendment

| | Solar | | Small Solar | | Large Solar | | Mega Solar | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | OLS | FE | OLS | FE | OLS | FE | OLS | FE |
| Approved Capacity | 0.186*** | 0.035 | 0.850*** | 0.887*** | 0.320*** | 0.148*** | 0.039*** | -0.038*** |
| | (0.019) | (0.028) | (0.004) | (0.006) | (0.018) | (0.032) | (0.010) | (0.012) |
| Approved Capacity × Post | 0.265*** | 0.212*** | 0.104*** | 0.092*** | 0.360*** | 0.298*** | 0.129*** | 0.111*** |
| | (0.018) | (0.017) | (0.003) | (0.003) | (0.011) | (0.013) | (0.023) | (0.022) |
| House | 3.300*** | -1.239*** | -0.001 | -0.022*** | 0.972*** | -0.329** | 0.313** | -0.225* |
| | (0.584) | (0.345) | (0.006) | (0.006) | (0.220) | (0.162) | (0.145) | (0.134) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 10,446 | 10,446 | 10,446 | 10,446 | 10,446 | 10,446 | 10,446 | 10,446 |
| Adjusted $R^2$ | 0.770 | 0.614 | 0.999 | 0.998 | 0.920 | 0.769 | 0.286 | 0.216 |

Note: Constant terms are excluded in OLS regressions. Robust standard errors in parentheses. $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

### 4.2 Locations of non-operating projects

In this subsection, we apply cross-sectional regressions to explore the municipality characteristics that locate non-operating projects. Table 5 reports the estimation results using cross-sectional data in 2014. In the specification containing all types of solar power, the most contrasting results are found in the coefficient for terrain slope: it is negative in the operating capacity model and positive in the non-operating capacity model. Because a steep land surface may lead to higher construction and maintenance costs, the results indicate that non-operating projects are located in municipalities with higher construction costs. Estimated coefficients for other variables also suggest that the non-operating projects are located in municipalities with less attractive conditions for solar projects. Solar insolation has statistically significant and positive effects on operating and non-operating capacity, but the coefficient is lower in the non-operating capacity model. According to column 2, for every 1% increase in solar insolation, the non-operating capacity of solar power projects is increased by 10%. This indicates that solar power project developers tend to choose municipalities with rich solar resources as their plants' locations to obtain FIT approval, but their response is lower than that of operating projects. The estimated coefficients of electricity grid access on non-operating capacity are negative and statistically significant. The response of the non-operating capacity to a 1% increase in distance to the grid is less sensitive than the operating capacity.

The estimated results of large-scale solar projects are quite similar to those of the overall solar power in columns 1 and 2. This similarity is reasonable because more than half (about 56%) of the non-operating capacity comes from large-scale solar projects. Regarding small-scale solar power, the estimated coefficients between models of operating and non-operating capacity do not differ substantially, suggesting that determinants for the location of residential solar between the operating and non-operating projects do not differ in structure. Regarding the operating capacity of mega solar projects, the sizes of estimated coefficients are generally smaller than those of the non-operating capacity. This outcome can be attributed to the excess zero value in the operating capacity of mega solar projects. There are only 83 municipalities that locate operating mega solar, indicating that 95% of the municipalities has zero operating capacity. The low value of $R^2$ in column 7 also indicates that the model explains slight variation in the dependent variable. Therefore, we cannot simply compare the non-operating and operating models in mega solar projects.

Table 6 presents regression results of the cross-sectional analysis in 2019. We found similar impacts of solar insolation, electricity grid access, and slope, while the differences between operating and non-operating capacity models are smaller compared to the results in Table 5. Because the FIT amendments reduced unreasonable non-operating projects, such as projects without a mature business plan and careful consideration of the practical operation, we can expect both the operating and non-operating projects to be located in similar municipalities after 2017.

To test the statistical difference of coefficients between the operating and non-operating regressions, we apply the Chow test. This test examines the equality of the regression coefficients between different samples. The null hypothesis is that the coefficients of the variables in one model are equal to those in another model (Chow, 1960). Tables 7 and 8 present the results of the Chow test. In general, the difference in coefficients between the operating and non-operating capacity models is less statistically significant in 2019 than in 2014, implying that that operating and non-operating projects are both located in more similar municipalities in 2019. Specifically, the coefficients for solar insolation were not statistically different between the operating and non-operating models in 2019. The non-operating solar locations were no more different from those of the operating solar projects with regard to the richness of solar resources.

Table 5. Location of projects in 2014 (cross-sectional analysis)

| | Solar | | Small Solar | | Large Solar | | Mega Solar | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | Operating Capacity | Non-Operating Capacity | Operating Capacity | Non-Operating Capacity | Operating Capacity | Non-Operating Capacity | Operating Capacity | Non-Operating Capacity |
| Solar Insolation | 11.546*** | 10.278*** | 7.919*** | 8.597*** | 14.192*** | 11.673*** | 2.310*** | 10.885*** |
| | (0.952) | (1.047) | (0.751) | (0.646) | (1.058) | (1.023) | (0.574) | (1.046) |
| House | 0.367*** | 0.315*** | 0.399*** | 0.384*** | 0.361*** | 0.311*** | 0.115*** | 0.314*** |
| | (0.012) | (0.016) | (0.010) | (0.010) | (0.014) | (0.015) | (0.018) | (0.016) |
| Arable Land | -0.017 | 0.033 | -0.038** | -0.014 | -0.010 | 0.022 | 0.032 | 0.036 |
| | (0.023) | (0.032) | (0.016) | (0.017) | (0.029) | (0.032) | (0.024) | (0.033) |
| Electricity Grid Access | -0.271*** | -0.164*** | -0.221*** | -0.170*** | -0.275*** | -0.163*** | -0.020 | -0.198*** |
| | (0.047) | (0.064) | (0.037) | (0.034) | (0.052) | (0.061) | (0.043) | (0.061) |
| Slope | -0.151*** | 0.201*** | -0.213*** | -0.190*** | -0.142*** | 0.136*** | 0.083** | 0.114*** |
| | (0.032) | (0.042) | (0.026) | (0.026) | (0.037) | (0.041) | (0.035) | (0.039) |
| Constant | -7.900*** | -5.184*** | -4.986*** | -7.539*** | -11.676*** | -7.306*** | -2.905*** | -5.725*** |
| | (1.212) | (1.349) | (0.945) | (0.814) | (1.368) | (1.331) | (0.706) | (1.366) |
| Observations | 1741 | 1741 | 1741 | 1741 | 1741 | 1741 | 1741 | 1741 |
| Adjusted $R^2$ | 0.447 | 0.226 | 0.564 | 0.577 | 0.402 | 0.256 | 0.041 | 0.251 |

Note: All variables are in log-form. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6. Location of projects in 2019 (cross-sectional analysis)

| | Solar | | Small Solar | | Large Solar | | Mega Solar | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | Operating Capacity | Non-Operating Capacity | Operating Capacity | Non-Operating Capacity | Operating Capacity | Non-Operating Capacity | Operating Capacity | Non-Operating Capacity |
| Solar Insolation | 8.852*** | 9.771*** | 6.762*** | 9.995*** | 10.963*** | 10.425*** | 1.821 | 9.678*** |
| | (0.934) | (1.176) | (0.763) | (0.631) | (1.028) | (1.117) | (1.283) | (1.057) |
| House | 0.420*** | 0.425*** | 0.512*** | 0.516*** | 0.401*** | 0.400*** | 0.379*** | 0.383*** |
| | (0.016) | (0.023) | (0.013) | (0.013) | (0.018) | (0.022) | (0.041) | (0.018) |
| Arable Land | 0.032 | 0.081** | -0.019 | -0.024 | 0.039 | 0.096*** | 0.096** | 0.047 |
| | (0.023) | (0.034) | (0.016) | (0.017) | (0.028) | (0.033) | (0.049) | (0.030) |
| Electricity Grid Access | -0.242*** | -0.208*** | -0.243*** | -0.135*** | -0.245*** | -0.194*** | -0.023 | -0.246*** |
| | (0.049) | (0.066) | (0.036) | (0.032) | (0.053) | (0.064) | (0.083) | (0.057) |
| Slope | -0.045 | 0.227*** | -0.182*** | -0.137*** | -0.045 | 0.147*** | 0.558*** | 0.046 |
| | (0.033) | (0.049) | (0.026) | (0.030) | (0.036) | (0.049) | (0.063) | (0.038) |
| Constant | -3.316*** | -6.080*** | -2.704*** | -10.011*** | -6.413*** | -7.512*** | -1.081 | -4.244*** |
| | (1.197) | (1.518) | (0.962) | (0.789) | (1.335) | (1.438) | (1.624) | (1.379) |
| Observations | 1741 | 1741 | 1741 | 1741 | 1741 | 1741 | 1741 | 1741 |
| Adjusted $R^2$ | 0.354 | 0.222 | 0.561 | 0.606 | 0.304 | 0.326 | 0.088 | 0.065 |

Note: All variables are in log-form. Robust standard errors in parentheses. $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table 7. Chow test of location analysis in 2014

| | Solar | Small Solar | Large Solar | Mega Solar |
|---|---|---|---|---|
| Solar Insolation | * | ** | *** | *** |
| House | *** | *** | *** | *** |
| Arable Land | ** | ** | * | |
| Electricity Grid Access | *** | ** | *** | ** |
| Slope | *** | * | *** | |

Note: The difference of coefficients between operating and non-operating regressions are tested.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8. Chow test of location analysis in 2019

| | Solar | Small Solar | Large Solar | Mega Solar |
|---|---|---|---|---|
| Solar Insolation | | *** | | *** |
| House | | | | |
| Arable land | ** | | *** | |
| Electricity grid access | | *** | | *** |
| Slope | *** | ** | *** | *** |

Note: The difference of coefficients between operating and non-operating regressions is tested.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

## 5 Conclusion and Policy Implications

This study examined the impact of amended FIT policies on the gap between operating capacity and approved capacity of solar power. Our empirical results suggest that amendments to the FIT scheme reduced the gap and thus mitigated the problem of non-operating solar power projects. However, the impacts are heterogeneous across different facility sizes. In large and mega scales, the effects of the amended FIT are more substantial than in small ones. Furthermore, we apply cross-sectional analyses to explore the municipal characteristics that locate non-operating capacity. Regression results indicate that, in general, municipalities with steeper land have a more non-operating solar capacity. Using a chow test, we confirmed that operating and non-operating solar projects are located in municipalities with similar characteristics.

Our findings have several policy implications. First, there is a trade-off between attracting investment in renewable power and controlling the financial burden of FIT. Under the 2012 Japanese FIT scheme, generous procurement prices are provided to reduce the risks and uncertainty for the project developer. While the high procurement price attracts substantial capital investment in solar power generation, there is no explicit regulation on the deadline for approved projects to start operation. Project developers have an incentive to obtain FIT approval as soon as possible, even if the project is immature and even without careful consideration of the practical operation. Similarly, the decreasing price of the solar panel may tempt some project developers to maximize profits by intentionally delaying the installation. This leads to a large discrepancy between the approved and operating capacity of solar power projects.

Second, the results of this study shed light on how the revisions of existing policies based on actual market situations can effectively support renewable energy. The previous FIT scheme had a policy loophole for solar power project developers to undermine the program's effectiveness. The amendments in 2017 prescribe the deadline for the starting operation and the requirement of grid connection contracts with relevant utility companies when determining the FIT rates. In addition, a reverse auction system is introduced for the FIT price of solar projects with a capacity larger than 2 MW. The system encourages competition among project developers and signals the solar power market the commitment of the government to reduce the cost of the FIT scheme. These amendments are effective in addressing the issue of non-operating solar power projects.

Third, the findings of this study provide lessons for other countries or regions on designing a better energy policy and on avoiding the adverse effects of programs. The design of the policy is as important as the choice of a particular policy instrument (Ekins et al., 2019). The obtained results of our study highlight the importance of a well-designed FIT scheme in supporting the sustainable development of renewable energy. They corroborate Gómez et al. (2016) and Xia et al. (2020), who posit that the economic efficiency of renewable support policy could be improved with a better policy design adapted to market conditions.

Finally, besides subsidizing the deployment of renewable energy by the FIT scheme, disaster management is necessary for the sustainable development of renewable energy. Our estimation results show that non-operating solar projects are likely to be located in municipalities with steeper land surfaces. Once these projects start their operations, they are exposed to a higher risk of damage from natural disasters such as landslides and earthquakes. According to METI[7], at least 102 solar power plants were damaged by natural disasters between 2018 and 2020. An example is the 750 kW solar power plant in Himeji City, where more than half of the installed solar PV panels were damaged by the landslides caused due to heavy rains in July 2018. The renewable energy policy should integrate adaptation measures to address the ever-increasing risk of such climate disasters.

This study has some limitations. The data used in this study cannot distinguish how many non-operating projects are delayed intentionally or how many are yet to operate within a reasonable period. In practice, for instance, it takes an average of 1∼1.5 years for solar power from FIT approval to start their operation (Li et al., 2019). Therefore, this study does not exactly capture the extent to which the amended FIT reduces the intentional delay of solar PV installation. In addition, in the location analysis, poor electricity grid access is measured by the distance from the municipal office to the nearest electricity grid. If detailed data such as voltage information[8] on the grid are available, the distance can represent the electricity grid access more accurately. Moreover, it is possible that the learning effect exists throughout the deployment of solar PV. [9] The learning mechanism, such as learning-by-doing and learning-by-interaction, may increase the

[7]Source: `https://www.meti.go.jp/shingikai/sankoshin/hoan_shohi/denryoku_anzen/newenergy_hatsuden_wg/index.html`

[8]The voltage information on the grid can distinguish whether the grid line is, for instance, low voltage ($\leq AC600V$, or $\leq DC750V$) or high voltage ($> AC600V$ and $\leq DC70,000V$ or $> DC750V$ and $\leq DC70,000V$) and help identify the availability of grid connections for solar size.

[9]We appreciate the insightful comments and suggestions on this point from an anonymous reviewer.

operating capacity. The effect of the accumulated experience and expertise on the implementation of solar power projects could contribute to proficiency in making mature business plans and cost reduction in practical operation. We have adopted a fixed effect estimator in the panel analysis model to capture either time-varying or municipality-varying learning effects. However, there might be both municipality and time-specific learning effects, which is out of the scope of this study. Exploring the learning effect on the operation of solar power projects would be an important and interesting topic for future research.

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