# Backup Power: Public Implications of Private Substitutes for Electric Grid Reliability

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**Abstract**

Private substitutes for electric grid reliability are common. We study their adoption and distributional implications. We first show that U.S. households buy substitutes in response to a perceived decrease in grid reliability and that higher-income households are more likely to adopt them. We then develop a theoretical model of public provision of grid reliability in the presence of private substitutes that is consistent with these facts. The existence of substitutes increases aggregate welfare and reduces the efficient level of reliability spending. Using a calibrated version of the model, we find that, even though only a few households adopt batteries, most non-adopting households benefit from their availability. Battery adoption reduces utilities' reliability spending, resulting in lower electricity bills for all customers. Most non-adopting households value these bill savings more than the reduced grid reliability.

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# 1 Introduction

Many households purchase private substitutes to improve the reliability of their electricity supply. For example, 14% of U.S. households own a backup generator. Home storage batteries have also become increasingly mainstream as technology has matured and prices have fallen. Advice columns like the *New York Times's Wirecutter* now publish guidance on purchasing backup battery systems that help households avoid the costs of power outages (Heffernan, 2022).

While power outages impose costs on households, it is also expensive to prevent them. Power outages reduce productivity, destroy goods in cold storage, and can even lead to death – especially for people who warm themselves in unsafe ways or are unable to avoid high temperatures (Barreca et al., 2016; Trevizo et al., 2021). Yet, reducing or eliminating power outages requires expensive investments, resulting in larger utility bills for households. Many U.S. households already struggle to pay their energy bills (Jessel et al., 2019; Doremus et al., 2022; Barreca et al., 2022). Climate change is also increasing the cost of providing reliability through more frequent extreme weather, such as wildfires in California and extreme cold in Texas.

Replacing publicly provided reliability with privately provided reliability raises important distributional questions. An unreliable electric grid increases the benefits from purchasing private substitutes. As more households buy substitutes and decrease their dependence on the grid, the grid will not need to be as reliable. In turn, even more households will buy substitutes. This positive feedback loop raises the concern that households without substitutes will be left behind. Which households benefit from private substitutes depends on who is purchasing them and how responsive these purchases are to grid reliability.

This paper contributes to answering these questions through two major avenues. First, we document who purchases substitutes and empirically estimate how household purchases respond to major electricity outages. These private substitutes affect the efficient provision of public reliability by reducing the damage from outages. We next develop and calibrate a model of public reliability provision and household behavior and use it to consider the distributional consequences of private substitutes. To our knowledge, this is one of the first papers demonstrating the causal relationship between grid reliability and private reliability investments. We are also the first to investigate the interplay between public and private reliability investments.

To understand who is likely to benefit from private substitutes for grid reliability, we first describe who is buying them and how they are increasingly common. Nationally, 14.3% of households in 2020 have a backup generator, an increase of 2.5 percentage points from 2015. Higher income households are more likely to own a backup generator, as are households in rural areas. Households with incomes over $100,000 are nearly twice as likely to have a backup generator as households with incomes below this threshold. We find broadly consistent patterns for battery purchases.

Next, we show that a major power outage leads to a significant increase in battery purchases in the following year. We estimate this effect by combining data on battery adoption with data on power outages for the state of California. Our city-level data span 2017-2021, a period where California enacted power shutoffs to reduce the risk of wildfires. We estimate two-way fixed effects, event study models of quarterly battery adoption in response to major outages. The impact of the outage on battery adoption starts the next quarter and peaks two quarters after the outage before returning to zero at five quarters. Our point estimates imply that a major outage leads to a 0.8 standard deviation increase in the rate of battery purchases two quarters later. We view these estimates as conservative because households in the control group may also respond to news coverage about outages by purchasing batteries. As long as a power outage causes households to perceive a future outage as being more likely, this finding implies households buy private substitutes in response to a perceived decrease in electricity grid reliability.

Motivated by these empirical facts, we consider how the efficient level of grid reliability responds to changes in the availability of private substitutes; we view this as informative for how Public Utility Commissions (PUCs) are likely to adjust spending on reliability. Utilities propose investments in grid reliability to PUCs that decide which investments to approve. These commissions are tasked with ensuring reliable electricity service, while also keeping electricity rates reasonable.[1] They are often explicitly required to evaluate the costs and benefits of proposed investments. For example, the Florida Public Service Commission is required by law to consider the "[t]he estimated costs and benefits to the utility and its customers of making the improvements proposed in the plan" when deciding whether to approve utilities' plans for storm hardening (Florida Senate, 2019). Due to data limitations, we are unable to test empirically how PUCs respond to private investments in reliability.

We develop a theoretical model to describe centralized decisions over grid reliability and how they interface with household decisions to purchase substitutes. In our model, a benevolent planner sets the level of spending on grid reliability at the efficient level for

[1] For example, the California Public Utilities Commission works to "ensur[e] the provision of safe, reliable utility service and infrastructure at reasonable rates" (California Public Utilities Comission, n.d.). Florida's Public Service Commission's mission statement begins "[T]o facilitate the efficient provision of safe and reliable utility services at fair prices" (Florida Public Service Commission, n.d.). Pennsylvania's Public Utilities Commission works to "ensure safe and reliable utility service at reasonable rates" (Pennsylvania Public Utilities Commission, n.d.).

electricity customers. These customers differ in their potential loss from power outages and hence their willingness to pay for grid reliability. Substitutes like generators or backup batteries reduce the loss from an outage. Using the model, we compare two scenarios: one in which a private substitute is available and one in which it is not.

The model has three main results. First, when households purchase private substitutes, the efficient level of grid reliability is reduced. Second, it is not possible for a central planner to improve upon private decisions over whether to buy substitutes. Because households with substitutes continue to contribute to grid reliability, they do not impose costs on others. Third, under many circumstances, some households will be hurt by the existence of substitutes. It is possible for all households to benefit from the existence of substitutes, but it requires that, at a minimum, the average household purchases a substitute.

The households with the lowest willingness to pay (WTP) for reliability, and hence the lowest income households, are not typically harmed by private substitutes. Instead, when households are hurt, it is a group with higher WTP who preferred paying for a higher level of grid reliability. Households with both lower and higher WTP than these households benefit from the substitute. The higher WTP group benefits because they purchase a substitute and enjoy the lower potential loss from outages that they provide. The lower WTP group benefits because they value the electricity bill savings more than the lost reliability.

Using a calibrated model, we find the overall welfare benefit of battery backup systems to households in California is \$45 million per year. This includes a benefit of \$125 million to households in the bottom 80% of the WTP distribution, a \$18 million benefit to households in the top 0.3% of the WTP distribution, and a \$98 million loss to those in between. More effective or cheaper substitutes increase the magnitudes of each of these welfare effects, reflecting larger shifts in the efficient level of grid reliability.

This paper relates to the literature on the economic costs of power outages. Much of the economics literature focuses on developing countries where outages are more common.[2] It finds that outages lead to small decreases in firm productivity in India and China (Fisher-Vanden et al., 2015; Alcott et al., 2016), and large decreases in sales for firms in Sub-Saharan Africa (Cole et al., 2018). Because fewer outages are a challenge for quantifying these costs empirically, the economics literature on outages in developed countries has focused on stated preference methodologies (Carlsson and Martinsson, 2007; Blass et al., 2010) or the related question of how electricity market design affects the reliability of electricity supply (Wolak, 2021; Elliot, 2022; Borenstein et al., 2023). A separate engineering-oriented

[2]The incentives for public provision of reliability also differ. For example, Jha et al. (2023) find that one cause of blackouts in India is utilities buying less electricity when wholesale prices are high. Regulations prevent utilities in developed countries from not meeting electricity demand simply because the price is high.

literature has developed tools to help utilities estimate the costs to customers of outages to evaluate potential investments in grid reliability (see, e.g., Sullivan et al. (2018)). These analyses often quantify the value of lost load, a single number that captures the benefits of enhanced reliability (Gorman, 2022).

We contribute to this literature in two ways. First, we provide revealed preference evidence on the economic costs of power outages in the United States. We find that power outages increased spending on home storage batteries by over $20 million over a four-year period in California. Two contemporaneous papers also use a revealed preference approach to quantify household willingness to pay to avoid outages. Harris (2022) uses national generator purchases and outage data to find that U.S. households are willing to pay $1.57/kWh to avoid outages. Similarly, Brown and Muehlenbachs (2023) uses variation caused by California power shutoffs and battery purchase data to quantify a revealed preference measure of the value of lost load. Second, our theoretical model highlights how these battery purchases themselves affect households' willingness to pay for grid reliability. We show that investments in grid reliability have distributional impacts, and these impacts are affected by the availability of private substitutes.

This paper also contributes to the literature on the distributional impacts of new energy technologies. These new technologies are often heavily subsidized, so a salient concern is which households are adopting them. Previous work has focused on electric vehicles (Borenstein and Davis, 2016; Holland et al., 2019) and distributed generation (Eid et al., 2014; Borenstein, 2017; Brown and Sappington, 2017). Like Brown (2022), we describe which households adopt home storage batteries. We also investigate how non-adopters are affected via public reliability provision.

Finally, our work is part of a broader literature examining publicly provided goods with private alternatives. Public education is the most prominent example (Glomm et al., 2011). In finding that high and low WTP households benefit while those in the middle do not, this paper is similar to Epple and Romano (1996a,b). They find that the availability of private schools causes households at the top and bottom of the WTP distribution to have similar preferences over school spending. However, their result arises in the context of a voting model, while ours has a regulator implementing the efficient level of spending.

# 2 Background

Electricity grids are complicated networks that require electricity supply to exactly equal electricity demand at every second. Failure to do so can result in blackouts (too little supply) or damage to the infrastructure (too much supply).

Electric grid reliability generally means that this careful balance is maintained with a high level of confidence. Planned or unplanned outages mean that electricity is not available to the end-user. These can be especially costly when electricity is a critical input – for example, at military bases, hospitals, or for residential users who use electricity to power oxygen pumps.

The U.S. electricity grid is increasingly unreliable (Blunt, 2022), and this trend is expected to continue as climate change increases the prevalence of extreme weather. Already, wildfires in California (2019), hurricanes on the Gulf Coast (2020), extreme heat in California (2020), and extreme cold in Texas (2021) have left millions of people without power (Canon, 2019; Schwartz, 2020; Roth, 2020; Blunt and Gold, 2021). Further, the transition to a grid based on intermittent renewable energy makes it more challenging to provide reliable electricity (Potter, 2022).

## 2.1 Public Spending on Grid Reliability

There are many types of spending that increase reliability. Many outages are caused by weather downing power distribution lines. Utilities that own these lines can undertake regular tree-trimming around lines or hire more staff so that downed lines are repaired more quickly. Moving distribution lines underground is another option, though a costly one. Outages can also be caused by inadequate capacity, i.e., there is not enough generation supply to meet demand during the highest demand hours. This type of outage is expected to become more common as the grid becomes more dependent on renewable energy (Potter, 2022). Investment in additional generation reserves can make this type of outage less likely. Similarly, investment in the transmission system can increase reliability by smoothing regional supply and demand shocks.

Regulated utilities are the entities that typically perform this work, but many expenditures require regulatory approval from a Public Utility Commission.[3] Most expenditures that improve reliability are capital investments. Utilities propose these investments, and the regulator decides whether to approve them. For approved investments, utilities are allowed to pass the cost on to consumers in the form of higher rates. Regulated utilities earn a profit on capital investment, so they have an incentive to propose more investment than the efficient level (Averch and Johnson, 1962).[4]

Most PUCs make decisions about reliability spending in the context of their mission,

[3] In the United States, the regulator is a state-level commission with 3-7 members. Commissioners are political appointees in about three-quarters of states and elected in the rest (Howe, 2019).

[4] Some reliability expenditures, such as regular tree trimming, fall under operations and maintenance. Utilities have more discretion over this spending, which they do not profit from.

which is to facilitate high-quality service and reasonable prices. Something akin to the efficient level of reliability spending is the goal of this process, and private substitutes including generators and backup batteries may affect these decisions. By choosing what projects to approve, the regulator influences the level of reliability of the electrical grid and is tasked with approving an amount of investment that balances the costs and benefits to consumers. Specifically, most states task the regulator with "assuring that utilities provide reasonable, adequate and efficient service to customers at just and reasonable prices," and holding utilities to a "resource adequacy" standard, most commonly that blackouts due to insufficient supply occur only once per ten years. The prices that the regulator approves must allow the utility to recover its costs, including a fair rate of return on its capital (U.S. Environmental Protection Agency, 2010).

For reliability spending decisions, the expected payoff is in terms of avoided interruptions of electrical services. Regulators use a variety of methods to assess the benefits of these avoided interruptions relative to the costs. While some regulators do not attempt to monetize these benefits, others do so by using estimates of the cost to consumers of outages (LaCommare et al., 2017; Zamuda et al., 2019). These estimates reflect the willingness to pay of customers to avoid outages as well as lost economic activity during outages. Since private substitutes make customers less reliant on their utility company, they can affect these estimates and thus feed back into the policy making process.

However, the efficient level of reliability spending need not be the outcome of these policy processes. Regulatory capture or asymmetric information could result in too much investment in reliability. Regulators overly focused on the short run or the time inconsistency problem studied in Lim and Yurukoglu (2018) could result in too little investment. Yet, given the regulator's stated objective, developments that shift the *efficient* level of investment will also likely shift the *equilibrium* level of investment.

Ensuring high levels of grid reliability is expensive. For example, consider capital spending on transmission and distribution, much of which is aimed at maintaining reliability. Deloitte (2016) reports that, for 47 investor-owned utilities representing 89% of the total market capitalization of U.S. utilities, these expenditures were $42 billion in 2015.

All electricity consumers share the costs of reliability spending, with low-income households paying nearly as much as higher income households. Because most expenditures to improve reliability are fixed costs, the efficient two-part tariff would recover them entirely via the fixed charge. In this case, all households would share the costs equally regardless of income. In reality, utilities in the United States recover fixed costs mostly with volumetric charges (Borenstein and Bushnell, 2022). Low-income households use less electricity on average, but there is substantial overlap in the electricity use distributions for low and higher-income households (Doremus et al., 2022). Even California's aggressive use of increasing block volumetric charges for cost-recovery only results in modest wealth redistribution and creates substantial deadweight loss relative to the size of the transfers (Borenstein, 2012).

Bill assistance programs like LIHEAP at the federal level or California's CARE program could mean that vulnerable households pay little to none of the cost of reliability spending. Yet, only a small fraction of households receives this assistance. As of 2020, only 4.6% of U.S. households report ever receiving any energy assistance, a category that includes both bill assistance and help fixing broken equipment (U.S. Energy Information Administration, 2022).

## 2.2 Private Substitutes for Grid Reliability

We now discuss two private substitutes for grid reliability: backup generators and batteries.[5] Backup generators typically cost between two and twenty thousand dollars and provide small-scale, at-home generation in the event of an outage. They usually use fossil fuels like diesel, natural gas, or propane. They are less efficient than traditional power plants but can reliably operate in the event of an outage. While backup generators are an established technology, ownership has been growing in response to climate change, and 2021 was a record year for generator sales (Phillips, 2021).

Batteries like Tesla's Powerwall are in the same broad cost range as generators. They allow households to store power for use during a power outage. If a household is not connected to the grid, the battery can store electricity production from solar cells for use overnight. Recently, blackouts in the Western U.S. (due, in part, to faulty transmission lines) have caused demand for behind-the-meter batteries to surge (Hering and Copley, 2021).

# 3 Data

The empirical analysis uses three main data sources: survey data from the U.S. Energy Information Administration, battery purchase data from the State of California, and power outage data from Bluefire Studios.

[5] Appendix C.3 discusses microgrids, another substitute that is also increasingly popular. While data is sparser and incomplete, it appears that adoption is highest for wealthier, coastal states. The data also suggests that the number of microgrids in the United States grew rapidly from 2017 to 2020.

## 3.1 Backup Generator Ownership Data

We use data from Residential Energy Consumption Survey (RECS) to describe which households own backup generators (U.S. Energy Information Administration, 2022). The RECS is a nationally representative survey conducted every 4-6 years by the U.S. Energy Information Administration. A novel feature of the RECS is that it collects data on respondents' electricity billing and use directly from their utilities. The American Housing Survey (AHS) also collects data on backup generators in some survey waves, and patterns of adoption in the AHS are similar to those in the RECS (see Appendix Section C.2) (U.S. Census Bureau, 2021).

## 3.2 Battery Purchase Data

We use data from the State of California to describe which households purchase batteries and estimate how these purchases respond to power outages. These data come from a subsidy program, the Self-Generation Incentive Program (SGIP).[6] The SGIP dates from 2001 and was created as a peak-load reduction program in response to the California electricity crisis. Starting in 2014, most program funds were allocated to subsidizing batteries (Center for Sustainable Energy, 2021). The subsidy for battery purchase is large, over 30 percent of total costs on average.[7] Thus, we expect these data to cover nearly the universe of battery purchases in periods when SGIP funds were available. We focus on residential battery purchases, which increased rapidly after 2017 (see Appendix Figure A1). While it was not necessary to have solar panels to receive the subsidy, nearly all the batteries in our sample (97%) were paired with photovoltaic systems.

During our study period, the program introduced higher subsidies for some customers, and our analysis excludes batteries that received a higher subsidy because of a power shutoff. The change to the program increased subsidies to vulnerable households in fire-prone areas. Households are classified as vulnerable if they are low-income, have medical needs, or rely on an electric pump for drinking water. These vulnerable households can qualify for a higher subsidy if they either (i) reside in a Tier 2 or Tier 3 high fire threat district or (ii) have experienced two or more Public Safety Power Shutoff events (California Public Utilities Commission, 2020). To ensure our results are not driven by a change in the effective price of batteries after power shutoffs, we exclude battery purchases that received this higher

[6] These data are available at https://www.selfgenca.com/report/public. We use the January 12, 2023 version for our analysis.

[7] The 2021 incentive was $150-$200/kWh for residential customers. Higher incentives of $850-$1,000/kWh were available for low-income households and those with critical resilience needs (State of California and the Self-Generation Incentive Program, 2023).

subsidy because of a power shutoff. Some of these households would likely have purchased batteries without the higher subsidy, so our estimated effect of outages on battery purchase is conservative.

This change to the program occurred right after significant power shutoffs, and we do two robustness checks to ensure our results are not due to the timing of this change. The SGIP was changed in late 2019 and began accepting applications for these higher subsidies in May 2020 (California Public Utilities Commission, 2019, n.d.). Many of the outages in our sample occurred in the fourth quarter of 2019. We first re-estimate the model dropping all batteries that received this higher subsidy, as opposed to only those that received it because of a power shutoff. We find a smaller, but still statistically significant, impact of a major outage on battery purchase (Appendix Figure A2). As an additional check, we limit our analysis to fire prone areas that were all treated with the same change to the subsidy.[8] This restriction drops 88% of battery purchases. We find larger effects of an outage on battery purchase for this sample, but the coefficients are less precisely estimated and not statistically significant (Appendix Figure A3).

The battery analysis also relies on data on the following zip code characteristics: median household income, number of housing units, and whether the zip code is located in a rural county. We use data on ZCTA-level median income and number of housing units from the U.S. Census's 2019 American Community Survey. Our definition of rural is based on the 2003 Rural-Urban Continuum codes, and we define all non-metro areas as rural. We use a data set from the University of Michigan's Population studies center that has matched these county-level codes to ZCTAs (University of Michigan Population Studies Center, 2022). Finally, we use a crosswalk between zip codes and cities from zip-codes.com to match the battery data to the outage data (Zip-Codes.com, 2021).

## 3.3 Outage Data

We also use city-level outage data from Bluefire Studios (Bluefire Studios, 2021). These data are collected from utility outage management systems and begin in late 2017 when Bluefire began to track large California utilities. The data end in October 2021. For each city and for each hour, we observe the number of customer-hours of outage.[9] We first drop

[8] Specifically, we keep battery purchases from ZCTAs (the areas corresponding to zip codes) with at least 99% of their area located in Tier 2 or Tier 3 high fire threat districts.

[9] While the total number of customers is reported, this statistic is sometimes incorrectly based on the maximum number of customers that have experienced an outage up to that point in their dataset (confirmed via email on 4/25/23). We instead proxy for the number of customers with the number of housing units in the city. We construct this number by aggregating up ZCTA-level data from the American Community Survey. For each quarter, we construct total customer hours (used to construct the fraction of customer-hours out) by multiplying the number of housing units by the number of hours that are covered by the outage data in

observations without city information or from unspecified unincorporated areas (about 6 % of observations). The resulting data set covers 49 months and expands in coverage over time: it contains roughly 1,050 cities in October 2017 and 1,500 cities by October 2021. Most of the cities that were added over this period were very small.[10]

# 4 Motivating Empirical Facts

This section presents two empirical analyses that motivate the theoretical model. We first describe the types of households that buy private substitutes for grid reliability. We then show that major power outages spur adoption.

## 4.1 Wealthier households are more likely to purchase private substitutes

### 4.1.1 Backup generators

More than one in eight U.S. households own a backup generator and this share has been increasing over time. In 2020, 14.3 percent of households had a backup generator, an increase of 2.5 percentage points from 2015.[11] These national numbers conceal important regional heterogeneity; 18% of households in the Northeast own one, compared to only 10% of households in the West.[12]

Table 1 shows that wealthier households, those living in rural areas, and those with higher electricity consumption are more likely to own backup generators.[13] Column 4 shows that a $10,000 increase in annual income is associated with a 0.4 percentage point increase in the probability that a household owns a backup generator.[14] Similarly, increasing annual

that quarter.

[10]Bluefire reports that cities that are present for all 49 months average 8,436 customers in October 2021, while cities that were present for less than 45 months average 612 customers in October 2021. A "customer" generally covers more than one person; it can refer to, e.g., a business, a house, or an apartment building. There are occasional missing months for some cities.

[11]Authors' calculation using the household-level Residential Energy Consumption Survey (U.S. Energy Information Administration, 2022). Residents of apartment buildings with more than 4 units were not asked about generator ownership in 2015, so this statistic is calculated for a sample that excludes residents of apartment buildings with more than 4 units. Of these respondents, 15.4% owned generators in 2020, up from 12.9% in 2015.

[12]For more detail, please see Appendix Figure C1, which summarizes data from the 2020 RECS.

[13]This table uses data from the 2015 RECS because electricity consumption data is not yet available for the 2020 RECS. Appendix Section C.1 presents regression results using the available 2020 RECS data; available results are similar to those presented here.

[14]We construct household income using the midpoint of $20,000 income bins. Incomes above $140,000 are top-coded into one bin, and we use an income of $150,000 for this group. The standard deviation is $44,500.

Table 1: Predictors of Backup Generator Ownership

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Household Income ($10,000/year) | 0.007*** | | 0.005*** | 0.004*** | 0.004*** |
| | (0.001) | | (0.001) | (0.001) | (0.001) |
| Electricity Consumption (MWh/year) | | 0.006*** | 0.006*** | 0.004*** | 0.005*** |
| | | (0.001) | (0.001) | (0.001) | (0.001) |
| Average Electricity Price (Cents/kWh) | | | 0.002 | 0.000 | -0.001 |
| | | | (0.002) | (0.002) | (0.002) |
| Rural | | | | 0.149*** | 0.159*** |
| | | | | (0.015) | (0.017) |
| Census Region Fixed Effects | No | No | No | Yes | Yes |
| Structure Type Fixed Effects | No | No | No | Yes | No |
| Mean Generator Ownership | 0.129 | 0.129 | 0.129 | 0.129 | 0.151 |
| R squared | 0.009 | 0.017 | 0.022 | 0.074 | 0.068 |
| Observations | 4828 | 4828 | 4828 | 4828 | 3752 |

The dependent variable is a binary variable for whether a household owns a backup generator. Data is from the 2015 RECS and results are presented using survey weights. Rural is defined as an area with fewer than 2,500 residents. Residents of large apartment buildings are excluded. Household income is constructed using the midpoint of $20,000 income bins. Incomes above $140,000 are top-coded into one bin, and we use an income of $150,000 for this group. Columns (1) through (4) include mobile homes, single-family detached houses, single-family attached houses, and small apartment buildings, while Column (5) reports results only looking at single-family detached houses. Heteroskedastic-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

household electricity consumption by 1 MWh (0.14 SD) is associated with a 0.4 percentage point increase in the probability of owning a backup generator. Living in a rural area is associated with having a 15 percentage point higher probability of owning a generator. These results are similar whether we include fewer covariates (column 3), more covariates (column 4), or only look at single-family detached houses (column 5).

#### 4.1.2 Batteries

We find that households in higher income areas are more likely to adopt batteries, but rural households are not. Table 2 correlation between zip-code median household income and new batteries per household is 0.25. This correlation is also evident in the spatial distribution of batteries and income within urban areas; Appendix Figure A4 shows this pattern for Los

Angeles and San Francisco. Conditional on income, adoption is uncorrelated with living in a rural county (Table 2, column 3). Why are rural households more likely to adopt generators, but not batteries? One explanation is that rural areas have historically had less reliable power and residents may already own generators by the time batteries became a feasible alternative. The vast majority of batteries are also paired with rooftop solar panels, and solar panels may be less appealing to households in rural areas.

These patterns have also changed over time, likely due to the change to California's battery subsidy program discussed in section 3. In the first quarter of 2020, the SGIP program began offering much higher subsidies to vulnerable households in areas with high fire risk. Having a low-income is one way a household can qualify as vulnerable, and columns 4 and 5 show that the correlation between adoption and zip-code income falls after this change. Yet this correlation is still substantial at 0.18. Rural households, which are disproportionately located in fire prone areas, are also more likely to adopt batteries after this change to the subsidy program.

Table 2: Predictors of Battery Adoption

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Median HH Income | 0.25*** | | 0.25*** | 0.36*** | 0.18** |
| | (0.02) | | (0.02) | (0.04) | (0.02) |
| Rural County | | -0.07*** | -0.02 | -0.11*** | 0.00 |
| | | (0.02) | (0.02) | (0.02) | (0.02) |
| Years | All | All | All | 2017-2019 | 2020-2021 |
| Observations | 1,246 | 1,246 | 1,246 | 1,246 | 1,246 |
| R-squared | 0.18 | 0.01 | 0.18 | 0.21 | 0.14 |

*Notes*: Observations at the zip code level. All variables are normalized, so coefficients are correlations. For columns 1-3, the dependent variable is total batteries purchased per 10,000 HHs in that zip code from 2017-2021. For columns 4 and 5, the counts are for 2017-2019 and 2020-2021. Median HH income is median household income for the zip code. Rural county is an indicator for if the zip code is located in a non-metro county. Robust standard errors in parentheses, clustered by county (N=173). *** p<0.01, ** p<0.05, * p<0.1.

## 4.2 Households purchase private substitutes in response to a perceived decrease in grid reliability

We next present evidence that households buy private substitutes in response to a perceived decrease in grid reliability. We assume that experiencing a major power outage makes households believe the grid will be less reliable in the future. Given this assumption, it is sufficient to show that households buy more private substitutes in response to a major power outage. We focus on purchases of batteries because we can link them to outage data at a fine geographic scale. We estimate the dynamic treatment effect of experiencing a major power outage on city level purchases of residential batteries.

Our model of battery purchases for city $i$ in quarter $t$ is the following:

$$b_{it} = \sum_{k=-3}^{5} \beta_k m_{ik} + \phi_i + \gamma_t + \epsilon_{it} \tag{1}$$

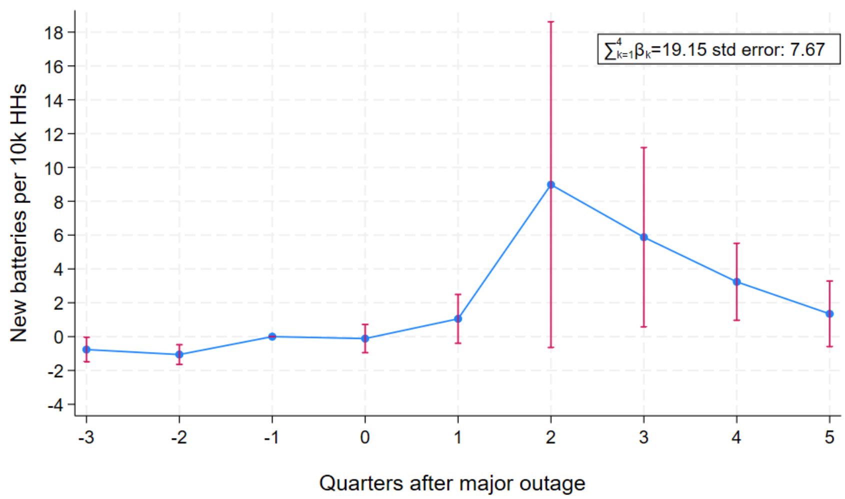
where $b_{it}$ is new batteries per ten thousand housing units. $m_{ik}$ is an indicator for if the observation for city $i$ is $k$ quarters away from a major outage; it is zero for all observations for cities without a major outage. The coefficient $\beta_k$ is the effect of a major outage on battery adoptions per ten thousand housing units $k$ quarters after a major outage. $\phi_i$ are city fixed effects, and $\gamma_t$ are year-by-quarter fixed effects. We treat the quarter before a major outage as the omitted category, restricting $\beta_{-1} = 0$, and compare purchase decisions in this quarter to quarters with and following a major outage.

We define a major outage as a quarter where power is out for at least 3 percent of customer-hours (as defined in section 3). In our sample, 0.9% of city-quarters are classified as having a major outage. Because we use customer-hours for our definition, we do not differentiate between major outages in which all customers lost power for nearly three days within a quarter and those where a smaller share of customers experienced very long outages. Much of the identifying variation comes from wildfire-induced power shutoffs in Fall 2019. The fourth quarter of 2019 accounts for 54% of the city-quarters with a major outage and for 79% of the city-quarters with a major outage for the sample of cities with only one major outage.

We estimate this model using the interaction-weighted estimator proposed in Sun and Abraham (2021). Because this estimator is designed for an absorbing treatment, we exclude the 7.7% of cities with multiple major outages over the sample. Of the remaining cities, 13.4% experience a major outage. Results are similar if we instead use the two-way fixed effects estimator with leads and lags.

We find that a major outage leads to an increase in battery purchases in the following quarters. Figure B1 plots the estimated $\beta_k$ coefficients and 95% confidence intervals. We do not find an impact on purchases during the quarter that a major outage occurs. There is a positive but statistically insignificant effect in the subsequent two quarters, and we find statistically and economically significant increases in purchases three and four quarters after the outage. The point estimate for the second quarter (9.0) implies that a major outage leads to a 0.8 standard deviation increase in the rate of battery purchase two quarters later. Overall, the estimated quarterly effects are noisy. However, the estimated total effect in the year following the outage is 19.2 more batteries per ten thousand households, which is significantly different from zero. This effect is the same as a city moving from the median to the 91st percentile of annual batteries purchased per ten thousand households.

Figure 1: Impact of Outages on Battery Purchases




Estimated coefficients and 95% C.I.s from model (1). N = 10,694 city-quarters from 646 cities in 2017-2021. Sample excludes the 7.7% of cities with more than one major outage. A major outage is defined as one where over 3% of customer-hours are out for the quarter; 0.9% of city-quarters have a major outage. The mean of the dependent variable (batteries per 10k housing units) is 2.0, with a standard deviation of 8.4. SE clustered by city.

Results are robust to including more lags, keeping cities with multiple outages, and using alternative definitions of a major outage. Appendix Figure A5 presents results from four alternative specifications. First, we include more leads and lags in the model. We still find no effect on purchases outside the four quarters following the outage. Second, we keep cities with multiple major outages. For this specification, we define all coefficients relative to the first outage. We find the estimated effects are similar, though slightly smaller. Third, we re-estimate the model using a less stringent definition of a major outage: more than one percent of customer-hours without power. We find a similar pattern but slightly smaller point estimates; we estimate the total effect on battery purchases in the year following the outage is 15.5 batteries per ten thousand households. Finally, we use a more stringent definition of a major outage: more than five percent of customer-hours without power. The estimated coefficients are similar but slightly smaller than those for our main specification.

We also find similar results in an alternative analysis that uses more granular data on power shutoffs. Appendix B presents results that use an outage measure based on circuit-level data on Public Safety Power Shutoffs. This analysis is at the zip code level and only for the area of California served by PG&E. Our estimates imply that a major outage caused by power shutoffs leads to 27.1 more batteries purchased per ten thousand households in the following year, and this effect is statistically different from zero, with a p-value<0.001.

Of note, because of the possibility of spillovers to the control group, we view these estimates as a lower bound. One possible mechanism for spillovers is that hearing about nearby areas losing power affects the beliefs of households in other cities. Indeed, major power outages can receive considerable media attention. We expect this attention to cause untreated households' perceptions of grid reliability to decrease and thus make them more likely to adopt a substitute. As a result, our point estimates will be smaller than if the "untreated" households did not have any information about their neighbors.

It is also unlikely that our estimates are simply capturing a shift forward in the timing of purchases. Panel A of Appendix Figure A5 shows that the estimated effects return to zero after the outage, rather than below zero. Thus, at least in the medium run, these outage-induced purchases appear to be new and additional.

Our estimates suggest that the outages in our sample increased battery spending by over 20 million dollars. We find that a major outage leads to 1,915 more batteries per million households. Over our four-year sample, households experienced 0.61 million major outages, and the mean cost of the battery systems purchased was 21,525 dollars (in real $2022). Thus, the implied outage-induced spending on batteries—by both households and the state of California—was 25.1 million dollars. This number captures only a fraction of the response to outages since batteries are not the only private substitute available: Appendix Figure A6 shows that the time series of google searches for a common home backup generator (Generac) mirrors that of searches for a common battery (Tesla Powerwall). Overall, our results imply that outages can lead to economically significant increases in spending on private substitutes.

# 5 Theoretical Model

We next develop a model to describe centralized decisions over grid reliability and individual decisions over purchasing a private substitute. The planner in our model approximates a regulator that sets the level of reliability by choosing how much spending to approve. The model allows us to compare how the efficient level of grid reliability changes as private substitutes are introduced. We compare the welfare of households in these two scenarios to examine the distributional consequences of private substitutes. We then calibrate the model to features of backup batteries in California to describe the magnitude of these effects.

## 5.1 Primitives

There is some probability that households will experience a grid power outage. This probability, $\pi(R)$, is a function of spending on grid reliability, $R$.[15] We assume that this function is twice continuously differentiable and for any $R$ we have that $\pi(R) > 0$, $\pi'(R) < 0$ and $\pi''(R) > 0$.

There is a set of households of size one who differ in the degree of their loss in the event of a power outage. We denote the size of the loss for household $i$ as $L_i$. This parameter can be thought of as the household's willingness to pay (WTP) to eliminate the risk of an outage. Thus, it is a reduced form parameter that may capture both differences in underlying preferences and differences in economic resources. We denote the PDF of the distribution of $L_i$ as $\ell$, the CDF by $\mathcal{L}$, and its mean by $\tilde{L}$. We assume that all households have a positive WTP.

Households can abate their potential loss by purchasing a private substitute. We assume that the purchase of a private substitute (e.g., a generator or backup battery) is a binary choice. Purchasing a private substitute costs $P\lambda$, where $\lambda$ represents the effectiveness of the substitute and $P$ represents its price per unit of effectiveness. A household who purchases a substitute would experience a loss of $L_i(1-\lambda)$ in the event of a power outage, where $\lambda$ exceeds zero and is less than one. With no substitute it experiences its full loss, $L_i$. We assume that even if everyone purchased a substitute it would still be efficient to have some spending on grid reliability and hence $-\pi'(0)(1-\lambda)\tilde{L} > 1$.

## 5.2 Policymaker's problem

We consider the spending decision on grid reliability, $R$, as chosen by a benevolent planner.[16] The planner balances the benefits and costs of providing reliability and chooses the level that maximizes utilitarian social welfare. The planner knows the distribution of losses, $\ell$, but cannot observe an individual customer's loss $L_i$. As a result, the costs of grid reliability $R$ are shared equally by all customers. This reflects situations in which the fixed costs of the utility are recovered via a flat fee to all households.

[15] As discussed in Section 2.1, this spending could take a range of forms, including investments in transmission reliability and generation adequacy or staffing to make repairs more quickly.

[16] The planner in the model most closely corresponds to the state regulator of utilities. While it does not directly determine grid reliability, the regulator can influence it by approving utility investments and setting required levels of resource adequacy. Section 2.1 discusses the goals of the regulator and its ability to influence grid reliability.

We consider this problem for two cases. In the first, households rely exclusively on the grid and cannot purchase private substitutes. In this case, the planner solves the problem

$$\max_R \int_0^\infty -\pi(R)L_i\ell(L_i)dL_i - R. \tag{2}$$

Let $R_N^*$ denote the solution to this problem. In the second case, substitutes are available. For this case, the planner's problem takes into account that households will purchase substitutes if it benefits them to do so and can be written as

$$\max_R \int_0^\infty \max\{-\pi(R)L_i, -\pi(R)(1-\lambda)L_i - P\lambda\}\ell(L_i)dL_i - R. \tag{3}$$

We denote the solution to this problem as $R_S^*$.

It is possible for either no households or all households to purchase substitutes depending on the substitute's price per unit effectiveness. Here, we focus on the case where some, but not all, households purchase substitutes. Households with $L_i \geq \frac{P}{\pi(R)}$ will purchase substitutes and so, $R_S^*$ will satisfy

$$-\pi'(R_S^*)\left[\int_0^{\frac{P}{\pi(R_S^*)}} L_i\ell(L_i)dL_i + (1-\lambda)\int_{\frac{P}{\pi(R_S^*)}}^\infty L_i\ell(L_i)dL_i\right] - 1 = 0. \tag{4}$$

There will always be a solution to Equation 4 where the optimal level of grid reliability with substitutes $R_S^*$ exceeds zero and is no more than the optimal level of reliability without them $R_N^*$.[17] The efficient level of spending on reliability is increasing in the price of the substitute.[18] As the price increases, fewer people purchase the substitute. This increases the potential total loss were an outage to occur and thus increases public provision of grid reliability. Reliability spending is decreasing in the effectiveness of the substitute, $\lambda$. Holding the price per effectiveness, $P$, constant, an increase in effectiveness does not directly change who buys the substitute. However, it does reduce the total loss in the case of an outage, which then decreases reliability spending and results in more people buying substitutes.

It is not possible for the planner to improve upon the private decisions about whether to purchase a substitute. Because households who purchase a substitute continue to pay for the grid, purchasing a substitute does not impose costs on other households, which would

[17]This is proven in Appendix Section D.1. Note that in cases where the WTP distribution is bounded, $R_N^*$ will be a solution in any case where $P/\pi(R_N^*)$ exceeds its upper bound and as a result no one buys a substitute when reliability spending is set at $R_N^*$. However, there can be another local maximum in which households purchase the substitute and grid reliability is lower.

[18]From the implicit function theorem $\frac{\partial R}{\partial P} = \pi'(R)\lambda\frac{P}{\pi(R)^2}\ell\left(\frac{P}{\pi(R)}\right)\left[\frac{\pi''(R)}{\pi'(R)} + \frac{P^2\pi'(R)^2}{\pi(R)^3}\ell(\frac{P}{\pi(R)})\right]^{-1}$. The numerator is negative and at any local maximum the denominator is negative.

create a fiscal externality. As a result, were the planner to simultaneously choose both who purchased a substitute and the level of grid reliability, they would make the same choices as the households do.[19,20]

Before discussing the welfare consequences of substitutes, it is worth noting that this model applies only to substitutes that do not fully replace the electrical grid. We assume that households that purchase substitutes remain connected to the grid. This is realistic, as very few households currently go "off grid."[21] However, as substitute technologies continue to develop, households leaving the grid may become more common. This would affect our model in two important ways. First, households with substitutes would no longer care at all about grid reliability. Second, they would no longer contribute to the cost of grid reliability. Hence, our setting is similar to publicly provided goods funded via taxation, like public schooling, where all households contribute even if they choose not to use the public services.

Some outages, like Public Safety Power Shutoffs, are active choices motivated by limiting the risk of wildfires, a factor that is not directly in our model, but accounting for this would not alter the model's implications. Excluding wildfire risk from the model implicitly assumes that the existence of substitutes would not alter these decisions about when to shut off power to avoid wildfires. However, if households care about wildfires, then private substitutes would lead the planner to want to reduce wildfire risk in addition to electric bills. If all households care equally about wildfire risk, then the main results of the model are unchanged. When substitutes are available, the grid will be less reliable. Utility bills would be higher than our model indicates, but households would be compensated for this by decreased wildfire risk.

We also note that our static model abstracts from possible dynamic responses to changes in available substitutes or grid reliability. Grid reliability is a durable good that depreciates, and policy decisions determine investment in it, not its overall level. A dynamic model may produce interesting transitions between the steady states that are represented by instant responses in our static model.[22]

[19]This is proven in Appendix Section D.2.

[20]Households that buy home storage batteries usually also install rooftop solar panels. Under net-metering, installing these panels can impose costs on other households, but this effect is not due to the substitute.

[21]Gorman et al. (2020) show that disconnecting from the grid in favor of self-generation and storage is unlikely to benefit consumers under current utility practices.

[22]For example, if we begin in a steady state where private substitutes are prohibitively expensive and then the price decreases, some households will purchase private substitutes. This will induce the policy maker to lower the investment level in the next period. As reliability depreciates, more people will purchase private substitutes, and hence the policy maker will allow further depreciation, until we reach the new steady state.

## 5.3 Welfare Consequences

To analyze the welfare consequences of private substitutes to households with different potential losses, we compare two settings: with and without substitutes. If reliability spending were fixed at $R_N^*$, the availability of substitutes would be Pareto improving. However, because the efficiency-targeting planner will adjust reliability spending as a result of substitutes' existence, some households may be harmed.

In principle, there are many possible outcomes. Even if all households do not purchase substitutes, all households can benefit from their existence. One common, if surprising, result is that households with both high and low potential losses can benefit while those in the middle are hurt. Alternatively, it is possible for only households with potential losses below a cutoff to benefit, or for only households with potential losses above a cutoff to benefit. The specific outcome depends on the curvature of the probability of an outage function, $\pi$, the distribution of potential losses, $\ell$, and the characteristics of the substitute, $\lambda$ and $p$. However, we show one important general result. Appendix Section D.3 shows that if the household with the average potential loss does not buy a substitute, then there are households that would be better off if substitutes were not available. While this condition is sufficient for households to be hurt by substitutes, it is not necessary. The average household purchasing a substitute does not preclude households from being hurt.

## 5.4 Calibration

The previous section shows the range of possible welfare effects of private substitutes but is not informative as to the actual welfare effects of the substitutes that are and may become available to electricity customers. In this section, we fill this gap. To fully specify our model would require knowing the full distribution of willingness to pay to eliminate power outages, the risk of power outages that would result from any given level of reliability spending, and the price and effectiveness of the available substitute. It is not possible to know all of these factors with any degree of confidence, but we calibrate our model to reasonable specifications. We do so in the context of backup batteries in California.

We take the WTP distribution from Sullivan et al. (2018). This distribution is based on surveys of residential customers in the Western United States. Utilities asked these customers how much they would be willing to pay to avoid a one-hour outage. We fit a log normal distribution to the percentiles of this empirical distribution. The resulting log normal distribution has $\mu$ and $\sigma$ of 0.77 and 1.72 respectively. The surveys are from no later than 2015, prior to the wide availability of backup batteries, so we treat it as the WTP distribution without batteries.

We approximate the probability of outage as a function of reliability spending $\pi(R)$ with a second order Taylor polynomial around the current level of spending. We take spending on grid reliability to be \$776 per year per household, the estimate of the average household contribution to residual costs among customers of the three largest California investor-owned utilities from Borenstein et al. (2022), in 2022 dollars. To make it comparable to the WTP distribution, we convert it to an hourly rate. We take the probability of outage from the California outage data for the year 2020 (the last full calendar year in our data). It is the empirical probability that at any given time a household in California is facing a power outage. This is approximately 0.0007. Since we assume that the planner is setting reliability spending optimally, this probability determines the first derivative of the $\pi$ function at this level of spending. The curvature of the function is unknown, so we show results for multiple possibilities.

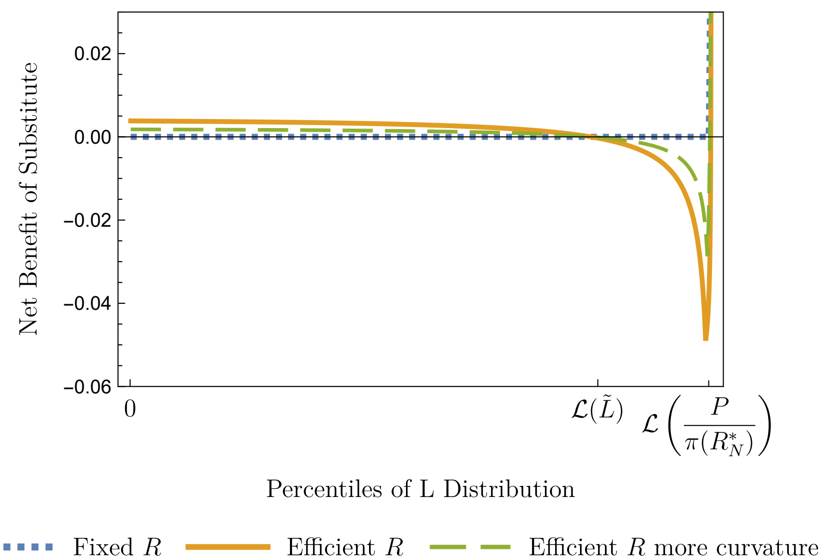
We consider the welfare effects from the availability of a residential backup battery, like those sold by Tesla. These cost approximately \$12,000 and are expected to last for 20 years. We illustrate the effects if owning a battery reduces the WTP to eliminate outages by 50% and show how the results would differ under other assumptions.

Figure 2 shows the resulting welfare effects for households with different WTP to eliminate outages. The horizontal axis shows WTP transformed into percentiles of the distribution. Because WTP is log-normally distributed, mean WTP ($\tilde{L}$) is greater than median WTP. If reliability spending is fixed at $R_N^*$, individual welfare benefits are given by the blue line. In this case, substitutes are Pareto improving but only benefit households that purchase them. The planner can increase total welfare by adjusting reliability spending. The orange and green lines represent the welfare gains or losses if the planner efficiently adjusts reliability spending under two different assumptions about the curvature of the function mapping reliability spending to the outage probability, $\pi$.[23] In both cases, the average WTP household does not purchase a substitute and some households are hurt by the decrease in grid reliability. This includes some households that choose to purchase a battery. Since the grid is less reliable after the social planner adjusts reliability spending, more households purchase batteries than with fixed reliability spending.

Under efficient readjustment, low- and high-WTP households are better off when backup batteries are available. High-WTP households are spending more money in total but receiving increased reliability. On the other hand, low-WTP households value the saving on their electricity bills more than the lost grid reliability. Some of those in the middle are hurt; they were previously close to their ideal reliability level, but now are buying too

[23] The orange and green lines reflect $\pi''(R_N^*)/\pi'(R_N^*)$ of -40 and -70 respectively. When this ratio is larger in magnitude, the function's curvature is greater, and $R_S^*$ is closer to $R_N^*$.

Figure 2: Calibrated Individual Welfare Gain from Batteries



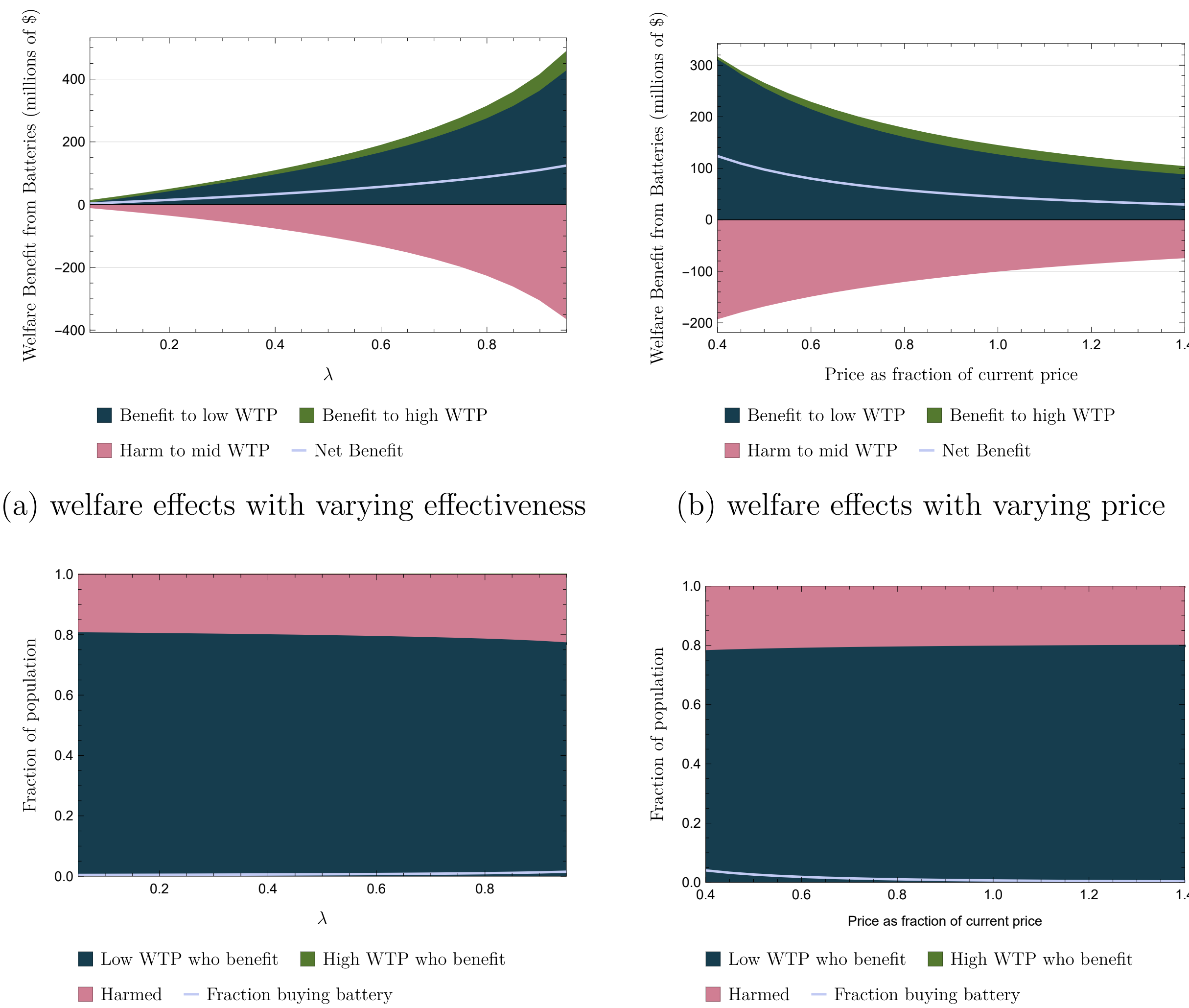

The blue dotted line describes the individual welfare benefit to households with different potential losses (X-axis) from the existence of batteries when reliability spending does not adjust. The orange solid and green dashed lines represent potential welfare benefits with different curvatures of the $\pi$ function which result in different $R_S^*$. In these calibrations, most households, including those at the top and bottom of the WTP distribution benefit from the substitute, but some households in between do not.

little reliability (if they do not buy a battery) or too much reliability (if they do buy a battery in response to decreased grid-level reliability).

In our preferred calibration, described by the dashed green line in Figure 2, batteries provide a total net surplus of \$45 million per year to households in California. This includes the households in the bottom 79.5% of the WTP distribution who benefit, the next 20.3% of households with higher WTP who are hurt, and the remaining 0.25% with the highest WTP who benefit. The total benefit to the bottom 79.5% of households in the WTP distribution is \$125 million per year. On average these households receive a surplus of \$11.87 per year. The next 20% of households in the WTP distribution are hurt by the substitute and on average would each be willing to pay \$36.66 per year to eliminate the substitutes. The lost surplus to this group totals \$98.2 million per year. The top 0.25% of households in the WTP distribution benefit from the substitute and on average receive a surplus of \$551 per year, totaling \$18 million.

Figure 3 shows how the welfare implications differ for substitutes with different characteristics. Panels (a) and (c) describe the effects of a substitute with different values for the substitute's effectiveness $\lambda$. Panels (b) and (d) describe the effects of a substitute with different prices per unit effectiveness. In all cases, the group of households with very high WTP who benefit is extremely small. The more effective the substitute is the more it will

Figure 3: Effect of Substitute Price and Effectiveness




(a) welfare effects with varying effectiveness (b) welfare effects with varying price

(c) fraction benefiting with varying effectiveness (d) fraction benefiting with varying price

Panels (a) and (c) display outcomes from substitutes with varying effectiveness while panels (b) and (d) vary their price. Panels (a) and (b) display the resulting welfare effects while the panels (c) and (d) show the fractions of people who benefit and are hurt by the existence of batteries. The fraction of people at the top who benefit is at most 0.45% and hence not visible. The $\pi$ function and $\ell$ distribution follow the calibration in section 5.4 with $\pi''(R_N^*)/\pi'(R_N^*) = -70$.

benefit this group. Households can only choose between buying or not buying the substitute, so effectiveness can be thought of as the 'quantity' of substitute that is available to purchase. Thus, when more is available, the high WTP group will purchase it and benefit. Effectiveness has a small effect on the fraction of households who buy substitutes because it only affects purchasing decisions through the decline in grid reliability. A low price per effectiveness benefits the high WTP group *less* because more households will purchase the substitute and thus grid reliability will decline more, while the amount of loss mitigated for those already purchasing the substitute remains the same. The magnitude of the welfare benefit to the low WTP group and the harm to the middle WTP group are both larger with more effective or cheaper substitutes.

We expect most low-income households to be in the low WTP group that benefits from the availability of substitutes. Fewer resources results in a lower WTP for all goods, and we see empirically that low-income households are less likely to purchase substitutes.[24] We model grid reliability spending as being paid through a flat tax on all households. As discussed in section 2.1, it may be more accurate to model these charges as varying with electricity use. Yet, because household income is not highly correlated with use, this alternative model would yield similar conclusions. An alternative funding structure like paying for grid investments with income tax revenue, as discussed in Borenstein et al. (2022), would alter the policy preferences of all households and make it unlikely that low-income households benefit from private substitutes.

We model private substitutes and do not differentiate between generators and batteries. While the two are similar in many ways, they differ in that home storage batteries may provide power back to the grid during periods of high demand. Thus, private adoption of batteries could also lower the cost of reliability. This feature would not change our main conclusion, that most households benefit from substitute adoption, but it could result in fewer (if any) households being worse off due to the availability of private substitutes.[25]

# 6 Discussion and Conclusion

Ownership of private substitutes can both affect and be affected by policy decisions over grid reliability. In Section 4.2, we show that power outages cause households to purchase batteries, i.e., households purchase substitutes in response to the perceived unreliability of the electrical grid. Had large investments been made to prevent power outages, fewer batteries would have been purchased. More widespread ownership of private substitutes then has the potential to affect policy decisions as PUCs seek to balance meeting the changed needs of their constituents with the impact of investment on electricity rates. When more households own batteries, the marginal benefit from spending on reliability is lower and hence the efficient level of reliability is lower. The missions of PUCs suggest that changes in the efficient

[24] We note that there are alternative measures of the marginal benefit of reliability. For households for which outages can result in severe health consequences, the marginal benefit as measured by these expected health costs could be higher than the revealed preference WTP, i.e., WTP could be constrained by ability to pay. Policies like SGIP's higher subsidies for households with medical needs directly target these households.

[25] Households with batteries may also be compensated by the utility for providing this backup power. This compensation would make batteries more affordable for all households but is unlikely to change the relationship between WTP for reliability and adoption that is central to our model.

level of provision should be reflected in the actual level of spending. However, the extent of this response is an outstanding and important question. We model the welfare effects associated with the efficient level to understand the potential effects of private substitute ownership on all households.

The availability of substitutes and the resulting decrease in spending on grid reliability affects households differently, depending on their valuation for reliability. Households who do not value reliability highly benefit from cost savings on their electric bill. The reduced reliability hurts other households who were served well by the prior level of grid reliability. A small group of households who value reliability very highly purchase substitutes and are better off despite the lower level of grid reliability.

Empirically, we see that high income households are more likely to purchase private substitutes. This holds true both for backup generators, where we observe these purchasing patterns in the RECS, and for batteries, where we observe these patterns in the SGIP data. This positive correlation between income and willingness to pay for reliability suggests that low-income households are likely to benefit from private substitutes even if they do not buy them.

Three structural factors are likely to increase adoption of private substitutes. First, the price of new substitute technologies like home storage batteries is likely to fall as the technology develops. At the same time, more extreme weather may make the grid less reliable, at least absent larger investments than were previously necessary. Finally, spurred by policies to reduce carbon emissions, more households are expected to use electricity for heat and transportation, potentially increasing their need for reliability. As long as the households buying substitutes continue to use and pay for the grid, those that cannot afford these substitutes are unlikely to be left behind. Yet not all households will benefit, and substitutes' distributional effects are likely to increase.

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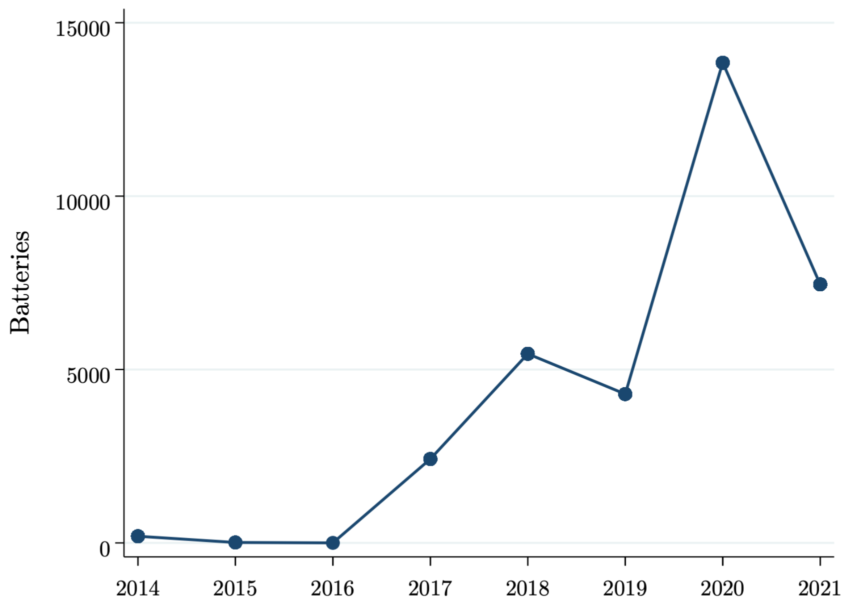
# Appendices

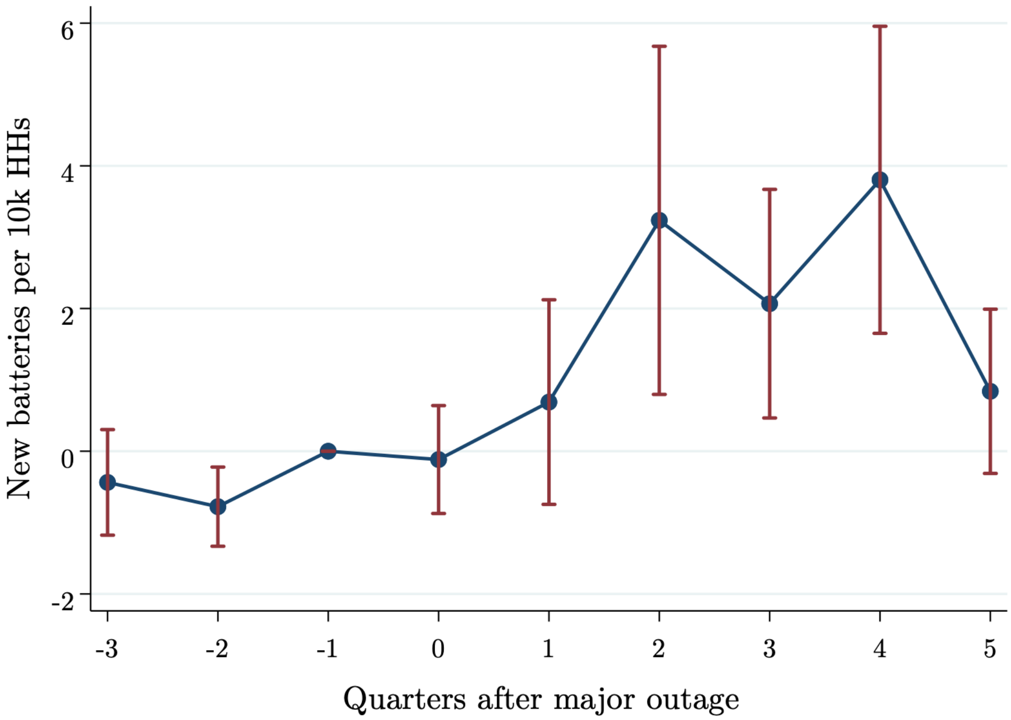
## A Additional Figures and Tables

Figure A1: CA New Battery Installations over Time



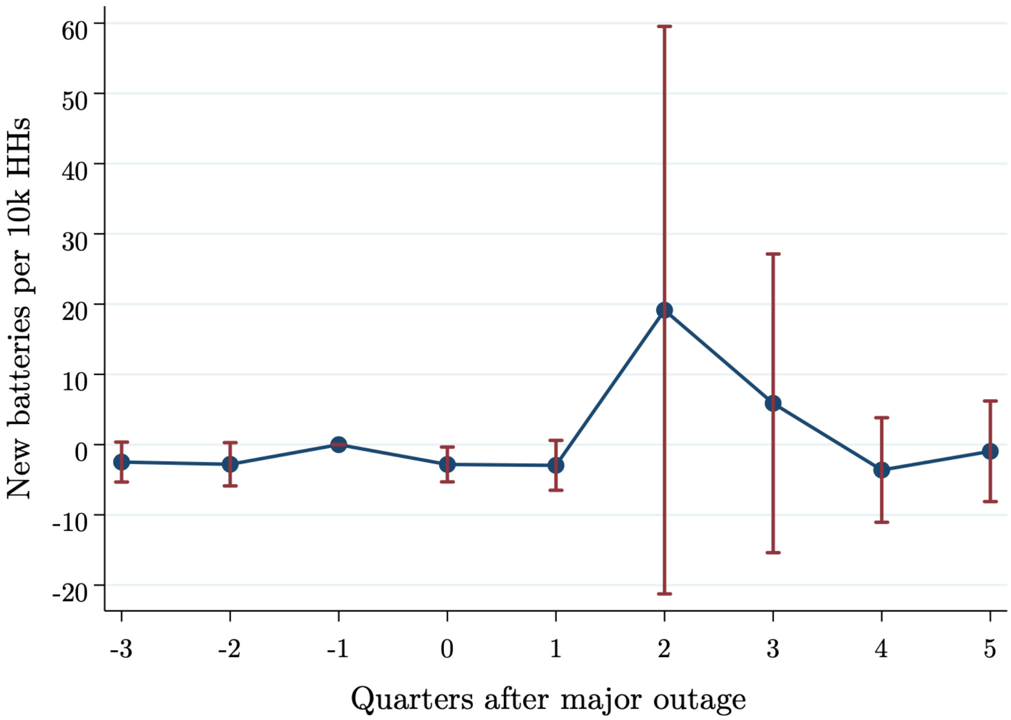

Counts of residential batteries subsidized by SGIP by year. Year corresponds to the year the application was received. Average subsidy size by year for 2017 through 2021: 465, 362, 281, 572, and 392, all in 2022 \$/kWh.

Figure A2: Main Specification Dropping Equity Resilience Batteries




Estimated coefficients and 95% C.I.s for model (1) for a sample that drops all batteries that received the higher equity resilience subsidy. This higher subsidy was introduced in the second quarter of 2020 and was available to a subset of households. SE clustered by city.

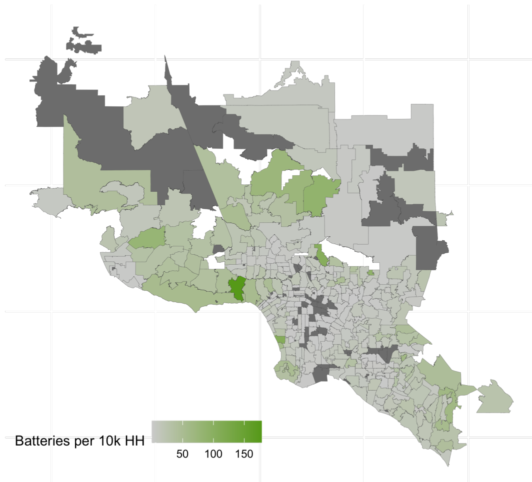
Figure A3: Main Specification, Only High Fire Threat Districts



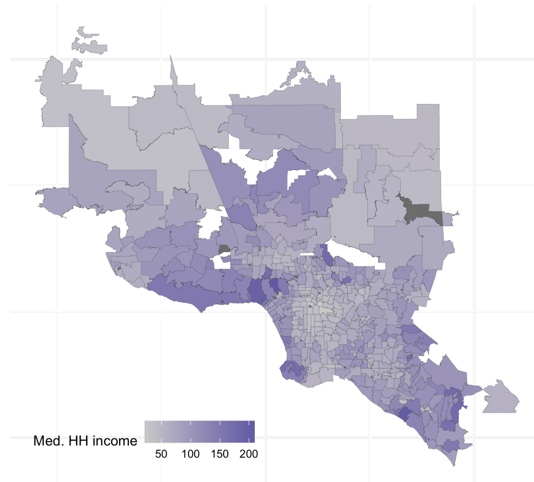

Estimated coefficients and 95% C.I.s for model (1) for a sample that only includes zip codes that are completely located in Tier 2 or Tier 3 high fire threat districts. All vulnerable households in these areas qualified for a higher subsidy that was introduced in the second quarter of 2020. SE clustered by city.

Figure A4: Spatial Distribution of Batteries and Income

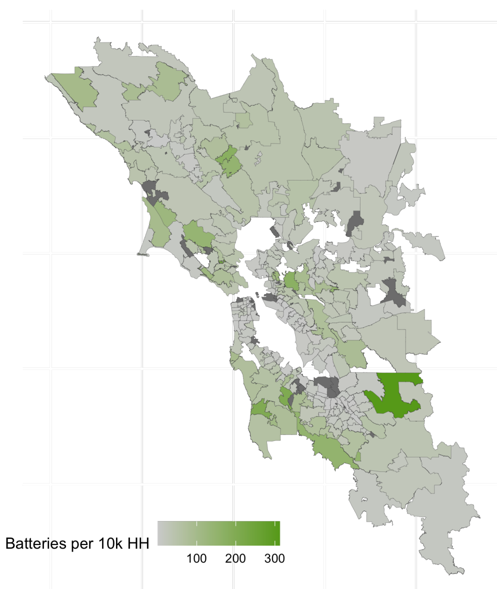
(a) LA: Batteries



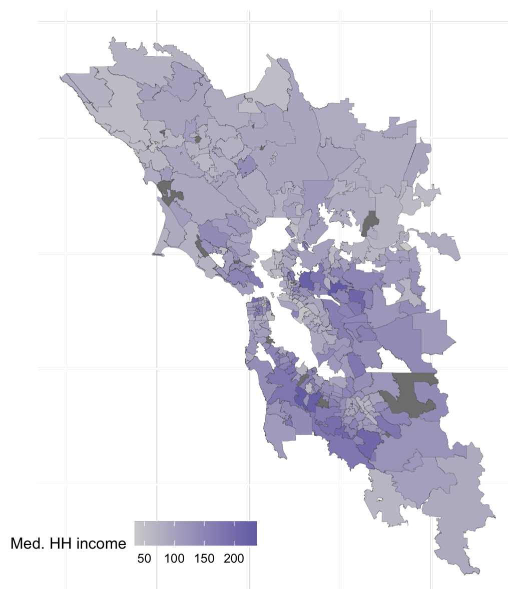

(b) LA: Household Income




(c) SF: Batteries



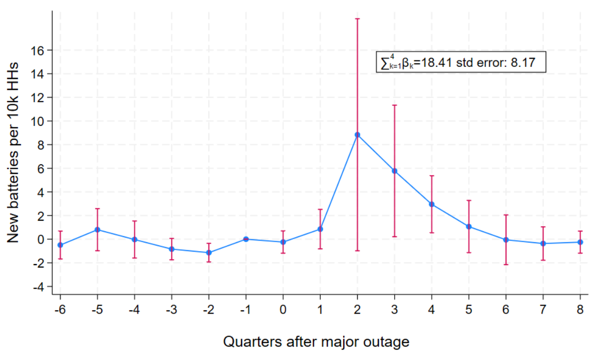

(d) SF: Household Income



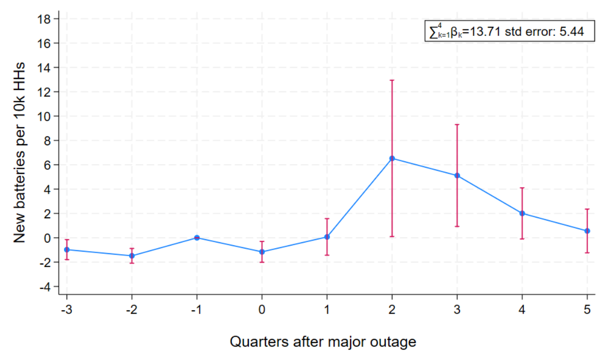

Battery counts per 10,000 housing units. Counts come from residential HHs claiming a subsidy from the state of California under the SGIP. Battery counts for 2017-2021. Median household income in \$1,000s for each zip code from the ACS. LA is Los Angeles MSA; SF is San Francisco MSA.

Figure A5: Robustness of Impact of a Major Outage on Battery Purchase

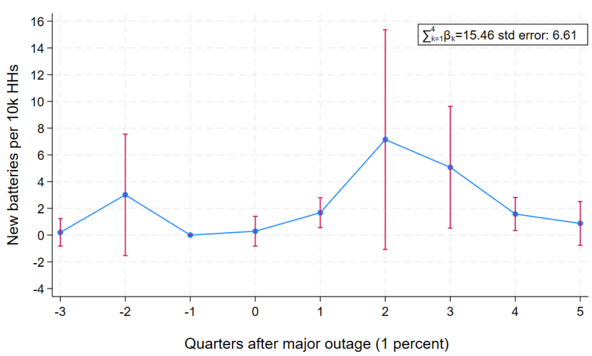
(a) Including more leads and lags



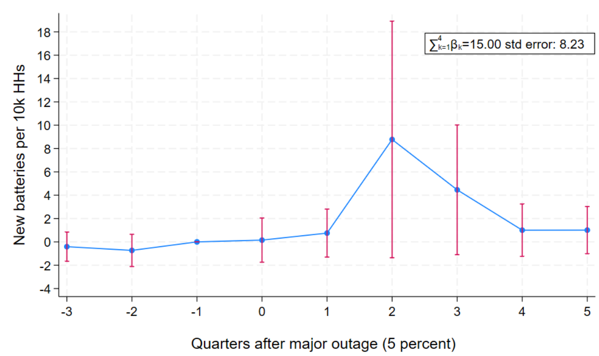

(b) Keeping multiple outages, using first as treatment




(c) Major outage cutoff of 1 percent

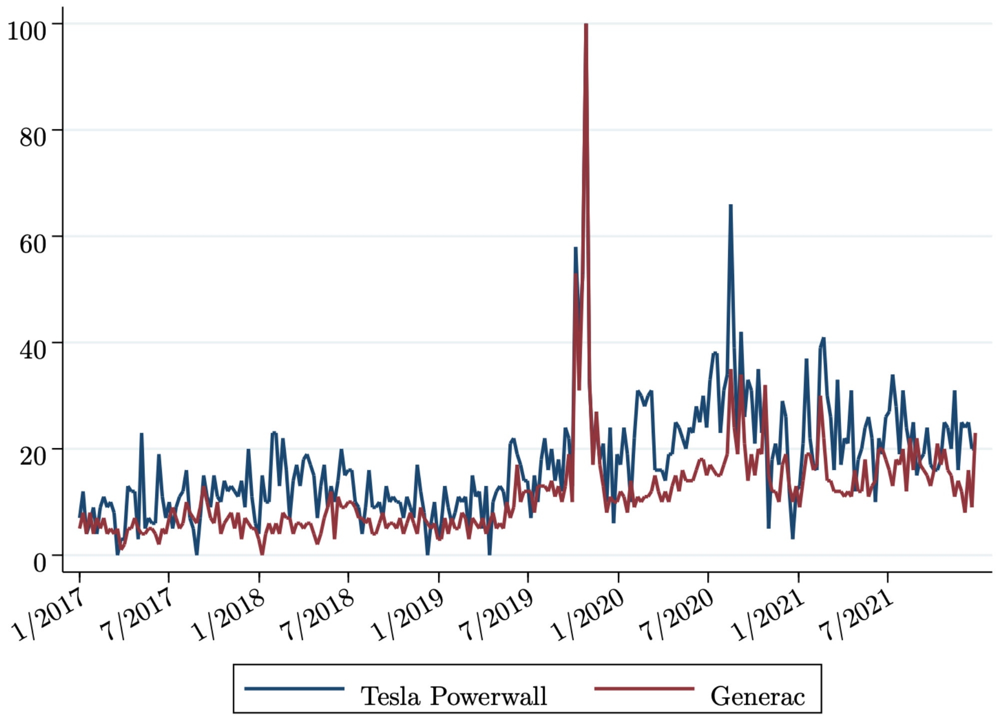



(d) Major outage cutoff of 5 percent




Estimated coefficients and 95% C.I.s for model (1) when (a) including 6 leads and 8 lags rather than 3 leads and 5 lags, (b) keeping cities with multiple outages in the sample and using the first outage as treatment, (c) using a lower 1 percent cutoff when defining a major outage, and (d) using a higher 5 percent cutoff when defining a major outage. SE clustered by city.

Figure A6: Google Search Intensity for "Tesla Powerwall" and "Generac"




Data from Google Trends for the search terms "Tesla Powerwall" and "Generac" for the state of California. Data are weekly from 01/01/2017 through 12/31/2021. They are normalized by Google.

# B Alternative Outage Analysis using PSPS events

We also conduct an alternative analysis of the impact of outages on battery purchase that is based upon Public Safety Power Shutoff (PSPS) events. Here, we gather data on PSPS events at the circuit level and then use these data to re-estimate our primary specification. This approach is similar to the one in Brown and Muehlenbachs (2023) and relies on data available from Pacific Gas & Electric (PG&E), a major utility that serves about 5.7 million households in the northern two-thirds of California.[26] This analysis differs from our primary analysis in three ways:

1. It relies on PSPS events, rather than all major power outages.
2. The geographical unit of analysis is the zip code rather than the city.
3. It covers the subset of California that is served by PG&E, rather than the entire state.

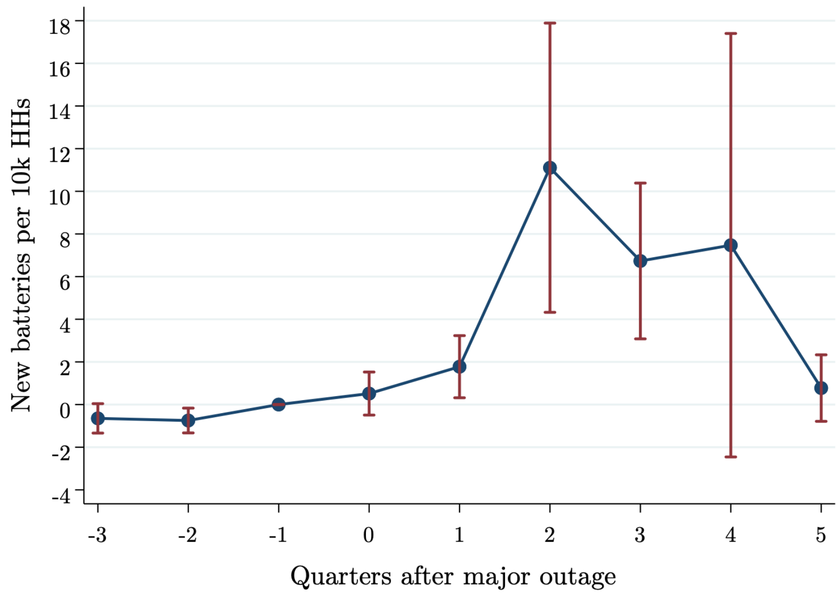
To implement this analysis, we use feeder line level data on PSPS events to construct a zip code level outage measure. Our primary data source is PG&E's reports to the California Public Utilities Commission (CPUC) on the location, start, and stop times of the power shutoffs. We assign these PSPS events to individual zip codes so that we can construct zip-code level outage metrics and merge with battery purchase data from the SGIP (which is provided at the zip code level). Using QGIS, we calculate the length of each feeder line within each zip code, and then calculate the weighted average number of outage hours for each zip code.[27] For each quarter, we calculate the fraction of hours out for that zip code by dividing the number of hours out due to PSPS events divided by the total number of hours in the quarter. We classify zip code-quarters with over three percent of hours out as major outages.

We note that 32 feeder lines affected by PSPS shutoffs do not successfully merge with the PG&E feeder line data (764 feeder lines successfully merge). It appears that well over half of these failed merges are due to fire damage or feeder line terminations due to wildfire risk, though we are unable to verify the reason for all lines. For example, the feeder line "Bucks Creek 1101" was shut off during a PSPS event, but appears to no longer be listed in the PG&E feeder data because it started the Dixie Fire and was subsequently destroyed during it. Of note, this line was scheduled to be upgraded due to its fire risk.

[26] Because this is the main approach in Brown and Muehlenbachs (2023), their analysis is more comprehensive than the one in this Appendix.

[27] For example, if feeder A comprises 60% of the feeder length within a zip code and is out for 10 hours, while feeder B comprises 40% of the feeder length and is never out, the weighted average will be 6 hours of outage. Brown and Muehlenbachs (2023) shows that if the data is weighted by population density data from WorldPop instead of by feeder line lengths, their results are very similar.

Figure B1: Impact of PSPS on Battery Purchases




Estimated coefficients and 95% C.I.s from model (1) estimated using outages due to Public Safety Power Shutoff events. N = 10,880 zip code-quarters from 544 zip codes in PG&E service territory in 2017-2021. Sample excludes the 7.1% of zip codes with more than one major outage. A major outage is defined as one where over 3% of customer-hours are out for the quarter; in the sample used for analysis, 1.4% of zip code-quarters have a major outage. The mean of the dependent variable (batteries per 10k housing units) is 2.1, with a standard deviation of 11.5. SE clustered by zip code.

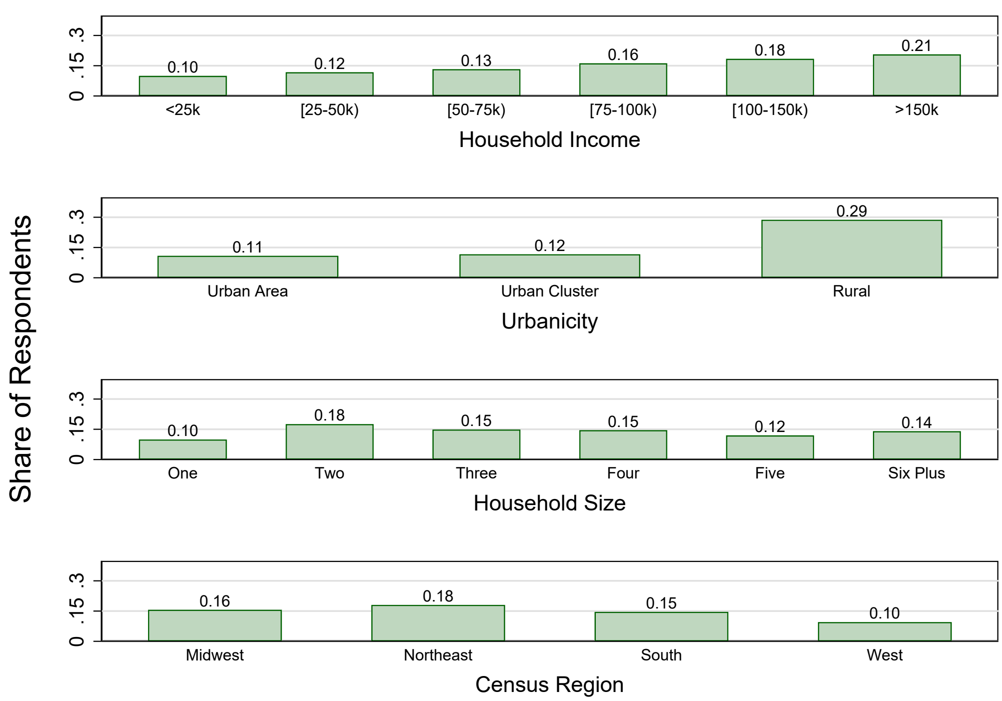
This analysis using PSPS data yields similar estimates to our main analysis. We find that a major outage caused by PSPS events leads to an increase in batteries purchased in subsequent quarters. As in our main analysis, the point estimates imply that these effects peak in the second quarter following a major outage. The point estimate for the second quarter (11.1) implies that a major outage leads to a 0.97 standard deviation increase in the rate of battery purchase two quarters later. The estimated total effect in the year following the outage is 27.1 more batteries per ten thousand households. This estimate of the total effect is statistically different from zero with a p-value $<0.001$. As noted above, these estimates are not directly comparable to our main analysis as they use different identifying variation and a different sample.

# C Who owns private substitutes? Alternative data sources

## C.1 Additional RECS Analysis

Figure C1 summarizes data from the 2020 RECS in greater detail. While only 10% of households making less than $25,000 per year have a backup generator, 21% of households making more than $150,000 per year have a backup generator. Rural households are more than twice as likely to own backup generators. Homes with two to four residents are more likely to own a generator than larger or smaller households. Finally, we see that residents of the Northeast and Midwest are more likely to own a generator than residents of the South and West.

Figure C1: Household Characteristics and Likelihood of Owning a Backup Generator




Data are from the 2020 RECS and are presented using survey weights. N = 18,496.

Data from the 2020 RECS do not yet include information on electricity usage. Nonetheless, we provide conditional correlations using the available covariates. Table C1 is analogous to Table 1, except for the missing variables. It shows that higher incomes and living in a rural area are consistently correlated with being more likely to own a backup generator, even in the presence of a range of other covariates. A $10,000/year increase in household income is associated with about a 0.7 percentage point increase in the probability that a household owns a backup generator. Living in a rural area is associated with having a roughly 16 percentage point higher probability of owning a generator. Results are relatively similar to those using the 2015 RECS. The absence of electricity consumption data may explain why the correlation between income and backup generator ownership is stronger here.

Table C1: Predictors of Backup Generator Ownership (2020 RECS)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Household Income ($10,000/year) | 0.007*** | 0.006*** | 0.006*** | 0.008*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Rural | | 0.160*** | 0.149*** | 0.182*** |
| | | (0.009) | (0.010) | (0.010) |
| Census Region Fixed Effects | No | Yes | Yes | Yes |
| Structure Type Fixed Effects | No | Yes | Yes | No |
| Mean Generator Ownership | 0.143 | 0.143 | 0.135 | 0.181 |
| R squared | 0.011 | 0.066 | 0.054 | 0.063 |
| Observations | 18496 | 18496 | 14839 | 12319 |

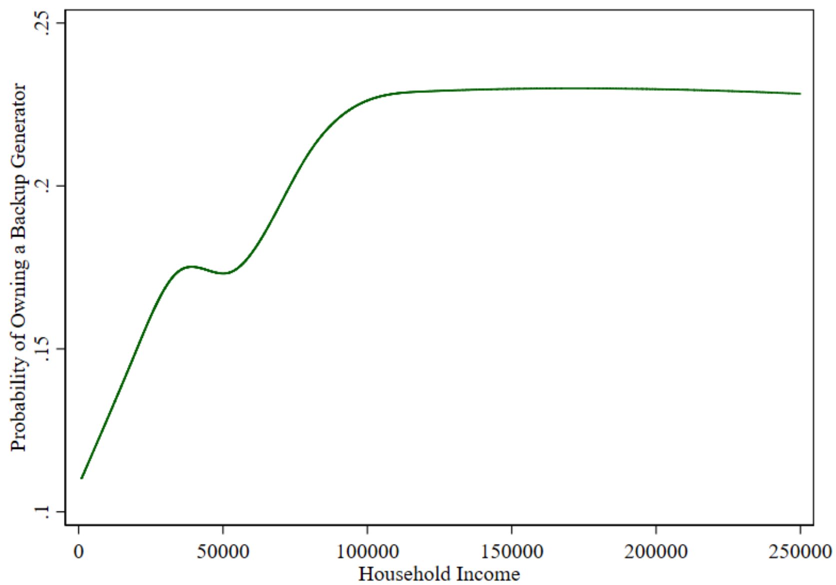
*Notes:* The dependent variable is a binary variable for whether a household owns a backup generator. Data is from the 2020 RECS and results are presented using survey weights. Heteroskedastic-robust standard errors are used. Rural is defined according to the census as an area with less than 2,500 residents. Household income is constructed using the mid-point of $20,000 income bins. Incomes above $140,000 are top-coded into one bin, and we use an income of $150,000 for this group. Columns (1) through (3) include all types of homes (mobile, single-family detached, single-family attached, small apartment buildings, and large apartment buildings), while Column (4) reports results only looking at single-family detached houses.

## C.2 American Housing Survey: Backup Generators

The American Housing Survey (AHS) also collected data on generator ownership in 2013 and 2017. Like the RECS, these data show that many U.S. households own backup generators. Most census divisions have backup generator ownership rates of 17-20%. Yet, 26.0% of homes in New England own generators, while only 14.4% of homes in the combined Pacific and Mountain divisions do. There is also a statistically significant, but modest, increase in the ownership of backup generators over time (17.4% of respondents report owning them in 2013, increasing to 19.2% in 2017).

These data also show that higher incomes are associated with greater backup generator ownership rates (see Figure C2). Note that this effect wanes at incomes above $100,000 per year.

Figure C2: Probability of Owning a Backup Generator by Household Income




Results from a regression of whether a household owns a backup generator in 2017 on a spline for real household income. Households reporting income below $1,000 per year and above $1,000,000 per year are excluded. The graph is censored above household incomes of $250,000 per year to provide a clearer picture. Results including indicators for region of the U.S. and year of survey are similar.

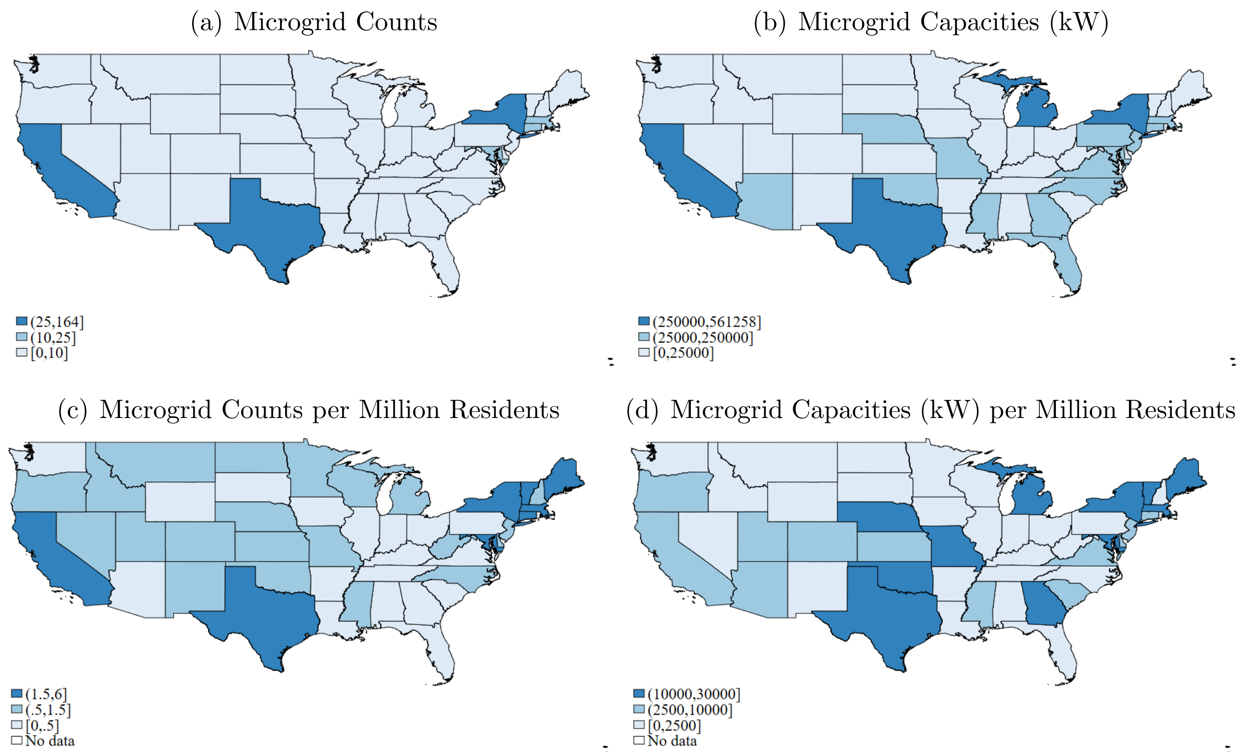
## C.3 Department of Energy Microgrid Database

A microgrid is a "local energy grid with control capability, which means it can disconnect from the traditional grid and operate autonomously" (U.S. Department of Energy, 2014). Microgrids come in many sizes – from being able to power an individual shop or residence, up to a small community. They exist in the industrial, residential, commercial, and military sectors. A microgrid can continue operating in the event of a full- or partial-scale grid failure.

The U.S. Department of Energy collects data on known microgrids; through 2020, they have identified 461 different locations (U.S. Department of Energy, 2021). Because there is no registration or reporting requirement, this dataset omits locations that the Department of Energy does not know about.

Ninety-two percent of included microgrids list an operating year of 2010 or later, with the five most common years being 2016 through 2020. Common settings are Commercial (42%), City/Community (12%), Military (11%), College/University (10%), Schools (6%), and Hospital/Healthcare (5%).[28] Note that only 15 "Multi-Family" installations (primarily apartment buildings in New York City) are listed, which is suggestive that many similar installations are missing.

Figure C3: Spatial Distribution of Microgrids across U.S. States




Microgrid data are from the U.S. Department of Energy. This is a partial dataset based on microgrids that the DOE knows about. Counts are the number of independent installations, while capacities represent the sum across all microgrids within a state. Subfigures (c) and (d) divide numbers in subfigures (a) and (b) by the number of residents (in millions). Hawaii and Alaska are excluded.

Figure C3 shows the spatial distribution of microgrids across the United States. The most common states in the data are Texas (36%), California (14%), New York (8%), Massachusetts (5%), Puerto Rico (4%), Hawaii (3%), and Alaska (3%). While bigger states generally have more and larger grids, this is not always true. For example, Massachusetts has a large number, while Illinois does not.

[28]Many microgrids in Texas are at H-E-B supermarket locations; microgrids in other states are less concentrated in the commercial sector.

# D Proofs

## D.1 Existence of a solution

Equation 4 has a solution in the range $(0, R_N^*]$.

At $R = 0$ the expression on the left-hand side is greater than zero.

$$-\pi'(0)\left[\int_0^{\frac{P}{\pi(0)}} L_i\ell(L_i)dL_i + (1-\lambda)\int_{\frac{P}{\pi(0)}}^{\infty} L_i\ell(L_i)dL_i\right] - 1 \geq -\pi'(0)\left[(1-\lambda)\int_0^{\infty} L_i\ell(L_i)dL_i\right] - 1$$
$$= -\pi'(0)(1-\lambda)\tilde{L} - 1]$$

By assumption we have that this exceeds zero.

At $R = R_N^*$ the expression on the left-hand side of Equation 4 is no greater than zero.

$$\begin{aligned}
&-\pi'(R_N^*)\left[\int_0^{\frac{P}{\pi(R_N^*)}} L_i\ell(L_i)dL_i + (1-\lambda)\int_{\frac{P}{\pi(R_N^*)}}^{\infty} L_i\ell(L_i)dL_i\right] - 1 \\
&= -\pi'(R_N^*)\left[\int_0^{\infty} L_i\ell(L_i)dL_i - \lambda\int_{\frac{P}{\pi(R_N^*)}}^{\infty} L_i\ell(L_i)dL_i\right] - 1 \\
&< -\pi'(R_N^*)\int_0^{\infty} L_i\ell(L_i)dL_i - 1
\end{aligned}$$

Since its objective function is concave and continuously differentiable and its first order condition is positive when $R$ is equal to zero, the problem in Equation 2 has a solution, $R_N^*$, which exceeds zero. This implies that

$$-\pi'(R_N^*)\int_0^{\infty} L_i\ell(L_i)dL_i - 1 = 0$$

and as a result, the expression on the left-hand side of Equation 4 is no greater than zero. Since the expression is continuous, the equation must have a solution on the interval.

## D.2 The planner cannot improve upon private purchasing decisions

The benefit of purchasing a substitute is increasing in the household's willingness to pay to avoid an outage. Thus, if it is desirable for a household with $L_i = L'$ to purchase a substitute, it is desirable for all households with $L_i \geq L'$ to purchase a substitute. It suffices to show then that were the planner to choose simultaneously both $R$ and a cutoff $L^*$ above which households would purchase a substitute that the planner would choose $R_S^*$ and $P/\pi(R_S^*)$.

In that case, the planner would solve

$$\max_{R,L^*} - \int_0^{L^*} \pi(R) L_i \ell(L_i) dL_i - \int_{L^*}^{\infty} \left(\pi(R)(1-\lambda)L_i + P\lambda\right) \ell(L_i) dL_i - R$$

A necessary condition for a solution to this problem requires that $L^* = \frac{P}{\pi(R)}$. A second necessary condition is as described in Equation 4. This results in the same solution.

## D.3 If the average loss household does not buy a substitute, some households are hurt

The household with average loss has $L_i$ equal to $\tilde{L} = \int_0^{\infty} L_i \ell(L_i) dL_i$. If they do not purchase a substitute, their payoff is maximized when $R$ is equal to

$$\arg\max_R -\pi(R) \int_0^{\infty} L_i \ell(L_i) dL_i - 1$$

This is equivalent to the problem in Equation 2. As a result, any deviation from $R_N^*$ will decrease the welfare of this household. If $\tilde{L}\pi(R_S^*) < P$, then this household will not purchase a substitute. If any households purchase a substitute, then $R_S^* < R_N^*$ and as a result, the existence of the substitute harms this household.