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神戸大学大学院経済学研究科

経済学専攻

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for Renewable Energy

(再生可能エネルギー政策の影響に関する実証研究)

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Chapter 1

General Introduction

Approximately two-thirds of global greenhouse gas emissions can be attributed to the use of energy from fossil fuels (IRENA, 2017), which results in a rise in the global temperature. Increasing concerns about global climate change require the shift from fossil fuels to renewable energy in the electricity sector for both developed and developing countries. The costs of renewable energy sources are high at the initial stage when the scale of the renewable energy industry is small and related technologies are immature. To promote the deployment of renewable energy, supporting policies are needed desperately at both the international and domestic levels. Most countries use either feed-in tariff (FIT) or renewable portfolio standard (RPS) systems to support renewables. For Japan, the policy was shifted from the RPS to a national FIT in 2012. After the introduction of the FIT scheme, renewable energy, especially solar power, has expanded rapidly. Renewable energy has become the third largest energy source after liquefied natural gas (LNG) and coal (REI, 2017). In addition to domestic policies, global climate change policies also promote the development of renewable energy. For example, the Clean Development Mechanism (CDM) under the framework of the Kyoto Protocol encourages developed countries to fulfill their carbon emission reduction commitments by implementing renewable energy projects in developing countries. China's wind power sector has benefited greatly from the implementation of the CDM. The installed capacity of wind power increased to the world's largest in 2011. The technology of wind turbines has also improved substantially in China since then.

As the renewable energy sector matures and the levelized cost of electricity (LCOE) declines, the fulfillment of the deployment target of renewable sources at the lowest possible overall costs becomes the main interest of policymakers. FIT has proven to be effective in promoting renewable energy, but often at the expense of overly generous subsidization (Winkler et al., 2018). Auctions are introduced as a remedy for FIT to reduce the supporting costs of renewable energy. By the end of 2018, 106 countries have held at least one auction for renewables (IRENA, 2019). Essentially, auctions refer to competitive bidding processes for electricity from renewable energy. Project developers bid the lowest prices they would be willing to accept to develop renewable energy projects. Auctions can lead to more competitive prices as they let the competitive market determine the prices paid for renewables. Therefore, ensuring sufficient competition is the key factor when designing auctions for renewable sources.

This research is intended to evaluate the impacts of policies for renewable energy from three aspects: technology development of the wind sector in China, operation of solar projects, and reverse auctions for solar photovoltaic (PV) in Japan. We have three main objectives. The first is to investigate the role of CDM in inducing the subsequent development of domestic technology for wind power generation. Wind power capacity has undergone rapid expansion in China, which is a key player in the CDM. The implementation of CDM wind projects expands the wind market and makes foreign advanced technology available, which could also promote domestic technological development in China's wind power sector.

The second objective is to investigate the impact of the amended FIT policy on the operation of solar power in Japan. FIT has helped to increase renewable power generation, particularly solar power, but has also encountered a number of challenges. The major one is the large discrepancy between the approved capacity and operating capacity of solar power projects. Project developers of proposed solar power facilities obtain FIT approval as soon as possible, but intentionally delay their start of installation to maximize profits. It is undesirable for FIT to perform as a supporting policy in promoting renewable electricity generation. It also adds an excess financial burden to future consumers of electricity. The amendments to the FIT policy in 2017 address this unexpected non-operating problem by imposing stricter requirements on approval of FIT eligibility.

The third objective is to determine whether reverse auctions under FIT slow the expansion of mega-solar in Japan. To reduce the supporting costs of solar power, the Japanese government launched a reverse auction system for mega-solar PV in 2017. The eligibility, capacity allocation, and electricity procurement prices of solar PVs above 2 MW are determined by a bidding process. In parallel to the FIT prices determined by the bidding process for mega-solar, the administratively set FIT prices are adopted for solar projects less than 2 MW. The later prices are higher than the former ones, which may generate an incentive for project developers to manipulate project size in order to attain higher FIT prices. Such incentives, coupled with strict compliance rules of reverse auctions, could lead to a reduction in solar projects above 2 MW and an increase in those slightly below 2MW. This is considered to be the spillover effect of reverse auctions.

The remainder of this dissertation is organized as follows. In Chapter 2, we estimate the effects of wind CDM projects on the development of China's domestic wind power technology. We use province-level patent counts to measure wind technology development. The annual number, annual installed capacity, and average capacity size of successfully registered CDM wind projects are used as indicators of the implementation of the CDM. In Chapter 3, we focus on the impact of the amended FIT policy on the operation of approved solar power in Japan. We estimate the relationship between operating capacity and approved capacity before and after the amendment by using municipality-level data of solar power capacity. In addition, we examine the characteristics of municipalities that tend to locate non-operating solar projects. In Chapter 4, we investigate the impact of reverse auctions on the number of FIT-approved solar PV projects on mega-solar PV. We use data on solar projects above 50 kW that were newly approved by the FIT scheme and break down these projects into different size categories. We also estimate the spillover effect of reverse auctions on solar projects that are not the target of the recent reverse auction system. In Chapter 5, we conclude the study's findings and policy implications.

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Chapter 2

Development of Wind Power-related Technology in China: the Role of the Clean Development Mechanism

2.1 Introduction

Climate change is a global thread that requires cooperation among all countries. Being the world's largest energy consumer and pollution emitter, China is responsible for adopting countermeasures to mitigate the negative impact of this issue. China is witnessing a massive expansion of renewable energy capacity, particularly in the wind power sector.

China's wind power sector has experienced unprecedented growth in the past decade, and its capacity increased to the world's largest in 2011. The domestic wind power industry is also witnessing a continuous growth. According to the 2015 market data, a Chinese wind turbine manufacturer, Xinjiang Goldwind, took over GE (General Electric) as the top onshore wind turbine manufacturers[1].

Steady expansion of China's wind power capacity can be traced back to the Clean Development Mechanism (CDM) projects implemented under the Kyoto Protocol. The CDM is an innovative market-based carbon credit mechanism. It allows industrialized countries to fulfill their carbon emission reduction commitments (also called Annex I Parties) by implementing emission-reduction projects in developing countries. This earns them certified emission reductions (CERs), each equivalent to one one tone of CO_2, which can be counted toward meeting Kyoto targets. By the end of 2015, more than 7,500 CDM projects have issued CERs totaling more than 1.5 gigaton carbon dioxide equivalent[2]. Apart from greenhouse gas (GHG) mitigation, the secretariat of the United Nations Framework Convention

[1] https://www.scientificamerican.com/article/chinese-wind-turbine-maker-is-now-world-s-largest/

[2] UNFCCC ⟨http://cdm.unfccc.int/Statistics/Public/archives/201512/index.html⟩

on Climate Change (UNFCCC) (2013) reported that CDM projects have contributed substantially to sustainable development in many local communities, such as by stimulating the local economy, and technology development and diffusion.

By November 2016, China had 3,866 CDM projects, accounting for about 50% of the world's total[3], making China the largest host of CDM projects worldwide. China has been engaged in CDM for over a decade since it registered its first CDM project (Huitengxile Windfarm project) successfully in 2005. The CDM projects have been widely implemented in all provinces of China except Tibet. Nearly 43% of China's CDM projects are in the wind power sector, with up to 1,518 projects and 84,034 MW installed capacity by November 2016. China's CDM wind power projects were developed mainly in the northeastern, northern, and northwestern regions due to wind resource distribution.

The development of wind turbine manufacturing in China started with three 55 kW Danish wind turbines that were introduced in the 1980s. The main sources of wind turbine technology are license, joint development with foreign firms and independent R&D. Manufacturers strengthened their technological capability through technology import, assimilation, and re-innovation (Yuan et al., 2015). Before 2005, most turbines and key components were imported from other countries, and only a few domestic turbine manufacturers existed in China[4]. Nevertheless, Chinese manufacturers have made efforts to promote their wind technological capabilities to develop larger wind turbines[5]. The size of domestic wind turbines has increased significantly since 2009 (see Figure 2.1). In 2012, China exported 225 sets of complete wind turbines to 11 countries totaling 430.45 MW. The major exporters were Sinovel, Goldwind, HEAG, SANY, Mingyang, XEMC, and WINDEY. (Gosens and Lu, 2013).

[Figure 2.1]

Mitigation of climate change requires continuous technological development to promote a substantial increase in renewable energy. There are no "one size fits all" renewable energy technologies, and thus attracting technology transfer from foreign countries is not the ultimate goal. To promote the wide usage of wind power, especially for developing countries such as China, developing domestic technological capacities is more important than just importing advanced technologies. Therefore, this chapter focuses on the role

[3] CDM Pipeline Overview ⟨http://www.cdmpipeline.org/⟩

[4] http://www.worldwatch.org/node/5758

[5] Large wind turbines with longer blades sweep wind from a larger area and produce greater output energy (Kumar et al., 2016).

of CDM in inducing the subsequent development of domestic technology for wind power generation.

The remainder of this chapter is organized as follows. Section 2.2 provides an overview of previous studies. Section 2.3 describes the data. Section 2.4 presents the empirical strategy for the analysis. Section 2.5 presents the regression results. Section 2.6 presents the related discussion, and section 2.7 draws conclusions.

2.2 Previous Studies

Many studies have focused on technology transfer within CDM projects. Dechezlepretre et al. (2008) investigated the project design documents (PDDs) of registered CDM projects. They found that Mexican and Chinese projects more frequently attract technology transfer, while European countries are the main technology suppliers. Technology transfer increases with the size of the projects and the presence of subsidiaries of Annex I companies. Weitzel et al. (2015) explored the determinants of technology transfer in CDM projects. They concentrated on technology transfer within CDM projects initiated in China and confirmed that more advanced technologies, such as wind energy, are more likely to involve technology transfer. Moreover, previous projects applying the same technology have a negative effect, while FDI and R&D have positive effects on technology transfer.

Some studies have also investigated the impact of CDM projects from the perspective of learning processes and cost reduction. Tang and Popp (2016) identified four channels of learning: learning by doing, spillover, learning by searching, and learning by interacting. They examined how CDM wind projects in China led to technology change measured by cost reduction in unit electricity generated from wind power. They suggested that interacting experience between CDM wind project developers and turbine manufactures contributes greatly to project cost reduction and improvement of wind farm productivity.

This chapter is also related to the broader literature on Chinese innovation activities. Cheung and Lin (2004) examined the spillover effect of FDI on patent applications in China. They found that FDI has positive effects on the number of domestic patent applications, and the spillover effect is the strongest for minor innovations such as external design patents. Because CDM can be interpreted as FDI in the renewable energy generation, it is expected to have a spillover effect on domestic technology development.

This chapter departs from these studies by addressing the effect of CDM wind projects on the subsequent development of domestic wind power technology measured by patent counts in Chinese provinces. We consider CDM as a promoter of technology development in the Chinese wind power sector. Thus, this chapter sheds light on whether CDM could induce technological development in China's wind power sector.

2.3 Data

2.3.1 Patent Counts

This chapter uses patent counts to measure technological development. Patents are important carriers of technical literature. They contain more than 90% of industrial technical information and play a crucial role in promoting technology progress (He, 2014). Patent data have several advantages. They provide rich information on the nature of the invention and applicant, and they are further disaggregated to specific technological areas using classification codes (Dechezlepretre et al., 2013). Meanwhile, using patent data has some shortcomings. For example, inventors may prefer secrecy to prevent public disclosure of the invention, and the quality of individual patents varies widely (Popp, 2006). The approach of using patent data to indicate or reflect innovation, technology diffusion, technology transfer, and technology change has been widely adopted, especially in the environmental field (Popp, 2006; Dechezlepretre et al., 2008; Verdolini and Galeotti, 2011). Therefore, this chapter follows previous well-established literature by utilizing patents as indicators of technology development.

The dependent variable in this chapter is province-level patent applications that have been granted in the field of wind power generation in China. The examination process for an invention patent application to be granted takes 22 months[6]. Hence, the patent grants are organized by their application year to avoid the time lag in the patent examination process. The data source for patent applications is the Patent Searching Platform of SIPO (State Intellectual Property Office of China). The International Patent Classification (IPC) code F03D, which covers wind motors and turbines, can be used to identify patents in the field of wind power generation (Johnstone et al., 2010; Dechezlepretre et al., 2011). While the IPC code F03D covers mechanisms for converting natural wind energy into

[6] https://www.ccpit-patent.com.cn/node/3659

useful mechanical energy and then to its point of use, it excludes arrangements or systems for supplying or distributing electric power[7]. In addition to IPC code identification, a simple nested query strategy was applied to extract patent applicant's location or address information. For bias reduction, simultaneous keyword searches were conducted in the patent applicant's location by typing the name of province and provincial capital.

We also attempted to collect patent application data from a global patent database, the PATSTAT. However, the coverage of information on applicants and inventors' addresses is very poor for most non-European countries. Without address information, patent data cannot be classified based on the provinces. Moreover, Chinese wind turbine manufacturers have secured only 16 patents in the European Patent Office (EPO) from 1980 to 2014 (Lam, Branstetter and Azevedo, 2017). Therefore, SIPO is chosen as the data source for patents. Even SIPO has missing information regarding applicants' addresses in the patent applications, but the coverage of residential information is higher than that in PATSTAT. The extracted patent data from SIPO only contain wind patent applications with explicit address information.

Figure 2.2 shows wind patent grants in different provinces in China's mainland. Eastern provinces have relatively higher number of patent grants because of the economic openness and technological capacity. Shanghai owns the largest number of wind patents.

[Figure 2.2]

2.3.2 CDM Projects

Information on China's wind power CDM projects is collected from the statements contained in the PDDs. To request registration, project developers must submit PDDs[8] of CDM projects to the Executive Board. The registration and management process of each CDM project is transparent and highly standardized, and therefore, extracting data from PDDs is reasonable. Although PDD is an ex-ante description that reflects the expectation of project proponents when the project is being planned, it does not matter for the location information collection since a CDM project's location hardly changes. We collected the location information of wind CDM projects from the individual PDD and classified these projects according to the name of the province or administrative city.

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[7] USPTO ⟨https://www.uspto.gov/web/patents/classification/cpc/html/defF03D.html⟩

[8] The review of project design documents on UNFCCC website ⟨https://cdm.unfccc.int/Projects/projsearch.html⟩

An alternative data source for CDM projects used in existing CDM-related literature (e.g., Dechezleprêtre et al., 2008) is the United Nations Environmental Program (UNEP) DTU[9] CDM Pipeline Database. This is an aggregated dataset in Excel format that contains information about CDM projects such as name, host country, registration status, project size (estimated as amount of annual and total emission reduction), and capacity [10].

To check the data accuracy, we compared location data based on PDD with that offered by the UNEP DTU Partnership[11]. Data from PDDs are consistent with that from UNEP DTU in most CDM projects' location information. Deviations in location data exist only in a few provinces. For instance, according to the data from PDD, the Shanxi province owns 45 and the Shaanxi province owns 20 wind CDM projects registered in 2012, while UNEP DTU's data show the number as 30 in Shanxi and 37 in Shaanxi. By re-examining PDD to eliminate any possible errors in the data collection process, we prefer data gathered from PDD. The final dataset consists of 1,489 wind CDM projects located in 30 provinces[12] from 2005 to 2012.

Figure 2.3 depicts the distribution of wind CDM projects in the mainland of China. Wind CDM projects are dispersed unevenly in China, with more than half of the projects located in Northern regions. Inner Mongolia has the largest number of wind CDM projects. More than 100 projects also implemented in Shandong, Hebei, Liaoning, Ningxia, benefiting from richer wind resource.

[Figure 2.3]

2.3.3 Control Variables

To explain the variations in wind patent applications, we also included several control variables, such as total research and development (R&D) expenditure and inward foreign direct investment (FDI) in the empirical models. R&D expenditure is widely used as an indicator of innovation input[13] in previous studies. R&D expenditure is highly correlated over time, and the association between R&D expenditure and patents exists only at the

[9] Formerly called UNEP Risø Centre (URC)

[10] See more on http://www.cdmpipeline.org/

[11] CDM project distribution within host countries by region and type (available online at http://www.cdmpipeline.org/)

[12] Note that due to the lack of provincial characteristic data and no involvement of CDM activities, Tibet is excluded from the dataset.

[13] For example, Pakes and Griliches (1984), Klaassen, Miketa, Larsen and Sundqvist (2005)

contemporaneous level (Hu and Jefferson, 2009). However, inward FDI could trigger technology transfer in CDM projects (Weizel, Liu and Vaona, 2015) and has a spillover effect on innovation in China (Cheung and Lin, 2004; Hu and Jefferson, 2009). Following these studies, we included contemporaneous total R&D expenditure and inward FDI in the empirical analysis. These data were collected from the China Statistical Yearbook and Chinese Yearbook of Science and Technology.

Because the study period in this chapter started in 2005, this chapter cannot explore the effect of the Renewable Energy Law[14]. As for the policy variable, we used a set of wind energy feed-in tariff (FIT) rate issued by the National Development and Reform Commission of China (NDRC)[15]). The NDRC released the Notice on Policy to Improve Grid-Connected Power Pricing for Wind Power Generation in 2009. The notice divided China's mainland into four different categories based on wind-energy resource distribution and windfarm construction conditions, and set four different benchmark price floors accordingly from RMB 0.51/kWh to 0.61/kWh (Wang et al.,2012; Hu et al.,2013; Zhao et al.,2014). Lower rates are applied to regions with richer wind resources. The first and second revisions were announced in 2014 and 2015, respectively.[16]

[Table 2.1]

2.4 Empirical Analysis

We used patent application data related to wind power technology as a proxy of technology development and investigated the impact of CDM on domestic technology development. The number of patent applications has non-negative integer values. Poisson regression and negative binomial regression were applied regarding the nature of the count data. However, Poisson regression models are quite vulnerable to the effects of over-dispersion[17]. Because of over-dispersion, standard errors are under-estimated, resulting in biased statistical significance. Due to the count data nature of the explained variables

[14] The first Renewable Energy Law of China, enacted in 2005, plays an important role in the development of China's wind power industry (Wang et al., 2012; IRENA, 2013). In the year 2005, China's first wind CDM project was successfully registered just after Renewable Energy Law.

[15] The State Council and the National Development and Reform Commission are China's most powerful and influential regulators of clean energy. Other government agencies play supporting roles and regulate narrower parts of clean energy planning, program management, and implementation (IRENA, 2013).

[16] See Table 2.1 A1 in appendix for regional breakdown and revisions.

[17] Over-dispersion in Poisson models occurs when the conditional variance is greater than the conditional mean. Highly unbalanced data as well as clustered or longitudinal (panel) format data give rise to over-dispersion (Hilbe, J. M., 2011).

and the over-dispersion of the data, we adopted a negative binomial regression approach in this study. The distribution function for the negative binomial model can be derived by including gamma heterogeneity, where the gamma noise variable has a mean of 1 in the Poisson distribution[18]. The negative binomial probability mass function is expressed as

$$\Pr\left(Y = y_i \mid \mu_i, \theta\right) = \frac{\Gamma\left(y_i + \theta\right)}{\Gamma\left(y_i + 1\right)\Gamma(\theta)} \left(\frac{\mu_i}{\mu_i + \theta}\right)^{y_i} \left(\frac{\theta}{\mu_i + \theta}\right)^{\theta}$$

where $\mu_i = exp(x'_i\beta)$, which is the expected value of y_i, and is estimated by a set of regressor variables. θ is a scale parameter. If we let $\delta = 1/\theta$, δ is also interpreted as a negative binomial heterogeneity or over-dispersion parameter.[19]. $\Gamma(\cdot)$ is a gamma function.

In this paper, μ_{it} is thereby written as

$$\mu_{it} = exp(\beta_0 + \beta_1 CDMit + \beta_2 LOG\_R\&D_{it} + \beta_3 LOG\_FDI_{it} + \beta_4 FIT_{it} + \lambda_t + \theta_i + \epsilon_{it}),$$

where μ_{it} refers to the patent counts in the field of wind power generation from Chinese entities in province i in year t. The key independent variable $CDMit$ represents the indicators of CDM wind projects. We used three indicators in different models: the annual number, annual installed capacity, and average capacity size of successfully registered CDM wind projects. Other independent variables include the logged total amount of R&D expenditure, the logged inward FDI, and the wind power feed-in tariff rate. λ_t denotes year fixed effects that control for unobserved variables that change over time and are constant across provinces. Provinces' fixed effects are captured by θ_i, which accounts for unobserved time-invariant heterogeneity. ϵ_{it} is an error term. Table 2.2 provides a summary of variable definitions and descriptive statistics for the panel dataset (see Table 2.3 for a correlation matrix in the appendix).

[Table 2.2]

[18] The Poisson distribution is $P(y = j) = \frac{e^{-\lambda}\lambda^j}{j!} where\, \lambda > 0, \forall j \in Z$.

[19] As $\delta \to \infty$, the negative binomial distribution converges to the Poisson distribution.

[Table 2.3]

In addition to the basic regression model covering the entire research period (2005-2012), we also applied the two-period subdivision model. The entire research period is divided into two periods: the early period and the later period. The early period is from 2005 to 2008, and the later period is from 2008 to 2012. The early and later periods are quite different in terms of the development of wind CDM projects. The number of CDM wind projects in the early and later period is 97 and 1392, respectively. Meanwhile, the later period has a lower rate of technology transfer, and most of the wind CDM projects in the later period tend to use domestic wind technology instead of importing foreign equipment or technology. Moreover, in 2009, the Chinese government first introduced a national FIT scheme for wind power generation, which applies for the entire operational period (usually 20 years) of a wind farm. Considering these aspects, we assume that the impact of wind CDM projects on wind patents is different between time periods.

2.5 Results

We use negative binomial regressions to estimate the impact of CDM wind projects on wind patent counts in China. CDM wind projects are measured by annual number, annual installed capacity or average capacity size. Estimation results are displayed in Table 2, Table 3 and Table 4. The results suggest that the implementation of CDM wind projects has promoted wind power-related technological development in the early period which is from 2005 to 2008.

2.5.1 Summary of Findings

Table 2.4 presents regression results with annual number of CDM wind projects. In the whole period model, the estimated coefficient of CDM is positive but not statistically significant. The annual number of CDM wind projects has a statistically significant and positive effect on wind patent grants in the early period. According to column 2 in Table 2.4, an additional CDM wind project is related to 9.4% increase in wind patents from 2005 to 2008. In contrast, the effect of annual number of CDM wind projects is positive but not statistically significant in the later period. R&D expenditure shows a statistically significant and positive effect on the number of wind patents. In column 1, the coefficient of R&D indicates that 1% increase in R&D expenditure leads to 1.7% additional wind patent counts from 2005 to 2012. In the later period, total R&D expenditure is highly and positively correlated with wind patent applications at 1% significance level, implying that 1% increase in R&D expenditure leads to 2.1% increase in wind patents. The estimated coefficients for FDI are not statistically significant in all models. In column 3, the estimated coefficient of FIT price is negative at 10% significant level.

[Table 2.4]

Table 2.5 reports regression results with annual installed capacity of CDM wind projects. The results are similar to Table 2.4 because areas with more wind CDM projects tend to install larger amount of wind-power capacity. In the early period, annual installed capacity has a statistically significant and positive effect on wind technology. According to column 2 in Table 2.5, 1 MW increase in total installed capacity of CDM wind projects is related to 0.2%more wind patents.

[Table 2.5]

Table 2.6 shows regression results with average capacity of CDM wind projects. The coefficients of average installed capacity of wind CDM projects are statistically significant and positive in column. From column 2 in Table 2.6, the estimated coefficient of average capacity indicates that 1 MW increase is related to 0.6% increase in wind patents. The large average installed capacity of wind CDM projects can be attributed to the adoption of large-size wind turbines. An approximate measure of technological progress in the wind power sector is the average size of wind turbines being installed (Lewis, 2016). The average installed size reflects the improvement of wind-turbine technological capabilities to some degree, and thus is related to wind patent counts. The estimated coefficients of other explanatory variables are consistent with those in Table 2.4 and Table 2.5.

[Table 2.6]

2.5.2 Discussion

The estimated results suggest that the impact of CDM wind projects is different between the early and later period models. CDM wind projects have a statistically significant and positive effect on wind patent grants only in the early period. There are several reasons for this. In the early period, the technological capacity of domestic wind turbine manufacturers is relatively low, so most CDM wind projects tend to use wind turbines of foreign brands and international expertise. About 28% of CDM wind projects in the early period, while only 0.06% in the later period, explicitly claim that technology transfer will be involved according to their PDDs. Moreover, to accelerate the localization of wind power construction, the Chinese government issued a regulation [20] in 2005, which required 70% of the equipment used during wind farm construction to be domestically manufactured (Dai and Xue, 2014). Meeting this requirement facilitated the construction of wind farm. Foreign wind turbine manufacturers have to build assembly lines for complete turbines and component production facilities in China (Jin, Rong and Zhong, 2014). Therefore, CDM wind projects in the early period may promote more technology transfer from developed countries that affect wind technology development in China.

In the later period, total R&D expenditure contributes to wind patent applications. Domestic wind power manufacturers have grown, and their share in the Chinese wind market has gradually increased. Leading wind manufacturers conduct indigenous R&D throughout the entire innovation process (Ru et al., 2012) and have sufficient innovation capacity for new technologies, such as large wind turbines and low-speed turbines (Dai and Xue, 2014). Accordingly, R&D expenditure has a positive effect on the increase in wind patents. Although FDI is considered an important channel for technology transfer from developed countries to China (Cheung and Lin, 2004; Hu and Jefferson, 2009), the estimated coefficients of FDI are not statistically significant in our models.

FIT shows a statistically significant and negative effect on wind patents, which is contradictory to the findings of other studies about the promotion effect of FIT schemes on innovation in renewable energy technologies (Böhringer, Cuntz, Harhoff and Asane-Otoo, 2017; Lin and Chen, 2019). This may be caused by the endogeneity of FIT policy since the ambition of the Chinese government to foster the wind manufacturing industry could both affect the introduction of national FIT policy and innovation in wind technology. Another possible reason is that the FIT rate for a certain province is time-invariant during our research period, so the effect of FIT could be absorbed by province fixed effects. We also used model selection criteria such as AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) to test the model with and without FIT variable and

[20] The regulation terminated in 2009.

the results are presented in Table 2.7. The AIC and BIC statistics suggest that there is no obvious difference between the models with and without FIT.

[Table 2.7]

2.6 Conclusion

In this chapter, we applied the negative binomial regression approach to estimate the effects of wind CDM projects on the development of China's domestic wind power technology. The estimation results suggest that the implementation of CDM could promote the technological innovation activities of wind energy in China. Because CDM makes more sophisticated foreign wind technology available in the domestic market, imitative innovations become easier and more efficient. Simultaneously, CDM works as a demand-pull policy providing financial support through international carbon trade and creating huge demand for wind technology in China (Tang and Popp, 2016).

The promotion effect of CDM wind projects measured by annual number, installed capacity, and average capacity size was found to be statistically significant in the early period from 2005 to 2008. In contrast, R&D expenditure promotes technological development in the later period from 2009 to 2012. One possible reason is that technology transfer had occurred before the implementation of the proposed CDM projects, and the CDM project only extended the scale of technology transfer (Teng and Zhang, 2010), thus positively affecting technology imitation and innovation in wind technology. Eventually, the solid development of wind technology in China depends on its involvement in R&D and indigenous innovation activities.

This chapter has several limitations. First, wind turbine manufacturers may set up their R&D and technical departments and manufacturing plants in different provinces or conduct joint research with universities from neighboring provinces, while the locations of manufacturing plants are registered as applicants' addresses of these patent applications. However, this chapter has not distinguished these types of patents. Second, this chapter is limited to the number of patent applications and does not emphasize on the quality of these patent applications. Moreover, the development of technology is a rather comprehensive concept that includes not only the improvement in the efficiency of equipment, but also the acquisition of undocumented knowledge. Therefore, the results of this patent-based analysis should be interpreted with caution.

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Table 2.1. Regional breakdown of wind power FIT

Region	Areas Included in Region	Benchmark tariff (yuan/kWh)				
		2009-2014	2015	2016	2017	2018
1st	Inner Mongolia Autonomous Region excludes Cifeng, Tongliao, Xing'anmeng, Hulunbei'er; Urumqi, Yili Autonomous Region, Changji Autonomous Region, Karamay, Shihezi in Xinjiang Province	0.51	0.49	0.47	0.47	0.44
2nd	Zhangjiakou, Chengde in Heibei Province; Cifeng, Tongliao, Xing'anmeng, Hulunbei'er in Inner Monglolia Autonomous Region; Zhangye, Jiayuguan, Jiuquan in Gansu Province	0.54	0.52	0.5	0.5	0.47
3rd	Baicheng, Songyuan in Jilin Province; Jixi, Shuangyashan, Qitaihe, Suihua, Yichun, Daxing'anling in Heilongjiang Province; Gansu Province excludes Zhangye, Jiayuguang, Jiuquan; Xinjiang Province Excludes Urumqi, Yili Autonomous Region, Changji Autonomous Region, Karamay, Shihezi; Ningxia Autonomous Region	0.58	0.56	0.54	0.54	0.51
4th	All remaining regions	0.61	0.61	0.6	0.6	0.58

Table 2.2. Definition of Variables and Descriptive Statistics (N=240)

Variable	Definition	Unit	Mean	Std.Dev.	Min	Max
Dependent variables						
Wind Patent	Counts of granted patent applications on wind power technology	piece	17	30	0	178
Independent variables						
CDM	Number of wind CDM projects	unit	6	16	0	123
CDMMW	Annual cumulative installed capacity of wind CDM projects	MW	345	934	0	7693
Avg.CDMMW	Average installed capacity of wind CDM projects	MW	25	30	0	150
R&D	Total R&D expenditure	100 million yuan	190	240	2	1288
FDI	Total amount of inward FDI	100 million yuan	370	428	2	2257
FIT	Wind power feed-in tariff	yuan/kw	0.3	0.3	0	0.61

Table 2.3. Correlation analysis of variables

	Wind Patent	CDM	CDMMW	Avg.CDMMW	LOG_R&D	LOG_FDI
Wind Patent	1					
CDM	0.1	1				
CDMMW	0.1	0.98	1			
Avg.CDMMW	0.27	0.39	0.44	1		
LOG_R&D	0.58	0.1	0.08	0.20	1	
LOG_FDI	0.47	0.07	0.04	0.16*	0.81	1

Table 2.4. Regression results with annual number of CDM wind projects

	Whole period (2005-2012)	Early period (2005-2008)	Later period (2009-2012)
WindPatent	(1)	(2)	(3)
CDM	0.003	0.094*	0.001
	(0.003)	(0.056)	(0.002)
LOG_R&D	1.740***	-0.286	2.118***
	(0.604)	(1.242)	(0.722)
LOG_FDI	0.312	-0.310	-0.256
	(0.355)	(0.754)	(0.595)
FIT	7.642		-66.509*
	(5.068)		(36.679)
Constant	-12.781**	5.245	31.723*
	(6.033)	(7.165)	(17.291)
Year fixed effects	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes
Observations	240	120	120
Log-likelihood	-620.498	-200.679	-377.454

Robust standard errors in parentheses

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

Table 2.5. Regression results with installed capacity of CDM wind projects

WindPatent	Whole period (2005-2012) (1)	Early period (2005-2008) (2)	Later period (2009-2012) (3)
CDM MW	0.000	0.002**	0.000
	(0.000)	(0.001)	(0.000)
LOG_R&D	1.732***	-0.055	2.108***
	(0.604)	(1.197)	(0.710)
LOG_FDI	0.312	-0.377	-0.245
	(0.355)	(0.747)	(0.591)
FIT	8.039		-66.266*
	(5.311)		(36.111)
Constant	-12.965**	4.131	31.619*
	(6.132)	(6.985)	(17.035)
Year fixed effects	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes
Observations	240	120	120
Log-likelihood	-620.533	-200.490	-377.474

Robust standard errors in parentheses

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

Table 2.6. Regression results with average capacity of CDM wind projects

	Whole period (2005-2012)	Early period (2005-2008)	Later period (2009-2012)
WindPatent	(1)	(2)	(3)
Avg.CDMMW	0.002	0.006**	0.003
	(0.001)	(0.002)	(0.002)
LOG_R&D	1.735***	0.629	1.992***
	(0.627)	(1.121)	(0.647)
LOG_FDI	0.312	-0.322	-0.342
	(0.353)	(0.751)	(0.608)
FIT	5.891		-57.709*
	(4.553)		(33.514)
Constant	-11.682**	-0.062	27.369*
	(5.884)	(6.613)	(15.900)
Year fixed effects	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes
Observations	240	120	120
Log-likelihood	-620.505	-200.312	-376.342

Robust standard errors in parentheses

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

Table 2.7. Regression results with or without FIT

	Later period (2009-2012)					
WindPatent	(1)	(2)	(3)	(4)	(5)	(6)
CDM	0.001	0.001				
	(0.002)	(0.002)				
CDM MW			0.000	0.000		
			(0.000)	(0.000)		
Avg.CDMMW					0.003	0.003
					(0.002)	(0.002)
LOG_R&D	2.118***	2.118***	2.108***	2.108***	1.992***	1.992***
	(0.722)	(0.722)	(0.710)	(0.710)	(0.647)	(0.647)
LOG_FDI	-0.256	-0.256	-0.245	-0.245	-0.342	-0.342
	(0.595)	(0.595)	(0.591)	(0.591)	(0.608)	(0.608)
FIT		-66.509*		-66.266*		-57.709*
		(36.679)		(36.111)		(33.514)
Constant	-8.848*	31.723*	-8.803*	31.619*	-7.834*	27.369*
	(5.196)	(17.291)	(5.115)	(17.035)	(4.667)	(15.900)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	120	120	120	120	120	120
Log-likelihood	-377.454	-377.454	-377.474	-377.474	-376.342	-376.342
AIC	828.909	828.909	828.949	828.949	826.684	826.684
BIC	932.046	932.046	932.086	932.086	929.821	929.821

Robust standard errors in parentheses

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

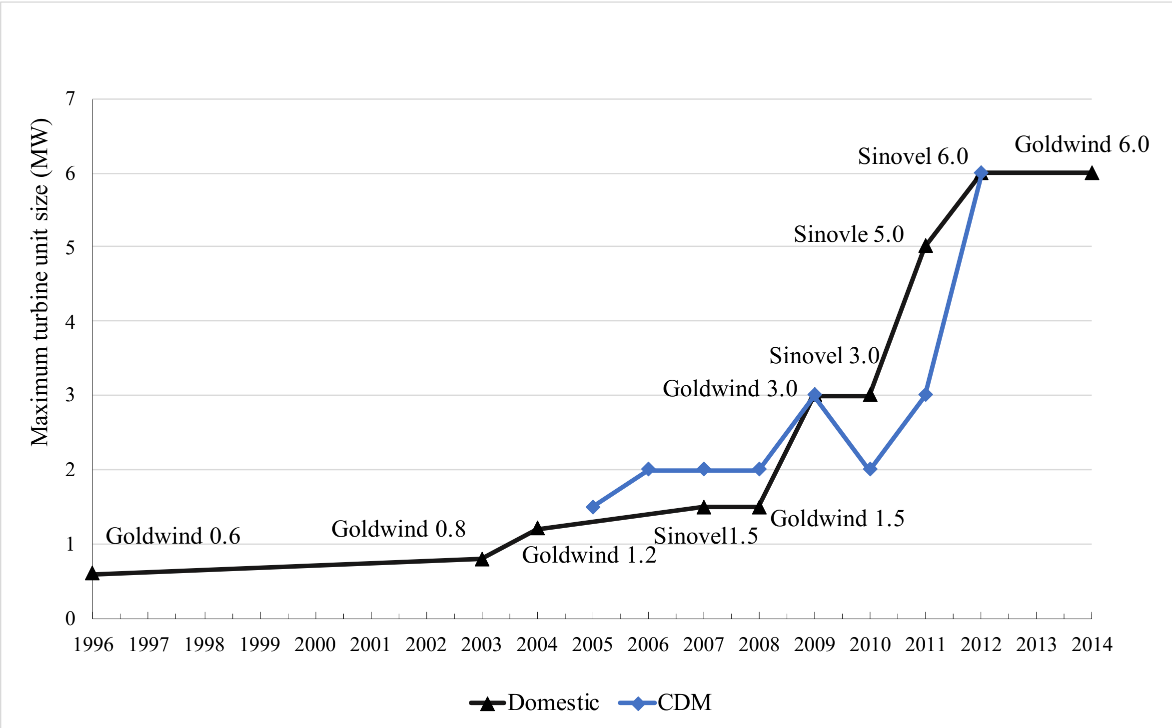

Fig. 2.1. Size of wind turbines developed by Chinese manufacturers

Source: Lewis (2016) and IGES CDM Project Database

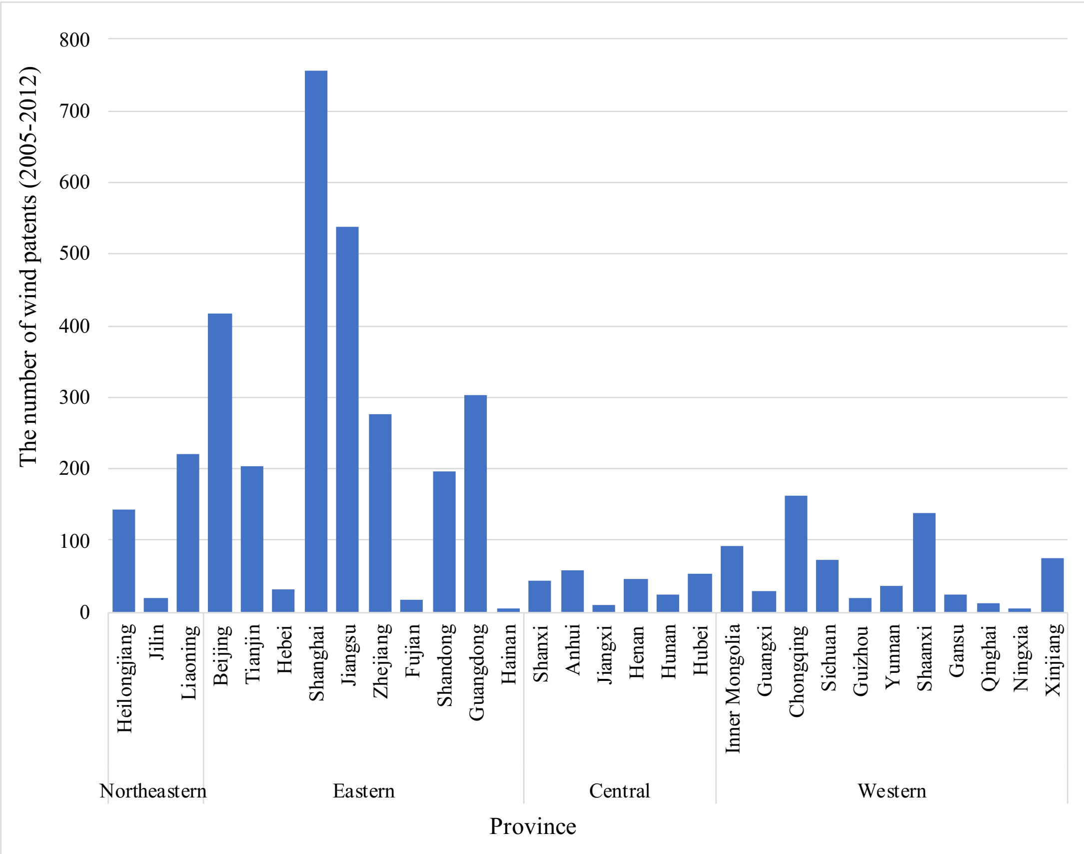

Fig. 2.2. The number of wind patents (2005-2012)

Source: Edited by author based on SIPO

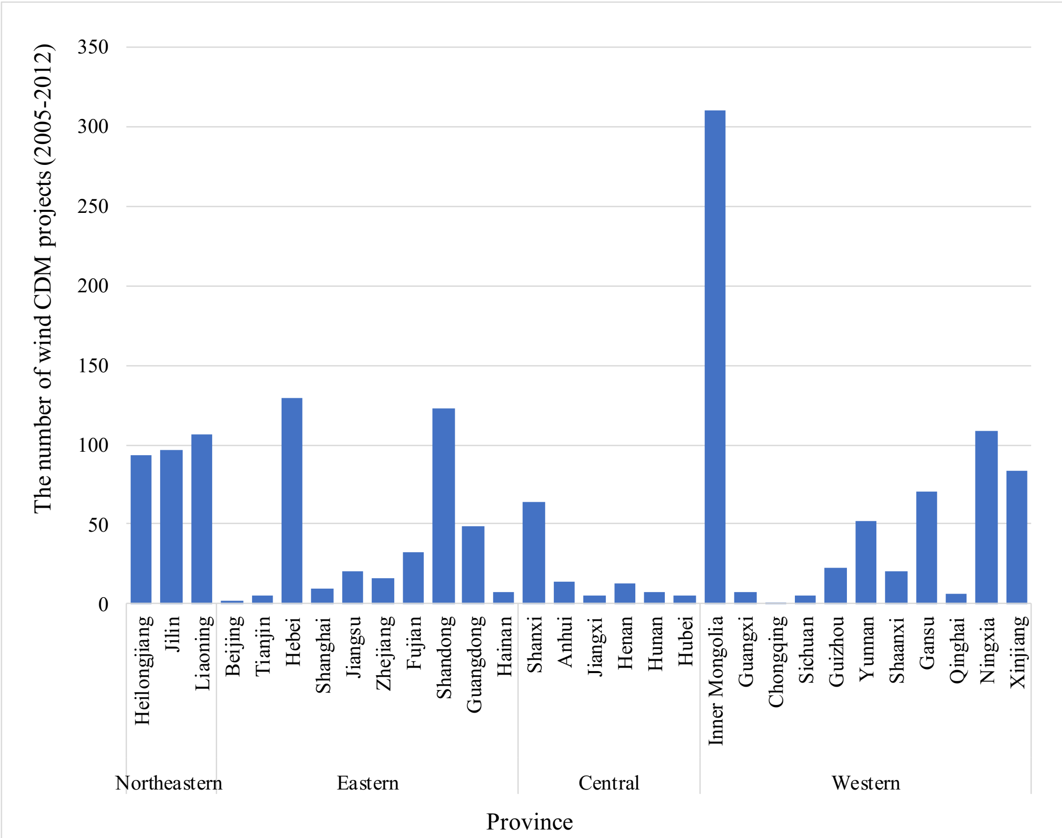

Fig. 2.3. The number of wind CDM projects (2005-2012)

Source: Edited by author based on PDDs of CDM wind projects

Chapter 3

Examining the Impact of the Feed-in Tariff Amendment in Japan on the Relationship between Approved and Operating Capacity

3.1 Introduction

With the growing interest in sustainable development and climate change mitigation, renewable energy has been expanding dramatically in the past three decades globally. Renewable energy is highly required in Japan for its importance in reducing GHG emissions and attaining energy self-sufficiency after the Fukushima Daiichi accident in 2011. The Japanese government unveiled the Basic Energy Plan in July 2018, which emphasizes the need for renewable energy as a main power source (METI, 2018b). However, as of 2016, the share of renewable energy in electric power generation in Japan was 14.6% (7.1% if hydroelectric power is excluded) (?), which seems low compared to that in major developed countries. Japan launched the feed-in tariff (FIT) scheme as a main policy measure to promote the deployment of renewable energy. FIT has helped increase renewable power generation particularly in solar cells, but it encountered several challenges, the biggest of which is the large discrepancy between the approved capacity and operating capacity of solar power projects. The amendments on FIT were made in 2017 to address these challenges.

The objective of this chapter is to empirically investigate 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 by using municipality-level data of solar power capacity 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 if the policy impact differs according to project size. In addition, the chapter examines the characteristics of municipalities, which help locate non-operating solar projects.

This chapter contributes to the literature concerning the evaluation of policy instruments that 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 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 into 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 more effective for mature technologies such as wind. Böhringer et al. (2017) examines the impact of the German FIT on innovation of renewable energy technologies from 1990 to 2014. The results imply a positive effect of FIT on inducing innovation. However, the inducement effect of prior FIT 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.

This chapter is also related 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 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 contribute to reducing the decision-making time, leading up 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 the purchase of 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) investigated the impact of policy incentives on commercial solar power capacity. They find that rebates, sales exemptions, and renewable portfolio standards have statistically significant and positive effects. The 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.

The chapter differs from the existing literature in two aspects. First, we focus on the non-operating capacity of solar power projects that obtained approval of FIT eligibility but have not yet started operation. This chapter empirically examines whether the amended FIT policy alleviates the problem of non-operating solar projects. Few studies have mentioned the discrepancy between the actual operating capacity and FIT approved capacity. For instance, Kuramochi (2015) reviews policy measures on energy and climate change implemented in Japan and points out a large discrepancy between actual installed capacity and the approved installation capacity, particularly for non-household facilities. However, no quantitative analysis was conducted in this policy review. To the best of our knowledge, this chapter is the first to investigate the problem of non-operating solar projects by examining the effect of FIT amendments on improving the relationship between operating capacity and approved capacity. Second, instead of only 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 affecting the location of non-operating facilities and explore the differences in the characteristics of non-operating capacity before and after the amended FIT.

The results of our panel data analysis show that the amended FIT policy has improved the relationship between operation and approved capacity of solar power. The impacts are heterogeneous across the size of solar power projects: the effects are more substantial in large- and mega-scale solar power than in small ones. In addition, the findings from cross-sectional analysis indicate that, in general, municipalities with steeper slopes have more non-operating solar capacity. The results of the Chow test suggest that characteristics of municipalities that locate operating and non-operating solar projects become similar after the amendments on FIT.

The remainder of this chapter is organized as follows. Section 3.2 provides an overview of Japan's FIT policy and the problem of non-operating solar projects. Section 3.3 introduces the main revisions on existing FIT rules under the amended FIT scheme. Section 3.4 presents the regression model and describes the dataset used in the analysis while Section 3.5 discusses the empirical results. Finally, Section 3.6 draws conclusions.

3.2 Feed-in Tariff Policy in Japan

To promote the penetration of renewable energy in the energy mix[21], Japan launched a national FIT scheme based on the Act on Special Measure 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[22] from the Japanese government. Electric utilities[23] 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 transmission grid of the electric utility and distributed to end-users. All electricity customers then pay a surcharge for renewable energy proportional to their usage to cover the expense of purchasing renewable power (METI, 2012).

Table 3.1 presents the purchase price under FIT from 2012 to 2016. A source-specific and size-specific but nationwide uniform purchased price scheme is adopted by the Japanese government. A unified FIT scheme would reduce unfavorable renewable capacity allocations, foster market competition, and reduce electricity costs, but would not be beneficial for some high-cost renewables. In contrast, setting differentiable purchase prices would encourage investment by ensuring profit margins, but it also could risk increasing the economic burden on electricity consumers (Li et al., 2019). Therefore, 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

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

[22] It is the FIT application of an existing (or proposed) renewable energy power facility confirmed and recognized by the Ministry of Economy, Trade and Industry.

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

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 those for other technology types were relatively stable.

[Table 3.1]

Since the FIT scheme guarantees a fixed price (tariff) for a designated period, which enhances certainty and stability for FIT-eligible renewable electricity producers, the approved capacity of renewable energy has been growing rapidly (Ito, 2015). By the end of December 2016, the approved capacity of new facilities was 88,773 MW. However, only 33,659 MW was the operating capacity, which indicates 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 (≥10 kW) projects because most of the non-operating capacity fall under this category.

The purchase price applied to a renewable power facility is the FIT's tariff at the time when the METI approved the facility, and so earlier approval means higher tariff and thus more 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 indicates that the later installation of solar PV can enjoy a lower equipment cost. Moreover, there was no explicit regulation on the deadline for approved projects to connect to the electricity grid and start their operation. Thus, solar power developers got 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. It was found that a total 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 finished their installation and started generating electricity but have not yet started operation. The existence of non-operating projects means that a substantial amount of potential electricity from renewable resources is not available despite the rapid expansion of approved capacity, thus suggesting that the original FIT scheme is not effective in promoting the penetration of renewable electricity. Furthermore, even if these non-operating projects might start to operate and generate electricity long after they obtain FIT approval, they have the privilege[24] to sell their electricity with higher FIT prices. The higher purchase price would then be transferred to future consumers on their electricity bill.

3.3 Amended FIT Policy in Japan

To address the problem of non-operations, the Japanese government has promulgated the amendment to the FIT Act on June 2, 2016. These amendments came into force on April 1, 2017 and made three main revisions to the existing rules. First, grid connection contracts with relevant utility companies are required for project developers of renewable energy. Renewable power producers must conclude grid connection agreements before the approval of FIT. With regard to existing FIT-approved projects, a deadline for connection agreements is set to ensure the continued validity of the applicable purchase price and purchase period after April 2017. Projects approved on or prior to June 30, 2016 are required to make a grid connection agreement by March 31, 2017, while projects approved between July 1, 2016 and March 31, 2017 are required to do so within 9 months of the approval (?) The projects lose eligibility of FIT if they fail to complete the grid connection agreements by the due date.

Second, METI has replaced a facility certification system with a business-plan-based certification system for FIT applications. Renewable energy developers must submit a detailed business plan, including the commencement date for operation and the description of the interconnection arrangement to maintain a valid FIT approval. Third, a bidding system for FIT approval is introduced to reduce the applicable purchase price to promote competition among developers. A reverse auction system is introduced for the FIT price of large-scale solar projects. The bidding process is managed by a nonprofit organization designated by the METI. In summary, the amended FIT policy tightens the requirements for the process of FIT approval and introduces competition to determine FIT prices.

Figure 3.1 shows the total approved capacity and operating capacity of solar power during 2012-2019. According to METI (2017), 456,000 approved projects with total capac-

[24] Once the proposed renewable energy projects obtain FIT approval, they can fix the purchase price, no matter how low the current FIT prices are in the year when they start to operate.

ity of 27.66 GW were expected to lose their validity of FIT approval after the amendment. There is a sharp decline in the cumulative capacity of approved projects from 2016 to 2017. The original FIT policy requires only information on facility location and the PV system specifications for approval. Conversely, the amended FIT introduced stricter requirement on the start of operation, such as grid connection agreements and information on the commencement date in 2017, thus increasing the operating capacity. The gap between operating capacity and approved capacity decreased after 2017, indicating that the amended FIT policy enhanced the relationship between the capacities and mitigated the problem of non-operating projects.

[Figure 3.1]

3.4 Empirical Strategy and Data

3.4.1 Model Specification

Our empirical analysis investigates the impact of amended FIT policies on the operation of new solar power facilities[25] 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 becomes different after the amendment of FIT. Figure 3.2 illustrates this hypothesis. FIT policies promote the deployment of renewable energy sources such as solar energy.

[Figure 3.2]

The abovementioned relationship reflected by the 45 degree dashed-line implies that the operating capacity equals the approved capacity. However, in reality, because neither deadline for starting operation nor grid connection agreements were required when approving new facilities under the initial 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 is steeper than before. The change in slope reflects the impact of the FIT amendment.

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

A linear fixed effects 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} indicates the installed capacity of operating solar facilities with FIT approval in municipality i by the end of year t. A_{it} is the FIT approved capacity of new solar power facilities in municipality i by the end of year t, which has not necessarily started operation. $A_{it} \times Post$ is an interaction term that denotes the approved capacity after the enforcement of the amended FIT. Time-varying and municipality-varying economic conditions are captured by E. λ_t is the vector of the year dummy capturing year fixed effects. It controls for unobserved factors that change over time and that are constant across municipalities. θ_i denotes the municipality fixed effects estimator, which accounts for time-invariant municipality characteristics. ϵ_{it} is the error term. The operating capacity in this chapter 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, constant term is removed in the ordinary least squares (OLS) model.

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

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

where Y_i denotes the operating or non-operating capacity of solar power facilities that have received FIT approval in a municipality i by year 2014 or 2019. M_i is a meteorological factor. Solar radiation is used to indicate the abundance of solar resources in a municipality i. E_i is an economic condition. P_i is a geographic factor. The slope of the land is the gradient or incline of the land surface. Hilly areas with steep slopes tend to suffer from more natural disasters, such as landslides, than flat areas. It is also connected to the higher construction costs and risks of a project. Electricity grid access is denoted by D_i. L_i is an area indicator of land availability for developing solar power projects. ϵ_i is the disturbance term.

Because the amendment might have heterogeneous solar power with different sizes, we decompose solar facilities according to capacity. An upper bound of 10 kW capacity is used for residential solar PV facilities. For large-scale commercial solar power, we use a lower bound of 10 kW capacity and an upper bound of 2 MW capacity. Projects larger than or equal to 2 MW capacity are sorted into the category of mega commercial solar.

3.4.2 Data

We construct a panel dataset of 1,741 municipalities from 2014 to 2019. A sub-dataset for 2014 and 2019 is also used in our cross-sectional analysis. Table 3.2 and Table 3.3 present the descriptions and summary statistics of the variables used in the empirical analysis.

[Table 3.2]

[Table 3.3]

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[26]. It collects capacity information from the application documents submitted by renewable energy project developers for FIT approval. As shown in Table 3.3, 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 3.3 depict 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.

[Figure 3.3]

Data on new housing construction are used as a proxy of economic conditions. They are collected from the Survey on Construction Statistics of the Ministry of Land, Infrastructure, Transport and Tourism (MLIT). Data on the area of arable land and abandoned

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

farmland are from the Statistical Survey on Crops of the Ministry of Agriculture, Forestry and Fisheries (MAFF).

Data on solar insolation are 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 average irradiance in kilowatt-hours per square meter per day ($kWh/m^2/day$).

Electricity grid access is related to the construction cost of the grid connection. Thus, it may affect the operation of solar power plants. The distance from the municipal office to the nearest electricity grid is used as an index of access to the electricity grid. It was measured using Geographic Information System (GIS) software.

3.5 Results and Discussion

3.5.1 Regression Results of Panel Data

We estimate the effects of amended FIT on the relationship between operation and approved capacity of solar power using a fixed-effect linear model. We put solar power into three categories : residential solar ($< 10kW$), large commercial solar ($\geq 10kW and < 2MW$), mega solar($\geq 2MW$) to run the regressions accordingly. The OLS model with time fixed effects was used as a baseline regression.

Table 3.4 presents regression results on solar power regarding the effect of amended FIT. The OLS model with year fixed effects and fixed effects estimator approach are adopted. The interaction term between approved capacity and post captures the effect of the amended FIT on the relationship between operating and approved capacity. In all the model specifications, coefficients for interaction term are statistically significant and positive. The results suggest that the amendment of FIT increased the operation of solar power projects. The estimated coefficient in column 1 indicates that, after the amended FIT, 1 kW added approved capacity related to an additional 0.265 kW increase of operating solar PV capacity. When controlling for the municipality fixed effects in column 2, the estimated coefficient of interaction term decreases by 0.053.

[Table 3.4]

The results from columns 3 to 8 show the heterogeneous effects across different scales 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 a 0.320 kW operating capacity. After the amendment, it is associated with a 0.68 kW operating capacity. The estimated coefficients decrease slightly when including the municipality fixed effects shown in column 4. In contrast, the change after the amendment is marginal for small-scale solar. As shown in column 4, the correlation between approved and operation 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 affects the relationship 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.

3.5.2 Regression Results of Cross Section Data

We apply cross-sectional regressions to investigate municipality characteristics that locate non-operating projects. All variables are transformed into natural logarithms in cross-sectional regressions.

The estimation results using cross-sectional data in 2014 are shown in Table 3.5. We focus on large- and mega-scale solar projects since about 56% of the non-operating capacity comes from large-scale solar projects. Solar insolation has statistically significant and positive effects on operating and non-operating capacity, but the coefficient is higher in the former regression model. According to column 6, for every 1% increase in solar insolation, the non-operating capacity of large-scale projects is increased by 11%. This indicates that solar power project developers tend to choose municipalities with rich solar resources as their plants' locations to obtain FIT approval. 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 operating capacity. The coefficient for slope 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 in municipalities with higher construction costs.

[Table 3.5]

Table 3.6 presents regression results of cross section data in 2019. We found similar impacts of solar insolation, electricity grid access and slope, but the differences between operating and non-operating capacity become smaller compared to Table 3.5. Because the amended FIT reduced unreasonable non-operating projects, we can expect operating and non-operating projects to be located in similar municipalities after 2017.

[Table 3.6]

To test the statistical difference of coefficients between operating and non-operating capacity, we apply the Chow test to the regression results of analysis in 2014 and 2019, respectively. The Chow test was used to examine the equality of 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 3.7 and 3.8 present the results of the Chow test. Generally, in 2019, the difference in coefficients between the operating and non-operating capacity models are less statistically significant than those in 2014. This implies that non-operating and operating projects are both located in similar municipalities in 2019. Specifically, the effects of solar insolation on the non-operating and operating capacity of large-scale solar were not statistically different in 2019. The richness of solar resources is associated with electricity generation, so richer solar insolation would not lead to a difference in the status of large solar power, which is either in operation or non-operating. One possible explanation is that large solar power projects that delayed operation were not because of poor solar resources. The locations of the non-operating solar were suitable for developing solar energy projects if only considering the conditions of solar resources.

[Table 3.7]

[Table 3.8]

3.6 Conclusion

This chapter has examined the impact of amended FIT policies on the relationship between operating capacity and approved capacity of solar power by using municipality-level panel data from 2014 to 2019. Our empirical results suggest that amendments to the FIT scheme improved the relationship and thus mitigated the discrepancy between approved capacity and operating capacity. The impacts are heterogeneous across different sizes of solar power projects. The effects of the amended FIT are more substantial in solar power with large and mega scales than small ones. Moreover, we apply cross-sectional analyses to identify municipal characteristics related to non-operating capacity in 2014 and 2019. Regression results indicate that, in general, municipalities with steeper land have more non-operating solar capacity. Using a chow test, we confirmed the statistically significant differences in rationality between operating and non-operating capacities. The results imply that in general, non-operating solar projects have similar rationality to operating capacities of solar power in 2019 concerning municipality-specific factors such as solar insolation.

Our findings have several policy implications. First, the rules of renewable energy policy, such as the Japanese FIT scheme, may offer a policy loophole for solar power generation companies to undermine the effectiveness of the program. Second, this chapter sheds light on how the revisions of existing policies based on actual market situations could support renewable energy more effectively. The obtained results suggest the importance of a well-designed FIT scheme in supporting the sustainable development of renewable energy. In this regard, our finding is consistent with Xia et al. (2020), which explores wind-power curtailment issues under the Chinese FIT policy.

This chapter also has some limitations. The capacity data of solar power used in this chapter could only identify facilities in the status of non-operation. However, it could not distinguish how much non-operating capacity was due to intentional delay of solar PV installation, and how many facilities have not yet started operation, albeit 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 with the operation (Li et al., 2019). Therefore, this chapter does not capture exactly how much the amended FIT contributed to reducing the intentional delay of solar PV installation. In addition, in the cross-sectional 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[27] on grid are available, the distance can represent the electricity grid access more accurately.

[27] 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.

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Table 3.1. Purchase price under Japan's FIT scheme (JPY/kWh), 2012 - 2016

Energy source	Category	2012	2013	2014	2015	2016	Duration (year)
Solar PV	<10 kW	42	38	37	35	33	10
	$\geq$ 10 kW	43.2	37.8	32	27	24	20
Wind	<20 kW	59.4	57.75	55	55	55	20
	$\geq$ 20 kW	23.76	23.1	22	22	22	20
Geothermal	<15,000 kW	43.2	42	40	40	40	15
	$\geq$ 15,000 kW	28.08	27.3	26	26	26	15
Hydro	<200 kW	36.72	35.7	34	34	34	20
	200 kW$\sim$1000 kw	31.32	30.45	29	29	29	20
	1000 kW$\sim$3000 kW	25.92	25.2	24	24	24	20
Biomass	Manure biogas	42.12	40.95	39	39	39	20
	Forest residues	34.56	33.6	32	32	32	20
	Primary mill residues	25.92	25.2	24	24	24	20
	General waste	18.36	17.85	17	17	17	20
	Recycled wood	14.04	13.65	13	13	13	20

Source: METI (2012-2016), Dong and Shimada (2017)

Note: Duration means the period for purchasing electricity generated by each power source

Table 3.2. 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 3.3. 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 all solar PV facilities.

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

Table 3.4. Main results of panel data regression

	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	10446	10446	10446	10446	10446	10446	10446	10446
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

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

Table 3.5. Regression results of cross section data in 2014

	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: Variables are in log form.

Robust standard errors in parentheses

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

Table 3.6. Regression results of cross section data in 2019

	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: Variables are in log form.

Robust standard errors in parentheses

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

Table 3.7. Chow test of cross sectional regression results in 2014

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

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.8. Chow test of cross sectional regression results in 2019

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

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

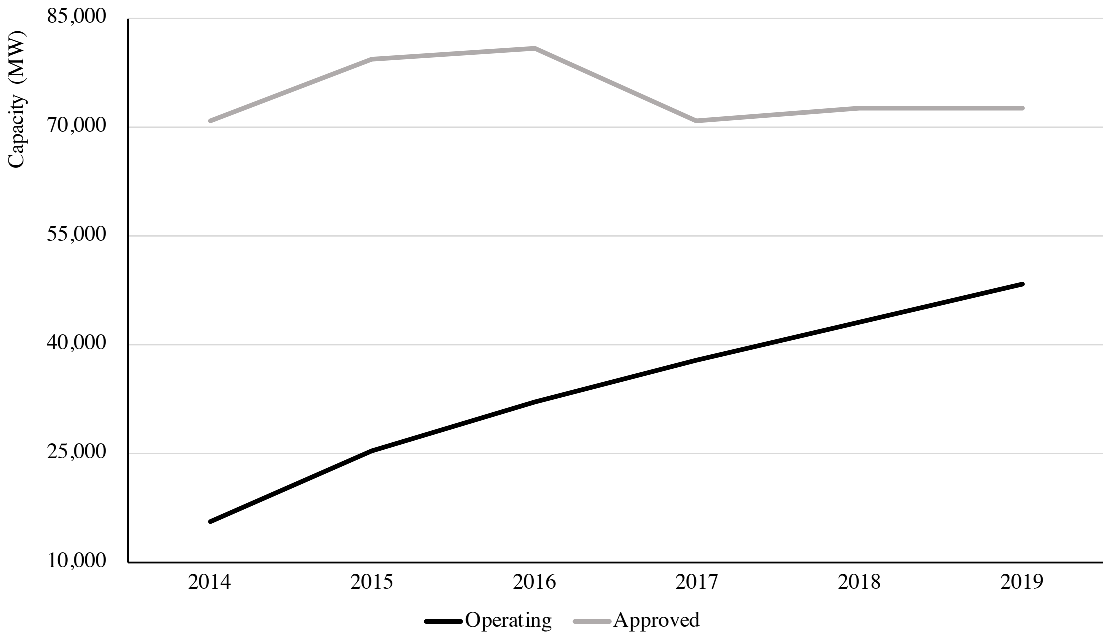

Fig. 3.1. Time trend of FIT approved capacity and operating capacity

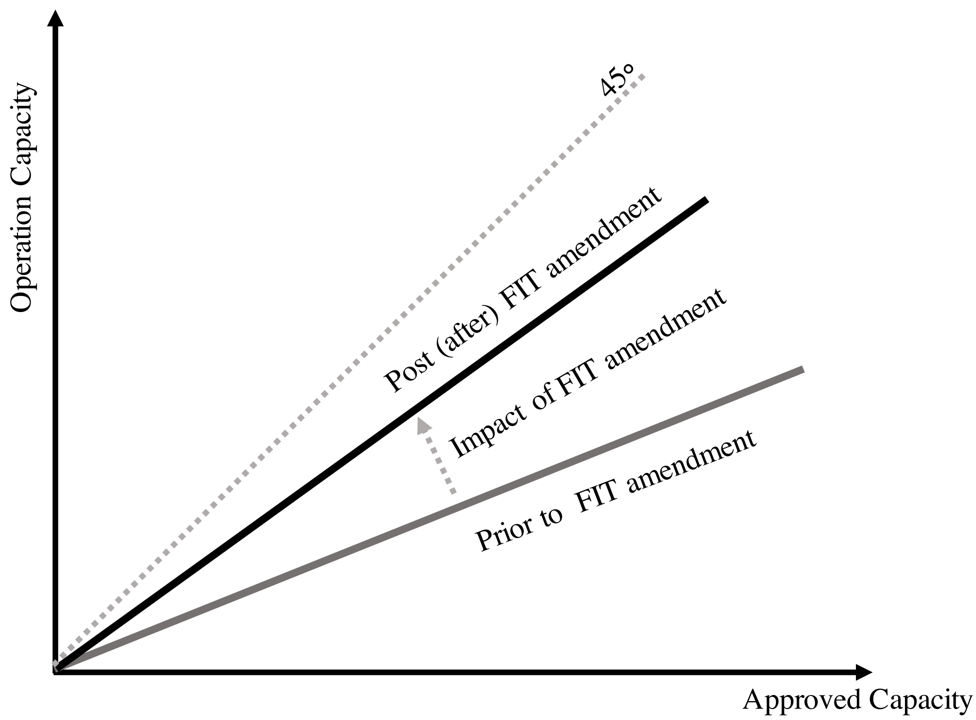

Fig. 3.2. Hypothesis on the effect of amended FIT

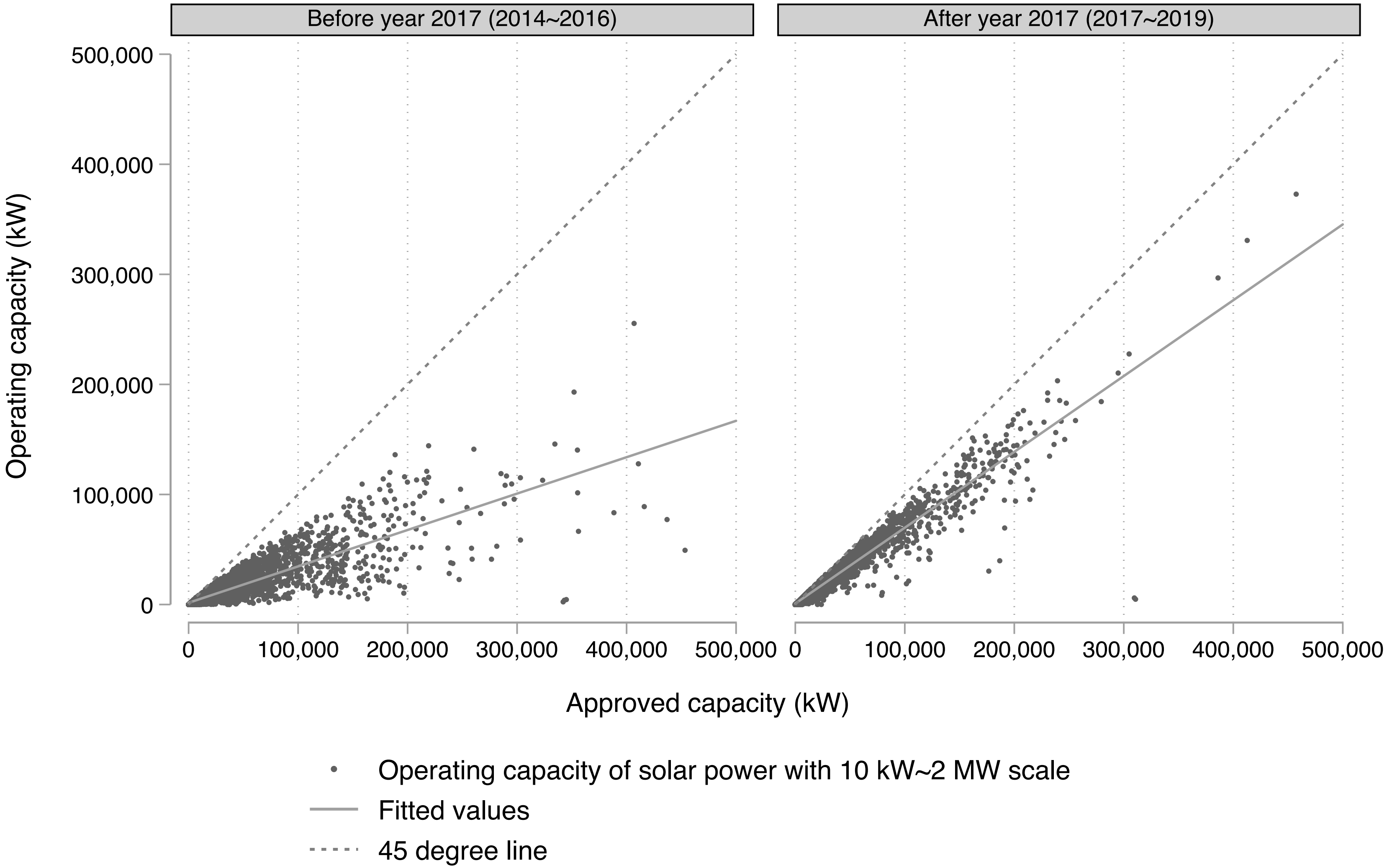

Fig. 3.3. Scatter plots of operating and approved capacity (large-scale solar power)

Chapter 4

Are Reverse Auctions under the Feed-in Tariff System Slowing the Expansion of Mega-solar Power in Japan?

4.1 Introduction

Since the introduction of a national feed-in tariff (FIT) scheme in 2012, Japan has approved 93 GW renewable energy projects, as of June 2020. Nearly 80% of these FIT-approved projects are solar photovoltaic (PV) projects. Approximately 296.9 billion kWh of electricity generated by solar PV power has been purchased under the FIT scheme, at a cost of 11.59 trillion Japanese yen [28]. This has created a tremendous burden on Japanese consumers since the cost of this support is transferred to consumers through their electricity bills [29], after subtracting the portion supported by the power utilities. To reduce the support costs of solar power, the Japanese government launched a reverse auction system for mega-solar PV projects in 2017. In the mega-solar reverse auction, the bidding process determines eligibility, capacity allocation, and electricity procurement prices for solar PV projects above 2 MW. However, in Japan, reverse auctions have suffered from the issue of underperformance. As of 2019, the awards met only 34.5% of the capacity target of the reverse auctions, an unexpected outcome for policymakers.

The research question examined here is whether reverse auctions under FIT have slowed the expansion of mega-solar projects in Japan. To answer this, we investigate the impact of reverse auctions on the number of FIT-approved solar PV projects of different sizes. Additionally, we estimate the spillover effect of reverse auctions on solar projects that

[28] More information is available at https://www.fit-portal.go.jp/PublicInfoSummary

[29] Consumers pay the "Renewable Energy Power Promotion surcharge" in their monthly bills proportional to their electricity usage.

were not the target of the recent reverse auction system; whether a solar PV project is subjected to the reverse auction system is based on the project's size. In 2017 and 2018, the minimum size requirement for reverse auctions was 2MW, which meant that participation in the auctions was mandatory for solar PV project developers with an installed capacity of more than 2 MW. In parallel with the FIT prices determined by the mega-solar bidding process, administratively set FIT prices were adopted for solar projects less than 2 MW. The latter prices were higher than the former ones, which may have generated an incentive to manipulate project size to attain higher FIT prices. Such incentives, coupled with strict compliance rules for the reverse auctions, may have led to fewer solar projects above 2 MW and a slight increase in those below 2MW. We consider this as the spillover effect of the reverse auction.

The approach of using auctions to support renewable energy has attracted considerable attention in the literature. Winkler et al. (2018)conducted case studies on support scheme effectiveness and efficiency for renewable energy by comparing countries using reverse auctions with those not using them. They conclude that auctions are more effective if auction volumes are in line with renewable energy extension targets and include sufficient guarantees and penalties. However, auctions do not generally lead to higher efficiency than schemes with administratively set support levels. Buckman et al. (2019) compared the processes and outcomes of FIT reverse auctions for large-scale solar and wind in Australia between 2012 and 2016. They suggest that auctions can deliver significant local economic benefits successfully as well as decreasing FIT prices. They also point out the general potential auction weaknesses as uncertainty about bidding delivery and the FIT prices of successful bids, high transaction and administrative costs, and locational concentration of successful proposals. Botta (2019) used a conjoint analysis based on a survey dataset to investigate the impact of renewable energy auctions on the capital costs for renewable energy projects in Europe. He shows that the adoption of moderate financial bid bonds, a long-term auction schedule, and a technology-specific auction can reduce the cost of equity between 0.5% and 1.5%.

Our study contributes to the literature on renewable energy auctions in three aspects. First, we investigate the reverse auctions for solar PV conducted under the FIT policy in Japan. Many studies have examined renewable energy auctions in other countries, such as Germany (Leiren and Reimer, 2018; Lundberg, 2019), Australia (Buckman et al., 2014, 2019), and India (Bose and Sarkar, 2019), but there is a lack of research on Japanese reverse auction systems. This chapter fills this gap. Second, we adopt an empirical approach to estimate the causal effect of reverse auctions on the number of FIT-approved solar projects. Specially, we examine the spillover effect of reverse auctions when generous FIT prices are administratively set at the same time for non-auctioned solar projects. Third, we explore the impact of a change in the minimum size threshold on the number of FIT projects in the reverse auctions.

The results suggest that the introduction of a reverse auction system in Japan has slowed the expansion of mega-solar projects in the country. The approved number of solar projects above 2 MW decreased by 83 between 2017 and 2018. In parallel, reverse auctions had a spillover effect on solar power projects of less than 2 MW: the number of FIT-approved solar projects between 1 MW and 2MW increased. However, the impact of the change in the minimum size threshold, which happened in 2019, on the number of FIT projects in 2019, were not statistically significant.

The rest of the paper is organized as follows. Section 4.2 presents an overview of Japan's reverse auction under the feed-in tariff scheme. Section 4.3 provides our hypotheses, the empirical strategy for the analysis, and describes the data used in the estimation. Section 4.4 presents our regression results and Section 4.5 concludes.

4.2 Japan's Reverse Auction under the Feed-in Tariff Scheme

Japan first launched a national FIT scheme in July 2017, which was then amended in April 2017. The amended FIT scheme introduced a reverse auction system for solar PV projects above 2 MW. In the reverse auction system, project developers bid for electricity procurement prices on a per kW/h basis. The aim of the auction is to reduce the cost of supporting solar PV projects by including a bidding [30] process and competition among project developers.

4.2.1 Reverse Auction Mechanism

Figure 4.1 shows the procedure for bidders. The qualification process is based on an examination of the business plans submitted by the solar PV project developers. Only qualified bidders are allowed to participate in the bidding process, and only winning bid-

[30] Bidding refers to the price-discovery procedure in auctions.

ders are entitled to FIT approval. In addition to the registration fee for bidding, two deposits are required: the bid deposit, as a condition for participating in the auction, which is returned to losing bidders; and the completion deposit, which serves as a guarantee against issues that may be encountered before commencement of the operation. The completion deposit is 5,000 Japanese yen per kW, which is 10 times the bid deposit. The bid deposit is forfeit if a winning bidder fails to pay the completion deposit or sign a grid connection contract before the deadline. Moreover, if a winning bidder delays operation commencement or fails to meet other contractual commitments, the completion deposit will be forfeit. These strict rules of compliance increase the auctions' perceived risk, acting as entry barriers to reverse auctions (IRENA, 2019).

[Figure 4.1]

Figure 4.2 illustrates the award process in the reverse auction system. The format is a pay-as-bid auction in which the winning bidders receive exactly the price of their bid. The main advantage of pay-as-bid auctions is that bidders face no uncertainties about their award price if they win (Haufe and Ehrhart, 2018). The Japanese government sets the ceiling price and target capacity for the reverse auction. The winning bidders are selected among participants whose bid prices are below the ceiling price and ranked based on their bid prices. The bidder with the lowest bid price is awarded capacity first, followed by the second lowest price, and so forth, until the target of the auction's capacity is attained. The bid prices of the winning projects are adopted as their FIT rates, which are the electricity procurement prices.[31] Thus, FIT eligibility, approved capacity, and FIT rates are determined through the process of these competitive auctions.

[Figure 4.2]

4.2.2 Auction Results

As of 2019, The Japanese government had implemented five auction rounds. The reverse auctions initially applied only to solar projects above 2 MW; however, in 2019, the minimum project size requirement was revised to include solar projects above 500 kW. Figures 4.3 and 4.4 show the auction results in terms of capacity and number of bids,

[31] In parallel to the FIT rate determined by the bidding process for winning projects, administratively set FIT rates are determined for solar projects below the minimum size thresholds of the reverse auctions.

respectively. In total, the reverse auctions selected 104 winning projects with a combined capacity of 574 MW. However, except for the third auction in 2018, all the other auctions were under-subscribed, which means participating capacity was below the auction target capacity. As a result, the awards met only 34.5% of the target capacity. Thus, the auctions proved ineffective in achieving the auctions' target capacity.

[Figure 4.3]

[Figure 4.4]

The bid prices in the reverse auctions reflect the competitive procurement prices of electricity generated by solar PV projects. Since the introduction of the reverse auction system, the bid prices have decreased substantially. Table 4.1 shows the bid prices and administratively set FIT prices. The lowest bid prices decreased from 17.2 in 2017 to 10.5 Japanese yen per kWh in 2019, which equates to a 39% reduction in three years. The administratively set FIT prices were higher than the bid prices. The differences between the administratively set FIT prices and the bid prices may have proved to be an incentive for project developers to change their business plans regarding project size to maximize their profits. For example, as shown in Table 4.2, when FIT approval was successfully obtained and the highest bid price adopted as the electricity procurement price, a 2 MW solar PV project in 2018 generated 31,000 JPY/h. In contrast, for projects from 2 MW to 1.99 MW in size, project developers avoided the risks of participating in reverse auctions and generated 6,810 JPY/h more in revenue. Developing two solar projects with 1 MW scale was also more profitable than one 2 MW project, not considering economies of scale. When the minimum project size dropped from 2MW to 500kW in 2019, the difference in revenue across the different sizes of solar projects decreased (see Table 4.3).

[Table 4.1]

[Table 4.2]

[Table 4.3]

4.3 Empirical Analysis

4.3.1 Hypotheses

We established three hypotheses regarding the introduction of the reverse auction system for solar power in 2017, the change in the minimum size threshold of reverse auctions in 2019, and the spillover effect of the reverse auctions.

Hypothesis 1: Reverse auctions reduced the number of FIT-approved solar power projects $\geq 2MW$ in 2017 and 2018.

Solar projects $\geq 2MW$ are directly affected by the reverse auction system as developers bid for electricity purchase prices and obtain FIT eligibility through these auctions. The bid ceiling's low price and the auction's strict rules of compliance lead to the underperformance of successful bids.

Hypothesis 2: The change in the minimum project size requirement from 2MW to 500kW in 2019, reduced the number of FIT-approved 500 kW $\sim$ 2MW solar projects in the reverse auction that year.

Hypothesis 3: Reverse auctions had a spillover effect on solar projects above 500 kW and less than 2 MW in 2017 and 2018.

The administratively set (non-auctioned) FIT rates were higher than those decided by reverse auctions in the timeframe evaluated. In 2018, the government announced that reverse auctions in 2019 would include 500 kW $\sim$ 2MW solar PV. To maximize profits, project developers may have decided to invest in 500 kW $\sim$2 MW solar PV projects in 2017 and 2018 to avoid this change. Therefore, the number of FIT-approved solar projects above 500 kW and less than 2 MW in that year could have been indirectly affected by the spillover effect of reverse auctions:

4.3.2 Model Specification

To estimate the impact of the reverse auction system on the number of FIT-approved solar projects, we used the difference-in-differences (DID) approach with multiple treatment groups and time periods. A DID estimator [32] identifies the differences between the number of FIT-approved solar projects that are subject to the reverse auction and those

[32] Since different potential outcomes cannot be observed for the same unit at the same time, the DID estimator of interest is the average treatment effect on the treated.

that are not. All solar PV projects above 2 MW were part of the bidding for electricity purchase prices for FIT eligibility in the auctions of 2017. Meanwhile, the existence of the reverse auction may have indirectly affected solar projects slightly below 2 MW. Therefore, the treatment groups are by size category of solar power project: over 2 MW and slightly smaller than 2 MW; while the control groups are those barely affected by the spillover from the reverse auction. The general estimation equation is expressed as follows:

$$\begin{aligned} Number\_projects_{it} = \alpha &+ \beta_1 Bin\_above2MW_i \times After_t + \beta_2 Bin[1MW\_2MW)_i \times After_t \\ &+ \beta_3 Bin[500kW\_1MW)_i \times After_t + \lambda_t + \theta_i + \epsilon_{it} \end{aligned}$$

where $Number\_projects_{it}$ denotes the newly approved number of solar PV projects by size category (bin) i in year t. $Bin\_above2MW_i \times After_t$ is a treatment indicator of reverse auctions on solar projects above 2 MW. It takes the value of one if the size category i is greater than or equal to 2 MW after 2017 and zero otherwise. $Bin[1MW\_2MW)_i \times After_t$ indicates the indirect impact of auctions on solar PV projects between 1 MW and 2 MW (not containing 2MW). It equals one if size category i is $\geq 1MW$ and $< 2MW$ after 2017 and zero otherwise. $Bin[500kW\_1MW)_i \times After_t$ captures the impact of an auction on solar projects between 500 kW and 1 MW (not containing 1 MW). It equals one if the size category i is $\geq 500kW$ and $< 1MW$ after 2017 and zero otherwise. λ_t denotes year fixed effects, accounting for any time-specific factors common to all solar power projects, such as the technological development of solar PV. The fixed effects of the size category are captured by $\theta_i$controlling for unobserved time-invariant variables affecting a certain size category. ϵ_{it} is the error term.

To explore the change in the minimum size threshold of reverse auctions from 2 MW to 500 kW in 2019, we also use another regression model for the period from 2017 to 2019. The treatment groups in this model are size bins above 500 kW and less than 2 MW because $\geq 2MW$ solar projects only bid for FIT prices in 2017 and 2018 and were not affected by the change in the minimum size threshold. The remaining bins are in the control group. The model specification is written as

$$\begin{aligned} Number\_projects_{i\tau} = \alpha &+ \beta_1 Bin[1MW\_2MW)_i \times 2019_\tau + \beta_3 Bin[500kW\_1MW)_i \times 2019_\tau \\ &+ \lambda_\tau + \theta_i + \epsilon_{i\tau} \end{aligned}$$

where $Number\_projects_{it}$ is the newly approved number of solar PV projects in size bin i in year τ. $Bin[1MW\_2MW)_i \times 2019_\tau$ equals one if size bin i is $\geq 1MW$ and $< 2MW$ in 2019, and zero otherwise. $Bin[500kW\_1MW)_i \times 2019_\tau$ equals one if size bin i is $\geq 500kW$ and $< 1MW$ in 2019, and zero otherwise. λ_τ and θ_i are year fixed and size bin fixed effects, respectively. $\epsilon_{i\tau}$ is the error term.

4.3.3 Data

We used a panel dataset consisting of 198 size bins of solar PV projects from 2012 to 2019 in our empirical analysis. The auction rounds were held in the third or fourth quarter of each year, with the winning projects becoming FIT eligible in the first quarter of the year following the administrative procedure. To account for the time lag between the auction date and the FIT approval date, we organized the data by fiscal year instead of calendar year. Table 4.4 presents the summary statistics of the variables.

[Table 4.4]

Data on the number of solar projects newly approved by the FIT scheme were collected from the Ministry of Economy, Trade and Industry (METI) of Japan [33]. The raw data contain basic information on FIT-approved commercial solar projects above 20 kW, such as the installed capacity and approval date. We limited the data to $\geq$ 50 kW solar PV projects as 50 kW is a turning point for the electricity grid connection and safety regulations according to the Electricity Business Act. For example, $\geq$ 50 kW solar PV projects must connect to a high-voltage grid through a cubicle, and are required to appoint a chief electrical engineer and confirm this with METI. These additional costs equate to between 1 and 1.5 million Japanese yen compared with solar projects below 50 kW [34]. Subsequently, we grouped these solar projects into size bins. For project sizes less than 2 MW, the bin width is 10 kW; projects $\geq$ 2MW were gathered in one bin as the frequency of such projects was sparse after 2017 for a 10 kW bin width. In the final dataset, there were 196 bins containing 36,650 solar projects. We also obtained information on auctioned solar projects from the Green Investment Promotion Organization (GIO) [35] to crosscheck our dataset. As shown in Table 4.4, the average number of solar PV projects in one size

[33] The website for information disclosure of FIT in Japanese. Available at https://www.fit-portal.go.jp/PublicInfo.
[34] See https://www.tainavi-next.com/library/194/
[35] Available at https://nyusatsu.teitanso.or.jp/.

bin was 24 from 2012 to 2018, and 11 from 2017 to 2019. Figure4.5 depicts the time trend of solar projects in the different size groups. From 2014 to 2016, parallel trends hold for all groups. In 2017, the number of projects $\geq 2MW$ decreased significantly compared with the other groups.

[Figure 4.5]

4.4 Results

4.4.1 Estimation Results

Table 4.5 reports our results regarding the impacts of reverse auctions on the number of FIT-approved solar projects. Columns 1 and 2 show the results of the bins above 500 kW and those above 50 kW from 2012 to 2018, respectively. We use the time period 2014 to 2018 to calculate the results shown in columns 3 and 4 since the time trends for the groups [1MW, 2MW) and [500kW, 1MW) were not consistent with the other groups from 2012 to 2014 in figure4.5. The interaction terms capture the impacts of reverse auctions on the number of solar projects. The estimated coefficients of $Bin\_above2MW \times After$ are statistically significant and negative in all models. This indicates that the reverse auction system reduced the number of mega solar projects approved by FIT during this timeframe. As shown in column 4, the number of approved projects $\geq 2MW$ decreased by 83 after the introduction of reverse auction system compared with the projects not affected by reverse auctions. The coefficients on $Bin[1MW\_2MW) \times After$ are positive and statistically significant, as shown in columns 2 and 4, but only at 10% significance in the latter one. This suggests that reverse auctions might have increased the number of solar projects above 1 MW and less than 2MW slightly. As shown in column 4, the coefficients of $Bin[500kw\_1MW) \times After$ are positive, however, not statistically significant. Thus, reverse auctions might not have affected solar projects less than 1 MW and above 500 kW.

[Table 4.5]

Table 4.6 shows the regression results related to the impacts of reverse auctions in 2019 when the minimum size threshold changed from 2 MW to 500 kW. The interaction terms capture the impacts of reverse auctions in 2019 on the number of solar projects from

500 kW to 2 MW. Column 1 shows the bins between 500 kW and 2 MW in one group. The coefficient of $Bin[500kw\_2MW) \times 2019$ is negative but not statistically significant. Column 2 shows the bins of 500 kW and 2 MW divided into two groups: $1MW \sim 2MW$ and $500kW \sim 1MW$. Similarly, the coefficients associated with the interaction terms are negative but not statistically significant. These results indicate that the reverse auctions in 2019 did not reduce the number of solar projects between 500 kW and 2 MW. One possible explanation is that 2018 affected any decrease in the approved number of solar projects from 500 kW to 2 MW in 2019; this also relates to the "time spillover" effect induced by the announcement of the minimum size threshold change in 2018. Project developers tended to pursue FIT approval of $500kW \sim 2MW$ solar projects in 2018 when they were informed in advance that the government would be including solar projects from 500 kW to 2 MW in reverse auctions in 2019.

[Table 4.6]

4.4.2 Impact on FIT Purchase Expenditure between 2017 and 2018

The estimated results in Table 4.5 suggest that the number of approved projects $\geq 2MW$ decreased by 83 after the introduction of reverse auction system. If the reverse auction system were not introduced, an additional 83 mega-solar with 1572.2 MW [36] capacity would be approved and we would expend 34,587,655 JPY/h to purchase the electricity, based on the average FIT prices [37] for projects $< 2MW$ between 2017 and 2018.

In reality, the bid prices were cheaper than fixed FIT prices and less mega solar projects were approved. As a result, reverse auctions reduced the expenditure of FIT scheme on purchasing electricity generated by mega solar PV. The total approved capacity of mega solar determined by reverse auctions is 236.6 MW in 2017 and 2018. It will cost 3,752,354 JPY/h to purchase electricity generated by these winning projects [38]. It is almost one-tenth of the above hypothetical expenditure.

Reverse auctions reduced the price as well as the total approved capacity, thus lead to a dramatic reduction in expected expenditure for the electricity generated by renewable

[36] The average size of FIT-approved mega solar projects is 18.9 MW from 2014 to 2016.
[37] The administratively-set FIT price is 23 and 21 JPY/kWh in 2017 and 2018 respectively.
[38] These winning projects haven't finished construction yet. The generated electricity will be purchased by FIT at their bid prices when they start operation.

sources. What if there were enough participation to the reverse auction and the target capacity were fulfilled? If we assume the target capacity (946.96 MW) were awarded at the the ceiling prices of reverse auctions, the expenditure for purchasing solar power would be 17,427,880 JPY/h, which is less than the case without reverse auction but higher than the case with it.

4.5 Conclusions

In this chapter, we investigated the impact of reverse auctions in Japan on the number of FIT-approved solar projects in different size categories. We grouped FIT-approved solar projects into size bins and constructed a panel dataset from 2012 to 2019. The DID approach was adopted to estimate the causal effect of reverse auctions on solar projects above 2 MW, where FIT eligibility and electricity procurement prices were determined in the bidding process. We also defined the spillover effect of reverse auctions on solar projects slightly below 2 MW. In addition, we examined the impact associated with the change in the minimum size threshold of reverse auctions in 2019.

The results indicate that the introduction of the reverse auction system for solar PV reduced the number of approved solar projects above 2 MW. Thus, it has slowed the expansion of mega-solar energy in Japan. In contrast, the number of FIT-approved solar projects above 1 MW and below 2 MW increased due to the spillover effect of the reverse auctions. However, the results on the impact of the change in the minimum size threshold in 2019 were not statistically significant. Thus, we cannot conclude that different minimum size thresholds in the reverse auctions had different impacts on the number of FIT-approved solar projects.

Renewable energy auctions have been widely adopted as policy instruments for determining subsidy levels for renewable energy sources (IRENA, 2017, 2019). Policymakers are looking to promote renewable energy at the lowest possible cost, while simultaneously attaining other social benefits, such as alleviating the financial burden on consumers' electricity bills. Well-designed auctions can improve the effectiveness and efficiency of supporting renewable energy. For example, Germany conducted renewable energy auctions with high frequency to increase planning security for the bidders and to ensure the continuous development of renewable energy. Solar PV auctions in Germany have proven to be an effective tool to award support because the volume of bids have exceeded the auctioned volume in all solar PV auction rounds. Sufficient competition among bidders drives down support costs and at the same time ensures steady renewable power deployment with high realization rates (AURES, 2019).

However, the reverse auctions in Japan as of 2019 have underperformed. From 2017 to 2019, there have been 256 bidders qualified by the government in five auctions, but 34% of these bidders dropped out and did not participate. Among the 106 winning bidders, 15 bids were cancelled because the organizations did not pay the completion deposit by the deadline. Therefore, the biggest challenge encountered by Japanese solar PV auctions is how to attract sufficient participation to ensure competition and meet the capacity target. Further investigation on other factors that may affect the participation of project developers in reverse auctions is necessary to extend our understanding of the relationship between reverse auction design and the expected policy outcome.

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Table 4.1. Bid price and administratively-set FIT price (JPY/kWh, 2017-2019)

	Bid price		Administratively-set
Year	Max	Min	FIT price
2017	21	17.2	23
2018	15.5	14.25	19
2019	13	10.5	15

Note: Bid price for projects above 2MW (2017-2018) and above 0.5MW (2019).

FIT price for projects between 10kW to 2MW (2017-2018) and 10kW to 0.5MW (2019).

Table 4.2. Example: Revenue of solar projects in 2018

Size (MW)	Number of Projects (#)	Revenue [39](JPY/h)
2	1	31,000
1.99	1	37,810
1	2	38,000

Table 4.3. Example: Revenue of solar projects in 2019

Size (kW)	Number of Projects (#)	Revenue [40](JPY/h)
500	1	6,500
490	1	7,350
250	2	7,500

[39] The revenues are calculated assuming solar power facilities are in full operation of installed capacity and the highest bid price is the electricity procurement price for 2MW solar projects where 1 MW = 1000 kW.

[40] The revenues are calculated assuming solar power facilities are in full operation of installed capacity and the highest

Table 4.4. Summary statistics

Variable	Unit	Obs	Mean	Std. Dev.	Min	Max
2012-2018						
Dependent						
Number_projects	project	1,372	24	74	0	957
Independent						
bin_above2MW × After	dummy	1,372	0.002	0.04	0	1
bin_[1MW_2MW) × After	dummy	1,372	0.15	0.35	0	1
bin_[500kW_1MW) × After	dummy	1,372	0.07	0.26	0	1
2017-2019						
Dependent						
Number_projects	project	588	11	33	0	539
Independent						
bin_[500kW_2MW) × 2019	dummy	588	0.26	0.44	0	1
bin_[1MW_2MW) × 2019	dummy	588	0.17	0.38	0	1
bin_[500kW_1MW) × 2019	dummy	588	0.09	0.28	0	1

bid price is the electricity procurement price for 500 kW solar projects.

Table 4.5. Results on the impact of the reverse auction for $\geq$ 2 MW solar projects

Dependent variable:	2012-2018		2014-2018	
Newly approved number of solar projects	$\geq$ 500kW	$\geq$ 50kW	$\geq$ 500kW	$\geq$ 50kW
	(1)	(2)	(3)	(4)
Bin_above2MW $\times$ After	-208.222***	-186.924***	-90.943***	-83.156***
	(8.235)	(9.420)	(3.548)	(4.843)
Bin[1MW_2MW) $\times$ After	5.977	27.275***	1.815	9.603*
	(9.135)	(10.214)	(3.658)	(4.925)
Bin[500kw_1MW)$\times$ After		21.298*		7.788
		(12.505)		(6.001)
Year fixed effect	YES	YES	YES	YES
Bin fixed effect	YES	YES	YES	YES
Constant	6.272**	12.536***	6.272***	12.536***
	(2.629)	(2.493)	(0.516)	(0.634)
Observations	1057	1372	755	980
Adjusted R^2	0.099	0.143	0.109	0.148

Robust standard errors in parentheses

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

Table 4.6. Results on the impact of reverse auctions for $\geq$ 500 kW solar projects

Dependent variable:	2017-2019	
Newly approved number of solar projects	$\geq$ 50kW	
	(1)	(2)
Bin[500kw_2MW)$\times$ 2019	-3.691	
	(8.511)	
Bin[1MW_2MW)$\times$ 2019		-1.906
		(8.556)
Bin[500kw_1MW)$\times$ 2019		-7.261
		(8.618)
Year fixed effect	YES	YES
Bin fixed effect	YES	YES
Constant	18.026***	18.026***
	(1.036)	(1.032)
Observations	585	585
Adjusted R^2	0.077	0.079

Robust standard errors in parentheses

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

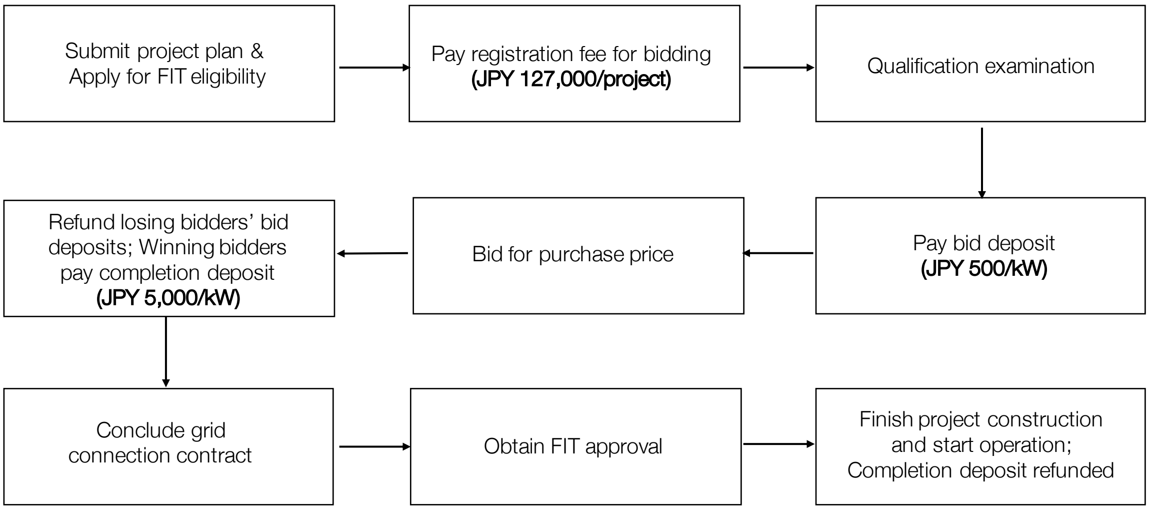

Fig. 4.1. Implementation procedure for bidders
Source: METI

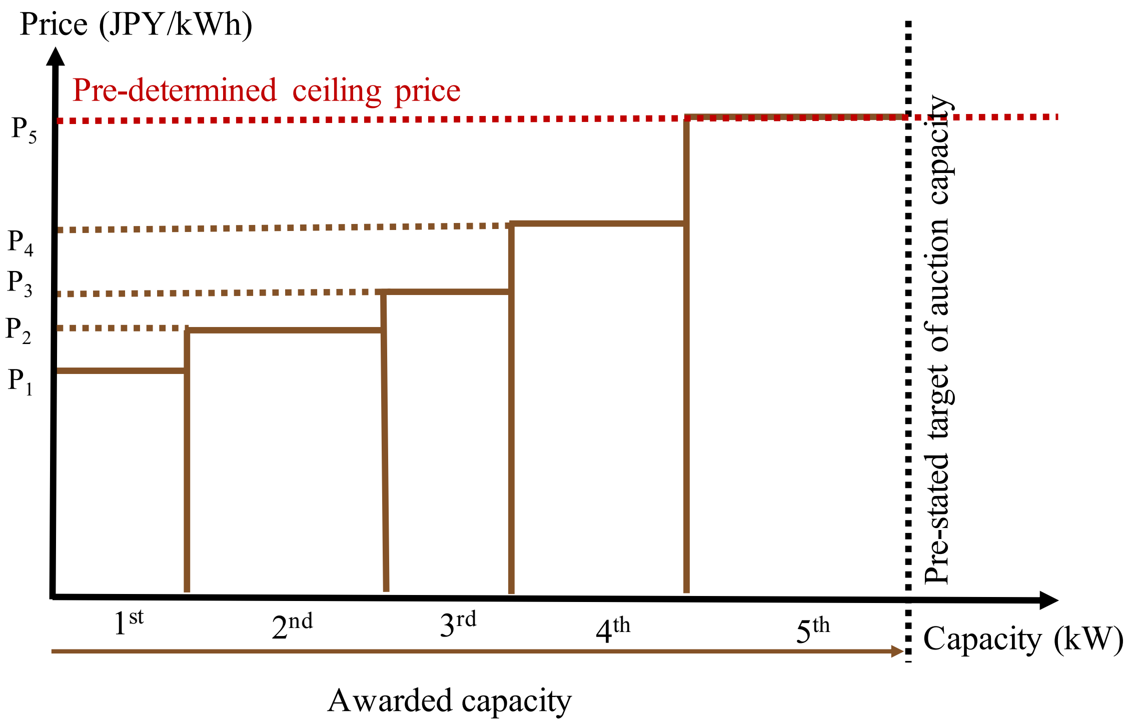

Fig. 4.2. Awarding process of reverse auction system
Source: METI

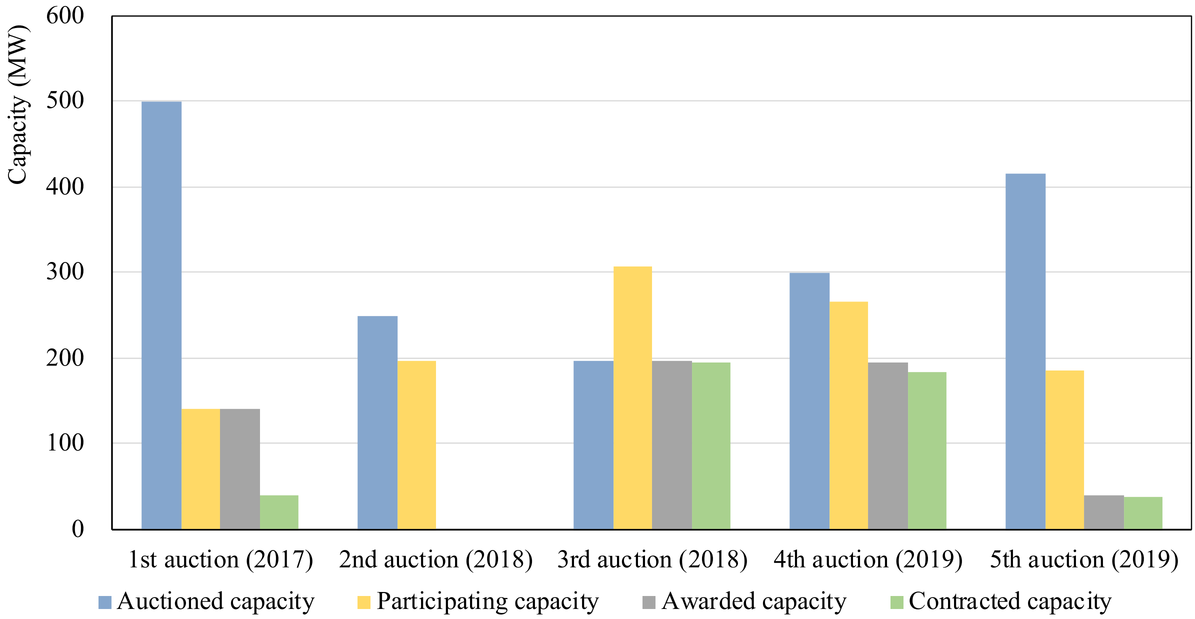

Fig. 4.3. Capacity in solar PV reverse auctions
Source: GIO

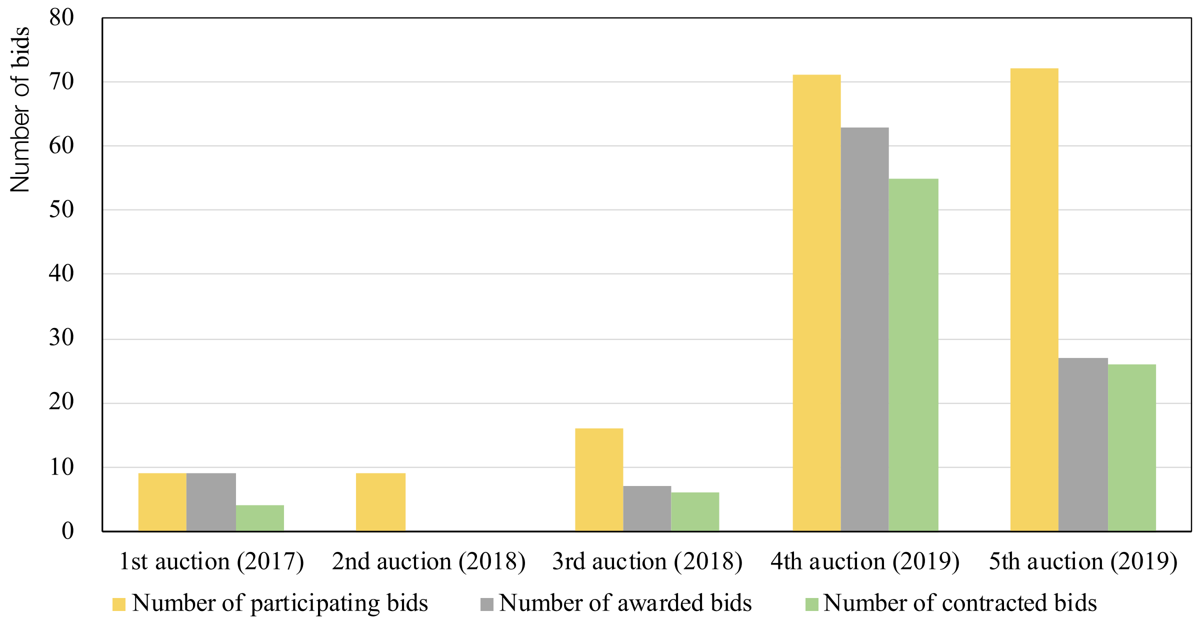

Fig. 4.4. Number of bids in solar PV reverse auctions
Source: GIO

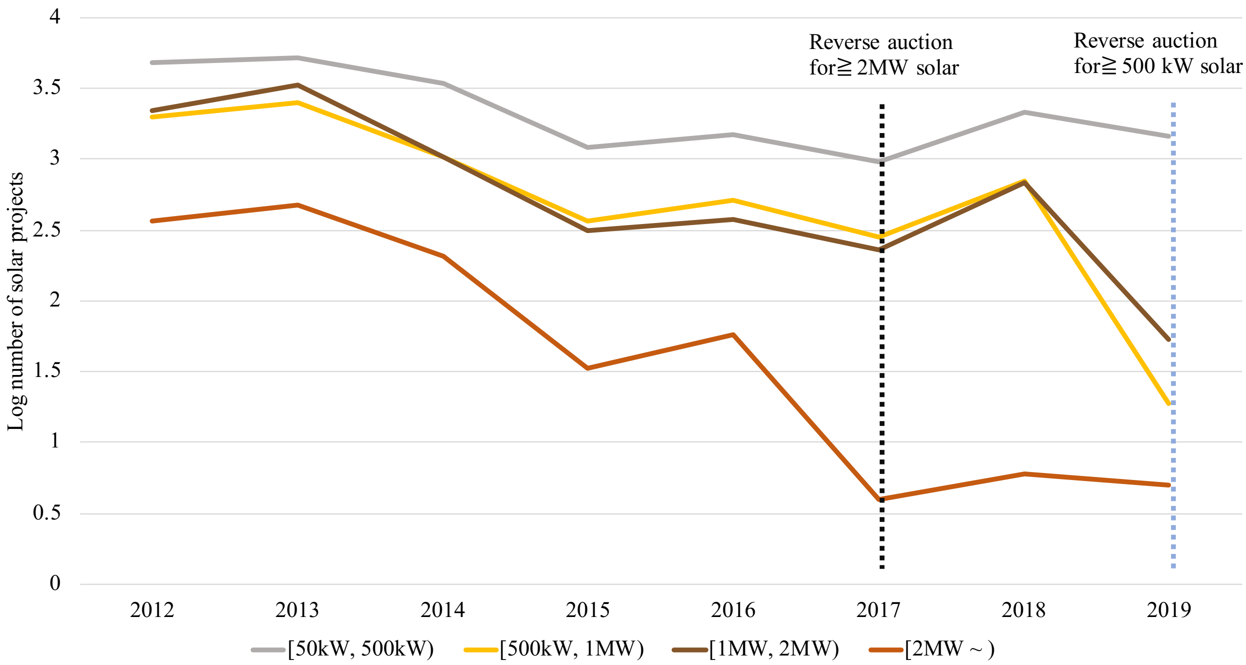

Fig. 4.5. Time trend of different groups (log)

Chapter 5

Concluding Remarks

This research empirically analyzed the impact policies for renewable energy have from different perspectives. We focused on both international climate change policy and domestic policy instruments on the development of renewable energy. We explored the role of CDM in wind power-related technological development in China. Then, we investigated the impact of amended FIT policies on the operation of solar power by examining the relationship between operating capacity and approved capacity before and after the amendment. We also examine the impact of reverse auctions on the number of FIT-approved solar PV projects of different sizes.

To summarize, the following conclusions can be drawn: First, developing countries can benefit from international climate change policy by its positive externalities. In Chapter 2, we saw how the implementation of CDM wind projects encouraged more technology transfer from developed countries to China, where the technological capacity of domestic wind turbine manufacturers is relatively low. CDM makes sophisticated foreign technology available in the wind market and makes it easier for Chinese wind turbine manufacturers to assimilate and re-innovate. Nevertheless, sufficient improvement of wind power-related technology relies on indigenous R&D throughout the entire innovation process.

Second, domestic supporting policies promote the deployment of renewable energy, but they must be adapted to reflect changes in market conditions. In Chapter 3, the purchase price applied to a renewable power facility is the FIT's tariff at the time when the METI approved the facility, and earlier approval means higher tariff and thus more revenue from selling electricity. Meanwhile, the price of the solar panel is decreasing, which indicates that the later installation of solar PV can enjoy a lower equipment cost. Moreover, there was no explicit regulation on the deadline for approved projects to connect to the electricity grid and start their operation. As a result, many solar projects have obtained FIT approval but have not yet started operation, which is called the "non-operating" issue. Considering actual market situations, the amendments on FIT policy impose stricter requirements on approval of FIT eligibility, which mitigates the discrepancy between approved capacity and operating capacity.

Third, domestic supporting policies have different focus at different stages of renewable energy. The incentives generated by policies should be in line with the exact policy target. In Chapter 4, as the renewable energy sector matures and the LCOE declines, the main focus of policy design shifts from fulfilling the deployment target of renewable sources to reduce the financial burden of FIT subsidization. Reverse auctions are introduced to allow the competitive market to determine the prices paid for renewables. The ability to provide appropriate incentives to ensure sufficient competition is the key factor when designing auctions for renewable sources.