Valuing Technology Complementarities: Rooftop Solar and Energy Storage*

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Product complementarities can shape market patterns, influencing the demand for related products and their accessories. This study examines complementarities in the demand for rooftop solar and an accessory, battery energy storage. Using nationwide administrative data, we estimate a dynamic nested-logit model of solar and storage adoption. We quantify the demand complementarity between solar and storage, and find that if storage was not available, 20% of households who coadopt solar and storage would not adopt anything. We find that the demand for solar and storage bundles increases with power outages, with a larger effect in California.

Keywords: product complementarity, electricity resilience, demand estimation, new technology
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1 Introduction

Complementarities are known to play a key role in the demand for many technologies (Samuelson, 1974; Gentzkow, 2007; Grzybowski and Verboven, 2016), and economists have documented the power of bundling in influencing demand and welfare (Ho et al., 2012; Crawford and Yurukoglu, 2012). Accessory goods are one extreme example of demand complementarity; the accessory has little to no value if consumed without another primary product, and the primary product may increase its value if bundled with the accessory. For example, consumers may buy video game consoles for access to certain games available only on that console (Liu et al., 2018).[1] Similarly, we document that residential energy battery storage can be thought of as an accessory since it acquires value when installed alongside a rooftop solar photovoltaic (PV) system and is seldom adopted alone.

This study estimates the value of pairing the residential battery accessory with solar. We develop a dynamic discrete choice model of solar and storage adoption using data on nearly a million solar installations and nearly 50,000 solar and storage installations nationwide 2011-2021. We find that if battery storage was not available, 20% of households that installed solar paired with batteries would not install solar at all. We further find that power outages greatly influence the complementarity, with a 20% increase in outage intensity increasing total rooftop solar capacity installed by roughly 4.5%. This effect turns out to be even stronger in California than in other states.

Measuring the impact of new accessory goods is important for firm decisions and for economists aiming to understand firm behavior. In many cases, the same firm provides both the "access product" (the product that is needed to make use of the accessory) and the add-on (Sharma and Mehra, 2021). There are multiple reasons firms may benefit from offering the accessory. For example, in the video game industry, Lee (2013) show that exclusivity favors the access product that is required to utilize the accessory (i.e., the gaming platform). Indeed, providing the add-on product not only can increase demand for the access product, but can also provide an additional revenue stream to the firm (Sharma and Mehra, 2021). In prosocial contexts, understanding the role of accessory products is also critically important for policymakers seeking to develop policies to incentivize behavior, for it provides useful input into policy debates about the effect of different policy approaches.

[1] Accessory products are common in many markets. For instance, smartphone apps are designed for specific operating systems, ink cartridges only suit certain printer brands, and coffee pods fit specific coffee machines. In all of these cases, the primary product is perceived as necessary for valuing the accessory.

Residential batteries are a relatively new technology to the market and have the potential to influence the demand for rooftop solar, which has been available to consumers for nearly two decades. In fact, substantial adoptions of residential batteries have only occurred in the past few years. Batteries allow rooftop solar adopters to store some or all of the solar electricity generated for use when the sun is not shining. This can be especially valuable to the electricity system by allowing rooftop solar to offset electricity consumption at times with the highest wholesale electricity prices. There is also value to consumers under dynamic time-varying pricing of electricity because solar generation can be moved to more expensive hours. In some cases, the consumer can also receive a payment if the battery is enrolled in a virtual power plant.[2]

Batteries also provide backup generation to consumers if there is a power outage. In most cases (without expensive inverters), standard rooftop solar alone is not capable of providing backup power. However, stand-alone batteries are *much* more expensive as a backup option than a home generator, and there is no way to recharge during an outage if the battery is not paired with another generation source, so the value to the customer is limited to a single discharge from the battery during the outage. As a result, battery storage alone is quite rare, as we will document below, and thus, residential battery storage can be considered as an accessory good that only provides utility to consumers when complemented with solar. Accordingly, we do not include stand-alone batteries in our choice set, as the financially-relevant option for stand-alone backup capacity is a generator.

Given that residential batteries are reasonably treated as an accessory item, the coadoption we observe can be attributed to a complementarity between batteries and solar. The focus of this paper is on quantifying the extent of this complementarity by estimating the impact of the accessory item, batteries, on the adoption of the access product, solar PV. Our first counterfactual aims at gauging how much of the adoption of solar is due to the entry of batteries. Thus, we simulate solar adoption in a scenario in which the solar plus battery option was not available. We develop and estimate a structural discrete choice model of dynamic consumer demand for rooftop solar and battery storage with a nested-logit framework. Consumers first choose an installer and then one of the options offered by the installer, a structure that fits the data much better than any other. The nesting structure in the model is especially important in our setting because not all installers offer the battery storage option, and it is important to allow for a stronger correlation in the demand unobservable for product options offered by the same

[2] A virtual power plant allows the electric utility to draw from the battery during times of scarcity on the system in return for some compensation to the consumer.

installer. Relatively few storage systems in our data involve a retrofit of an existing solar system, and hence, we focus on the solar and storage coadoption decision. Identification in our setting is facilitated by instrumenting with a set of supply shifters, including changes in rebates and wages for construction workers, as well as the timing of the battery option entering the market.

While there is always an inherent complementarity when there is an accessory item, our model does not preordain the extent of the complementarities; rather, they come about based on the patterns of adoption in the data. Our nested-logit structure is especially useful in allowing us to disentangle complementarities from correlations due to utility shocks. Including dynamics in the consumer decision is critical in our context because there is an option value of waiting in the coadoption decision. Consumers will have expectations about future declines in the price of rooftop solar and batteries, as well as increases in future electricity prices and decreases in rebates, based on historical trends. We employ a conditional choice probability approach to estimation, roughly following Hotz and Miller (1993) and Arcidiacono and Miller (2011), akin to De Groote and Verboven (2019).

Quantifying the complementarity between batteries and solar is especially useful given that incentivizing the pairing of rooftop solar with battery storage is at the heart of policy debates around the country. In addition to sizable direct incentives for storage, California also has had a set of vibrant debates about the compensation of solar and tariff design for solar households (Net Metering 3.0), which has led to a substantial decrease in the remuneration of rooftop solar-fed into the grid. The stated goal of at least some California regulators is to encourage the adoption of energy storage to allow rooftop solar to be used in later (more valuable) hours rather than fed into the grid. Similar debates are occurring in states such as Illinois, Michigan, Mississippi, Washington, and Virginia.[3]

We run two additional counterfactuals designed explicitly for policy relevance. In our second counterfactual, we examine the effect of power outages on solar adoption that results from the complementary between solar and battery storage. The connection is that outages increase the value of batteries to consumers and if batteries are more valuable, coadoption is more valuable. This counterfactual is useful because climate change is widely expected to increase the number and duration of power outages.[4] It is also a valuable counterfactual because electric utilities can make investments to reduce outages, and thus, the counterfactual provides guidance on the extent of a secondary impact on solar and storage adoptions from reducing outages. We find that increasing

[3]See https://www.dsireinsight.com/blog/2021/5/25/status-of-state-net-metering-reforms.
[4]See https://www.climatecentral.org/climate-matters/surging-weather-related-power-outages

outages increases solar and storage coadoption. Although this occurs largely by leading consumers to substitute from solar-only adoption, there is a net increase in solar adoption as a result of the complementarity. As mentioned above, California differs from all other states in exhibiting a stronger effect of outages on solar and storage adoption.

In our final counterfactual, we examine the effect of reduced battery storage prices on solar and storage adoption, due to either a subsidy or technical change. Direct subsidies for residential battery storage are a common policy tool. Some states, such as California, provide generous subsidies for battery storage, and there is currently a 30% investment tax credit available for battery storage. We find that a 20% price reduction for coadoptions of solar and batteries would increase battery storage capacity by 300 MWh per year and solar capacity by 40 MW. As with the first counterfactual, the increase in total solar adoption can be attributed to the complementarity between residential batteries and solar. These findings underscore the importance of accounting for complementarities in policy design.

Our work contributes to the broad literature on product complementarities, which has long received attention in economic literature (Hicks and Allen, 1934; Samuelson, 1974). There is also a large related empirical literature allowing for products with interrelated demand (Train et al., 1987; Archsmith et al., 2020; Gentzkow, 2007). Our paper more specifically relates to growing literature on the demand for accessory goods (Liu et al., 2018; Sharma and Mehra, 2021).[5]

Our study is among the first to analyze battery storage. The most related paper is Brown and Muehlenbachs (2022), which focuses on the California Public Safety Power Shutoff (PSPS) outages and uses a demand model of battery storage to estimate the value of electricity reliability by calculating the willingness to pay to avoid outages. In comparison, our work covers states across the nation and is focused on quantifying the extent of product complementarities and the mediating role that power outages play in these complementarities. We also use a dynamic nested-logit model of demand, allowing us to explicitly model the decision of which installer to choose. This is an important factor to model for our research question since many installers do not offer storage, and we want to correctly capture how the cross-price elasticities across choice options are affected by differences in the technology versus differences in the installers.

More broadly, our work relates to a small, but growing literature on utility-scale battery

[5] Two related review articles are Berry et al. (2014), which reviews recent structural models of demand complementarities, and Seetharaman et al. (2005), which discusses econometric models of multi-category choices. There is also a small literature outside of economics that discusses batteries being beneficial when coupled with solar, with some evidence from small-scale engineering studies (Gomes et al., 2020)

storage, a different implementation of battery storage technology (Kirkpatrick, 2018; Karaduman, 2023; Butters et al., 2023; Andres-Cerezo and Fabra, 2023b). Andres-Cerezo and Fabra (2023a) examine a possible complementarity in the value of utility-scale renewables and energy storage in the Spanish grid, a useful counterpart to our work on demand-side product complementarities. Our study also relates to emerging work on the economics of electricity resiliency (Borenstein et al., 2023) and the large literature examining the impacts of subsidies for rooftop solar adoption (Hughes and Podolefsky, 2019; Gillingham and Tsvetanov, 2019; De Groote and Verboven, 2019; Langer and Lemoine, 2022; Feger et al., 2022; Bollinger et al., 2023). We focus on product complementarities, but also model the effect of subsidies on the residential battery storage and solar adoption decision, in a highly policy-relevant setting.

2 Empirical Setting, Data, and Descriptives

2.1 Background

Residential battery energy storage in the United States can be traced back to the early 2000s, when small numbers of homeowners began using lead-acid batteries to store excess solar power generated by their rooftop solar panels, inspired by off-grid applications. These early systems were relatively expensive, somewhat difficult to manage, bulky, and had a relatively short lifespan. In the past decade, the market was disrupted by the introduction of residential lithium-ion battery storage systems, which are smaller, lighter, and have a longer lifespan. While there are five major manufacturers in the market, two currently dominate the residential energy storage market in the U.S.: Tesla and LG Chem. Tesla's Powerwall was launched in 2015 and currently makes up roughly 60% of residential battery installations (based on our data). LG Chem's RESU (Residential Energy Storage Unit) was first launched in 2013, and currently covers a little over 30% of all battery installations. Figure A1 shows pictures of these two products.[6]

Battery storage systems designed for residential customers vary in how much energy they can hold, but tend to have a capacity in the range of 10 to 30 kilowatt-hours (kWh). While the duration of backup depends on the the electricity consumption by the household, batteries in this range are usually sufficient to back up most common loads (lights, refrigerator, water, cooking, etc.) for 12 hours or more. More substantial loads,

[6] Appendix Figure A2 shows how the market share of each manufacturer has evolved in recent years.

such as electric clothes drying and charging an electric vehicle, would deplete the battery very quickly. But a battery system paired with rooftop solar would be well-positioned to provide backup for critical loads for several days or more. The battery can also be used for arbitrage when consumers are facing higher electricity prices in the evening after the sun goes down, such as under a time-of-use pricing scheme, or when consumers are facing lower compensation rates for solar generation fed into the grid. With a battery system, consumers can choose to charge the batteries during the sunny hours of the day and consume electricity from the battery later in the evening to displace higher-priced grid electricity. Further, battery storage can also be used to allow energy independence-minded households to be largely off the grid on many days, although this use of the battery in a "self-consumption" setting would lead to more cycles of the battery and potentially a shorter battery lifespan.

Battery storage installation is offered to households by contractors that install rooftop solar. The market for solar installers has a small number of very large firms, and many smaller firms.[7] Not all installers provide a battery storage option. Figure A3 shows the market share of the top 25 U.S. installers in recent years in our data. Seventeen of the top 25 installers also have a battery storage option in at least some markets by 2020.

Both batteries and solar have been the beneficiary of government subsidies. At the federal level, the primary subsidy is the Investment Tax Credit (ITC) which offers a tax credit to homeowners to deduct a percentage of the post-rebate cost of installing a solar panel system from their federal taxes. In January 2020, the tax credit decreased from 30% to 26% and remained at that level through the end of 2021, but was increased again to 30% by the Inflation Reduction Act of 2022 and it set to slowly sunset by 2035. If batteries are installed along with the solar system and only charged from the solar system, they are included in the total cost and hence eligible for the ITC.[8]

Several states either had or currently maintain incentives for solar and/or storage. For example, California introduced the California Solar Initiative (CSI) in 2007 to promote solar adoption via subsidies (and sunset the program in 2016). Many other states followed suit with similar initiatives. More recently, incentives for battery storage have also emerged. Notably, California introduced the Self Generation Incentive Program (SGIP) in 2017, which provides rebates for residential battery storage systems, amongst other technologies. In some cases, utilities or municipalities offer additional incentives at a

[7]Tesla, Vivint Solar, and Sunrun are the three largest installers and make up roughly 30% of installations. In 2016, Tesla acquired SolarCity, which was the leading installer in the U.S.

[8]The Inflation Reduction Act expanded the ITC to include storage systems regardless of whether coadopted with solar.

local level or only to low-income populations. While residential solar incentives that all consumers are eligible for are now relatively rare, incentives for battery storage are becoming increasingly common.

2.2 Data

2.2.1 Data sources

Solar and battery installations. Our primary data set is compiled by Lawrence Berkeley National Laboratory (LBNL) and covers over three quarters of all solar and battery installations in the United States. The data include the customer segment (residential, commercial, government, or nonprofit), total system price, system characteristics (including size and technology), whether the system is third-party owned (TPO), any financial incentives, the system installer, solar panel, inverter, and battery (if applicable) manufacturer and model, the interconnection date, and the street address of the installation.

The raw data set has over 2.2 million installations. Between 2010 and 2021, we observe almost 2 million residential installations. We complement this data set with the 2010 Census downloaded from National Historical Geographic Information System (NHGIS). This data set includes demographic data, but for our purposes, we use the number of owned housing units by ownership status. Specifically, we use the number of owned houses as a proxy of market size by geographic unit (zip-code, county, or state).

Power outages. We gathered data on power outages from *PowerOutage.US*, which collects live power outage data from 742 utilities throughout the United States. To the best of our knowledge, these data are representative of outage trends in the United States. The data are structured as city-level snapshots recording the number of customers without electricity at different times. A set of snapshots with a positive number of customers without power allows for identifying outage events.[9] Between January 2017 and December 2021, we identified over 4 million events, each with a starting time-stamp, duration (until power is fully restored), and the number of customers affected. The median outage event lasts for three hours and affects 28 customers.[10] We aggregate these events to compute statistics to capture the frequency and intensity of power outages at the county-quarterly level.

[9] To avoid household-level electricity issues, we exclude events that involved fewer than 10 households or lasted less than 10 minutes.

[10] See Appendix Table A1 for some descriptive summary statistics in the raw data.

2.2.2 Estimation sample

Home batteries were a niche and generally not commercially-available product until late 2016, and our outage data begins in January 2017. Thus, we focus our analysis on residential installations that occurred between 2017 and 2021. We also exclude observations from Colorado, Florida, and Texas, where solar and battery storage data reported by utilities and programs are missing key variables. Finally, we exclude multi-family residential units and new construction, because the decisions involved in these cases deviate substantially from standard household choice.

Our final data set includes 993,223 solar PV systems, which are divided into two groups: "PV-Only" and "PV+Battery." The latter refers to coadoption of solar PV and a battery storage system at the same time. Table 1 provides summary statistics for our full data set and these two groups. We observe that solar systems paired with batteries have 10% larger solar systems and cost nearly one third more than stand-alone solar systems. They also are somewhat less likely to be third-party owned (versus household-owned). We also observe that 87% of solar and storage coadoptions are in California, as opposed to 61% of solar-only systems in our data set, emphasizing the importance of California for the coadoption market.

Table 1: Summary Statistics

	(1) All Systems	(2) PV-Only	(3) PV+Battery
Panel A: System Size:			
Solar PV Size (kW)	7.05	7.01	7.72
Battery Size (kWh)	16.38	.	16.38
Panel B: Installation Cost:			
Price ($)	27,266	26,775	36,073
Rebates ($)			
for PV	277	284	139
for Battery	97	0	1,831
Federal ITC ($)	7,584	7,491	9,250
Price post Rebates and ITC ($)	19,309	19,000	24,853
Price post Rebates and ITC per Watt ($)	2.85	2.82	3.42
Panel C: Other Characteristics:			
Third-Party Owned (TPO)	0.33	0.33	0.19
In California	0.62	0.61	0.87
Number of Installations	993,223	940,769	52,454

Notes: This table presents summary statistics of residential systems installed between 2017 and 2021. Price is the total cost of installation of the system. Rebates include all incentives the household received, potentially from more than one State or Local program. Federal ITC stands for Solar Investment Tax Credit (ITC). Until 2019, the tax credit rate was 30%; starting in 2020, the credit rate was 26%, but it went up again to 30% with the Inflation Reduction Act. Third-Party Ownership (TPO) is a popular financing solution and usually occurs in two forms: solar leases and power purchase agreements (PPAs).

2.3 Trends in the Solar and Battery Market

We now provide some further context on the solar and battery market by providing descriptives to clarify the trends in solar and batteries relevant to our study.

Prices and Subsidies. As we saw in Table 1, the pre-incentive price of a PV+Battery system is nearly $10,000 higher than the pre-incentive price of PV-Only systems. The difference in price is reduced to $4,800 once we account for rebates and the ITC. These are averages across the full sample period, but the technology costs for solar have been dropping since 2011.

For reference, Figure 1(a) shows the pre-incentive total price per watt of solar installed for a system with and without batteries. There is a clear trend downward in per-watt prices of solar only, while prices of solar and batteries combined have been relatively flat or increasing. The slightly increasing price of coadoption (per watt) likely reflects an increase in battery system sizes from 12.3 kWh in 2016 (with only 63 installations that year) to 17.6

kWh in 2021 (with 19,570 installations).

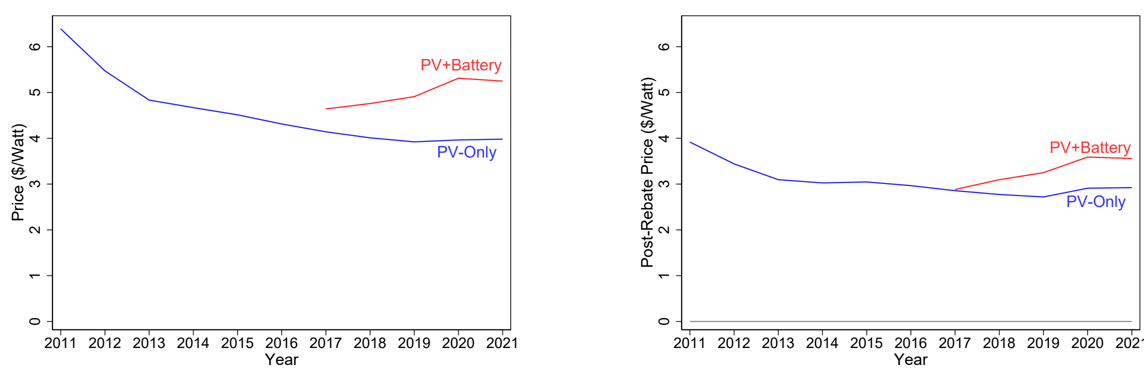
Figure 1(b) shows the evolution of the post-rebate price.[11] We assume that all installing households take the ITC either through their own tax liability or through a solar lease or PPA product whereby a third party can take the tax credit. The post-subsidy price per installed watt of solar has declined since 2011, but not as quickly as the pre-subsidy price. In fact, since 2019, the post-subsidy price per watt for solar-only has very slightly increased in part due to the reduction of the ITC in 2020.

The overall financials of a solar investment or battery coadoption investment vary substantially across the United States due to differences in sunlight hitting the roof, the density of installers, and other local factors. In most places that have solar subsidies, solar installations have a reasonable rate of return or payback period. Consumers install batteries for multiple reasons (e.g., backup, self-consumption, electricity rate arbitrage, virtual power plants), so a simple financial calculation is usually not possible.

Figure 1: Price per watt of Solar

(a) Price per watt of Solar

(b) Post-Rebate Price per watt of Solar



Notes: Panel (a) shows the total price of a solar system (per watt of capacity). The blue line captures total price of PV-Only systems, the red line is the total price per watt of solar of PV+Battery systems. Panel (b) shows the price per watt of solar after deducting rebates and ITC tax credit received by PV-Only systems (blue line) and PV+Battery co-installed systems (red line). Overall, the price per watt has decreased over time as well as the magnitudes of the rebates offered.

Adoption. Figure 2(a) illustrates how installed residential solar capacity has increased between 2011 and 2021. The total capacity, in terms of megawatts installed, is the sum of the capacity installed by stand-alone solar systems and combined solar and energy storage systems. We observe that only a small fraction of the systems are coadopted, but this fraction has been steadily increasing since 2017.

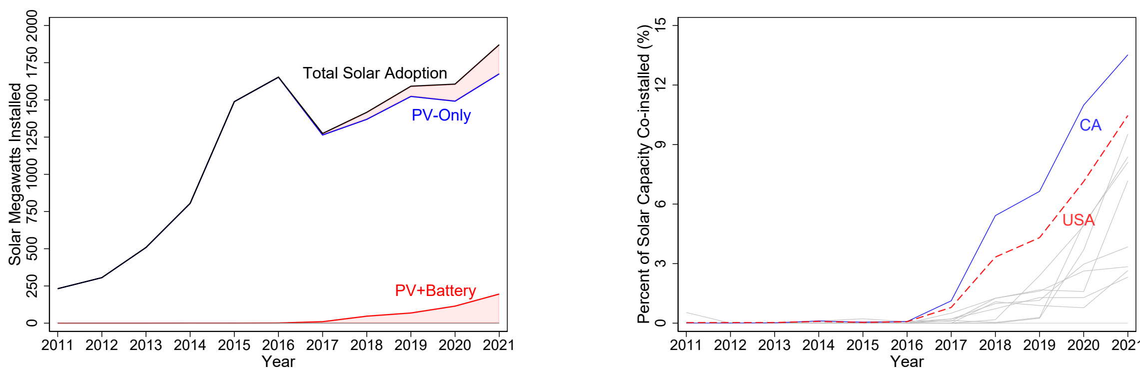
[11] The levelized cost, which describes the present value of the costs over time divided by the generation, shows a very similar decline.

Figure 2(b) plots the fraction of total solar capacity that is from solar and storage coadoptions in our data. The red dashed line shows the fraction in the United States as a whole, while each of the other lines corresponds to an individual state. We label California (solid blue line) separately, as the fraction of coadopted systems is higher than in any other state (the grey lines). Figure 2(b) shows even more clearly that the coadoption share has increased substantially in the last few years. Coadoption was largely unavailable in 2016, but reached more than 10% nationwide and 14% in California by 2021.

Figure 2: PV and Battery Adoption

(a) Aggregate Adoption

(b) Co-adoption Share (%)



Notes: Panel (a) shows the solar capacity (in Megawatts) installed by year. The black line is the aggregate capacity, and the blue line corresponds to the capacity installed in systems without Storage (PV-only). The red line is the capacity coadopted with storage. Panel (b) shows the fraction of Solar capacity coadopted with storage. The red dashed line corresponds to the nation's aggregate share, the blue-solid line is California, and the grey lines are Arizona, Connecticut, Illinois, Massachusetts, North Carolina, New Jersey, Nevada, and New York. These figures use LBNL's installation level data.

Two additional questions relating to adoption are central to motivating our modeling approach. The first is whether the data support our argument that batteries can be viewed as an accessory. Stand-alone batteries are unquestionably much more expensive and less useful for very long periods of backup than home fossil-fuel generators. Of course, some households who cannot install solar might still be interested in batteries because they do not like the emissions from home generators, and in some cases contractors may be willing to install stand-alone batteries. Indeed, we observe 856 residential battery-only systems in the data. However, this is only 0.04% of the over two million solar installations and only about 1% of all battery installations. Furthermore, these battery-only systems are mostly observed in a few specific counties, primarily in California and Rhode Island where there are utility programs encouraging battery adoption. In fact, it can difficult to convince a contractor to install a battery-only system because off-the-shelf system designs almost always include a battery. In short, the data strongly support our argument that battery-only systems are a rare exception, rather than a serious viable option in the broader market. Appendix E.2 further discusses the storage-only option.

The second question is whether coadoption of solar and batteries only occurs as a simultaneous installation, or if it can occur with two sequential decisions. For instance, it is technically possible that a household could install solar first and later install battery storage. However, this appears to be rare in our data as well. The reason for this is that a retrofit battery installation nearly always requires a new inverter (costing several thousand dollars), and in many cases additional electrical work. Compatibility issues between older solar systems and newer batteries can also be an issue. Many contractors are unwilling to handle battery retrofits, even if the contractor performed the initial solar installation. Furthermore, retrofits would exhibit double marginalization (Luco and Marshall, 2020). Finally, in our sample period, the retrofit battery installation would not be eligible for the ITC, raising the price further.[12] Indeed, we calculate that retrofitted systems are 37% more expensive than co-installed systems.

In the data, we observe 11,359 retrofits where batteries are added to an existing solar system. All but a small number of these were for solar systems installed before 2017, when simultaneous coadoption was not possible. These findings motivate our decision to focus on simultaneous coadoption of solar and batteries in our analysis. Appendix E.1 provides further information on battery retrofit adoptions and costs.

2.4 Outages and coadoption

Before moving to our structural estimation methodology, we present evidence on how outages affect the coadoption of solar and battery storage as motivating reduced-form evidence for some of the results that will follow from our structural model. Standard economic logic suggests that energy storage can serve as a defensive investment in response to unreliable electricity provision, and outages can influence the consideration of renewable energy.

To explore this possibility, we estimate the effect of power outages on adoption using the following event study specification:

$$ln(s_{jmt}) = \sum_{\tau=-3}^{6} \beta_{\tau}^{\text{PV-Only}} \cdot Outages_{m,t-\tau} + \sum_{\tau=-3}^{6} \beta_{\tau}^{\text{PV+Battery}} \cdot Outages_{m,t-\tau} + \gamma_{s(m)t} + \lambda_{jm} + \xi_{jmt}, \tag{1}$$

[12] This was relaxed after the 2022 Inflation Reduction Act and stand-alone batteries are currently eligible.

where $ln(s_{jmt})$ is log-share of adoption for installation choice j offered by each installer, in market (i.e., county) m, in quarter t. We use the log share as the dependent variable to align with what we use in our later modeling. Installers can offer the following two choices: *PV-Only*, or *PV+Battery*. The regression includes state-quarter ($\gamma_{s(m)t}$) and choice-county (λ_{jm}) fixed effects. The variable $Outages_{m,t}$ captures outage intensity defined in two ways: (1) the log number of customer-hours out in period t in market m, and (2) the share of customers who experience at least one outage event that lasted more than six hours in period t in market m. The first definition is commonly used by policymakers (it corresponds to the quarterly version of the SAIDI index used by the EIA) and the related literature (Brown and Muehlenbachs, 2022). The second outage definition helps capture how outage increases are distributed within the county by separating the intensive from the extensive margin, and focuses on longer outages, for which battery backup power would be especially beneficial.[13]

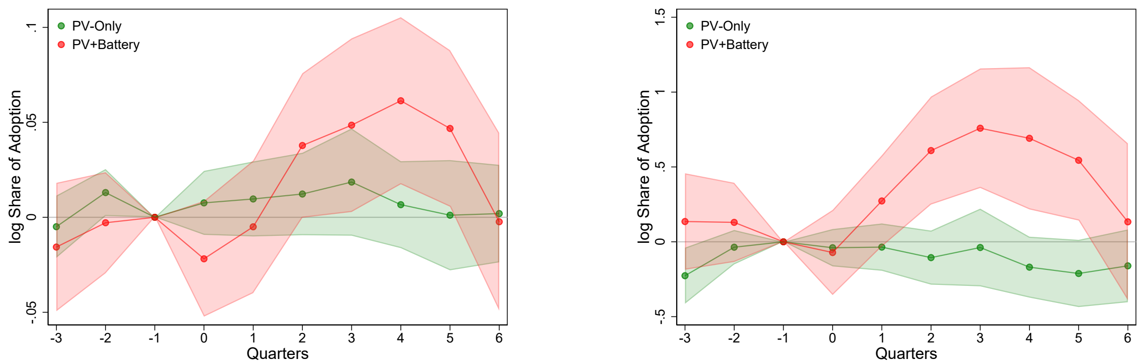
The coefficients $\beta_\tau^{\text{PV-Only}}$ and $\beta_\tau^{\text{PV+Battery}}$ capture the effect τ periods after the outage shock. This empirical specification is motivated by the idea that it may take several months after a power outage before a household has performed a search for a contractor, signed a contract, has had the system planned, and then actually installed solar and battery storage. For example, as a reference, the median solar installation took place 100 days after the household made the request in the California Solar Initiative program. For California's SGIP, the gap between request and installation dates is 90 days.

Figure 3 plots the $\beta_\tau^{\text{PV-Only}}$ and $\beta_\tau^{\text{PV+Battery}}$ coefficients and their corresponding confidence intervals. Figure 3(a) shows that increasing the number of log customer hours by 1 unit, equivalent to increasing outage hours by 10 hours (per housing unit) in the average county-quarter, is associated with increasing the installer-level coadoption share 4-7% each quarter between two and five quarters later. Adding these effects across the four quarters would lead to a 22% increase in the share of coadoption in total. Figure 3(b) shows that increasing the share of households affected by outages 6+ hours by 10 percentage points (0.1 units), is associated with increasing the installer-level coadoption share by 5-8% between two and five quarters later. This implies an increase of 28% in the share of coadoption by each installer on average. As mentioned before, the units of these two variables are not directly comparable as they capture specific changes in outage intensity. However, it is reinforcing that both show results in the same direction. Appendix Figure

[13]More specifically, this second outage definition aims at capturing that the marginal cost of outage duration is (likely) convex; long-lasting events are more costly than multiple brief interruptions. Also, given that the adoption decisions are taken at the household level, the fraction of households exposed to long-lasting outage events matches with to the level at which adoption decisions are made.

Figure 3: Effect of Power Outages on Adoption

(a) Log-Number of Customer Hours (b) Share of Cust. exposed to 6+ hours Outage



Notes: These figures show the coefficients $\beta_\tau^{\text{PV-Only}}$ and $\beta_\tau^{\text{PV+Battery}}$ of regression equation (1), with their respective confidence intervals. These coefficients and normalized to the period $\tau = -1$. The panel (a) defines outage intensity as log-number of customer-hours out of power. Panel (b) defines as outage intensity as share of customers exposed to 6+ hours outages. Both regressions include option-county and quarter-state fixed effects. The estimating data set is at the option-county-quarter level, it includes all quarters and counties previously described.

A4 extends panel (b) and shows outage effects under alternative definitions of extreme outages events (three and twelve hour events).[14]

Brown and Muehlenbachs (2022) carry out a similar exercise studying the effects of Pacific Gas & Electric's PSPS outages on battery adoption. They find that battery adoption increases between two and seven months after the PSPS outage event. However, they define the adoption date based on the date of application of installation. The lag between the outage and the PV+Battery coadoption that we find is consistent with their results once we account for the usual time difference between the application and installation dates. Our results are mostly driven by California, as it makes up much our sample, but are not notably different in other states. In addition, California is not an outlier in the number and duration of outages in our data.

The change in adoption is small and insignificant for PV-Only systems. Our event study findings indicate that outages can influence the value of coadoption, providing motivation for including outages as a major determinant of coadoption in our structural model.

[14]We tried a specification separating daytime and night-time outage events. We find that daytime events tend to have stronger effects, although the difference is not statistically significant.

3 Model and Estimation

3.1 A Model of Solar and Battery Adoption

We model residential solar coadoption decisions with a dynamic nested logit framework, focusing on quantifying the extent of complementarities between solar and the battery storage accessory. Households are organized in local markets m, where each market is served by a set of installers that install rooftop solar panels and could potentially attach battery storage. Thus, in every quarter t, households choose among options $j \in \mathcal{J}_{mt}$, which correspond to combinations of installer-installation type. In our setting, individual installers offer solar installations in four types: {PV-Only, PV+Battery, TPO-PV-Only, TPO-PV+Battery}, where TPO refers to third-party-owned systems, which are solar leases or power purchase agreements. Installers, g, are assumed to offer a specific type of installation if they have at least one system of this type installed in period t. We treat TPO systems as separate product options since the product characteristics are different (there is a difference in the relative up-front cost and long-term benefit), and as with the decision to model installer choice, we want to make sure that our model accounts for other product differences so as to accurately capture cross-product substitution. We suppress the subscript m to ease the notation in the remainder of this section.

Each option $j \in \mathcal{J}_t$ is characterized by time-invariant characteristics, ξ_j, and a set of time-varying state variables, $\mathbf{x}_{jt}$, that include the price per watt of solar installed, p_{jt}. The consumer expected mean utility of option j in period t, δ_{jt}, is defined as $\delta(\xi_j, \mathbf{x}_{jt})$, which captures the full set of benefits and costs of choosing option j over its lifespan. All installation options are carried out by $G+1$ different installers $g = 0, 1, \ldots, G$, and we denote the set of products offered by installer g as $\mathcal{J}_{gt}$. The outside option, denoted by $j = 0$, represents the no-installation option and is the only member of $g = 0$. The mean utility of option j in period t is δ_{jt}. Each household i has a idiosyncratic random utility shock for installation $\zeta_{igt} + (1-\sigma)\epsilon_{ijt}$, where ϵ_{ijt} is iid extreme value, and ζ_{igt} is an idiosyncratic group preference such that $\zeta_{igt} + (1-\sigma)\epsilon_{ijt}$ is also an extreme value random variable. The parameter $\sigma \in [0, 1)$ captures the within-group correlation of utility shocks.[15]

The household installation decision is dynamic, i.e., households consider expectations about future conditions in their current installation decisions. We model any installation

[15]We also estimated a model with the reverse nesting structure–where consumers choose an installation type and then an installer. This structure led to an estimated nest parameter either inconsistent with random utility theory, or equivalent to zero when constraining it to be positive. Following common practice (see, for example, Björnerstedt and Verboven (2016)), we thus rule out this reverse nesting structure.

of option $j \in \mathcal{J}_t \setminus 0$ as a termination state, as in De Groote and Verboven (2019), which aligns with observed market characteristics in that very few households ever retrofit an existing system. The no-installation utility $j = 0$ includes the option value of waiting, where the household forms expectations about the transition to future state variables as well as installer composition and pricing. To formalize this idea, we denote the vector of time-invariant characteristics of the set of options available in period t as $\boldsymbol{\xi}_t = \{\xi_j, \ \forall j \in \mathcal{J}_t\}$, and $\mathbf{x}_t = \{\mathbf{x}_{jt}, \ \forall j \in \mathcal{J}_t\}$ is the set of state variables, including prices. Hence, the value of each adoption option in period t is:

$$\begin{aligned} v_{ijt} &= \delta_{jt} + \zeta_{igt} + (1-\sigma)\epsilon_{ijt} \\ &= \delta(\xi_j, \mathbf{x}_{jt}) + \zeta_{igt} + (1-\sigma)\epsilon_{ijt}. \end{aligned} \tag{2}$$

For non-adoption, the consumer receives a flow utility of u_0 and has the option value of adopting in the future:

$$\begin{aligned} v_{i0t} &= u_0 + \rho \mathbb{E}_t \left[\overline{V} \left(\boldsymbol{\xi}_{t+1}, \mathbf{x}_{t+1} | \boldsymbol{\xi}_t, \mathbf{x}_t \right) \right] + \zeta_{i0t} + (1-\sigma)\epsilon_{i0t} \\ &= \delta_0(\boldsymbol{\xi}_t, \mathbf{x}_t) + \zeta_{i0t} + (1-\sigma)\epsilon_{i0t}, \end{aligned} \tag{3}$$

where ρ is the discount factor and the value function $\overline{V}\left(\boldsymbol{\xi}_{t+1}, \mathbf{x}_{t+1} | \boldsymbol{\xi}_t, \mathbf{x}_t \right)$ is:

$$\begin{aligned} \overline{V}\left(\boldsymbol{\xi}_{t+1}, \mathbf{x}_{t+1} | \boldsymbol{\xi}_t, \mathbf{x}_t \right) &= \int_{\zeta', \epsilon'} \max \left\{ v_{i0t+1}, \max_{j' \in \mathcal{J}_{t+1} \setminus 0} \left\{ v_{ij't+1} \right\} \right\} dG(\zeta', \epsilon' | \boldsymbol{\xi}_t, \mathbf{x}_t) \\ &= \int_{\zeta', \epsilon'} \max \Bigg\{ \delta_0(\boldsymbol{\xi}_{t+1}, \mathbf{x}_{t+1}) + \zeta_0' + (1-\sigma)\epsilon_0', \\ &\qquad \max_{j' \in \mathcal{J}_{t+1} \setminus 0} \left(\delta(\xi_{j'}, \mathbf{x}_{j't+1}) + \zeta_{g'}' + (1-\sigma)\epsilon_{j'}' \right) \Bigg\} dG(\zeta', \epsilon' | \boldsymbol{\xi}_t, \mathbf{x}_t). \end{aligned} \tag{4}$$

Our modeling choices take into account that batteries have negligible value in the absence of a solar system because battery-only systems are so clearly dominated by home generators for backup purposes. Accordingly, as mentioned above, we discard the battery-only option as a viable option. Thus, in our framework, the battery operates as an accessory (like a video game to a console) rather than a related good, as in papers like Gentzkow (2007). This fact allows us to model the PV+Battery bundle as a separate option where the extent to which the battery complements the PV system can be assessed by comparing the utility of the bundle to the utility of PV-Only. Our nest structure allows for correlation across utility shocks, so the added utility of the PV+Battery bundle is separately identified and not confounded by a correlation between preference shocks.

3.2 Empirical Implementation

Given the structure of extreme-value error terms, the predicted market share of option $j \in \mathcal{J}_{g(j)t}$ follows the usual nested logit expression and corresponds to the multiplication of the predicted share of the group $g(j)$ and the predicted share of the option j conditional on choosing $g(j)$:[16]

$$s_{jt} \quad = \quad s_{j|g(j)t} \cdot s_{g(j)t} = \frac{\exp\{\delta_{jt}/(1-\sigma)\}}{D_{g(j)t}} \frac{D_{g(j)t}^{1-\sigma}}{\sum_{g'} D_{g't}^{1-\sigma}} \tag{5}$$

with $D_{g(j)t} = \sum_{k \in \mathcal{J}_{g(j)t}} \exp\{\delta_{kt}/(1-\sigma)\}$, the inclusive value of group $g(j)$. The predicted share of the outside option $j = 0$, the only element of the group $g = 0$, is the following:

$$s_{0t} \quad = \quad \frac{(\exp\{\delta_{0t}/(1-\sigma)\})^{1-\sigma}}{\sum_{g'} D_{g't}^{1-\sigma}}. \tag{6}$$

Thus, equations (5) and (6) allow us to express the difference in log-market shares in terms of mean utilities and within-group shares following Berry (1994):

$$ln(s_{jt}) - ln(s_{0t}) \quad = \quad \delta_{jt} - \delta_{0t} + \sigma ln(s_{j|g,t}). \tag{7}$$

This expression holds if all households are considering solar at period t. However, many households may not be considering solar. Thus, we relax this assumption by defining a term κ as the share of non-adopting households who are considering solar in the market at time t. We show in Appendix A that we can express the difference in log-market shares in terms of mean utilities and within-group shares as follows:

$$ln(s_{jt}) - ln(s_{0t}) \quad = \quad \delta_{jt} - \delta_{0t} + \sigma ln(s_{j|g,t}) + (\kappa(o_t) - 1), \tag{8}$$

in which we will allow κ to depend on the level of outages o_t. If all non-adopting households are considering solar, the last term drops out, and we back to equation (7).

The mean value of option j (for $j \neq 0$) in period t is the expected total value of adopting option j in period t, which is a linear function of the post-rebate price, p_{jt}, option-time

[16] Please see Appendix A.1 and Mansley et al. (2019) for further details on the derivatives for nested logit demand.

specific covariates captured in x_{jt} (recall that the state variables, $\mathbf{x}_t$, contain p_{jt} and all of the other variables in x_{jt}), and any other factors that may shift the value option j provides to consumers. We allow utility of coadoption to also depend on a function of outages, $h_j(o_t)$ and option-county and state-quarter fixed effects (as a reminder, we are suppressing the market subscripts for notational simplicity):

$$\delta_{jt} \equiv \delta(\xi_j, x_{jt}) = -\alpha p_{jt} + x'_{jt}\beta + h_j(o_t) + \xi_j + \eta_t + \mu_{jt}. \tag{9}$$

The error term, μ_{jt}, captures mean-zero option-time unobserved shocks.

We normalize the utility of non-adoption ($j = 0$, the outside option) as $u_0 = 0$. Hence, the mean value of the outside option corresponds to the option value of waiting. We express the continuation value function as a function of the conditional choice probabilities (CCPs) for one of the terminating options, set without loss of generality as $j = 1$ (Hotz and Miller, 1993; Arcidiacono and Miller, 2011):[17]

$$\delta_{0t} \equiv \delta_0(\boldsymbol{\xi}_t, \mathbf{x}_t) \quad = \quad \rho \int \left[\delta_{1t+1}(\mathbf{x_{t+1}}) + \psi\left(\mathbf{S}_{t+1}(\mathbf{x}_{t+1})\right)\right] dF(\mathbf{x_{t+1}}|\mathbf{x}_t), \tag{10}$$

where ρ is the discount factor and $\psi\left(\mathbf{S}_{t+1}(\mathbf{x}_{t+1})\right)$ is a real-valued function such that under a nested logit structure can be expressed as follows (Arcidiacono and Miller, 2011):

$$\begin{aligned} \psi\left(\mathbf{S}_{t+1}(\mathbf{x}_{t+1})\right) &= \gamma - (1-\sigma) ln\left(S_{1t+1}(\mathbf{x}_{t+1})\right) - \sigma ln\left(S_{\mathcal{G}t+1}(\mathbf{x}_{t+1})\right) \\ &= \gamma - ln\left(S_{1t+1}(\mathbf{x}_{t+1})\right) - \sigma\left(ln\left(S_{\mathcal{G}t+1}(\mathbf{x}_{t+1})\right) - ln\left(S_{1t+1}(\mathbf{x}_{t+1})\right)\right), \end{aligned} \tag{11}$$

where γ is the Euler's constant, $S_{1t+1}(\mathbf{x}_{t+1})$ is the reference group ($j = 1$) next period's conditional choice probability, and $S_{\mathcal{G}t+1}(\mathbf{x}_{t+1})$ is the sum of next period's conditional probabilities of options other than the outside option.

We can express the mean utility of the outside option as a function of expectations of the next period's mean utility and conditional probability of adoption:

$$\begin{aligned} \delta_0(\boldsymbol{\xi}_t, \mathbf{x}_t) \quad = \quad & \rho\gamma + \rho\mathbb{E}\left[\delta_{1t+1}\left(\mathbf{x}_{t+1}\right) - ln(S_{1t+1}(\mathbf{x}_{t+1}))\right. \\ & \left. -\sigma\left[ln\left(S_{\mathcal{G}t+1}(\mathbf{x}_{t+1})\right) - ln(S_{1t+1}(\mathbf{x}_{t+1}))\right] |\mathbf{x_t}\right]. \end{aligned} \tag{12}$$

[17] Hotz and Miller (1993) proves that differences in conditional value functions can be expressed as functions of the conditional choice probabilities and the per-period payoffs. Arcidiacono and Miller (2011) builds upon Hotz and Miller (1993) and shows that the value function can be expressed as a function of *one* conditional value function, plus a function of the conditional choice probabilities.

We can now combine (8) and (12) into one equation, which is our main specification. We use a (quarterly) discount factor of 0.966, which is equivalent to an annual discount factor of 0.87 (De Groote and Verboven, 2019). We re-organize terms to keep parameters of interest on the right-hand side. In a slight abuse of notation, we omit dependence on current state variables, with the understanding that expectations over future states are conditional on current state variables:

$$\begin{aligned} ln(s_{jt}) - ln(s_{0t}) \quad &+ \quad \rho\gamma - \rho\mathbb{E}[ln(S_{1t+1})] = \delta_{jt} - \rho\mathbb{E}\left[\delta_{1t+1}\right] \\ &+ \quad \sigma\left(ln(s_{jt|g}) + \rho\mathbb{E}\left[ln(S_{\mathcal{G}t+1}) - ln(S_{1t+1})\right]\right) + (\kappa(o_t) - 1). \end{aligned} \tag{13}$$

The expression (13) depends solely on current and expected next period states and adoption probabilities. These probabilities are calculated at the county-quarter level. The model includes market-level unobservables. The state vector $\mathbf{x}_t \equiv \{\mathbf{x}_{jt}\}$ includes the market average post-rebate price, the log installer base,[18] the market average solar system size (kW), and the average storage system size (kWh) for every option j.

3.2.1 Consumer expectation formation

We now turn to our assumptions about consumer expectations needed to estimate (13). We assume that consumers have rational expectations, modeling the transition of the state variables within the expectation in equation (12) as an AR(1) process plus a mean zero, stochastic short-run prediction error. Although we assume a specific form for state variable evolution, we follow Scott (2014) and De Groote and Verboven (2019) by allowing for a short run prediction error. Like those authors, we assume that households are correct on average.[19] By estimating the AR(1) process over the range of data used for estimation, the error is mean zero by construction.[20] The prediction process includes time and county-choice fixed effects to account for anticipated differences across markets and time. Hence, conditional expectations about next period's term Y_{jt+1} take the following structure:

$$\mathbb{E}[Y_{jt+1}|Y_{jt} = y_{jt}] = \phi y_{jt} + \iota_j + \lambda_t. \tag{14}$$

[18]Installer base is defined as the cumulative solar capacity (watts) by the installer in the county up to $t-1$.

[19]Those papers use the realization of the next period state variables and value function plus stochastic short-run prediction errors. We follow suit in a robustness check, but find that modeling expectations as an AR(1) process fits our data better.

[20]This is convenient as it implies that it would not affect our results if the AR(1) process is slightly misspecified, since rational expectations would still hold.

The terms ι_j and λ_t capture differences in levels across times and options. The inclusion of (county-)option and (state-)quarter fixed effects allows consumers to predict future state variables from current state variables in a way that anticipates common shocks, such as aggregate policy changes.

We estimate $\{\phi, \iota_j, \kappa_t\}$ for every option-level state variable, instrument, and element for the reference choice in the set of adoption probabilities, $\mathbf{S}_{t+1}$, using ordinary least squares (OLS) regression. For the main specification, we use the AR(1) process to govern the expectations for each state variable and for the expected probability of adopting the omitted option in the next period, following the approach used in Scott (2014) for predicting expected prices. We assume consumers know the next period's time fixed effects (which, among other things, capture changing policies) and product fixed effects (including the set of products which will be available).[21]

Finally, we assume that beliefs about future outages are given by $\mathbb{E}[o_{t+1}] = \bar{o}$, i.e., consumers form expectations assuming outages have a market-specific stationary mean. In particular, we assume that o_t corresponds to the log of the average per-household outages within the county that have occurred over the last four quarters.

3.2.2 Empirical specification

We can rewrite (13) as:

$$\begin{aligned} ln(s_{jt}) \quad &- \quad ln(s_{0t}) + \rho\gamma - \rho\mathbb{E}[ln(S_{1t+1})] \\ &= \quad \delta_{jt}^{\Delta} + \sigma\left(ln(s_{jt|g}) + \rho\mathbb{E}\left[ln(S_{gt+1})\right] - \mathbb{E}\left[ln(S_{1t+1})\right]\right) + (\kappa(o_t) - 1), \end{aligned} \tag{15}$$

in which we use the superscript Δ to denote that the term is subtracting the discounted next period's expected term for the reference choice ($j = 1$), as follows:

$$\begin{aligned} \delta_{jt}^{\Delta} &= -\alpha\left(p_{jt} - \rho\mathbb{E}[p_{1t+1}]\right) + \left(x_{jt} - \rho\mathbb{E}[x_{1t+1}]\right)'\beta + \left(h_j(o_t) - \rho\mathbb{E}[h_1(o_{t+1})]\right) \\ &\quad + \left(\xi_j - \rho\xi_1\right) + \left(\eta_t - \rho\eta_{t+1}\right) + \mu_{jt}^{\Delta} \\ &= -\alpha p_{jt}^{\Delta} + x_{jt}^{\Delta'}\beta + h_j(o_t)^{\Delta} + \xi_j^{\Delta} + \eta_t^{\Delta} + \mu_{jt}^{\Delta}. \end{aligned} \tag{16}$$

For the expectation term we use the AR(1) process as estimated in (14) for each state variable and the adoption probability of the omitted option. As a robustness check, we use the next period realizations for the expectations, as in De Groote and Verboven (2019).

[21] One alternative approach would be to assume consumers believe the next period's fixed effects should be equal to today's fixed effects. The change in results is negligible if we use this alternative approach.

Although current outages can affect both utility and whether households consider of solar, future outages only directly affect utility through the option value of waiting, through $h_j(o_t)$. We specify $h_j(o_t)$ and allow outages to affect the utility of co-adoption using a linear function of o_t as follows: $h_j(o_t) = o_t\,(\nu_1 + \nu_2 \cdot \mathbb{1}\{\text{CA}\})\,\mathbb{1}\{\text{PV+Battery}\}$. This function provides additional flexibility in allowing the effect in California (CA) to differ from elsewhere.

Whether households consider solar is governed by $\kappa(o_t)$, which allows current outages to influence consideration. We assume a linear form for $\kappa(o_t)$, specified as the difference between current outages and expected outages in the market: $\kappa(o_t) - 1 \equiv (k_1 + k_2 \cdot \mathbb{1}\{\text{CA}\})\,(o_t - \overline{o})$. Again, we allow for a different effect in California than the rest of the market.[22]

3.2.3 Reference group

The estimation approach requires defining the reference option ($j = 1$). Should there be a single installer-option available in every single market-time period, then we could simply use this universal installer-option. However, this is not the case. Thus, instead of fixing different reference groups across market-times, we define our reference group as the arithmetic average of the next period's PV-Only options, with the average taken over all PV-Only options offered in the market the next period. Accordingly, the conditional expectations about the next period's reference option's term, Y_{1t+1} take the following structure:

$$\overline{\mathbb{E}[Y_{t+1}|\mathbf{y}_t]} = \frac{1}{|\mathcal{J}'_{t+1}|} \sum_{j' \in \mathcal{J}'_{t+1}} \mathbb{E}[Y_{j't+1}|Y_{j't} = y_{jt}],$$

where $\mathbb{E}[Y_{j't+1}|Y_{j't} = y_{j't}]$ is next period's conditional expectation of option j'. $\mathcal{J}'_{t+1}$ denotes the set PV-Only options available next period in the market, and $|\mathcal{J}'_{t+1}|$ is the cardinality of the set. Using the average of the fitted values used for next period's expected values of the state variables and adoption probability yields the same results asymptotically as a particular one since we simply average equation (16) for each possible choice and it allows us to deal with variations in the composition across markets (Bollinger and Gillingham, 2019). In addition, the $\rho\mathbb{E}[h_1(\mathbf{o}_{t+1})]$ terms drops out of (16) because $h_j(\cdot)$ only affects coadoption options and we use PV-Only alternatives for the reference options.

[22] Note that consideration effects are not separately identified from effects that both shift utility and are not anticipated in future periods. Due to this, we ensure that outages enter functionally in the same way for both consideration and utility.

3.2.4 Identification and Instruments

The fixed effects at both the option-county level (recall that an option is the combined choice of the installer and installation type) and the state-quarter level address unobserved heterogeneity in demand across options and space and over time.[23] However, our nested logit specification is still likely to have endogeneity biasing the coefficients on the post-rebate price and the within-group share due to standard simultaneity concerns in estimating demand models. Thus, we use two cost-shifters as instruments for price: quarterly average wage in the construction sector in the county and average rebate per watt received at the county level as well as the average rebate per watt at the installation type level (PV-Only, TPO-PV+Battery, TPO-PV-Only, TPO-PV+Battery). Both sets of instruments are commonly used in the literature estimating solar demand. The use of construction wages is motivated by the labor cost of installing solar, which should be influenced by larger labor market forces. The use of county-level average rebates is motivated by the fact that at least some portion of the average rebate per watt is likely to be passed on to consumers, so the post-incentive cost to the option will be lower. Moreover, by using the average incentive, we can avoid possible omitted variables bias relating to endogenous sizing of installations. This instrumental variables strategy is important for our identification.

We also include the number of periods since the first battery entry in the county and the same variable interacted with coadoption as additional instruments.[24] This instrument is motivated by the idea that more battery options will become available over time after the period of first entry. The availability of PV+Battery options in different markets affects the share of coadoption and the number of periods since the first battery entry is indicative of coadoption, so we should expect this instrument for σ to have sufficient first-stage power. The identifying assumption for validity of this instrument is that the number of periods since the entry of PV+Battery options in each market is not correlated with the local unobserved demand shock after the inclusion of the control variables and fixed effects. This is reasonable because most companies work in multiple markets and make decisions at the headquarters about what options to offer for all markets the firm works in. In our data, we observe that the options that installers offer are usually the same across

[23] It is important to note that, as usual, these fixed effects serve as main effects in our specification, and are included in our counterfactuals.

[24] More specifically, the "number of periods since entry" instrument takes a value of zero if demand for PV+Battery options was zero in all previous periods. It takes a value of one in the period immediately after a positive demand for any PV+Battery is recorded; it takes value two in the subsequent period, then a value three, and so on.

multiple markets. Indeed, installers operate in 5.5 counties per quarter on average. Further, we observe that 88% of the time when there is a first battery installation in a county, it is carried out by installers with previous presence in the county and who also began installing batteries in other counties at the same time.[25] In other words, the very first installer to offer PV+Battery option in a market with no previous coadoption options is likely adding the PV+Battery option in response to market conditions in all of the many markets it operates in, rather than just responding to the demand shock in that single market, thus supporting the exogeneity of our instrument after conditioning on the fixed effects.

3.3 Final Estimation Data Set

To develop our final estimation data set, we collapse the installation-level data to an installer-option-county-quarter panel. The market share of every option is calculated by dividing the total capacity (watts) of new installations by the potential capacity in the market (i.e., market size). We use the 2010 Census data to obtain the number of residential units per county. We focus on owned units and multiply this total by 0.35 to account for the fact that only a fraction of buildings are suited for solar, thus giving us a measure of the potential market size.[26] Then, each potential unit is multiplied by 6,600 to approximate the potential adopters' total capacity (watts).[27]

The other relevant variables follow the same panel structure. Our estimation data set includes almost 59,000 option-county-quarter observations from 284 counties between 2017 and 2021. To deal with installers that seldom appear in our data, we group installers with fewer than 100 installations into one "other" category, which accounts for 6% of the installations. Table A2 provides summary statistics for the final estimation data set.

[25] In addition, we observe that nearly 90% of the time, the number of quarters between when an installer first offers the coadoption option in any county and when they offer it in a given county is less than four quarters, and most often it is zero or one quarters. Since there may be a lag of a few quarters before a first coadoption installation is completed after the option was first offered, this is strong evidence that the decision to offer batteries is based on broader market-wide phenomena (which are picked up in our fixed effects), rather than local demand shocks.

[26] We define a fixed 0.35 factor because only a subset of buildings is suitable for solar, given their roof's orientation, slope, type, and clearance. Google Sunroof Project data allow us to calculate the net present value of installing solar.

[27] We set 6,600 watts as the reference adoption size. That number is the average size across observations in LBNL. Using a slightly different number does not appear to affect our results.

4 Results

4.1 Demand Estimates

We estimate the model of demand for solar and coadopted PV+Battery using both OLS and instrumental variable regression, as discussed above. Table 2 presents the results.[28] Columns (1) and (2) show the demand estimation without controls for outages, while columns (3) and (4) include outages as covariates. To account for outage intensity, we use "log-customer hours in the last four quarters" following the usual outage definition, and account for the fact that the outages show effects on actual installations with some delay, as shown previously. Columns (1) and (3) are OLS fixed effects regressions, while (2) and (4) instrument for the post-rebate price and the within-group share using the instrumental variables discussed above.

The results in Table 2 show a negative coefficient for the post-rebate price per watt in the IV regressions, as would be expected. Based on the marginal effect and at the means, the point estimate in column (2) corresponds to a short-run (quarterly) mean own-price elasticity of demand for solar systems of -2.3, which is roughly in line with previous literature.[29] The nest coefficient (σ) near one underscores the value of the nested logit.

In columns (3) and (4) of Table 2, we include interactions with a set of variables relating to outages. There are four variables, all of which are based on the log of the number of hours of outages that consumers in that county experienced on average in the last four quarters.[30] We further interact this outage variable with a dummy for the system being a coadoption PV+Battery system, a dummy for California, and an interaction with dummies for both California and coadoption. The dummy for California is included due to California's large role in the coadoption market and unique circumstances, such as additional SGIP incentives for batteries and highly publicized power outages.

We first observe a near-zero and insignificant coefficient for the main effect on outages, indicating that outages alone do not increase PV-Only demand outside of California. Based on our model, this can be interpreted as outages not increasing the consideration of PV-Only outside of California. We next observe a positive and significant coefficient on our outage variable interacted with coadoption. This indicates that outages increase the utility

[28] Appendix Table A3 presents the full set of demand estimation results, including the controls.

[29] The mean own-price elasticity is $\frac{\alpha p_{jt}}{(1-\alpha)}\left(1 - \sigma s_{jt|g} - s_{jt}(1-\sigma)\right)$, and was calculated over the estimating sample.

[30] The Appendix table A5 presents results under a different outage definition: log-number of households exposed to 6+ hours outage events. Coefficients are qualitatively the same.

Table 2: Demand Estimates

	(1) OLS	(2) IV	(3) OLS	(4) IV
Post-rebate price/watt (α)	-0.001	-0.210	-0.001	-0.245
	(0.004)	(0.119)	(0.004)	(0.124)
Nest coefficient (σ)	0.602	0.929	0.600	0.908
	(0.013)	(0.084)	(0.013)	(0.094)
Log-outage hours in last 4 quarters			-0.001	0.001
			(0.007)	(0.007)
Log-outage hours in last 4 quarters*Coadopt			0.111	0.105
			(0.027)	(0.035)
Log-outage hours in last 4 quarters*CA			0.071	0.078
			(0.031)	(0.030)
Log-outage hours in last 4 quarters*Coadopt*CA			-0.026	-0.060
			(0.033)	(0.042)
Installer-Adoption Type-County FE	Yes	Yes	Yes	Yes
State-Quarter FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
R-squared	0.78	0.16	0.78	0.15
Observations	58514	58514	58514	58514

Notes: This table presents our demand estimates. Columns (1) and (3) show OLS regressions, columns (2) and (4) display IV estimates. Columns (1) and (2) show the coefficients without outage variables, while (3) and (4) include outages as covariates. The "installer cum. installations" refers to the cumulative installations by the installer up to the previous quarter, often called the "installed base." The first stage coefficients are shown in the Appendix table (A4). The excluded instruments are construction wage, rebates per watt, periods since battery entry in the county, and the interaction between periods since battery entry and co-installation. Adoption type refers to whether adoption is PV-only, PV+Battery, and third-party owned interacted with each. FE refers to fixed effects and CA refers to California. The controls include the loginstaller base, system size, and battery size. Details of the estimation dataset are described in the table (A2). Standard errors are clustered at the county level.

of coadopting solar and battery storage, with a 10 percentage point increase in outages (roughly one hour per quarter) raising willingness to pay by $43 per watt or $312 for an average-sized system.

The two interactions with California provide some nuance to these findings. California has the greatest uptake of batteries in the United States and very highly publicized outages, so it may not be surprising that we see a positive and significant effect of outages on PV-Only demand in California. This effect suggests that more households in California consider solar after outages. Many potential customers in California may associate solar with a way to avoid outages at home, and may not fully recognize that batteries are needed. The coefficient on the triple interaction between outages, coadoption, and California is negative but not significant. The negative sign could suggest that in California, the utility boost from coadoption is less than in other states (although it is still certainly positive). We are cautious about this interpretation though due to the insignificant coefficient.

In Appendix Table A4, we show the first stage results with and without outages. Notably, the F-statistics are all greater than 15, indicating that we do not have to worry about weak instruments (i.e. our set of instruments are relevant). These coefficients are key for our counterfactuals. Note that our fixed effects act as the main effects for adoption type and are included in our counterfactuals as well.

Model Fit. Using these demand estimates, we predict the mean utility of each option (equation (9)) and the continuation value (equation (12)). These terms allow us to predict adoption shares (equation (18)) of each option available in our data set. Appendix Figure A5 compares model-based predicted and actual adoption shares. Panel (a) shows the distribution of adoption shares, panel (b) compares actual versus predicted option-level shares, and panel (c) transforms adoption shares into solar capacity (watts) and then aggregates across options quarterly. Overall, our model prediction of adoption matches well with actual adoption shares. When we transform adoption shares into capacity and aggregate, our model predicts slightly lower aggregate solar capacity than the actual solar capacity in our sample. This slight underprediction is driven by PV-Only options in a few large markets, where the differences in shares get amplified by the size of the markets.

Robustness Exercises. We examined a number of alternative specifications varying aspects of our approach. Appendix Table A5 presents estimates under an alternative definition of outage intensity: the number of households exposed to outages lasting 6 hours or more. Not surprisingly, the coefficients on the outage interactions are larger. For our primary specification, we opt for the more common outage measure. Appendix Table A6 shows estimates of our primary specification but without instrumenting the within-group share. The results are largely similar, but the nest coefficient is somewhat smaller. Appendix Table A7 presents the demand estimates using the realizations of the state variables for household expectations. The outage coefficients are similar, but the price coefficient is about half as large (in absolute value); the smaller estimate suggests an own-price elasticity of solar demand roughly half as large (in absolute value) and out of line with the literature.[31] Finally, Appendix Table A8 shows demand coefficients under a fully static demand model, which can be thought of as the opposite extreme to the use

[31] We believe this may be due to a lack of responsiveness to next period price shocks in the data, which we believe is more likely due to incomplete information rather than low responsiveness to price.

of next period state variable realizations, since in the static case, responsiveness to next period prices is ruled out completely by assumption. Once again, the outage coefficients are similar to our primary specification, but the price coefficient is nearly double, and the implied price elasticity is nearly -14, far out of line of the literature in the other direction. The static model, of course, fails to account for the fact that when incentive regimes change, the prices will experience long-term shifts (which may continue to increase), and so a large price response in the data is not due to extreme price coefficients in a static framework but instead to the combination of price changes and the concurrent changes to expectations of future prices.

4.2 Counterfactual Scenarios

We use our demand estimates to explore three counterfactual scenarios. First, we evaluate how the recent introduction of battery storage as an accessory option affected how consumers value solar PV systems. This scenario allows us to model how the availability of the battery option can introduce substitution from stand-alone solar adoption to PV+Battery coadoption. Second, we illustrate the role of power outages on solar adoption and PV+Battery coadoption by varying the degree of power outages, consistent with utility investments reducing the likelihood and duration of outages or climate change exacerbating outages. Third, we examine the effect of energy storage-specific incentives and how they can affect the demand for both PV+Battery coadoption as well as the total aggregate demand for solar. As in our demand estimation, we allow for different results for California than the rest of the United States in our data.

Developing consistent counterfactual estimations is not necessarily straightforward. Any manipulation introduced by our counterfactual exercises would not only affect current utilities but would also affect the continuation value. Thus, we explicitly model the structure of the continuation value as a function of manipulable state variables. We next explain our approach for quantifying the effects on the continuation value.

4.2.1 Modeling counterfactual continuation values

Given our nested logit specification, the continuation value under an arbitrary state variable $\mathbf{x}_t$ can be expressed as follows (Mansley et al., 2019):

$$
\begin{aligned}
\delta_0(\boldsymbol{\xi}_t, \mathbf{x}_t) &= \beta \mathbb{E}_t \left[\max_{j \in \mathcal{J}_{t+1}} v_{ijt+1} | \boldsymbol{\xi}_t, \mathbf{x}_t \right] \\
&= \beta(1-\sigma) ln \Bigg(\exp \left\{ \delta_0(\boldsymbol{\xi}_{t+1}, \mathbf{x}_{t+1} | \boldsymbol{\xi}_t, \mathbf{x}_t) / (1-\sigma) \right\} \\
&\qquad\qquad + \sum_{g \in G_{t+1} \setminus 0} \exp \left\{ I_g(\boldsymbol{\xi}_{t+1}, \mathbf{x}_{t+1} | \boldsymbol{\xi}_t, \mathbf{x}_t) / (1-\sigma) \right\} \Bigg) \qquad (17) \\
I_g(\boldsymbol{\xi}_{t+1}, \mathbf{x}_{t+1} | \boldsymbol{\xi}_t, \mathbf{x}_t) &= (1-\sigma) ln \left(\sum_{j' \in J_g} \exp \left\{ \delta(\xi_{j'}, x_{j't+1} | \boldsymbol{\xi}_t, \mathbf{x}_t) / (1-\sigma) \right\} \right),
\end{aligned}
$$

where $I_g(\boldsymbol{\xi}_{t+1}, \mathbf{x}_{t+1} | \boldsymbol{\xi}_t, \mathbf{x}_t)$ is the inclusive value of group g.

As in estimation, under each counterfactual we again assume that consumers expect a deterministic evolution of the state variables with a short-run prediction error. This evolution may differ under the counterfactual, so we first apply the change dictated by the specific counterfactual (e.g., a price reduction of some amount) and then re-estimate the transition functions using the same approach as in estimation, shown in equation (14).

Once the parameters that govern expectation formation are estimated, we simulate expectations in any period t about state variables in $t + \tau$ under alternative state scenarios many periods into the future. Then, starting from an arbitrary distant future period, we iterate backward until the "current" period t, to directly calculate the value function recursively using equation (17). In our preferred specification, we allow consumers to believe the future choice set will remain the same as the current one and to have perfect foresight about time fixed effects, and the iterative process starts 40 quarters ahead. Simulating $\delta_0(\boldsymbol{\xi}_t, \mathbf{x}_t)$ explicitly under an arbitrary $\mathbf{x}_t$ allows us to recover the counterfactual solar and PV+Battery adoptions using equation (18).

Discussion of our Approach. The underlying assumption in this approach to simulating our counterfactuals is that the evolution of the state variables would have followed a similar transition function under the counterfactual environment exclusive of the counterfactual adjustment. For example, with a 20% price decrease for PV+Battery, we assume that the prices would be 20% lower than what they were in the observed environment, in the current and future periods. In other words, a 20% price decline for PV+Battery in the first period does not change the projected price transition function for PV+Battery later, but only its level (due to the price reduction). If this price decline led the installer to price differently in a future period, or to make adjustments in the stand-alone solar price, then our assumption would be violated.

We believe our assumption is reasonable for the three counterfactuals we examine because coadoptions are such a small fraction of the total solar sales in our setting. Thus, it seems very likely that any change in the paths of the state variable transitions would be negligible. For example, is unlikely that firms would adjust the prices of the PV-Only option in our counterfactuals in response to changes that modestly affect the utility of the coadoption option. Further, it seems unlikely that the composition of consumers would change under our counterfactuals, as long as these counterfactual changes are not too large in relation to the overall solar market. Such changes in the composition of consumers could possibly lead to changes in state variables, such as price, in the future. But, the small market share of battery coadoption implies that changes in the composition of consumers should not be an issue in our context. Similarly, the small market share of coadoptions also means that it is unlikely that there are changes in the supply side under the counterfactuals.

4.2.2 Does battery storage entry contribute to the adoption of solar?

We first explore the value and effects of the availability of the battery accessory by removing batteries from the choice set entirely and simulating counterfactual demand. In particular, we are interested in how much of the coadoption is diverted to the outside option of not installing versus how much is diverted to installing only solar.[32] In other words, how much does the coadoption spur new solar adoptions versus simply cannibalizing existing solar adoptions? This is a core economic question about how complementarities govern patterns of demand. To run this counterfactual simulation, we assume the PV+Battery option is unavailable (or too costly) in current and future periods.

The main results of this counterfactual simulation are shown in Figure 4. Panel (a) presents the total capacity installed of solar and battery storage by month from 2019 to 2021 and how it is divided up between coadoption consumers who would switch to stand-alone solar and those who would switch to the outside option, which would mean not installing solar at all. We observe that in 2021, 80% of the PV+Battery coadoption demand would have switched to stand-alone solar systems had batteries not been an option. But this also means that 20% *would not have installed solar at all* without the coadoption option.

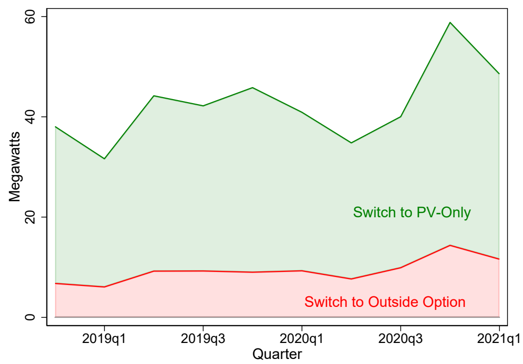
Panel (b) shows the same results, only cumulative over time since 2017. By the first

[32] Conlon and Mortimer (2021) discuss using diversion ratios to simulate variation in product availability and willingness to pay. That framework is useful in a static setting; however, in a dynamic setting, the diversion to the outside option involves changes in the continuation value as well.

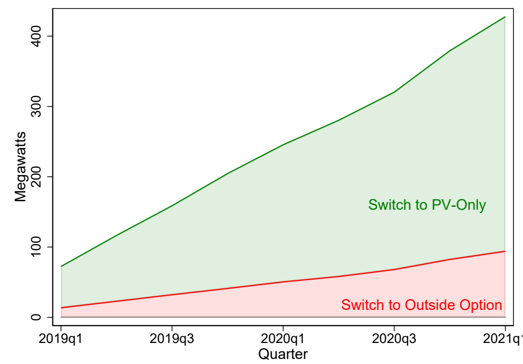
quarter of 2021, the total demand that would not have adopted solar if batteries were not an option totals 80 MW. This is relatively modest in the context of total electricity demand, but it is likely to continue increasing over time as coadoption demand increases.

Figure 4: Demand Diversion if PV+Battery is Removed

(a) Aggregate



(b) Cumulative



Notes: Panel (a) shows the total PV+Battery capacity (Megawatts of Solar) installed per quarter in our estimation sample. The red area corresponds to the capacity that would have diverted to the outside option (no solar installation) if the co-installation option weren't available. The green area shows the capacity that would have diverted to PV-Only systems. Overall, we find that 80% of PV+Battery capacity would have switched to PV-Only.. Panel (b) shows the cumulative capacity diverted to each of the options.

4.2.3 The role of power outages

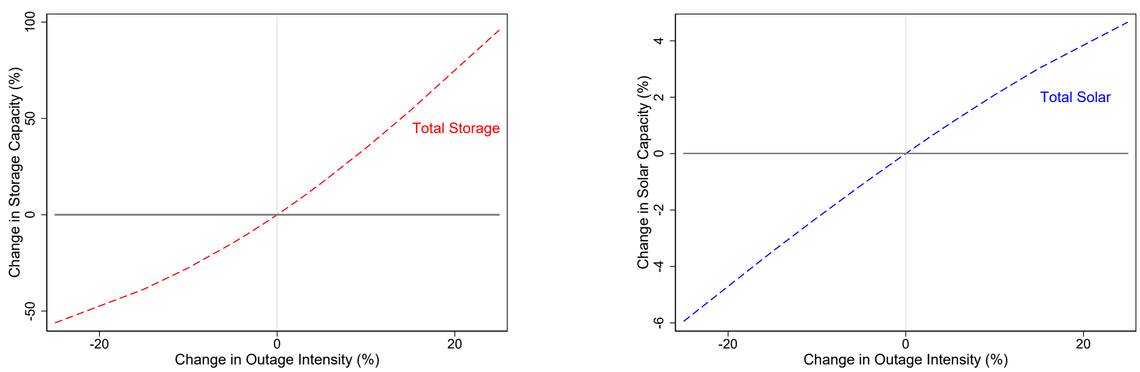
Our next counterfactual simulation focuses on the role of power outages in the adoption of solar and coadoption of PV+Battery systems. Again, this analysis is motivated by the fact that climate change could lead to continued increases in the frequency and intensity of natural disasters and, hence, power outages in the near future. Meanwhile, major efforts from utilities could reduce power outages. Understanding the effects of these factors is important from a policy and planning perspective. These exercises are carried out by manipulating the county's average level of outage intensity by a fixed fraction in the current and future periods. Given our model specification, higher outage levels increase the utility of PV+Battery systems as well as the level of solar consideration.

Figure 5 shows the changes in storage capacity in Panel (a) and solar capacity in Panel (b) in response to changes in the outage intensity (outage customer-hours). The results clearly show a positive relationship between the outage intensity and both solar and storage capacity. Specifically, we observe that a 20% increase in outage intensity (equivalent to roughly two additional outage hours per housing unit) implies a roughly 75% increase in storage capacity, while a 20% decrease in outage intensity implies a roughly 50% decrease in storage capacity. This quantification of how outage intensity influences battery adoption highlights the value of batteries as backup power. We also see an increase in total solar installed, which highlights the complementarity between solar and the battery accessory. We find that with a 20% increase in outage intensity, solar capacity increases approximately 4%.

Figure 5: Change in Adoption by Levels of Power Outages

(a) Change in Storage Capacity

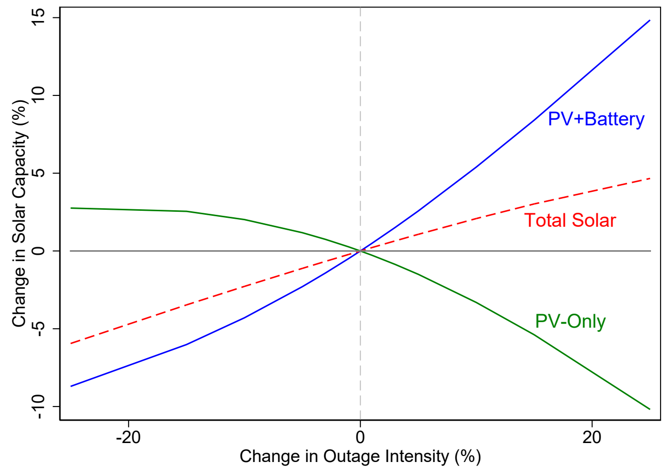
(b) Change in Solar Capacity



Notes: Panel (a) describes the percentage change in storage capacity installed (Watt-hours) as a function of changes in outage intensity. Panel (b) shows the percentage change in total solar capacity installed (Watts) depending on changes in changes in outage intensity (customer hours). To carry out these exercises, we vary the county's average level of outage intensity in the current and future periods. Both panels are based on adoption levels for the year 2020.

Figure 6 breaks up Figure 5(b) to show the effect of outage intensity on total solar installations, through the increase in coadoption. Specifically, we observe that when the outage intensity increases, PV+Battery coadoption increases, and stand-alone solar adoption decreases as solar adopters switch to coadopting. As noted, the increase in PV+Battery is larger than the reduction in stand-alone systems leading to the aforementioned increase in aggregate solar adoption. This increase in aggregate adoption stems from consumers who would not have adopted (would have chosen the outside option), and instead choose to coadopt solar and storage. Put differently, outages increase the value of battery storage and thus spur the adoption of solar in aggregate. This finding is especially relevant because it uncovers a secondary impact of climate change: by increasing power outages it would also increase battery storage (and solar) adoption. Conversely, if outages decrease, we observe a small decrease in aggregate solar installations but a clear shift from coadoption of solar and storage to stand-alone solar adoption.

Figure 6: Aggregate Solar Adoption by Levels of Power Outages



Notes: This Figure break up the Figure 5(b) by adoption type. It shows the percentage change in solar capacity installed (Watts) depending on changes in outage intensity (customer hours). The green-solid line corresponds to the change in PV-Only systems; the blue-solid line is the change in PV+Battery format. The red dashed line is the total change and aggregates the changes in both forms. To carry out these exercises, we vary the county's average level of outage intensity in the current and future periods. Both panels are based on adoption levels for the year 2020.

4.2.4 Financial Incentives

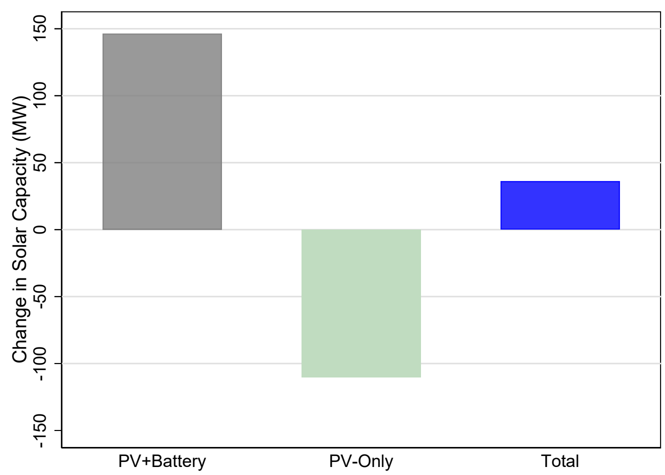
Many state and federal programs offer rebates or tax credits for installing energy storage technology. For example, the California SGIP offers a rebate between \$400 to \$200 per kWh of storage. This rebate can be in the thousands of dollars, as the average system has 16.4 kWh. There is still a federal tax credit for installing solar (with or without storage), but at this time, most state and local rebate incentives for solar have been sunset. However, incentives for battery storage appear to be continuing in many locations and are likely to continue for some time. Thus, it is useful to understand the effect of financial incentives for battery storage on PV+Battery coadoption and on solar adoption.

To illustrate the effect of financial incentives, we simulate a policy that reduces the post-rebate price of PV+Battery systems by 20%, a price reduction that is on the same order of magnitude as California's SGIP rebate.[33] This simulation can be thought of as a less extreme and more realistic case of the first counterfactual, which was primarily run to highlight the complementarity. While our analysis is motivated by potential policies to encourage PV+Battery coadoption, our findings are also relevant for price reductions that occur due to innovation and technological change improving the technology.

[33] As a reference, a 20% discount the average post-rebate price of a PV+Battery system is is equivalent to \$5,128. The California SGIP provides between \$3,280 and \$6,560 to the average battery size.

We find that the 20% price decrease of PV+Battery would lead to an increase in storage capacity by 300 MWh, which is a 78% increase. The reduction in the cost of PV+Battery systems leads to a substitution across installation types towards coadoption. Figure 7 shows changes in solar capacity due to this price decline. It shows that an increase in sales of PV+Battery systems, equivalent to 146 MW, is partly offset by a decrease in sales of stand-alone solar by 110 MW. Thus, about three-quarters of the additional PV+Battery coadoptions are switches from stand-alone solar adoptions. In total, the price decline for PV+Battery systems increases the aggregate solar capacity by 36 MW per year. Our results suggest that the rate of freeridership is 56%, which means that 56% of the solar capacity that would be installed under the 20% price decline would have occurred anyway without the price decline. This increase in solar capacity per year that we observe creates an annual environmental benefit on the order of 5,700 tons of averted CO_2 emissions nationwide.[34]

Figure 7: Change in Solar and Storage Capacity



Notes: These figures show the effects of introducing a 20% reduction in the price of PV+Battery. It shows that the rebate would induce high substitution from PV-Only to PV+Battery systems, although with a positive effect over total solar adoption. A 20% reduction in the price of PV+Battery would increase storage capacity by 300 MWh (not in this figure). These exercises use the year 2020 to set market conditions.

Considering the counterfactual adoption levels, we find that a 20% PV+Battery price reduction due to a subsidy policy would cost $215 million per year (using 2020 as a reference) if we assume 100% passthrough of incentives, in line with the results on solar from Pless and van Benthem (2019). We believe that the market is changing rapidly enough

[34] This calculation combines state-level effects of the subsidy with state-specific long-run marginal emission rates for electricity generation (Gagnon et al., 2022) and a solar capacity factor of 30%. These calculations only focus on solar and do not include any positive (or negative) environmental effects from energy storage given how context-specific such effects of storage are.

(with new battery offerings from different firms often entering and trying to gain market share) that this passthrough assumption is not unreasonable for the battery market. But our results would simply scale with a different passthrough assumption.

We can further calculate the return on investment of public funds of the subsidy policy under our passthrough assumption. We find that every million dollars of public funds used in these PV+Battery rebates would increase storage capacity by 1.37 MWh of additional storage in our sample. Moreover, since increased PV+Battery coadoption also occurs, the subsidy would also lead to 168 kW of additional solar capacity. These results highlight why it is important to consider complementarities in policy design and not think about solar and batteries in isolation, but rather, consider them together.

We can go further and evaluate how the marginal effect of an additional rebate dollar spent varies with the levels of outages (again, under our 100% passthrough assumption). Overall, the returns are slightly lower with greater outage intensity (see Appendix Figure A9). This is because more coadoption would occur anyway from the higher outage intensity, so an additional dollar of incentives does not incentivize as many new coadoptions. This is a crowding-out effect: greater outage intensity crowds out some of the coadoptions that would have occurred from greater financial incentives.

The importance of California. As mentioned above, a large fraction of the coadopted systems in our sample are in California. California also has some of the most generous subsidies for coadoption through the Self-Generation Incentive Program (SGIP) and is also facing widely-publicized power outages, some of which last for days. For these reasons, as well as the extremely active solar market in California, we find it useful to examine California separately from the rest of the country in our data.

The 2020 average share of solar installations that are coadopted with a battery in California is substantially greater than elsewhere in the country, at over 12%, compared to under 4% in the rest of the country. The share of coadoption also changes with the outage intensity, but the changes between California and other states are largely similar (see Appendix Figure A6). Fortunately, the same patterns that we observe in Figure 6 also occur in California. This can be seen in Figure A7. The core results of our analysis are in large part driven by California, but the results are broadly similar across states, with just a stronger effect in California than elsewhere.

5 Conclusions

This study focuses on quantifying the complementarities between rooftop solar and battery energy storage. It examines how outages affect such complementarities and explores what the complementarities mean for the policy implications of battery rebate subsidies. The empirical setting of solar and battery storage coadoption is ideal; not only is the degree of complementary highly relevant for current policy proposals around storage subsidies and feed-in-tariff rates, but the increased availability of battery options over time helps provide the necessary variation to disentangle complementarities from correlated preferences.

Our results clearly show that consumers increase their valuation of solar when the PV+Battery coadoption option is available, and indeed 20% of solar adopters would not have installed solar or batteries had PV+Battery coadoption not been available as an option. This, of course, also implies a strong preference correlation, since 80% of the PV+Battery coadoption is drawn from stand-alone solar adoption. Outage intensity plays a strong role in the demand for PV+Battery coadoption, and through the complementarity, a spillover role in the demand for aggregate solar. Increasing outage intensity, such as due to climate change or other factors, increases the value of battery storage and spurs the adoption of solar in aggregate. The reverse is also true. Financial incentives for batteries increase the adoption of storage and lead to substantial substitution between stand-alone solar systems and PV+Battery coadoption, which occurs alongside an increase the total adoption of solar as well.

These findings underscore a notable complementarity between solar and battery storage that is akin to many other complementarities, including between video game consoles and exclusive video games and between smartphones and certain apps that are only available on such phones. They provide guidance to policymakers by exploring the effects of actions that affect the demand for battery story, and thus, indirectly affect the demand for solar. Future work could explore the welfare effects and distributional consequences of the complementarity between solar and batteries, helping the further guide policymakers focused on the solar and battery storage markets.

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Appendix - For Online Publication

A Model Incorporating Consideration

This appendix section lays out further details of our model, which explicitly models consideration of solar.

A.1 Base Model

We present the base model (without consideration) first to clarify how consideration comes in. Given the structure of extreme-value error terms, the predicted market share of option $j \in \mathcal{J}_{g(j)}$ follows the usual nested logit expression and corresponds to the multiplication of the predicted share of the group $g(j)$ and the predicted share of the option j conditional on choosing $g(j)$:[35]

$$\begin{aligned} s_{jt} &= s_{j|g(j)t} \cdot s_{g(j)t} = \frac{\exp\{\delta_{jt}/(1-\sigma)\}}{D_{g(j)t}} \frac{D_{g(j)t}^{1-\sigma}}{\sum_{g'} D_{g't}^{1-\sigma}} & (18) \\ ln(s_{jt}) &= \frac{\delta_{jt}}{(1-\sigma)} - \sigma ln\left(D_{g(j)t}\right) - ln\left(\sum_{g'} D_{g't}^{1-\sigma}\right) & (19) \end{aligned}$$

with $D_{g(j)t} = \sum_{k \in \mathcal{J}_{g(j)t}} \exp\{\delta_{kt}/(1-\sigma)\}$, the inclusive value of group $g(j)$. The predicted share of the outside option $j = 0$, the only element of the group $g = 0$, is the following:

$$\begin{aligned} s_{0t} &= \frac{\left(\exp\{\delta_{0t}/(1-\sigma)\}\right)^{1-\sigma}}{\sum_{g'} D_{g't}^{1-\sigma}}. & (20) \\ ln(s_{0t}) &= \delta_{0t} - ln\left(\sum_{g'} D_{g't}^{1-\sigma}\right) & (21) \end{aligned}$$

Substracting (19) - (21) we have:

[35]See Mansley et al. (2019) for further details on the derivatives for nested logit demand.

$$
\begin{aligned}
ln(s_{jt}) - ln(s_{0t}) &= \frac{\delta_{jt}}{(1-\sigma)} - \sigma ln\left(D_{g(j)t}\right) - \delta_{0t} && (22)\\
&= \frac{\delta_{jt}}{(1-\sigma)} - \sigma\frac{\delta_{jt}}{(1-\sigma)} + \sigma\frac{\delta_{jt}}{(1-\sigma)} - \sigma ln\left(D_{g(j)t}\right) - \delta_{0t} && (23)\\
&= \frac{\delta_{jt}}{(1-\sigma)}(1-\sigma) + \sigma \underbrace{\left[\frac{\delta_{jt}}{(1-\sigma)} - \sigma ln\left(D_{g(j)t}\right)\right]}_{ln(s_{j|g(j)t})} - \delta_{0t} && (24)\\
&= \delta_{jt} - \delta_{0t} + \sigma ln(s_{j|g(j)t}) && (25)
\end{aligned}
$$

A.2 Model with Consideration

We define s_{0t} as the share of those not purchasing solar out of a market M of potential adopters. It could be that some of the potential adopting households are not considering solar. If the actual number of households considering adopting solar is m_t, then the log-odds expression (25) only holds for the set of households considering adopting:

$$\log(s_{jt|a_t}) - \log(s_{0t|a_t}) \quad = \quad \delta_{jt} - \delta_{0t} + \sigma \log(s_{j|g(j)t}) \tag{26}$$

where $s_{0t|a_t}$ is the share of households that, conditional on considering solar, decide not to adopt solar (i.e., $q_{0t|a_t}/m_t$). We do not observe $q_{0t|a_t}$ nor m_t, instead we observe $q_{0t} = q_{0t|a_t} + (M - m_t)$, the sum of those choosing to not install and those not considering. We can write:

$$
\begin{aligned}
\log(s_{jt|a_t}) - \log(s_{0t|a_t}) &= \log(q_{jt}/m_t) - \log(q_{0t|a_t}/m_t) && (27)\\
&= \log(q_{jt}/m_t) - \log\left((q_{0t} - (M - m_t))/m_t\right)\\
&= \log(q_{jt}/M) - \log\left((q_{0t} - (M - m_t))/M\right)\\
&= \log(s_{jt}) - \log\left(s_{0t} - (M - m_t)/M\right)\\
&= \log(s_{jt}) - \log(s_{0t}) - \log\left(1 - \left(\frac{M - m_t}{M}\right)\frac{1}{s_{0t}}\right) && (28)
\end{aligned}
$$

Defining the share not considering as $s_t^{nc} \equiv (M - m_t)/M$, we can use the original expression (25) but with an additional term:

$$\log(s_{jt}) - \log(s_{0t}) \quad = \quad \delta_{jt} - \delta_{0t} + \sigma \log(s_{j|g(j)t}) + \log\left(1 - \frac{s_t^{nc}}{s_{0t}}\right) \tag{29}$$

We further define $\kappa(\mathbf{o}_t) = 1 - s_t^{nc}/s_{0t}$, the share of households who don't adopt solar who considered solar, which we allow to be a function of the outages. An increase in outages should *decrease* s_t^{nc}. We can use a first order approximation and estimate:[36]

$$\log(s_{jt}) - \log(s_{0t}) = \delta_{jt} - \delta_{0t} + \sigma \log(s_{j|g(j)t}) + (\kappa(\mathbf{o}_t) - 1) \quad (30)$$

If all households consider solar, the last term drops out.

B Additional Tables

This short appendix provides further tables that could not make it into the main text to allow the reader to better understand our data and our results.

Table A1: Descriptive Statistics Outage Events

	Mean	Min	p10	p25	p50	p75	p90	Max
Event Duration (hours)	10.697	0.22	0.66	1.35	2.99	7.17	16.68	764.70
Weighted Av. Number of Cust. Out	119.710	0.00	8.17	13.00	28.34	79.76	243.21	2,440,373.00
Max Number of Cust. Out	290.493	10.00	13.00	20.00	46.00	153.00	635.00	2,440,374.00

Notes: This table presents summary statistics of power outage events. An event is a set of city-level snapshots involving ten or more customers without electricity. The time difference between the first customer out and power restoration is 10 minutes or more. These two restrictions allow for excluding customer-level casualties. Between 2017 and 2021, we identified over 4.04 million events; every event has a starting time stamp and a duration (until power is fully restored). The number of customers is not stable over time; we focus on two measures: the maximum and the weighted average number of customers without power, which is calculated considering the duration each number was out of power across snapshots.

[36]The Taylor expansion of $\log(1-x)$ is $-x - x^2/2 - x^3/3 - \ldots$

Table A2: Summary Statistics Estimation Data

	(1) Mean	(2) SD	(3) Min	(4) Max
Panel A: Option Categorization				
PV+Battery Co-Installation	0.10	0.30	0.00	1.00
Third-Party Owned	0.20	0.40	0.00	1.00
In California	0.57	0.49	0.00	1.00
Panel B: Variables				
Post-Rebate Price ($/W)	2.84	0.96	0.00	19.75
log-Installer Cum. Installations	12.56	2.94	0.00	18.87
Solar Size (kW)	7.77	2.65	1.56	19.50
Battery Size (kWh)	1.63	5.37	0.00	40.50
log Outage Hours in Last 4 Quarters	1.93	1.15	-2.81	9.07
Construction Wages (000's $)	1.36	0.26	0.50	2.48
Rebate ($/W)	0.09	0.31	0.00	10.06
Periods since Battery Entry	14.04	9.70	0.00	50.00
Panel C: Observations				
Number of Observations	58,514			
Number of Counties	284			
Number of Installers	999			

Notes: This table presents summary statistics of the estimation dataset. The dataset is at the quarter-county-option level. We exclude from the analysis observations from Colorado, Florida, and Texas. The dataset includes observations between 2017 and 2021; however, given that outage data accumulates in the last four quarters, the first "effective" quarter corresponds to the first quarter of 2018. We group installers with fewer than 100 installations into the category "other" which represents 6% of the share of installations. The variable "log installer base" corresponds to the logarithmic capacity (watts) installed by the installer in the county until $t-1$. The variable "wage construction" is the county's average weekly wage (in thousand dollars) in the construction sector. The variable "periods since battery entry" is the number of quarters since the cumulative sale of PV+Battery options surpassed a near-zero level in the county.

Table A3: Full Demand Estimates Including Controls

	(1) OLS	(2) IV	(3) OLS	(4) IV
Post-rebate price/watt (α)	-0.001	-0.210	-0.001	-0.245
	(0.004)	(0.119)	(0.004)	(0.124)
Nest coefficient (σ)	0.602	0.929	0.600	0.908
	(0.013)	(0.084)	(0.013)	(0.094)
log-installer cum. installations to $t-1$	0.068	0.074	0.067	0.074
	(0.004)	(0.005)	(0.004)	(0.005)
Solar system size (kW)	0.092	0.068	0.093	0.066
	(0.002)	(0.011)	(0.002)	(0.012)
Battery size (kWh)	0.002	-0.003	0.001	-0.003
	(0.003)	(0.003)	(0.003)	(0.004)
Log-outage hours in last 4 quarters			-0.001	0.001
			(0.007)	(0.007)
Log-outage hours in last 4 quarters*CA			0.071	0.078
			(0.031)	(0.030)
Log-outage hours in last 4 quarters*Coadopt			0.111	0.105
			(0.027)	(0.035)
Log-outage hours in last 4 quarters*Coadopt*CA			-0.026	-0.060
			(0.033)	(0.042)
Installer-Adoption Type-County FE	Yes	Yes	Yes	Yes
State-Quarter FE	Yes	Yes	Yes	Yes
Observations	58514	58514	58514	58514

Notes: This table presents our demand estimates. Columns (1) and (3) show OLS regressions, columns (2) and (4) display IV estimates. Columns (1) and (2) show the coefficients without outage variables, while (3) and (4) include outages as covariates. The "installer cum. installations" refers to the cumulative installations by the installer up to the previous quarter, often called the "installed base." The first stage coefficients are shown in the Appendix table (A4). The excluded instruments are construction wage, rebates per watt, periods since battery entry in the county, and the interaction between periods since battery entry and co-installation. Adoption type refers to whether adoption is PV-only, PV+Battery, and third-party owned interacted with each. FE refers to fixed effects and CA refers to California. Details of the estimation dataset are described in the table (A2). Standard errors are clustered at the county level.

Table A4: First Stage

	(1)	(2)	(3)	(4)
	First Stage		First Stage	
	Price/Watt (Δ)	Regressor	Price/Watt (Δ)	Regressor
Log-installer cum. installations	0.017	-0.007	0.017	-0.007
	(0.003)	(0.001)	(0.003)	(0.001)
Solar size (kW)	-0.078	0.025	-0.078	0.025
	(0.003)	(0.001)	(0.003)	(0.001)
Battery size (kWh)	-0.007	0.001	-0.007	0.001
	(0.008)	(0.003)	(0.008)	(0.003)
Log-outage hours in last 4 quarters			0.011	0.001
			(0.009)	(0.004)
Log-outage hours in last 4 quarters*CA			-0.011	-0.016
			(0.014)	(0.007)
Log-outage hours in last 4 quarters*Coadopt			-0.098	-0.084
			(0.032)	(0.027)
Log-outage hours in last 4 quarters*Coadopt*CA			0.167	0.188
			(0.042)	(0.038)
Construction wage (thousand dollars)	-0.046	-0.003	-0.043	-0.008
	(0.074)	(0.032)	(0.074)	(0.032)
Average rebate/watt	0.824	-0.102	0.825	-0.068
	(0.203)	(0.074)	(0.200)	(0.065)
Average rebate per type/watt	-0.432	-0.028	-0.450	-0.054
	(0.070)	(0.055)	(0.069)	(0.048)
Periods since battery entry	-0.002	-0.005	-0.000	-0.004
	(0.009)	(0.004)	(0.009)	(0.004)
Periods since battery entry*Coadopt	0.048	0.077	0.046	0.073
	(0.007)	(0.006)	(0.007)	(0.006)
Installer-Adoption Type-County FE	Yes	Yes	Yes	Yes
State-Quarter FE	Yes	Yes	Yes	Yes
Observations	58514	58514	58514	58514
F-stat	16.48	32.55	15.39	35.57

Notes: This table presents the first stage regressions corresponding to IV estimates presented in table (A3). Columns (1) and (2) the regression specification without outage variables. Columns (3) and (4) include outages as covariates. The excluded instruments are construction wage, rebates per watt, periods since battery entry in county and the interaction between periods since battery entry and co-installation. Details of the estimation dataset are described in the table (A2). Standard errors are clustered at the county level.

Table A5: Demand Estimates: Alternative Outage Variable

	(1) OLS	(2) IV	(3) OLS	(4) IV
Post-rebate price/watt (α)	-0.001	-0.210	-0.001	-0.239
	(0.004)	(0.119)	(0.004)	(0.119)
Nest coefficient (σ)	0.602	0.929	0.599	0.894
	(0.013)	(0.084)	(0.013)	(0.100)
Log-installer cum. installations	0.068	0.074	0.067	0.074
	(0.004)	(0.005)	(0.004)	(0.005)
Solar size (kW)	0.092	0.068	0.093	0.067
	(0.002)	(0.011)	(0.002)	(0.011)
Battery Size (kWh)	0.002	-0.003	0.001	-0.003
	(0.003)	(0.003)	(0.003)	(0.004)
Log-cust. out for 6+ hours last 4 quarters			-0.013	-0.011
			(0.008)	(0.009)
Log-cust. out for 6+ hours last 4 quarters*CA			0.119	0.134
			(0.040)	(0.041)
Log-cust. out for 6+ hours last 4 quarters*Coadopt			0.155	0.159
			(0.036)	(0.048)
Log-cust. out for 6+ hours last 4 quarters*Coadopt*CA			0.003	-0.062
			(0.049)	(0.068)
Installer-Adoption Type-County FE	Yes	Yes	Yes	Yes
State-Quarter FE	Yes	Yes	Yes	Yes
Observations	58514	58514	58514	58514

Notes: This table presents our demand estimates. Columns (1) and (3) show OLS regressions, columns (2) and (4) display IV estimates. Columns (1) and (2) show the coefficients without outage variables, while (3) and (4) include outages as covariates. The excluded instruments are construction wage, rebates per watt, periods since battery entry in the county, and the interaction between periods since battery entry and co-installation. Adoption type refers to whether adoption is PV-only, PV+Battery, and third-party owned interacted with each. FE refers to fixed effects and CA refers to California. Details of the estimation dataset are described in the table (A2). Standard errors are clustered at the county level.

Table A6: Demand Estimates Instrumenting Post-Rebate Price Only

	(1) OLS	(2) IV	(3) OLS	(4) IV
Post-rebate price/watt (α)	-0.001	-0.325	-0.001	-0.299
	(0.004)	(0.147)	(0.004)	(0.136)
Nest coefficient (σ)	0.602	0.609	0.600	0.606
	(0.013)	(0.015)	(0.013)	(0.014)
Log-installer cum. installations	0.068	0.073	0.067	0.072
	(0.004)	(0.005)	(0.004)	(0.005)
Solar size (kW)	0.092	0.067	0.093	0.069
	(0.002)	(0.012)	(0.002)	(0.012)
Battery Size (kWh)	0.002	0.001	0.001	-0.000
	(0.003)	(0.004)	(0.003)	(0.003)
Log-outage hours in last 4 quarters			-0.001	0.002
			(0.007)	(0.007)
Log-outage hours in last 4 quarters*CA			0.071	0.067
			(0.031)	(0.030)
Log-outage hours in last 4 quarters*Coadopt			0.111	0.092
			(0.027)	(0.032)
Log-outage hours in last 4 quarters*Coadopt*CA			-0.026	0.023
			(0.033)	(0.045)
Installer-Adoption Type-County FE	Yes	Yes	Yes	Yes
State-Quarter FE	Yes	Yes	Yes	Yes
Observations	58514	58514	58514	58514

Notes: This table presents our demand estimates. Columns (1) and (3) show OLS regressions, columns (2) and (4) display IV estimates. Columns (1) and (2) show the coefficients without outage variables, while (3) and (4) include outages as covariates. The excluded instruments are construction wage, rebates per watt, and they instrument post rebate price. Adoption type refers to whether adoption is PV-only, PV+Battery, and third-party owned interacted with each. FE refers to fixed effects and CA refers to California. Details of the estimation dataset are described in the table (A2). Standard errors are clustered at the county level.

Table A7: Demand Estimates: Perfect Foresight on State Variables

	(1) OLS	(2) IV	(3) OLS	(4) IV
Post-rebate price/watt (α)	-0.001	-0.183	-0.002	-0.121
	(0.004)	(0.123)	(0.004)	(0.115)
Nest coefficient (σ)	0.602	0.917	0.600	0.835
	(0.013)	(0.093)	(0.013)	(0.104)
Log-installer cum. installations	0.068	0.073	0.067	0.071
	(0.004)	(0.005)	(0.004)	(0.005)
Solar size (kW)	0.092	0.070	0.093	0.077
	(0.002)	(0.012)	(0.003)	(0.011)
Battery size (kWh)	0.002	-0.002	0.001	-0.002
	(0.003)	(0.004)	(0.003)	(0.003)
Log-outage hours in last 4 quarters			-0.001	-0.001
			(0.007)	(0.007)
Log-outage hours in last 4 quarters*CA			0.071	0.079
			(0.031)	(0.030)
Log-outage hours in last 4 quarters*Coadopt			0.111	0.111
			(0.027)	(0.032)
Log-outage hours in last 4 quarters*Coadopt*CA			-0.026	-0.063
			(0.033)	(0.038)
Installer-Adoption Type-County FE	Yes	Yes	Yes	Yes
State-Quarter FE	Yes	Yes	Yes	Yes
Observations	58514	58514	58514	58514

Notes: This table presents demand estimates assuming households perfectly predict state variables in $t+1$. We exclude future outages from the perfect foresight process as we assume households form stationary beliefs equal to the mean in the county. Columns (1) and (3) show OLS regressions, and columns (2) and (4) display IV estimates. Columns (1) and (2) show the coefficients without outage variables, while (3) and (4) include outages as covariates. The excluded instruments are construction wage, rebates per watt, periods since battery entry in the county, and the interaction between periods since battery entry and co-installation. Adoption type refers to whether adoption is PV-only, PV+Battery, and third-party owned interacted with each. FE refers to fixed effects and CA refers to California. Details of the estimation dataset are described in the table (A2). Standard errors are clustered at the county level.

Table A8: Demand Estimates: Static Model

	(1) OLS	(2) IV	(3) OLS	(4) IV
Post-rebate price/watt (α)	0.002	-0.416	0.002	-0.505
	(0.004)	(0.188)	(0.004)	(0.207)
Nest coefficient (σ)	0.597	0.944	0.597	0.975
	(0.014)	(0.102)	(0.014)	(0.120)
Log-installer cum. installations	0.069	0.079	0.069	0.080
	(0.004)	(0.007)	(0.004)	(0.007)
Solar size (kW)	0.095	0.053	0.095	0.045
	(0.003)	(0.017)	(0.003)	(0.020)
Battery size (kWh)	0.002	-0.004	0.001	-0.005
	(0.003)	(0.005)	(0.003)	(0.005)
Log-outage hours in last 4 quarters			0.005	0.009
			(0.011)	(0.013)
Log-outage hours in last 4 quarters*CA			0.092	0.100
			(0.046)	(0.046)
Log-outage hours in last 4 quarters*Coadopt			0.110	0.088
			(0.028)	(0.040)
Log-outage hours in last 4 quarters*Coadopt*CA			-0.048	-0.056
			(0.036)	(0.052)
Installer-Adoption Type-County FE	Yes	Yes	Yes	Yes
State-Quarter FE	Yes	Yes	Yes	Yes
Observations	58514	58514	58514	58514

Notes: This table presents demand estimates under static demand model. The static specification considers that outside option is constant and normalized to zero. The dependent variable is the current log odds ratio, the nest coefficient is the coefficient associated to the log within-group share. Columns (1) and (3) show OLS regressions, and columns (2) and (4) display IV estimates. Columns (1) and (2) show the coefficients without outage variables, while (3) and (4) include outages as covariates. The excluded instruments are (current) construction wage, rebates per watt, periods since battery entry in the county, and the interaction between periods since battery entry and co-installation. Adoption type refers to whether adoption is PV-only, PV+Battery, and third-party owned interacted with each. FE refers to fixed effects and CA refers to California. Details of the estimation dataset are described in the table (A2). Standard errors are clustered at the county level.

C Additional Figures

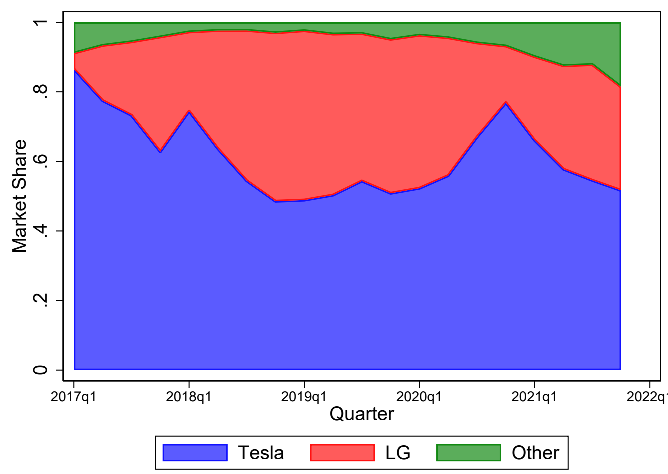
Figure A1: Battery Models

(a) Tesla Powerwall

(b) LG RESU10H

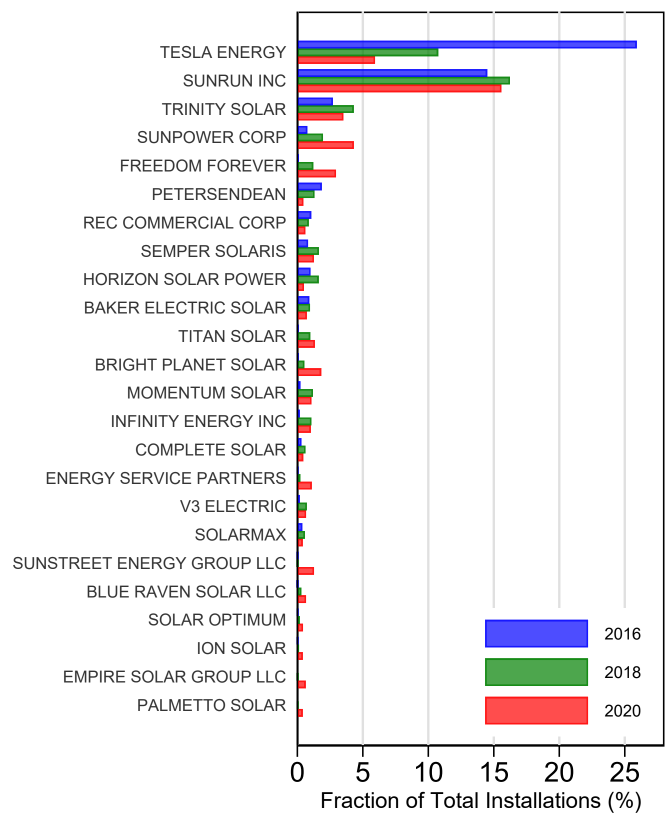
Notes: Figure A1(a) shows a Tesla Powerwall. Figure A1(b) shows LG's RESU10H. These are the two main battery models in the dataset; together, they represent over 90% battery installations.

Figure A2: Market Share Battery Manufacturers



Notes: This figure shows the market share of battery manufacturers: Tesla, LG, or Other. The market share of each manufacturer is computed using the number of battery installations by each manufacturer in each quarter over the total number of battery installations.

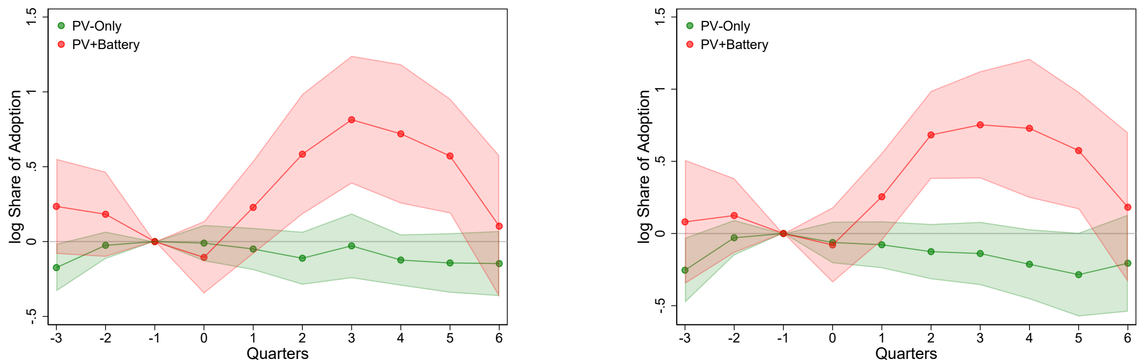
Figure A3: Top Solar Installers



Notes: This graph shows the fraction of the total installations made by the top 25 installers. The blue, green and red bars correspond to the fraction of installations by each installer for years 2016, 2018 and 2020. In 2016, Tesla acquired SolarCity, which by that time was the was the leading residential solar installer in the U.S.

Figure A4: Effect of Power Outages on Adoption

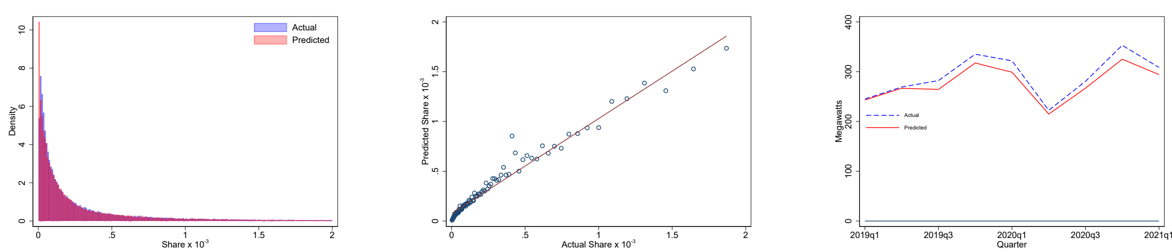
(a) Share of Cust. exposed to 3+ hours Outage (b) Share of Cust. exposed to 12+ hours Outage



Notes: These figures show the coefficients $\beta_{\tau}^{\text{PV-Only}}$ and $\beta_{\tau}^{\text{PV+Battery}}$ of regression equation (1), with their respective confidence intervals. These coefficients and normalized to the period $\tau = -1$. The panel (a) defines as outage intensity as share of customers exposed to 3+ hours outages. Panel (b) defines as outage intensity as share of customers exposed to 12+ hours outages. Both regressions include option-county and quarter-state fixed effects. The estimating data set is at the option-county-quarter level, it includes all quarters and counties previously described.

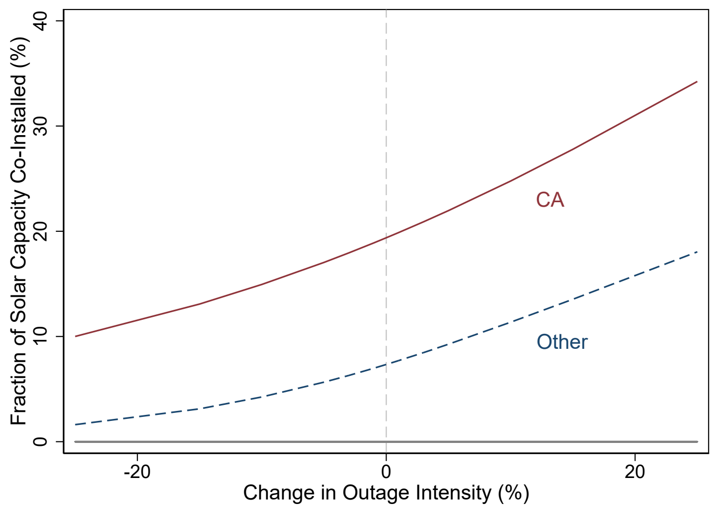
Figure A5: Model Fit

(a) Distribution of Shares (b) Predicted vs. Actual Shares (c) Aggregate Solar Capacity



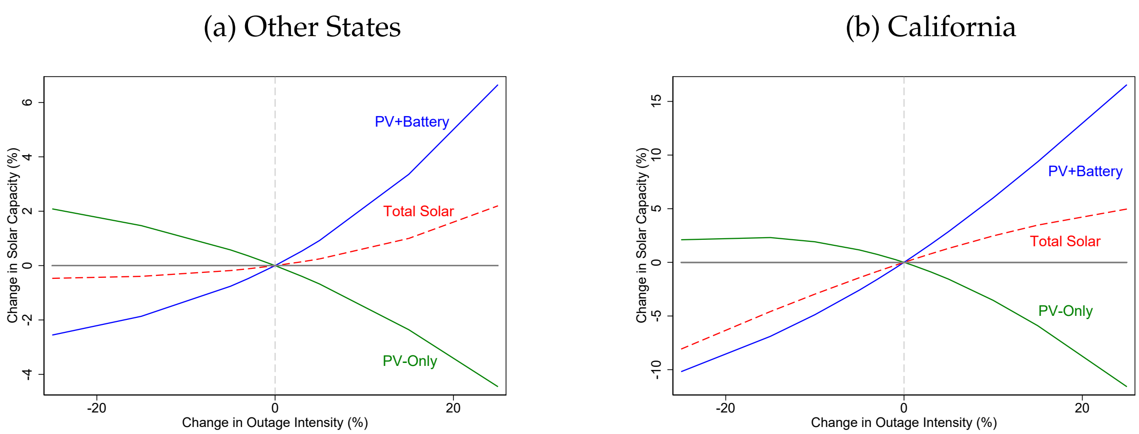
Notes: Panel (a) shows the distribution of predicted and actual market shares of every option in each market-time. Panel (b) compares the actual and predicted shares of adoption; every dot corresponds to a percentile of actual shares. Panel (c) compares the predicted and actual aggregate capacity installed (Megawatts of Solar). We calculate each option's installed capacity by multiplying the adoption share with the market size shares. The aggregate adoption adds across all the options offered in each quarter. The dashed blue line correspond to the aggregate installed solar capacity, and the red solid lines correspond to the predicted solar capacity.

Figure A6: Share of Co-Installation by Levels of Power Outages



Notes: This figure shows the share of co-installation as a function of changes in outage intensity (customer hours). The solid red line correspond to California, the sahsed blue line agregates states other than California. To carry out these exercises, we vary the county's average level of outage intensity in the current and future periods. Both panels are based on adoption levels for the year 2020.

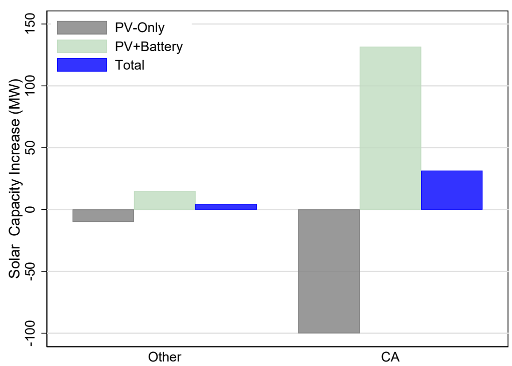
Figure A7: Aggregate Solar Adoption by Levels of Power Outages



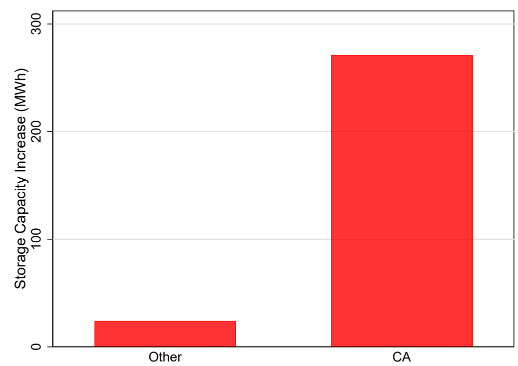
Notes: Panels (a) and (b) break up the Figure 5(a) by state and adoption type. These figures show the percentage change in solar capacity installed (Watts) depending on changes in outage intensity (customer hours). The green-solid line corresponds to the change in PV-Only systems; the blue-solid line is the change in PV+Battery format. The red dashed line is the total change and aggregates the changes in both forms. Panel (a) shows the effects in states other than California, and panel (b) shows the effects in California. To carry out these exercises, we vary the county's average level of outage intensity in the current and future periods. Both panels are based on adoption levels for the year 2020.

Figure A8: Change in Solar and Storage Capacity

(a) Solar Capacity (MW)



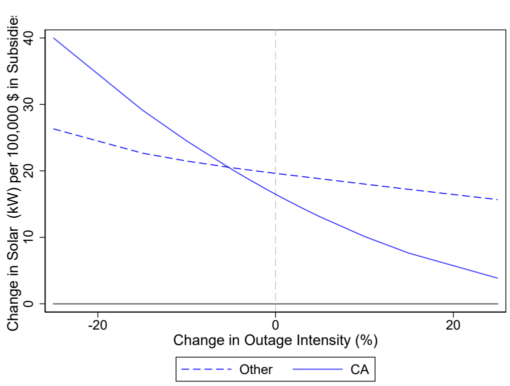
(b) Storage Capacity (MWh)



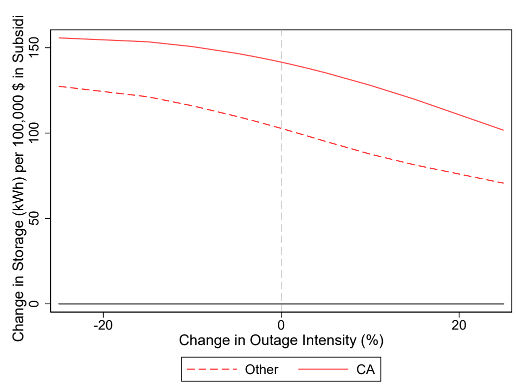
Notes: These figures show the effects of introducing a 20% reduction in the price of PV+Battery. Panel (a) shows the effects on solar capacity, and shows that the rebate would induce high substitution from PV-Only to PV+Battery systems although with a positive effect over total solar adoption. Panel (b) shows how would increase the total storage capacity. Both panels use the year 2020 to set market conditions and separate California from other states.

Figure A9: Return on Investment (ROI) of Rebates by Levels of Power Outages

(a) Solar Capacity (kW) per 100,000 $



(b) Storage Capacity (kWh) per 100,000 $



Notes: This graph shows the return on investment (ROI) of the financial incentives for coadoption as a function of different levels of power outages. The ROI is calculated by dividing the increase in installed capacity by the increase in government spending (in millions of dollars). Panel (a) shows the ROI over solar capacity (kilowatts), and panel (b) shows the ROI over storage capacity (kilowatt hours). These calculations are based on market conditions in 2020.

D Data Description

D.1 Power Outages

We use outage data from PowerOutageUS, which collects real-time data from distribution utilities to record how many electric customers are experiencing power shutdown every moment without distinguishing the root cause of the outage. It includes data collected from over 800 electric utilities and, to our knowledge, is the most granular and complete source of outage data available for the United States.

The data are structured at the city level, providing snapshots of the number of customers without power. For example, the number of customers out of power in a city in South Carolina on 2018/02/10 was 431 at 00:21, 437 at 00:31, 438 at 00:41, . . . , 6 at 01:21, 1 at 01:31, 0 at 1:41, i.e., the power was fully restored at 1:41. We refer to a collection of snapshots as one *event*, with a starting and ending time, a duration (in our example, 1 hour and 21 minutes). Since the number of customers is not stable over time, we focus on two measures: the maximum and the weighted average number of customers without power, which is calculated considering the duration each number was out of power across snapshots. In our example, the maximum is 438, and the weighted average is 328.5.

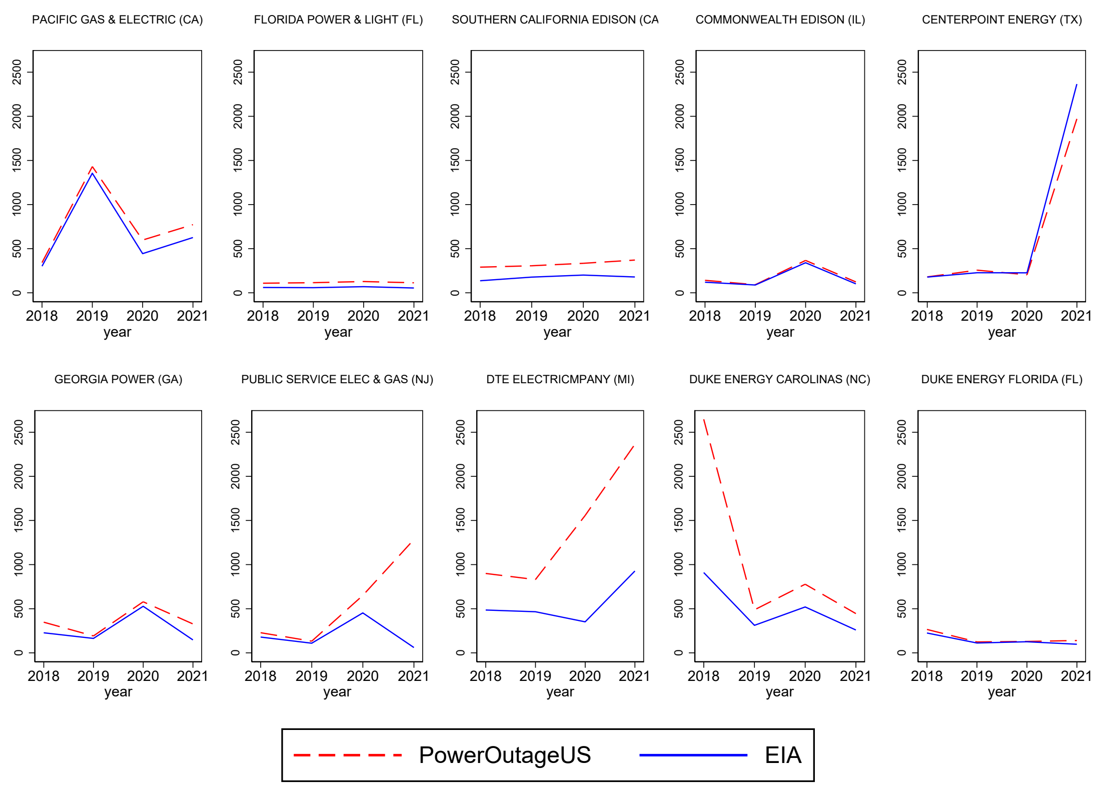
Sample: We focus our analysis on outage events that last more than ten minutes and involve more than ten customers. These criteria were set to rule out events generated by customer-specific actions and are perceivable by customers. As a result, our sample includes slightly more than 4 million events. The median outage event lasts for 3 hours and covers a (maximum) number of customers of 153. The table A1 provides descriptive statistics.

D.1.1 Comparison: PowerOutageUS vs. EIA Outage Reports

To our knowledge, the PowerOuatgeUS dataset is the only nationwide dataset that is granular from a geographic and time perspective. This section compares it to aggregate administrative data by the U.S. Energy Information Administration (EIA). In particular, the EIA puts together an Annual Electric Power Industry Report (Form EIA-861S), which collects data from distribution utilities on the intensity of power outages annually.

Utilities report the number of customers served, the system average interruption duration index (SAIDI), the system average interruption frequency index (SAIFI), and decomposition depending on whether major events occurred. The SAIDI index is the total customer duration divided by the number of customers served, considering events that lasted five minutes or more. PowerOuatgeUS data includes the number of customers out of power at different moments, so we can aggregate the utility-year level and divide it by the number of customers served by the utility. Figure A10 shows the SAIDI reported by EIA and the one constructed using data from PowerOutageUS for the ten largest utilities in the US. Figure A11 shows the ratio EIA total customer-hours divided by the customer-hours calculated using POwerOutageUS.

Figure A10: System Average Interruption Duration (SAIDI)

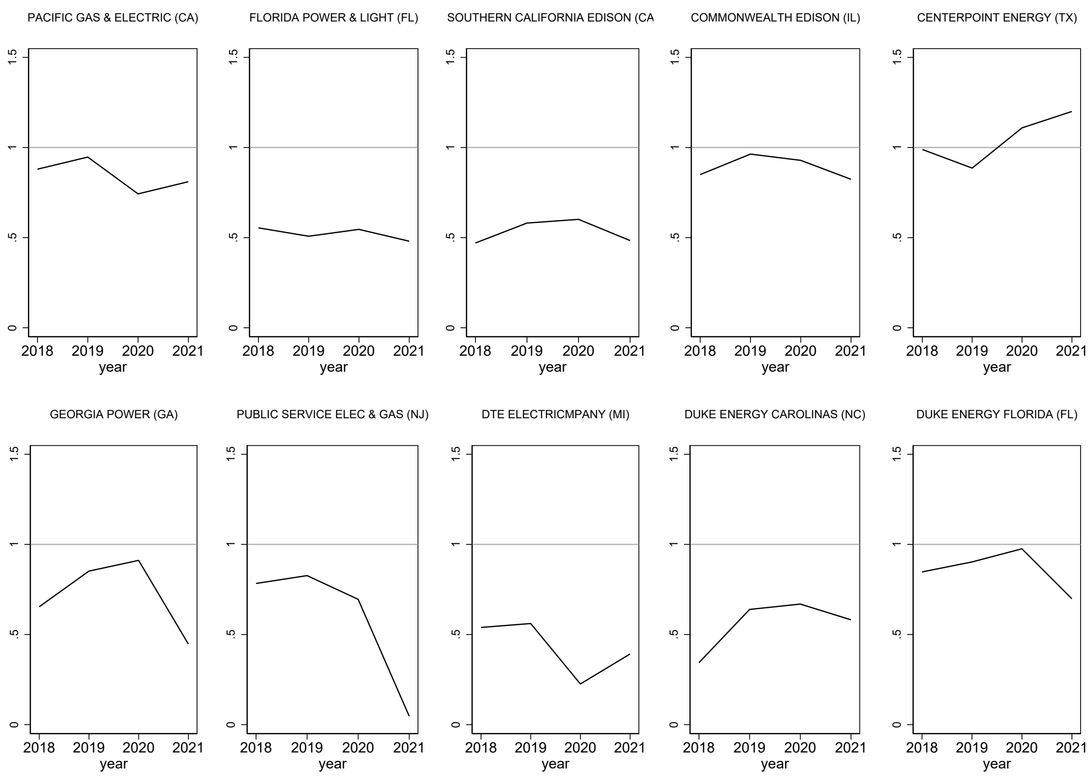


Notes: Each plot shows the System Average Interruption Duration Index (SAIDI) for the ten largest utilities in the country (by the number of customers). This index is calculated by dividing the total number of customer minutes by the number of customers served by the utility. The blue line shows the SAIDI reported by each utility in Form EIA-861 annually. The red dashed line shows the SAIDI calculated using the data from PowerOutage.US, following the guidelines provided by the EIA, including all the interruptions that lasted for more than five minutes and aggregates at the utility-year level.

From Figures A10 and A11 we conclude: (i) The outages by PowerOutageUS are at a "similar level" of intensity (duration$\times$customer) than the EIA reports, although PowerOutageUS tend to capture, on average, more outages than the EIA, (ii) The difference between EIA and PowerOutageUSA varies by utility: For example, PG&E (CA), Commonwealth (IL), and Centerpoint (TX) are at very similar levels. For Southern

Edison (CA) and DTE (MI), the EIA shows lower levels of outages. (iii) The ratio between these levels (Figure A11) seems relatively stable over time, suggesting that the EIA may exclude some observations or customers that we include in PowerOutageUS. Still, the fact the ratio is stable tells that the two levels go up and down together, capturing outage shocks at the same time. (iv) There are occasional departures between these two indexes, e.g., Public Service E&G (NJ) reported almost zero outages in 2021 in the EIA data, which is relatively surprising relative to other sources like media coverage.

Figure A11: Ratio Total Customer-Duration Interruptions EIA over PowerOutageUS



Notes: Each plot shows the ratio between the total customer minutes of power interruption reported by each utility to EIA divided by the total customer minutes calculated using PowerOutage.US data for the ten largest utilities in the country (by the number of customers). The calculation of total customer minutes follows the Guidelines provided by the EIA, including all the interruptions that lasted for more than five minutes and aggregates at the utility-year level. As a reference, a ratio equal to 0.9 means that the total outage duration of outages reported by utilities to EIA (Form EIA-861) is 90% to the total outage duration calculated using data from PowerOutage.US.

E Battery Installations

E.1 Battery Retrofit

Our data include roughly 11 thousand battery retrofitted systems. These are battery attached to previously installed PV systems, i.e., the date of battery installation is posterior to the date of PV installation. The subsection E.1.1 describes how the price is substantially higher for retrofitted systems than co-installed systems. The subsection E.1.2 describes the timing of retrofitted adoption.

E.1.1 System Prices

Table A9 compares the total price of PV+Battery systems. These regressions include both co-installed and retrofitted systems and aim to compare system costs between these two groups. We focus on the pre-rebate, columns (1) and (3), and the post-rebate and ITC prices, columns (2) and (4). The coefficient of interest is "PV+Battery Co-installed," which captures differences in the total cost of co-installed relative to retrofitted PV+Battery systems.

Overall, the total price paid by co-installed systems is substantially lower than that of retrofitted systems. The price difference is roughly 30% of the average pre-rebate system price, columns (1) and (3). The gap increases when we deduct rebates and ITC and becomes 32% and 37% in columns (2) and (4), respectively. These magnitudes are substantial and explained by retrofitting an existing PV system requires changing the inverter. Moreover, the gap increases once we consider rebates and deductions; since the ITC does not allow tax credits for existing solar systems, the cost of retrofitted is not subject to tax credits.

Table A9: System Cost

VARIABLES	(1) System Cost (dollars)	(2) Post Rebates and ITC System Cost (dollars)	(3) System Cost (dollars per Watt)	(4) Post Rebates and ITC System Cost (dollars per Watt)
PV+Battery Co-installed	-11,585	-8,172	-1.73	-1.32
	(230)	(188)	(0.03)	(0.03)
Third-Party Owned	967	-1,759	0.21	-0.23
	(413)	(337)	(0.06)	(0.05)
Third-Party Owned*Co-installed	-2,752	142	-0.50	-0.03
	(433)	(353)	(0.07)	(0.05)
PV Size (kW)	2,919	2,171	-0.28	-0.15
	(16)	(13)	(0.00)	(0.00)
Battery Size (kWh)	288	27	0.05	0.00
	(7)	(5)	(0.00)	(0.00)
Installer FE	Yes	Yes	Yes	Yes
State-Quarter FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Mean Dep Variable	38066	25628	5.38	3.58
N Obs	51650	51578	51650	51578

Notes: This table shows coefficients of regressions on systems that have a battery attached (both co-installed and retrofitted). The dependent variable is the total system cost, PV cost plus Battery cost, explained by whether the PV and the Battery were co-installed, the system is owned by a third party (leased), and solar and storage sizes. Columns (1) and (2) show the cost in dollar terms, and columns (3) and (4) show the cost in terms of dollars per watt of solar. The main coefficient of interest is "PV+Battery Co-installed," which shows the difference in the total cost of adopting PV and Battery at the same time. The coefficients show a sizable difference in the cost of co-installation. Co-installed systems are considerably cheaper. The difference in cost is 32% relative to the average pre-rebate cost per watt and 37% relative to the average after deducting rebates and ITC.

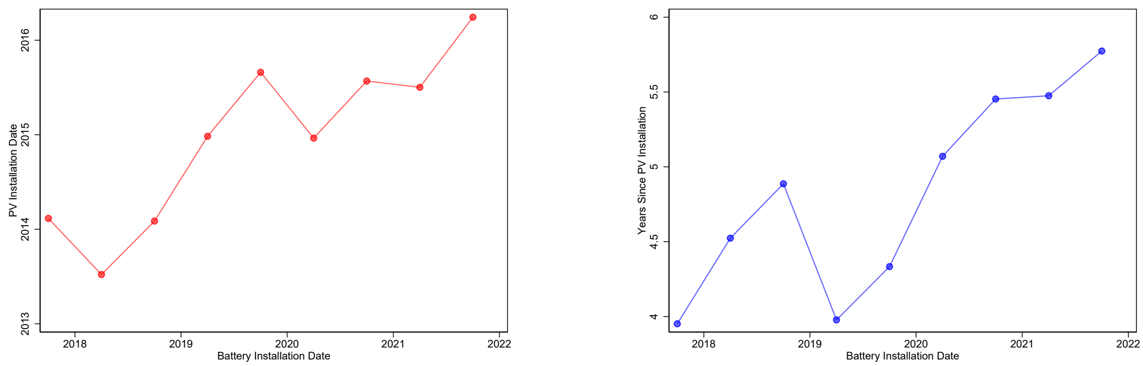
E.1.2 Timing of adoption

The figure A12(a) compares the dates of the solar installation and the date of the battery installation. Panel (a) shows the average solar PV installation date as a function of the date of battery installation. Panel (b) shows the average difference (in years) between the date of installation of PV and Battery. These figures show that the bulk of households that decided to retrofit their PV system correspond to PV installations that took place before the battery "entry" in 2017 (or later), i.e., the co-installation option was not available when they decided to install a PV. The latter is true even for systems that were retrofitted in 2021 as we see that the gap between the date of PV and battery adoption increases steadily.

Figure A12: Retrofitted Batteries: Date of Installation PV and Battery

(a) Date of PV vs. Battery

(b) Time Difference: Battery vs. PV



Notes: These figures focus on retrofitted batteries. Panel (a) compares the date of installation of PV (y-axis) to the date of battery installation (x-axis). Every dot corresponds to the average per semester. Panel (b) shows the difference (in years) between the PV and Battery Installation dates. Panel (a) and (b) show that households' PV systems that were installed before the battery "entry" in 2017 (or later), i.e., the co-installation option was not available when they decided to install a PV. The latter is true even for systems that were retrofitted in 2021, as we see that the gap between the date of PV and battery adoption increases steadily.

E.2 Stand-alone storage

We observe 856 residential storage-only systems, which represent 1.24% of all battery installations and 0.04% of the total solar systems.[37] These batteries are directly charged from the power grid and are primarily located in specific utilities under time-of-use electricity rates. Also, storage-only can be used as a backup power source during an outage. Nevertheless, the very small amount of adoption of the storage-only option suggests that these are primarily exceptions. This is not surprising as there is little value in a battery-only system relative to a much-cheaper stand-alone generator. Future work could explore these stand-alone battery systems in more depth.

[37] We observe one thousand stand-alone batteries in industrial sites (out of the scope of this study). The number remains small, although it represents a more meaningful share of the total battery installations for industrial sites.