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solar installations

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Light after the darkness: Estimating the impact of power outages on subsequent solar installations

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Abstract

Unexpected shocks to the electricity supply can influence people's decision to invest in renewable energy, particularly when these technologies serve as substitutes for backup power. This study investigates the impact of a large-scale power outage on subsequent photovoltaic (PV) installations and examines how households and firms evaluate the expected benefit of PV systems as an emergency power source. Using a doubly-robust difference-in-differences design, we exploit the 2018 Hokkaido Eastern Iburi Earthquake in Japan as a natural experiment to estimate the effect of the subsequent blackout on municipality-level PV installations. Our results show that the blackout significantly increased commercial PV installations but had no effect on residential installations. In particular, commercial PV capacity rose by 3.900 kW per 1,000 people per half-year following the blackout. Additional analysis suggests that the intermittent nature of solar power may limit the reliability of residential PV systems during emergencies, especially under adverse weather conditions. These findings highlight the need to address intermittency to enhance the role of PV systems as a resilient infrastructure.

Keywords: Solar power; blackout; backup energy; doubly-robust DID

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1 Introduction

Frequent natural disasters and climate-related shocks highlight the vulnerability of electricity systems. When outages occur, people experience firsthand the consequences of energy insecurity, which can alter their preferences for self-sufficient energy sources such as photovoltaic (PV) systems (Zanocco et al., 2021). These systems enable households and firms to generate their own electricity and can function as a form of self-insurance against blackouts. However, whether such experiences translate into the greater adoption of PV systems remains an open empirical question.

This study investigates how a large-scale blackout influences subsequent PV installation behavior. We focus on the 2018 Hokkaido Eastern Iburi Earthquake in Japan, which triggered a region-wide blackout on PV installations. The Iburi event—the first large-scale blackout in Japan—was caused by cascading failures in the power grid following the earthquake. This event has three main features that make it suitable for our analysis. First, it provides exogenous variation in blackout exposure, as both Hokkaido and the neighboring Tohoku region experienced seismic shaking from the unexpected earthquake but only Hokkaido suffered a complete power outage. Second, the blackout was sufficiently extensive to plausibly influence post-outage behavior, forcing three million residents in Hokkaido to live without electricity for up to 64 hours. Third, unlike power outages caused by hurricanes and typhoons, those triggered by earthquakes are not necessarily accompanied by bad weather, allowing PV systems to operate and thus demonstrate their resilience. These unique features make the Iburi blackout a compelling case to examine how direct exposure to a major outage influences perceptions of energy resilience.

We employ a doubly-robust difference-in-differences (DID) estimator to identify the impact of the blackout on municipality-level PV installations. Using Tohoku as a comparison allows us to isolate the effect of the blackout from that of the earthquake (e.g., PV installations related to housing or infrastructure reconstruction). The doubly-robust DID approach combines regression adjustment and inverse probability weighting, improving both efficiency and robustness to model misspecification when pre-treatment covariates differ across regions.

Our analysis reveals a clear contrast between the residential and commercial sectors: while residential PV installations did not increase after the blackout, commercial installations rose significantly. Specifically, for commercial PV systems, an additional 3.900 kW of PV capacity—equivalent to a 53.5% increase relative to the control group average—was installed per 1,000

people per half-year in Hokkaido following the blackout. These findings imply that differences in the perceived severity of damage and system performance between sectors influenced residents' responses to the event. The additional analysis of complementary energy systems shows that households increase PV installations supported by supplementary technologies such as batteries and electric vehicles, which help mitigate the intermittency of solar power. Heightened concern over intermittency may therefore explain why residential PV installations did not increase after the blackout.

To identify the underlying mechanisms, we examine three possible channels through which the disaster may have influenced PV system decisions by altering the perceived benefits of such installations: (1) the subjective probability of a blackout occurring, (2) the perceived severity of blackout damage, and (3) the expected performance of PV systems during an outage. Analyzing these channels in the context of the Hokkaido blackout allows us to understand how the residential and commercial sectors responded differently to the event.

Among the three channels, the damage and performance channels yield consistent results across both residential and commercial PV systems. Municipalities that were likely to experience greater economic losses from the blackout saw more PV installations afterward. Conversely, municipalities that faced unfavorable weather during the blackout subsequently exhibited fewer PV installations, suggesting that poor system performance under cloudy conditions discouraged adoption.

To the best of our knowledge, this is one of the few studies to examine how a large-scale blackout influences subsequent PV installations. It provides evidence on how individuals and firms evaluate the resilience of PV systems to outages and offers economic insights. Our findings suggest that commercial PV installations can function as a form of self-insurance against electricity supply disruptions, reflecting adaptive behavior in response to a large-scale disaster. In other words, the results highlight voluntary private efforts to enhance energy security, as opposed to resilience measures driven by public regulation.

This study makes several contributions. First, it enriches the literature on the determinants of renewable power technology adoption. While numerous studies have examined the effects of financial incentives such as subsidies and tax credits on PV adoption (Hughes and Podolefsky, 2015; Crago and Chernyakhovskiy, 2017; Johnston, 2019; Feger et al., 2022; De Groote and Verboven, 2019; Aldy et al., 2023), relatively few have investigated non-monetary drivers. Moreover, psychological factors and peer effects have been identified as important influences

on PV adoption (Bollinger and Gillingham, 2012; Graziano and Gillingham, 2015). Our study complements this strand of the literature by highlighting resilience to power outages—an underexplored determinant—and by leveraging a disaster-induced outage as an exogenous shock. This approach allows us to assess whether exposure to a large-scale blackout leads individuals and firms to recognize the self-generation value of PV systems, emphasizing resilience as a secondary incentive alongside financial benefits.¹

Second, this study contributes to the literature linking disaster experiences with adaptive behavior. Research shows that exposure to natural disasters affects housing prices and insurance take-up, as individuals update their beliefs about future risks (MacDonald et al., 1987; Bin and Landry, 2013; Gallagher, 2014; Gibson and Mullins, 2020; Wolf and Takeuchi, 2022). By contrast, we focus on how blackout experiences influence subsequent PV installation decisions as a form of adaptation to mitigate electricity loss. Our analysis differs from the analyses of studies on mandatory resilience investments such as the hurricane-resistant infrastructure examined by Brannlund et al. (2023) by focusing on voluntary private investment at the municipality level.

Third, we advance the literature examining the mechanisms behind behavioral change. For example, Xie et al. (2023) show that air pollution disclosure affects individuals' mental health both directly and through behavioral adjustments, such as reducing their participation in outdoor activities. Similarly, Liao (2020) identifies the psychological mechanisms (projection bias and salience) driving the cancellation of PV installations after extreme weather events. Our contribution lies in uncovering the mechanisms linking blackout experiences to PV adoption. Specifically, we find that an increased perceived probability of outages promotes residential PV installations as well as that the recognition of blackout damage and solar intermittency influence both residential and commercial installations.

Our research is also closely related to that of Brown and Muehlenbachs (2024), who estimate households' willingness to pay for electricity reliability by examining solar battery adoption in areas affected by wildfire prevention outages. However, our study differs in three key respects. First, while their maximum outage exposure was 768,000 people, our setting involves a jurisdiction-wide blackout that left approximately three million residents without electricity, providing a substantially stronger treatment shock. Second, we analyze both the residential and the commercial sectors, with the latter accounting for a significant proportion of solar capacity.

¹See, for example, Borenstein (2017) and Kiso et al. (2022) on electricity bill reductions; Liao (2020) on the weather-induced cancellation of PV installations; and Delmas et al. (2017) and Lyu (2023) on the complementarities between PV systems and electric vehicles.

The commercial sector also faces greater potential economic losses from blackouts due to profit reductions and disruptions to production and supply chains. Third, we explicitly explore the mechanisms connecting outages and solar adoption, developing a behavioral framework that explains how individuals and firms update the expected benefits of PV systems in response to disaster-induced disruptions.

The remainder of this paper is organized as follows. Section 2 introduces the background of this study. Section 3 describes the data and methodology. Section 4 presents the empirical results. Section 5 examines the mechanisms through a channel analysis. Section 6 concludes.

2 Background

2.1 The Iburi Earthquake

The Hokkaido Eastern Iburi Earthquake struck northeastern Japan on September 6, 2018, with a magnitude of 6.7, causing injuries and damage to infrastructure.² The epicenter was located in the central-eastern part of Hokkaido and the tremors were felt not only in Hokkaido but also in Tohoku.³ In addition to direct damage, the earthquake triggered a large-scale blackout that caused significant secondary impacts. The blackout occurred due to the emergency shutdown of a major thermal power station, which was triggered by shaking and the resulting imbalance in power supply frequency. Consequently, the entire jurisdiction of the Hokkaido Electric Power Company experienced a power outage, affecting approximately three million households for up to 64 hours.⁴ While 64 hours may not seem extremely long, the severity of a blackout is determined not only by its duration but also by its disruption to daily life. Electricity is essential for virtually every aspect of modern life and even a single day without power can cause substantial inconvenience. The Iburi case—as the first jurisdiction-wide blackout in the history of Japan’s power system—drew considerable attention to the stability of the country’s electricity supply. While the Great East Japan Earthquake in 2011 also threatened a jurisdiction-wide blackout in TEPCO’s service area, a full-scale blackout was prevented by planned rotating power outages and power saving campaigns.

²Source: Hokkaido Prefecture. <https://www.pref.hokkaido.lg.jp/sm/ktk/300906jisin/top.html>.

³Source: Japan Meteorological Agency. https://www.jma.go.jp/jma/kishou/books/saigaiji/saigaiji_201901.pdf.

⁴Source: Ministry of Internal Affairs and Communications. https://www.soumu.go.jp/main_content/000585075.pdf.

2.2 Blackouts and PV Installations

Although the entire Hokkaido region lost its electricity supply during the blackout, privately owned PV systems allowed some households and firms to continue accessing electricity. Reports highlight that one major advantage of PV installations, observed globally, is their resilience during power outages.⁵ During a power outage, PV systems automatically shut down; however, they can operate as an emergency power sources if switched to stand-alone mode.

According to Kotani and Nakano (2023), 74.8% of PV homeowners used their systems during the Iburi blackout. Among those who did not, 38% reported that they did not know how to activate stand-alone mode. This indicates that many PV owners were unaware of their systems' potential as an emergency power source. We are therefore interested in whether potential PV adopters—some of whom may not fully understand the resilience benefits of PV systems—became more aware of their importance after experiencing the blackout. The same study also notes that bad weather limited power generation for some users, underscoring the intermittency challenge of PV systems during emergencies.

Zanocco et al. (2021) examine the related case of public safety power shutoffs in California caused by wildfire risks. Their survey shows that individuals with greater outage experience express stronger intentions to adopt solar power, suggesting that extreme events can drive technology adoption. Moreover, about one-third of existing solar or storage system owners considered additional investments, reflecting the recognition that PV systems combined with storage can provide more reliable backup power.

Although power outages impose costs on both the residential and the commercial sectors, the damage is generally larger for the latter for several reasons. First, households mainly experience inconvenience such as non-functioning appliances, the loss of communication, and disrupted transportation, whereas commercial users face operational shutdowns and profit losses. Based on a survey, Ariu and Goto (2007) estimate the average losses per hour of outage at JPY 1,706 (about USD 12 as of January 2006) for households and JPY 220,000 (about USD 1,570) for commercial users with low-voltage contracts (below 50 kW). Second, electricity usage patterns differ across sectors: commercial demand peaks during the day—coinciding with PV generation—allowing direct on-site consumption and increasing the system's economic ap-

⁵Source: Japan Photovoltaic Energy Association (<https://www.jpea.gr.jp/house/merit/>), Ministry of the Environment (https://www.env.go.jp/earth/report/sankou1%20saiene_2019.pdf) and the website of KANTAR in Australia (<https://www.theenergycharter.com.au/wp-content/uploads/2021/10/QHES-2020-Report.pdf>).

peal. Third, although households can use PV systems in stand-alone mode during emergencies, power is typically supplied through a single outlet connected to the power conditioner, limiting appliance use. This constraint may have become evident during the blackout, discouraging further residential adoption. By contrast, commercial users often install PV systems as part of business continuity planning for disaster preparedness, with circuits preconditioned to automatically draw power from PV systems during outages.⁶ Even when direct operational benefits are limited, resilience-oriented investment with business continuity planning frameworks may signal effective risk management to stakeholders. These institutional and operational differences suggest that blackout exposure likely stimulated PV adoption more strongly among commercial than among residential users.

3 Methodology and Data

3.1 Methodology

We apply a doubly-robust DID approach to examine the impact of the blackout on PV installations. The study period spans March 2016 to March 2022, divided into pre- and post-blackout subperiods. The treatment group consists of all municipalities in Hokkaido, which experienced both the earthquake and the ensuing blackout, whereas the control group consists of all municipalities in the Tohoku region (Figure 1).⁷ As shown in Figure 2, residents in the control group experienced seismic shaking of similar intensity to Hokkaido—except in areas near the epicenter—but did not experience the blackout. This comparison enables us to isolate the effect of the blackout on PV installations, abstracting from the direct impacts of the earthquake. For example, seismic activity could damage existing PV systems, thereby influencing subsequent installation behavior. Although information on damage to smaller PV systems (below 50kW) is unavailable, incidents involving larger systems must be reported to the authorities in Japan. Among the 757 PV systems exceeding 50 kW in Hokkaido, only three accidents were reported during the earthquake.⁸

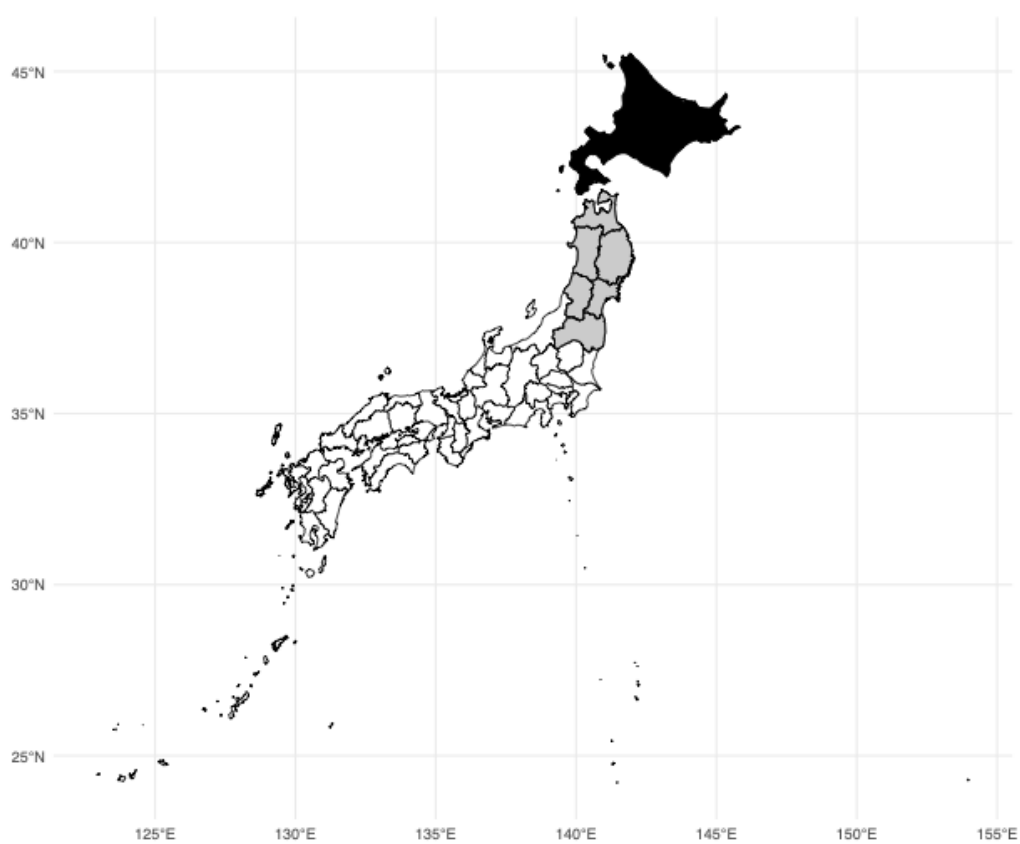
We decompose the original doubly-robust DID estimator and conduct a subsample analysis.

⁶Source: https://socialsolution.omron.com/jp/ja/products_service/energy/doc/cat/kand-060a.pdf?utm_source=chatgpt.com.

⁷We exclude 11 municipalities in Fukushima Prefecture designated as evacuation zones as of March 2016 following the 2011 nuclear accident.

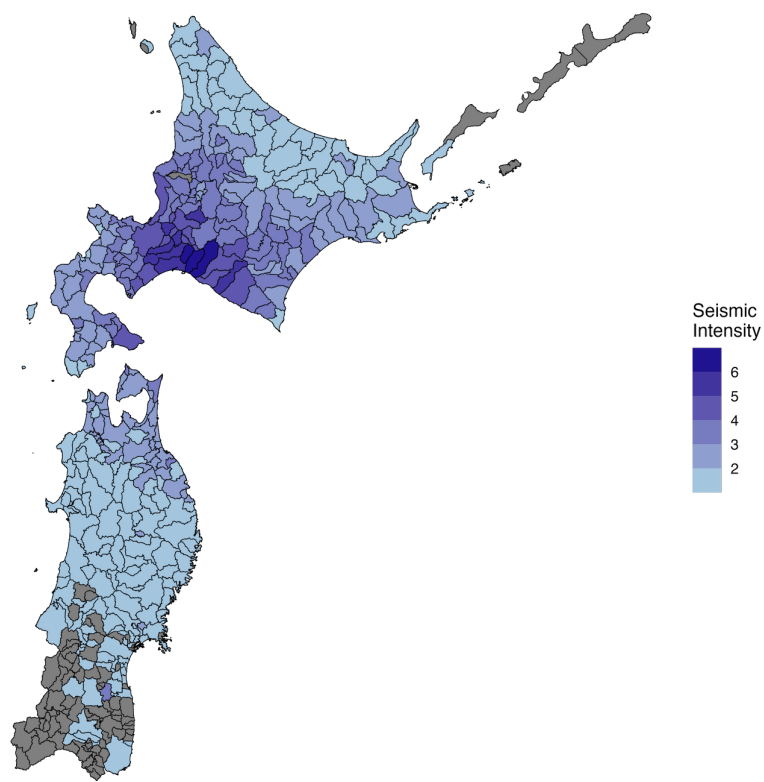
⁸Source: https://www.meti.go.jp/shingikai/sankoshin/hoan_shohi/denryoku_anzen/newenergy_hatsuden_wg/pdf/014_01_00.pdf?utm_source=chatgpt.com.

Figure 1: Map of Japan



Note: The treatment group, Hokkaido, is in black, while the control group, the Tohoku region, is in gray.

Figure 2: Seismic intensity



Source: https://www.adeq.or.jp/kanren/Eq_data/180906.html

The original estimator relies on the conditional parallel trend assumption for identification, meaning that, in the absence of the treatment, outcomes would evolve in parallel between the treatment and control groups, conditional on several pre-treatment covariates. As noted by Meyer (1995) and Abadie (2005), simply including pre-treatment covariates in a two-way fixed effects model may introduce bias when estimating the treatment effect. To address this, we adopt the doubly-robust DID estimator introduced by Sant’Anna and Zhao (2020) and Callaway and Sant’Anna (2021). This approach combines outcome regression and inverse probability weighting, ensuring a consistent estimate even if either the outcome regression model or the propensity score is misspecified.

Our outcome of interest is the total capacity of newly installed PV systems in a municipality, measured on a half-year basis. The average treatment effect on the treated (ATT) at half-year t is specified as follows:

$$ATT(g, t) = \mathbb{E} \left[\left(\frac{D_g}{\mathbb{E}[D_g]} - \frac{\frac{P_g(X)C}{1-P_g(X)}}{\mathbb{E}[\frac{P_g(X)C}{1-P_g(X)}]} \right) (Y_t - Y_{g-1} - m_{g,t}(X)) \right], \quad (1)$$

where D_g is a dummy variable indicating treatment at time g . The propensity score, $P_g(X)$, and the change in the conditional outcome of the never-treated group, $m_{g,t}(X) = \mathbb{E}[Y_t - Y_{g-1} | X, C = 1]$ ($C = 1$ denotes the never-treated group), are estimated using logit and linear regression models, respectively. The outcome linear regression model, $\mathbb{E}[Y_t - Y_{g-1} | X] = \alpha_0 + \alpha_1 X$, includes the pre-treatment covariates as independent variables.

Since our treatment (i.e., the blackout) occurs only once at time g , there is no variation in the ATTs across treatment cohorts. However, the estimator can still capture the temporal heterogeneity in ATTs, allowing us to track the evolution of the treatment effect over time. This feature enables the estimation of multiple one-period ATTs and the construction of an event study plot.

We can estimate the one-period ATT at time t using a sample analog:

$$\widehat{ATT}(g, t) = \frac{1}{N} \sum_{i=1}^N \left[\left(\frac{D_{i,g}}{\frac{1}{N} \sum_{j=1}^N D_{j,g}} - \frac{\frac{\hat{P}_{i,g}(X)C_i}{1-\hat{P}_{i,g}(X)}}{\frac{1}{N} \sum_{j=1}^N \frac{\hat{P}_{j,g}(X)C_j}{1-\hat{P}_{j,g}(X)}} \right) (Y_{i,t} - Y_{i,g-1} - \hat{m}_{i,g,t}(X)) \right]. \quad (2)$$

We first estimate the propensity score function, $P_{i,g}(X)$, and the outcome regression model, $m_{g,t}(X)$, with the treatment and control groups, respectively. These functions are then used as predicted values in Eq. (2). The predicted propensity score, $\hat{P}_{i,g}(X)$, serves as a weight to construct the average outcome change for the control group. The ATT over the entire treated period (from g to T) can be estimated as follows:

$$\widehat{ATT}(g) = \frac{1}{T-g} \frac{1}{N} \sum_{t=g}^T \sum_{i=1}^N \left[\left(\frac{D_{i,g}}{\frac{1}{N} \sum_{j=1}^N D_{j,g}} - \frac{\frac{\hat{P}_{i,g}(X)C_i}{1-\hat{P}_{i,g}(X)}}{\frac{1}{N} \sum_{j=1}^N \frac{\hat{P}_{j,g}(X)C_j}{1-\hat{P}_{j,g}(X)}} \right) (Y_{i,t} - Y_{i,g-1} - \hat{m}_{i,g,t}(X)) \right]. \quad (3)$$

Eq. (3) allows us to estimate the overall post-treatment ATT.

However, we need to address an issue that arises when conducting subsample analysis using the doubly-robust DID estimator. As mentioned above, we predict the propensity score for each municipality in the control group and calculate the average outcome change for the group, weighted by the propensity score, as shown in Eq. (3). When using a subsample, the resulting propensity score function differs from that in the baseline estimation because the subsample excludes certain treated municipalities. Consequently, each control unit has a different predicted propensity score, leading to different weights when constructing the average outcome change for the control group. This makes results from different subsamples not directly comparable, as the comparisons (i.e., the control group's weighted outcome changes) vary.

To resolve this issue, for each municipality i , we compute the weighted average outcome change over the entire treated period (from g to T), $\delta_i(g)$, as follows:

$$\delta_i(g) = \frac{1}{T-g} \sum_{t=g}^T \left[\left(\frac{D_{i,g}}{\frac{1}{N} \sum_{j=1}^N D_{j,g}} - \frac{\frac{\hat{P}_{i,g}(X)C_i}{1-\hat{P}_{i,g}(X)}}{\frac{1}{N} \sum_{j=1}^N \frac{\hat{P}_{j,g}(X)C_j}{1-\hat{P}_{j,g}(X)}} \right) (Y_{i,t} - Y_{i,g-1} - \hat{m}_{i,g,t}(X)) \right]. \quad (4)$$

$\delta_i(g)$ is a component of Eq. (3). Here, the propensity score is the same as in the baseline estimation because we use all the treated units to estimate it. We then obtain the ATT for each subsample by averaging $\delta_i(g)$ across the selected municipalities. Specifically, for a subsample of N_{sub} treated municipalities, the subsample ATT is given by

$$\widehat{ATT}_{sub}(g) = \frac{1}{N_{sub} + N_c} \frac{1}{T-g} \sum_{i=1}^{N_{sub}+N_c} \sum_{t=g}^T \left[\left(\frac{D_{i,g}}{\frac{1}{N} \sum_{j=1}^N D_{j,g}} - \frac{\frac{\hat{P}_{i,g}(X)C_i}{1-\hat{P}_{i,g}(X)}}{\frac{1}{N} \sum_{j=1}^N \frac{\hat{P}_{j,g}(X)C_j}{1-\hat{P}_{j,g}(X)}} \right) (Y_{i,t} - Y_{i,g-1} - \hat{m}_{i,g,t}(X)) \right], \quad (5)$$

where N_c is the number of municipalities in the control group. This modification allows us to calculate the subsample ATT without changing the predicted propensity scores from the baseline estimation. Therefore, the comparison of the subsample and baseline ATTs is valid because the control group's weighted outcome changes are constructed consistently.

To estimate the propensity scores and outcome regressions in the control group, we include the following pre-treatment covariates (X). First, we add long-term climate conditions that may affect PV productivity such as the average temperature, annual precipitation, and annual sunshine duration. These variables are averaged over 2005–2015. Second, we include non-weather covariates that may influence PV installation decisions such as population density, average income, age, and the proportion of single-person households. Finally, we use the pre-treatment outcome—the newly installed PV capacity in the last half-year of 2015—as an additional covariate.

3.2 Data

We construct a municipality-level panel dataset combining information on PV installations, weather conditions, and demographic characteristics for March 2016 to March 2022. The data on PV installations are drawn from the feed-in-tariff program administered by Japan's Agency

of Natural Resources and Energy, which records all registered PV systems nationwide. Because the dataset comprises the entire population of feed-in-tariff program-registered PV systems, it covers all installations during our study period.

Although the data are reported quarterly, we aggregate them to the half-year level to smooth seasonal fluctuations. In particular, installations typically surge in the second quarter following announcements of annual subsidy programs—an effect that could otherwise confound our estimation. Our main outcome variable is the newly installed PV capacity per 1,000 residents per half-year, defined as the change in total installed capacity between consecutive periods. The post-treatment period begins in October 2018, immediately following the September blackout.

We analyze residential and commercial PV systems separately. Residential systems are defined as those below 10 kW, while commercial systems range from 10 to 50 kW and are typically installed on the rooftops of farm buildings, offices, and small factories. To focus on privately operated systems that primarily serve on-site electricity demand, we exclude installations exceeding 50 kW, which are generally owned by utilities or large companies. Observations categorized as “municipality unknown” are also excluded from the analysis.

The weather data are obtained from 1,316 monitoring stations operated by the Japan Meteorological Agency. Each municipality is matched to the nearest station using geographic coordinates from the Ministry of Land, Infrastructure, Transport and Tourism, from which we calculate the average temperature, annual precipitation, and sunshine duration for 2005–2015.

The demographic and socioeconomic covariates are derived from the 2015 Population Census and the Statistical Observations of Municipalities. We include population, population density, taxable income, average age, and the proportion of single-person households as pre-treatment covariates. Population is also used to normalize installation capacity on a per capita basis.

Table 1 reports the summary statistics. While residential PV capacity is higher in the control group, commercial PV capacity is greater in the treatment group. Several pre-treatment characteristics also differ significantly between the regions, reinforcing the need to control for these covariates in our doubly-robust DID estimation.

Finally, we assess potential concerns about the validity of the control group. Hokkaido receives less sunlight than Tohoku but Figure 3 shows that the installation trends in both regions are similar, suggesting the comparison is appropriate. We also address potential peer effects: although the awareness of people in neighboring regions about the blackout may have influenced

their behavior, Figure 5 shows a clear surge in Google searches for “PV systems” in Hokkaido only, not in Tohoku (except in Fukushima). Figure 4 further shows no geographic gradient in installation changes across Tohoku. As a robustness check, we exclude Fukushima Prefecture from the sample, confirming that these peer effects do not materially affect our results.

Table 1: Summary statistics

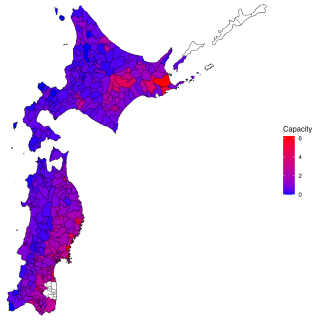
	Treatment			Control			Difference
	Obs.	Mean	Std.Dev.	Obs.	Mean	Std.Dev.	
Newly installed residential PV capacity (kW)	2148	1.665	2.975	2592	2.891	2.731	-1.226***
Newly installed commercial PV capacity (kW)	2148	8.715	21.452	2592	7.284	16.508	1.431*
Newly installed residential PV number (N)	2148	0.238	0.356	2592	0.537	0.529	-0.299***
Newly installed commercial PV number (N)	2148	0.193	0.463	2592	0.184	0.365	0.010
Average capacity of newly installed residential PV (kW)	2148	4.187	3.510	2592	4.835	2.161	-0.648***
Average capacity of newly installed commercial PV (kW)	2148	18.997	22.365	2592	24.252	20.148	-5.255***
Average temperature (degree Celcius)	2148	6.958	1.179	2592	10.770	1.188	-3.812***
Annual total precipitation (mm)	2148	1163.582	253.174	2592	1475.882	403.815	-312.300***
Annual total suntime (h)	2148	1575.844	180.379	2592	1553.460	237.428	22.384***
Population density (sq. km)	2148	197.653	437.118	2592	395.866	465.097	-198.213***
Average age of the citizen	2148	51.383	3.032	2592	50.959	3.541	0.423***
Taxable income per 1000 people (million JPY)	2148	1111.706	287.952	2592	971.767	170.340	139.939***
The share of single household	2148	0.343	0.059	2592	0.242	0.069	0.102***

Note: Residential and commercial PV capacity and the number of installations are expressed per 1,000 people. The total number of observations is 4,740, covering municipalities over 12 half-year periods. Of these, 179 municipalities belong to the treatment group and 216 to the control group.

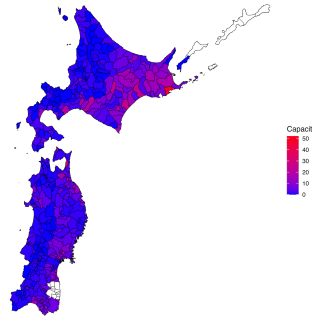
$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 3: Average newly installed PV capacity (kW)

(a) Residential PV systems



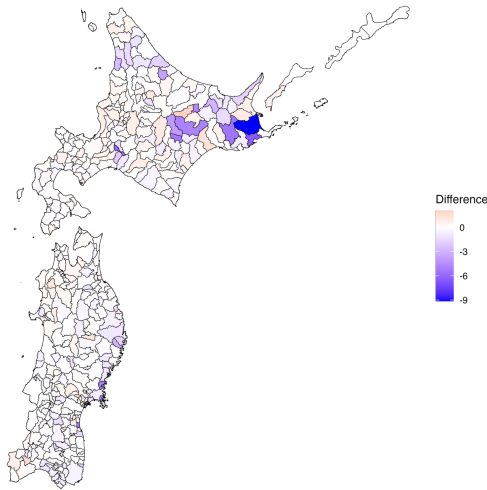
(b) Commercial PV systems



Note: The figures show the average capacity of newly installed PV systems over our sample period. We exclude 11 municipalities in Fukushima Prefecture designated as evacuation zones as of March 2016 following the 2011 nuclear accident.

Figure 4: Average change in newly installed PV capacity before and after the blackout (kW)

(a) Residential PV systems



(b) Commercial PV systems

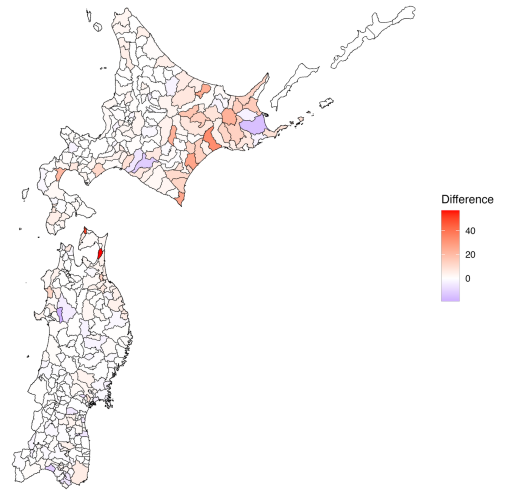
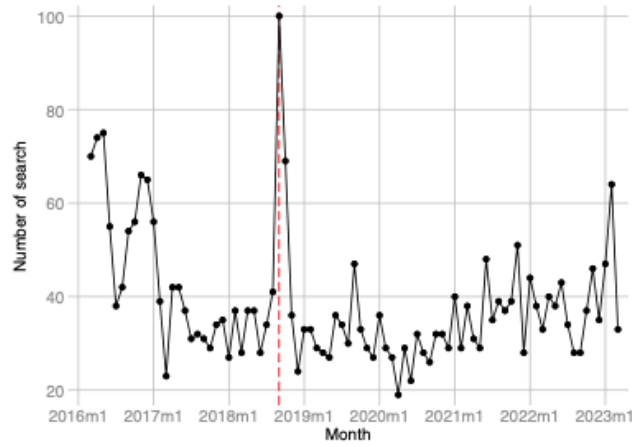
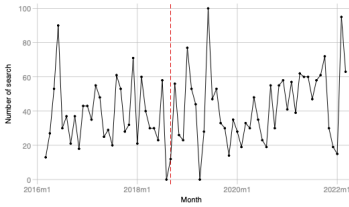


Figure 5: Google searches using “PV systems”

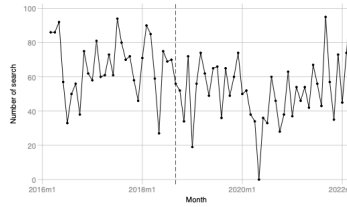
(a) Hokkaido



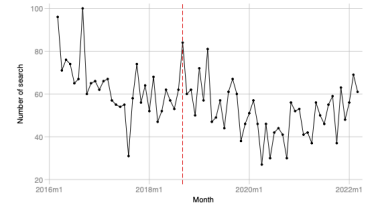
(b) Aomori



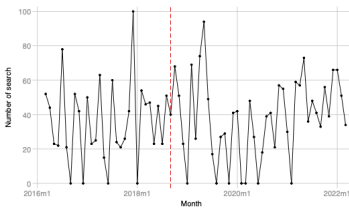
(c) Iwate



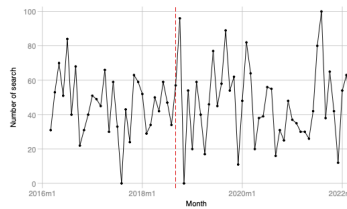
(d) Miyagi



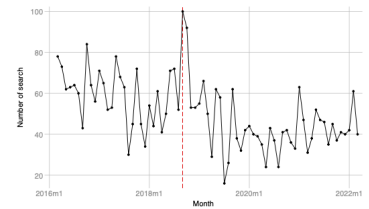
(e) Akita



(f) Yamagata



(g) Fukushima



Note: The number of searches is normalized by the maximum number of searches.

4 Results

4.1 Main Results

Table A1 reports the estimation results for the propensity score model. For both the residential and the commercial sectors, annual total sunshine duration is not statistically significant. In addition, population density and the pre-treatment outcome are not significant for the residential and commercial sectors, respectively. As discussed in Section 4.3, our results are generally robust to alternative specifications of the covariates used in the model.

Table 2 presents the main results. Columns (1) and (2) report the estimated impact of the blackout on residential and commercial PV capacity, respectively. Although the ATT for residential PV installations is negative, it is not statistically significant, indicating that the blackout had no discernible effect on residential PV adoption. By contrast, the ATT estimates for commercial PV installations are positive and statistically significant, suggesting a substantial increase in capacity following the blackout. As shown in Column (2), commercial PV capacity rose by 3.900 kW per 1,000 people per half-year—equivalent to 53.5% of the average capacity installed in the control group. Overall, the post-blackout patterns differ sharply across sectors: residential adoption remained unchanged, whereas commercial installations expanded, consistent with our expectations outlined in Section 2.2.

Figure 6 presents the event study estimates for residential and commercial PV systems. None of the pre-treatment ATT estimates are statistically significant for either sector, consistent with the p-values of the pre-trend tests in Table 2. This supports the validity of the parallel trend assumption. For the residential sector, the post-treatment ATT estimates remain not significant and close to zero, except for the first post-treatment period. By contrast, for commercial PV systems, most post-treatment ATTs are positive, although only a few reach statistical significance. The fading pattern over time may reflect a diminishing awareness of the disaster-related risks. Evidence from studies on flood events shows that housing prices and insurance uptake often revert to pre-disaster levels within five to ten years (Atreya et al., 2013; Bin and Landry, 2013; Beltrán et al., 2019). Similarly, the effect of power outages on PV adoption may also decline as memories of the blackout fade, unless reinforced by subsequent experiences or policy interventions.

To examine whether the observed effects are driven by changes in the number of installations

or in system size, we re-estimate the model using two alternative dependent variables.⁹ Table 3 reports the results using the number of new installations and average capacity per new installation. For the commercial sector, the results are similar to the main findings when the number of new installations is used as the dependent variable. Moreover, the coefficient is comparable to the control mean, indicating that the increase in commercial PV capacity is primarily due to a higher number of installations. By contrast, the coefficient of commercial PV capacity becomes not significant when average capacity per new installation is used. These findings suggest that the main results are driven by changes in the total number of installations rather than in average capacity per new installation.

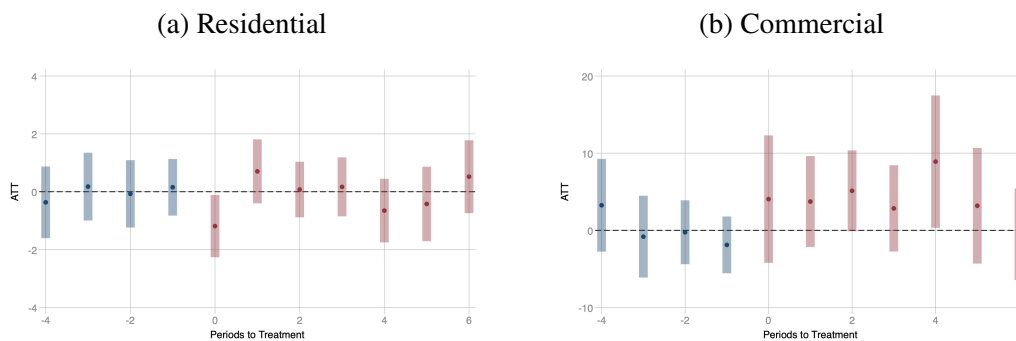
Table 2: Effect of the blackout on the total capacity of newly installed PV systems

	(1) Residential	(2) Commercial
ATT	-0.113 (0.316)	3.900** (1.699)
Control mean	2.891	7.284
Observations	395	395
P-value of pre-trend test	0.916	0.271

Note: We obtain the ATTs by averaging $\delta_i(g)$ in Eq. (4) across all the municipalities. Bootstrap standard errors are reported in parentheses. The pre-trend test is conducted under the null hypothesis that all the pre-treatment ATT estimates are equal to zero.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 6: Event study plots



Note: The reference period for calculating the ATTs at time t is set to $t - 1$ for the pre-treatment periods (including $t = 0$) and to $t = 0$ (time of treatment) for the post-treatment periods.

⁹While it is tempting to interpret the analysis as capturing both the intensive and the extensive margins, such an interpretation should be made with caution. Because the data are aggregated at the municipality level, we cannot exactly identify whether the observed changes stem from capacity expansion at existing PV sites or from new installations.

Table 3: Effect of the blackout on the total number and the average capacity of newly installed PV systems

	Number of systems		Average PV capacity	
	(1)	(2)	(3)	(4)
	Residential	Commercial	Residential	Commercial
ATT	0.00629 (0.0482)	0.0957** (0.0376)	-0.458 (0.384)	0.0985 (3.137)
Control mean	0.537	0.184	4.835	24.25
Observations	395	395	395	395
P-value of pre-trend test	0.858	0.149	0.184	0.253

Note: We obtain the ATTs by averaging $\delta_i(g)$ in Eq. (4) across all the municipalities. Bootstrap standard errors are reported in parentheses. The pre-trend test is conducted under the null hypothesis that all the pre-treatment

ATT estimates are equal to zero.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2 Impact on PV Installations with Supplementary Power Systems

The main results show that the blackout had no statistically significant effect on residential PV installations, whereas commercial PV installations increased significantly. As discussed in Section 2.2, this difference likely reflects the intermittency of PV systems, whose generation is concentrated during daylight hours and drops to zero at night. Because residential electricity demand is typically higher during nighttime, PV systems are less attractive for households than for the commercial sector.

To examine this mechanism more closely, we conduct an additional analysis focusing on residential PV systems. Specifically, we test the hypothesis that households become more aware of the intermittency of PV systems following the blackout. The database used in this study also identifies residential PV installations combined with supplementary power storage systems such as residential fuel cells, batteries, and electric vehicles. Residential fuel cells, which typically generate electricity from liquefied natural gas and store the produced power, are unaffected by intermittency and can therefore serve as reliable backup sources during power outages. If households recognized the limitations of PV systems during the blackout, they may have been more inclined to install PV systems together with fuel cells. Batteries and electric vehicles, which store electricity generated by PV systems, could also mitigate intermittency. Consequently, the proportion of PV installations with these storage systems should have increased if households sought to address the intermittency problem.

To test this hypothesis, we replace the dependent variable with the proportion of PV installations equipped with supplementary systems relative to total PV installations.¹⁰ As shown in Table 4, the proportion of PV installations with storage systems increased by 0.710 percentage points after the blackout. The estimated ATT is statistically significant and its magnitude is comparable to the mean of the control group. These results suggest that households exposed to the blackout subsequently increased PV installations with supplementary energy systems to mitigate the intermittency of standard PV systems. In short, households appear to have recognized the intermittency of PV systems during the blackout, leading to a relative increase in PV-plus-storage installations.

These findings are consistent with those of Brown and Muehlenbachs (2024), who also report a statistically significant increase in residential storage capacity following outage events.

¹⁰Information on standalone storage systems is unavailable. Co-installation data are reported because the feed-in-tariff rates differ for PV installations with storage systems.

Their results further indicate that solar-only adoption is only weakly related to outages, whereas the adoption of solar-plus-storage systems rises markedly after such events. Although the two studies differ in the size and frequency of outage shocks, both suggest that the residential adoption of solar installations with storage systems responds more strongly to outage experiences than solar-only installations.

Table 4: Effect of the blackout on PV installations with supplementary systems

	(1)
	Share of PV installations with supplementary system
ATT	0.00710*** (0.00212)
Control mean	0.0193
Controls	Yes
Observations	391

Note: We obtain the ATTs by averaging $\delta_i(g)$ in Eq. (4) across all the municipalities. Bootstrap standard errors are reported in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.3 Robustness Check

We investigate the robustness of our analysis to ensure that results are not driven by factors other than the blackout.¹¹ The estimation results may be biased upward if they are affected by PV installations associated with the reconstruction of housings and buildings. To address this, we exclude municipalities with seismic intensity of level three or higher, which simultaneously removes 20 municipalities that experienced housing damage (houses destroyed or half destroyed) due to the earthquake.¹² Columns (3) and (4) in Table 5 show that the estimated ATTs remain consistent in both direction and magnitude with baseline results, allowing us to reject the hypothesis that the direct effect of the earthquake drives the observed impacts. Next, we address the concern that Fukushima Prefecture in the Tohoku region may have been influenced by a peer effect from the blackout, as it exhibited a noticeable spike in Google search activity during the blackout month, albeit smaller spike than that in Hokkaido. By including Fukushima in the control group could therefore bias the estimated treatment effect toward zero. Columns (5) and (6) present results excluding Fukushima from the control group. As expected, the

¹¹ Figures A1 and A2 show the event study plots of these analyses.

¹² *Source:* Hokkaido Prefecture. <https://www.pref.hokkaido.lg.jp/sm/ktk/300906jisin/top.html>.

point estimates become slightly larger but remain generally consistent with the baseline results, confirming the robustness of our findings.

We also examine whether local government subsidy programs influenced the results. To do so, we exclude municipalities that introduced or abolished PV subsidy programs during the study period and re-estimate the ATT. Columns (7) and (8) present results that are comparable to the main analysis, indicating that changes in subsidy policies had minimal impact.¹³

We further check the robustness of our main results using various sets of control variables. As shown in Tables A2 and A3 in the Appendix, the estimated ATTs for both residential and commercial PV systems are largely consistent with those in Table 2, except for the models that omit the average temperature from the set of covariates. Without the average temperature, we observe a significant and positive effect of blackout exposure on residential PV installation, while the ATT of commercial PV systems turns statistically insignificant. However, those are changed when the variable is included, suggesting that regional average temperature is a confounding factor that must be accounted for to identify the net impact of blackout.

Table 5: Robustness check

	Full sample		Seismic intensity below 3		Excluding Fukushima		No subsidy changes	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Residential	Commercial	Residential	Commercial	Residential	Commercial	Residential	Commercial
ATT	-0.113 (0.303)	3.900** (1.676)	-0.214 (0.410)	3.736* (2.104)	-0.0392 (0.295)	4.066** (1.890)	-0.240 (0.337)	3.251* (1.676)
Control mean	2.891	7.284	2.891	7.284	2.891	7.284	2.891	7.284
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	395	395	271	271	347	347	333	386

Note: We obtain the ATTs by averaging $\delta_i(g)$ in Eq. (4) across the municipalities in each subsample. The control group remains unchanged, consisting of 216 municipalities. Bootstrap standard errors are reported in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.4 Heterogeneity in the Blackout Effects

We further explore the heterogeneity in the blackout effects.¹⁴ First, we consider the timing of recovery from the blackout. According to the report by the Hokkaido Electric Power Company, approximately half of the municipalities had recovered from the blackout by 3 a.m.

¹³We further test whether the blackout affected retail electricity prices, which could in turn influence PV adoption. A simple DID regression of monthly retail prices on the treatment indicator shows no statistically significant change attributable to the blackout. We also examine potential differences in housing age across treatment and control groups, as construction year may be related to investment cost. The distributions of housing age are similar across the two groups, suggesting no systematic bias.

¹⁴Figures A3 and A4 display the event study plots for these analyses.

on September 7 (24 hours after the event).¹⁵ Analysis of these early-recovery municipalities (Columns (3) and (4)) shows a lower likelihood of PV installations compared with late-recovery municipalities, suggesting that the longer people live without power, the more they recognize the value of emergency power sources.

Second, given that solar power generation depends on the climate, the blackout's impact is likely greater in municipalities with conditions favorable for solar power generation. We divide Hokkaido's municipalities by location to capture this heterogeneity. The northern area, with heavier snowfall, is less suitable for generating solar power. Column (6) in Table 6 shows that the ATT for commercial PV systems is not significant and smaller in the northern area than in other regions, indicating that municipalities with less favorable climates for producing solar energy experienced no significant post-blackout increase in PV installations. Limiting the sample to municipalities with above-average sunshine duration (Columns (7) and (8)) yields larger installations for both residential and commercial PV systems relative to the baseline, although the differences are not statistically significant (Table A6). Longer sunshine duration likely increases expected solar productivity, supporting greater PV adoption.

Table 6: Heterogeneous impacts of the blackout

	Full sample		Early recovery		Northern area		Long sunshine duration	
	(1) Residential	(2) Commercial	(3) Residential	(4) Commercial	(5) Residential	(6) Commercial	(7) Residential	(8) Commercial
ATT	-0.113 (0.303)	3.900** (1.676)	-0.137 (0.345)	2.936 (1.892)	-0.109 (0.371)	2.244 (1.947)	-0.0750 (0.390)	5.408** (2.220)
Control mean	2.891	7.284	2.891	7.284	2.891	7.284	2.891	7.284
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	395	395	312	312	258	258	298	298

Note: We obtain the ATTs by averaging $\delta_i(g)$ in Eq. (4) across the municipalities in each subsample. Bootstrap standard errors are reported in parentheses. The control group remains unchanged, consisting of 216 municipalities. Tables A4 to A6 compare the ATTs across the two subsamples.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

¹⁵Source: Hokkaido Electric Power Company. https://www.hepco.co.jp/info/2018/1229720_1753.html.

5 Channel Analysis

5.1 Expected Benefit of PV Systems as Self-insurance

To examine the channels through which the blackout affected subsequent PV installations, we first decompose the expected benefit of PV systems as a form of self-insurance against power outages into three components:

$$\mathbb{E}[B] = P(\text{blackout}) * \text{Damage} * (\lambda * \mathbf{1}[\text{goodweather} = 1]), \quad (6)$$

where $P(\text{blackout})$ denotes the probability of a blackout occurring, Damage represents the total damage caused by a blackout, and λ is the proportion of that damage that could be avoided by installing a PV system ($0 < \lambda < 1$). We assume that PV systems are effective only under favorable weather conditions, as they cannot generate electricity during a blackout when weather conditions are unfavorable. Accordingly, the indicator $\mathbf{1}[\text{goodweather} = 1]$ is included in the equation. Economic agents are more likely to install PV systems when the expected benefit, $\mathbb{E}[B]$, is larger. In the following sections, we examine which components in Eq. (6) drive the extent to which the blackout influenced subsequent PV installations. Following studies such as Rouhi Rad et al. (2021) and Sekhri and Hossain (2023), we investigate the mechanisms through a channel analysis that compares the ATTs across the subsamples, as doubly-robust DID estimators are unsuitable for incorporating interaction terms.

5.2 Probability Channel

We first examine the probability channel. The blackout may have influenced subsequent PV installations by updating people's subjective probability of a blackout occurring. Previous studies such as Kieu and Senanayake (2023) show that experiencing events like floods and storms often raises people's perceived likelihood of similar future events, suggesting that blackout experiences could similarly shift perceived risk. To investigate this channel, we use a subsample that excludes municipalities that experienced either of the the outages caused by typhoons in August 2016, two years before the Iburi Earthquake.¹⁶ We assume that municipalities that had already experienced either of these earlier outages had updated their perceived probability of a

¹⁶Source: Hokkaido Electric Power Company. <https://www.hepco.co.jp/info/2023/2023.html>.

blackout occurring, suggesting that the Iburi Earthquake would have a smaller marginal effect on their perception than in municipalities without any such experience. Columns (3) and (4) in Table 7 show the results for municipalities without any experience of outages.¹⁷

As shown in Table A7, although the difference in the ATTs between the two subsamples is not statistically significant, the point estimates differ substantially. The negative effect of the blackout on residential PV systems disappears and turns to positive in municipalities without prior outage experience, although the estimate is not statistically significant. In other words, residents in municipalities without outage experience appear more likely to update their perceived probability of a blackout occurring and install additional PV systems compared with those in municipalities that had already experienced outages.

Regarding commercial PV installations, however, the results in Table 7 indicate that municipalities with a prior outage experience increased their subsequent PV installations to a greater extent, suggesting an upward revision of their subjective probability of a blackout occurring. One possible explanation for this unexpected finding is that the recurrence of blackouts influences those subjective probabilities. Municipalities that had already experienced an outage may have learned from these repeated events and come to expect future blackouts, thereby altering their behavior.

5.3 Damage Channel

We next examine the damage channel. As expressed in Eq. (6), greater damage from a blackout increases the expected benefit of installing PV systems as a precaution against similar future losses. To test this mechanism, we define municipalities with greater damage differently for the residential and commercial sectors.

For the residential sector, we use the municipal average number of household members to construct the subsamples. Larger households are likely to consume more electricity and therefore experience greater inconvenience or loss during outages. Municipalities with above-average household members are thus classified as high-damage areas. For the commercial sector, we proxy potential economic losses using the average annual profit of firms in each municipality, obtained from the 2021 Economic Census for Business Activity.¹⁸

¹⁷Figures A5 and A6 present the event study plots of the channel analyses for residential and commercial PV systems, respectively.

¹⁸Source: 2021 Economic Census for Business Activity. <https://www.stat.go.jp/data/e-census/2021/index.htm>.

Columns (5) and (6) of Table 7 report the estimation results. For the residential sector (Column (5)), municipalities with greater residential damage—proxied by a larger household size—experienced a smaller and not statistically significant decline in subsequent PV installations compared with other areas. This pattern implies that municipalities with greater potential damage are more inclined to install PV systems to reduce the risk of future power outage-related losses.

For the commercial sector (Column (6)), municipalities with higher average firm profits exhibit a larger ATT, indicating that commercial areas with potentially greater economic damage increased their post-blackout PV installations more than other areas. This finding supports the hypothesis that the blackout-induced awareness of potential business losses motivated commercial entities to invest in PV systems to mitigate risk.

5.4 Performance Channel

Lastly, we examine the performance channel. As noted above, a key disadvantage of PV systems is their intermittency under unfavorable weather conditions. To test whether this factor influenced the post-blackout adoption of PV systems, we exploit the variation in weather conditions during the daytime of the blackout days (September 6 and 7). Specifically, we use a subsample of municipalities that recorded zero precipitation on both days—hereafter termed *good weather municipalities*—based on data from the Japan Meteorological Agency. Furthermore, to isolate the effect of intermittency, we exclude municipalities that had already recovered from the blackout by 3 a.m. on September 7, as residents there were unlikely to experience prolonged electricity loss.¹⁹

Columns (7) and (8) in Table 7 present the estimation results. For residential PV systems, the ATT in Column (7) suggests that the decline in installations was less pronounced in good weather municipalities, although the coefficient is not statistically significant. For commercial PV systems, the estimated ATT is larger than that in the baseline results, implying that good weather during the blackout substantially increased subsequent PV installations in those municipalities. Although Table A9 shows that the differences in the ATTs between good and bad weather municipalities are not statistically significant, the point estimates are statistically significant in both sectors. Specifically, municipalities with favorable weather conditions experienced greater PV installations in both the residential and the commercial sectors. These results suggest that

¹⁹Source: Hokkaido Electric Power Company. https://www.hepco.co.jp/info/2018/1229720_1753.html.

the perceived effectiveness—represented by λ in Eq. (6)—was revised upward in these areas in which PV systems could function during the blackout. Therefore, the decrease (increase) in residential (commercial) PV installations was smaller (larger) than that in municipalities that faced poor weather. Conversely, in bad weather municipalities in which PV systems failed to operate during the blackout, households and firms likely revised their expected benefit downward, recognizing the limitations of PV generation under unfavorable weather conditions. This finding is consistent with the increase in the installation of supplementary power systems, as analyzed in the previous section.

Table 7: Channel analyses

	Full sample		No outage experience		Greater damage		Good weather	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Residential	Commercial	Residential	Commercial	Residential	Commercial	Residential	Commercial
ATT	-0.113 (0.288)	3.900** (1.708)	0.0377 (0.336)	3.185* (1.852)	-0.0685 (0.369)	5.076*** (1.927)	-0.0758 (0.369)	5.380*** (2.032)
Control mean	2.891	7.284	2.891	7.284	2.891	7.284	2.891	7.284
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	395	395	300	300	305	305	275	275

Note: We obtain the ATTs by averaging $\delta_i(g)$ in Eq. (4) across the subsample municipalities. Bootstrap standard errors are reported in parentheses. The control group remains the same throughout, consisting of 216 municipalities. Tables A7 to A9 compare the ATTs across the subsamples.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6 Conclusion

This study examines the role of PV systems as a form of self-insurance against blackouts, enabling system owners to generate electricity even during power outages. We investigate whether the 2018 blackout in Japan influenced subsequent PV installation decisions. Using a doubly-robust DID approach, we estimate the impact of the blackout on both residential and commercial PV installations. Our results show no significant effect in the residential sector, whereas commercial installations increased following the blackout. Our additional analysis of PV installations with supplementary power systems shows that households increase installations of supplementary energy systems that mitigate the intermittency of PV systems. This finding suggests that the increase in concern about the intermittency of PV systems may explain why households did not increase residential PV installations after the blackout.

To understand the underlying mechanisms, we analyze three channels: probability, damage, and performance. We find that the damage and performance channels are particularly important. Municipalities that would have had greater damage from the blackout have larger subsequent PV installations. Moreover, municipalities facing intermittent generation were less likely to install PV systems, which helps explain the absence of an increase in residential installations. Overall, the blackout influenced PV adoption by highlighting the limited performance of PV systems during outages.

A limitation of this study is that we cannot distinguish whether the observed increase was driven by first-time PV adopters or existing owners expanding capacity. If first-time installations dominate, the effect may be driven by information dissemination or neighborhood peer effects; if additional installations dominate, the effect reflects actual blackout experiences. Differentiating these motivations would provide a deeper understanding of PV adoption behavior.

Nevertheless, our findings offer two important implications for renewable energy policy. First, the results suggest that the role of PV systems as a form of self-insurance against power outages remains underrecognized. The observed increase in commercial PV installations after the large-scale blackout implies that many people only became aware of this benefit when they personally experienced system disruptions. Second, the results highlight the importance of intermittency in shaping PV installation decisions. Intermittency affects not only the reliability of PV systems during blackouts but also their daily generation potential, as electricity demand during periods of poor weather must be met by other, often carbon-intensive, power sources.

Addressing this challenge is crucial for designing electricity networks that integrate large-scale PV capacity while ensuring both reliability and resilience.

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Appendix

Table A1: Propensity score estimation

	(1) Residential	(2) Commercial
Hokkaido		
Pre-treatment New PV capacity (under 10kW)	-0.267*** (0.0791)	
Pre-treatment New PV capacity (10-50kW)		-0.0440 (0.0361)
Average temperature (degree Celcius)	-2.418*** (0.378)	-2.278*** (0.310)
Annual total precipitation (mm)	-0.00436*** (0.00153)	-0.00337*** (0.00120)
Annual total sunshine (h)	0.00426 (0.00303)	0.00170 (0.00247)
Population density (sq. km)	-0.000213 (0.000625)	
Average age of the citizen	0.399** (0.161)	0.461*** (0.129)
Taxable income per 1000 people (million JPY)	0.00783* (0.00417)	0.0102*** (0.00252)
The share of single household	18.93*** (6.296)	
Observations	395	395

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Robustness checks for residential PV systems

	Residential PV capacity (kW)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Baseline								
ATT	-0.113 (0.301)	2.506*** (0.918)	-0.145 (0.313)	-0.0240 (0.319)	-0.189 (0.301)	-0.191 (0.292)	-0.240 (0.262)	-0.190 (0.274)	-0.0798 (0.330)
Average temperature	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Precipitation	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Suntime	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
Population density	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Average age	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
Income	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes
Share of single household	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes
Pre-treatment outcome	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Observations	395	395	395	395	395	395	395	395	395
P-value of pretrend test	0.916	0.035	0.864	0.845	0.771	0.845	0.830	0.862	0.893

Note: We obtain the ATTs by averaging $\delta_i(g)$ in Eq. (4) across all the municipalities. Bootstrap standard errors are in parentheses. The pre-trend test is based on the null hypothesis that all the pre-treatment ATTs are equal to 0.
 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Robustness checks for commercial PV systems

	Commercial PV capacity (kW)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Baseline						
ATT	3.900** (1.535)	0.344 (3.051)	4.970*** (1.504)	4.247** (1.697)	6.362*** (1.595)	3.232* (1.655)	4.239** (1.692)
Average temperature	Yes	No	Yes	Yes	Yes	Yes	Yes
Precipitation	Yes	Yes	No	Yes	Yes	Yes	Yes
Suntime	Yes	Yes	Yes	No	Yes	Yes	Yes
Population density	Yes	Yes	Yes	Yes	No	Yes	Yes
Income	395	395	395	395	395	395	395
Pre-treatment outcome	0.271	0.546	0.0604	0.249	0.0427	0.459	0.0975

Note: We obtain the ATTs by averaging $\delta_i(g)$ in Eq. (4) across all the municipalities. Bootstrap standard errors are in parentheses. The pre-trend test is based on the null hypothesis that all the pre-treatment ATTs are equal to 0.
 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Heterogeneous impacts of the blackout (early recovery)

	(1) Early recovery	(2) Late recovery	(3) Difference [(1) – (2)]
Panel A: Residential PV systems			
ATT	-0.137 (0.345)	-0.0956 (0.337)	-0.0418
Observations	312	299	.
Panel B: Commercial PV systems			
ATT	2.936 (1.892)	4.824** (2.012)	-1.887
Controls	Yes	Yes	.
Observations	312	299	.

Note: We obtain the ATTs by averaging $\delta_i(g)$ in Eq. (4) across the subsample municipalities. Bootstrap standard errors are in parentheses. The control group is always the same, consisting of 216 municipalities.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Heterogeneous impacts of the blackout (northern area)

	(1) Northern area	(2) Other area	(3) Difference [(1) – (2)]
Panel A: Residential PV systems			
ATT	-0.109 (0.371)	-0.123 (0.342)	0.0145
Observations	258	353	.
Panel B: Commercial PV systems			
ATT	2.244 (1.947)	5.041*** (1.809)	-2.797
Controls	Yes	Yes	.
Observations	258	353	.

Note: We obtain the ATTs by averaging $\delta_i(g)$ in Eq. (4) across the subsample municipalities. Bootstrap standard errors are in parentheses. The control group is always the same, consisting of 216 municipalities.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Heterogeneous impacts of the blackout (sunshine duration)

	(1) Long sunshine duration	(2) Short sunshine duration	(3) Difference [(1) – (2)]
Panel A: Residential PV systems			
ATT	-0.0750 (0.390)	-0.157 (0.328)	0.0818
Observations	298	313	.
Panel B: Commercial PV systems			
ATT	5.408** (2.220)	2.386 (1.777)	3.021
Controls	Yes	Yes	.
Observations	298	313	.

Note: We obtain the ATTs by averaging $\delta_i(g)$ in Eq. (4) across the subsample municipalities. Bootstrap standard errors are in parentheses. The control group is always the same, consisting of 216 municipalities.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Channel analysis (outage experience)

	(1) With outage experience	(2) No outage experience	(3) Difference [(1) – (2)]
Panel A: Residential PV systems			
ATT	-0.266 (0.371)	0.0377 (0.336)	-0.304
Observations	311	300	.
Panel B: Commercial PV systems			
ATT	4.511** (2.059)	3.185* (1.852)	1.326
Controls	Yes	Yes	.
Observations	311	300	.

Note: We obtain the ATTs by averaging $\delta_i(g)$ in Eq. (4) across the subsample municipalities. Bootstrap standard errors are in parentheses. The control group is always the same, consisting of 216 municipalities.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A8: Channel analysis (degree of damage)

	(1) Greater damage	(2) Smaller damage	(3) Difference [(1) – (2)]
Panel A: Residential PV systems			
ATT	-0.0685 (0.369)	-0.165 (0.334)	0.0968
Observations	305	306	.
Panel B: Commercial PV systems			
ATT	5.076*** (1.927)	2.648 (1.921)	2.428
Controls	Yes	Yes	.
Observations	305	306	.

Note: We obtain the ATTs by averaging $\delta_i(g)$ in Eq. (4) across the subsample municipalities. Bootstrap standard errors are in parentheses. The control group is always the same, consisting of 216 municipalities.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A9: Channel analysis (weather on the blackout day)

	(1) Good weather	(2) Bad weather	(3) Difference [(1) – (2)]
Panel A: Residential PV systems			
ATT	-0.0758 (0.369)	-0.143 (0.406)	0.0677
Observations	275	240	.
Panel B: Commercial PV systems			
ATT	5.380*** (2.032)	3.253 (2.199)	2.127
Controls	Yes	Yes	.
Observations	275	240	.

Note: We obtain the ATTs by averaging $\delta_i(g)$ in Eq. (4) across the subsample municipalities. Bootstrap standard errors are in parentheses. The control group is always the same, consisting of 216 municipalities.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A1: Event study plot of residential PV systems (robustness check)

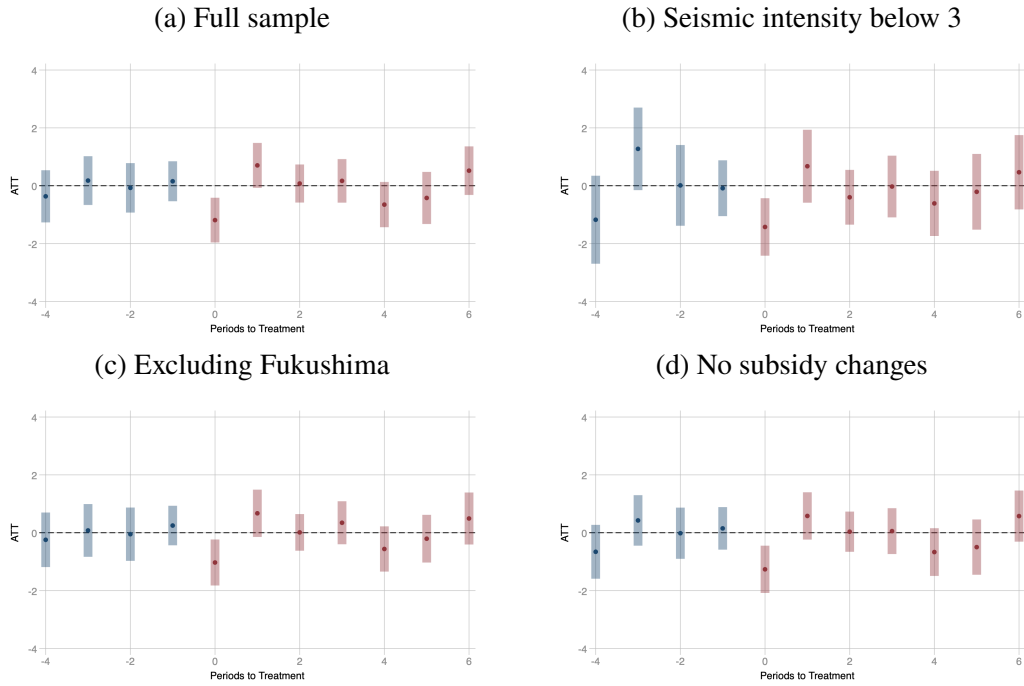


Figure A2: Event study plot of commercial PV systems (robustness check)

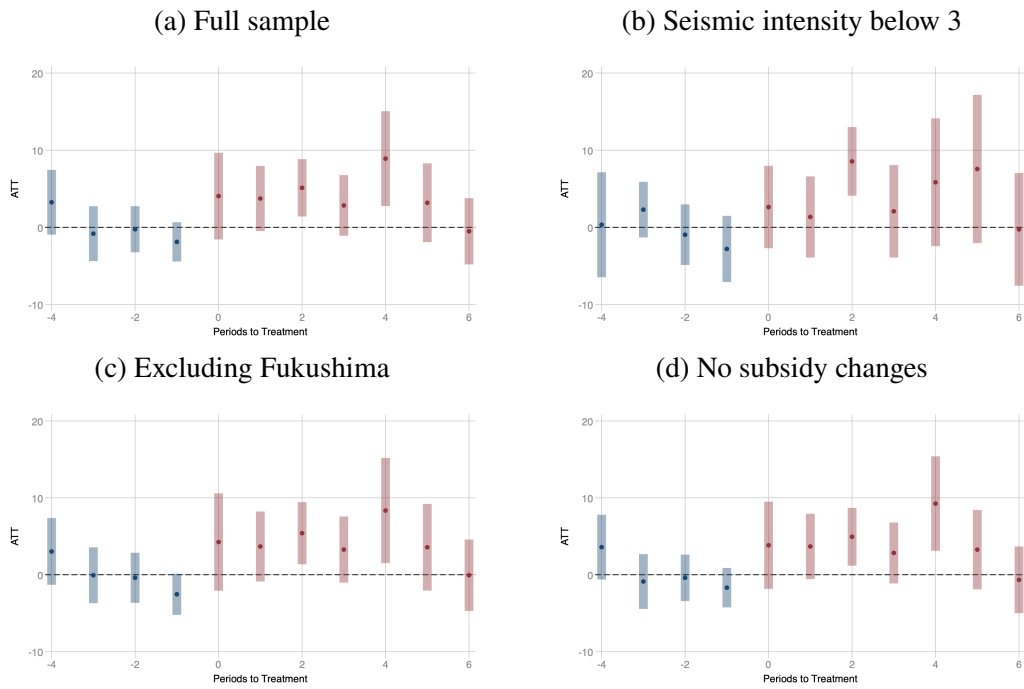


Figure A3: Event study plot of residential PV systems (heterogeneity impacts)

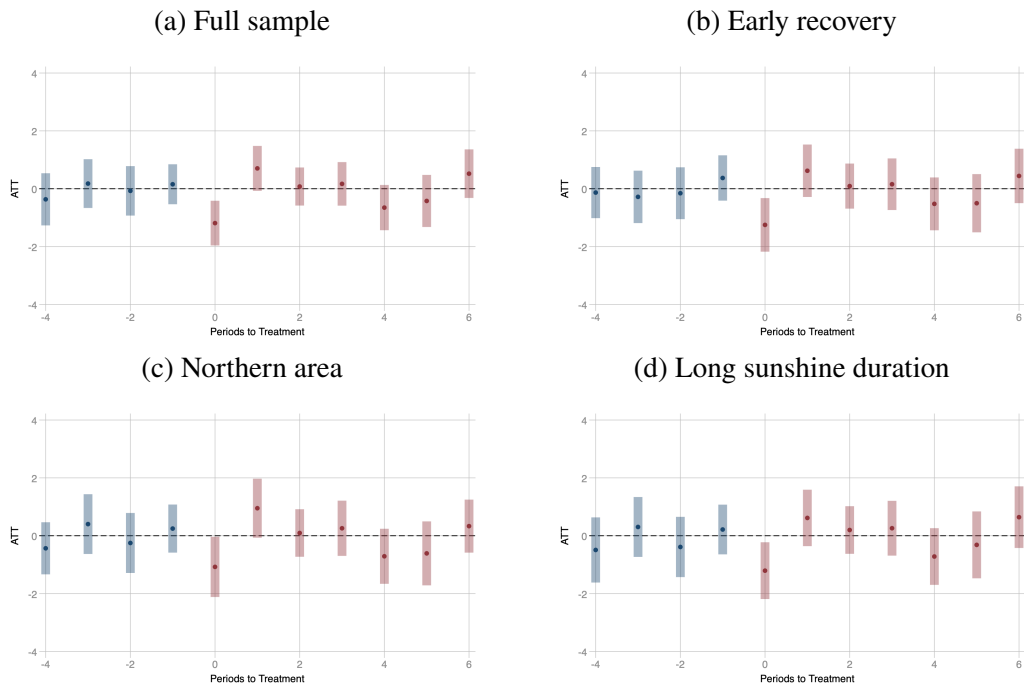


Figure A4: Event study plot of commercial PV systems (heterogeneity impacts)

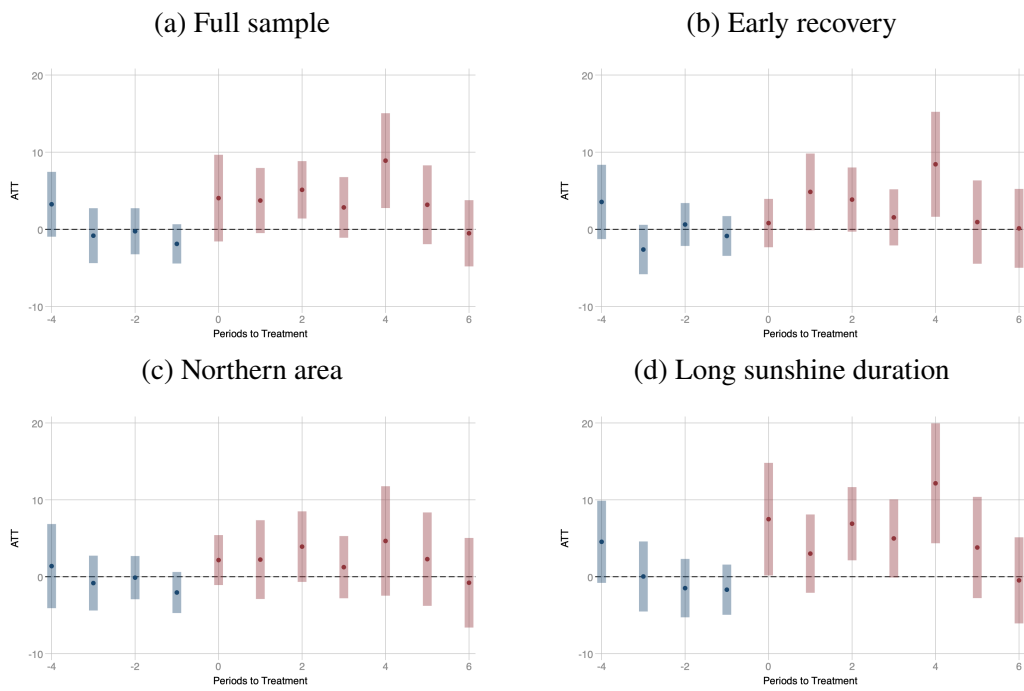


Figure A5: Event study plot of residential PV systems (channel analysis)

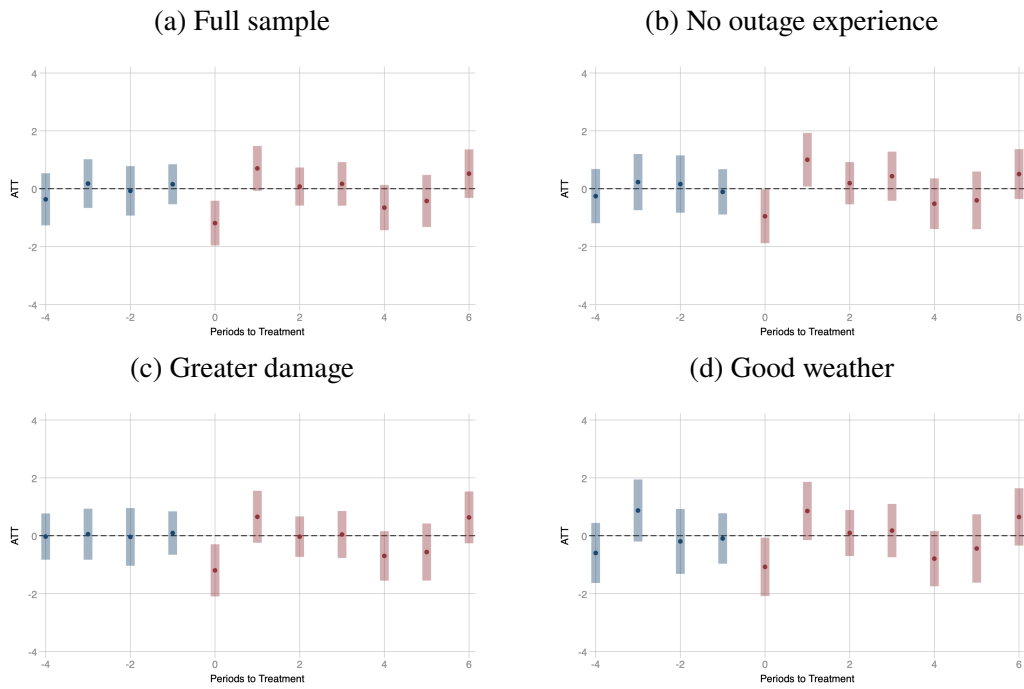


Figure A6: Event study plot of commercial PV systems (channel analysis)

