Wildfire, Power Shutoff, and Residential Energy Storage Adoption

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Abstract

Extreme weather poses a growing threat to electrical grid stability. On-site battery storage connected to solar power —known as a solar-plus-storage system—can buffer the impact. Despite its crucial benefits, the widespread adoption of this technology is hindered by its high costs. This study examines the impact of recent salient events—namely, preemptive power shutoffs to prevent wildfires, or Public Safety Power Shutoffs (PSPSs)—on residential solar-plus-storage adoption. I demonstrate that while communities at risk of wildfires lacked proactive investments before wildfire seasons, prolonged PSPSs increased solar-plus-storage adoption during the subsequent two months. This increased storage uptake can be attributed to heightened awareness of the need for backup power. Additionally, households' choices between purchasing and leasing options were influenced by latent wildfire hazards and education levels. These findings highlight the role of risk awareness in promoting storage adoption and underscore the potential for using public information to enhance wildfire preparedness.

Keywords*:* Public Safety Power Shutoff, residential solar plus energy storage, wildfire

JEL classification*:* D83; Q42; Q54; R22

1. Introduction

Energy reliability and resilience are becoming critical concerns due to climate change and the growing threat it poses. From 2011 to 2021, the United States witnessed a 78% rise in annual power outages related to extreme weather compared to the preceding decade (Climate Central, 2022). Among potential solutions, battery storage integrated with solar panels (referred to as "storage" hereafter) provides a backup power solution by storing excess solar energy while potentially curbing carbon emissions (Center for Climate and Energy Solutions, 2018). However, a primary barrier to storage adoption is the substantial upfront costs, which can exceed $40,000 (Verdant Associates, 2022). Policymakers aiming to promote storage adoption must understand how individuals weigh the rising risk of weather-related power outages against the cost of storage investment.

This paper examines decisions regarding the adoption of residential storage systems in California amid the dual risks of wildfire and associated power disruptions. Electric utilities in the state are authorized to shut off power to prevent potential wildfire hazards during severe weather conditions, a practice known as Public Safety Power Shutoffs (PSPSs). In preparation for PSPSs, local governments in California actively encourage households to use battery storage.[2] Individuals can finance the adoption of storage through purchasing or leasing. The former provides greater long-term bill savings and tax benefits, whereas the latter entails minimal upfront costs (Fikru, 2019; Pless and Benthem, 2019). Studies find that exposure to weather-related power outages has spurred the adoption of generators (Harris, 2023) and storage systems (Brown and Muehlenbachs,

[2] For example, Santa Barbara County advises people who rely on electric devices to prepare backup and external batteries for multi-day power outages (County of Santa Barbara, 2023). Likewise, the City of Willits suggests residents plan for batteries and alternatives to meet their needs during extended power outages (City of Willits, 2023).

2023). However, there remains a gap in understanding the underlying mechanisms driving these investment decisions. Little is also known about individuals' ownership preferences for storage systems in response to PSPSs. Specifically, while a PSPS event can incentivize storage investment by signaling a higher risk of future power outages, concurrent wildfire damage may discourage residential investment by exacerbating uncertainties about future disaster risks (McCoy and Zhao, 2018). Additionally, individuals' willingness and ability to translate perceived risks into costly investments are often shaped by socioeconomic characteristics such as education, income, and homeownership. Identifying factors that may hinder the adoption of storage in response to PSPSs can shed light on reactions to information-provision policies in disaster preparedness. Furthermore, these same risk considerations and household characteristics may also influence the preferred type of ownership (i.e., purchasing vs. leasing). This ownership choice is of interest to California's policymakers who are currently promoting storage adoption to address the impacts of climate change (California Office of Governor, 2023).

This study examines the impact of PSPSs on storage adoption using monthly panel data from 853 California cities in the service area of Pacific Gas & Electric Company (PG&E) from 2018 to 2020. I analyze changes in monthly new applications for storage systems, which can be host-owned or third-party-owned. The former refers to direct purchases, while the latter includes leasing or Power Purchase Agreements (PPAs), in which a third party owns and installs a storage system on a residential property for a pre-negotiated rate (Bardhan et al., 2014). The identification of this study stems from exogenous variations in the duration of PSPSs in the previous month. Additionally, I account for the impact of concurrent wildfire damage by controlling for wildfire-burned areas within a city and account for the impact of solar technology penetration by controlling for the number of existing solar systems.

The baseline results reveal a significant increase in storage adoption after prolonged PSPSs. Conditional on the city-by-year fixed effects and the county-by-year-month fixed effects, a one percent longer duration of PSPSs resulted in a 0.036% rise in host-owned systems (p-value<0.01) and a 0.022% increase in third-party-owned systems (p-value<0.01), whereas concurrent wildfire damage had an insignificant impact on storage adoption. The effects of PSPSs persisted during the subsequent two months. A back-of-the-envelope calculation indicates that PG&E's PSPS events between 2018 and 2020 prompted the adoption of an additional 1,248 host-owned storage systems, equivalent to a total investment of $56 million. These purchases represent 72 percent of the 2023 investment made by the U.S. Department of Energy to strengthen electrical grid resilience and reliability in California (Grid Deployment Office, 2023). In contrast, PSPSs over 2018-2020 resulted in a marginal increase of only 87 third-party-owned systems, as storage adoption through leasing or PPAs was less common and less responsive to PSPSs compared to direct purchases.[3] The relatively modest increase in storage adoption compared to the social costs of PSPSs suggests that many households opted for more affordable solutions like generators or no backup power in response.[4]

I interpret the baseline findings as indicative of the salience effects of PSPSs, which raise awareness of power outage risks, accentuate the need for backup power, and eventually reshape expectations regarding the future utility of storage systems. To analyze this salience effect, I follow the approach of Busse et al. (2015) by further scrutinizing whether individuals responded to

[3] See Appendix for detailed calculation.

[4] PG&E's outages in 2018 and 2019 caused $322 million in residential damage (Brown and Muehlenbachs, 2023). This value is derived from a revealed preference estimate of the Value of Lost Load, i.e., consumers' willingness to pay for electricity reliability.

deviations in PSPS duration or wildfire damage in the previous month compared to the average over the preceding year or the level of the same month of the previous year. I confirm that longer-than-average PSPS duration spurred storage adoption. Moreover, households decreased storage purchases when experiencing greater-than-average wildfire damage despite no responses to the absolute level of concurrent wildfire damage. These results highlight individuals' inclination to focus on recent information shocks, supporting the interpretation of the salience effect (Kőszegi and Szeidl, 2012; Bordalo et al., 2013). Furthermore, the increased storage systems were mainly provided by installers outside the county, suggesting a minimal post-PSPS sales promotion effect in local markets. Additionally, I do not observe significant changes in storage adoption by non-residential sectors following PSPSs, in which investment decisions are less likely driven by the risk salience effect (Liao, 2020).

As individuals focus on immediate backup power needs, they may overlook the long-term benefits of owning storage systems (Dastrup et al., 2012; Qiu et al., 2017) and instead opt for short-term solutions, particularly when perceiving lower latent wildfire hazards and the associated power outage risks. Heterogeneous analysis supports that households' choice of ownership options varied with latent wildfire hazards. Specifically, prolonged PSPSs increased the likelihood of adopting third-party-owned systems in cities outside the High Fire Threat District (HFTD), which are exposed to lower latent wildfire hazards, whereas no such difference was observed in HFTD cities. However, cities with a higher rate of college-educated individuals were more responsive to PSPSs in storage purchases. Even within non-HFTD cities, where leasing and PPAs were generally preferred following PSPSs, those with higher education levels responded with storage purchases. These findings suggest the role of knowledge and information in promoting long-term storage investment.

This study adds to the literature on averting behavior, which investigates how individuals take actions such as consuming energy, bottled water, and air purifiers to defend against environmental threats (Deschênes and Greenstone, 2011; Wrenn et al., 2016; Allaire et al., 2019); Ito and Zhang, 2020). In the specific context of weather-related power disruptions, Harris (2023) and Brown and Muelenbachs (2023) focus on individual purchasing decisions regarding generators and storage systems, respectively, to estimate the value of lost load and the costs of power outages. This paper extends these studies by delving into various ownership options of storage systems to understand the choices individuals make when grappling with uncertain power outage risks and the considerable investment costs. Moreover, this study contributes to the literature on behavioral factors influencing solar adoption. While Liao (2020) finds that adverse short-term weather conditions prompted consumers to cancel solar contracts, my findings similarly indicate that heightened awareness of backup power needs encouraged storage adoption. Both studies demonstrate how short-term salient information can affect long-run renewable energy investments.

2. Background

California has experienced a rise in wildfires over the last decade-plus. One of the major contributors is insufficient investment in electrical grid maintenance and modernization, including vegetation trimming, power line inspections and repairs, and upgrading technology for improved grid detection and isolation. Climate change exacerbates these risks by raising temperatures and intensifying droughts, creating conductive weather conditions for wildfires.

To mitigate escalating wildfire risks, the state authorized electric utilities to implement PSPSs in 2012. The decision to declare a PSPS relies on various factors such as fuel moisture, firefighting capabilities, ongoing fires, local humidity, wind conditions, and additional information from fire agencies, the National Weather Service, and the United States Forest Service (California Public Utilities Commission (CPUC), 2018). The CPUC reviews the reasonableness of these decisions, while utilities are obliged to inform customers and minimize the disruptions. Following the destructive 2017 wildfire season, the CPUC strengthened reporting, outreach, and mitigation guidelines, extending these rules to all investor-owned utilities (IOUs) (CPUC, 2020).

While PSPSs reduce infrastructure-related wildfire risks, they introduce additional risks and costs to communities and essential facilities. The wildfire-related power outage risk is inherently higher within the HFTD due to greater latent wildfire hazards, however, PSPSs can occur in communities both within and outside the HFTD. In particular, as the primary utility in northern and central California, PG&E initiated 4,457 PSPS events across 433 cities in its service area from 2018 to 2020 (Figure 1), including 339 cities in HFTD and 94 cities in non-HFTD. The impacts of these events extended to 2.15 million residential customers—including 112,000 customers dependent on uninterrupted power for home medical care—and nearly 290,000 commercial and industrial customers. These events concentrated around the wildfire season in northern California, which usually runs from June or July through October or November (Western Fire Chiefs Association, 2022).

3. Data and Empirical Model

3.1 Data

My analysis focuses on 853 cities distributed in 47 counties in the service area of PG&E in California. Given that PG&E started initiating PSPSs in 2018 (CPUC, 2018), I obtain its archived PSPS port-event reports from the CPUC for the years 2018-2020.[5] This dataset provides details for each PSPS event, including the start and end times, impacted cities, and the total number of impacted customers. To capture the overall impact of PSPS events on a given city, I aggregate the cumulative duration days across all PSPS events it experienced every month.

I supplement this dataset with several additional sources of data. First, I access the California Distributed Generation Interconnection Data Sets to identify applications for residential projects involving storage technology. All these projects are solar-plus-storage systems. Second, I source the monthly number of existing solar projects from the California Interconnected Project Sites Data Set. Third, I obtain geospatial data of wildfire history from the California State Geoportal to calculate the total burned areas within a city as a measure for wildfire damage. Finally, using the shapefile of the High Fire-Threat District provided by the CPUC, I identify the overlap of each city with wildfire zones to measure latent wildfire hazards.

3.2 Lack of Pre-season Investment

Individuals in at-risk communities often lack proactive actions before disasters, likely due to limited risk awareness or uncertainties about the benefits of preparation (Beatty et al., 2019). To examine pre-season storage investment, I compare storage applications across cities in the HFTD and cities outside the HFTD, which differ in their exposure to wildfire risks and associated PSPS risks, across calendar months within a year. Figure 2 illustrates that the two regions had statistically similar numbers of storage applications between January and June. The pre-season

[5] See more at https://www.cpuc.ca.gov/consumer-support/psps/utility-company-psps-reports-post-event-and-post-season/archived-psps-post-event-reports-2017-2020

parallel trends validate a strategy that leverages exogenous occurrences of PSPSs during wildfire seasons to identify households' responses in storage adoption. The difference-in-differences (DID) estimates indicate that HFTD cities exceeded non-HFTD cities in monthly storage applications by 3.5 to 9.1 percent from July to December, largely corresponding to the wildfire season in northern California. The findings suggest that individuals at risk of wildfires lacked preparedness before wildfire seasons but were more likely to adopt storage after PSPSs, resulting in avoidable economic losses.

3.3 Empirical Model

Using exogenous variations in the duration of PSPSs, I estimate changes in the storage adoption status in city *i* over time period *t* (by year-month) using the following equation:

$$\log\left(Storage_{i,t} + 1\right) = \alpha \log\left(\mathrm{PSPS}_{i,t-1} + 1\right) + \beta \log\left(\mathrm{Fire}_{i,t-1} + 1\right) + \gamma \log\left(\mathrm{Solar}_{i,t} + 1\right) + city_{i,y} + county_{i,t} + \varepsilon_{i,t} \quad (1)$$

where $Storage_{i,t}$, is the monthly number of new applications for storage systems; $PSPS_{i,t-1}$, is the aggregated duration days of all PSPS events in the previous month; $Fire_{i,t-1}$ is the total burned areas within a city in the previous month; $Solar_{i,t}$ is the number of existing solar projects observed at the beginning of a month; $city_{i,t}$ and $county_{i,t}$ are city-specific year trends and county-specific year-month trends, respectively. In some specifications, the dependent variable is differentiated by host-owned systems and third-party-owned systems, serving as indicators of long-term and short-term backup power solutions, respectively.

Most of the independent variables have a theoretically clear sign *a priori*. Longer PSPSs is expected to boost storage investment by signaling an increased risk of future power outages. The number of existing solar projects is also expected to have a positive effect on storage adoption by serving as a proxy for communities' receptiveness to solar technologies. The effect of wildfire damage, however, is unclear *a priori*. On the one hand, investment may decline due to financial losses from wildfires or increased awareness of future wildfire risks. On the other hand, investment may increase if recent wildfires signal a higher likelihood of future power outages.

I control for the city-specific year trends, $city_t$, and the county-specific year-month trends, $county_t$, to capture unobservable time-varying local and regional confounders that impact solar-plus-storage investment decisions. These factors include electricity price (Kwan 2012; Crago and Chernyakhovskiy 2017), financial incentives (Hughes and Podolefsky, 2015; Crago and Chernyakhovskiy 2017; Best et al. 2019; Gillingham and Tsvetanov 2019), and communities' socioeconomic status in terms of income, age, homeownership, dwelling conditions, and pro-environmental preferences (Kwan 2012; De Groote et al. 2016; Briguglio and Formosa 2017; Crago and Chernyakhovskiy 2017). I cluster standard errors at the city level to address potential serial correlations within a city.

4. Results

In this section, I estimate the effects of PSPS duration on the adoption of storage systems. I begin by presenting the descriptive statistics of the baseline sample and proceed to report the baseline results based on the model in Equation (1). Subsequently, I conduct robustness checks using an alternative dataset and a different measure for PSPS intensity.

4.1 Descriptive Statistics

Table 1 presents the descriptive statistics for the baseline sample. Across all cities from 2018 to 2020, the monthly number of new applications for storage systems ranged from 0 and 94, with an average number of 0.401. Over the sample period, storage applications increased by 2.7 times for host-owned systems and 8.6 times for third-party-owned systems (Figure 1). However, the average monthly applications for the former surpassed those for the latter (0.320 versus 0.081), indicating that leasing and PPAs are less prevalent forms of storage adoption. Additionally, the sample cities had an average of 482 existing solar projects. PSPS events persisted for an average of 0.3 days every month. The monthly average wildfire damage was 13.4 acres, with 36% of the city area overlapping with wildfire zones.

4.2 Baseline Results

Table 2 shows that the PSPS elasticity of total storage adoption was 0.046 (p-value<0.01), indicating that a one percent longer duration of PSPSs in the previous month led to a 0.046 percent increase in applications for storage systems (Column 1). However, individuals' responses to PSPS did not vary significantly with concurrent wildfire damage. Additionally, storage applications were positively correlated with the number of existing solar projects as expected. When differentiating the ownership of increased storage systems, the PSPS elasticity of host-owned systems was 0.036 percent (p-value<0.01) (Column 2), whereas that of third-party-owned systems was 0.022 percent (p-value<0.01) (Column 3).

4.3 Robustness Checks

A potential concern with the baseline estimates is the varying timing of PSPS events across cities. The presence of cities that initially experienced power disruptions but later served as control cities may violate the common trend assumption and thus bias the estimates (Goodman-Bacon, 2021). To address this concern, I follow the approach by Wing (2021) by constructing a stacked dataset with a seven-month window, including three months before and after a PSPS event. Given a PSPS event, I retain those cities impacted by the event as the treatment group while taking cities that did not experience any PSPS event during the seven-month window as clean control counterparts. Thus, I eliminate cases in which a treated city switched to a control city shortly after encountering a PSPS event. The estimation results, based on this stacked dataset, show qualitatively similar patterns to the baseline findings, albeit with slightly reduced magnitudes of the PSPS elasticities (Panel A of Table A1).

Due to data limitations, the baseline measure for PSPS duration does not account for the range of customers impacted by an event. To address the concern that a PSPS event with a given duration could be more influential by disrupting more customers, I perform a robustness check by multiplying the duration days by the number of impacted residential customers in each city. Given the lack of data on the actual impacted customers in each city, I assign the total number of impacted customers in an event to all involved cities based on their respective population weights. In cases of missing population data, I evenly distribute the total customers among all affected cities. My baseline results are robust to this alternative measure of PSPS duration (Panel B Table A1).

5. Mechanisms

In this section, I delve into potential mechanisms driving the baseline findings. First, I focus on the interpretation of information salience effects. Following this, I rule out alternative mechanisms, including supply-side changes due to sales promotion and demand-side shifts influenced by the availability of rebate funding or weather conditions.

5.1 Information Salience

Individuals adopting durable goods typically weigh future utility against current benefits and costs. However, psychological factors often influence this decision-making process. If prolonged power disruptions increase awareness of power outage risks and the need for backup power, the increased adoption of storage systems may be explained by the salience effect of PSPS events (Kőszegi and Szeidl, 2012; Bordalo et al., 2013).

To test this salience effect, I first examine whether individuals responded to deviations in PSPS duration from expectations (Busse et al, 2015), which could be based on past experience on average or the experience during the same period of the previous year. Thus, I measure individuals' expectations of regular power reliability in two ways: the average monthly PSPS duration in the previous year and the PSPS duration in the same month of the previous year. Likewise, I construct two measures for wildfire shocks as deviations in burned areas within a city in the previous month relative to these two measures of expectations. To facilitate a logarithmic transformation, I add 10^{-5} to each deviation value, dropping observations with negative shocks in PSPS duration or wildfire damage. Subsequently, I re-estimate the baseline model using the new measures of PSPS and wildfire shocks, excluding the baseline measures due to high collinearity. For both measures of PSPS shocks, I consistently find that unusually longer PSPS duration increased storage adoption.

For instance, a one percent longer PSPSs relative to the average of the previous year led to a 0.006 percent increase in host-owned systems (p-value<0.01) and a 0.004 percent increase in third-party-owned systems (p-value<0.01) (Panel B of Table 2).[6] These findings support the interpretation of the information salience effect. Moreover, although the absolute level of wildfire damage did not influence storage adoption in baseline results, greater-than-average wildfire damage significantly reduced storage purchases, indicating that wildfires could discourage defensive spending against the risks of the associated power outages through the salience effect.

To strengthen my interpretation of the information salience mechanism, I estimate the time-varying effects of PSPS duration and wildfire damage on storage adoption. Driven by information shocks from recent salient events, individuals' responses are expected to be short-lived. I introduce additional lag terms of PSPS duration to the baseline model while controlling for wildfire damage in each period. Column 1 of Table 3 shows that a one percent longer PSPSs resulted in a 0.032 percent rise (p-value<0.01) in total storage applications in the current month. This trend continues with larger elasticities of 0.04 percent (p-value<0.01) and 0.071 percent (p-value<0.01) during the following two months, respectively. Storage adoption slightly decreased by 0.018 percent (p-value<0.05) in the third subsequent before the effect of PSPS turns insignificant. The effects of PSPS exhibit similar temporal patterns for host-owned and third-party-owned systems (Columns 2-3 of Table 3). These short-lived responses align with the explanation of temporarily elevated risk awareness following PSPS events. In contrast, I do not find any significant persistent effects of wildfire damage on storage adoption.

[6] I obtain similar effects of PSPS shocks relative to the same month of the previous year (Panel C of Table A1).

Lastly, while residential customers may alter their behavior due to perceived risk salience, customers in non-residential sectors, including commercial, industrial, and government sectors, are less likely to be influenced by psychological factors in decisionmaking (Liao, 2020). Moreover, these sectors typically have established backup power plans. Consistent with this expectation, I confirm that storage applications from non-residential customers were uncorrelated with the PSPS duration or the penetration of residential solar projects (Column 1 of Table 4). Meanwhile, wildfire damage significantly reduced non-residential storage investment. The results substantiate that the investment decisions of non-residential sectors are more likely guided by rational considerations of profitability than being swayed by psychological factors.

5.2 Alternative Mechanisms

In this section, I discuss and reject three alternative mechanisms for the baseline results, further reinforcing the salience effect as the primary mechanism. Table 4 reports the test results for these three mechanisms.

The first alternative suggests that storage providers might bolster their marketing efforts following PSPSs. If this mechanism holds, local providers near the PSPS impacted areas would possess an informational advantage over non-local providers about the potential demand increase after PSPSs, resulting in additional adoption of storage systems from local providers. To test this possibility, I differentiate storage systems installed by providers located in the same county as the PSPS events ("local provider") from those located outside the local county ("non-local provider").[7]

[7] The estimation results are similar if local providers are defined as those from the same city where the storage system was installed.

Table 4 shows that longer PSPSs increased storage installations by non-local providers (Column 2), with no corresponding impact on those from local providers (Columns 1). At the storage application level, I estimate the effect of PSPS duration on the likelihood of choosing a local provider, controlling for system cost, system size, storage size, whether self-installed, whether financed by a Property Assessed Clean Energy loan, and access to electric vehicle charging at the service address. I consistently find that the likelihood of choosing a local provider remained unchanged following PSPSs (Columns 1-2 of Table A2). These results imply that the baseline findings are less likely to be driven by sales promotions from local providers.

Besides supplier-driven sales promotions, financial assistance from government rebate programs presents another potential mechanism for the baseline results by alleviating the cost burden of storage adoption. During the sample period, solar adopters in California can receive federal income tax credit. In addition, the state Self-Generation Incentive Program (SGIP) offers incentives to support the adoption of distributed energy resources (DER), such as solar, wind, and battery storage. This program covers about 25 percent of the average cost of storage systems in the general market. For lower-income groups, medically vulnerable individuals, and communities at risk of wildfire hazards, the SGIP can cover up to 85 percent to 100 percent of the cost through the Equity Budget and the Equity Resiliency Budget (CPUC, 2021), respectively. If changes in SGIP funding coincided with PSPS events, households' investment responses might be influenced by reduced costs rather than heightened risk awareness. To capture the potential impact of SGIP funding availability on the demand for storage systems over time, I control for the year-month trends specific to the eligible zones for the two budgets, using the SGIP Eligibility Mapping Tool from the CPUC. The results exhibit qualitative consistency with the baseline findings with slightly diminished magnitudes of the estimates (Columns 3-4 in Table 4).

Finally, given that PSPS is a proactive measure enacted during extreme weather conditions, such as low humidity, strong winds, and hot temperatures, post-PSPSs storage adoption might be influenced by increased energy demand resulting from these weather conditions (Deschênes and Greenstone, 2011). To eliminate this possibility, I explicitly include a series of weather variables - maximum temperature, snow depth, wind gust, visibility, cloud cover, and relative humidity - as part of a robustness check.[8] The baseline findings remain robust with the inclusion of these weather controls (Columns 5-6 in Table 4), dispelling concerns of a demand surge induced solely by extreme weather.

6. Heterogeneous Effects

In this section, to investigate the key factors influencing individuals' responses to PSPSs, I estimate the heterogeneous effects of PSPSs along two dimensions: latent wildfire hazards, which impact perceptions of future wildfire risks and the associated power outages, and socioeconomic characteristics, which affect individuals' ability and willingness to avert perceived power outages.

6.1 Across Wildfire Zones

Given that PSPS is a wildfire prevention measure, individuals may assess power outage risks alongside latent wildfire hazards. In regions with lower latent wildfire hazards, recent PSPSs may appear particularly salient, signaling the emergence of new risks. However, the conveyed

[8] I obtain the monthly weather data at the city-level from Visual Crossing Weather. The weather data are available for 90 percent of cities in the baseline sample.

power outage risks may also be perceived as relatively low in these regions, as disaster associated risks are usually deemed relevant only to those residing in the corresponding designated disaster zones (Hallstrom and Smith, 2005; McCoy and Zhao, 2018).

To estimate how responses to PSPSs vary across latent wildfire hazards, I re-estimate the baseline model using subsamples of cities outside the HFTD and cities overlapping with the HFTD (Table 5). In non-HFTD cities, the duration of PSPSs did not affect the adoption of host-owned systems (Column 1). Instead, residents in these cities increased applications for third-party-owned systems, with an average PSPS elasticity of 0.037 (p-value<0.01) (Column 2). Among HFTD cities, longer PSPS duration increased the adoption of both host-owned and third-party-owned systems, with elasticities of 0.053 (p-value<0.01) and 0.02 (p-value<0.05), respectively (Columns 3-4).[9] Accounting for system characteristics at the storage application level, I also find that the likelihood of choosing third-party-owned systems increased after longer PSPSs in non-HFTD cities, whereas no such change was observed in HFTD cities. The findings demonstrate that individuals facing lower wildfire hazards tended to adopt storage systems through leases or PPAs as short-term adaptive measures.

6.2 Across Socioeconomic Characteristics

Previous research highlights the effects of socioeconomic characteristics on risk avoidance behaviors (Shimshack et al., 2007) and adoption decisions regarding residential solar technologies

[9] By estimating the heterogeneous effects of PSPS duration across the share of the city area in HFTD using the full sample, I also find significantly smaller PSPS elasticities for third-party-owned systems in cities with a higher share in HFTD. The results are available upon request.

(Kwan 2012; De Groote et al. 2016; Briguglio and Formosa 2017; Crago and Chernyakhovskiy 2017). To identify communities more responsive to PSPSs in storage investment, I recalibrate the baseline model by incorporating a range of socioeconomic variables interacted with PSPS duration and the same variables interacted with wildfire damage.

First, a higher income level can alleviate liquidity and credit constraints for solar adoption (Mills and Schleich, 2009; Kwan, 2012). In response to PSPSs, higher-income households can bear the high costs of storage systems (Brown and Muelenbachs, 2023), whereas lower-income households may turn to cheaper alternatives such as generators or leasing options. Thus, I measure the affordability of storage systems by the median family income of a city.

Second, landlords often lack incentives to invest in energy-efficient technologies for rental properties due to challenges in allocating benefits and costs between tenants and landlords (Mills and Schleich, 2009; De Groote et al., 2016). I capture the incentive of storage investment by the share of owner-occupied units in a city, which serves as a proxy for the percentage of households who can fully benefit from such investments.

Third, individuals' decisions to adopt solar also depend on their basic knowledge of the technology or their ability to process underlying information (Arkesteijn and Oerlemans, 2005; Faiers and Neame, 2006; Rebane and Barham, 2011), such as financial returns across diverse future scenarios. I capture the costs of acquiring and processing information on storage technology by the share of individuals with a bachelor's degree or higher in a city.

Table 6 shows that, among the three socioeconomic factors considered, education emerged as the sole determinant influencing individuals' responses to PSPSs. Across all cities, given a one percentage point increase in the share of the college-educated population, the PSPS elasticity of host-owned systems increased by a 0.002 percentage points (p-value<0.01) (Column 1). In contrast, education did not significantly affect the PSPS elasticity of third-party-owned systems (Column 2). Notably, in response to occasional PSPSs in non-HFTD regions, although average cities tended to adopt third-party-owned systems as short-term solutions, cities with higher education levels displayed a preference for host-owned systems. It is worth noting that education captures not only knowledge access and information assimilation ability but also unobservable factors such as pro-environmental preferences (Hersch and Viscusi, 2006). In any case, the effects of education on storage adoption as well as ownership choices suggest that education and knowledge may serve as crucial levers for boosting storage purchases to mitigate wildfire-related power outage risks in the long term.

7. Conclusions

This study investigates household decisions regarding storage adoption in response to power outage risks associated with extreme weather, using evidence from PSPSs in California. The findings reveal that while communities at risk of wildfires lacked proactive investment in storage systems before the wildfire seasons, prolonged PSPS events during these seasons increased storage system adoption by raising awareness of power outages risks. Meanwhile, greater-than-average wildfire damage reduced investment decisions. The preference for purchasing or leasing options varied based on latent wildfire hazards and socioeconomic factors: individuals leaned towards leases or PPAs in regions less accustomed to wildfire hazards, while communities with higher education levels were more inclined to purchase storage systems in response to PSPSs.

This paper refrains from asserting whether Californians are irrationally underinvesting in battery storage. The rationality of individual responses to PSPSs hinges on evaluating the costs and the expected benefits of storage investment across different future scenarios, which encompass factors such as wildfire regimes and policy effectiveness in enhancing grid reliability. For instance, although high temperatures and low precipitation may heighten wildfire risks in the short term, repeated extreme drought can reduce biomass and mitigate wildfire threats in the long term (Kennedy et al., 2021). Additionally, individuals may exhibit projection bias in power reliability by overestimating the future's resemblance to the current state (Conlin et al., 2007; Busse et al., 2015), especially given recent and future potential initiatives to improve electrical grid reliability against wildfires and extreme weather.

Nevertheless, this study demonstrates a reactive response to salient risk information, which carries implications for policymakers to promote storage adoption and enhance community resilience against wildfire-related power disruptions. These findings underscore the importance of leveraging public messaging channels, such as early warning systems, emergency notifications, and power outage maps, to communicate the risk of power disruptions proactively. Given the transient nature of consumer responses to risk information, a recurring communication strategy is essential to guide communities in early-season preparation.

Moreover, this study highlights that communities with lower education levels were less responsive to power disruptions when making storage investments. These results emphasize the necessity of implementing broader, targeted outreach strategies to engage less-educated communities in wildfire preparedness. Policymakers may consider providing information on storage technologies, the long-run risks of climate change, and regional disaster dynamics to facilitate individuals to fully appreciate the costs and benefits of different storage ownership options.

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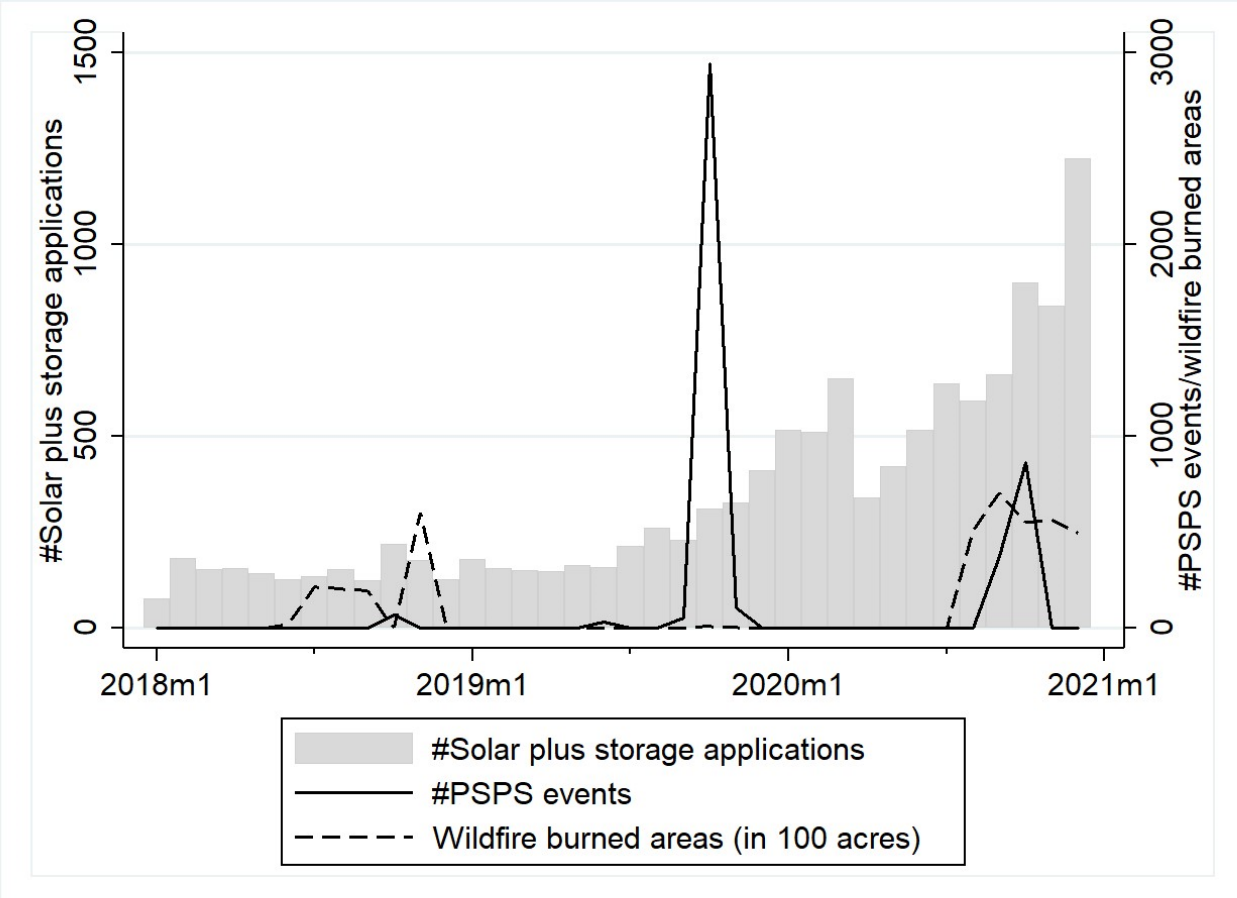
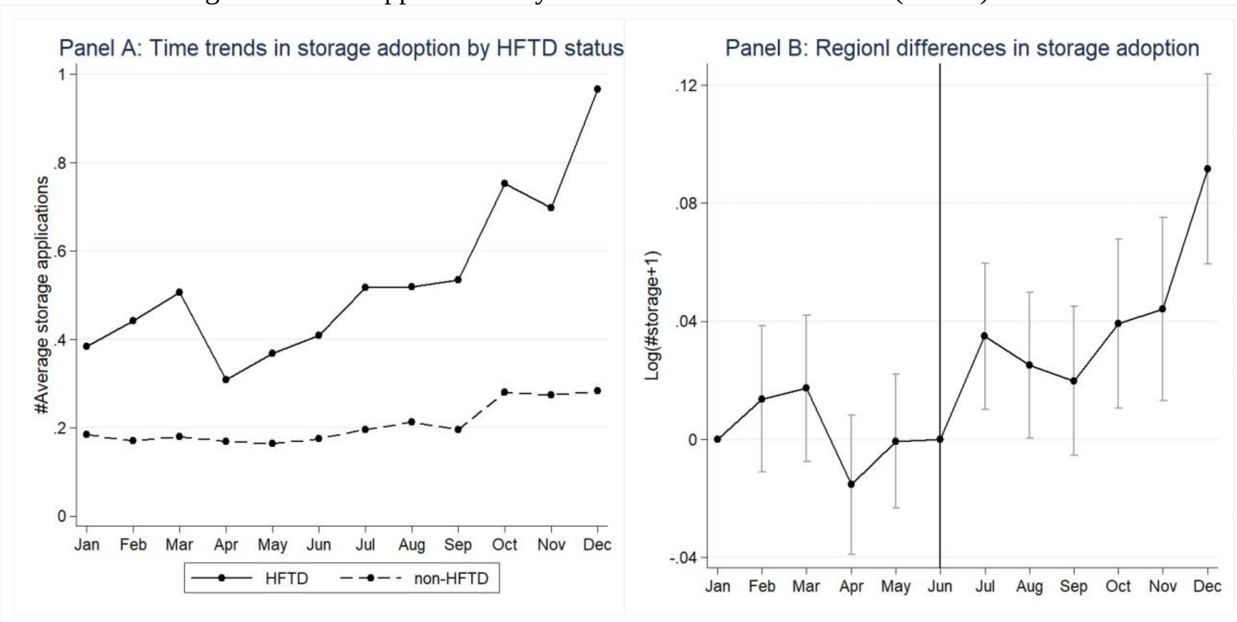
Figure 1. Solar Applications, PSPS Events, and Wildfires Damage



The underlying data are the baseline sample of cities in PG&E service area in California.

Figure 2. Solar Applications by the Hire Fire Threat District (HFTD) Status



Panel A plots the average number of applications for solar plus storage systems from HFTD cities and non-HFTD cities respectively across calendar months in a year. Panel B plots the estimated coefficients and the standard deviation of the additional differences across the two regions relative to the baseline difference in June across calendar months in a year, controlling for the city fixed effects and the year-month fixed effects. Standard errors are clustered at the city level. The underlying data are the baseline sample of cities in PG&E service area in California.

Table 1. Descriptive Statistics

	Mean	Std. Dev.	Min	Max
Dependent variables				
#Total storage systems	0.401	1.838	0	94
#Host-owned systems	0.320	1.522	0	85
#Third-party-owned systems	0.081	0.467	0	20
Independent variables				
Total duration (days)	0.301	3.103	0	149.2049
Burned area within a city (acres)	13.373	487.408	0	32459.39
#Solar projects	482	1,803	0	35,458
%Wildfire zones	0.357	0.415	0	1
N				30,708

Notes: The table reports the summary statistics for the baseline sample of 853 cities in PG&E's service area from January 2018 to December 2020.

Table 2. The Effects of PSPS and Wildfires on Storage Adoption by Ownership Type [c]

VARIABLES	(1) Total	(2) Host-owned	(3) Third-party-owned
	Panel A: Baseline results [a]		
Log(1+PSPS)	0.046***	0.036***	0.022***
	(0.009)	(0.008)	(0.006)
Log(1+Fire)	-0.002	-0.002	0.001
	(0.003)	(0.003)	(0.002)
Log(1+Solar)	0.084***	0.079***	0.030**
	(0.025)	(0.024)	(0.015)
Observations	30,636	30,636	30,636
R-squared	0.751	0.720	0.520
	Panel B: Deviations from the previous year's average [b]		
Log(PSPS shock)	0.008***	0.006***	0.004***
	(0.001)	(0.001)	(0.001)
Log(Fire shock)	-0.003**	-0.002*	-0.000
	(0.001)	(0.001)	(0.001)
Log(1+Solar)	0.048**	0.047**	0.010
	(0.020)	(0.022)	(0.014)
Observations	23,715	23,715	23,715
R-squared	0.631	0.589	0.422

[a] In Panel A, the results are based on the baseline sample. *PSPS* is the total number of duration days across all PSPSs in the previous month. *Fire* is wildfire burned acres within a city in the previous month.

[b] In Panel B, the results are based a subsample of cities experiencing nonnegative shocks in PSPS duration and wildfire damage compared to the previous year's average. *PSPS shock* and *Fire shock* are deviations in PSPS durations and wildfire burned areas, respectively, in the previous month from the previous year's average. A value of 10^{-5} is added to each deviation measure for a logarithmic transformation.

[c] In all panels, the dependent variables are the log form of the number of storage systems by ownership type. *Solar* is the number of existing solar projects observed at the beginning of a month. The model controls for the city-by-year and the county-by-year-month fixed effects. Standard errors are clustered at the city level.

Table 3. Persistent Effects of PSPS [a]

VARIABLES	(1) Total	(2) Host-owned	(3) Third-party-owned
Log(1+$PSPS_t$)	0.032***	0.026***	0.019***
	(0.008)	(0.008)	(0.006)
Log(1+$PSPS_{t-1}$)	0.040***	0.031***	0.019***
	(0.009)	(0.008)	(0.006)
Log(1+$PSPS_{t-2}$)	0.071***	0.070***	0.022***
	(0.009)	(0.009)	(0.006)
Log(1+$PSPS_{t-3}$)	-0.018**	-0.007	-0.025***
	(0.009)	(0.008)	(0.008)
Log(1+$PSPS_{t-4}$)	-0.014	-0.017	0.002
	(0.010)	(0.011)	(0.007)
Log(1+$Fire_t$)	0.005	0.000	0.007**
	(0.004)	(0.003)	(0.003)
Log(1+$Fire_{t-1}$)	-0.006	-0.004	-0.001
	(0.004)	(0.003)	(0.003)
Log(1+$Fire_{t-2}$)	0.001	0.002	-0.005*
	(0.004)	(0.004)	(0.003)
Log(1+$Fire_{t-3}$)	-0.002	-0.003	0.001
	(0.004)	(0.004)	(0.003)
Log(1+$Fire_{t-4}$)	-0.005	-0.006	0.000
	(0.004)	(0.004)	(0.003)
Log(1+Solar)	0.052**	0.051**	0.015
	(0.023)	(0.023)	(0.014)
Observations	30,636	30,636	30,636
R-squared	0.752	0.722	0.522

[a] The results are based on the baseline sample. *PSPS* is the total number of duration days across all PSPSs in a month. *Fire* is wildfire burned acres within a city in a month. *Solar* is the number of existing solar projects observed at the beginning of a month. The dependent variables are the log form of the number of storage systems by ownership type. The model controls for the city-by-year and the county-by-year-month fixed effects. Standard errors are clustered at the city level.

Table 4. Alternative mechanisms [a]

VARIABLES	(1) Non-residential	(2) Local providers	(3) Non-local Providers	(4) Host owned	(5) Third party owned	(6) Host owned	(7) Third party owned
Log(1+PSPS)	-0.0001	0.005	0.047***	0.035***	0.020***	0.036***	0.024***
	(0.002)	(0.005)	(0.009)	(0.008)	(0.006)	(0.009)	(0.007)
Log(1+Fire)	-0.0006**	-0.001	-0.000	-0.002	0.001	-0.003	0.000
	(0.000)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Log(1+Solar)	-0.0019	0.029***	0.074***	0.074***	0.025*	0.075***	0.026*
	(0.003)	(0.011)	(0.023)	(0.024)	(0.014)	(0.024)	(0.016)
Equity zone by year-month FE	N	N	N	Y	Y	N	N
Equity resiliency zone by year-month FE	N	N	N	Y	Y	N	N
Weather controls	N	N	N	N	N	Y	Y
Observations	30,636	30,636	30,636	30,636	30,636	27,720	27,720
R-squared	0.144	0.566	0.728	0.722	0.522	0.722	0.523

[a] The results of Columns 1-5 are based on the baseline sample, whereas the results of Columns 6-7 are based on subsamples of cities with available weather conditions data. The dependent variables are the log form of the number of storage systems by ownership type. *Local (non-local) providers* are defined as solar installers located in the same (different) county where a storage system was installed. *PSPS* is the total number of duration days across all PSPSs in the previous month. *Fire* is wildfire burned acres within a city in the previous month. *Solar* is the number of existing solar projects observed at the beginning of a month. Weather controls include maximum temperature, snow depth, wind gust, visibility, cloud cover, and relative humidity. The model controls for the city-by-year and the county-by-year-month fixed effects. Standard errors are clustered at the city level.

Table 5. Heterogenous Storage Adoption Responses Across Wildfire Zones [a]

	(1)	(2)	(3)	(4)
	Non-HFTD		HFTD	
VARIABLES	Host owned	Third party owned	Host owned	Third party owned
Log(1+PSPS)	0.017	0.037***	0.039***	0.017**
	(0.024)	(0.014)	(0.009)	(0.007)
Log(1+Fire)	-0.014	-0.011	-0.004	0.000
	(0.015)	(0.011)	(0.003)	(0.002)
Log(1+Solar)	0.058**	0.011	0.107**	0.049**
	(0.027)	(0.019)	(0.043)	(0.020)
Observations	12,276	12,276	18,000	18,000
R-squared	0.609	0.507	0.756	0.546

[a] The results of Columns 1-2 are based on subsamples of cities outside the High Fire-Threat District (HFTD), whereas the results of Columns 3-4 are based on subsamples of cities overlapping with the HFTD. The dependent variables are the log form of the number of storage systems by ownership type. *PSPS* is the total number of duration days across all PSPSs in the previous month. *Fire* is wildfire burned acres within a city in the previous month. *Solar* is the number of existing solar projects observed at the beginning of a month. The model controls for the city-by-year and the county-by-year-month fixed effects. Standard errors are clustered at the city level.

Table 6. Heterogeneous Storage Adoption Responses Across Socioeconomic Characteristics [a]

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline Sample		Non-HFTD		HFTD	
VARIABLES	Host owned	Third party owned	Host Owned	Third party owned	Host owned	Third party owned
Log(1+PSPS)	0.038***	0.025***	0.029	0.042***	0.042***	0.019**
	(0.008)	(0.007)	(0.030)	(0.015)	(0.009)	(0.008)
Log(1+PSPS)×%Owner-occupied	-0.018	-0.026	0.020	0.011	-0.019	-0.031
	(0.045)	(0.029)	(0.193)	(0.085)	(0.048)	(0.031)
Log(1+PSPS)×Log(Income)	0.021	0.002	-0.094	0.053	0.033	-0.004
	(0.023)	(0.015)	(0.124)	(0.054)	(0.023)	(0.016)
Log(1+PSPS)×%Bachelor+	0.002***	0.001	0.004*	-0.002*	0.001**	0.001*
	(0.001)	(0.000)	(0.003)	(0.001)	(0.001)	(0.000)
Log(1+Fire)	-0.004	0.001	-0.025	-0.021*	-0.006	0.000
	(0.004)	(0.004)	(0.016)	(0.012)	(0.004)	(0.003)
Log(1+Fire)×%Owner-occupied	0.008	-0.002	0.488*	0.310	0.008	0.004
	(0.014)	(0.015)	(0.253)	(0.204)	(0.013)	(0.013)
Log(1+Fire)×Log(Income)	-0.006	0.016	-0.067	-0.077	-0.008	0.013
	(0.010)	(0.012)	(0.076)	(0.050)	(0.008)	(0.010)
Log(1+Fire)×%Bachelor+	-0.000	-0.000	0.000	0.001	-0.000	-0.000
	(0.000)	(0.000)	(0.002)	(0.001)	(0.000)	(0.000)
Log(1+Solar)	0.083***	0.032*	0.057*	0.008	0.124**	0.062**
	(0.028)	(0.017)	(0.029)	(0.020)	(0.053)	(0.026)
Observations	26,028	26,028	11,148	11,148	14,700	14,700
R-squared	0.724	0.525	0.610	0.514	0.761	0.552

[a] The results of the table are based on the baseline sample of cities with available socioeconomic characteristics data (Columns 1-2), cities outside the High Fire-Threat District with available socioeconomic characteristics data (HFTD) (Columns 3-4), and cities overlapping with the HFTD with available socioeconomic characteristics data (Columns 5-6). The dependent variables are the log form of the number of storage systems by ownership type. *PSPS* is the total number of duration days across all PSPSs in the previous month. *Fire* is wildfire burned acres within a city in the previous month. Solar is the number of existing solar projects observed at the beginning of a month. *%Owner-occupied* is the share of owner-occupied units. *Income* is the median family income. *%Bachelor* is the share of populations with a bachelor's degree or above. The model controls for the city-by-year and the county-by-year-month fixed effects. Standard errors are clustered at the city level.

Appendix. Total Expenditures on Storage Adoption Due to PSPS

To estimate total expenditures on storage purchases associated with PSPS events, I estimate the time-varying effects of PSPS duration on the number of host-owned storage systems (Column 2 of Table 3). A one-percent increase in PSPS duration led to a 0.26 percent (p-value<0.01) uptake in host-owned systems in the current month, followed with a 0.031 percent (p-value<0.01) and a 0.07 percent (p-value<0.01) increase in the subsequent two months. To extrapolate total changes in the number of host-owned systems associated with an additional hour of PSPS events, I multiply the numerator of the PSPS elasticity in each period by the sample average number of host-owned systems, 0.32, and the denominator of the elasticity by the sample average hours of PSPS duration, 0.301, as follows.

$$\frac{\Delta Storage}{\Delta PSPS} = \frac{\frac{\Delta Storage}{\overline{Storage}} * \overline{Storage}}{\frac{\Delta PSPS}{\overline{PSPS}} * \overline{PSPS}} = e * \frac{\overline{Storage}}{\overline{PSPS}}$$

An additional hour of PSPS event raised the number of host-owned system by 0.135 within the following quarter (=0.32*(0.026+0.031+0.07)/0.301). Thus, 9,240 hours of PSPS events across the sample cities and periods resulted in an additional 1,248 storage purchases, equivalent to a total investment of $56 million given an average cost of $44,702 for host-owned storage systems.[10]

Likewise, a one-percent increase in PSPS duration was associated with a higher number of third-party-owned systems by 0.019 percent (p-value<0.01), 0.019 percent (p-value<0.01), and 0.022 percent (p-value<0.01) within the subsequent three months, respectively, followed with a

[10] This cost estimate excludes the: (1) non-monetary transaction costs of searching for providers and applying for rebate problems, (2) operation and maintenance expenses, and (3) the benefits derived from lower utility bills due to reduced energy costs (Center for Climate and Energy Solutions, 2018).

0.025 percent (p-value<0.01) reduction eventually. Given an average of 0.081 third-party-owned systems and an average PSPS duration of 0.301 hours, the PSPS events during the sample period resulted in an additional 87 third-party-owned systems (=(0.081*(0.019+0.019+0.022-0.025)/0.301)*9,240).

In October 2023, DOE announced a $3.5 billion investment across 44 states via the Grid Resilience and Innovation Partnerships program (Grid Deployment Office, 2023). Specifically, Holy Cross Energy, operating in 16 states including California, received $145 million from the Wildfire Assessment and Resilience for Networks project. PacifiCorp, with operations in 3 states including California, obtained $206 million from the PacifiCorp's Equity-aware Enhancement of Grid Resiliency project. Calculating the state's average, California's estimated share of the received investment amounts to approximately $78 million (=145/16+206/3).

Table A1. A Stacked Dataset and Alternative Measures of PSPS Intensity [c]

VARIABLES	(1) Total	(2) Host-owned	(3) Third-party-owned
	Panel A: A stacked dataset [a]		
Log(1+PSPS)	0.034***	0.024***	0.015**
	(0.010)	(0.008)	(0.008)
Log(1+Fire)	0.002	0.004*	-0.002
	(0.003)	(0.003)	(0.002)
Log(1+Solar)	0.101***	0.104***	0.017
	(0.036)	(0.035)	(0.014)
Observations	29,252	29,252	29,252
R-squared	0.734	0.701	0.513
	Panel B: An alternative measure for PSPS duration [b]		
Log(1+PSPS)	0.015***	0.012***	0.006***
	(0.003)	(0.003)	(0.002)
Log(1+Fire)	-0.002	-0.002	0.001
	(0.003)	(0.003)	(0.002)
Log(1+Solar)	0.084***	0.079***	0.031**
	(0.025)	(0.024)	(0.015)
Observations	30,636	30,636	30,636
R-squared	0.751	0.720	0.520
	Panel C: An alternative measure for PSPS shocks [c]		
Log(PSPS shock)	0.007***	0.005***	0.004***
	(0.001)	(0.001)	(0.001)
Log(Fire shock)	-0.002*	-0.002*	-0.000
	(0.001)	(0.001)	(0.001)
Log(1+Solar)	0.079***	0.073***	0.033**
	(0.025)	(0.024)	(0.015)
Observations	29,979	29,979	29,979
R-squared	0.744	0.711	0.517

[a] In Panel A, the results are based on a stacked panel dataset that exclusively includes cities impacted by PSPS events and clean control cities-those not impacted by any PSPS event during a seven-month time window around each PSPS event. *PSPS* is the total duration days of PSPSs in the previous month.

[b] In Panel B, the results are based on the baseline sample. *PSPS* is the total number of duration days across all PSPSs, weighted by the number of impacted residential customers within a city for each event, in the previous month.

[c] In Panel C, the results are based a subsample of cities experiencing nonnegative shocks in PSPS duration and wildfire damage compared with the same month of the previous year. *PSPS shock* and *Fire shock* are deviations in PSPS durations and wildfire burned areas,

respectively, in the previous month from the same month of the previous year. A value of 10^{-5} is added to each deviation measure for a logarithmic transformation.

[d] In all panels, the dependent variables are the log form of the number of storage systems by ownership type. *Fire* is wildfire burned acres within a city in the previous month. *Solar* is the number of existing solar projects observed at the beginning of a month. The model controls for the city-by-year and the county-by-year-month fixed effects. Standard errors are clustered at the city level.

Table A2. Application-Level Changes After PSPS [a]

VARIABLES	(1) Local provider	(2) Local provider	(3) Third-party owned	(4) Third-party owned
	Non-HFTD	HFTD	Non-HFTD	HFTD
Log(1+PSPS)	-0.157	-0.032	0.100***	0.002
	(0.100)	(0.046)	(0.035)	(0.014)
Log(cost)	0.030***	0.020***	-0.068***	-0.057***
	(0.011)	(0.007)	(0.016)	(0.013)
Log(system size)	-0.001	-0.010	0.067**	0.066***
	(0.020)	(0.008)	(0.032)	(0.012)
Log(storage size)	-0.012	-0.006	-0.145***	-0.129***
	(0.013)	(0.008)	(0.037)	(0.013)
Self-installed	0.064	-0.010	-0.094	-0.159***
	(0.046)	(0.034)	(0.057)	(0.027)
Financed by PACE loan	-0.039	0.030	-0.303***	-0.158***
	(0.038)	(0.033)	(0.087)	(0.024)
Access to EV charging	0.005	0.015*	-0.041	-0.065***
	(0.019)	(0.008)	(0.036)	(0.011)
Log(1+Fire)		-0.015		-0.001
		(0.016)		(0.009)
Observations	2,314	9,398	2,314	9,398
R-squared	0.757	0.713	0.367	0.211

[a] The results of Columns 1 and 3 are based on the subsample of storage systems in cities outside the High Fire-Threat District (HFTD), whereas the results of Columns 2 and 4 are based on the subsample of storage systems in cities overlapping with the HFTD. The dependent variables in Columns 1-2 are dummies indicating whether a storage system was provided by suppliers located in the same county where the system was installed. The dependent variables in Columns 3-4 are dummies indicating whether individuals in that city acquired a storage system through leases or Power Purchase Agreements. *PSPS* is the total number of duration days across all PSPSs in the previous month. *Fire* is wildfire burned acres within a city in the previous month. The model controls for the city-by-year and the county-by-year-month fixed effects. Standard errors are clustered at the city level.