RESOURCES *for the* FUTURE

The Value of Electricity Reliability: Evidence from Battery Adoption

David P. Brown and Lucija Muehlenbachs

Working Paper 23-10
April 2023

About the Authors

David P. Brown holds a Canada Research Chair in Energy Economics & Policy at the University of Alberta. His research lies at the intersection of energy economics, industrial organization, and regulatory policy. In particular, David's research analyzes the effects of regulatory policies on the performance of electricity markets. This includes research that measures market power execution in wholesale power markets; analyzes the impacts of mergers and market structure changes; designing regulations to motivate utilities to invest in cost-effective distributed energy resources; and analyzing the distributional impacts of emerging technologies. The objective of his work is to gain insights into the impact of imperfect competition on market outcomes and to design regulatory policies to improve the operation of electricity markets.

Lucija Muehlenbachs is a university fellow at Resources for the Future and an associate professor of economics at the University of Calgary. Prior to joining the University of Calgary, she was a fellow at Resources for the Future. Her research is at the intersection of economics, environment, and energy. She has investigated issues such as methane leaks from the distribution system, price shocks in the electricity sector, enforcement of offshore oil spills, the impact of shale gas wells on property prices, the impacts of traffic accidents associated with shale gas truck traffic, a characterization of the chemical composition of shale gas wastewater, the water quality impacts on rivers and streams, the decision to permanently clean up oil and gas wells, and the use of in-kind settlements in environmental lawsuits to address Environmental Justice concerns.

Acknowledgments

This research project received support from the government of Canada's Canada First Research Excellence Fund under the Future Energy Systems Research Initiative at the University of Alberta. The authors thank Reid Fortier, Bonnie Luo, and Zack Moline for their research assistance and Nicolas Astier, German Bet, Jenet Dooley, Meredith Fowlie, Kristin Hayes, Jesse Jenkins, Ted Kury, Erin Mansur, Ignacia Mercadal, Mar Reguant, John Rust, David Sappington, Brandon Schaufele, Stefan Staubli, Frank Verboven, Frank Wolak, Joel Wood, and seminar participants at the 2022 ASSA Annual Conference, IAEE Webinar Series, Electricity Camp in the Rockies, Rutgers' CRRIWorkshop in Regulation and Competition, Thompson Rivers University, and the University of Florida for their helpful comments and suggestions.

About RFF

Resources for the Future (RFF) is an independent, nonprofit research institution in Washington, DC. Its mission is to improve environmental, energy, and natural resource decisions through impartial economic research and policy engagement. RFF is committed to being the most widely trusted source of research insights and policy solutions leading to a healthy environment and a thriving economy.

Working papers are research materials circulated by their authors for purposes of information and discussion. They have not necessarily undergone formal peer review. The views expressed here are those of the individual authors and may differ from those of other RFF experts, its officers, or its directors.

Sharing Our Work

The Value of Electricity Reliability: Evidence from Battery Adoption

David P. Brown and Lucija Muehlenbachs*

April 14, 2023

Abstract

To avoid electric-infrastructure-induced wildfires, millions of Californians have had their power cut for hours to days at a time. We show that rooftop solar-plus-battery-storage systems increased in zip codes with the longest power outages. Rooftop solar panels alone will not help a household avert outages, but a solar-plus-battery-storage system will. Using this fact, we obtain a revealed-preference estimate of the willingness to pay for electricity reliability, the Value of Lost Load, a key parameter for electricity market design. Our estimate, of around \$4,300/MWh, suggests California's wildfire-prevention outages resulted in losses from foregone consumption of \$322 million to residential electricity consumers.

JEL–Classification: Q40, Q54, Q58

Keywords: batteries, reliability, averting expenditures, power outages, Value of Lost Load

---

*Brown: University of Alberta. Muehlenbachs: University of Calgary and Resources for the Future. This research project received support from the government of Canada's *Canada First Research Excellence Fund* under the Future Energy Systems Research Initiative at the University of Alberta. The authors thank Reid Fortier, Bonnie Luo, and Zack Moline for their research assistance and Nicolas Astier, German Bet, Jenet Dooley, Meredith Fowlie, Kristin Hayes, Jesse Jenkins, Ted Kury, Erin Mansur, Ignacia Mercadal, Mar Reguant, John Rust, David Sappington, Brandon Schaufele, Stefan Staubli, Frank Verboven, Frank Wolak, Joel Wood, and seminar participants at the 2022 ASSA Annual Conference, IAEE Webinar Series, Electricity Camp in the Rockies, Rutgers' CRRI Workshop in Regulation and Competition, Thompson Rivers University, and the University of Florida for their helpful comments and suggestions.

1 Introduction

Recent large-scale power outages in Texas and California affected millions of households, resulting in losses of economic output, critical infrastructure, and even life (Roberts, 2019; King et al., 2021). In response to weather-related power outages, calls are increasing to spend billions of dollars on "hardening" the electricity grid to be more resilient (Dyson and Li, 2020). Decisionmakers thus face a complex task of balancing the costs of infrastructure investments with the value of improved reliability. A key component in such cost–benefit analyses is the consumers' willingness to pay (WTP) to avoid electricity outages, referred to as the "Value of Lost Load" (VoLL). Despite the importance of this parameter, decisionmakers rely on estimates from either stated-preference surveys or macro models, having limited evidence from revealed preferences.

In this paper, we estimate the impact of power outages on the household adoption of solar-plus-battery systems, an emerging technology that serves as a defensive investment to partially or fully avoid outages. The observed adoptions provide us the unique opportunity to provide among the first revealed-preference estimates of the WTP to avoid power outages for residential customers.

Our empirical application considers the case of California's largest electric utility, Pacific Gas and Electric (PG&E), which imposed large-scale power outages in 2018 and 2019. These outages—called Public Safety Power Shutoffs (PSPS)—came in the wake of unprecedented wildfire activity and were used as a preventative measure to avoid further electric-infrastructure-induced wildfires.[1] The outages affected millions of Californians for hours to days at a time. The longest outage event in October 2019 affected 700,000 customers, with an average duration of 70 hours and some customers out of power for six days. While these intense PSPS events were irregular, there were expectations that PSPS outages would continue, as emphasized by the controversial statements made by PG&E's CEO that PSPS-

[1]Fires initiated by electric infrastructure are larger than other fires because the conditions resulting in their ignition, such as high winds, are the same conditions that make the fire more easily spread (Kousky et al., 2018).

driven outages were expected to continue for up to a decade (Gonzales, 2019).[2]

We use zip-code-level solar and battery-storage adoption data and variation in the timing, location, and intensity of power outages to analyze residential households' responses to these large-scale outage events. We have detailed information on the length and intensity of each power outage at a granular distribution-feeder level, which we map to the zip-code level using the location of all distribution power lines in PG&E. We find that exposure to outages had a large and statistically significant impact on battery storage adoption. Although residential storage capacity is still scarce, we estimate that capacity increased by 45 percent in treated zip codes due to the power outages. We find that the capacity additions are concentrated in the top 25th percentile of the income distribution. These findings are consistent with a growing literature that demonstrates that households in lower-socioeconomic-status regions are less likely to adopt emerging energy technologies (Carley and Konisky, 2020).

To estimate the implied value households place on reliability, we estimate a dynamic discrete choice model for the decision to adopt solar versus solar-plus-storage systems. We estimate WTP for electric reliability of around \$4,292/MWh, ranging from \$2,477/MWh to \$5,239/MWh in the bottom to top quartile of the income distribution. We use these estimates to compute the damages residential households incurred as a result of foregone consumption during the PSPS outages in 2018 and 2019 in PG&E's territory. Our estimates suggest damages of \$322 million to residential customers alone. The total cost of the outages would also include damages to commercial and industrial customers. The benefits of the outages are reflected by PG&E's \$30 billion amassed wildfire liability (Penn, 2021). When evaluating the cost-effectiveness of outages for wildfire prevention, costs should be compared to the costs of other wildfire-prevention strategies, such as restricting development in the Wildland-Urban Interface (Kousky and Olmstead, 2010; Baylis and Boomhower, 2022b), mandating fire-resistant building codes (Baylis and Boomhower, 2022a), or burying power lines (McCarthy, 2021).

[2]We note that later California utilities made subsequent adjustments to their software, vegetation maintenance, and equipment to reduce the intensity of future PSPS outages (Pacific Gas & Electric, 2022).

Our study provides several contributions to the literature. First, our estimate is among the first revealed-preference estimates of the WTP to avoid outages—the VoLL. This parameter is widely used, for example, in evaluating the cost of reliability standards that determine investment in electric infrastructure, deciding which consumers should be subject to supply interruptions, quantifying liabilities from power outages, and setting wholesale price caps and pricing when supply is scarce (Hogan, 2013; Schröder and Kuckshinrichs, 2015).[3] The longstanding use of the VoLL has relied on stated-preference surveys or macro models, due to the historical nonexistence of revealed-preference estimates (see Section A.1 for a summary).[4] In a recent paper, Harris (2023) provides a revealed-preference estimate through observed portable generator purchases from a nationwide home improvement retailer in response to power outages and hurricane watches and warnings.[5] Our estimates are larger than Harris (2023), possibly due to California outages being much longer in duration on average, suggesting that VoLL increases with outage duration.

Second, a well-established literature uses data on individuals' averting or defensive expenditures to estimate the value of nonmarket goods. Averting expenditures have allowed researchers to estimate the value of a wide array of nonmarket goods, including improved air quality (Neidell, 2009; Deschenes et al., 2017; Ito and Zhang, 2020), water quality (Kremer et al., 2011; Zivin et al., 2011; Wrenn et al., 2016), and the value of a statistical life (Cropper et al., 2011). However, these studies have relied on the averting expenditures being marginal adoptions contributing to marginal changes in risk alone and have not addressed the context

[3]Value of Lost Load estimates used in practice to set wholesale price caps in North America range from \$1,000/MWh in Alberta, to \$3,500/MWh in the Midcontinent Independent System Operator region, to \$5,000/MWh in Texas (Chang et al., 2018; Rhodes, 2022). Reliability requirements that are used to determine capacity investment set standards that limit the probability of demand exceeding supply, such as limiting the probability to less than 1 occurrence in 10 years. Murphy et al. (2020) estimate the implied VoLL that would be required to justify this standard is in the range of \$100,000–700,000/MWh depending on the stringency of the standard.

[4]Contemporaneous work is underway to estimate the impact of outages in three California utilities on adoption of solar-plus-batteries by Coulter et al. (2023) and to obtain a revealed-preference estimate of VoLL using the California power outages by Burlig et al. (2023).

[5]In the case of non-residential VoLL, another exception is Beenstock et al. (1997) who estimates a revealed-preference VoLL for public-sector agencies and industrial firms in Israel using cross-sectional data on portable generator adoption.

of an averting expenditure being a durable good purchase that has nonmarginal implications on not only risk exposure but also some other household input. In this context, a model that disentangles the joint benefits from a large sunk cost purchase is required. The sunk costs of new distributed-energy technologies are rapidly changing, making it important to also capture the implications of uncertainty, such as the additional value of waiting to adopt. We provide a dynamic model that captures sunk investment costs, benefits from the nonmarket amenity (avoided outages), and a stream of co-benefits (lower bills in the future), all under uncertainty in future benefits and costs.

Third, the literature on power outages has largely been based in the context of developing countries, showing, for example, that electricity reliability increases household electricity consumption (McRae, 2015) and results in value at the household (McRae, 2015; Khanna and Rowe, 2021; Meeks et al., 2023) and firm (Fisher-Vanden et al., 2015; Allcott et al., 2016). However, our paper provides insights into the implications of power outages in places with previously stable supply; implications that are expected to increase with the increase in extreme weather events associated with climate change (Allen-Dumas et al., 2019; NOAA, 2022).

Fourth, we find recent outages amplify the growing disparity in the adoption of emerging energy technologies. Research correlates socioeconomic and demographic factors with the adoption of a wide range of technologies, including, electric vehicles (Borenstein and Davis, 2016), rooftop solar (Sunter et al., 2019; O'Shaughnessy et al., 2021), energy efficiency (Goldstein et al., 2022), and battery storage (Brown, 2022). Our analysis extends this literature by using a quasiexperimental approach and highlighting the disparity in residential households' abilities to ensure electricity reliability via investment in battery storage.

Fifth, a growing literature employs discrete choice models to analyze households' decisions to invest in rooftop solar that has focused on the impact of solar subsidies (Burr, 2016; Feger et al., 2017; Langer and Lemoine, 2018) and using variation in subsidies to back out households' underlying discount factors (De Groote and Verboven, 2019; Bollinger et al., 2023). We use features of these models to consider an empirical application where households can invest in rooftop solar or solar-plus-battery-storage systems, thus contributing to our knowledge of battery investment. The literature on battery investment has focused on utility-scale adoptions. A number of papers demonstrate additional benefits of utility-scale storage, including prices (Butters et al., 2021), price volatility (Kirkpatrick, 2020; Butters et al., 2021; Lamp and Samano, 2022), and greenhouse gas emissions (Carson and Novan, 2013; Linn and Shih, 2019). Our paper focuses on residential storage adoption, which of smaller scale, would be associated with similar external benefits in addition to the internal benefits of averting power outages.

Our analysis proceeds as follows. Section 2 describes the data. Section 3 provides a summary of the power outage events in PG&E and presents preliminary evidence and statistics. Our empirical methodology and results are provided in Section 4. Section 5 presents our dynamic discrete choice model and our estimates on WTP to avoid power outages. Section 6 concludes.

2 Data

We use multiple publicly available data sets. We obtained data on outage events from October 2013 to September 2020 from the California Public Utility Commission (CPUC) De-Energization database (California Public Utility Commission, 2020).[6] These data detail all PSPS outages at the distribution line ("feeder") level and include information on the location, start and end time, and the number of customers affected.

We overlay PG&E's distribution line geospatial data (Pacific Gas & Electric, 2020) with the Census's Zip Code Tabulation Areas to construct a measure of outage intensity at the zip code level. We match the outage data to the distribution lines to allocate outages to zip codes. We use data on the distribution of population density from WorldPop (WorldPop,

[6]CPUC expanded the use of PSPS outages to include all investor-owned utilities, such as PG&E, starting in 2018 (California Public Utility Commission, 2018). Our de-energization PSPS outage data ends on December 31, 2019, with no additional PSPS events until September 2020 (after our sample).

2020) to estimate the intensity of outage exposure weighted by population density (see Section A.2 for additional details).

For data on technology adoption, we use Go Solar California's (2020) Distributed Generation Interconnection data, which include solar and battery storage interconnections that are behind the meter at customer sites. These data provide information, including the zip code, the date they applied for interconnection, system capacity, customer class, and system costs. We focus on residential solar and/or battery storage installations in PG&E between January 2014 and June 2020. Residential adoptions represents 97 percent of all behind-the-meter solar and solar-plus-storage installations in our data (by count). In addition, 90 percent of residential customer outage hours from PSPS outages during our sample occurred in PG&E's jurisdiction.[7]

Our dynamic discrete choice model requires additional data sources. In particular, we require multiple data sets to estimate a residential customer's annual electricity bill with and without a distributed-energy technology. For the rate schedule of customers without solar or batteries, we use PG&E's E-TOU-C residential rate schedule, the default Time-of-Use (TOU) schedule for a customer without a distributed-energy technology. For the rate schedule of customers with solar-only or solar-plus-storage systems, we use the Net Energy Metering 2.0 retail rate policy that was in place in PG&E for our entire sample period (Pacific Gas & Electric, 2021a,b). For electricity use, we use PG&E's 2017–2020 representative hourly residential load profile (Pacific Gas & Electric, 2021b). We use solar irradiance data from the National Renewable Energy Laboratory (NREL) Multi-Year PSM Global Horizontal Irradiance data (NREL, 2021) and NREL System Advisor Model to estimate hourly solar output.

For estimates of the cost of solar adoption, we use reported system costs on non-third-party-owned residential solar systems in Go Solar California's (2020) Distributed Generation

[7]We focus on PG&E because our analysis requires access to geospatial distribution feeder-level data, which are only publicly available for PG&E.

Interconnection data set.[8] For estimates of the cost of battery adoption, we use data from California's Self-Generation Incentive Program (SGIP), which provides subsidies for residential battery storage projects, among other technologies (SGIP, 2020). These data provide information on system characteristics, battery costs, and subsidies.

Finally, for the median income and percent of single-family units in a zip code, we use data from the Census Bureau's five-year American Community Survey (Integrated Public Use Microdata Series, 2020).

3 Descriptive Background of the Power Outage Events

Electric infrastructure has been cited as a key driver of deadly wildfires in California (Kousky et al., 2018). In the wake of unprecedented wildfire activity, California utilities began implementing PSPS outages during periods of severe wildfire risk to reduce the threat of infrastructure-induced wildfires. Table 1 reports PG&E's PSPS outages by start date over our sample period, and summarizes the number of distribution feeders on outage, residential customers affected, and the average and maximum duration of the outages. This table illustrates the ramp-up in outages in September and October 2019 due to a series of hot, dry, and windy weeks of weather. These outages affected over 1.5 million residential customers with an average outage duration of 70 hours. Certain feeders experienced outages lasting up to 143 hours—nearly 6 days.

The PSPS outages in our sample are large compared to historical outages in PG&E. To demonstrate this, we use the EIA's Form-861 annual outage reliability data for 2013–2019 that includes outage metrics such as the System Average Interruption Duration Index (SAIDI), which measures the sum of customer-minutes interrupted by outages over the year divided by the number of total customers served (EIA, 2021). The average SAIDI between

[8] Other studies identified issues with reported system costs for third-party solar systems because they are installer-reported appraised values rather than actual prices households pay (Pless and Van Benthem, 2019). To avoid these possible data quality issues, we focus on non-third-party systems, which represent 70 percent of the observations in our data, to establish estimates on the costs of a solar system.

Table 1: PG&E Public Safety Power Shutoff (PSPS) Summary Statistics by Start Date

Start Date	# Distribution Feeders	# Residential Customers	Mean Duration (Hours)	Max Duration (Hours)
Oct. 14, 2018	32	40,544	30.62	60.38
June 8, 2019	21	19,500	15.42	15.42
Sept 23, 2019	17	18,524	19.66	23.47
Sept 25, 2019	44	12,182	15.00	32.12
Oct 5, 2019	17	9,981	14.27	17.70
Oct 9, 2019	415	628,005	47.58	89.13
Oct 10, 2019	26	8,347	26.31	42.93
Oct 23, 2019	136	156,152	28.87	51.55
Oct 24, 2019	5	864	27.46	37.25
Oct 26, 2019	659	768,538	70.12	143.42
Oct 27, 2019	62	60,599	56.66	101.48
Oct 29, 2019	7	497	37.60	41.78
Oct 30, 2019	1	900	0.03	0.03
Nov 20, 2019	56	42,310	26.30	38.68

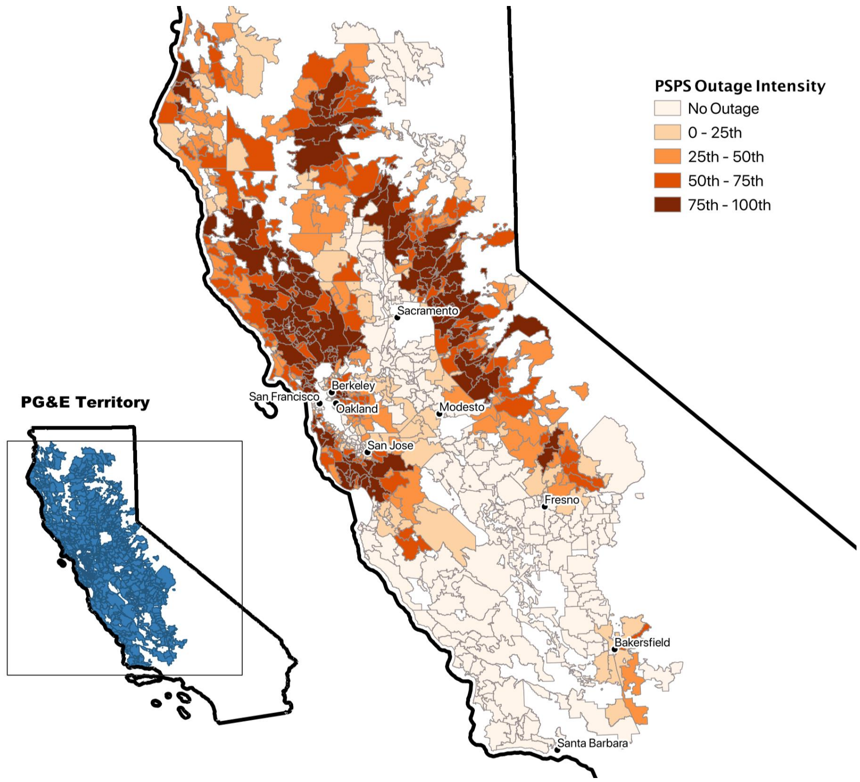
Notes: All PSPS outage events between October 2013 - August 2020. # Distribution Feeders and # Residential Customers reflects the number of distribution lines and residential customers that were affected by an individual outage. Mean and Max Duration reflect the average and maximum length of the PSPS outages on a given start date.

2013– 2017 equals 179.2. In 2018–2019, where PSPS outages occurred, SAIDI was 828.35 (a 362 percent increase).

PG&E is required to publish detailed reports on the methodology to determine when and where to implement a PSPS outage (e.g., Pacific Gas & Electric, 2019). PG&E first uses weather forecast models and historical weather data to identify thresholds for severe wildfire risks. If weather forecast models indicate a severe risk, PG&E identifies transmission and distribution lines within the footprint of the wildfire risk area, uses wind speed and fire threat indices to determine which lines are at most risk and de-energizes these lines.

Figure 1 presents a heat map of the outages during our sample period by zip code in PG&E. We measure outage intensity by the residential-customer-outage hours. The precise construction of this measure is summarized in Section 4.1. Figure 1 demonstrates a considerable spatial variation in the exposure to and intensity of outages. The hardest-hit areas are those located near mountainous regions with transmission lines. However, as can be seen in the map, these are not the only regions affected by outage events.

Figure 1: Power Outage Intensity

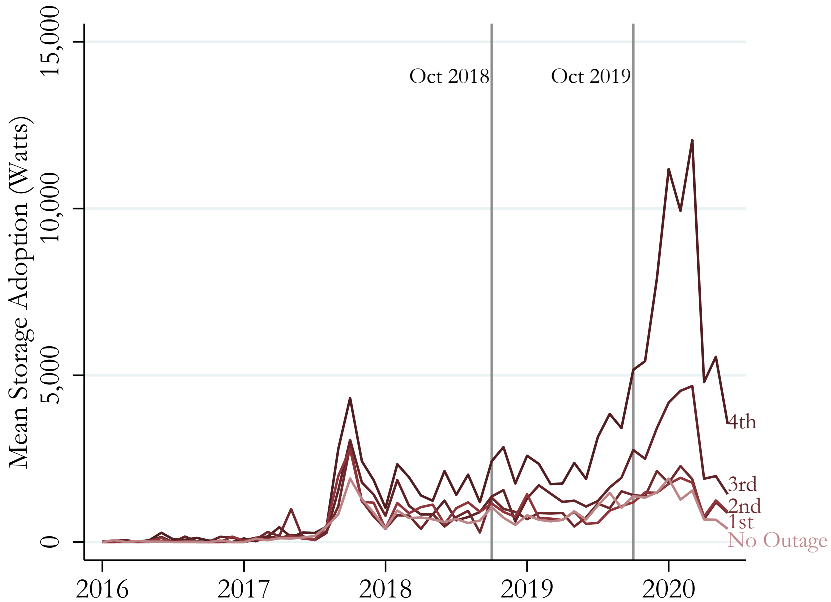


Notes. Percentiles of total residential customer-hours of outages in zip codes in PG&E's service territory. Outages occurred October 2018–November 2019.

The power outages garnered considerable controversy and criticism, but the widespread objections coincided with the deployment of marketing strategies by solar and storage retailers to motivate customers to install solar-plus-storage systems to circumvent future electric service interruptions (Sunrun, 2021). These systems have a distinct advantage over solar-only systems, which are unable to operate during outage events.

Figure 2 provides initial evidence that storage capacity increased in areas hardest hit by outages. This figure presents the average monthly storage capacity at the zip code level broken down by outage intensity quartiles, and shows a considerable divergence in storage investment starting in late 2019, with the regions most impacted by the outages installing more storage capacity. An unambiguous ranking of storage investment arises by quartile of outage intensity. Although compelling, this descriptive analysis does not rigorously control for differences across zip codes.

Figure 2: Average Monthly Storage Investment by Outage Intensity



Notes. Average storage capacity investment by quartile of outage intensity. Outages started in October 2018, with the largest and most intense outages in October 2019.

While outage locations were dictated primarily by weather forecasts and fire-threat risks, these areas often coincide with mountainous regions near city centers, which happen to also be choice locations for the affluent. Table 2 presents summary statistics of the zip code characteristics by outage exposure, demonstrating that two-thirds of zip codes in PG&E's territory have at least one outage. Outages tend to occur in regions that have a higher share of the population that is white, higher educational attainment, more owner-occupied housing, lower percentage below the poverty line, higher income, and lower density. However, we observe considerable variation in the characteristics of affected and unaffected zip codes over the full support of each of these variables. We control for differences in zip code characteristics via fixed effects in our empirical methodology, outlined next.

Table 2: 2019 Zip Code Average Characteristics by Outage Exposure

	Unit	No Outages	Outages
White	%	68.00	76.44
Black: Alone or in Combination	%	4.23	3.51
Hispanic: Any Race	%	39.38	18.61
Less than High School	%	21.86	10.88
High School	%	21.82	21.93
Some College	%	21.49	24.00
College or More	%	34.83	43.20
Below Poverty Level	%	16.79	12.57
Owner Occupied Housing	%	54.40	67.25
Median Household Income	$	73,412.48	83,229.60
Median House Value	$	499,850.52	599,311.46
Population Density	Pop./km^2	1,025.28	441.36
Observations		326	546

Notes: This table presents socioeconomic and demographic characteristics using the 2019 Census Bureau's American Community Survey data (Integrated Public Use Microdata Series, 2020), split by whether a zip code experienced a PSPS outage event during our sample period.

4 Solar-Plus-Storage Adoption: Event Study

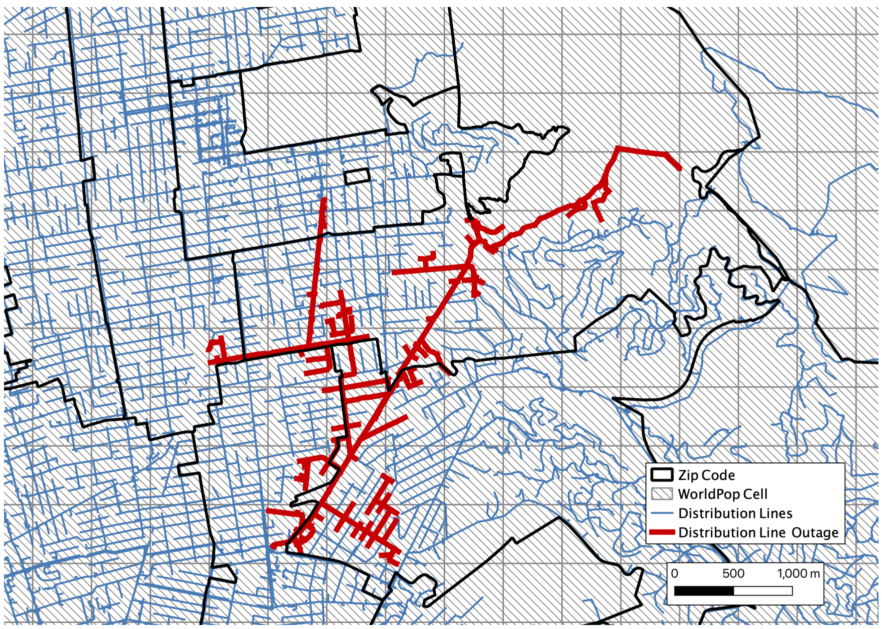
In this section, we empirically analyze the impact of the power outages on solar-plus-storage adoption.

4.1 Outage Intensity by Zip Code

Our outcome of interest, solar-plus-storage adoption, is measured at the zip-code-month level. We thus first construct a treatment variable to capture the intensity of outages at the zip-code-month level from data at the distribution-feeder level. The feeder data have information on which feeders experience outages, how many customers are on each feeder, and the number of outage hours. A complicating factor arises because a feeder can pass through multiple zip codes. For example, the red line in Figure 3 highlights a distribution feeder that was on an outage. It intersects multiple zip codes represented by the black lines.

We do not observe how many customers on a feeder live in a particular zip code, but assign customers to zip codes using a population-weighted measure. More specifically, we use an approach established in the geography literature that provides us with an estimate of the population distribution on a 500-by-500 meter square grid across PG&E's territory (WorldPop, 2020). The gray shaded squares in Figure 3 presents that grid of population estimates, where each square has a WorldPop cell estimate on population density. We then allocate residential customer outage hours to each zip code based on a feeder-length population-weighted measure. Appendix A.2 describes our population weights in more detail.[9]

Figure 3: Distribution Feeder Map—WorldPop Grid



4.2 Event-Study Specification

We exploit the variation in where power outages occur and the intensity to which outages affect residential customers to estimate the impact on the quantity of solar-plus-storage

[9]Note that we also employ weighting methods that allocate customers along a feeder based on the percentage of a feeder's line length in each zip code it intersects, assuming a uniform distribution of customers along a feeder, and find our results are robust to this alternative specification (Table A3).

adoption. We employ the following difference-in-difference (DID) event-study framework:

$$\text{Storage Capacity}_{zt} = \alpha_z + \delta_t + C_z \times f(t) + \sum_{\substack{k=-12 \\ k\neq -1}}^{8} \beta_k \, 1(t - T_z^* = k) \times \text{Outage Intensity}_{zk} + \epsilon_{zt}, \quad (1)$$

where Storage Capacity_{zt} reflects the number of watts of storage installed in zip code z and month t.[10] We allocate the capacity to months based on the date the application of installation was received to capture a customer's intention to adopt battery storage. We include zip code fixed effects, α_z, to capture time-invariant differences across zip codes and month-by-year fixed effects, δ_t, to capture time-varying factors that could impact technology uptake. We include zip-code-specific time trends, $C_z \times f(t)$, to absorb possible pre-existing zip code trends in distributed technology uptake.[11] ϵ_{zt} is the stochastic error term. We cluster our standard errors at the zip code-level.

We use a continuous measure of treatment, Outage Intensity_{zk}, that captures the number of residential-customer-outage-hours (i.e., residential customers affected times the number of outage hours) in zip code z in month k. Our identification strategy relies on the assumption of no underlying trends in battery storage uptake correlated with the exposure to and intensity of an outage, conditional on controls. To detect such trends, we consider a flexible time structure that includes leads and lags of our treatment variable. This also permits us to evaluate heterogeneous treatment effects over time. We create a series of event-month dummies, $1(t - T_z^* = k)$, which are equal to 1 when the month of the observation is $k = -12, ..., 0, ..., 8$ months from the date when the zip code was exposed to the treatment (T_z^*). The omitted regressor is one month before the event (i.e., $k = -1$ is omitted). Observations more than 12 months before or 8 months after are captured by the indicator

[10] Storage capacity is measured in either the rated power capacity (watts) or energy capacity (watthours). The former reflects the amount of energy that can flow into or out of the battery in any given instant, and the latter estimates the amount of energy that can be stored. Our data often have missing values on the energy capacity, so we focus on the rated power capacity. For residential storage systems, the ratio of the power rating and energy capacity is largely constant in the data when both numbers are reported.

[11] We consider a flexible specification on $f(t)$ that permits quadratic time trends. The Appendix Section A.4 shows specifications without these as well as different time controls.

variables $1(t - T_z^* \leq -12)$ and $1(t - T_z^* \geq 8)$, respectively.[12]

The estimated values on β_k for $k < 0$ capture the evolution of battery storage uptake in eventually treated zip codes before the PSPS outage event, net of changes in untreated zip codes after controlling for additional model covariates. These coefficients evaluate the assumption that the timing and location of outages are unrelated to pre-PSPS event changes in battery storage installations. β_k for $k > 0$ estimates the divergence in battery storage uptake k months after the outage, net of changes in untreated zip codes after controlling for additional model covariates. These coefficients are all relative to one month before the PSPS outage treatment, $t - T_z^* = -1$, which is the excluded category.

We look for heterogeneous treatment effects by socioeconomic characteristics and run a series of robustness checks to explore the sensitivity of our results. In particular, because our identification strategy exploits a certain degree of variation in the timing and intensity of outages (recall Table 1), our treatment effects represent the weighted average of all two-by-two DID estimates (Goodman-Bacon, 2021). We employ multiple robustness checks to demonstrate our results are not driven by the concerns raised in this literature.

4.3 Event-Study Results

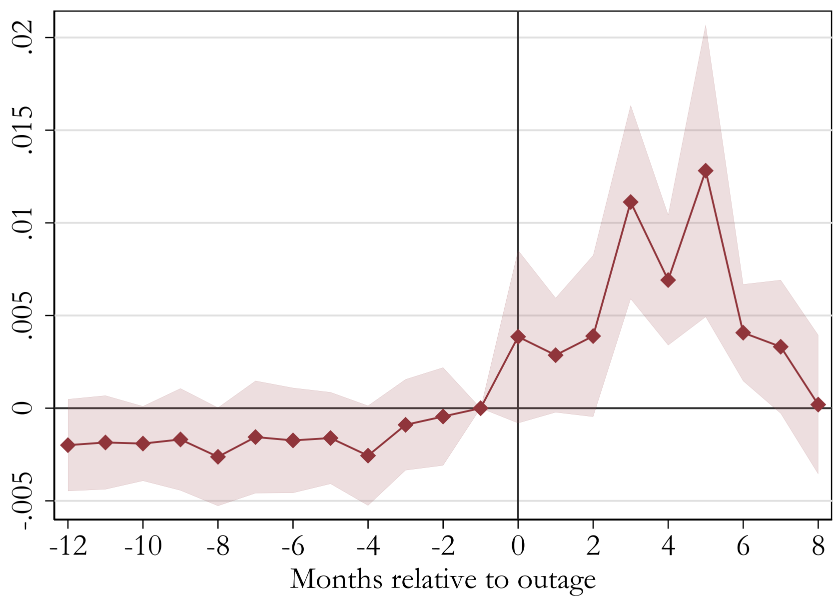
Figure 4 presents the event-study coefficient estimates on Outage Intensity in Equation (1). In the pretreatment period, we do not observe systematic differences in investment in zip codes that are eventually subject to outage events. Figure 4 demonstrates a positive and statistically significant impact of Outage Intensity on battery capacity investment starting three months after an outage event.[13] In months 3–5, a one standard deviation change in residential-customer-outage hours corresponds to a 32 percent increase in monthly storage

[12] We include event-month dummies for only eight months posttreatment because the largest and most intense outages occurred in October 2019 and our data set ends in June 2020, eight months after. Consequently, additional posttreatment variables are identified only off of the relatively infrequent outages that arose earlier in the sample.

[13] The lagged effect is consistent with a delay between being exposed to the outages, deciding to adopt a solar-plus-storage system, having to search for a provider of these systems, and finalizing all the necessary paperwork before submitting an interconnection application to PG&E.

capacity investment, relative to the average monthly storage capacity in the full calendar year before the first outage event. Although smaller, the same comparison for month zero and two months after the outage event reflects an 11 percent increase in storage capacity investment. We observe a decline in the coefficients six months after the outage events. This decline coincides with the beginning of the Covid-19 pandemic for the largest outage events in September and October 2019. Regardless of this empirical difficulty, Figure 4 presents a distinct effect of outage intensity on storage capacity investment 3–5 months after an outage event.

Figure 4: Impact of Outage Intensity on Storage Capacity (Watts)



Notes. Figure depicts estimates of β_k from our specification in (1) regressing installed storage capacity on leads and lags of outage intensity and quadratic zip-code-specific time trends. The shaded region reflects the 95 percent confidence intervals. Coefficients can be seen in Table A2.

We use the coefficient estimates to predict the amount of storage capacity installed compared to the amount of storage capacity that would have been installed in treated zip codes absent the outage events. Our estimates find an additional increase of approximately 4.86 MWs of storage capacity. Although this number is small in comparison to the level of utility-scale capacity in California, in percentage terms, the increase is large: we estimate a

45 percent increase in residential storage capacity due to the outage events.

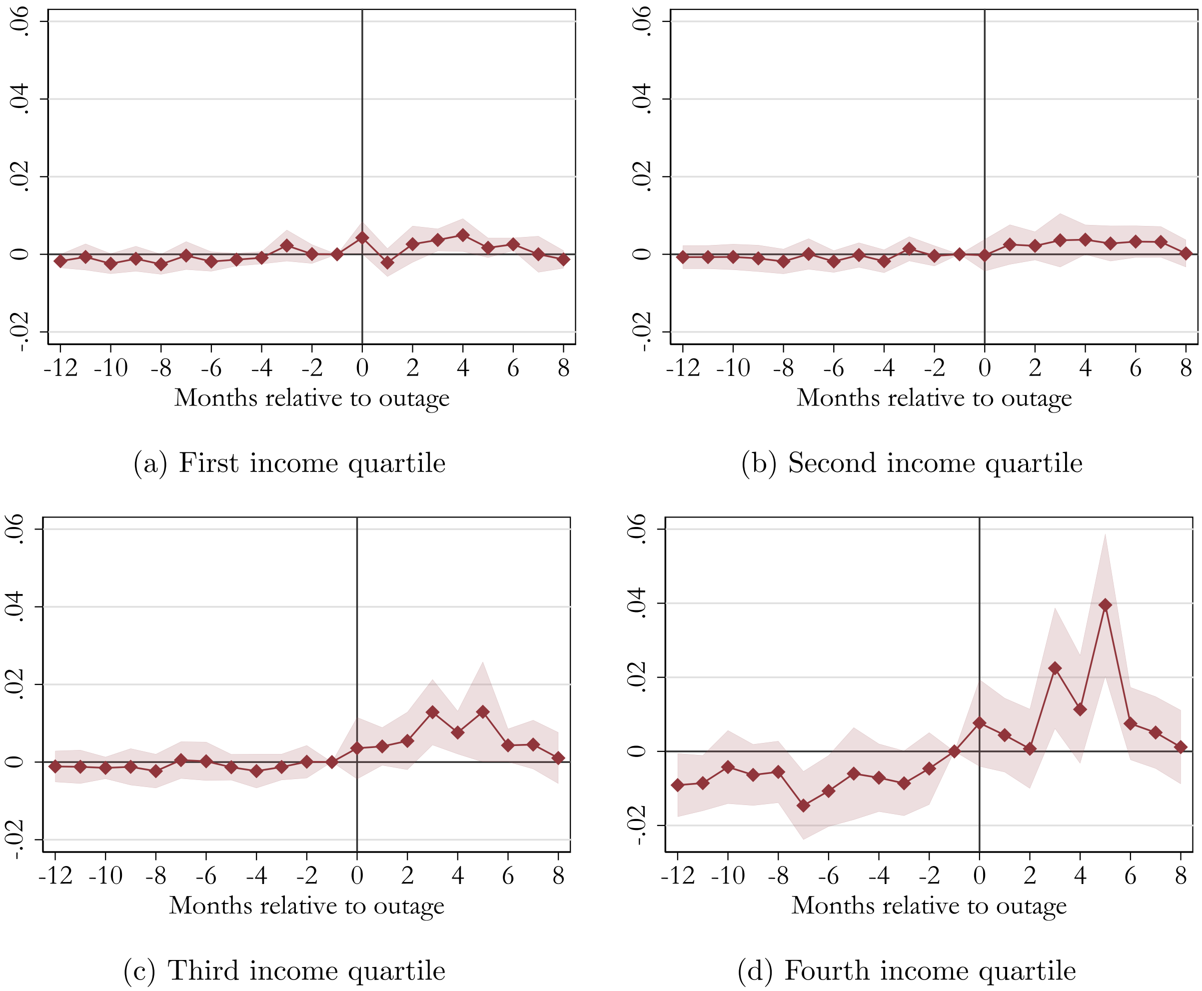
Because solar panels alone will not aid a household during a power outage, we would not expect to find a distinct relationship between outages and the adoption of solar panels alone. When examining the adoption of solar-only systems as the dependant variable in Equation (1), the relationship between outages and adoptions is less clear: the coefficients before and after treatment are noisy without the distinct increase we see with solar-plus-battery adoption (see Appendix Figure A1(a)). This nonfinding of solar-only adoption lends further support to the conclusion that outages drive solar-plus-battery adoptions.

The outages occurred in zip codes across the income distribution, but the largest treatment effect is estimated in the zip codes with the largest median incomes. Figure 5 illustrates heterogeneous treatment effects of outage intensities on storage capacity investment by median income quartiles.[14] The finding of predominant adoption coming from the highest incomes is in line with the growing literature that documents disparities in distributed technology adoption by socioeconomic characteristics (e.g., Sunter et al., 2019). More broadly, these findings raise the concern that individuals with lower socioeconomic status will face disproportional burdens associated with reduced electric reliability as a result of climate change.

We consider an array of robustness checks in the appendix and the key conclusion remains: outages led to a large percentage increase in battery-storage adoption. Section A.4 demonstrates that our key conclusion persists with alternative zip-code-specific time trends. Section A.6 presents additional model specifications that include focusing only on a comparison of the zip codes that were first and only exposed to PSPS outages in October 2019 (the largest outage event), compared to never-treated zip codes, the use of distribution feeder length weights rather than the population-based weighting detailed in Section 4.1, and the use of a discrete treatment variable.

[14] In the appendix, we show results by an Environmental Justice Index that captures socioeconomics, health, and environmental indicators. We find storage uptake is higher in the communities with the least environmental justice concerns, though the relationship is less strong than income alone (See Section A.5).

Figure 5: Impact of Outage Intensity on Storage Capacity by Income Quartiles



(a) First income quartile

(b) Second income quartile

(c) Third income quartile

(d) Fourth income quartile

Notes. Regression estimates by subsamples of income quartiles. Figures depict estimates of β_k in Equation (1), regressing installed storage capacity on leads and lags of outage intensity and quadratic zip-code-specific time trends. The shaded region reflects the 95 percent confidence intervals. Coefficients are in Table A2.

We provide assurance against the critiques raised in the case of two-way fixed effects estimates of DID with heterogeneous treatment (e.g., Goodman-Bacon, 2021 and Baker et al., 2022). Reassurance against bias is the finding that only positive weights are used in the treatment effect estimation using the Goodman-Bacon decomposition (Goodman-Bacon, 2021). In addition, the concerns associated with staggered treatment timing are mitigated because the largest and most intense outages occurred in a single month, October 2019; 76 percent of our treated zip codes were first and only subject to outages in this month. See

Section A.7 for a detailed discussion.

5 Estimation of the VoLL

In this section, we construct a dynamic discrete choice model to estimate the value of electricity reliability, separate from the other benefits that a solar-only or solar-plus-storage system provides a household. We exploit variation in outages that explain differences in adoption of the two technologies to obtain a revealed-preference estimate of the value customers place on averting outages, the residential VoLL.

5.1 Model of the Dynamic Discrete Choice of Technology

Our model consists of households that do not already have a solar or battery system. Every month, they face a decision d: (1) do nothing, (2) adopt a solar system, or (3) adopt a solar-plus-storage system.[15] We assume that households are rational and follow a decision rule that maximizes the expected discounted sum of payoffs from their decision. Payoffs depend on the state of nature, s, which includes: current ownership status, the current net-of-subsidy up-front investment costs of moving from no technology to one of the two technologies, $C_{1\to d}$, the annual electricity bill that depends on technology ownership, c_d, and the annual duration of outages, $Outage_{MWh}$. These state variables are stochastic, and the household has expectations for how they will evolve in the future, s'. The state variables enter the current-period payoff from making the adoption decision as follows:

$$\mathrm{u}(s,d,\epsilon)=\begin{cases}-c_1+\epsilon & \text{if d=1, no adoption}\\ -c_2+\gamma_2-C_{1\to 2}+\gamma_{1\to 2}+\epsilon & \text{if d=2, solar}\\ -c_3+\gamma_3-C_{1\to 3}+\gamma_{1\to 3}+\varphi Outage_{MWh}+\epsilon & \text{if d=3, solar+storage.}\end{cases} \tag{2}$$

[15] If a household adopts a system, then we model this as a terminal decision: we do not allow solar households to adopt a storage add-on or remove an adopted system. In the estimation, we set the payoff from changing states after adoption as prohibitively costly, and in the dataset, we only include single-family homes that do not yet have a solar or solar-plus-storage system. We think this simplification is reasonable given that storage add-ons are rare and also do not appear to respond to outages (Appendix Section A.3) and that we do not observe system removals in our data.

Each household has to pay an annual electricity bill, c_s, which varies by year, and the three endogenous states of ownership: (1) no technology, (2) solar, or (3) solar-plus-storage. The household also faces an unobserved annual cost, equal to 0 when it does not own a solar panel, γ_2 when it does own a solar panel, and γ_3 when it owns a solar-battery system. These costs capture, for example, an unexpected household shock that results in a higher or lower annual electricity bill, annual unobserved maintenance costs, or the warm glow from producing one's own power.

If the household adopts, it pays the current net-of-subsidy up-front cost and moves from owning nothing to its new state of ownership, $C_{1\to d}$. The household also faces an unobserved adoption shock, $\gamma_{1\to d}$, which captures any technology-specific unobservable fixed costs, such as the cost of finding an installer or the initial warm glow from purchasing the system. Once a system is adopted, it is an absorbing state, with no future decisions to revisit.

Our adoption data are at the zip-code level, which we expand to the household level using the number of single-family houses in the zip code (Integrated Public Use Microdata Series, 2020), less the number of existing solar and storage systems. In each month, we allocate households as adopters using the number of adoptions of solar and solar-plus-storage systems listed for the zip code. We are implicitly assuming that all households are the same within a zip code.

Avoided power outages enter the model as a unique benefit of adopting solar-plus-storage. We express outages in megawatt-hours, $Outage_{MWh}$, with the intended goal to estimate the residential VoLL in the same unit as used in market design. The household makes a decision each month, but it is based on the annual bill savings and annual expected outages. Thus, outages are the rolling sum of outage hours experienced in the zip code in the prior 12 months, which we convert to outage megawatt-hours by multiplying by the residential average electricity use per hour. The parameter estimate φ then provides a household's per-megawatt-hour WTP to avoid an outage. Finally, in each year, households also face a random, unobserved shock, ϵ, that reconciles the differences in the model's optimal choice and the actual choices observed.

In addition to the current-period payoff (Equation 2), the decision also depends on the expected future payoffs, which include the option of waiting to invest, the value of which arises from uncertainty in future costs and benefits. We account for household expectations in how the technology-specific investment costs, electricity bills, and annual megawatt-hours of power outages, $s = \{c_d, C_d, Outage_{MWh}\}$, will change over time, following transitions governed by the probability density function $f(s', \epsilon'|s, \epsilon, d, \theta)$. We assume a simple first-order Markov process, specifically an AR(1) process, and estimate the parameters θ from the observed past changes.[16] The future periods are discounted at the discount factor β. In the estimation, we set β at the annual discount factor estimated from solar adoption in De Groote and Verboven (2019): 0.869 or an annual discount rate of 15 percent.[17]

With the state transition probabilities and the discount factor, we can express the expected discounted value of the adoption decision as the unique solution to the Bellman equation:

$$V(s, \epsilon) = \max_{d}[\, u(s, d, \epsilon) + \beta \int_{s'} \int_{\epsilon'} V(s', \epsilon') f(s', \epsilon'|s, \epsilon, d) \mathrm{d}\epsilon' \mathrm{d}s' \,].$$

Following Rust (1987), we adopt the conditional independence assumption: the unobserved shock is independent over time and conditional on the state variables but the future state is independent of the unobserved shock, such that the state transition can be factorized as $f(s', \epsilon'|s, \epsilon, d) = f(s'|s, d)g(\epsilon'|s')$. The unobserved shock would, for example, capture the benefit a south-facing homeowner gets from the more prominent showcase of their panels on the front of their house. This unobserved benefit might increase as panel prices rise but would not increase the price of the panels themselves.

Under the assumption that ϵ is independent and identically distributed with a Type I

[16] Figures A5–A8 depict the changes in the state variables over time.

[17] We note that when using a larger discount factor, we cannot replicate the data as well as when using the discount factor estimated in De Groote and Verboven (2019). Our choice to use a 15 percent discount rate is also in-line with the preliminary estimates of (Bollinger et al., 2023), that California households have discount rates of 10–19 percent.

Extreme Value distribution, the Bellman equation becomes:

$$V_\theta(s,\epsilon) = \max_d [v_\theta(s,d) + b\epsilon(d)]$$

where θ represents the parameters to be estimated, that is, those governing the state transition probability densities, the unobserved costs, and the VoLL. And v_θ is the fixed point of $v_\theta = \Gamma(v_\theta)$, where Γ_θ is a contraction mapping (Rust, 1987):

$$\Gamma_\theta(v)(s,d) = u(s,d,\theta) + \beta \int_{s'} b \log \sum_{d'=1}^{3} \left[\exp\left\{ \frac{v_\theta(s',d')}{b} \right\} \right] f(s'|s,d)\mathrm{d}s' \tag{3}$$

with scale parameter, b, from the extreme value distribution of ϵ, which we normalize to 1 (equivalent to \$1,000). The extreme value distribution of the error ϵ gives us the multinomial-logit, closed-form solution of the choice probabilities, given each choice's value $v_\theta(s',d')$.

Our paper is an application of the nested fixed point algorithm, which is broken into three stages. In a first stage, we estimate a subsample of the parameters—the first-stage parameters, $\theta_{1^{st}}$—which are found in the transition probability density function, $f(s_{t+1}|s_t,\theta_{1^{st}})$, for each of the state variables: the annual electricity bill, the technology-specific investment costs, and annual megawatt-hours of power outage, $s = \{c_1, c_2, c_3, C_2, C_3, Outage_{MWh}\}$. We assume that households make predictions for the future values of these state variables based on their current levels and how they changed in the past. For each, we assume these variables evolve with an AR(1) process, with intercept $\alpha_{0,s}$, drift, $\alpha_{1,s}$, and normally distributed noise with standard deviation σ_s. Specifically, each state variable transitions according to:

$$s_t = \alpha_0 + \alpha_1 s_{t-1} + \sigma\varepsilon. \tag{4}$$

We assume the state transition probabilities are independent of each other and estimate $\theta_{1^{st}} = \{\alpha_{0,s}, \alpha_{1,s}, \sigma_s\}$ separately for each of the six state variables. For each state variable, we use data across all Z zip codes and T years, to find the $\theta_{1^{st}}$ that maximizes the likelihood:

$$L_1(\theta_{1^{st}}) = \prod_{z=1}^{Z_z} \prod_{t=1}^{T_i} f(s_{t+1}^z | s_t^z, \theta_{1^{st}}). \tag{5}$$

These estimated transition probabilities, $f(s_{t+1}|s_t, \hat{\theta}_{1^{st}})$, form the expectations for how the future states will evolve. For the outage state variable, when it is zero for current outages, we set the expectation to be that future outages are also 0 and only follow the AR(1) process after a household experiences an outage.[18]

The second-stage parameters, $\theta_{2^{nd}} = \{\gamma_2, \gamma_3, \gamma_{1\to 2}, \gamma_{1\to 3}, \varphi\}$, are the unobserved costs/benefits of the decision and the VoLL, from the current payoffs, Equation (2).

The estimated first-stage parameters, $\hat{\theta}_{1^{st}}$, are taken as given in the second-stage estimation that exploits the monthly variation in outages and monthly data on zip-code solar and storage uptake. Using the data on T month-year decisions from N households, we estimate $\theta_{2^{nd}}$ by maximizing the second-stage maximum likelihood:

$$L_2(\theta_{2^{nd}}) = \prod_{i=1}^{N_i} \prod_{t=1}^{T_i} p(d_t^i | s_t^i, \theta_{2^{nd}}, \hat{\theta}_{1^{st}}). \tag{6}$$

The Extreme Value distribution of the error ϵ gives us the multinomial-logit, closed-form solution of the choice probabilities:

$$p(d|s,\theta) = \frac{\exp \frac{v_\theta(s,d)}{b}}{\sum_{d'} \exp \frac{v_\theta(s,d')}{b}}. \tag{7}$$

Apropos of its name, when finding the parameters that maximize the likelihood equation (6), for each candidate $\theta_{2^{nd}}$, the fixed point of the Bellman equation (3) is solved. The parameter estimates are from the two-stage estimation, and to obtain consistent estimates of the standard errors, we use the full likelihood function that includes both the first and second stage. The full likelihood of observing the adoption decision and state variable transitions is

$$L_f(\theta) = \prod_{i=1}^{N_i} \prod_{t=1}^{T_i} p(d_t^i | s_t^i \theta) f(s_{t+1}^i | s_t^i, \theta). \tag{8}$$

[18]Results from different expectations of outages are explored in Table A10.

We run one iteration of minimizing the negative of the full log-likelihood, invert the Hessian matrix, and take the square root of the diagonal elements as our standard errors.

5.2 Identification

Our identification strategy relies on observing adoptions of two similar technologies that vary in both (1) costs and (2) the ability to avert outages, paired with observing these adoptions following exogenous exposure to varying intensities of outages.

First, on costs, the decision to invest in a solar-only or a solar-plus-storage system involves weighing future bill savings against the up-front installation costs. Both types of systems reduce a household's electricity bill, with a modestly larger reduction from solar-plus-storage.[19] The bill savings can only partly justify the higher price tag for a solar-plus-storage system. We account for bill savings as one driver of the adoption of solar-plus-storage using variation in annual bills and up-front installation costs, including spatial variation in bills due to solar irradiance in California's different climate zones. Specifically, the observed differences in the adoption of solar-only, $d = 2$, versus solar-plus-storage, $d = 3$, in response to changes to the annual bill or up-front installation costs, identifies estimates of the unobserved costs and benefits of choosing one system over the other, which are interpreted in relation to any benefit (also unobserved) from not adopting any system, which we implicitly set to 0.

Important for our estimation is that only solar-plus-storage adoption provides the additional benefit of allowing households to avert power outages. An observed increase in the adoption of solar plus storage, $d = 3$, in response to an exogenous increase in outages, $Outage_{MWh}$, identifies our parameter of interest, WTP to avoid outages, φ.

In addition to the conditional independence and additive separability assumptions of the nested fixed point algorithm (Rust, 1987), we also make the following assumptions. Within an income quartile, households may vary by outage duration and electricity bills, but all households are identical in preferences. On expectations, our main specification has

[19] Both systems will reduce a household's electricity bill, solar by roughly 50 percent and solar-plus-storage by roughly 60 percent.

the assumption that outages are expected to follow as they did for those that experienced outages, with those who never experienced outages not expecting them (the appendix presents results with different assumptions on expectations). Our model also assumes that batteries avert the full length of outages households experience and that it is the only averting expenditure available to households. In Section 5.4, we describe how violation of these last two assumptions would imply our estimate is a lower bound.

5.3 Data Inputs for the Discrete Choice Model

In this section, we summarize the data inputs used in the discrete choice model. We begin by describing the annual electricity bill of the representative consumer and how it varies by the household's installed distributed-energy technology. We incorporate heterogeneity in our model by allowing the scale of the household consumption to vary by income quartile. We then detail how we establish estimates on the cost of solar and storage technologies.

Annual electricity bills

The electricity bill of a representative residential customer who has a solar or solar-plus-storage system will vary over time at the hourly level. The difference in bills will depend on how much electricity is consumed and produced and at what time of day. In addition, it has been shown that electricity consumption is increasing in household income. We use a representative load profile, the utility's rate schedule, and hourly solar output to compute the electricity bills of residential customers under the different technology choices for each year of our sample. We use annual electricity consumption values from Borenstein et al. (2022) to scale consumption by income quartile.

For the rate schedule of a customer without a distributed-energy technology, we use PG&E's E-TOU-C residential rate schedule, the default Time-of-Use (TOU) schedule that customers are shifted onto as PG&E moves its residential customers to TOU tariff schedules. For the rate schedule of customers with solar-only or solar-plus-storage systems, we use the Net Energy Metering (NEM) 2.0 retail rate policy that was in place in PG&E for our entire sample period. It includes mandatory TOU pricing and other bill components, such as a minimum bill and nonbypassable charges (Pacific Gas & Electric, 2021a,b).[20]

To calculate solar output, we need a measure of solar irradiance. We take the geographical centroid of California's 16 Climate Zones and gather solar irradiance data from the NREL Multi-Year PSM Global Horizontal Irradiance data at these locations to permit geographical variation (NREL, 2021).[21] We use NREL's System Advisor Model and the solar irradiance data to simulate hourly solar output at each location. We match each zip code with its relevant Climate Zone.

For customers with solar-plus-storage systems, we use this approach to characterize hourly solar output. Under the NEM 2.0 TOU pricing tariff, the primary financial incentive for using the battery is to arbitrage off of the peak-to-off-peak TOU price differential. We develop an algorithm to model the charge and discharge operational decisions of the battery system. The battery is charged in hours with excess solar production in the off-peak hours and discharged in the evening peak hours to offset demand from the grid when the sun sets during peak hours. We assume a 10 percent round-trip efficiency loss of the battery system.

For electricity consumption, we use PG&E's 2017–2020 representative hourly residential load profile (Pacific Gas & Electric, 2021b). This provides us with the demand profile shape of a typical residential customer throughout the day and year. We scale this consumption profile to achieve 2019 annual gross consumption levels in PG&E reported in Borenstein et al. (2022) by income thresholds. More specifically, we use the income quartiles in our data and the annual consumption values reported in their analysis to establish annual consumption

[20]A minimum bill serves as a floor on a customer's bill and requires a NEM customer to have to pay a minimum amount per-day to cover the costs of maintaining the electric grid. Consumers face nonbypassable charges when they consume electricity from the grid. These charges cannot be offset by exporting excess solar to the electricity grid; rather, excess solar can only be used to offset energy charges.

[21]California's Climate Zones were established to create energy efficiency standards and are based on energy use, temperature, weather, and other climatic factors (CEC, 1995).

levels for each income quartile.[22] For each income quartile, we scale the representative load profile uniformly in each hour to achieve the targeted 2019 annual consumption levels.

We scale the solar PV system capacity to achieve an average annual solar output-to-consumption ratio of 60 percent across all climate zones. This is consistent with the solar PV system sizing observed in PG&E (Darghouth et al., 2011; Borenstein, 2017). This yields solar systems that range from 2 KWs to 2.73 KWs.[23] We observe that battery storage system rated power capacity (in KWs) is approximately equal to the capacity of the solar panels on average. Furthermore, the energy capacity of the battery (in KWhs), when it is reported, is approximately two times the rated power capacity.[24] We use these observed features to scale the battery systems for each income quartile.

Appendix A.8.4.1 presents an alternative approach that uses the observed solar and storage system capacities in the data and scales the annual consumption levels uniformly across all zip codes upward to achieve an annual solar output-to-consumption ratio of 60 percent at the observed capacity levels. Although this approximates the observed solar and storage system sizes well on average, it does not permit heterogeneity in consumption and system sizes across income quartiles. Regardless, we demonstrate that our qualitative conclusions are robust to this alternative approach.

After having established the rate structure, consumption profiles, and solar and storage system characteristics for each income quartile, we calculate the representative customer's hourly electricity bill and aggregate it to represent an annual electricity bill. We find that adding rooftop solar reduces the electricity bill by approximately 54 percent across the

[22]Using Figure 2 in Borenstein et al. (2022), we set the annual consumption threshold to be 5,500 KWhs, 5,800 KWhs, 6,000 KWhs, and 7,500 KWhs for the first to fourth income quartiles that have income thresholds of approximately [0, $50,000], [$50,000, $68,000], [$68,000, $97,000], and above $97,000, respectively. The reported annual consumption for incomes above $97,000 ranges from 6,000–9,000 KWhs; 7,500 KWhs reflects the midpoint of this range.

[23]The residential solar systems in our data range from 1.6 KWs to 16.5 KWs in the 1st–99th percentiles, with a median value of 5.4 KWs. Consequently, the systems that arise using our income-quartile scaled approach are relatively small. This is likely because the typical solar adopters are higher income and have higher annual consumption values (Borenstein, 2017; Borenstein et al., 2022).

[24]This is consistent with the standard Tesla Powerwall specifications that have a 7 KW rated power capacity and an approximately two times energy capacity at 13.5 KWhs.

four income quartiles on average. A solar-plus-storage system reduces the electricity bill by approximately 64 percent on average, resulting in an additional 10 percentage point reduction on average.[25] This reduction is consistent with the findings in the literature that the bill-reducing value of a battery system is modest relative to its costs for residential consumers under current retail tariffs, suggesting other reasons for adopting this technology (e.g., resiliency and reliability value) (Fares and Webber, 2017; Barbose et al., 2021).

Rooftop solar adoption costs

During our sample period, the only subsidy provided to rooftop solar systems is the federal income tax credit (ITC), which equals 30 percent of the project's costs in 2017–2019 and 26 percent in 2020 (U.S DOE, 2021).[26] For an estimate of the average solar cost and subsidy, we use reported system costs on non-third-party-owned residential solar systems in Go Solar California's (2020) Distributed Generation Interconnection data set.[27] We use this individual application-level data to compute the median monthly reported solar cost. This results in solar costs with an average of $4.1/watt over our sample.[28] We apply the ITC to these values to estimate the solar subsidy. As expected, the solar costs and ITC subsidy values have declined over our sample.[29]

Solar-plus-storage adoption costs

We use data from California's SGIP (SGIP, 2020; Go Solar California, 2020). The data provide information on the system characteristics, customer class, and cost of battery systems

[25]See Figure A5 for a detailed illustration of the estimated bill savings by technology configuration and income quartile over our sample.

[26]We follow Borenstein (2017) and Pless and Van Benthem (2019) and assume that the ITC is fully monetized by the households. The credit is nonrefundable, so the customer needs to have enough tax liability to absorb it. However, households can carry over unused credit to the next tax year reducing the amount of any unused credit (U.S DOE, 2021). We may be overstating the benefits associated with the ITC. For our analysis, any overestimates on the subsidy provided to solar will symmetrically impact customers who adopt solar-only and solar-plus-storage systems. Our estimate of the VoLL is identified from the difference between the household utility from adopting solar versus solar-plus-storage.

[27]Other studies have identified issues with reported system costs for third-party solar systems because they are installer-reported appraised values rather than actual prices households pay (Pless and Van Benthem, 2019). To avoid these possible data quality issues, we focus on non-third-party systems, which represent 70 percent of the observations in our data to establish estimates on the costs of a solar system.

[28]This estimate falls closely in line with those reported in the literature (Barbose et al., 2021).

[29]See Figure A6 for a summary of solar capital costs and subsidies over our sample.

installed and subsidies provided. We use the median monthly cost reported and subsidy received per kW. In 2020, the CPUC expanded the SGIP to include subsidies for communities affected by PSPS outages or households that lived in areas prone to wildfire prevention outages. However, the implementation of these subsidies occurred after our sample period (TerraVerde Energy, 2020).

We find costs and subsidies in the range of $1,418–2,880 per kW and $464–1,160 per kW over our sample, respectively.[30] Somewhat surprisingly, as shown in Figure A7, storage costs have increased over time. This is consistent with findings in other studies that suggest that this increase is driven by supply-chain constraints and value-based pricing (Barbose et al., 2021). Storage subsidies have declined over time because of the ratcheted nature of SGIP funding as storage enrollment increases (SGIP, 2020).

5.4 VoLL Estimates

We permit heterogeneity by estimating the model separately for zip codes stratified by median household income, a key socioeconomic indicator, as shown in Figure 5. We split our sample into quartiles based on the zip code's median household income. Our estimate of VoLL is increasing by income quartile, ranging from $2,477/MWh to $5,239/MWh, averaging $4,292/MWh (see Table 3).[31]

The literature has a broad range of residential VoLL estimates, from as low as $50/MWh to as high as $109,169/MWh, varying by country and estimation methodology (see Table A1). Most comparable in size to our estimates is the US meta-analysis by Sullivan et al. (2015) that includes 34 different data sets from various stated-preference surveys, ranging from $1,444/MWh to $6,555/MWh. Our revealed-preference estimates lie in the same general magnitude. Our estimates are larger than those of the only other available

[30] This equates to an average storage cost of $1,100/kWh before the subsidy and $787/kWh after the subsidy, assuming a system configuration that is 14 kWh/7 kW reflecting a standard Tesla Powerwall (Tesla, 2019). These storage cost estimates fall closely in line with other residential battery storage estimates in California (Barbose et al., 2021).

[31] The parameters from the first-stage transition probabilities and the other second-stage structural parameters are discussed in Appendix Table A5.

Table 3: Estimated Value of Lost Load by Income Quartile

	Income Quartile Subsample				Average
	First	Second	Third	Fourth	
φ_{VoLL} ($/MWh)	2,477	4,302	5,152	5,239	4,292
	(75)	(125)	(161)	(75)	(115)

Note: Value of Lost Load ($/MWh) is the estimated φ in the dynamic discrete choice model. In parentheses are standard errors calculated from the Hessian matrix of the full log-likelihood function. The other estimated parameters from the discrete choice model are found in Table A5. Final column shows the average across the four income quartiles with a standard error calculated from the average of the variances.

revealed-preference estimate at the writing of this paper, which has a central estimate of $1,570/MWh (Harris, 2023).[32] The difference could point to the importance of outage length in determining a household's WTP to avoid outages. The national average outage duration is five hours per year (Harris, 2023), which is low compared to those treated by the California power outages, which averaged 70 hours.

In the appendix, we show estimates under three variants of the model (Section A.8.4). First, we show the estimates when we use data without scaling consumption by income quartile. We assume households, regardless of income, consume the same amount of electricity, which results in a wider range of VoLL estimates from $3,662/MWh to $7,055/MWh (Table A7). Second, we show the estimates from alternative assumptions on what households expect future outages to be: (1) outages will remain the same as the current year with certainty, and (2) outages are expected to go to zero in the future. The case with certain, constant outages results in estimates similar to our main specification with uncertainty in outages, with values ranging from $1,731/MWh to $6,728/MWh (Table A10). In the extreme case in which a household expects zero outages in the future, the estimates are much larger, up to $42,757/MWh, and even with such a large VoLL, the simulations

[32] Using cross-sectional data from Israel with a sample of public sector agencies and industrial firms, Beenstock et al. (1997) estimates a VoLL of $7,200/MWh in 1991 USD ($13,680/MWh in 2020 USD). This is consistent with the survey-based literature that finds that commercial and industrial firms have a higher VoLL.

perform poorly, predicting far fewer adoptions than observed in the data. This extreme case reiterates that the benefit of being able to avert outages is needed to justify the expense of battery adoption today.

Our main estimates are likely lower bounds for at least three reasons. First, we do not have data on other potential averting expenditures. For example, households could have purchased portable generators (Harris, 2023), but no publicly available data exist that detail the universe of household generator adoption at the zip code level. Or, for example, households could be moving to different locations to avoid outages, an outcome that is outside the scope of this paper. By not observing these averting expenditures, we are implicitly assuming these households have zero WTP for outages, biasing our estimates downwards.

Second, we are assuming that the solar-plus-storage system completely averts a household's expected outage. If this is not the case, then we are underestimating their WTP for averting outages (i.e., they are paying the same but averting less).

Third, it is possible that only a subset of storage projects in our data are provided subsidies.[33] Consequently, we may be overstating the subsidies provided for residential storage projects, which would bias our estimates downward. We compare the total storage capacity that filed applications in PG&E to the SGIP subsidy dataset and find that SGIP-funded capacity makes up 78 percent of total storage capacity in PG&E during our sample period, which thereby limits the extent of the bias.

Nonetheless, our estimates are useful to provide a lower-bound estimate of the damages that residential households incurred during PG&E's outage events in 2018 and 2019. We take the estimated kWhs households were unable to consume as a result of the outages in each zip code and multiply by the income-quartile-specific VoLL.[34] Our estimates suggest damages of at least $322 million to residential customers alone for the foregone consumption

[33] California's Self-Generation Incentive Program has funding limits, and a subset of subsidies are tied to household income.

[34] More specifically, for each zip code and month, we estimate the total number of foregone kWhs by customer-outage-hours incurred by the average kWhs consumed. This number is multiplied by the zip code's income-quartile-specific VoLL estimate. We take the sum of these estimates over all zip codes in 2018 and 2019.

value. The full cost of the outages would include various other factors such as the losses by commercial and industrial customers, property damage, and potentially the loss of life.

6 Conclusion

We examine the defensive expenditure of solar-plus-storage adoption to reduce the exposure to power outages in California. We exploit variation in exposure to hours-to-days-long power outages. Using a DID empirical methodology, we demonstrate that zip codes exposed to more intense power outages adopted more solar-plus-storage systems. Residential battery storage is a nascent technology, so although the absolute value of capacity additions was small in magnitude, in percentage terms, battery capacity increased considerably (45 percent in affected zip codes). We find substantial heterogeneity by median household income, with the largest effects arising in the highest income zip codes.

We use a dynamic discrete choice model of solar-plus-storage adoption to estimate a household's WTP to avoid outages, an essential parameter widely applied in the electricity sector. This model allows us to disentangle drivers of adoption: the large capital investment costs, the direct benefits of bill savings, and the value of averting future power outages. We permit the WTP to vary based upon a zip code's median household income and estimate values averaging \$4,292/MWh. In the context of California, our parameter estimates can be used to compare the relative cost of wildfire-prevention strategies, such as burying power lines and vegetation management, to the consumer benefits of avoided power outages. More broadly, our revealed-preference estimates serve as an important contrast to estimates in the literature, which largely rely on stated-preference surveys.

Our analysis provides several directions for future research. First, our data are limited because we do not observe individual household-level exposure to power outages or the universe of all averting expenditures. Rather, we use zip-code-level information on the difference between solar-only and solar-plus-battery to infer responses to power outages.

Individual household-level data would allow additional evaluation of heterogeneous effects by household characteristics, and observing an array of averting expenditures would increase our lower-bound estimate. Second, our VoLL estimates include various frictions, such as credit constraints, that may limit lower-income households from adopting solar-plus-storage. Consequently, regulators should not extrapolate our estimates to implement broad strategies such as curtailing residential customers with lower VoLL estimates during periods of scarce supply. More direction in how to use VoLL estimates in curtailment decisions is warranted from future research.

References

Abrate, G., C. Bruno, F. Erbetta, G. Fraquelli, and A. Lorite-Espejo (2016). A Choice Experiment on the Willingness of Households to Accept Power Outages. *Utilities Policy 43*, 151–164.

Alberini, A., J. Steinbuks, and G. Timilsina (2022). How Valuable is the Reliability of Residential Electricity Supply in Low-Income Countries? Evidence from Nepal. *The Energy Journal 43*(4).

Allcott, H., A. Collard-Wexler, and S. D. O'Connell (2016). How Do Electricity Shortages Affect Industry? Evidence from India. *American Economic Review 106*(3), 587–624.

Allen-Dumas, M., K. Binita, and C. Cunliff (2019). Extreme Weather and Climate Vulnerabilities of the Electric Grid: A Summary of Environmental Sensitivity Quantification Methods. Technical report, Oak Ridge National Laboratory.

Baker, A., D. Larcker, and C. Wang (2022). How Much Should We Trust Staggered Difference-in-Differences Estimates? *Journal of Financial Economics 144*(2), 370–395.

Barbose, G., N. Darghouth, E. O'Shaughnessy, and S. Forrester (2021). Tracking the Sun: Pricing and Design Trends for Distributed Photovoltaic Systems in the United States 2021 Edition.

Barbose, G., S. Elmallah, and W. Gorman (2021). Behind-the-Meter Solar + Storage: Market Data and Trends. Lawrence Berkeley National Laboratory.

Baylis, P. and J. Boomhower (2022a). Mandated vs. Voluntary Adaptation to Natural Disasters: The Case of US Wildfires. *NBER Working Paper*.

Baylis, P. and J. Boomhower (2022b). The Economic Incidence of Wildfire Suppression in the United States. *American Economic Journal: Applied Economics*.

Beenstock, M., E. Goldin, and Y. Haitovsky (1997). The Cost of Power Outages in the Business and Public Sectors in Israel: Revealed Preference vs. Subjective Valuation. *The Energy Journal 18*(2).

Bollinger, B., K. Gillingham, and A. J. Kirkpatrick (2023). Valuing Solar Subsidies. Work-in-Progress.

Borenstein, S. (2017). Private Net Benefits of Residential Solar PV: The Role of Electricity Tariffs, Tax Incentives, and Rebates. *Journal of the Association of Environmental and Resource Economists 4*(S1), S85–S122.

Borenstein, S. and L. W. Davis (2016). The Distributional Effects of US Clean Energy Tax Credits. *Tax Policy and the Economy 30*(1), 191–234.

Borenstein, S., M. Fowlie, and J. Sallee (2022). Paying for Electricity in California: How Residential Rate Design Impacts Equity and Electrification — Next 10.

Broberg, T., R. Brännlund, and L. Persson (2021). Peak Load Habits for Sale? Soft Load Control and Consumer Preferences on the Electricity Market. *The Energy Journal 42*(1), 261–283.

Brown, D. (2022). Socioeconomic and Demographic Disparities in Residential Battery Storage Adoption: Evidence from California. *Energy Policy 164*, 112877.

Burlig, F., D. S. Callaway, W. Gorman, and C. D. Wolfram (2023). Estimating the Value of Reliability for Residential Electricity Consumers. Work-in-Progress.

Burr, C. (2016). Subsidies and Investments in the Solar Power Market. Working Paper. Boulder, CO: University of Colorado.

Butters, R. A., J. Dorsey, and G. Gowrisankaran (2021). Soaking Up the Sun: Battery Investment, Renewable Energy, and Market Equilibrium. NBER Working Paper.

California OEHHA (2018). CalEnviroScreen 3.0 (June 2018). California Office of Environmental Health Hazard Assessment. https://oehha.ca.gov/calenviroscreen/report/calenviroscreen-30. (accessed December 20, 2020).

California Public Utility Commission (2018). Resolution Extending De-Energization Reasonableness, Notification, Mitigation and Reporting Requirements in Decision 12-04-024 to All Electric Investor Owned Utilities. docs.cpuc.ca.gov/publisheddocs/published/g000/m218/k186/218186823.pdf.

California Public Utility Commission (2020). Utility Company PSPS Post Event Reports. cpuc.ca.gov/deenergization/. (accessed October 22, 2020).

Carley, S. and D. Konisky (2020). The Justice and Equity Implications of the Clean Energy Transition. *Nature Energy 5*(8), 569–577.

Carlsson, F., M. Kataria, E. Lampi, and P. Martinsson (2021). Past and Present Outage Costs–A Follow-Up Study of Households' Willingness to Pay to Avoid Power Outages. *Resource and Energy Economics 64*, 101216.

Carson, R. T. and K. Novan (2013). The Private and Social Economics of Bulk Electricity Storage. *Journal of Environmental Economics and Management 66*(3), 404–423.

Castro, R., S. Faias, and J. Esteves (2016). The Cost of Electricity Interruptions in Portugal: Valuing Lost Load by Applying the Production-Function Approach. *Utilities Policy 40*, 48–57.

CEC (1995). California Climate Zone Descriptions for New Buildings. California Energy Commission.

Chang, J., M. Aydin, R. Broehm, Y. Yang, and R. Sweet (2018). Shortage Pricing in North American Wholesale Electricity Markets. The Brattle Group.

Cohen, J. J., K. Moeltner, J. Reichl, and M. Schmidthaler (2016). Linking the Value of Energy Reliability to the Acceptance of Energy Infrastructure: Evidence from the EU. *Resource and Energy Economics 45*, 124–143.

Coulter, R., A. Fraser, and A. La Nauze (2023). Power Outages, Subsidies, and the Adoption of Household Batteries in California. Work-in-Progress.

Cropper, M., J. K. Hammitt, and L. A. Robinson (2011). Valuing Mortality Risk Reductions: Progress and Challenges. *Annual Review of Resource Economics 3*(1), 313–336.

Darghouth, N. R., G. Barbose, and R. Wiser (2011). The Impact of Rate Design and Net Metering on the Bill Savings from Distributed PV for Residential Customers in California. *Energy Policy 39*(9), 5243–5253.

De Groote, O. and F. Verboven (2019). Subsidies and Time Discounting in New Technology Adoption: Evidence from Solar Photovoltaic Systems. *American Economic Review 109*(6), 2137–2172.

Deschenes, O., M. Greenstone, and J. S. Shapiro (2017). Defensive Investments and the Demand for Air Quality: Evidence from the NOx Budget Program. *American Economic Review 107*(10), 2958–2989.

Dyson, M. and B. Li (2020). Reimagining Grid Resilience: A Framework for Addressing Catastrophic Threats to the US Electricity Grid in an Era of Transformative Change. Technical report, Rocky Mountain Institute.

EIA (2021). Annual Electric Power Industry Report, Form EIA-861, U.S. Energy Information Administration. https://www.eia.gov/electricity/data/eia861/. (accessed January 20, 2021).

Fares, R. and M. Webber (2017). The Impacts of Storing Solar Energy in the Home to Reduce Reliance on the Utility. *Nature Energy 2*(2), 1–10.

Feger, F., N. Pavanini, and D. Radulescu (2017). Welfare and Redistribution in Residential Electricity Markets with Solar Power. *Available at SSRN 3095567*.

Fisher-Vanden, K., E. T. Mansur, and Q. J. Wang (2015). Electricity shortages and firm productivity: evidence from China's industrial firms. *Journal of Development Economics 114*, 172–188.

Gaughan, A., F. Stevens, Z. Huang, J. Nieves, A. Sorichetta, S. Lai, X. Ye, C. Linard, G. M. Hornby, S. Hay, H. Yu, and A. Tatem (2016). Spatiotemporal Patterns of Population in Mainland China, 1990 to 2010. *Scientific Data 3*(1), 1–11.

Giaccaria, S., A. Longo, T. Efthimiadis, and T. Bouman (2018). Societal Appreciation of Energy Security: Volume 4: Value of Lost Load - Greece.

Go Solar California (2020). California Distributed Generation Statistics. californiadgstats.ca.gov/downloads/. (accessed November 12, 2020).

Goldstein, B., T. G. Reames, and J. P. Newell (2022). Racial Inequity in Household Energy Efficiency and Carbon Emissions in the United States: An Emissions Paradox. *Energy Research & Social Science 84*, 102365.

Gonzales, R. (2019). California Can Expect Blackouts For A Decade, Says PG&E CEO. *National Public Radio*. October 18.

Goodman-Bacon, A. (2021). Difference-in-Differences with Variation in Treatment Timing. *Journal of Econometrics 225*(2), 254–277.

Gorman, W. (2022). The Quest to Quantify the Value of Lost Load: A Critical Review of the Economics of Power Outages. *The Electricity Journal 35*(8), 107187.

Hämäläinen, H. (2018). The Value of Supply Security for Electricity Consumers in Finland. Working Paper.

Harris, R. (2023). Willingness to Pay for Electricity Reliability: Evidence from U.S. Generator Sales. Working Paper.

Hogan, W. (2013). Electricity Scarcity Pricing Through Operating Reserves. *Economics of Energy & Environmental Policy 2*(2), 65–86.

Integrated Public Use Microdata Series (2020). IPUMS: National Historical Geographic Information System. https://data2.nhgis.org/main. (accessed December 18, 2020).

Ito, K. and S. Zhang (2020). Willingness to Pay for Clean Air: Evidence from Air Purifier Markets in China. *Journal of Political Economy 128*(5), 1627–1672.

Khanna, S. and K. Rowe (2021). The Long-Run Value of Electricity Reliability in India. Working Paper.

Kim, K., H. Nam, and Y. Cho (2015). Estimation of the Inconvenience Cost of a Rolling Blackout in the Residential Sector: The Case of South Korea. *Energy Policy 76*, 76–86.

King, C., J. Rhodes, J. Zarnikau, N. Lin, E. Kutangolu, B. Leibowicz, D. Niyogi, V. Rai, S. Santoso, D. Spence, S. Tompaidis, H. Zhu, E. Funkhouser, and B. Austgen (2021). The Timeline and Events of the February 2021 Texas Electric Grid Blackouts. Technical report, University of Texas at Austin.

Kirkpatrick, A. J. (2020). Estimating Congestion Benefits of Batteries for Unobserved Networks: A Machine Learning Approach. Working Paper.

Kousky, C., K. Greig, B. Lingle, and H. Kunreuther (2018). Wildfire Costs in California: The Role of Electric Utilities. Risk Management and Decision Process Center Issue Brief, UPenn.

Kousky, C. and S. Olmstead (2010). Induced Development in Risky Locations: Fire Suppression and Land Use in the American West. *RFF Working Paper*.

Kremer, M., J. Leino, E. Miguel, and A. P. Zwane (2011). Spring Cleaning: Rural Water Impacts, Valuation, and Property Rights Institutions. *The Quarterly Journal of Economics 126*(1), 145–205.

Lamp, S. and M. Samano (2022). Large-Scale Battery Storage, Short-Term Market Outcomes, and Arbitrage. *Energy Economics 107*, 105786.

Langer, A. and D. Lemoine (2018). Designing Dynamic Subsidies to Spur Adoption of New Technologies. Technical report, National Bureau of Economic Research.

Linn, J. and J.-S. Shih (2019). Do Lower Electricity Storage Costs Reduce Greenhouse Gas Emissions? *Journal of Environmental Economics and Management 96*, 130–158.

Lloyd, C., A. Sorichetta, and A. Tatem (2017). High Resolution Global Gridded Data for Use in Population Studies. *Scientific Data 4*(1), 1–17.

Longo, A., S. Giaccaria, T. Bouman, and T. Efthimiadis (2019). Societal Appreciation of Energy Security: Volume 1: Value of Lost Load–Households EE, NL and PT.

McCarthy, E. (2021). California's Biggest Utility Plans to Bury 10,000 Miles of Power Lines. How Much Will that Cost Residents? *Canary Media*. August 6, 2021.

McRae, S. (2015). Infrastructure Quality and the Subsidy Trap. *American Economic Review 105*(1), 35–66.

Meeks, R., A. Omuraliev, R. Isaev, and Z. Wang (2023). Impacts of Electricity Quality Improvements: Experimental Evidence from Infrastructure Investments. Working Paper.

Morrissey, K., A. Plater, and M. Dean (2018). The Cost of Electric Power Outages in the Residential Sector: A Willingness to Pay Approach. *Applied Energy 212*, 141–150.

Murphy, S., L. Lavin, and J. Apt (2020). Resource Adequacy Implications of Temperature-Dependent Electric Generator Availability. *Applied Energy 262*, 114424.

Neidell, M. (2009). Information, Avoidance Behavior, and Health the Effect of Ozone on Asthma Hospitalizations. *Journal of Human Resources 44*(2), 450–478.

NOAA (2022). U.S. Billion-Dollar Weather and Climate Disasters. Technical report, NOAA National Centers for Environmental Information.

NREL (2021). National Solar Radiation Database. National Renewable Energy Laboratory. (accessed March 20, 2021).

O'Shaughnessy, E., G. Barbose, R. Wiser, S. Forrester, and N. Darghouth (2021). The Impact of Policies and Business Models on Income Equity in Rooftop Solar Adoption. *Nature Energy 6*(1), 84–91.

Ozbafli, A. and G. P. Jenkins (2016). Estimating the Willingness to Pay for Reliable Electricity Supply: A Choice Experiment Study. *Energy Economics 56*, 443–452.

Pacific Gas & Electric (2019). PG&E Public Safety Power Shutoff (PSPS) Report to the CPUC October 23 - 25, 2019 De-Energization Event.

Pacific Gas & Electric (2020). Integration Capacity Analysis Map. pge.com/en_US/for-our-business-partners/distribution-resource-planning/distribution-resource-planning-data-portal.page?ctx=large-business. (accessed October 22, 2020).

Pacific Gas & Electric (2021a). Time-of-Use Residential Transition Frequently Asked Questions. https://www.pge.com/pge_global/common/pdfs/rate-plans/rate-plan-options/time-of-use-base-plan/TOU-Transition-FAQs.pdf. (accessed March 20, 2021).

Pacific Gas & Electric (2021b). Understanding Energy Use and Prices. Pacific Gas & Electric. https://www.pge.com/nots/rates/tariffs/energy_use_prices.shtml. (accessed March 20, 2021).

Pacific Gas & Electric (2022). Wildfire Safety Report. https://www.pgecorp.com/corp_responsibility/reports/2022/pf08_wildfire_safety.html.

Penn, I. (2021). PG&E Aims to Curb Wildfire Risk by Burying Many Power Lines . *New York Times*. July 21, 2021.

Pless, J. and A. Van Benthem (2019). Pass-Through as a Test for Market Power: An Application to Solar Subsidies. *American Economic Journal: Applied Economics 11*(4), 367–401.

Rhodes, J. (2022). One Year Later: The Storm That Knocked Texas Out Cold. *Forbes*. February 15, 2022.

Roberts, D. (2019). California's Deliberate Blackouts were Outrageous and Harmful. They're Going to Happen Again. *Vox*. October 24, 2019.

Rust, J. (1987). Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher. *Econometrica 55*(5), 999–1033.

Schröder, T. and W. Kuckshinrichs (2015). Value of Lost Load: An Efficient Economic Indicator for Power Supply Security? A Literature Review. *Frontiers in Energy Research 3*(55).

SGIP (2020). Self-Generation Incentive Program Handbook. October 2, 2020.

Shivakumar, A., M. Welsch, C. Taliotis, D. Jakšić, T. Baričević, M. Howells, S. Gupta, and H. Rogner (2017). Valuing Blackouts and Lost Leisure: Estimating Electricity Interruption Costs for Households Across the European Union. *Energy Research & Social Science 34*, 39–48.

Sorichetta, A., G. Hornby, F. Stevens, A. Gaughan, C. Linard, and A. Tatem (2015). High-Resolution Gridded Population Datasets for Latin America and the Caribbean in 2010, 2015, and 2020. *Scientific Data 2*(1), 1–12.

Sullivan, M., J. Schellenberg, and M. Blundell (2015). Updated Value of Service Reliability Estimates for Electric Utility Customers in the United States. Technical report, Lawrence Berkeley National Lab.(LBNL), Berkeley, CA (United States).

Sunrun (2021). Solar Battery Storage - Brightbox. https://www.sunrun.com/solar-battery-storage/ca/brightbox. Accessed: February 14, 2021.

Sunter, D. A., S. Castellanos, and D. M. Kammen (2019). Disparities in Rooftop Photovoltaics Deployment in the United States by Race and Ethnicity. *Nature Sustainability 2*(1), 71–76.

TerraVerde Energy (2020). SGIP Status Update: Equity and Equity Resiliency Budgets. https://terraverde.energy/sgip-status-update-equity-and-equity-resiliency-budgets/.

Tesla (2019). PowerWall 2 Datasheet – North America. https://www.tesla.com/sites/default/files/pdfs/powerwall/Powerwall%202_AC_Datasheet_en_northamerica.pdf.

U.S DOE (2021). Homeowner's Guide to Federal Tax Credit for Solar Photovoltaics. U.S. Department of Energy. https://www.energy.gov/sites/default/files/2021/02/f82/Guide%20to%20Federal%20Tax%20Credit%20for%20Residential%20Solar%20PV%20-%202021.pdf.

Wolf, A. and L. Wenzel (2016). Regional Diversity in the Costs of Electricity Outages: Results for German Counties. *Utilities Policy 43*, 195–205.

Woo, C. K., T. Ho, A. Shiu, Y. Cheng, I. Horowitz, and J. Wang (2014). Residential Outage Cost Estimation: Hong Kong. *Energy Policy 72*, 204–210.

WorldPop (2020). Open Spatial Demographic Data and Research. https://www.worldpop.org/project/categories?id=3. (accessed November 22, 2020).

Wrenn, D. H., H. A. Klaiber, and E. C. Jaenicke (2016). Unconventional Shale Gas Development, Risk Perceptions, and Averting Behavior: Evidence from Bottled Water Purchases. *Journal of the Association of Environmental and Resource Economists 3*(4), 779–817.

Zivin, J. G., M. Neidell, and W. Schlenker (2011). Water Quality Violations and Avoidance Behavior: Evidence from Bottled Water Consumption. *American Economic Review 101*(3), 448–453.

Appendix

A.1 Recent Estimates of Value of Lost Load (VoLL) in the Literature

Surveying the most recent papers, Table A1 summarizes VoLL estimates from papers published between 2015–2022. For earlier papers: Schröder and Kuckshinrichs (2015) provide a survey of Value of Lost Load (VoLL) estimates from papers published 2004–2014 and Gorman (2022) provides a survey of meta-analyses that cover papers published 1948–2014.

Table A1: Summary of Residential VoLL Estimates in the Literature, 2015-2022

Study	Country	VoLL Estimate (2020 USD/MWh)	Method
Woo et al. (2014)	Hong Kong	21,834–109,169	Contingent Valuation
Kim et al. (2015)	South Korea	2,023–2,535	Contingent Valuation
Sullivan et al. (2015)	United States	1,444–6,555	Meta-Regression Analysis
Abrate et al. (2016)	Italy	20,693–56,155	Stated Choice Experiment
Castro et al. (2016)	Portugal	11,702	Production Function
Cohen et al. (2016)	EU	170–7,549	Stated Choice Experiment
Ozbafli and Jenkins (2016)	North Cyprus	370–1,418	Stated Choice Experiment
Wolf and Wenzel (2016)	Germany	10,332–23,799	Production Function
Shivakumar et al. (2017)	EU	4,723–24,041	Production Function
Giaccaria et al. (2018)	Greece	8,474–19,693	Contingent Valuation
Hämäläinen (2018)	Finland	4,655–23,632	Contingent Valuation
Morrissey et al. (2018)	England	856–7,511	Stated Choice Experiment
Longo et al. (2019)	The Netherlands Portugal Estonia	728–29,802 704–31,091 406–22,856	Stated Choice Experiment
Alberini et al. (2022)	Nepal	50–149	Contingent Valuation
Broberg et al. (2021)	Sweden	49,541–74,311	Contingent Valuation
Carlsson et al. (2021)	Sweden	573–810	Contingent Valuation
Harris (2023)	United States	500–2,510	Revealed Preference

Notes: VoLL estimates were adjusted by first converting to USD using the appropriate average exchange rate in the given reference year at `https://www.exchangerates.org.uk/`, then adjusting for inflation using the All Items in US City Average CPI Series (Seasonally Adjusted) from FRED. Estimates reported in dollar amounts per hour of outage were adjusted using an average hourly electricity consumption of 0.78 kW by households in any given hour. The Contingent Valuation and Stated Choice Experiments reflect stated-preference survey estimates. Production Function methods are macroeconomic models that assume that electricity is an essential input into production. The revealed-preference estimate uses purchases of portable generators.

A.2 Constructing Outage Intensity by Population Weights

Our primary treatment variable aims to capture the intensity at which a zip code was exposed to outage events. We use a measure that captures the residential-person-outage hours in each zip code and month. Figure 3 provides an illustration of our data and methods. We overlay the geospatial data of PG&E's ICA distribution feeders (blue lines) with the Census's Zip Code Tabulation Areas (ZCTAs) (black lines).[35] We then match the PSPS outage events provided at the distribution feeder level to zip code level. This matching is complicated because a feeder can pass through multiple zip codes. For example, the red line highlights an individual distribution feeder that was on an outage. Consequently, for each feeder, we must establish a method to allocate residential-person-outage hours to each zip code it intersects.

Although we know the number of customers affected by an outage on each feeder, we do not know exactly where these customers are located along it. We employ a method from the geography literature that uses machine learning algorithms to project aggregated population measures to high-resolution geospatial data. We use the 2020 WorldPop gridded population dataset to project the population distribution across California on a 500-meter by 500-meter square grid (WorldPop, 2020). WorldPop uses the most granular census population data (i.e., block groups), projects additional land cover topology layers (rivers, elevation, forests, roads, etc.), the geography literature research on where humans live by land use type, and random forest machine learning models to project the census population onto a more granular scale.[36,37]

The gray shaded squares in Figure 3 presents the 500-by-500 meter square grid of population estimates, where each square has a WorldPop cell estimate on population density. We use this data to allocate outage intensity to zip codes as follows. Suppose feeder i passes through $j = 1, 2, ..., N$ WorldPop cells and $z = 1, 2, ..., \overline{Z}$ zip codes. Denote w_j as the population weight of a specific WorldPop cell. Let L_{ijz} denote the length of feeder i in WorldPop cell j in zip code z. For feeder i, we assign the following residential customer weight to zip code z:

$$W_{iz} \;=\; \frac{\sum_{j=1}^{N} w_j \, L_{ijz}}{\sum_{z=1}^{\overline{Z}} \sum_{j=1}^{N} w_j \, L_{ijz}}.$$

[35] We crosswalk postal zip codes in the Go Solar data set to ZCTAs and find that only 0.3 percent of zip codes do not match their corresponding ZCTA counterpart.

[36] More specifically, we use the 2020 unconstrained top-down 1km resolution WorldPop data. These data provide an estimate on the population density as a point every 1,000 meters across California. We project the point-based data into a spatial measure using QGIS's Inverse Distance Weighting (IDW) Interpolation methodology to fill in the gaps between the points in order to assign a population weight to all locations in California. Using IDW Interpolation, population density at any location reflects a weighted average of nearby WorldPop population density points, where the weight is declining in distance. Using this methodology, we are able to establish a 500-meter by 500-meter spatial grid that allocates a population per pixel number to all locations in California.

[37] For additional details, see Sorichetta et al. (2015), Gaughan et al. (2016), and Lloyd et al. (2017).

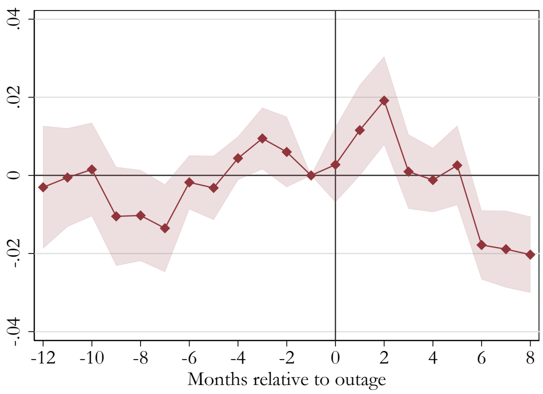
For each feeder i, this method places more weight on zip codes with a higher WorldPop gridded population estimate along cells intersected by the distribution feeder. The weighting method equals 1 when it is summed across all z zip codes a feeder intersects. For each PSPS outage event and zip code in PG&E's territory, the feeder weight is used to allocate the number of residential customers affected and the number of residential-person-outage hours (i.e., residential customers affected times the number of outage hours). We use these measures to capture the intensity of outage event a zip code is exposed to in any given month.[38] Finally, we match this zip-code-based PSPS outage data set to the Go Solar California's (2020) data set that provides information on solar and solar-plus-storage adoption.

A.3 Different Outcomes of Interest

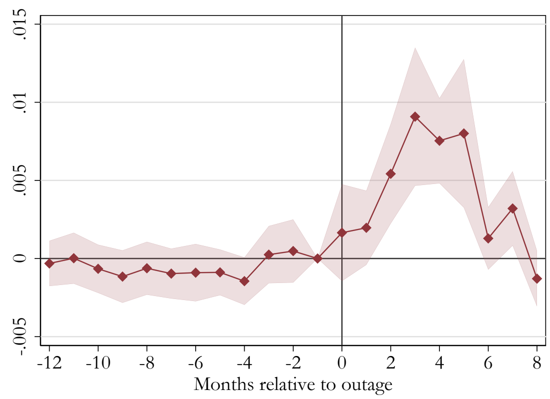
Figure A1 presents estimates from Equation (1) but with different outcome variables: (a) solar capacity from the adoption of solar-only systems, (b) solar capacity from the adoption of solar-plus-storage systems, (c) storage capacity from the adoption of solar-plus-storage systems, and (d) storage capacity added onto existing solar systems. Although solar is much more prevalent than storage (as seen by the capacity in watts), evidence is limited of a distinct systematic increase in solar-only adoption in zip codes that experience outage events. The point estimates in the regression of storage add-on capacity are noisier after the outages, with a statistically significant positive coefficient six months after an outage event.

[38] We also employ weighting methods that allocate customers along a feeder based on the percentage of a feeder's line length in each zip code it intersects. This assumes a uniform distribution of customers along a feeder. Our results are robust to this alternative specification, as shown in Table A3.

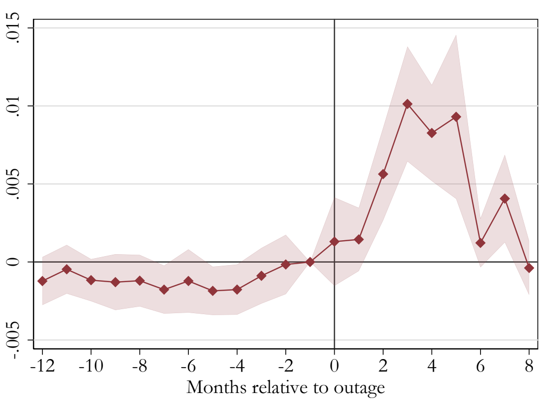
Figure A1: Impact of Outage Intensity on Solar and Storage Capacity (Watts)



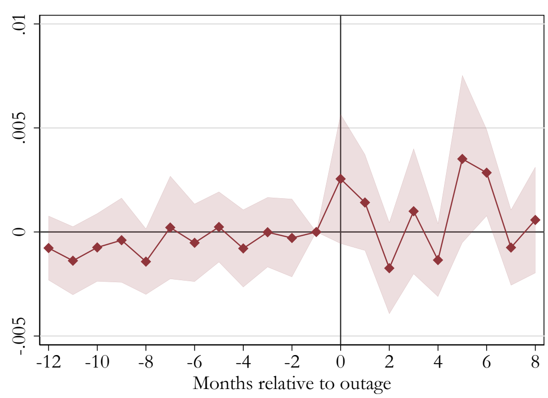
(a) Solar Capacity (When Solar Only)



(b) Solar Capacity (When both Solar & Storage)



(c) Storage Capacity (Both Solar & Storage)



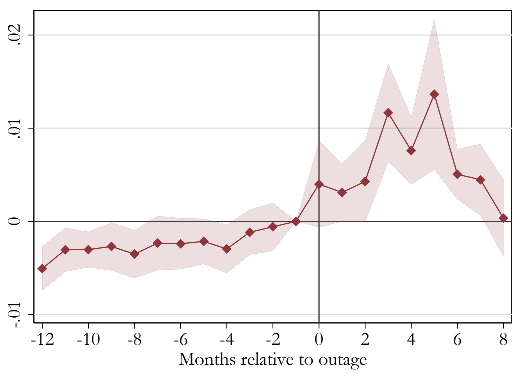
(d) Storage Capacity (Storage Add-On)

Notes. The dependent variables reflect watts of installed capacity for (a) solar capacity on solar-only systems, (b) solar capacity on solar-plus-storage systems, (c) storage capacity on solar-plus-storage systems, and (d) storage capacity added onto existing solar systems. The coefficients are reported in the solid lines and are the estimates of β from our specification in (1) with quadratic zip-code-specific time trends. The shaded region reflects the 95 percent confidence intervals.

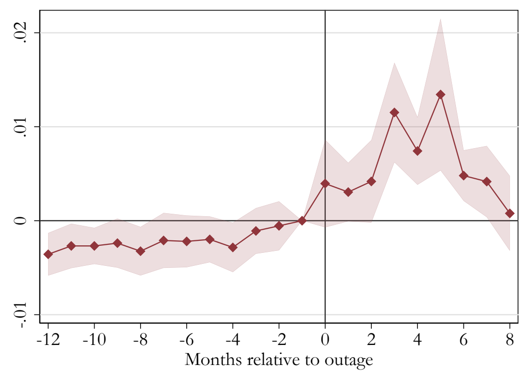
A.4 Robustness of Event Study to Different Time Trends

Figure A2 presents the results of our specification in (1) with (a) no trend, (b) a linear trend, and (c) a quadratic zip-code-specific time trends. In each case, the distinct positive and statistically significant posttreatment effect persists. As we remove the flexible zip-code-specific trend, we observe a small pretreatment trend 8–12 months prior to the treatment. However, this effect is small in magnitude.

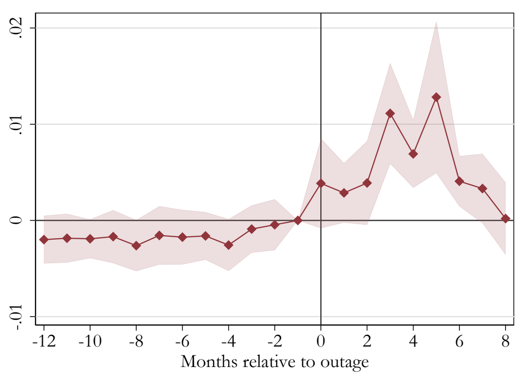
Figure A2: Impact of Outage Intensity on Storage Capacity (Watts)—Zip Code Time Trend



(a) No Zip Code Time Trend



(b) Linear Zip Code Time Trend



(c) Quadratic Zip Code Time Trend

Notes. The dependent variables reflect watts of installed storage capacity. The coefficients are reported in the solid lines and are the estimates of β from our specification in (1) with (a) no trend, (b) a linear trend, and (c) a quadratic zip-code-specific time trends. The shaded region reflects the 95 percent confidence intervals.

A.5 Heterogeneity by Different Subsamples

In the main paper, we examined subsamples by a zip code's median income. In Figure A3, we present results broken out by an Environmental Justice Index. We use California OEHHA's (2018) CalEnviroScreen 3.0 EJ metric that is calculated using 20 socioeconomic, demographic, health, and environmental indicators grouped into two categories: (1) pollution burden and (2) population characteristics.[39,40] The EJ measure ranges from 0 to 100, where a higher number reflects a more disadvantaged community. Despite a statistically significant effect at various quartiles of the Environmental Justice metric distribution, Figure A3 illustrates that the treatment effect of PSPS outage events is largest in zip codes with the lowest EJ concern (i.e., lowest CES scores). Table A2 presents the coefficient estimates for the main specification in equation (1), the results by income quartile shown in Figure 5, and the results for the CES EJ measure in Figure A3.

Table A2: Event Study Regression Main Results and Heterogeneous Treatment Effects

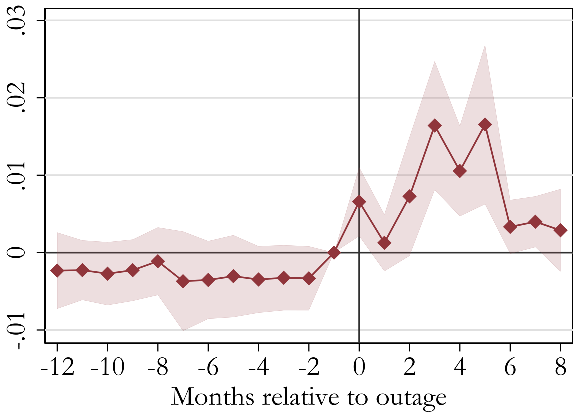
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Full	Income Quartiles				CalEnviroScreen Quartiles			
	Sample	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Month ≤ -12	-0.0020	-0.0019*	-0.0006	-0.0011	-0.0090**	-0.0024	-0.0024	-0.0022	-0.0011
	(0.0013)	(0.0010)	(0.0015)	(0.0021)	(0.0043)	(0.0026)	(0.0025)	(0.0015)	(0.0013)
Month -7 to -11	-0.0019	-0.0016	-0.0008	-0.0011	-0.0078**	-0.0024	-0.0021	-0.0021	-0.0006
	(0.0012)	(0.0015)	(0.0015)	(0.0020)	(0.0035)	(0.0021)	(0.0023)	(0.0018)	(0.0013)
Month -2 to -6	-0.0015	-0.0005	-0.0005	-0.0009	-0.0074*	-0.0034	-0.0009	-0.0017	0.0007
	(0.0011)	(0.0007)	(0.0011)	(0.0016)	(0.0044)	(0.0021)	(0.0022)	(0.0010)	(0.0008)
Month 0 to 2	0.0035**	0.0014	0.0015	0.0044	0.0043	0.0050**	0.0030	0.0014	0.0018*
	(0.0018)	(0.0014)	(0.0015)	(0.0031)	(0.0047)	(0.0020)	(0.0039)	(0.0019)	(0.0011)
Month 3 to 5	0.0102***	0.0034***	0.0034*	0.0111***	0.0244***	0.0145***	0.0091*	0.0046***	0.0076***
	(0.0025)	(0.0009)	(0.0019)	(0.0042)	(0.0068)	(0.0032)	(0.0050)	(0.0016)	(0.0022)
Month ≥ 6	0.0025*	0.0002	0.0022	0.0033	0.0046	0.0034**	0.0025	0.0008	0.0026
	(0.0014)	(0.0014)	(0.0015)	(0.0025)	(0.0042)	(0.0016)	(0.0033)	(0.0014)	(0.0025)
Observations	68,094	16,692	16,614	16,692	16,614	17,004	17,004	17,004	17,004
R^2	0.4927	0.2877	0.3043	0.5152	0.5229	0.5376	0.4990	0.4257	0.3751
F-Stat	12.41***	10.44***	2.90*	8.79***	6.04***	6.62***	7.13***	6.04**	56.90***

Notes: Models presented are estimates of Equation (1) with quadratic zip-code-specific time trends. We bin the individual event month indicator variables, $1(t - T_z^* = k)$, into 6 groups: (i) $k \leq -12$, (ii) $-11 \leq k \leq -7$, (iii) $-6 \leq k \leq -2$, (iv) $0 \leq k \leq 2$, (v) $3 \leq k \leq 5$, and (iv) $k \geq 6$. We bin the treatment effects 6 months and after into a final group because this indicator variables coincide with the start of the Covid-19 pandemic for the largest PSPS outage events in September and October 2019. This partitioning allows us to clearly separate out the likely confounding effects of the pandemic on storage adoption. Column (1) reflects the binned coefficient estimates of the full sample. Columns (2)–(5) and (6)–(9) are the binned coefficient estimates on subsamples broken down by income and CalEnviroScreen (CES) quartiles, respectively. Cluster robust standard errors at the zip code are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

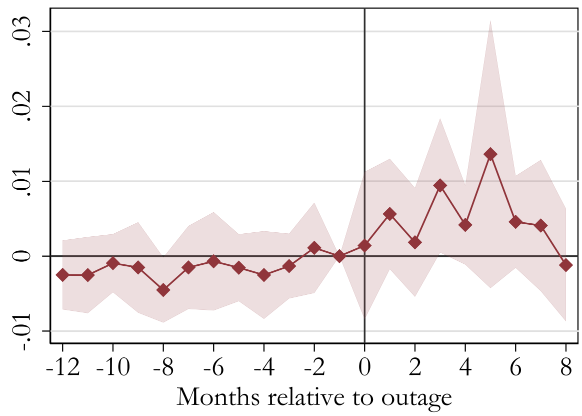
[39]The pollution burden measures exposure to ozone, $PM_{2.5}$, diesel PM emissions, drinking water contamination, pesticides, toxic releases, traffic density, cleanup sites, groundwater threats, hazardous waste, impaired water bodies, and solid waste sites. The population characteristics measure educational attainment, housing burden, linguistic isolation, poverty, unemployment, asthma emergency room visits, cardiovascular disease emergency room visits, and percent low-birthweight births (California OEHHA, 2018).

[40]We use the US census's crosswalk data file to crosswalk the CalEnviroScreen census tract-level data to the zip code level based on population weighting.

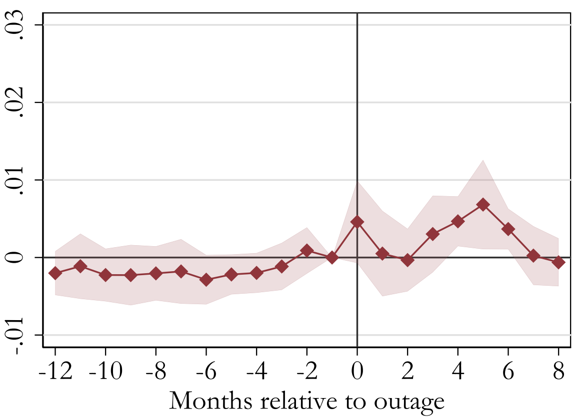
Figure A3: Impact of Outage Intensity on Storage Capacity by CalEnviroScreen Quartiles



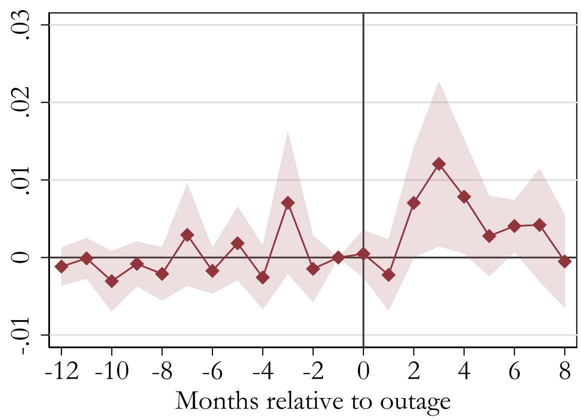
(a) First CalEnviroScreen Quartile



(b) Second CalEnviroScreen Quartile



(c) Third CalEnviroScreen Quartile



(d) Fourth CalEnviroScreen Quartile

Notes. The dependent variables reflect watts of installed storage capacity. The coefficients are reported in the solid lines and are the estimates of β from our specification in (1) with quadratic zip-code-specific time trends, and the sample is separated by CalEnviroScreen quartiles. The shaded region reflects the 95 percent confidence intervals. We use California OEHHA's (2018) CalEnviroScreen 3.0 environmental justice metric.

A.6 Additional Robustness Specifications

Table A3 presents several additional model specifications. For comparison purposes, column (1) provides the results from our main specification over the full sample. Column (2) considers the results of our analysis when we compare zip codes that were first and only subject to PSPS outage events in October 2019 (reflecting 76 percent of treated zip codes) to never-treated zip codes. This comparison focuses on the most intensely treated zip codes and does not have variation in treatment timing.

Table A3: Event Study Regression Robustness Results

	(1) Main	(2) Oct. 2019 Only	(3) Length Weights	(4) Outage Dummy
Month $\leq$ -12	-0.0020	-0.0024	-0.0021	-227.09
	(0.0013)	(0.0024)	(0.0013)	(280.65)
Month -7 to - 11	-0.0019	-0.0020	-0.0019	-276.53
	(0.0012)	(0.0020)	(0.0012)	(274.26)
Month -2 to -6	-0.0015	-0.0024	-0.0015	-313.48
	(0.0011)	(0.0022)	(0.0011)	(271.34)
Month 0 to 2	0.0035**	0.0057**	0.0035**	408.60
	(0.0018)	(0.0029)	(0.0018)	(288.57)
Month 3 to 5	0.0102***	0.0168***	0.0102***	1,615.33***
	(0.0025)	(0.0044)	(0.0025)	(350.45)
Month $\geq$ 6	0.0025*	0.0037	0.0026*	452.22
	(0.0014)	(0.0029)	(0.0015)	(308.10)
Observations	68,094	58,032	68,094	68,094
R^2	0.4927	0.4886	0.4920	0.4830
F-Stat	12.41***	5.70***	11.45***	5.68***

Notes: Models presented are estimates of equation (1) with quadratic zip-code-specific time trends. We bin the individual event month indicator variables, $1(t - T_z^* = k)$, into six groups: (i) $k \leq -12$, (ii) $-11 \leq k \leq -7$, (iii) $-6 \leq k \leq -2$, (iv) $0 \leq k \leq 2$, (v) $3 \leq k \leq 5$, and (iv) $k \geq 6$. Column (1) reflects the binned coefficient estimates of the full sample. Column (2) reflects the results for the zip codes that were first and only treated in October 2019 compared to never-treated zip codes. Column (3) reflects the setting where outages at the distribution feeder level were allocated to zip codes based on the percentage of line length. Column (4) reflects the setting where the continuous Outage Intensity treatment variable is replaced by an indicator variable. Clustered robust standard errors at the zip code are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Column (2) demonstrates that our key conclusions hold, with a positive and statistically significant effect of the outage intensity measure on battery storage adoption in months 0–5 after the October 2019 PSPS events. These effects are larger than those identified in Column (1). There are no pretreatment trends. Our model predicts that this PSPS outage event increased storage capacity investment in the zip codes exposed only to the October 2019 PSPS outage events by an additional 106 percent compared to the setting where the October 2019 PSPS outage events did not occur. These results suggest that the October 2019 outage events and the affected zip codes were a key source for our estimated outage-driven storage investments using the full sample.

Column (3) presents the results of our main specification when we use feeder-length-based weighting to allocate distribution feeder-level outage data to zip codes rather than our WorldPop weighting method. This approach assumes a uniform distribution of customers along a feeder. Despite this simple approach, the results are closely related to those that arise using our population-weighting estimates.

Column (4) presents the results of our analysis when we define our treatment variable to be an indicator that equals 1 when a zip code has been exposed to a PSPS event. This specification reflects a standard difference-in-difference (DID) with a discrete treatment variable. We continue to find a positive and statistically significant treatment effect 3–5 months after the PSPS events, and no evidence of pretreatment trends. We use the coefficient estimates to predict the amount of storage capacity that was installed using the specification in Column (4). We compare this level to the amount of storage capacity that would have been installed in treated zip codes absent the outage events. Our model predicts that storage capacity in treated zip codes increased by approximately 55 percent as the result of PSPS outage events. We prefer our continuous treatment variable that reflects residential customer-outage-hours because it captures the considerable heterogeneity in the intensity of outage events over our sample.

A.7 Staggered DID

We revisit concerns that arise because our analysis has variation in treatment timing (see Table 1). Goodman-Bacon (2021) demonstrates that the staggered DID estimate is equivalent to the weighted average of all possible two-by-two DID estimators. Unless potentially strong assumptions are imposed on the nature of the treatment effects, it has been shown that this approach can lead the DID regression model to be misspecified and fail to identify the average effect of the treatment on the treated. In essence, this arises because already-treated units act as controls for groups treated later in the sample (Baker et al., 2022).

Importantly, we demonstrate in Table A3 column (2) that our key conclusions are robust when we compare zip codes that were first and only treated in October 2019 (76 percent of zip codes) to never-treated zip codes. This comparison is not subject to the key critiques that arise as a result of staggered treatment timing.

To understand the potential implication of the concerns raised in the literature on our main specification, we use the diagnostic tests developed by Goodman-Bacon (2021). This method isolates the DID estimate and weights for the two-by-two DID that uses already-treated zip codes as a control group for zip codes treated later in the sample. We demonstrate that the possible biases associated with using an already-treated zip code as a control group are minimal in our setting. This likely arises because the majority of treated zip codes in our sample (76 percent) receive their first and only treatment in October 2019. Furthermore, the October 2019 outage events were the largest in magnitude and duration.

Goodman-Bacon's (2021) decomposition method focuses on the standard two-way fixed effects DID absent covariates, which can be represented by augmenting equation (1) as follows:

$$\text{Storage Capacity}_{zt} = \gamma_z + \delta_t + \beta D_{zt} + \varepsilon_{zt} \tag{A.1}$$

where D_{zt} is the zero-one treatment variable that equals 1 if a zip code z has ever experienced a PSPS outage and 0 otherwise. Although this does not reflect our fully dynamic event-study framework with flexible zip-code-specific time trends and a continuous treatment variable, we believe that the Goodman-Bacon decomposition approach is informative of the performance of our analysis and which two-by-two DID estimators are driving our primary findings. Furthermore, as shown in Column (4) in Table A3, our conclusions are robust to the use of a discrete DID specification. Goodman-Bacon (2021) decomposes the staggered DID estimate into three groups: (i) never treated, (ii) early treated (e.g., October 2018), and (iii) late treated (e.g., October 2019).

Figure A4 provides the results of the Goodman-Bacon decomposition using the specification in (A.1). The weights for each two-by-two DID comparison are provided on the x-axis, and each DID estimate is provided on the y-axis. The red line represents the overall DID estimator.

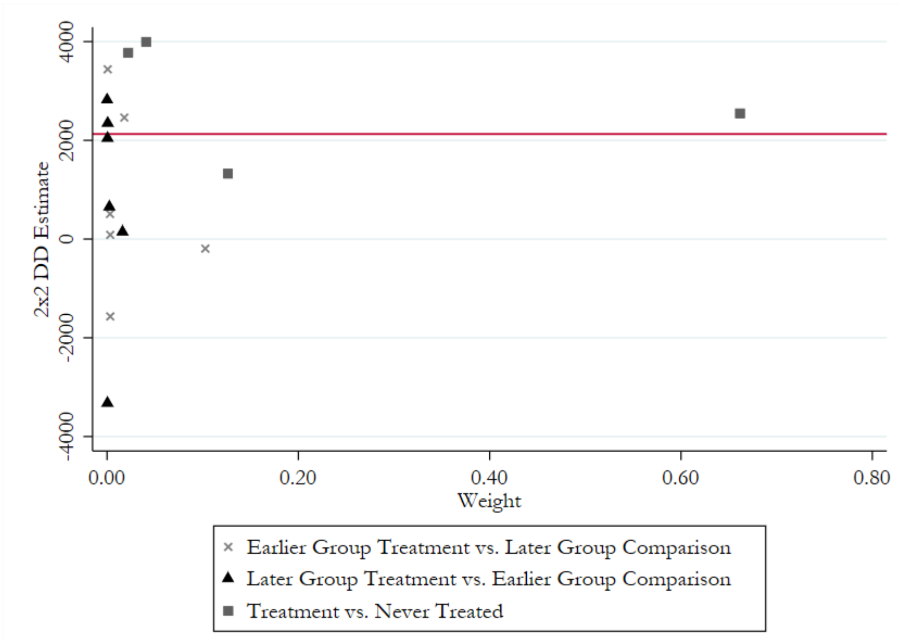
Figure A4 demonstrates a two-by-two DID comparison between a treated and never-treated group that receives considerable weight in the identification of the overall DID estimate. This group reflects the October 2019 treated group compared to the never-treated zip codes. This is consistent with the fact that the majority of the treated zip codes in our sample (76 percent) were first (and only) treated in this month. Furthermore, these figures demonstrate that despite variability in the size of the DID estimate, the treated versus never-treated comparisons are all positive, as are their weights.

As documented by Goodman-Bacon (2021), the two-by-two estimators that can generate biased results are the ones that compare the later-treated to the earlier-treated group (represented by the triangles). Figure A4 demonstrates that these two-by-two DID estimates receive limited weight in the overall DID estimator. This helps defend our analysis against the concerns over bias in two-way fixed effects DID under heterogeneous treatment effects.

Table A4 provides detailed results of Goodman-Bacon decomposition. We present the average DID estimates across each group and their relative weights to clearly quantify how these two-by-two DID estimates contribute to the overall DID estimator. Table A4 demonstrates that the key driver of the overall DID estimator is the comparison of the treated and never treated. The comparison of concern, later versus earlier treated, receives only 2 percent of the weight of our DID estimator. This raises our confidence that the possible biases documented by the econometrics literature is not a key driver of our results.

We follow Goodman-Bacon (2021) and use the Decomposition Theorem to manually adjust the DID estimator by subtracting the components of the DID estimator that introduce the bias (i.e., subtract the later versus early treated comparisons). These results are presented in the Adjusted DID Estimate column in Table A4 and further illustrate that these two-by-two DID comparisons have a limited effect on our overall DID estimate.

Figure A4: Goodman-Bacon Decomposition—Discrete Two-Way Fixed Effects DID



Notes. This figure implements Goodman-Bacon's (2021) Decomposition Theorem for the two-way fixed effects DID specification in Equation (A.1). The x-axis provides the weights placed on each two-by-two DID estimator, and the y-axis provides the corresponding DID coefficient estimate.

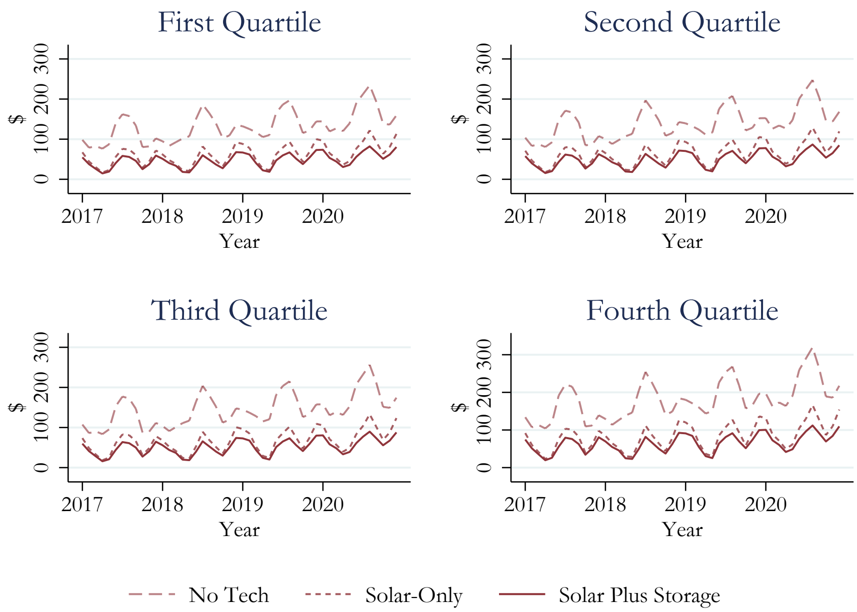
Table A4: Goodman-Bacon Decomposition—DID Estimates and Weights

	Overall DID	Average DID			
		Treated vs Never Treated	Earlier Treated vs. Later Treated	Later Treated vs. Earlier Treated	Adjusted DID Estimate
Storage Capacity	2,127.85	2,470.06	176.21	268.29	2,122.40
Weights		0.85	0.13	0.02	

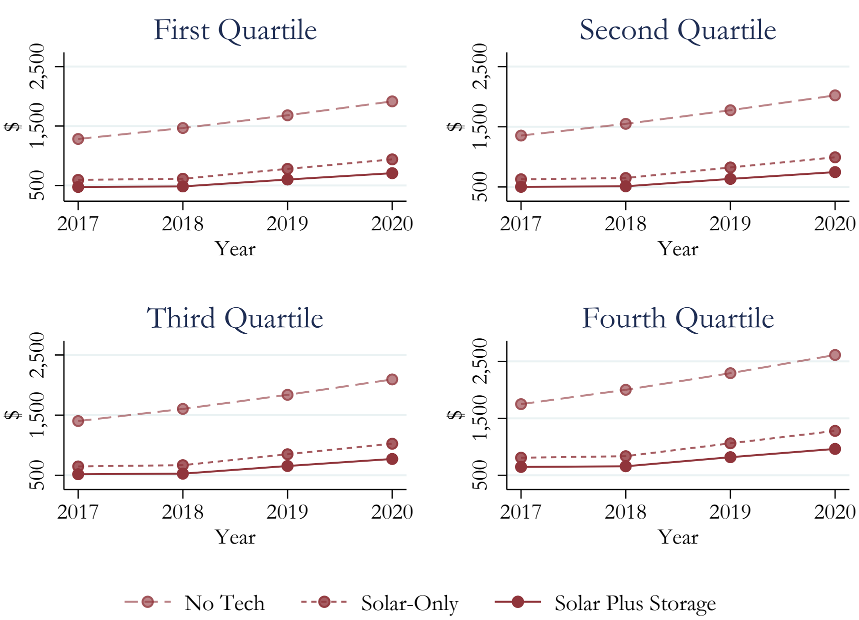
A.8 Discrete Choice Model Data Inputs and Results

A.8.1 Representative Consumer Figures

Figure A5: Average Monthly and Annual Electricity Bills by Technology and Income Quartile

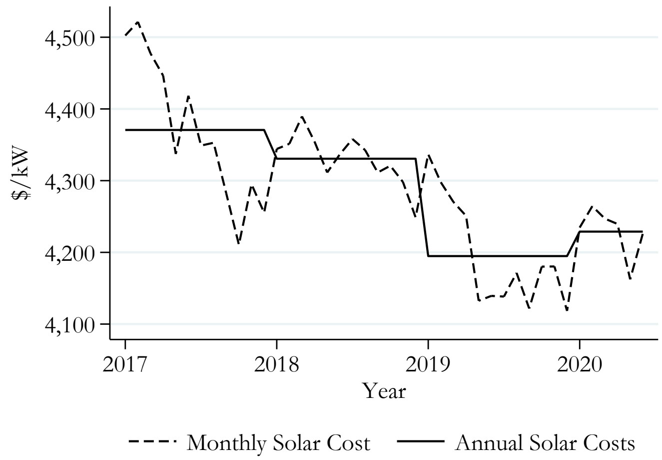


(a) Average Monthly Bill

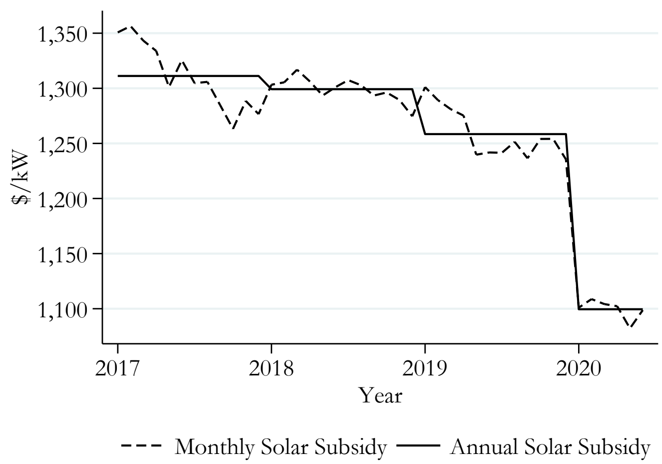


(b) Average Annual Bill

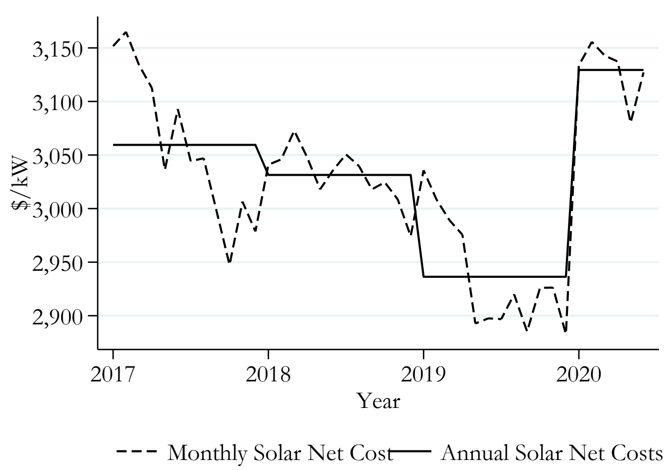
Figure A6: Residential Rooftop Solar Average Cost, ITC Subsidy, and Net Costs Per KW



(a) Solar Costs

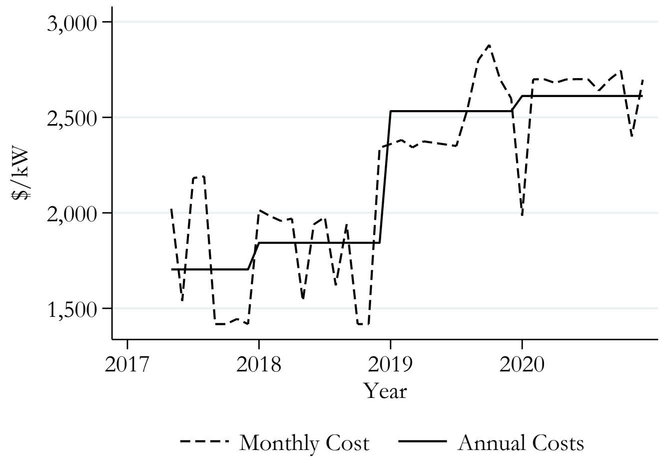


(b) Solar ITC Subsidy

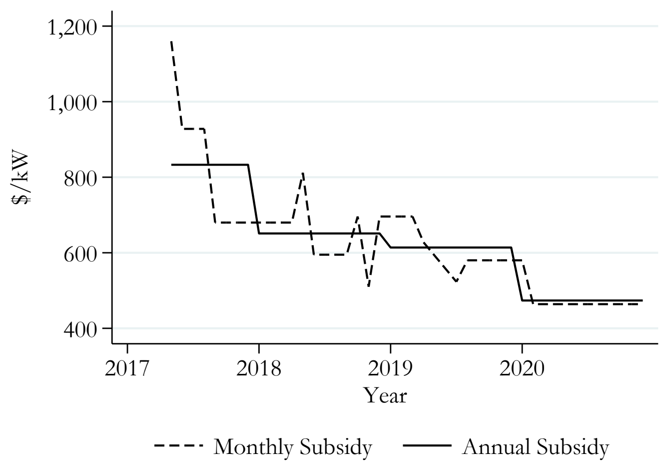


(c) Solar Net Costs

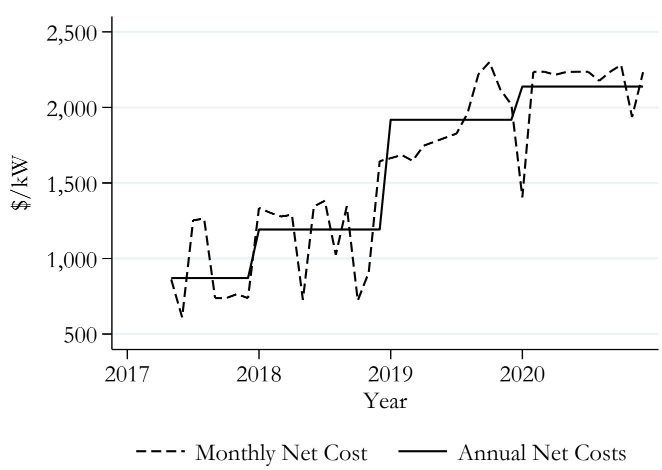
Figure A7: Residential Battery Storage Average Cost, Subsidy, and Net Costs for Per KW



(a) Storage Costs

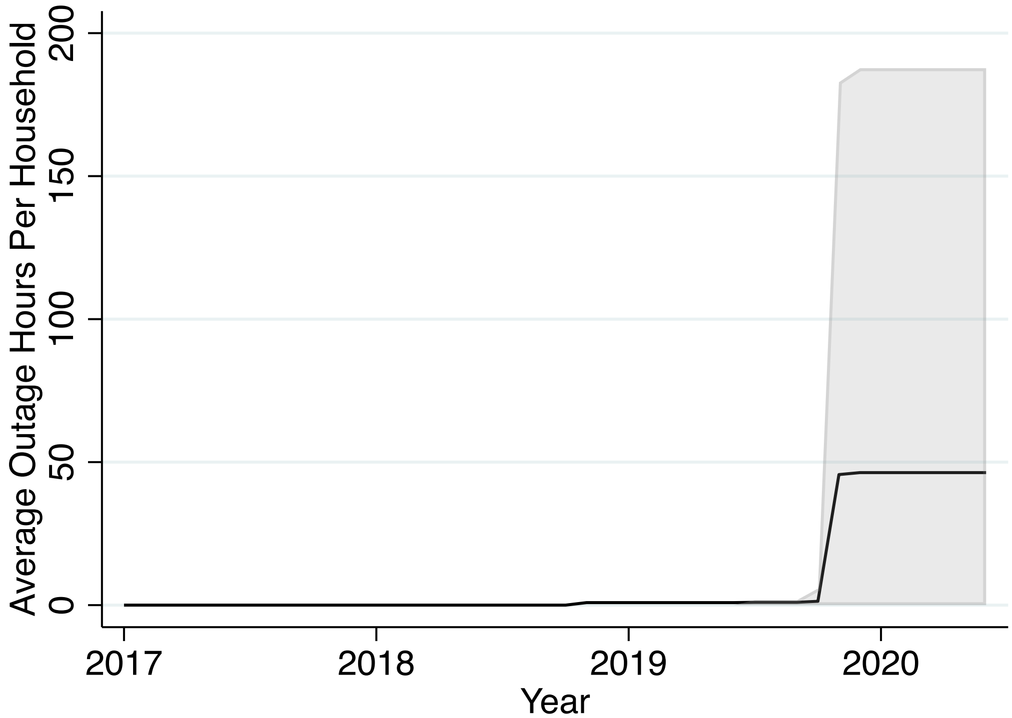


(b) Storage SGIP Subsidy



(c) Storage Net Costs

Figure A8: Outage Hours Per Household



Notes. The solid line represents the average outage hours per household across all zip codes at the monthly level. The gray shaded area contains the 5th and 95th percentile of the distribution.

A.8.2 Parameter Estimates in the Dynamic Model

In the main paper, Table 3 shows estimates for our main parameter of interest, the VoLL, φ. Table A5 provides the estimates of all parameters θ estimated in the discrete choice model.

First, we discuss the first five parameters in Table A5, $\theta_{2^{nd}} = \{\varphi, \gamma_2, \gamma_3, \gamma_{1\to 2}, \gamma_{1\to 3}\}$, the second-stage structural parameters found in the flow utility (Equation 2). These are estimated by maximizing the partial likelihood function, Equation (6), with standard errors from the full likelihood function, equation (8).

The VoLL, φ, as described in the main text, gives households the benefit of averting outages from \$2,477/MWh to \$5,239/MWh. In addition to this parameter, we estimate that owning a solar panel gives households a warm-glow benefit, γ_2, of roughly \$600 per year, and owning a solar-plus-storage panel gives households a benefit, γ_3, of roughly \$1,000 a year. Switching from no system to a solar system provides households with a one-time unobserved benefit, $\gamma_{1\to 2}$, of roughly \$1,500-3,000, and switching to a solar-plus-storage system results in a one-time unobserved benefit of \$2,700-8,800. These unobserved shocks could also be driven by measurement error in the cost to install a system; if we over predict the cost to adopt, the model will compensate by allowing a positive benefit from adoption. The VoLL is identified through observing adoption decisions made under variation in experienced outages. The other parameters are identified through observing adoption decisions under variation in the up-front costs over time and annual bills over time and space.

Second, we discuss the remaining parameters, $\theta_{1^{st}} = \{\alpha_{0,s}, \alpha_{1,s}, \sigma_s\}$, the first-stage parameters those of the state transition matrices, for each state variable. These are estimates of Equation 4 and estimated from maximizing the likelihood function 5 with standard errors from the full likelihood (8). The time series of these variables are found in Figures A5 and A6.

In estimating the transitions, we found that using data from the full sample, not the quartile-specific data alone, resulted in estimates that better fit the data. In the case of the annual bill without technology, c_1, the positive coefficient on the drift parameter α_{1,c_1} suggests expectations that it will increase over time. This is the same for the annual bill with solar α_{1,c_2} and the annual bill with a solar-plus-storage system, α_{1,c_3}, though solar-plus-storage has much more uncertainty in the size of the shock, σ_{c_3}. The cost of installation of solar, C_2, is expected to decrease over time, with a coefficient less than 1, α_{1,C_2}, but with large uncertainty, σ_{C_2}. The cost of installation of solar-plus-storage, C_3, is expected to increase over time, with a positive drift α_{1,C_3}, but with even more uncertainty, σ_{C_3}. Outages are also expected to decrease over time with a coefficient $\alpha_{1,Outage}$ less than one.

A.8.3 Model Fit

Table A6 compares the actual adoptions to the model-predicted adoptions. Although a Chi-squared goodness-of-fit test suggests only the fourth quartile replicates the actual decisions, we nonetheless think the model performs remarkably well. We are able to predict the adoptions with an error of just a couple thousand across over 100 million month-household decisions.

Table A5: All Parameter Estimates in the Dynamic Discrete Choice Model

	Income Quartile Subsample			
	First	Second	Third	Fourth
φ_{VoLL} (\$/MWh)	2,476	4,301	5,151	5,239
	(75)	(125)	(161)	(75)
γ_2	693.17	778.89	675.48	942.33
	(0.6)	(2.35)	(0.64)	(5.29)
γ_3	966.29	839.89	1,089.42	270.43
	(6.86)	(8.07)	(3.41)	(1.05)
$\gamma_{1\to2}$	1,703.29	1,496.81	2,557	2,721.19
	(5.72)	(15.27)	(1.92)	(37.23)
$\gamma_{1\to3}$	2,762.66	4,527.02	3,305.43	8,876.85
	(29.24)	(31.66)	(15.65)	(36.19)
$\alpha_{0,c1}$	0.01	0.01	0.01	0.01
	(0.001)	(0.001)	(0.001)	(0.001)
$\alpha_{1,c1}$	1.13	1.13	1.13	1.13
	(0.0003)	(0.0003)	(0.0003)	(0)
σ_{c1}	4.48	4.48	4.48	4.48
	(0.07)	(0.07)	(0.06)	(0.07)
α_{0,c_2}	-0.14	-0.14	-0.14	-0.14
	(0.006)	(0.008)	(0.005)	(0.003)
$\alpha_{1,c2}$	1.38	1.38	1.38	1.38
	(0.009)	(0.011)	(0.007)	(0.004)
σ_{c2}	57.24	57.24	57.24	57.24
	(0.8)	(0.8)	(0.8)	(0.8)
α_{0,c_3}	-0.11	-0.11	-0.11	-0.11
	(0.006)	(0.011)	(0.005)	(0.002)
$\alpha_{1,c3}$	1.35	1.35	1.35	1.35
	(0.011)	(0.02)	(0.009)	(0.005)
σ_{c3}	43.58	43.58	43.58	43.58
	(0.61)	(0.61)	(0.61)	(0.61)
$\alpha_{0,C2}$	0.28	0.28	0.28	0.28
	(0.01)	(0.02)	(0.01)	(0.01)
$\alpha_{1,C2}$	0.97	0.97	0.97	0.97
	(0)	(0)	(0.001)	(0.002)
σ_{C2}	278.67	278.67	278.67	278.67
	(3.82)	(3.94)	(3.53)	(3.57)
$\alpha_{0,C3}$	0.18	0.18	0.18	0.18
	(0.01)	(0.02)	(0.01)	(0.01)
$\alpha_{1,C3}$	1.08	1.08	1.08	1.08
	(0)	(0)	(0.001)	(0.001)
σ_{C3}	290.24	290.24	290.24	290.24
	(3.92)	(4.19)	(3.5)	(3.65)
$\alpha_{0,Outage}$	11.76	11.76	11.76	11.76
	(0.16)	(0.3)	(0.19)	(0.04)
$\alpha_{1,Outage}$	0.92	0.92	0.92	0.92
	(0.01)	(0.03)	(0.016)	(0.001)
σ_{Outage}	34.63	34.63	34.63	34.63
	(0.24)	(0.25)	(0.09)	(0.14)

Note: This table is an extension of Table 3 from the main text, presenting all (first- and second-stage) estimates from the dynamic discrete choice model. In parentheses are standard errors from the square root of the diagonal of the inverse Hessian matrix of the full log-likelihood function.

Table A6: Actual Versus Model-Predicted Decisions, Household-Month Counts

	Income Quartile Subsample			
	First	Second	Third	Fourth
Actual				
No adoptions	10,379,370	21,716,372	30,745,649	40,154,522
Solar-only adoptions	23,419	43,872	67,379	70,671
Solar-plus-storage adoptions	419	1,051	2,465	3,775
Predictions from main specification				
No adoptions	10,379,884	21,717,042	30,748,677	40,154,345
Solar-only adoptions	22,940	43,684	66,139	70,776
Solar-plus-storage adoptions	384	569	677	3,847
χ^2 p-value	0	0	0	0.47

Note: Actual compared to predicted adoptions by zip code quartile of income using the assumptions in the main specification. The first panel contains the actual adoptions, the second panel contains the adoptions predicted from the model.

A.8.4 Structural Model Robustness

We consider alternative assumptions to determine the annual representative consumption profile and solar and storage capacities.

A.8.4.1 Alternative Representative Consumer Approach: Uniform Bills

Our main analysis scales PG&E's representative hourly residential consumption profile to consider income-quartile-specific consumption profiles. Borenstein et al. (2022) reports annual electricity consumption values by income for PG&E in 2019. As detailed in Section 5.3, we use these numbers to scale the representative hourly load profile to the achieve the annual consumption levels for each income quartile in their analysis. We scale the solar systems to achieve an average annual solar output to consumption ratio of 60 percent for each income quartile reflecting values observed in practice. Finally, we adjust the storage systems to reflect ratios of solar-to-storage capacity observed in the data.

As an alternative approach, we take the observed mean solar and storage systems sizes in the data and scale the representative consumption profile uniformly across each income quartile. The average solar system in the data is 6.06 KWs, and the average battery system has an energy capacity equal to 6.61 KWs.[41] For electricity use, we continue to use PG&E's 2017–2020 representative hourly residential load profile (Pacific Gas & Electric, 2021b). This provides us with the demand profile shape of a typical residential customer throughout the day and year. We scale up the demand profile by a constant each hour to ensure the representative solar PV system (with capacity 6.06 kWs) yields an average annual output-to-consumption ratio of 60 percent, consistent with solar PV system sizing that is observed in PG&E (Darghouth et al., 2011; Borenstein, 2017).[42]

All other features of the data inputs including the retail tariff, solar irradiance to calculate hourly solar output, and battery operational decisions and efficiency characteristics remain unchanged. The representative customer's hourly electricity bill is aggregated to represent an annual electricity bill. How the electricity bill changes as the households adopt solar-only and solar-plus-storage, relative to the baseline with no technology, parallel those in the main analysis. We find that the addition of rooftop solar reduces the electricity bill by approximately 54 percent on average. A solar-plus-storage system reduces the electricity bill by 64 percent on average. The minimal changes in the electricity bill from the main analysis arise because both scale the analyses to have solar systems with an average annual output-to-consumption ratio of 60 percent. Furthermore, the

[41] We consider a battery system with a rated power capacity that equals two times the energy capacity (i.e., we consider a 13.22 kWh/6.61 kW battery system). This is close to the residential battery specifications in practice (e.g., Tesla's Powerwall is a 14 kWh/7 kW system Tesla, 2019). Furthermore, when both the kWh and kW rating of the battery system are reported in our data, the kWh rating is systematically 2 times the kW rating of the residential battery systems.

[42] If we do not scale up PG&E's representative load profile, the estimated solar output exceeds annual consumption. This is inconsistent with observed solar sizing in practice. This result is likely because solar PV adopters consume more electricity on average than the typical residential customer which includes renters and owners and all housing types, such as apartments, condos, single-family homes.

battery systems in our main analysis are scaled to reflect the observed solar-to-storage capacity ratios observed in practice. Consequently, although the solar and battery systems differ in scale, they are similar in terms of their proportion to the representative load profiles.

Table A7 reports the VoLL estimates under these alternative assumptions. The VoLL ranges from \$3,662/MWh to \$7,055/MWh, with a mean value of \$5,632. With these estimates, the damages to residential electricity consumers from the wildfire prevention outages would total to \$459 million. The degree of spread across the estimates by quartiles is larger, but the spread is also more likely to be over-estimated. To back out the VoLL, we make an assumption on the kW of electricity a household uses per hour, that all households consume the representative load. However, high-income households will consume more and low-income households less than average, and so this version compensates with a larger range of estimates than our main specification, which allows for differences in load across quartiles.[43]

Table A7: Value of Lost Load: Alternative Representative Consumer Approach of Uniform Bills

	Income Quartile Subsample				Average
	First	Second	Third	Fourth	
φ_{VoLL} (\$/MWh)	3,662	5,145	6,666	7,055	5,632
	(299)	(160)	(106)	(55)	(180)

Note: Value of Lost Load (\$/MWh) is the estimated φ in the dynamic discrete choice model. In parentheses are standard errors calculated from the Hessian matrix of the full log-likelihood function. The other estimated parameters from the discrete choice model are found in Table A5. The final column shows the average across the four income quartiles with a standard error calculated from the average of the variances.

A.8.4.2 Alternative Outage Expectations

The estimation requires an assumption on what households expect future outages to look like. In our main specification, we are assuming that households with outages expect outages will progress as they have in the past following a stochastic AR(1) process. In an alternative case, we show the estimates when outages are assumed to remain the same as the current outage state (i.e., in the month of decision, the outages they had in the last 12 months dictate future outages with certainty). In this case, the transition matrix is simply an identity matrix of ones on the diagonal, zeros elsewhere. The estimates (Table A10) and fit (Table A6) is similar to our main specification with stochastic outages.

[43] Dividing a larger use of kWh from the high-income quartile's WTP would lower its estimated VoLL and dividing a lower use of kWh in the low-income quartile would raise its estimated VoLL.

Table A8: Actual Versus Model-Predicted Decisions: Assuming Uniform Bills

	Income Quartile Subsample			
	First	Second	Third	Fourth
Actual				
No adoptions	11,749,415	20,999,891	29,737,868	40,224,637
Solar-only adoptions	26,209	43,830	65,723	69,365
Solar-plus-storage adoptions	407	1,052	2,430	3,813
Predicted assuming uniform bills				
No adoptions	11,749,026	21,000,011	29,737,101	40,206,731
Solar-only adoptions	26,335	43,767	67,037	90,445
Solar-plus-storage adoptions	670	995	1,883	639
χ^2 p-value	0	0.2	0	0

Note: Actual compared to predicted adoptions by zip code quartile of income. The first panel contains the actual adoptions, the second panel contains the adoptions predicted from the model.

We also examine the case in which households expect no outages in the future. Regardless of current outages, households expect next period's outages to be zero with certainty. In this case, even with an estimate of VoLL that is much larger, we observe little adoption of batteries, differing from the actual decisions. This extreme case highlights the need to include electricity reliability when justifying the costly expenditure of residential battery storage today.

Table A9: Value of Lost Load: Alternative Assumptions on Expectations

	Income Quartile Subsample				Average
	First	Second	Third	Fourth	
Outages expected to remain same, with certainty					
φ_{VoLL}	1,731	3,404	6,385	6,728	4,562
	(75)	(125)	(161)	(75)	(115)
Zero outages expected in future					
φ_{VoLL}	18,366	7,046	17,292	42,757	21,365
	(390)	(436)	(160)	(59)	(305)

Note: Estimates under different assumptions for expectations: that outages remain the same in the future or revert to zero in the future. When households have no expectation of future outages, then the WTP to avoid the current period's outages are large, but as show in Table A10, still unable to replicate the data.

Table A10: Actual Versus Predicted: Alternative Assumptions on Expectations

	Income Quartile Subsample			
	First	Second	Third	Fourth
Actual				
No adoptions	10,379,370	21,716,372	30,745,649	40,154,522
Solar-only adoptions	23,419	43,872	67,379	70,671
Solar-plus-storage adoptions	419	1,051	2,465	3,775
Outages expected to remain same, with certainty				
No adoptions	10,379,512	21,717,010	30,748,657	40,154,447
Solar-only adoptions	23,170	43,367	66,554	70,695
Solar-plus-storage adoptions	526	918	282	3,826
χ^2 p-value	0.00	0.00	0	0.71
Zero outages expected in future				
No adoptions	10,380,909	21,718,595	30,749,849	40,164,791
Solar-only adoptions	22,296	42,645	65,516	64,145
Solar-plus-storage adoptions	3	55	128	32
χ^2 p-value	0	0	0	0

Note: Actual compared to predicted adoptions by zip code quartile of income using alternative expectations. The second is that outages remain the same as the current period, with certainty, and the third panel is the expectation that the future will not have outages. The third panel demonstrates the importance of future outage avoidance in explaining observed battery adoption.