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Gorman, Will

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Sunsetting the Grid? Opportunities for Customer-Sited Solar and Storage in Modern
Electricity Systems

by

Will Gorman

A dissertation submitted in partial satisfaction of the

requirements for the degree of

Doctor of Philosophy

in

Energy and Resources

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Professor Duncan Callaway, Chair

Professor Severin Borenstein

Professor Meredith Fowlie

Fall 2022

Sunsetting the Grid? Opportunities for Customer-Sited Solar and Storage in Modern
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Will Gorman

Abstract

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Professor Duncan Callaway, Chair

This dissertation opens with a discussion of three key transformations of the electricity grid in the 21st century: (1) integration of renewable electricity and electricity storage, (2) growth and increased public popularity of distributed, rather than centralized, electricity supply, and (3) increasing concerns about reliability in modern power systems. These trends broadly motivate a central question that links each chapter of the dissertation: what role can distributed energy play towards providing power locally and mitigating electric system reliability concerns?

My second chapter sets the conceptual stage for the remainder of the dissertation by discussing the microeconomics of power outages. Its general premise is that estimating the benefits of policies that enhance the reliability of the electricity grid is challenging. I outline a microeconomic framework that ties electricity demand to the industry metric meant to encapsulate power outage avoidance benefits, the “value of lost load” or VoLL. This metric, which I argue is too often presented as a singular point estimate, is used in cost-benefit analyses (CBA) that inform infrastructure investment decisions, and the framework leads to insights about its inherent complexity. I describe the public good properties of electric reliability and review the historical development of VoLL literature, highlighting distinctions of applying the VoLL in CBA versus electricity rationing decision-making. Finally, I outline rarely-implemented revealed preference approaches to VoLL estimation that take advantage of recent adoption of backup power systems like solar-plus-storage and that offer attractive theoretical advantages over traditional estimation methods such as macroeconomic proxies and contingent valuation. I argue that the underlying uncertainty of VoLL estimation suggests that cost-effectiveness analysis should remain a cornerstone of electric reliability decision-making.

My next two chapters then apply different empirical strategies to estimate the VoLL by con-

sidering the adoption of backup power technologies. Chapter 3 implements an experimental stated-preference survey. The survey asks whether notification timing of power outages affect consumers willingness-to-pay (WTP) to avoid power outages and compares how ownership of backup power technologies differentiates the results. The setting is the recent major power outages in California, where utilities have begun using targeted demand-side shut offs of the grid to prevent their equipment from sparking wildfires. We find positive and statistically significant WTP to avoid power outages (\$86/month or \$11/kWh); however, we did not find that advanced notice of a power outage led to statistically significant reduced WTP. Heterogeneity analysis suggested that household wealth is negatively correlated with WTP, though household income was not a strong determinant of our respondents WTP. Customers who owned backup power at the time of the survey reported higher WTP.

Chapter 4 complements the stated-preference survey by describing a revealed preference approach to VoLL estimation. I estimate the causal impact of Pacific Gas & Electric's Power Safety Public Shutoff Program (PSPS) on the adoption of solar and storage technologies. The research design centers around a regression discontinuity that estimates the difference in adoption trends between neighbors who experience differing amounts of power outages and takes advantage of PG&E's differential use of nearby electrical feeder lines to mitigate wildfire risk. The VoLL is then estimated using the incremental costs of such investments and how they compare to a scenario analysis of customer expectations of future power outages. Overall, I calculate a VoLL range of \$0.3 - \$0.8 per kWh. I conclude this chapter with a discussion of limitations and challenges of applying the mitigation cost framework to estimate the VoLL.

Chapter 5 then aims to understand what the technical limitations are for solar-plus-storage systems to provide residential household electricity during long-duration power outage events in the United States. I develop a methodology to model the performance of behind-the-meter solar-plus-storage systems (PVESS) to provide backup power across a wide range of customer types, geography / climate conditions, and power outage scenarios, considering both whole-building backup and backup of specific critical loads. Such analysis provides new information about the conditions PVESS technologies can be relied on to serve load during long-duration outage events. The results indicate that PVESS can meet a limited set of critical loads that includes refrigeration, nighttime lighting, well-pumps, and internet / computer load for 93% of counties, though this percentage drops to 27% in a critical load scenario that includes heating and cooling. Backup performance is lowest in winter months where electric heat is common (southeast and northwest U.S.) and in summer months in places with large cooling loads (southwest and southeast U.S.). Winter backup performance varies by roughly 20% depending on infiltration rates, while summer performance varies by close to 15% depending on the efficiency of the central air-conditioning system. Differences in temperature set-points correspond to a 40% range in winter backup performance and a 20% range in summer performance. A back-of-the-envelope calculation combines the costs with the performance of PVESS in a set of historical case studies to offer comparisons of what VoLL is needed to

justify PVESS investment.

Finally, in chapter 6, I explore concerns that the proliferation of PVESS technologies could lead to widespread grid defection. The cost declines of PVESS technologies have led to suggestions that a non-insignificant number of customers would disconnect from utility service and self-supply electricity. Prior research addressing this issue focused on average electricity tariffs, solar profiles, and demand without considering detailed customer heterogeneity. This chapter fills the gap by analyzing how electricity tariffs that shift cost recovery away from variable charges towards fixed charges influence a customer's decision to disconnect from utility service. A linear optimization model is developed to size an off-grid PVESS. Technology cost and reliability parameters of the optimization model are then adjusted to calculate a range of off-grid costs. Unique rate structure information for over 2,000 utilities in the United States is then used to compare grid costs to off-grid costs. The results show limited ability for solar-plus-storage systems to economically substitute for grid services. However, 1% of households might disconnect from utility service in a scenario that accounts for future off-grid costs and updated tariff designs. We find that 3% of households in the Southwest and California have private economics that favor defection in this scenario, rising to as much as 7% in Hawaii. Grid defection could increase from 1% to 7% of United States households in a slightly reduced reliability scenario. These results indicate that utilities and regulators seeking to limit rooftop solar adoption by lowering variable charges face a possibility that the corresponding increase in fixed charges could lead to inefficient grid defection, though at relatively low penetration rates.

To Jenna

For your love,
and being with me through it all.

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Chapter 1

Introduction: A tale of two electricity systems

*“This [FERC order] has absolutely nothing to do with subsidies. This is all about unleashing the power of our markets. We’re talking about smaller energy resources located in our homes, our businesses, within communities. What our rule did was say, ‘You know what, these smaller assets should be able to join together through the power of technology and compete in our wholesale electric markets, just like the large power plant down the street.’ This action, in my view, is revolutionary and will help us pave the way for the grid of the future. It makes our grid more nimble, flexible and **reliable**.”*

Statement by FERC chairman Neil Chaterjee on FERC order 2222

October 5, 2020

1.1 An electricity system in transition

At the turn of the 21st century, the electricity system started to transform. Regulators opened up electric generation to competition and renewable electricity, particularly wind and solar, entered a period of rapid cost decline (Borenstein and Bushnell, 2015). These developments ushered in a significant amount of change to how and from where society supplied its electricity. At the same time the popularity of distributed, rather than centralized, supply of electricity grew, giving end consumers new options to meet their electricity demand. While these developments have begun to help society transition away from the fossil-fueled grid of the past, they also have established a level of uncertainty about the future design of the electricity system. This dissertation aims to investigate and critically examine the opportunities for distributed energy resources in this uncertain future.

Historically, electricity flowed in one direction—from large scale generation plants through a transmission and distribution network into the homes and businesses of end-consumers.

Large network investments over decades resulted in a transmission ‘supergrid,’ which has been designated the most impressive engineering feat of the last century by the National Academy of Engineers.¹ The expansion of the network from the 1950s through the 1970s took advantage of substantial economies of scale for firms producing electric power ([Christensen and Greene, 1976](#); [Gorman et al., 2019](#)).

However, the one-way electricity-flow paradigm resulted in a disconnect between the two main functions of the electricity system: (1) the utility-scale and wholesale generation and transmission of electricity and (2) the retail selling and local distribution of electricity to end consumers (see historic flow in figure 1.1). This basic disconnect remained even as the underlying regulatory structure of the system was changed. Throughout the 20th century, the electric industry was organized along the principles of natural monopoly regulation where one firm would be given complete domain to provide electricity over an entire geographic territory and be subject to significant government oversight ([Joskow, 2007](#)). With the deregulation of power generation at the turn of the 21st century, market structures were implemented by regulators to increase competition in the wholesale generation of electricity ([Fabrizio et al., 2007](#); [Hobbs and Oren, 2019](#); [Harrison, 2020](#)). Though these regulatory changes altered the approach to pricing wholesale electricity generation, they did not significantly alter the technical design of the underlying system ([Schweppe et al., 1988](#)). Furthermore, the natural monopoly regulation of the electric distribution utility, the ultimate retail supplier of electricity to society, largely remained in tact. Ultimately, with limited adoption of retail pricing schemes to mirror costs in wholesale markets ([Borenstein and Holland, 2003](#)), the deregulation of power generation further separated the end-users of electricity from the companies who ultimately construct and operate power generation (see current flow in figure 1.1).

¹See National Academy of Engineering list: [NAE website](#)

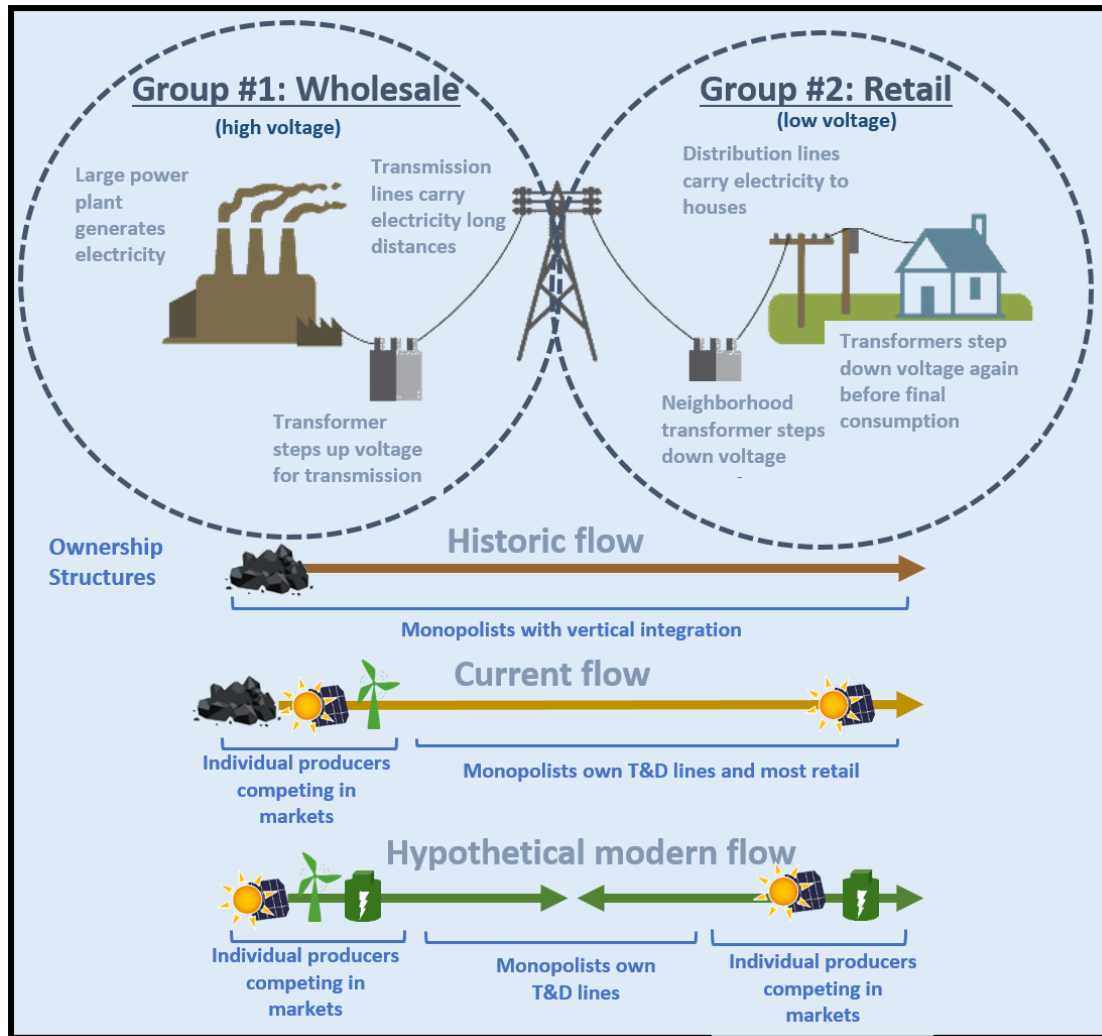


Figure 1.1: Electricity system conceptual structure, adapted from EIA

At the same time, the dramatic cost decline of solar technologies made it more economic to install solar generators closer to load (Barbose et al., 2021a), and technological development of battery storage has led to even more options for the local supply and control of electricity (Kittner et al., 2017; Barbose et al., 2021b). The growing popularity of distributed energy has led some to envision the disjointed and unidirectional electricity paradigm shifting into a more unified connection between the wholesale and retail electricity systems (see hypothetical modern flow in figure 1.1). Some incumbent utilities are concerned about a potentially reduced role in electricity provision that may be brought about by this transition (Costello and Hemphill, 2014), but the strongest proponents of this shift believe that a future grid involving more distributed resources working in unison could establish a network that is more flexible, resilient, and pollution free (Jain et al., 2017).

However, there are serious concerns about how to make such a paradigm shift equitably. A large academic literature examines the economic efficiency and equity of end-user electricity prices and finds that many retail tariff designs fail to adequately reflect the underlying cost structure within the industry (Borenstein and Davis, 2012; Borenstein and Bushnell, 2021; Burger et al., 2020). This mismatch results in inappropriate mechanisms to collect revenues for an electricity system with large fixed costs where some electricity consumers are inequitably asked to bear a larger burden of those costs (Borenstein, 2016; Borenstein et al., 2021). Regulated utility pricing is, on some level, the key competitor to customer-supplied distributed energy (Burger et al., 2019). Since these price signals ultimately drive consumer decisions on electricity consumption and distributed energy resource adoption, they are critical when determining how to allocate the costs and benefits of a shift to distributed energy. Due to legitimate concerns over who benefits from the adoption of distributed technology, fights over rate design, economic equity, and environmental responsibility have broken out in state utility commissions and the marketplace.

1.2 Reliability concerns in modern power systems

Admited these regulatory and market transformations are increasing concerns about the underlying reliability of modern electricity systems. In high-income countries, interruptions in power supply are rare and electricity systems are generally viewed as highly reliable (Arlet, 2017). In the past decade, however, United States natural disasters such as Superstorm Sandy in the Northeast, Hurricane Maria in Puerto Rico, electricity-induced wildfires in California, and polar-vortex weather conditions in Texas have led to increasing calls for grid hardening (Walton, 2017; Schwartz et al., 2021). These weather events comport with the growing consensus that climate change will increase strain on the reliability of electricity grids (Chen et al., 2017; Brockway and Dunn, 2020) and have shown that modern electricity systems remain vulnerable to long-duration outages which are extremely costly for societies which rely on electricity services (Sanstad et al., 2020).

The retail portion of the electricity system (i.e. the lower voltage distribution network introduced in figure 1.1) accounts for the majority of power outages in modern electricity systems. Past research in the United States found that the distribution network incurs between 92-94% of all power interruptions, a breakdown that has been consistent overtime (Eto et al., 2019). Though distribution system outages tend to be localized and short in duration, caused by vegetation interference at individual circuits (Graziano et al., 2020),² they can also extend for long periods of time and impact a wide area if large portions of the network are taken offline by extreme weather events (Forssén et al., 2017). The distribution network, built predominantly with above-ground equipment, is particularly vulnerable to geographic circumstances and ambient weather conditions.

²Or squirrels, see: [cybersquirrel website](#)

Common proposals to mitigate distribution outages involve forest management, undergrounding otherwise overhead lines, and/or providing backup power services via distributed energy resources which can be located closer to customers and thus avoid some of the vulnerable distribution network (Forssén et al., 2017). While these technical solutions are proposed, there is less discussion on overarching incentive structures that might motivate or facilitate the appropriate level of reliability investment by utilities in their distribution networks. Some work has been done to create an economic framework to evaluate how investments in undergrounding overhead equipment might improve reliability outcomes, but adoption of such proposals in regulatory settings is limited (Larsen, 2016). Alternatively, many regions use industry standard reliability metrics like SAIDI (system average interruption duration index) and SAIFI (system average interruption frequency index) to penalize particularly poor reliability outcomes. This approach represents a standard-setting mechanism design rather than an economically-informed mechanism design (Kaufmann et al., 2010).

This limitation contrasts with numerous frameworks developed to mitigate bulk power system outages (i.e. the higher voltage transmission network introduced in figure 1.1). Though failures of the high voltage bulk power system make up a small fraction of outages, they take up much space in policy conversations. Bulk system outages can be caused not only by a lack of available generation supply but also by failures of the high voltage transmission network, and to limit these outages, grid planners focus on (1) holding specific generators in reserve to manage supply and demand balancing *in the short-term* and (2) providing incentives for achieving adequate generation resources *in the long-term*.

In most jurisdictions, short-term balancing is ensured via payments to generators to provide these reserve services, oftentimes called ancillary services. While some regions provide these payments via formalized market structures, other regions, which maintain monopoly control over electric generation, manage their reserves directly in a least-cost unit commitment strategy (Denholm et al., 2019).

Much effort has been made in ensuring long-term generator supply. Regulators measure long-term resource adequacy by using a ‘reserve-margin’ metric which is calculated by dividing the total power generator supply available within a region for a given year by a forecast peak demand in the same region and year, with supply targets typically set to exceed peak demand by 15-40% (Pfeifenberger et al., 2013). The larger targets insure against the possibility that any collection of generators might be offline during critical times due either to maintenance or unforeseen failures of equipment (Spees et al., 2013; Joskow, 2008), and there are substantial differences in how jurisdictions ensure these reserve margin targets.

Some power jurisdictions (e.g. Northeast/Mid-Atlantic United States, Australia) ensure supply through economically-informed capacity markets which require utilities to engage in long-term power contracting via market mechanisms. Other jurisdictions (e.g. Texas, Alberta, New Zealand) use energy-only market constructs that allow electricity prices to spike above

marginal cost in the short-run during times of constrained supply (Hogan, 2013), hopefully incentivizing enough power plant construction in the long-run. Finally, more command-and-control jurisdictions (e.g. Southeast and Northwest United States) approve projects proposed by individual utilities on a case-by-case basis and allow utilities to fully recover costs for any power plant ultimately approved.

The variety of resource adequacy approaches between jurisdictions should not obfuscate but rather emphasize the point that regulators are particularly concerned about the long-run generation short-fall problem in electricity networks, developing many potential solutions to the challenge. No such comprehensive discussion is found for regulatory solutions that could mitigate or more optimally achieve societal preferences for distribution system outages.

Potentially one explanation for this difference could be the public reproach that occurs after generator-induced power outage events, most recently occurring in California (2020) and Texas (2021) (Montgomery et al., 2021; Penn, 2020; Busby et al., 2021). Generation outages tend to affect large swaths of society and so are particularly acute and widespread experiences for the public. On the other hand, distribution outages are more localized and limited in scope. Furthermore, the inevitability of extreme weather events disrupting a heterogeneous and expansive distribution network makes outage mitigation harder on the distribution system, and therefore might lead to less culpable grid planners. Deciding how many power plants to build is generally easier for a grid planner to impact.

1.3 What is the role for distributed energy?

Given that distribution systems cause the majority outages, a question emerges. Could these new distributed technologies be used to improve reliability outcomes? Though grid planners have not developed any overarching regulatory frameworks to manage distribution grid reliability in the past, given the new opportunities for both distributed energy choices, maybe they should in the future (Narayanan and Morgan, 2012).

This dissertation sits at the intersection of these emerging trends. With this research, I aim to evaluate distributed resource potential in the electricity landscape which is being transformed by new technologies, regulatory innovation, and concerns over reliability. My broad motivating question that I attempt to answer in the remaining chapters is: what opportunity does distributed energy have towards providing power locally and mitigating electric system reliability concerns?

In many respects, the benefits of ‘local’ power seem alluring. It could represent an alternative for societies who wish to provide more choices to energy consumers. Given the vulnerability of our networked infrastructure, there is a chance that reducing reliance on the grid could increase electric grid resiliency as we would limit the need to rely on a vulnerable and exposed infrastructure network. In the first half of the dissertation (Chapters 2, 3, and 4),

I describe and implement approaches to estimating and valuing electric reliability, with a specific focus on backup power adoption. In the second half of the dissertation (Chapters 5 and 6), I interrogate claims about the capabilities and limitations of distributed solar and storage to provide power to end-consumers and in the process, comment on some of the equity concerns of our current retail pricing schemes.

The research encapsulated in this dissertation combines concepts and methods from economics (i.e. the value of lost load, causal inference, and rate design) with tools from engineering (i.e. optimization, renewable energy modeling, and electric load simulation). I do not outline and describe the specific research gaps addressed in the dissertation in the remainder of this introductory chapter but rather leave that detailed literature review to the corresponding research chapters. Nevertheless, to provide a summary of the contributions of my work, I list the specific research questions for my dissertation below. These questions, taken together, provide a rough sketch of the main gaps I aim to address in this dissertation.

Economic value of reducing power outages

1. How do economists define, measure, and quantify the societal benefits of reduced power outages?
2. How does and could society use such quantitative estimates of the Value of Lost Load (VoLL)?
3. Does notification of power outages impact customer willingness-to-pay to avoid power outages?

Impact of power outages on behind-the-meter solar and storage adoption

1. Do power outage events increase the adoption of distributed energy technologies?
2. Can such adoption trends be used to estimate a willingness-to-pay to avoid outages?

Mitigation of power outages via distributed energy

1. What is the backup power potential of solar and storage resources across customer type, geography / climate conditions, and power outage scenarios in the United States?
2. How do building stock conditions impact the capability of solar and storage to provide backup power?

Assessing the capability for distributed energy to replace the bulk power system

1. How realistic is it for electricity customers to go completely ‘off-grid’ with solar and storage systems?
2. How does rate design impact the customer decision to defect from the grid?

Chapter 2 provides a literature review on the associated value of reducing societal power outages. The industry term for the metric that represents such quantification is the ‘value of lost load’ or ‘VoLL’, and this chapter describes the definition of this term while providing an economic framework to connect the VoLL to consumer demand for electricity. Then, I provide historical context on the creation and use of this term in the electricity industry. Finally, I review the literature which aims to empirically estimate this metric, highlighting how it is used in both academic and regulatory contexts, and conclude with some of the limitations of the value of lost load metric.

The next four chapters focus on individual research projects which aim to answer different portions of the key research questions outlined above. In Chapter 3, I implement a stated-preference survey to estimate the VoLL. The survey randomly samples individuals from the California population and asks general questions about their exposure and experience to recent large scale power outage events. Then, the experimental question focuses on whether notification of an imminent power outage affects their willingness-to-pay to avoid power outages. Chapter 4 augments the prior chapter’s empirical strategy by estimating the impact of public safety power shutoffs (PSPS) in California on the adoption of solar and storage technologies. Then, using administrative data on power consumption, I attempt to quantify the willingness-to-pay to avoid power outages (i.e. the VoLL). This chapter highlights a novel means by which to estimate the VoLL through a revealed preference rather than stated preference approach, relying on a spatial regression discontinuity design to study how reliability levels affect the probability of installing backup power.

In Chapter 5, I evaluate the potential for solar and storage systems (PVESS) to provide power to mitigate power outage events across a wide range of customer types, geography / climate conditions, and power outage scenarios in the United States, considering both whole-building backup and backup of specific critical loads. The chapter combines novel, disaggregated end-use load profiles across the United States with temporally and geospatially aligned solar generation estimates. Then, I present a backup-only PVESS dispatch algorithm to calculate the amount of load served during differing long duration outage events. Finally, I calculate how residential customers could deploy solar-plus-storage to mitigate long duration outages during different seasons of the year.

Finally, in Chapter 6, I extend the analysis of solar and storage capability to the concept of grid defection, a growing concern for utilities who observe more competition from distributed energy. This chapter combines standard linear optimization techniques with theoretical understanding of rate design in the United States context. The optimization program calculates

the required system size for a solar and storage system to meet a customer's entire demand profile over multiple years. Then, I compare the costs of such a system to two theoretical bookends for two part tariff designs. Evaluating these bookends has implications for the equitable means of cost recovery for utilities in high distributed energy worlds.

This dissertation provides evidence that customer experiences of an unreliable electricity network can drive customers to adopt backup power solutions. This result, perhaps, is unsurprising given the serious costs that can result from power loss. Still, the rise of solar and storage technologies as a novel outage mitigation investment will present opportunities for customers to reveal such preferences to future researchers. These new opportunities also pose serious questions for future regulators who have historically been focused on public good provision of electric reliability on the electricity network. Private opportunities for reliability enhancement may not lead to equitable outcomes. Such challenges and issues are ripe for future work; I do not consider them in substantial depth in this dissertation.

In addition to findings about customer adoption trends, the latter half of the dissertation showed that while solar and storage technologies could provide substitution options for customers to mitigate power outages, they would be less likely to support full grid defection. Even the backup power use case will be challenged by a household's electricity consumption context. I show that the distribution of electric consuming technologies within a household have a substantial impact on the capability for solar and storage to provide backup, especially in the case of electric heating and cooling technologies. Likewise, complete grid defection might only be reasonable for consumers who have relatively small total energy needs (whether through extreme energy efficiency or through limited installed electric devices). Such findings suggest that there are real opportunities for solar and storage to provide power and thereby value to end-consumers locally but it does not seem likely that these distributed technologies will supplant the bulk power system.

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Chapter 2

The microeconomics of power outages and the quest to quantify the value of lost load

2.1 Introduction: A cost-benefit analysis context

Elected officials, regulators, and researchers often aim to quantify the impact of policy choices.¹ The most dominant framework used for evaluating government policy has been cost-benefit analysis (CBA). The CBA framework focuses on the conversion of a variety of tangible, real-world benefits (e.g. pollution avoided) and costs (e.g. jobs lost) into a monetary unit so that those benefits and costs can be compared against each other. Ultimately, such a conversion is useful to weigh the good against the bad outcomes of policy decisions, a worthwhile goal if trying to ensure government policies, on net, help society more than they hurt. Given the influence of the CBA framework, much research has focused on honing the methods that measure and convert policy outcomes to dollar amounts (OECD, 2006).

These conversions are difficult given that many benefits are non-market goods; that is, there are no easily identifiable products in the marketplace that policy makers and researchers can use to measure society's willingness-to-pay for an outcome (Masur and Posner, 2016). Though the costs of a policy also contain uncertainty, they are generally more straightforward to estimate given available market prices for factors such as raw materials, manufacturing, and labor which can oftentimes be used for such estimates (Baik et al., 2019). Though CBA methods have received numerous critiques since they were established (Bronsteen et al., 2013), CBA survives because developing a comparably rigorous, quantitative, and workable

¹A version of this chapter was published in the journal, *The Electricity Journal*, in October 2022. An individual citation of this work can be made as follows: Will Gorman. "The quest to quantify the value of lost load: A critical review of the economics of power outages." *The Electricity Journal*, 2022. <https://doi.org/10.1016/j.tej.2022.107187>

alternative has proven challenging (Sunstein, 2017).

A common question thus arises: what should be done in circumstances when estimating a monetized outcome of a policy decision remains challenging or there is wide disagreement in its quantification? In this chapter, I will evaluate this challenge within the industrial context of power outages in the electricity sector. Society depends on electric power for virtually all individual, household, commercial, industrial, and government activity, making the inherent value of electricity service high. One would appropriately assume that the benefits of reducing or avoiding power outages to be, therefore, correspondingly high. But, how can decision makers evaluating reliability improvement investments place a monetary value on such an assumption? Maybe an easier question: How much would you be willing-to-pay to avoid a 24 hour power outage? Would you pay \$1 to have electricity for a few lights, refrigerator, and air conditioning during that outage? How about \$500? The answer to these questions matters because in many instances the cost of mitigating power outages could be higher than the corresponding benefits. If you could easily drive to your workplace, a neighbor's house with power, or some other outside extracurricular activity, maybe one day of lost power is insignificant. If you rely on electricity-dependent, life-supporting medical equipment, losing power could have severe health consequences and maintaining power access for that day is critical.

A great amount has been written on techno-economic approaches to improving the reliability of the electric system. This literature is often singularly focused on developing novel empirical strategies and estimates of the benefits of enhanced reliability (also known as the "value of lost load" or VoLL in the industry) such that other researchers and policymakers can then apply CBA frameworks effectively (LaCommare et al., 2018). To complement that work, this paper aims to synthesize and critically examine the VoLL estimation literature and provide a microeconomic perspective which captures the underlying complexity of the VoLL, highlighting the difference between average and marginal value of lost load. A key contribution this paper makes is to clearly distinguish applications of the VoLL concept between (1) CBA which informs centralized decision-making about grid reliability, most traditionally applied to transmission and distribution investments (Larsen, 2016) and (2) electric rationing decision-making during times of supply shortage (Spees and Lave, 2007). Applications of (1) directly compete with cost-effectiveness analysis where a central agency can choose a physical reliability objective (i.e. "one outage in ten years") rather than relying on uncertain VoLL estimates. However, applications of (2) can be facilitated by decentralized self-sorting arrangements, such as dynamic pricing or demand-response programs, which only need loose connection to VoLL estimation and which should be promoted over random outage strategies.

In section II, I define the VoLL, outline a microeconomic framework that relates electric demand to the VoLL, and explain the public good properties of electric reliability, highlighting the need for government involvement in electric reliability planning. Section III

provides brief historical context of the literature, and section IV summarizes the three main approaches to measuring the VoLL, presenting an assessment of the relatively understudied revealed preference approaches to VoLL estimation. Section V and VI conclude the paper with a discussion of the limitations of the techno-economic perspective that is often the focus of applications of VoLL estimates.

Such a chapter might seem like a slight departure for a dissertation focused on the capabilities of distributed energy to provide power locally and mitigate power outages. However, this chapter aims to frame the discussion of DER power outage solutions in the context of their potential monetary benefits. In a CBA framework, DER investments are prospective “costs” of an electric-sector policy that aims to improve grid reliability. These costs will be evaluated in greater detail in Chapters 5 and 6.

Chapter 3 and 4 are more closely connected to measuring the benefits of power outages and are thus more deeply connected to the conceptual ideas introduced in this chapter. They focus on methods to estimate the benefits of reduced power outages by studying distributed energy adoption. As I will describe later, investments in distributed energy serve as investments that can reduce power outage costs and thus can be linked to the benefits of reducing power outages. Though I will not attempt to perform a full CBA analysis in this dissertation, the results from each chapter provides information that ultimately could be used to do so in future work.

2.2 Defining the VoLL

The value of lost load is an electric industry metric meant to encapsulate the societal benefits of reduced outages in a monetary figure. More formally, it represents society’s willingness-to-pay (WTP) to avoid a power outage and can be estimated using various units of analysis. For instance, the VoLL is sometimes presented as willingness-to-pay to avoid 1 hour of outage (i.e. \$/hour). Alternatively, researchers sometimes measure willingness-to-pay on a kWh basis (i.e. \$/kWh), effectively representing the amount an individual would pay to consume a certain amount of electricity during an outage. This metric was developed given that different consumers’ WTP varies due to their different consumption levels (Caves et al., 1990).

Though the dimensions of this second VoLL metric are the same as those used for the retail price of electricity, the VoLL represents a distinct concept. The retail price is tied much closer to a utility’s revenue requirement and thus the cost of supplying electricity rather than the underlying value that customers place on consuming that electricity. While the \$/kWh unit of analysis might suggest a capability of the VoLL metric to distinguish between the cost of partial power outage, which involves a portion of a customer’s electricity demand, and a full power outage, the VoLL most commonly discussed in the industry refers to the cases where 100% of a customer’s electricity service is lost.

Assuming that the VoLL can be accurately measured, multiplying it by a power outage amount (i.e. units of kWh lost during an outage or units of hours of outage) generates an estimate of the societal benefits of reducing power outages, a key portion of a CBA analysis which considers the costs and benefits of reducing power outages.

There are serious challenges to using a point estimate for the VoLL. The VoLL varies not only by each individual end-user (e.g. industrial vs. residential) and electricity use-case (e.g. manufacturing vs. lighting) but also by the electricity consumption context (i.e. geographic location and/or exposure, outage timing/duration, and advanced warning). By focusing on population averages, the VoLL tends to obfuscate the inherent complexity of electricity consumption: multiple end-uses consumed at a variety of times with different available substitution options. Though there has been some effort to distinguish the VoLL by specific time frames (Baik et al., 2018), durations, and customer types (Sullivan et al., 2009), most applications tend to use a small number of individual VoLL point estimates.

Categorizing the components of the VoLL

It's informative to categorize the different benefits associated with reducing power outages. The various methods used to estimate the VoLL tend to focus on different subsets of these categories and rarely encapsulate all of them. The costs² of power outages vary for different sectors of the economy. Given this variance, it is common to split up the VoLL estimation between industrial and commercial electricity consumers, who depend on electricity to serve their customers and run their businesses, and residential electricity consumers, who rely on electricity for household work and leisure activities. For the industrial/commercial sector, direct costs from losing power (and therefore benefits from avoiding power outages) can be (1) opportunity cost of idle resources, (2) production shortfalls / delays, (3) damage to equipment and capital, and (4) any health or safety impacts to employees. There are also indirect or macroeconomic costs to downstream businesses/consumers who might depend on the products from a company who experiences a power outage (Sanghvi, 1982). For the residential sector, the direct costs are different. They can include (1) restrictions on activities (e.g. lost leisure time, lost work time, and associated stress), (2) financial costs through property damage (e.g. damage to real estate via bursting pipes, food spoilage, etc), and (3) health and safety issues (e.g. reliance on breathing machines, air filters, etc). Indirect costs are rarer for the residential sector since it is less likely that other members of society depend on any given household's power consumption (Munasinghe and Sanghvi, 1988).³

Though these cost categories are not meant to be exhaustive, they provide some insight into

²It is useful to note that language about measuring the benefits of avoiding power outages is equivalent to language which focuses on the costs of experienced power outages.

³As more people telecommute and perform work activities at home, indirect costs on employers would increase when residences lose power.

the potential impacts of power outages on businesses and individuals. Ultimately, the VoLL is calculated via a detailed accounting of these direct and indirect costs to a community that experiences a power outage. Some electricity customers in a community will only be impacted by a subset of these costs, others will likely be impacted by more. Though there is a substantial amount of heterogeneity between customers, the literature typically only differentiates the VoLL at the customer class level (Schröder and Kuckshinrichs, 2015).

There is a third category of costs that can be incurred: outage mitigation costs. These costs represent expenditures electricity consumers make in order to lessen the impact of the direct and indirect costs introduced above. Most commonly, mitigation investments involve the procurement either of back-up power generators and/or protective switch-gear or other grid-hardening investments made near specific electric consumers. While back-up power is typically available to all customer classes, grid hardening investments beyond an electric utility’s default spending levels are typically only an option for commercial and industrial customers.

Importantly, these mitigation investments affect the power outage experience of a customer and thus have a dynamic relationship with the direct/indirect costs mentioned above. More investment in mitigation measures leads to a lower VoLL because they reduce the probability of an outage impacting end-use consumption. In some instances, these investments might fully supply the electricity needs of an end consumer during an outage. In such a case, the direct costs of a grid power outage might be reduced to the marginal cost difference between running the back-up power system and paying a grid electricity provider for energy consumption. In other instances, back-up power investments might only be used on specific “critical” loads (e.g. oxygen machines for a hospital); therefore, additional direct costs would be incurred based on the costs of losing power to non-critical electricity services. These examples illustrate the trade-off between mitigation costs and the direct/indirect costs that result from a power outage.

Any interpretation of VoLL estimation needs to account both for the cost categories considered in the estimate as well as for the mitigation costs already incurred by the customer of focus. The key insight is that mitigation costs are not additive to the direct and indirect costs documented above but rather can be representative of the underlying costs of grid failure. Therefore, obtaining empirical data on mitigation costs can be used to estimate specific customers’ underlying VoLL, an approach introduced below as a “revealed preference” VoLL estimation method.

A microeconomic framework

People do not demand electricity itself but rather the end-services provided by products which require electricity as an input (Kalt et al., 2019). Common end-services are space and water heating/cooling, cooking (e.g. refrigeration, stove-tops, toasting), lighting, and

entertainment (e.g. television, internet) (Fell, 2017). The value of electricity is variable depending on the ultimate end-use, and prior research has shown that different customers of the same customer class value these end-uses differently (Hunt and Ryan, 2015; Fouquet, 2014). Therefore, when a power outage occurs, customers will have different VoLLs depending on their distribution of electricity services demanded at the time and for the duration of the outage.

Standard economics models consumer preferences for goods and services in the economy using demand curves which represent the relationship between willingness-to-pay and quantity demanded for any specific good or service. These curves are meant to embody the underlying value a consumer places on a product and are downward sloping, aligning with the reality that as prices increase, the quantity demanded for a good or service decreases.⁴

Demand curves can be built for a specific individual as shown in the left graph of Figure 2.1. If the electricity sector sets the variable price at \$0.2, this curve suggests that the particular consumer would want to consume up to Q_{1h} . However, if the variable price increased to \$0.4, this consumer would decrease their consumption to Q_{2h} . For an individual electricity consumer, the curve represents the willingness-to-pay for the variety of end-services that electricity might supply. The notation of different end-uses of electricity consumption from internet services to heating/cooling under the curve aligns with the notion that different end-uses ultimately have different average values for customers. Customers could have different orderings of end-services depending on their specific preferences.

Demand curves can also be conceptualized for aggregations of individuals (e.g. neighborhoods, regions, countries) that might place different average values on electricity services. The demand curve for a region could be built by distinguishing the willingness-to-pay of different end-consumers within that region as shown in the right graph in Figure 2.1.

⁴We will ignore giffen goods in this paper, which are the rare goods where consumption increases as their price goes up. Electricity is not thought of as a giffen good.

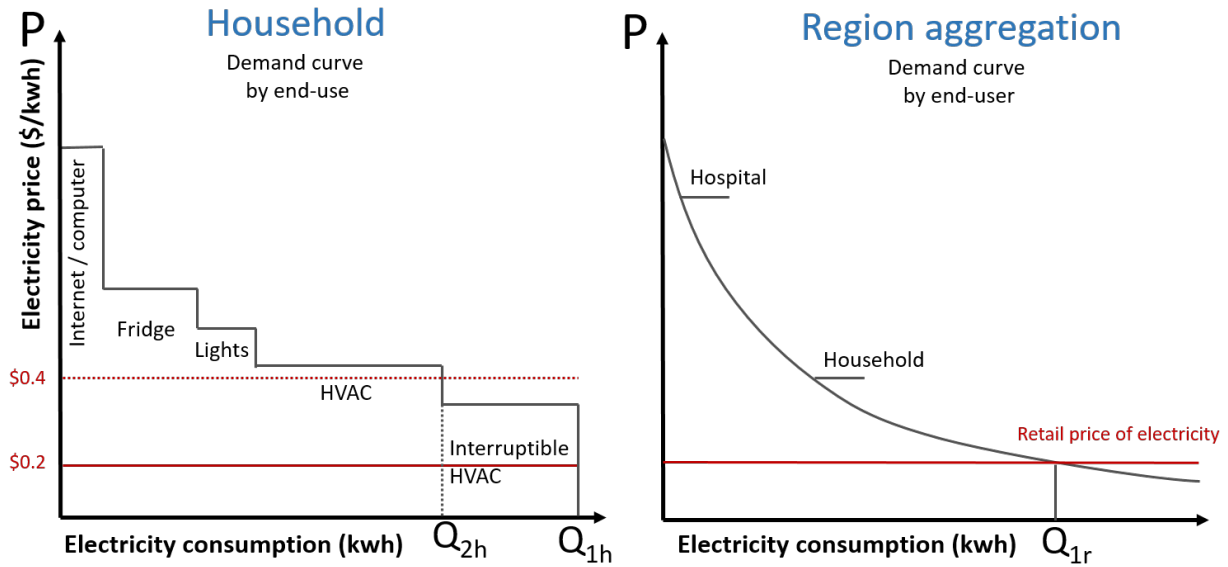


Figure 2.1: Theoretical conceptualization of demand curves corresponding to a specific individual and their different end-uses of electricity (left) and aggregated demand curves of an entire region that might correspond to different end-consumers of electricity (right)

These demand curves can be used to estimate the VoLL by applying the consumer surplus concept. The consumer surplus is an economic measurement of consumer benefits to buying a product and occurs when the price a consumer pays for a good or service is less than the price they are willing to pay. Graphically, the consumer surplus is represented by the difference between a demand curve and the supply curve, assuming the supply curve represents social marginal costs (SMC).

In the above example, the supply curve is simplified to a flat horizontal bar at the retail price of electricity, which we will assume equals SMC.⁵ When a power outage occurs, consumers lose their ability to use electricity, and the difference between their willingness-to-pay (i.e. their demand curve) and the social marginal cost of electricity (i.e. the supply curve) represents the outage cost, which is equivalent to the VoLL. The VoLL is theoretically estimated by taking the integral between the demand curve and supply curve along the portion of x-axis from zero to the quantity of electricity service foregone.

For an individual, a power outage typically means the loss of their entire electricity demand

⁵This is surely not true in reality as many researchers have shown that the retail price of electricity is not set to SMC (see (Borenstein and Bushnell, 2021; Borenstein et al., 2021; Joskow, 2007)), partially due to the need for natural monopolies to recover fixed costs. Nevertheless, it is likely that VoLL estimation is driven by the steep portions of the demand curve rather than by precisely estimating an accurate supply curve.

because rolling blackout events rarely involve partial demand reduction. For a region, unless a total network collapse occurs, power outages often occur by shutting off power for a selection of consumers using some randomization strategy, typically in an effort to make outages more equitable. Visualizations of these two different approaches are depicted in Figure 2.2.

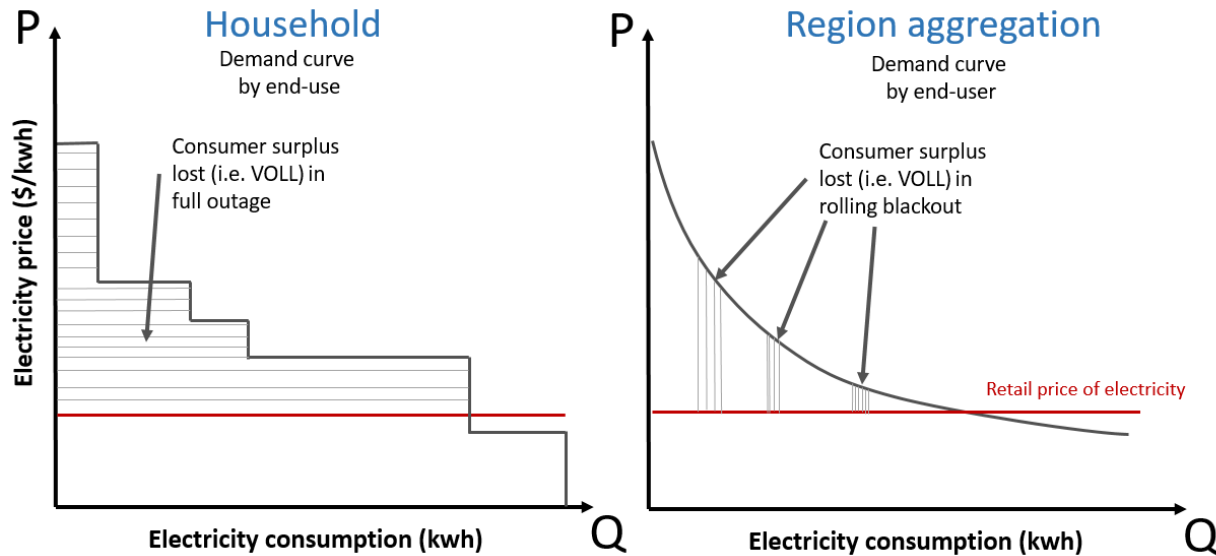


Figure 2.2: Cost of an outage (VoLL) represented by consumer surplus lost from full outage for a customer (left chart) or rotating outage in a region (right chart)

A fundamental challenge to the standard economic formulation is the inherent dynamics of electricity demand. Consumers' willingness-to-pay for electricity services is inextricably tied to the context of that electricity consumption. The notification, timing, duration, and scale of a power outage all have dynamic consequences for the willingness-to-pay for electricity given that they differentially impact the different end-uses of electricity. Due to the technical properties of different electric appliances, electric demand can be non-linear and non-monotonic which makes creating a smooth demand curve challenging.

Consider the following power outage scenarios. If a consumer has notice of an outage, they could shift electricity demand for a variety of end-uses (e.g. air conditioning, refrigeration, clothes washing) to before the outage occurs, thus decreasing their electricity demand during the outage and therefore reducing their power outage cost in the process.

Furthermore, the length of a specific outage also affects the underlying demand curve during that power outage. A short power outage (i.e. a few minutes) might negligibly impact the thermal storage embodied in a refrigerator or house and thus the power outage cost is minimal. A longer duration outage (i.e. a few days), however, would have a greater impact on thermal electric demands, leading to limited ability to shift demand to different hours. A long-term outage (i.e. a few months or more), may force individuals to adapt by either

moving or procuring back-up power and thus could theoretically have a lower cost on a per kWh basis given the foresight which allows for substitution. In general, the flexibility and time dependence of electricity demand make it difficult to model using the static economic demand curve formulation that does not consider such dynamics.

In some cases, electricity can also be substituted. Consider the difference between a localized power outage which might take out a single residential street vs. a wide-spread power outage over an entire city. In the localized example, households might find it easy to shift their leisure time (i.e. go out to eat, go to the movies, visit with a friend at their house). If a whole city or region loses power, such alternative activities will be limited as choices for alternative means to spend time are significantly reduced. In widespread outages, some individuals will employ a strategy of leaving the outage region altogether, a substitution approach that is often only available to the most affluent members of a community.⁶ All of these scenarios embody the immense empirical challenges of using the simple microeconomic framework to quantitatively represent complex demand functions and calculate the VoLL.

Implications for economic efficiency and equity

This economic framework highlights the inefficiency of a rotating blackout mitigation strategy in the event of emergency situations when demand needs to be shed in order to equal available supply. Rotating blackouts typically affect the entirety of an individual's demand and thus very high value uses of electricity are treated similarly to low value ones. At the same time, the randomization of outages likely results in some high value customers losing electricity service instead of potentially lower value users on the system.

A more sophisticated strategy would acknowledge these differences and apply a rotating outage strategy that focuses on shutting off less critical end-uses and/or end-users of electricity. In many regions, a strategy which shuts off less critical end-users first is employed when system operators identify critical circuits (e.g. circuits with hospitals and/or fire stations). Circuits, though, are oftentimes a blunt tool to implement a prioritization strategy as they typically serve many heterogeneous customer types and therefore are an imperfect means to identify lower value uses of electricity.

Identification and prioritization of high value uses of electricity, however, is also fraught by equity concerns, especially if the prioritization of rotating outages is solely informed by a WTP framework. WTP metrics are correlated with ability to pay and thereby with the distribution of income levels within society. If a policy-maker only considers different customers' WTP, low income individuals, who might rely on electricity for critical medical equipment, could be shutoff before high income electricity consumers who have a higher WTP (driven by their ability to pay). This issue would also affect the prioritization of residential compared

⁶Such a strategy, though, can oftentimes have political consequences for [Senator's from Texas](#).

to industrial customers. Such ethical concerns highlight the tradeoff between efficient and equitable reliability planning, a key challenge for policy designers.

Further complicating this story is that aggregating individual demand curves into a single regional curve is substantially more complicated than the simple sorting by customer type suggested by the household and hospital sorting in the right chart of Figure 1. Rather than organizing by end-consumer, a regional demand curve is likely sorted by an intermixed set of end-uses and end-users. Since any individual could have some extremely valuable end-uses (i.e. critical loads) and less valuable end-uses, identifying the marginal portion of the demand curve is not trivial and does not just rely on finding specific individuals with low value electricity demand. Thus a strategy which perfectly implements rolling black-outs by identifying end-customers with the lowest willingness-to-pay will likely still involve inefficiencies given that those customers may still have quite high willingness-to-pay for specific end-uses.

Dynamic pricing and demand response programs are popular alternatives to top-down identification of end-user shutoffs (Spees et al., 2013). These options involve electricity planners offering incentives to end-users to shut-off marginal, lower value end-uses (e.g. interruptible air conditioning demand). Dynamic pricing schemes such as real-time or critical peak pricing dramatically increase the price of electricity during shortages, offering financial benefit to customers who can reduce demand. Demand response programs, on the other hand, pay customers to give an external party control to reduce their lower-value end-use devices.

Public goods and reliability in the electric industry: why is there no value of lost milk?

The presence of the VoLL term in the electricity sector to capture the costs of electric shortages begs the question: why do we not have similar terms of art in other sectors of the economy? There can be shortages of most products circulating through the economy, not just products in the electricity system. The answer to this question has implications for how we design the regulatory institutions that support the reliable supply of electricity.

There are two key aspects of the modern electricity industry that result in the necessity of calculating the VoLL: (1) the socialized nature of electric reliability and (2) the corresponding challenge for markets to internalize the system-wide costs of grid failure into the price individual electric consumers pay and electric suppliers receive.

For the first key aspect, it is important to note that power outages caused by T&D delivery failure typically result from weather and natural disaster events rather than supply shortages. This network vulnerability of the grid is the key non-rivalrous characteristic of electric reliability. During these outages, consumption does not impact the electric reliability of impacted customers. This aspect of electricity systems is particularly important given prior research showing that distribution network failures cause between 92-94% of all power

interruptions in the U.S., a breakdown that has been consistent overtime (Eto et al., 2019). Society requires an evaluation of the VoLL in order to inform transmission and distribution (T&D) network reliability enhancement investments using CBA frameworks.

At the same time, the electric sector does not typically offer electricity products that have varying levels of reliability (non-excludability portion of a public good). The challenge of doing so is both technological and political. Switching-off or controlling an individual customer's access to electricity is difficult given the connectivity of individuals on a single electricity network (Joskow, 2008). Advanced metering infrastructure (AMI), if installed, can be used to control an individual's power access but has been used sparingly for this purpose. As mentioned earlier, there are serious equity concerns to differentially shutting-off different customer's power access Cicala (2021). Because of this, there is not an allocation mechanism for deciding how to optimally distribute black-outs amongst individual customers during a power outage event.

The second aspect introduced above is particularly relevant during times of supply-demand imbalance. In most electricity markets, any individual consuming electricity does fully internalize the social costs of a network collapse (Joskow, 2007). That is, if an electricity consumer increases demand beyond available supply and the network suffers a black-out, that marginal consumer is internalizing their direct power outage costs and not the outage costs for other users on the network. The same is true for a supplier of electricity. If a generator goes offline and a widespread outage occurs, that generator only internalizes its own opportunity cost of selling power to end-users. It does not internalize the costs of black-outs on others in the power network. For these reasons, regulatory regimes which ensure the reliability properties of a balanced electric grid are examples public good provision. Ancillary service products that ensure network reliability are a key example (Joskow, 2008).

The challenge of internalizing the costs of network collapse by individual actors in electricity systems leads to a need to develop and measure how individuals value electricity service. The VoLL is applied in an electric industrial context that has not yet developed a market alternative to allocate that value, thereby filling-in for a key electric sector market gap similar to how the social cost of carbon aims to represent the externality of carbon pollution not typically captured in market prices (Tol, 2011; Kotchen, 2018). A variety of administrative market constructs in the electricity sector use the VoLL as a price signal that can represent system-wide outage costs. Importantly, these applications of the VoLL are distinct from CBA.

Sophisticated dynamic pricing regimes, perhaps based on the VoLL, could help mitigate supply-demand imbalance issues that occur during periods of shortage. The electric industry has not yet implemented sophisticated and wide-spread time-varying prices which could facilitate electricity rationing by different consumer groups during periods of shortage. When shortages occur in other sectors of the economy, prices respond and facilitate an allocation

strategy for delivering a product to those who demand or value it most. Dynamic pricing is a tool currently underutilized for such an allocation role in the electricity sector. This market gap is further exacerbated by the limited availability of short-term substitutes for electricity compared to other products in the economy, leading, in part, to the relatively inelastic demand for electricity (Lijesen, 2007). If there is a shortage of milk, many substitutes exist (e.g. water, orange juice, soy/oat/pea milk) which combined with a pricing mechanism can allow for markets to equilibrate supply and demand more readily.

2.3 Historical developments and uses of the VoLL

Discussion of the *economic value* of reliability in electricity networks (and thus the VoLL) did not start in earnest until the 1970s, a period which saw dramatic changes in the international and United States energy industry due to the oil crisis (Yergin, 2008). This early work focused on generation, rather than distribution outages. A report from United States Department of Energy that was released during this period suggested that interest in electric reliability increased, in part, due to several major electrical power outages in the early 1970s, raising the public's awareness of the effects of widespread losses to electrical service (Samsa et al., 1978; Shew, 1977).⁷

During this time period, the electric industry was predominantly controlled by vertically integrated electric companies that were responsible for ensuring reliable electric supply in their territories. To do so, they sought approval from regulators to make capacity expansion and grid hardening investments. Most companies justified such expansion by using long-term system planning models which combined electric demand patterns, generator outage probabilities, and generation construction timelines to estimate the required investments needed to meet accepted reliability outcomes (Samsa et al., 1978). These models had been developed as far back as the 1930s, and most were based on engineering rules-of-thumb and reliability standards that were agreed upon by the industrial community. The metric used then was the loss of load probability (LOLP), which represented the probability of an electric supply shortage. The typical choice for this metric in the planning models was a one day in ten years reliability standard, representing the expected fraction of time that the system would not be able to meet customer demand.

In the 1970s, energy economists began to consider more comprehensive CBA frameworks that more explicitly tied electric system investments, which decrease the LOLP, to the total costs of power outages, which is functionally related to the LOLP (i.e. larger LOLP leads to larger total outage costs given the increased frequency of outages) (Telson, 1975). Such

⁷In particular, this work referenced (1) the 1972 British power shortage due to a coal miners' strike lasting more than a month, (2) the 1973 Los Angeles Power shortage resulting from lack of oil supplies, and (3) the 1973 pacific northwest outage resulting from a drought.

work became of interest after the energy crises partly because of concerns over the rising cost of electricity procurement. To represent the benefits of avoiding power outages, these researchers developed customer loss functions based on proxy indicators tying electricity consumption to the economy's output (e.g. GDP) or specific industrial applications (Shipley et al., 1972; Munasinghe and Gellerson, 1979). These early studies combined power outage (demand-side) cost functions with generation (supply-side) cost functions in an optimization problem that minimized the total costs of electricity supply (See Eq. 2.1), and tended to argue that the electricity network of the 1970s was more reliable than could be justified by economic analysis and that improved rationalization of the one-in-ten year reliability criteria could offer an opportunity for electric utilities to cut construction budgets (Crew and Kleindorfer, 1978). Telson's work specifically suggested that an economically justified reliability criterion should be five times higher (i.e. a LOLP of five-in-ten years rather than one-in-ten years).

$$\min_r \quad OC(r, d) + SC(r, d) \quad (2.1)$$

Where,

r = loss of load probability (%)

d = peak demand (kW)

OC = total outage costs (\$)

SC = total supply costs (\$)

Though the specific results of these early studies would continue to be refined, the underlying CBA framework continued to set the foundation for those studying the trade-off between minimizing investments in the network while ensuring an appropriate (small) number of electric outages (Munasinghe, 1981). Though engineering heuristics such as the one-in-ten standard remain common in today's discourse, many electric system planners and researchers use similar CBA approaches to those developed in the 1970s (Newell et al., 2018; Larsen, 2016). It is important to note that the focus of the early academic literature was on the bulk power system (i.e. supply-side) rather than the distribution network, a focus which remains today even though the distribution network failure leads to the majority of outages (Spees et al., 2013; Eto et al., 2019).

Given the reliance of these optimization models on a quantification of the benefits of reducing power outages, the academic literature increased its focus on the estimation of this key parameter (i.e. the VoLL) in the 1980s (Tollefson et al., 1991). This shift related to the growing interest in studying demand-side issues rather than supply-side ones (Munasinghe and Sanghvi, 1988) as the advancements in computer, electricity metering, and communications technologies were driving development in new tariff designs and demand control schemes. With this work, researchers began to realize the importance of heterogeneity in electricity consumers' demand for electricity (i.e. different customer classes and different electricity end-uses) in their modelling. Many of the different studies did not agree with each other,

resulting in a wide range of VoLL estimates. As shown in Figure 3, estimates of interruption costs for short duration outages in the residential sector ranged by three orders of magnitude, from \$0.05-30/kWh and two orders of magnitude for the industrial sector, from \$0.1-60/kWh (Sanghvi, 1982; Caves et al., 1990).

A wide range of outage costs, even if estimated accurately, posed complications to using a simple optimization formulation for electricity system planning. In part due to the increased understanding of the heterogeneity of demand, researchers and the industry more generally introduced proposals that focused on differentiation of electric power service quality (i.e. reliability) on the basis of consumer choice. These proposals sought to allow the customer to select between different levels of reliability (Chao et al., 1988). Earlier work by Shew had suggested that more sophisticated electricity rationing during periods of shortage that considered different customers' short-run price elasticities could be theoretically beneficial (Shew, 1977). However, the newer proposals acknowledged that estimating elasticities was challenging, and thus allowing customers to make individual choices about service quality would be attractive. Such differentiation held promise for dealing with capacity shortages, cost recovery, and other customer needs (Doane et al., 1988a). More sophisticated power outage allocation schemes, however, were not widely implemented and remain a gap today. Though the technical capabilities of the electric system has improved dramatically over the last 40 years with the introduction of advanced metering infrastructure, much of our management during electricity shortage events remains the same: rotating blackouts.⁸

Part of the reason such ideas were not implemented is that attention of both the industry and research community shifted in the 1990s and 2000s to implementing and designing market-based solutions to support electric deregulation. Focus turned to the market-mechanisms that moved the electricity system away from top-down planning towards bottom-up decision making by both consumers and suppliers of electricity.

Though there was a decreasing interest in advancing some of the theoretical frameworks used to assess the VoLL, deregulation was actually the origin of the VoLL terminology. At the outset of privatization in the United Kingdom, the VoLL metric was created in order to address concerns over ensuring adequate generation capacity expansion incentives for the private sector. As the deregulated system transitioned away from centralized reliability planning towards competitive generation procurement, regulators developed capacity payments that incentivized new generation entry (Allan, 1995; Newbery, 2005). In 1993/1994, the VoLL was set at £2.35/kWh (\$3.3/kWh), within the ranges estimated for this parameter

⁸Though no widespread adoption of such ideas has yet to appear, progress on these concepts is now being made in the related domain of demand response (Spees and Lave, 2007). However, as mentioned above, demand response through some sort of dynamic pricing regime would not eliminate the need for measuring the VoLL as investments in distribution network resiliency are not the result of supply-demand imbalance.

in the research from the 1980s and early 1990s and shown below in Figure 2.3 (Willis and Garrod, 1997).

Today, the VoLL remains an important parameter for electricity market design as a determinant of capacity payments, providing financial incentives for independent power plant developers to construct projects that ensure adequate generation supply over a specific geographic territory. More complex administrative constructs, including formal capacity markets and scarcity pricing regimes, were developed in the 2000s and 2010s which rely on the VoLL to effectuate their designs (Spees et al., 2013; Hogan, 2013). Importantly, the heterogeneous nature of the VoLL have not been integrated into these wholesale market designs. Instead, they usually relied on region-specific estimates (Fraye et al., 2013). Given the VoLL's importance, researchers continue to develop new VoLL estimates (Sullivan et al., 2009; Frayer et al., 2013; Schröder and Kuckshinrichs, 2015; Baik et al., 2020). Retail choice programs, which were developed in parallel to wholesale market deregulation, did result in new interest in differentiated service quality/reliability, and the VoLL remains important in order to understand the potential uptake of different reliability tariff designs (Woo et al., 2008).

2.4 Measuring the VoLL in practice

There are three main approaches to measure the VoLL: (1) Proxy/Macroeconomic modeling, (2) Survey-based tools, and (3) Revealed preference consumer analysis. Summaries of these methods are available in different forms throughout the academic (Schröder and Kuckshinrichs, 2015; Caves et al., 1990; Munasinghe and Sanghvi, 1988; Sanghvi, 1982) and grey (Fraye et al., 2013; Van der Well and Van der Zwaan, 2007) literature, so discussion here will be brief and focus on each method's strengths and shortcomings.

The ranges in Figure 2.3 indicate upper and lower bounds of the VoLL from the same study while the color indicates the method employed. The compilation shows that survey methods are the most popular (n=84) with Proxy methods the second most popular (n=48). There are only 2 revealed preference studies included in this compilation. Studies from more recent years appear to show both higher estimates and wider ranges of the VoLL. It is difficult to determine whether the higher VoLL estimates actually represent increases in the value of electricity in society or differences between the underlying methods used. The methods to measure the VoLL underwent substantial development over the decades shown here. While it is likely that as countries expanded electrification the value of electricity itself increased, it could be the case that more sophisticated methods and administrative datasets have become available for researchers during this time period.

Method Category	Specific Approaches	Applicable sector
Proxy	• Retail electric price • GDP indicators • Production functions • Wage rates	• commercial/industrial/residential • economy-wide • industrial • residential
Survey	• Contingent valuation • Contingent ranking • Direct cost questionnaire	• commercial/industrial/residential • commercial/industrial/residential • commercial/industrial/residential
Revealed preference	• Interruptible contracts • Mitigation investments • Demand-curve estimation	• commercial/industrial • commercial/industrial/residential • commercial/industrial/residential

Table 2.1: A variety of approaches have been developed to measure the value of lost load (VoLL). GDP: Gross Domestic Product

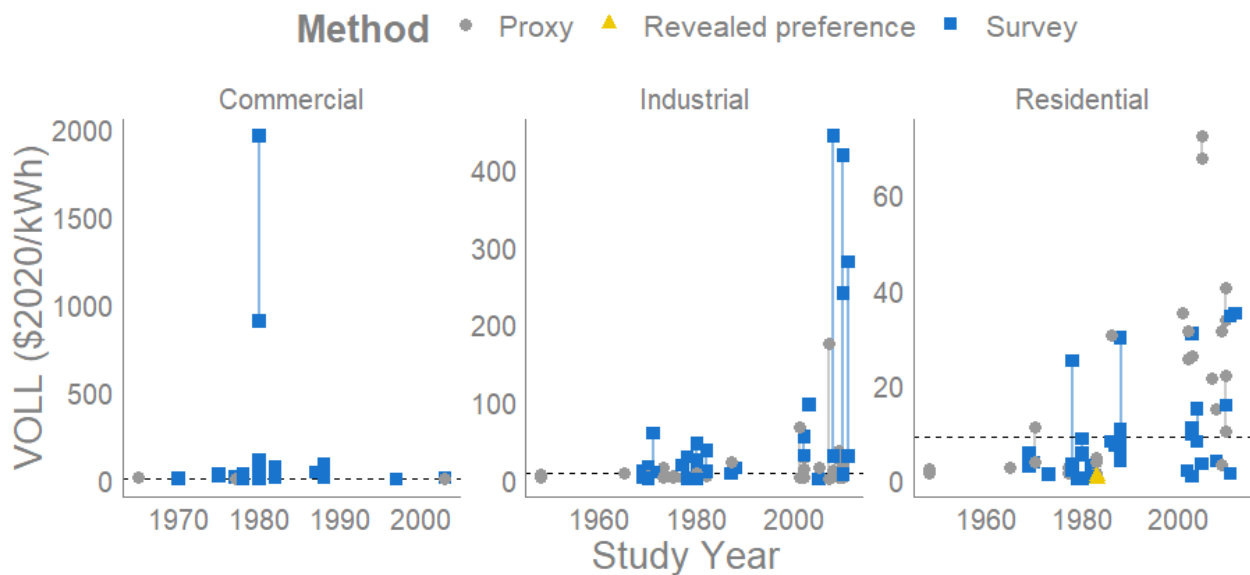


Figure 2.3: Range of VoLL estimates overtime, compiled from a selection of published meta-analyses in the literature. Dotted line indicates VoLL of \$9/kWh. (Sanghvi (1982) covers 1948 - 1980; Caves et al. (1990) covers 1975-1988; Ajodhia (2005) covers 1977-2003; Schröder and Kuckshinrichs (2015) covers 2001-2012)

Proxy/Macroeconomic modeling

Proxy methods measure the VoLL by linking the value of different goods and services to the underlying electricity consumption that facilitates the production of those goods and services. A low-bound approach assumes that the VoLL is equal to the retail price of electricity in the given region of study, which fails to measure the loss of intramarginal demand that outages cause. Another approach involves taking the ratio of the gross economic product of a geographical region (e.g. Gross Domestic Product (“GDP”) or Gross Value Added (“GVA”)) and the electricity consumption of the commercial and industrial consumers in that same region. This method was the original approach to measuring the VoLL, developed by researchers in the 1970s ([Shipley et al., 1972](#)).

The advantage of these two approaches is their simplicity, which in a literature rife with complicated methods, can be used to provide benchmarks and points of comparison. Much of the administrative data required to make the above calculations exists and can be collected at relatively little cost by researchers and electric industry decision makers. Another benefit is that given the networked nature of electric system planning, it can be useful to have an aggregated, societal estimate of the VoLL. Results from these two macroeconomic approaches are often more widely applicable to an entire electricity network given their broad geographic scope.

The drawbacks, however, are significant. The retail price for electricity tends to be quite low. In the U.S., prices range between \$0.07/kWh-\$0.20/kWh, and, on average, U.S. households only spend 2% of their income on electricity bills.⁹ In reality, individuals are likely willing-to-pay much more for electricity than what it costs the system to provide it. Similarly, many critiques of GDP metrics note that they do not capture all economic activity in society, and thus could result in an underestimate of electricity value ([Aitken, 2019](#)).

Furthermore, both the gross product and the retail price approaches average away the underlying heterogeneity of the VoLL throughout the population. In the residential context, different households will place different values on electricity depending on their end-uses. Critical appliances such as life-saving medical equipment, refrigeration, and/or internet services are likely more valuable as compared to more flexible electricity use-cases such as clothes washing, ancillary lighting, or dish washing. Unfortunately, there has been little research to quantitatively distinguish preferences of different electricity end-uses across households. The distribution of appliance ownership also differs across the population, further differentiating the VoLL within a given population. In the industrial and commercial sectors, end-uses of electricity are even more heterogeneous, and thus the VoLL likely has an even greater disparity across these customer types ([Munasinghe and Gellerson, 1979](#)).

⁹Median household income is taken from U.S. census bureau, 2019 amount was \$69,000. Average annual bill for residential households taken from U.S. 2019 EIA 861 and is \$1,400

These end-use limitations interact with another limitation of proxy approaches: lack of incorporating the timing of an outage. Costs incurred for outages during an evening weekday will be different than costs incurred mid-day during a weekend. Such temporal differentiation is also not uniform for all sectors of the economy, and these aggregated methods cannot be used to understand these effects.

More sophisticated proxy methods have been developed to try to account for some, though not all, of these shortcomings. For commercial and industrial customers, specific production function analyses (i.e. “input-output” models) tie a firm’s outputs to the required inputs including but not limited to electricity. Then, researchers calculate the output value lost with different electric outage duration events. This approach allows researchers to study the specific use-cases for electricity in different applications and can thus better differentiate the VoLL by customer-type. Depending on the modeling approach, sometimes the timing of a power outage can also be considered (de Nooij et al., 2007). Computable general equilibrium (CGE) models are a more expansive input-output modeling strategy that create more explicit relationships between firms, households, and underlying electricity demand.

No such functional-form approach has been developed for the residential customer class. However, a proxy method has been used which assumes that lost leisure time is equivalent to a person’s hourly wage rate, a method which is based on the foundational theory developed by Becker (1965). A detailed discussion can be found in (de Nooij et al., 2007), but common critiques involve limited incorporation of the stochastic (i.e. random time-of-day, season, frequency) nature of power outages on leisure time, limited differentiation between leisure and non-leisure costs of power outages, and limited acknowledgment of the imperfections in the labor market (e.g. many individuals do not work but would have direct costs of an incurred power outage). These shortcomings challenge the standard assumptions needed to convert wage information into a VoLL (Sanghvi, 1982).

Survey-based strategies

Survey methods involve interviewing individuals or businesses and asking them to estimate their specific VoLL. The most common approach for the residential sector is a stated preference (also known as contingent valuation) methodology where a researcher develops a hypothetical outage scenario and asks participants to provide their willingness-to-pay to avoid a power outage. An alternative approach, called contingent ranking, provides a set of electricity service scenarios with different reliability levels and corresponding prices while asking respondents to rank their service quality preference.

	Would you be willing to pay this amount to get full service on a hot summer weekend day?		
	Yes	Not sure	No
Less than \$5	☐	☐	☐
\$5 to \$9.99	☐	☐	☐
\$10 to \$14.99	☐	☐	☐
\$15 to \$19.99	☐	☐	☐
\$20 to \$24.99	☐	☐	☐
\$25 to \$29.99	☐	☐	☐
\$30 to \$34.99	☐	☐	☐
\$35 to \$39.99	☐	☐	☐
\$40 to \$44.99	☐	☐	☐
\$45 to \$49.99	☐	☐	☐
\$50 to \$54.99	☐	☐	☐
\$55 to \$59.99	☐	☐	☐
\$60 to \$64.99	☐	☐	☐
\$65 to \$69.99	☐	☐	☐
\$70 to \$74.99	☐	☐	☐

Figure 2.4: Sample contingent valuation question from (Baik et al., 2018) studying the VoLL in a hypothetical outage scenario in Allegheny County, Pennsylvania.

A critical strength of these approaches is that they can adjust different outage interruption parameters (e.g. length of outage, timing of outage, whether warning is provided) to study a wider heterogeneity of outage experiences (Doane et al., 1988b). Furthermore, these research approaches can be administered to a broader set of customers in order to generate wider distributions of VoLL estimates, rather than aggregate figures which constrain the various proxy approaches (Baik et al., 2020). Such flexibility is valuable given the importance of capturing heterogeneity in preferences. This strength combined with the relative ease of implementation has led to the popularity of survey-based approaches as the prominent VoLL estimation strategy in the literature (see Figure 2.3 and Caves et al. (1990)).

However, the central challenge of surveys is the hypothetical nature of asking customers to estimate their own VoLL. Critiques of contingent valuation methods are widespread and exist beyond the applications in the electricity sector (Hausman, 2012). Three of the key biases identified in the literature are (1) hypothetical response bias, where people say different things from what they would do in face of budget constraints and (2) the embedding/scope problem, where the WTP for the same good can vary over a wide range depending on whether

the good is assessed on its own or embedded as part of a more inclusive package (e.g. inability to distinguish the benefits of avoiding 1 or 5 power outage events), and (3) Lack of generality and external validity beyond a study's context (e.g. where a survey specifically asks about a peak event outage of a certain duration). Some of these problems are oftentimes evidenced by large differences between estimates of the willingness-to-pay (WTP) to avoid an outage and the willingness-to-accept (WTA) payment to incur an outage. Theoretically, the WTP and WTA should be equal ([Hartman et al., 1991](#)).

Beyond stated preference surveys, some researchers formulate surveys that explicitly separate the various cost categories that could result (or did result) from a blackout in order to prompt an individual or business to quantify the specific costs associated with power outages. Instead of relying on hypothetical scenarios, these studies tend to use real power outage events to identify their target research populations and focus participant attention on costs they recently incurred during that specific power outage event. These studies have less hypothetical bias given the focus on populations with actual (and ideally recent) power outage experiences. These are particularly effective for non-residential customers who have well understood direct economic impacts from power outages. However, there is still no real cost for a respondent to claim a high outage cost and it remains challenging to fully capture indirect and abstract costs (e.g. lost leisure, annoyance, stress). Lastly, since these types of studies focus on realistic power outage 'cases', they are especially challenging to implement in high-income countries given limited power outage experience (i.e. power grids in these countries have generally high reliability levels).

2.5 Interrogating revealed preference approaches to VoLL estimation

The above approaches suffer either from their hypothetical nature and/or their overly aggregated approach to the calculation of outage costs. To counter these issues, revealed preference strategies aim to observe market behavior decisions by electric consumers in order to infer the VoLL. The principal advantage of revealed preference approaches is that they are, or at least should be, based on actual consumer behavior. Therefore, these strategies are oftentimes preferred given that they rely on actual decisions that consumers make in the face of power outages and thus involve realistic responses to both internalized outage costs and the corresponding budget constraints that might limit the procurement of more reliable electric supply. Given their theoretical benefits, it is worth a deeper evaluation of revealed preference approaches. As we will explain, these estimation strategies are difficult to implement and thus are rare in the literature.

Interruptible contracts

The simplest revealed preference approach to calculating the VoLL would be to observe uptake of special priority service contracts which allow customers to pay more to avoid power outage events (Doane et al., 1988a). For example, suppose a customer with a 2 kW average daily load was offered a choice between avoiding a five-hour power outage and \$50. If she accepts the \$50, her value of lost load must be less than or equal to $\$50 / (5 \text{ hrs} * 2 \text{ kW}) = \$10$ per kWh. If a customer refuses this offer, she must value her uninterrupted power at more than \$10 per kWh.

However, due to the relative dearth of interruptible supply contracts in the electricity sector, especially for residential customers, such studies are rare or impossible to find in practice (Caves et al., 1992). Furthermore, because this approach assumes a full, rather than partial, power outage, this approach does not typically account for the heterogeneous value of different energy services. Future research that analyzes a variety of demand response contracts which might take into account different services, though, might improve upon prior work that focused on discrete power interruption conditions.

Demand-curve estimation

A second revealed preference approach uses electricity customer responses to price changes to infer the underlying demand curves for electricity. As discussed above, demand curves represent the willingness-to-pay for a given quantity of a specific good and the VoLL can be estimated by taking the integral between the demand curve and retail electricity price curve along the portion of x-axis defining the quantity of electricity lost during an outage. Here, the VoLL is equivalent to the lost consumer surplus during a power outage.

There are two principal advantages of demand-curve based VoLL estimation. Since demand curves should represent actual consumer financial constraints, they avoid the problem of hypothetical studies which rely on consumer beliefs. Second, demand curves can be used to measure the costs of partial outages, which is difficult to assess using survey-based methods.

But how does one go about estimating these demand curves? The main parameterization strategy involves running an experiment that measures how the price of electricity affects the amount of electricity demand. The result in such a study is an estimate of the demand elasticity, defined as the ratio of the percentage change in quantity demanded to the percentage change in the price. Demand elasticity studies are common in the economics literature due to their ability to describe marginal consumption patterns. In the electricity sector, for instance, such studies are useful to understand the effects of various electric tariff designs on consumer behavior (Zhu et al., 2018).

Once obtaining a demand elasticity estimate, there are two approaches to then trace out a demand curve. The first approach assumes a constant demand elasticity, meaning that

the percentage change in quantity demanded from a percentage change in electricity price is constant throughout the curve (See Figure 2.5 and Eq. 2.2).

$$P = A * Q^{\frac{1}{\epsilon}} \quad (2.2)$$

Where,

P = price of electricity (\$/kWh)

A = constant based on price and demand at point of elasticity estimation

Q = quantity demanded (kWh)

ϵ = demand elasticity (%)

A key shortcoming of the constant demand elasticity assumption relates to the fact that elasticity estimates are most reliable around the mean price in the marketplace (i.e. close to the elasticity estimation point in Figure 2.5). Extrapolating the demand curve back to the vertical axis, where quantity demanded is 0, is therefore extremely uncertain (Caves et al., 1990). With a constant elasticity assumption, as you approach the vertical axis, the demand curve asymptototes, implying an infinite VoLL.

An infinite VoLL aligns with the relative inelasticity of electricity demand when compared to other goods and services in the economy (Burke and Abayasekara, 2018) and is especially true for short-run electricity demand. However, as we will discuss below, mitigation investments in back-up power devices represent an important backstop technology that provides a non-infinite cost alternative to mitigating power outages. If a customer truly had an infinite VoLL, as would be suggested by perfectly inelastic demand, they could choose to invest in alternatives that are most certainly cheaper than infinity.

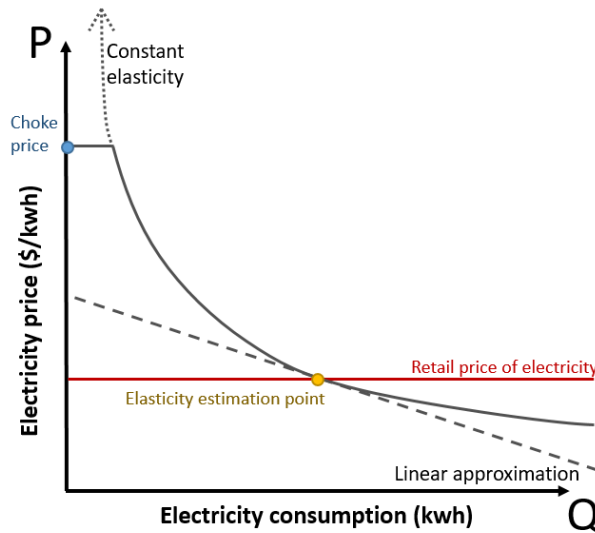


Figure 2.5: Visualizations of constant elasticity versus linear approximation demand curve estimation approaches

To avoid calculating an infinite VoLL, economists make an additional assumption about the electricity choke price or the price at which consumers will stop consuming electricity altogether (see Figure 2.5). Choosing an appropriate choke point, however, is incredibly challenging and ultimately is inextricably linked to prior beliefs on appropriate VoLLs. Thus any assumption about the appropriate choke price made to calculate the VoLL contains an inherent circularity.

There is an important analog to the choke price which has been deployed in capacity markets in the bulk power system of the electric industry. In these wholesale electricity markets, administrative demand curves are formulated using the cost of building a new power plant, also known as the cost of new entry or CONE. The CONE substitutes for a choke price assumption (Spees et al., 2013). This analog relates to the mitigation investment methodology to VoLL estimation introduced below where the assumption is that the maximum price society should be willing to pay for extra supply should be the backstop reliability technology.

The second demand elasticity approach, which avoids the choke price assumption, applies a linear approximation of the underlying demand curve. This approximation is derived in (Sanghvi, 1983) and reproduced below in Equation 2.3. The linear approximation avoids the asymptotic quality of the constant demand elasticity assumption. Instead, the approximation takes the slope of the demand curve at the elasticity estimation point and extrapolates it back to the vertical axis (see Figure 2.5).

$$P = Q * \frac{P_d}{Q_d * \epsilon} - \frac{(1 - \epsilon) * P_d}{\epsilon} \quad (2.3)$$

Where,

P = price of electricity (\$/kWh)

Q = quantity demanded (kWh)

P_d = price of electricity at point of elasticity estimation (\$/kWh)

Q_d = quantity of electricity at point of elasticity estimation (kWh)

ϵ = demand elasticity (%)

However, this approximation most certainly leads to an underestimation of the underlying value of electricity close to the vertical axis for a subset of the population. This conclusion relates to the fact that a certain segment of customers have invested in back-up power technologies to avoid power outages and the cost of such back-up power investments is significantly higher than the choke price implied by the linear demand curve estimation. A point that will be further elaborated on in the next section.

A comparison of the VoLL calculated using these two demand curve approaches is shown below in Table 2.2. We vary the demand elasticities from -0.5 to of -0.1, based on a range of short and long term elasticities from a recent meta-analysis of more than 100 individual elasticity studies (Zhu et al., 2018). In this table, we assume that a consumer loses their

entire daily electricity demand, therefore it incorporates both the marginal and inframarginal portions of the demand curve. In order to avoid infinite VoLL calculations in the constant elasticity approach, we assume a choke price of \$2/kWh, which has been used elsewhere in the literature ([Borenstein and Bushnell, 2021](#)), and compare it to a choke price of \$100/kWh.

Elasticity estimate	Constant elasticity \$2 choke	Constant elasticity \$100 choke	Linear approx.
-0.1	\$1.5	\$57.4	\$1.3
-0.2	\$1.3	\$33.4	\$0.6
-0.3	\$1.1	\$19.7	\$0.4
-0.4	\$0.9	\$11.8	\$0.3
-0.5	\$0.8	\$7.2	\$0.3

Table 2.2: Comparison of implied VoLL by demand curve estimation (\$/kWh)

The fundamental challenge with both these demand curve approximation approaches is that they rely on elasticity estimates that are made at electricity prices and quantities that exist in the marketplace (i.e. close to the elasticity estimation point in Figure 2.5) rather than at the extreme portions of the demand curve which are close to the vertical axis and generally not observed. This limitation is more significant for VoLL studies which do not solely care about the marginal demand of a household, commercial store, or industrial consumer. Marginal consumption behavior is more useful when studying the impact of electricity tariff changes given that mapping an entire demand curve is unnecessary. Power outages result in the loss of both marginal and inframarginal electricity demand and quantifying inframarginal demand elasticities requires more detailed studies which might distinguish the underlying flexibility of individual electric end-uses by studying the interaction of power outage timing and available substitutes. Since elasticities tend to be provided as single point estimates, it is challenging to incorporate the intertemporal variance involved with a power outage. Outages can last a few hours or a few days, with varying amounts of notice.

Electricity consumers might oftentimes be able to shift loads to periods before and after an outage but elasticity estimates tend to be aggregated by year or by month (to take into account seasonal demand differences), rather than separately for each hour of the year. These shortcomings might suggest that price elasticities could underestimate a customer's ability to respond to short-term power interruptions, leading to overestimates of the VoLL. Alternatively, some elasticity studies incorporate tariffs that provide advance warning of a price change, either via set time-of-use (TOU) rate definitions or day-ahead notifications (e.g. critical peak pricing). Using elasticity estimates from such studies could be too optimistic regarding a customer's ability to respond to short-term power interruptions, leading to underestimates of the VoLL. After the consumer surplus method was introduced in the 1980s,

limited extensions were made given the difficulty in realistically estimating a continuous electric demand function.

Mitigation investments

Alternatively, the VoLL can be indirectly estimated by collecting data on mitigation investments in back-up power and/or grid hardening. To do so, researchers combine the cost of investments in mitigation technologies with estimates for the amount of power outages avoided due to such investments. Since these mitigation expenditures reduce the direct costs of any outage, they relate to the underlying value of reliable power supply. Prior literature argues that customers will equate the expected cost of generating a kwh via backup power to the expected value of avoiding power outages (i.e. the VoLL) (Bental and Ravid, 1982). If mitigation investments are made, the cost of that self-generated electricity should be equal to or less than the underlying VoLL. Conversely, if customers do not make back-up power investments, their VoLL should be less than back-up power costs.

I show a simple lower-bound VoLL calculation using the mitigation investment framework in Eq 2.4 - 2.6. First, calculate the annualized costs of back-up power investments (A) as shown in Eq. 2.4. Then, Eq 2.5 can be used to calculate the annual operating costs (OC) of operating a backup power system. Typically, backup power technologies are solely used to provide energy during a power outage. However, new distributed energy resource technologies, such as solar and storage, also provide financial benefit to end-consumers via bill savings (B) (Barbose et al., 2021). Those savings offset the costs of owning and operating the backup power system; therefore, the all-in VoLL subtracts any bill savings from the annualized and operating costs as shown in Eq. 2.6.

$$A = \frac{(c * r)}{(1 - (1 + r)^y)} \quad (2.4)$$

$$OC = h * l * f \quad (2.5)$$

$$VOLL = \frac{A + OC - B}{h * l} \quad (2.6)$$

Where,

A = annualized capital cost (\$/yr)

c = capacity cost (\$)

r = discount rate (%)

y = operational years (yr)

OC = operating costs (\$/yr)

h = operational hours during outages (hrs/yr)

l = average load (kW)

f = fuel costs (\$/kWh)

B = bill savings (\$/yr)

To calculate the VoLL for a gasoline-based back-up generator, assume a customer has a discount rate of 5% (r) and pays \$2,000 (c) up front with an expected lifetime of 10 years (y). The customer expects 20 hours (h) of outages per year and will operate at an average load of 2 kilowatts (l) with fuel that costs \$0.5 per kWh (f). Finally, if we assume bill savings are \$0, as would likely be the case for a gasoline-based backup generator, their VoLL would be at least \$7/kWh.

Such a VoLL, though, would only be applied to customers who adopt that back-up technology. If customers do not purchase the generator, their VoLL would be lower than the estimate calculated using the above framework. To determine an average societal VoLL, these simple calculations could be combined with statistics on adoption patterns of back-up technologies across a given population. Furthermore, the underlying assumption is that the 2 kW generator is replacing all of the electricity demand of a customer. If the generator does not replace all of their consumption from a counterfactual case of no power outage then the underlying calculation is focused on measuring the VoLL for their most valuable load, at the top of their demand curve.

A comparison of the VoLLs that would be associated with different back-up power purchases is shown below in Table 2.3. In the first column, I vary the outage length a consumer expects in a year. Note the results for the gas generator in row 3 of the table match the above example calculation.

For storage, we assume a 10 kWh system, priced at \$1000/kWh, use a 20 year lifetime, and assume \$330 of annual bill savings. Bill savings are calculated by assuming daily battery cycling against a time-of-use rate with an average on-to-off peak price difference of \$0.10 and a battery efficiency of 90%. For solar+storage, we add a 5.5 kW solar system at an average cost of \$3,000/kW to the 10 kwh storage system and calculate the bill savings using the National Renewable Energy Laboratory's ReOpt model for a San Francisco household which cannot export to the grid (Cutler et al., 2017). The bill savings for such a system is \$1,700 per year.¹⁰ As a customer's expectations for the usage of the backup power device increases, the implied VoLL decreases as the capital cost is spread across a larger amount of self-supplied electricity.

The energy limitations of these different back-up technology options complicates the story

¹⁰The operational dynamics to achieve both economic and reliability performance from storage and solar+storage systems are complicated by competition in use cases during an outage. Such detailed modelling is beyond the scope of these simple calculations. Rather, we assume the most optimistic economic savings potential where both these bill savings and reliability mitigation can be achieved. Nevertheless, more sophisticated models can be used to more precisely estimate the VoLL given that operational decisions in the event of a power outage will cannibalize bill savings. Still, such impacts would likely be small in the above example since we have at most 4 days of outage while bill savings can be achieved year-round

Expected annual hours of outage	Gas generator	Storage	Solar / storage
1	\$130	\$237	\$206
5	\$27	\$47	\$41
20	\$7	\$12	\$10
50	\$3	\$5	\$4
100	\$2	\$2	\$2

Table 2.3: Comparison of implied VoLL using different back-up power technologies (\$/kWh)

presented in Table 2.3. The standalone 10 kWh battery could only supply roughly 5 hours of continuous backup power before shutting down¹¹, suggesting that the VoLL at 20, 50, and 100 hours of expected outage hours are unachievable. However, if outages occurred for at most 5 hours in length but days apart (an optimistic case), the VoLLs at the higher annual outage hours might be achievable. Similar energy limitations might be present for the solar+storage system but depend on the correlation of solar production with the outage timing. Given the potential to store days worth of fuel on site, the gas generator likely has limited energy constraints. But, if insufficient fuel supply is stored on site, similar limitations might apply.

In the case of low expectations for back-up power use (i.e. row 1 of Table 2.3, the implied VoLL can be extremely high. In those cases, back-up power technology would provide an expensive means to manage a highly unlikely outage experience. At the extreme, an infinite VoLL would be implied in the case where back-up power technology is purchased but with the advance *expectation* that it would never be used. Most customers, however, will expect to use their back-up power at least once, thus making a calculation of infinite VoLL highly unlikely. The key is that such VoLL calculations are based on expected usage of back-up power rather than actual usage since expectations should drive underlying back-up power purchase decision.¹²

Ultimately, given the highly reliable nature of the electricity system in high-income countries (i.e. low annual hours of outage), it is difficult to apply such market-based methods given the extremely high VoLLs that would be needed to justify investment. Furthermore, without sufficient randomization of the outage experience, selection bias issues are oftentimes present and people who adopt back-up power might not be representative of society. There is a limited but growing literature which applies revealed preference techniques either through

¹¹Assuming an average power demand of 2kW

¹²Observing customer expectations, however, is challenging and oftentimes survey-based methods which a subject to the biases mentioned earlier must still be used to measure them.

randomized control trial or natural experiment designs in low-income country contexts (Allcott et al., 2016; Burlig and Preonas, 2021). However, these studies cannot typically be used to infer the VoLL in countries with different contexts.

2.6 Discussing the challenges to applying the VoLL in CBA

As the above narrative illustrates, it is challenging to estimate the VoLL. Prior studies use a wide range of methods and can reach quantitatively different estimates of the VoLL. In Figure 2.3, I found that the VoLL range is, in part, driven by identifiable differences between different electricity customer groups (e.g. residential vs. industrial). However, the differences that exist within these customer categories suggests that there is considerable uncertainty regarding the distribution of costs of power outages across society.

As discussed in sections II and III, most applications of the VoLL typically do not consider this uncertainty. Implementing a tractable cost-benefit analysis requires choosing amongst these VoLL estimate studies. A 2018 Lawrence Berkeley National Lab (LBNL) study provides the most recent estimates of the benefits of reducing U.S. power outages. Once accounting for differences in the VoLL between customer classes, they find that the cost of sustained power interruptions in the United States is \$44 billion dollars – roughly 25% more than their 2006 estimate of \$35 billion (LaCommare et al., 2018). Just 3 years after this study’s release, the Biden administration’s \$2 trillion infrastructure proposal stated that power outages cost \$170 billion per year to the U.S. economy,¹³ 300% more than LBNL’s most recent estimate. This study did not evaluate other sources of heterogeneity in the VoLL beyond customer class differentiation and outage duration (Fischhoff and Furby, 1988; Venkatachalam, 2004; Broberg and Brännlund, 2008). Given the uncertainty with such estimates, the economy-wide costs of power outages reported by the study have to be applied cautiously in CBA which might be used to justify regulatory decisions.

Baik et al propose solutions to decision making under such preference heterogeneity by using distributions of the VoLL within a population to develop societal preference intervals to inform reliability enhancement investment decisions (Baik et al., 2019). Their proposal, however, still relies on contingent valuation studies to measure the distribution of societal preferences. There remains a ripe opportunity to study how the heterogeneity between different valuation approaches (i.e. proxy, surveys, and revealed preference) could be used to triangulate a VoLL and characterize a wider distribution of CBA than performed in previous studies. Such an assessment could also illuminate decision biases that might be inherent in CBAs which apply different VoLL estimation techniques.

¹³See promotional tweet: [The White House](#)

Still, even if the VoLL could be estimated accurately and precisely, there are equity concerns to applying the formulation given that the metric is likely a function of income levels. As mentioned above, particularly marginalized people might have much smaller willingness to pay – driven mostly by their ability to pay. Turning off an individual’s power who relies on life-saving medical equipment because they have a low ability to pay is an unsavory societal outcome. Alternatively, consider a world with wide adoption of solar+storage or “microgrids” by high-income communities who can afford such systems. Those communities would effectively be reducing their VoLL by increasing their mitigation investments. Such an outcome raises difficult system-planning decisions given the ability of some customer populations to potentially opt out of societal reliability and resiliency investments, which have historically been structured as public goods.

Uncertainty in the benefits of societal decision-making is not unique to the electricity industry and has been a longstanding question in policy analysis (Arrow, 1950). One option in such circumstances is to develop reasonable, non-economic goals and/or constraints for the outcome of interest and then determine the optimal pathway to achieve those goals. This approach is analogous to cost-effectiveness analysis, a common tool in many arenas of policy where the benefits are hard to evaluate (Stern and Stiglitz, 2021). Such tools have been proposed in the case of climate change, where a target temperature rise is accepted and the resulting economic analysis centers on the best (cheapest) way to achieve the temperature target given various system constraints.

In the electricity context, cost-effectiveness analysis is analogous to the methods used by the electricity sector before the introduction of cost-benefit analysis in the 1970s. As explained in Section III, electricity planners would establish a target of ‘acceptable’ power outages via a LOLP heuristic and investment decisions centered on minimizing system costs to achieve that target. Such an approach is relevant to evaluations of transmission and distribution system investments, which often enhance reliability of the network during non-shortage events (Larsen, 2016). Deciding the ‘acceptable’ level of power outages, however, is a non-trivial task.

The dynamic pricing mechanisms discussed in Section II offer a more efficient solution (compared to both cost-benefit and cost-effectiveness analysis) when managing supply-demand imbalance in real time. Though most outages do not currently result from such electricity shortages, these mechanisms might become increasingly important for a future electricity system with more energy constraints due to the integration of higher levels of renewable and variable supply-side resources (Tong et al., 2021). However, determining the most efficient price signals to send during scarcity events remains challenging for regulators given the uncertain estimates of the VoLL. This uncertainty suggests that cost-effectiveness analysis should remain an important tool of electric reliability decision-making.

2.7 Concluding remarks

In this chapter, I have defined and discussed the value of lost load, a key metric used by the electricity industry to plan for optimal reliability investments. I presented a microeconomic framework that illustrates the limitations of the historical quest to quantitatively estimate and apply the VoLL in electricity market reliability decision-making. My historical analysis showed that while much progress has been made in the field over the last half-century, much work still remains to better measure the full complexity and heterogeneity of the VoLL across society.

The challenges with accurately and precisely estimating the VoLL make it difficult to rely exclusively on CBA frameworks for electric reliability public policy decisions, and highlight the need to continue applying cost-effectiveness analysis in parallel. Recent power outages in California (CAISO, 2021) and Texas (Busby et al., 2021) and the resulting political backlash suggest that the VoLL and the current constructs which aim to balance system and power outage costs remain contentious issues.

The analysis I've presented focuses on the electricity customer perspective, and I avoided discussions of macroeconomic issues that may further motivate public policy responses to enhancing electric reliability. Such issues are tangentially related to the indirect costs of power outages discussed in Section II as well as the proxy VoLL estimation methods presented in Section IV. A detailed accounting of these issues was out of scope given my general focus on microeconomic frameworks, and future research, which will no doubt continue developing improved methods to VoLL estimation, could also integrate discussions of macroeconomy issues and their relation to industrial competitiveness.

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Chapter 3

Do notifications affect households' willingness to pay to avoid power outages? Evidence from an experimental stated-preference survey in California

3.1 Introduction

How much should society pay to maintain a reliable electricity system, and how can we reduce the social cost of power outages? This chapter aims to generate estimates of the value of lost load (VoLL) – a crucial input into decisions on the optimal reliability of the electricity system. I do this by asking: To what extent do the economic costs of outages vary as a function of the degree of advance notice customers receive about the outage?

Supply-side power outages are extremely rare in the developed world. This is not an accident, but rather the result of regulatory decisions. For example, in California, each load serving entity (LSE) faces “resource adequacy” requirements which specify that they must have contracts in place with electricity suppliers that are sufficient to meet their forecasted peak electricity demand, plus a 15% planning reserve margin (CPUC). This places a high premium on reliability. Because of the lack of time-varying pricing and a relatively inelastic demand for electricity, this resource adequacy requirement means that power plants are built and maintained which rarely operate, imposing a cost on society (Fruer et al., 2013; Economics, 2013; Pfeifenberger et al., 2013). To strike the right balance between the level of the planning reserve margin and cost, regulators need to understand the value of reliable electricity supply to consumers — the VoLL (Figure 3.1).

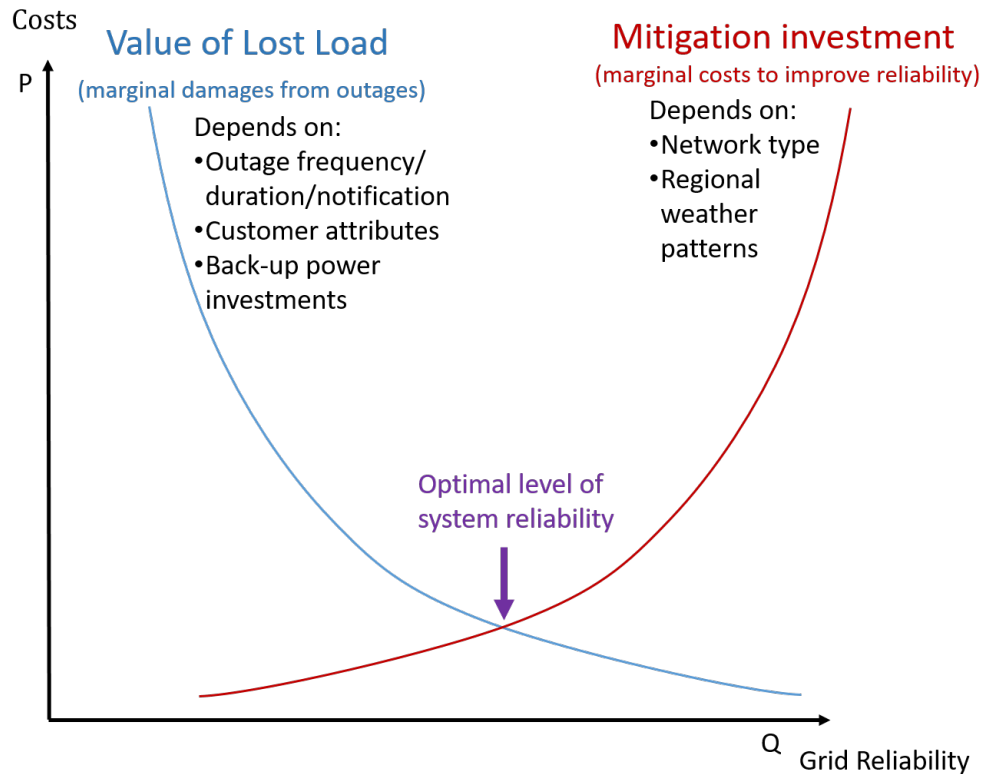


Figure 3.1: Illustration of tradeoff between grid investments (red line) and value of lost load (blue line).

The VoLL is not only an important input to resource adequacy decisions as discussed above but also a key parameter in decisions to manage, upgrade, and/or shut-off electric transmission and distribution infrastructure during extreme weather events (Larsen, 2016). For instance, without an understanding of the value of reliable electricity supply, it is difficult for regulators and utilities to make decisions in regards to the trade-offs between preventing electricity-induced wildfire ignitions, which has become more common in California, and imposing costs on consumers (Schröder and Kuckshinrichs, 2015).

This chapter aims to understand how advanced notification of future power outages impacts a customer's VoLL. The experimental stated-preference survey focuses on consumer behavior and expectation surrounding the recent major power outages in California, where utilities have begun using targeted demand-side shut offs of the grid to prevent their equipment from sparking wildfires. These 'Public Safety Power Shutoff' (PSPS) events have been endorsed by governments as a useful and necessary tool, but they impose economic costs on households and may undermine environmental policy if the outages lead to widespread purchases of fossil fueled back-up generators.¹ The survey tests the hypothesis that customer notifi-

¹Of course, to the extent that shutoffs reduce wildfires, they also reduce corresponding environmental

cations could be a cost-effective tool for policymakers to reduce the social cost of planned outages in the new context of wildfire risk. To do so, it experimentally estimates how the timing of notifications impact the residential sector's VoLL.

While the survey focuses on the electricity system, it also relates to the broader literature on the detrimental impact of uncertainty on economic outcomes (Jackson et al.; Kliesen et al., 2018; Ben-David et al., 2018; Baker et al., 2016). Though advance warning technology for natural disasters such as earthquakes, wildfires, and hurricanes is increasingly available (noa, 1991; Andrews et al., 2007; Serna, 2020; DeVries et al., 2018), society has limited empirical evidence on the benefits of these technologies (Escaleras and Register, 2008; Kellenberg and Mobarak, 2011). Such evidence is critical for determining the optimal level of investment in them, and this chapter contributes important knowledge about public investment in early-warning systems. The experiment focuses on wildfires and their interaction with electricity consumption, allowing for an estimate of the value of resolving uncertainty in the specific context of household electricity decision making.

Though prior work measuring the VoLL has indicated that advanced warning likely has a mitigating effect on the cost of power outages, there have been limited studies to quantify the cost reduction (Schröder and Kuckshinrichs, 2015; Caves et al., 1990). In one of the most recent meta-analyses of the VoLL, the authors make explicit recommendations to future questionnaire designers to develop surveys that create identical scenarios between no warning and advanced warning conditions. In their words, “scenarios with advanced warning are not necessarily paired with the identical scenario without advanced warning, so the aggregate analysis yield highly problematic or counter-intuitive results.” (Sullivan et al., 2009). This experimental survey design aims to help fill this gap in the literature.

Overall, I find positive and statistically significant WTP to avoid power outages. However, while results indicate that advanced notice of a power outage reduces the WTP to avoid those power outages, these effects were not statistically significant. The insignificance shows that there was no measurable effect of notification on a consumer's power outage cost within our sample, suggesting that notification may not have a central impact on WTP. Still, notification did serve to reduce WTP amounts between 10-20%. I calculate an average VoLL of \$11/kWh, within the range of estimates in prior work, though on the higher side for the residential sector (Schröder and Kuckshinrichs, 2015). Most recent estimates found by Baik et al found average values closer to \$2/kWh (Baik et al., 2020).

Other key results relate to heterogeneity across household wealth, which is found to be negatively correlated with WTP, a counter intuitive result if one expects that ability to pay to be positively correlated with WTP outcomes. Furthermore, on average, respondents did not have high expectations for the number future outage hours. Lastly, we find that back-up

pollution caused by wildfires.

power adoption ownership within the sample showed positive correlation with respondents' WTP to avoid outages. Of course, there are limitations to applying any of these results given the limitations of stated preference methodologies and the lack of any serious budget constraint being applied to the respondents ([Hausman, 2012](#)).

3.2 Methods

The experimental approach measures the stated VoLL among a randomized sample of California residents age 18+ as selected from the National Opinion Research Center's (NORC's) AmeriSpeak Panel. Though stated preference methods have a number of limitations (e.g. scope/embedding effects, hypothetical bias, the endowment effect), they also are the only setting with enough flexibility to evaluate identical scenarios that differ only in the advanced notice built into an experimental treatment ([Fischhoff, 1991, 2005](#); [Hausman, 2012](#)).

The panel uses sampling strata based on age, race/ethnicity, education, and gender (48 strata in total). The survey was offered in English and Spanish and was administered on the web. Limiting the sample to California should reduce hypothetical bias common to contingent valuation due to the state's recent wildfires and PSPS programs as residents of the state should have more familiarity with risks of power outages. Importantly, I apply panel base sampling weights provided by NORC that account for non-response. In addition, the focus on a California subsample of NORC's AmeriSpeak Panel led to a need to incorporate a nonprobability sample to increase the overall sample size. NORC used their TrueNorth calibration services to explicitly account for potential bias of combining probability and non-probability based samples ([Cornesse et al., 2020](#); [Ganesh et al., 2017](#); [Yang et al., 2018](#)). More details on sampling can be found in the Supplemental Information section.

The experimental question asks for a respondent's WTP to avoid power outages (VoLL) under different notification scenarios. Specifically, the survey states that a monthly fee will be added to the respondent's electricity bill every month for the upcoming year (i.e. 2022). Furthermore, to align with the California PSPS context, the survey describes that this fee would allow the respondent to avoid two separate, 40 hour power outages that would occur randomly during fire season (September through November).² Depending on which treatment group the respondent is randomized into, they were told that prior to each outage they would receive either 1) no, 2) 1-day, or 3) 7-day notice. Given a notification window, they then select the monthly fee they would be willing to pay over the entire year to avoid these outages. Payment was chosen to be monthly as it corresponds to their typical utility bill. However, as described below, there is some uncertainty as to whether respondents truly

²The specification of duration in these interruptions was loosely based on analysis of the large 2019 PSPS events that occurred in Pacific Gas & Electric's territory, summarized in the following state utility commission dataset: [CPUC website](#)

interpreted the fee as a monthly payment made 12 times throughout the course of the year or 1-2 distinct payments.

In addition to the experimental questions, all respondents answered a set of questions about their prior exposure and awareness of wildfire-related outages, expectations for future outages, and understanding of power outage defensive investments. These non-experimental questions increase statistical power via stratified randomization (i.e. I randomize treatment based on whether the respondent already owned backup power) and provide opportunity to explore more detailed heterogeneity among customers.

I assess how the results vary by respondent education, race, home type, home value, household income, and age to understand what equity concerns may exist in policy discussions if only applying an average WTP metric which might vary significantly depending on the population being studied. To avoid anchoring concerns, the survey concludes by asking respondents how much they pay monthly for electricity. Figure 3.2 provides a flow diagram illustrating the order of the questions and structure of the experiment, and the specific survey deployed can be found in Appendix B.

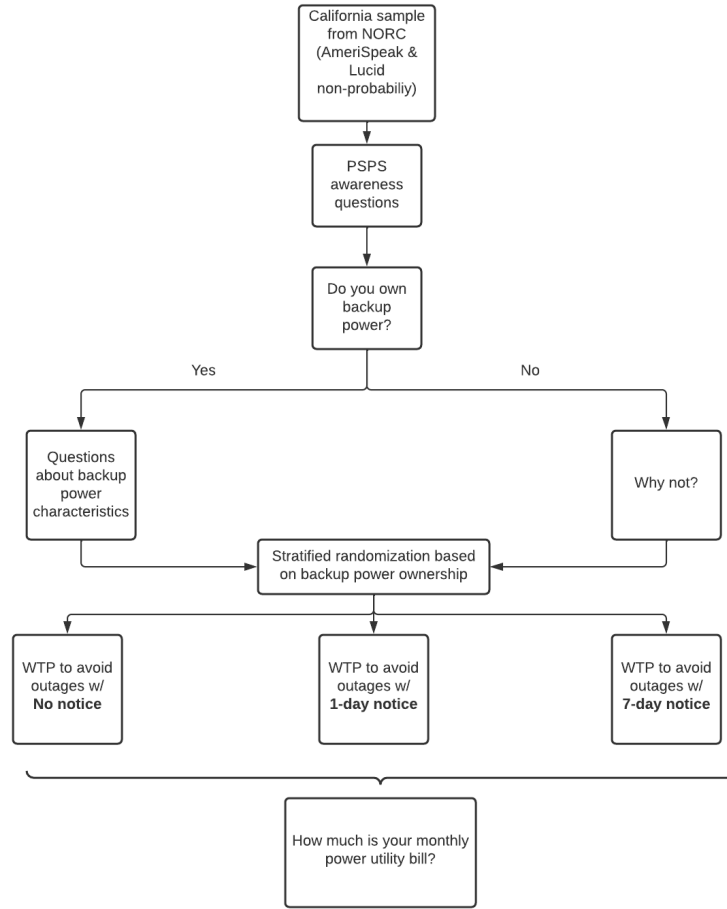


Figure 3.2: Flow diagram illustrating experimental design.

The null hypothesis is that level of advanced notification does not affect the WTP to avoid power outages. Power calculations find that detecting a 15-20% difference in the VoLL would require a sample size of 1500-2500 observations. In total, I collect responses from 2,120 households. Details of these power calculations are provided in the Supplemental Information section.

Eq. 3.1 estimates the effect of notification on the sample's WTP to avoid power outages. I control for back-up power ownership (i.e. either fossil-fuel generator and/or solar/storage system), which aligns with the stratification strategy. Furthermore, I control for a number of demographic characteristics, including education, race, home type, home value, household income, and respondent age.

$$WTP_i = \alpha + \beta_1 T + \beta_2 X_i + \eta_b + \epsilon_i \quad (3.1)$$

Where,

WTP_i = WTP for customer i to avoid power outages, calculated as either \$/month (paid

12 times over the year), % of monthly bill, or \$/kWh

T = indication of 0, 1 or 7-day notice

β_1 = change in WTP for treatment groups

X_i = set of demographic controls

η_b = fixed effect on stratification by back-up power ownership

ϵ_i = error term

In addition to showing the raw WTP outcome from the survey (\$ per month paid 12 times over the year), I also calculate WTP as a % of their reported monthly bill and in \$/kWh, based on an estimate of monthly energy consumption. To convert the \$/month WTP to a \$/kWh, I first multiply the raw WTP by 12 to account for the fact that the experimental question states that the monthly WTP would be added to their monthly bill for an entire year. Then, I estimate the avoided lost load by converting their reported monthly bill into monthly consumption using the Energy Information Agency's \$0.22/kWh estimate of the average residential retail price for electricity in California (EIA) and adjust that monthly kWh to an amount that represents the 80 hours of power outage specified in the experimental question.³

3.3 Results

Responses to non-experimental question

The first questions of the survey focused on respondent experiences and future expectations for sustained power outage events. I draw 3 key conclusions from the responses to these questions. First, I find that almost the entirety of the sample is aware of wildfire-related power outages, though only 25% experienced one. Second, I find that the annual mean expectations for future power outages are relatively low at 12 hours per year per respondent, with that number roughly doubling if respondents experienced a sustained power outage over the last three years (i.e. 2018-2021). Finally, I find that while backup power purchases have increased in recent years, low cost mitigation options like using flashlights and candles remain more popular.

Figure 3.3 summarizes the responses to questions about exposure to historical power outage and expectation for future outages. Almost all of the respondents were aware of the wildfire-related power outage program in California. Of the 2,120 total respondents, only 72 indicated that they were totally unaware of these shutoffs. At the same time, the majority of respondents did not directly experience a sustained power outage themselves ($n = 1368$

³In California, electricity customers do not have one fixed \$/kWh electricity price, rather they are on a mix of time-of-use and increasing block pricing rates. I do not know the rate design of the particular respondents, however, and have to calculate a rough estimate of monthly consumption.

out of 2120). However, roughly half suggested that someone in their social network (e.g. friends, neighbors, family, coworkers) did experience a sustained power outage.

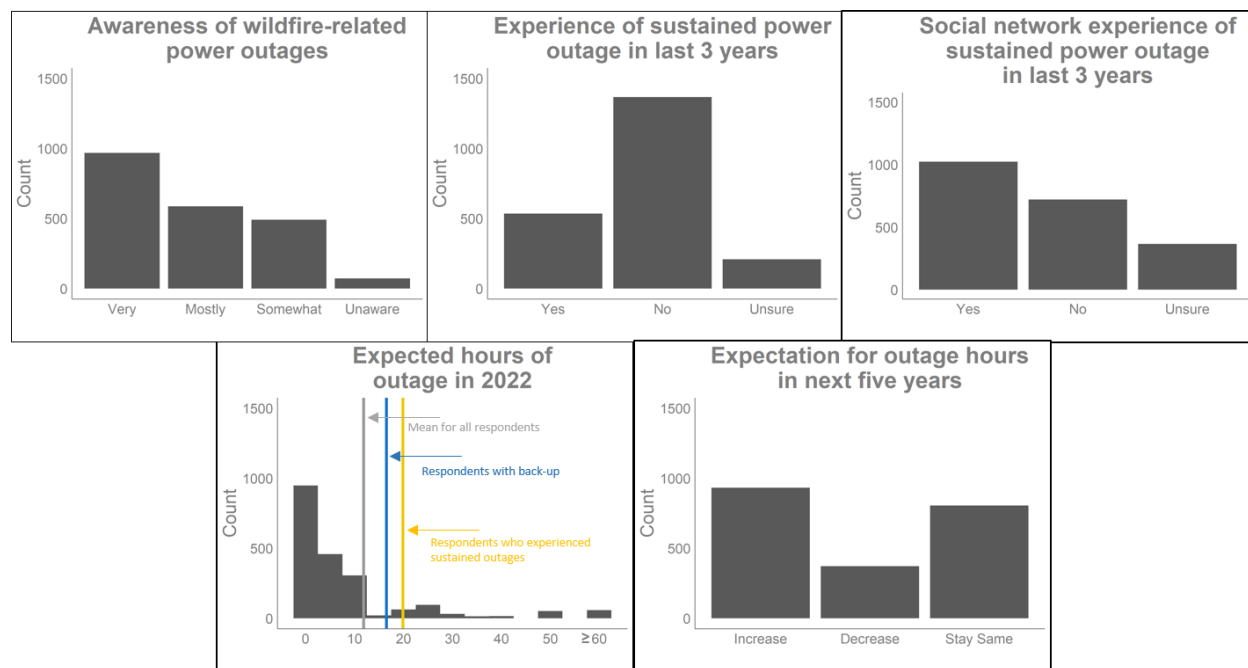


Figure 3.3: Respondent experiences with sustained power outage events, no breakdown

The breakdown of responses to these questions do not vary strongly based on whether respondents owned a backup power system. The one exception to this result was respondents' experience of a sustained power outage. Roughly 35% of respondents who owned backup power indicated they experienced a sustained power outage over the last 3 years, compared to only 20% of non-backup power owning respondents.

While many of the respondents indicated they experienced a sustained power outage event, they correspondingly indicated small expected hours of outage in 2022 (bottom left of Figure 3.3). The majority of respondents expect 0 hours of outage hours in 2022. On average, though, respondents expect 12 hours of outage with a median response of 3 hours. These numbers slightly varied depending on backup power ownership, where backup power owners expect 16.5 hours (median = 4) and non-owners expect 9.5 hours (median = 2). At the same time, 44% of respondents expect that these hours will continue to increase in the next five years while 38% expect the outage hours to stay relatively constant. The remaining 18% of respondents expect a decrease in future outage hours.

Expectations for future outages do substantially increase if respondents are subset by prior exposure to a sustained power outage event, which represents 25% of the sample. This subgroup expects an average of 20 hours of outages (median = 10) in 2022. Though higher than

the average response, this result is notably still lower than the 24 hr threshold used to define a single sustained power outage event in the survey.

The next set of non-experimental questions focused on mitigation strategies respondents would take in the case of a power outage event. The left graph in Figure 3.4 shows that the most common mitigation strategy was the most mundane – use of a flashlight and candles. Over 75% of respondents suggested they would use that mitigation strategy. All of the other strategies had no more than 20% of respondents select it. The right graphic shows that the majority of respondents did not indicate plans to purchase backup power in the next 6 months.

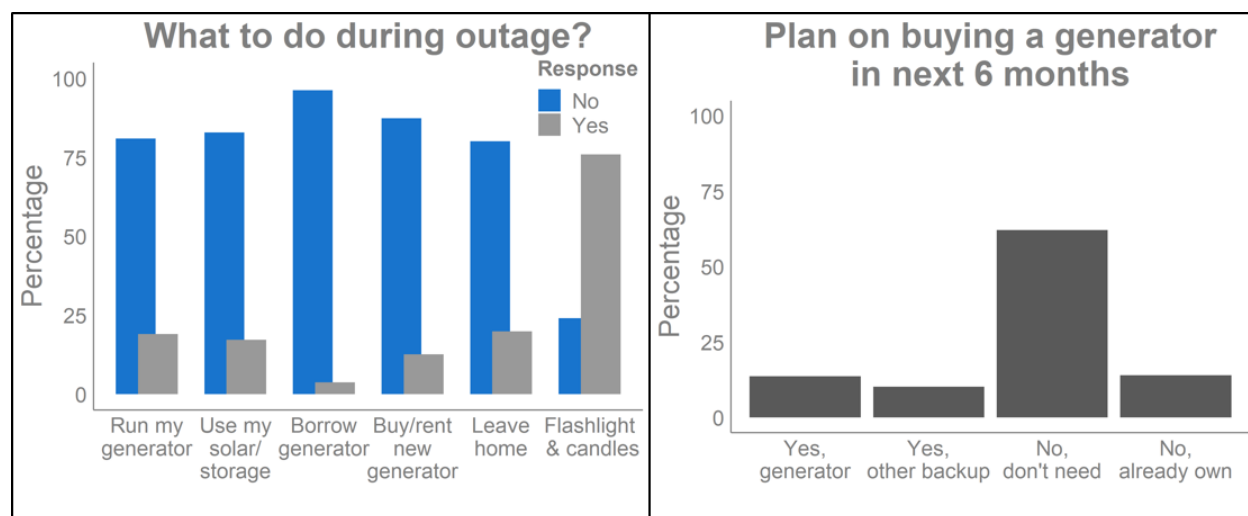


Figure 3.4: Respondent preferences during backup power experience

For respondents who owned backup power, Figure 3.5 shows both when that purchase was made as well as a histogram of the total amount spent on the purchase. There has been a notable increase in backup-power purchases after 2015, predating the experience of PSPS events in California. The majority of respondents spent \$1000 or less on their system, which is somewhat surprising for those that indicate they purchased a solar and/or storage system. Prior work has shown average costs of \$4,000/kW for solar and \$1,000/kWh for batteries with typical system sizes of 6 kW and 13 kWh, implying an overall installation cost of \$37,000. (Barbose et al., 2021).⁴ The survey also asks individuals who did not own backup power why they made this decision. Figure 3.6 shares their top 3 reasons: (1) too expensive, (2) they find other mitigation options, and (3) they do not experience significant outages.

⁴One explanation for this low amount could be that subsidies have been offered in California for certain individuals. The survey did not ask respondents if their cost estimates included or excluded subsidies. Alternatively, it could be that respondents were referencing car battery purchases or other cheaper forms of solar/battery solutions rather than rooftop solar and Lithium-ion batteries.

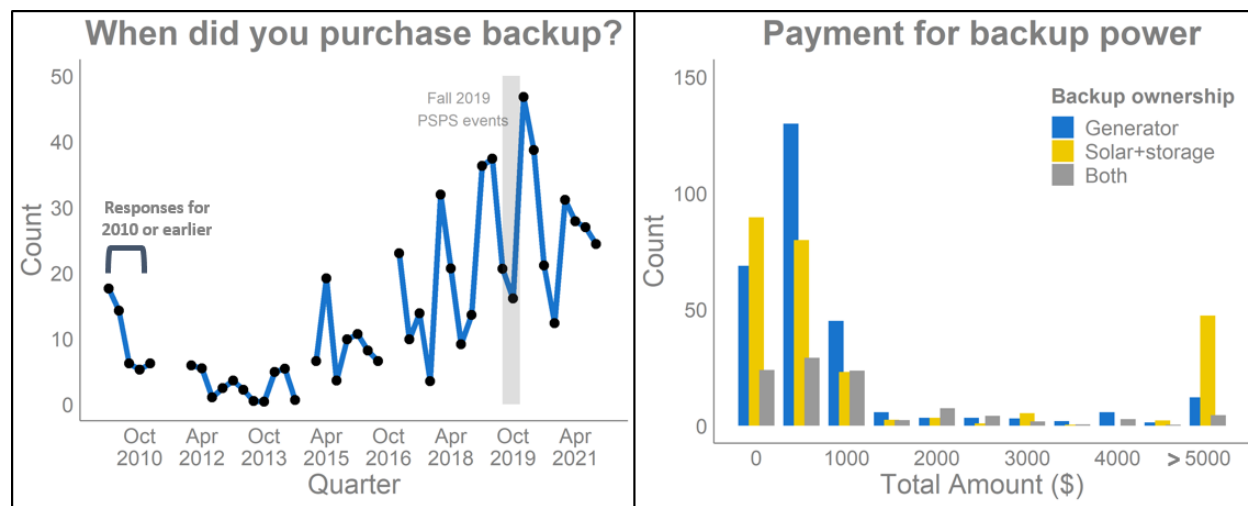


Figure 3.5: Breakdown of when respondents purchased backup power and how much it cost. Gaps in the left graphic indicate that no backup purchases were made in those quarters.

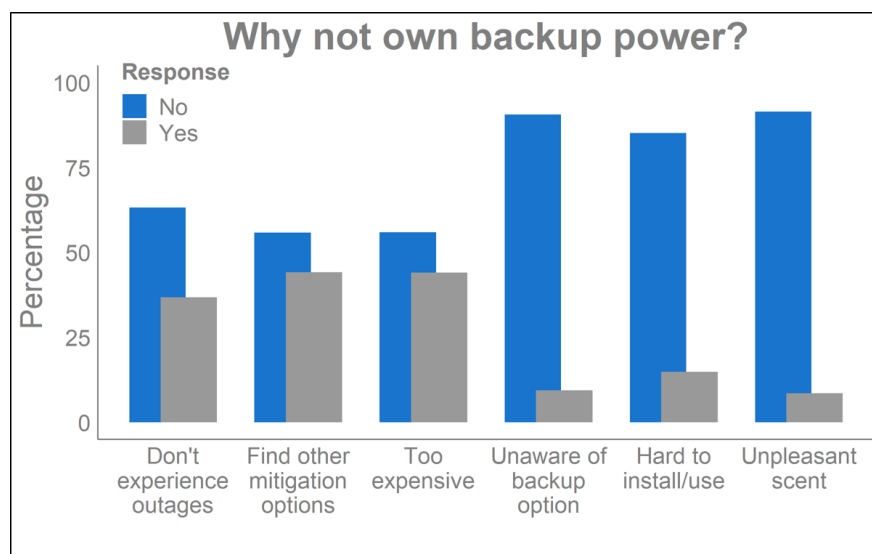


Figure 3.6: Indication for why some respondents did not own backup power.

Experimental effects

Overall, I find that respondents had positive and statistically significant WTP to avoid power outages. The WTP did not depend significantly on the advanced notification of the power outage. Respondents who indicated ownership of back-up power had a higher WTP to avoid power outages than non back-up power owners, a counter intuitive result if one expects back-up power ownership to mitigate the costs of grid power outages.

Table 3.1 presents the results of the regression on the population sample. The preferred specification in the regression applies the demographic and backup power controls, statistical weights from NORC, and robust standard errors. These results are shown in column 4 while columns 1-3 show the addition of various components of the preferred specification. I drop 55 of the 2,120 respondents who skipped the experimental question and find that a 1-day or 7-day notification results in a lower WTP. This coefficient is not statistically significant across any of the specifications. Prior research has suggested that notification would allow for preparation and substitution away from electricity during the outage, aligning with the direction of the findings. However, the insignificance of the effect shows that there was no measurable effect of notification on a consumer's power outage cost within our sample, suggesting that notification may not have a central impact on WTP. Still, notification did serve to reduce WTP amounts between 10-20%.

	WTP (\$/month)	WTP (\$/month)	WTP (\$/month)	WTP (\$/month)	WTP (% bill)	VoLL (\$/kWh)
	[1]	[2]	[3]	[4]	[5]	[6]
Intercept	85.7431*** (11.086)	56.4235*** (11.9559)	49.2175*** (9.1346)	264.1829*** (68.1596)	46.5351*** (6.6884)	11.0567*** (1.5892)
1-day notice	-15.8327 (15.7469)	-14.3929 (15.6068)	-13.4846 (13.8648)	-24.8469 (21.4403)	-6.2582 (9.1073)	-1.487 (2.1639)
7-day notice	-6.2222 (15.6893)	-5.7045 (15.5483)	-0.7902 (14.7865)	-21.5694 (22.4991)	-7.8372 (8.5458)	-1.8621 (2.0305)
Back-up ownership	NA NA	83.2726*** (13.3961)	74.7145*** (16.2609)	79.5726*** (20.256)	17.6575* (10.5273)	4.1954* (2.5013)
Backup ownership control	No	Yes	Yes	Yes	Yes	Yes
Weighted	No	No	Yes	Yes	Yes	Yes
Robust s.e	No	No	Yes	Yes	Yes	Yes
Demographic controls	No	No	No	Yes	No	No
Subsample	full	full	full	full	>\$10, no solar	>\$10, no solar
Total observations (n)	2,065	2,065	2,065	2,065	1,629	1,629
Ownership (n)	711	711	711	711	331	331

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3.1: Comparison of regression results across a variety of specifications.

The average WTP to avoid power outages was positive and significant, as suggested by the intercept coefficient. Without applying any controls, this coefficient equals \$86/month, representing the average WTP for the respondents that received no notice of the power outage event. The interpretation of the intercept coefficient when applying all controls is the expected mean of observations of the sample without backup power living in a single-family detached household with 1 individual without a high school education, aged between 18-30, and having a home value less than \$50,000 and household income less than \$35,000. The heterogeneity across these demographic categories is discussed in the next section.

The backup power ownership row shows the coefficient associated with the fixed effect on the stratification variable, backup power ownership. I find that respondents who indicate that they owned backup power reported a statistically significant higher WTP to avoid outages. Notably, respondents who owned generators had a higher WTP than respondents who just owned solar/storage systems. Respondents who indicated ownership of both generators and solar/storage had the highest WTP (see Figure 3.7). I propose three interpretations of this result. Prior researchers have found that ownership of backup power should mitigate power outage events and therefore lead to a lower WTP and VoLL, results that appear to conflict with the findings (LaCommare et al., 2018).

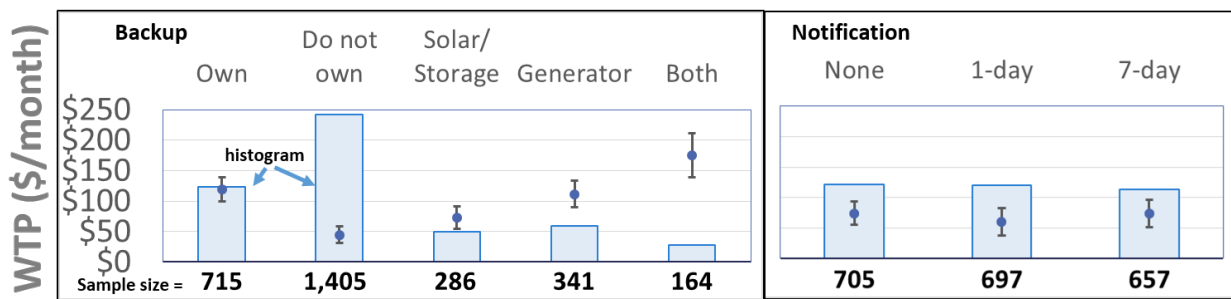


Figure 3.7: Comparison of treatment effect with effect from backup ownership with 95% confidence intervals

One explanation could be that respondents were not considering their mitigation ability when submitting their survey responses and thus are reporting their full WTP to avoid outages as if they were not able to mitigate the outages in the experimental question (scenario (a) in Figure 3.8). Their higher WTP, therefore, would align with their decision to purchase backup power. An alternative explanation, however, could be that these respondents purchased backup power technologies that cannot fulfill their entire electricity demands during outage events. Therefore, even though their backup power would be expected to meet their most critical and valuable electricity needs, some electric demand would still be lost. Under such a situation, if one further assumes that respondents who install backup power have significantly higher demand curves compared with respondents without backup power, the backup power owners could have higher WTP even with some mitigation capability (scenario (b) in Figure 3.8). Finally, I cannot rule out that anchoring may have led to higher WTP in the back-up power respondents as they were provided questions about how much they spent on prior back-up power purchases before answering the experimental question. Non back-up power owners were not exposed to a similar question. This last explanation, however, would not explain the difference found between respondents who only owned solar/storage vs. those who owned generators, as both these groups were exposed to the purchase price question.

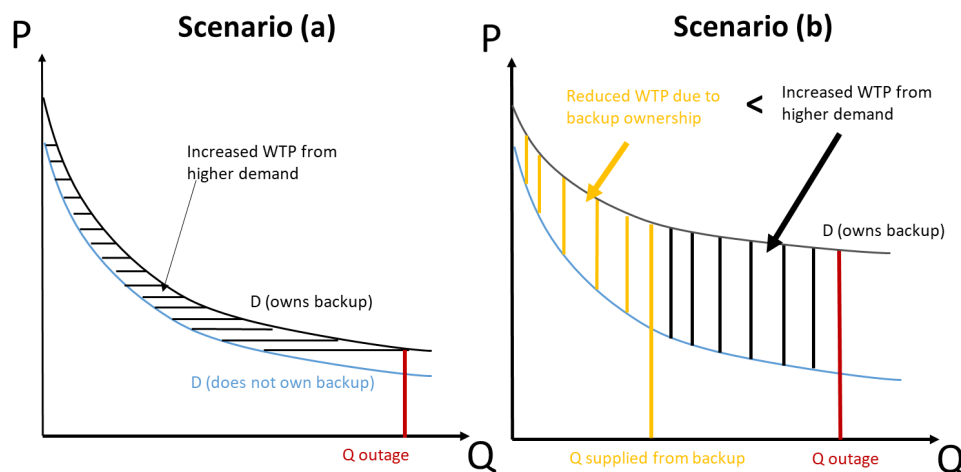


Figure 3.8: Hypotheses of demand variation with backup power and relation to overall WTP

In addition to showing the raw respondent WTP, Table 3.1 also shows the results as a % monthly bill and a \$/kWh metric. These results have a smaller sample size due to three additional filtering steps performed on the sample. First, I must drop respondents who skipped the monthly billing question. Second, I drop respondents who report having solar installed. Given net energy metering subsidies provided in California, the presence of solar could undermine the meaning of the reported monthly billing data which is needed to convert the raw WTP figure. Third, I drop customers who report monthly bills less than \$10, given the likelihood of erroneous data entry.

Despite the sample change, the results remain qualitatively the same. I find reductions in WTP to avoid outages as a result of the treatment notification but these reductions are not statistically significant. I similarly find reductions in WTP for the sample who do not own back-up power generators, though with less significance than the baseline results, likely because I drop roughly half of the backup power ownership sample since they own solar generators.

I calculate an average VoLL of \$11/kWh for respondents who do not own backup power, which is on the high side but still within the range (i.e. \$1/kWh - \$20/kWh) of results found in prior literature reviews that measure WTP (Schröder and Kuckshinrichs, 2015). Baik et al is the latest study to apply similar methods as this chapter, though with a slightly different scenario: A 10-day blackout during a very cold winter. They find an average VoLL of \$2/kWh among respondents (Baik et al., 2020). It is possible the difference between these results is driven by the different scenarios and contexts studied. However, a particular challenge with

this chapter's experiment is that it specifies that respondents would be charged 12 monthly fees to avoid power outages. It is possible that confusion over the yearly payment could be leading to the higher VoLL estimate. The small standard errors around the VoLL estimate, though, suggest that respondents had similar interpretations of the question. Nevertheless, if one believes respondents did not understand the yearly fee structure, the top level VoLL estimates should be divided by either 6 or 12, reducing the VoLL to be between \$1-2/kWh.⁵

Heterogeneity analysis

Figure 3.9 shows the distribution of responses to the experimental question, broken out by randomized notification assignment. The insignificant effect of notification on WTP reported in the above section on the regression analysis is corroborated by limited difference in the distribution of responses.

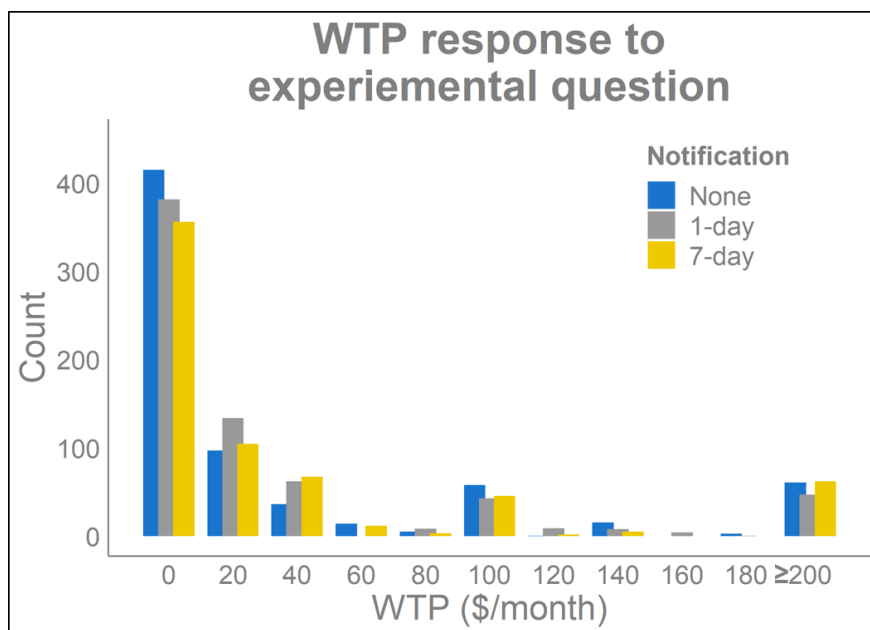


Figure 3.9: Histogram on WTP by randomized notification

I performed a descriptive analysis across the key demographic controls by running linear regressions of the WTP responses against each demographic control independently and then calculating the linear combination of the intercept with the different categories of the control specification. Figure 3.10 presents information on how the key financial controls (i.e. home type, home value, and household income) correlate with the WTP to avoid power outages. I

⁵The choice for 6 would be driven by the fact that the survey stated that the respondents would experience 2 distinct outages, so respondents could have interpreted payment as being applied over 2 separate months.

find little trend between home type and WTP, but these results are partially due to limited sample between some of the home categories.⁶

I find that home value is negatively correlated with the WTP to avoid outages. Respondents with high home values are willing to pay less to avoid outages. This finding is somewhat counter intuitive if one believes ability to pay is positively correlated with home value and could suggest that higher net worth individuals are less impacted by power outages. One hypothesis is that they have more substitution options available to them to mitigate the cost of a power outage. I see a similar decrease in WTP when moving from low-income to high-income respondents. However, this result was both smaller and less statistically significant than the home value result.

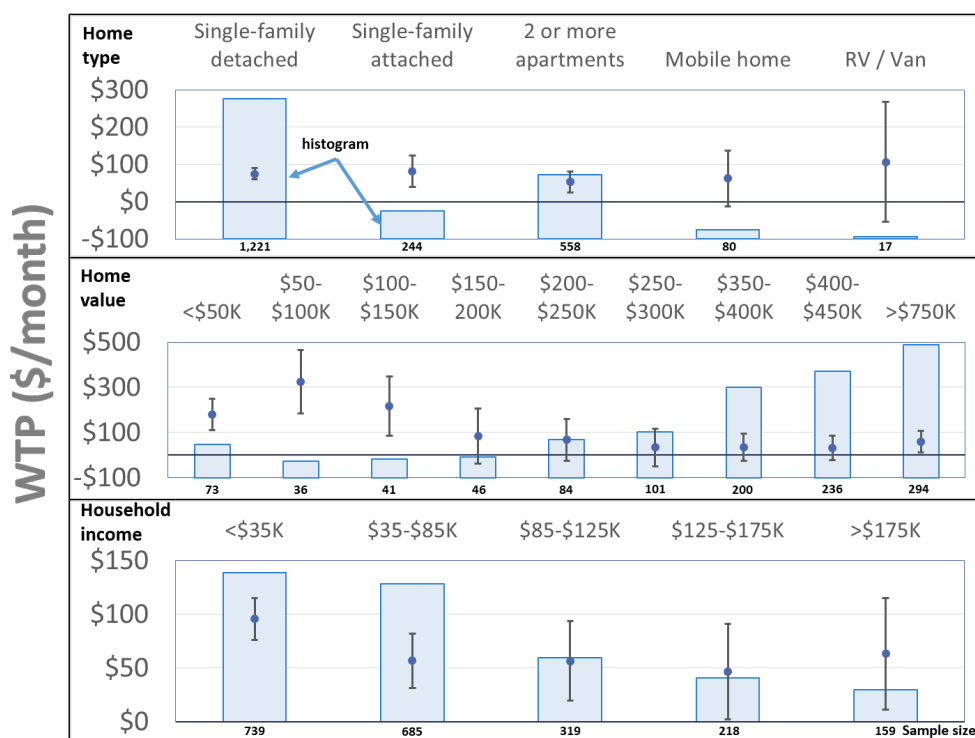


Figure 3.10: Variation on WTP by respondent characteristics (i.e. home type, home value, and household income)

Figure 3.11 presents information on the additional demographic controls (i.e. household size, education, race, and age). I find black and hispanic respondents reported higher WTP than

⁶Of particular note is that when I run the regression when controlling for all demographic controls at once, the last categories of home type (i.e. mobile homes and RV / van ownership) become statistically different from the null hypothesis of no change in WTP. These results suggest a lower WTP between \$150-250/month. This result aligns with the intuition that individuals with these home types are likely less reliant on electricity from the grid.

white and asian respondents, though this result is not statistically significant once controlling for other demographic variables. There is a large WTP increase between respondents without and with a high school education, but this increase does not exist for further education levels (i.e. vocational, bachelors, post-grad). Households with 2 or more individuals reported a lower WTP than households with 1 individual. Finally, older respondents reported a lower WTP than their younger counterparts. One hypothesis of such a result is that younger respondents have a higher value for electricity given different generational use-cases for electricity. In the COVID era, a time-frame relevant to the survey given its release in December 2021, more work has been happening in the household, which could have a larger impact on younger individuals.

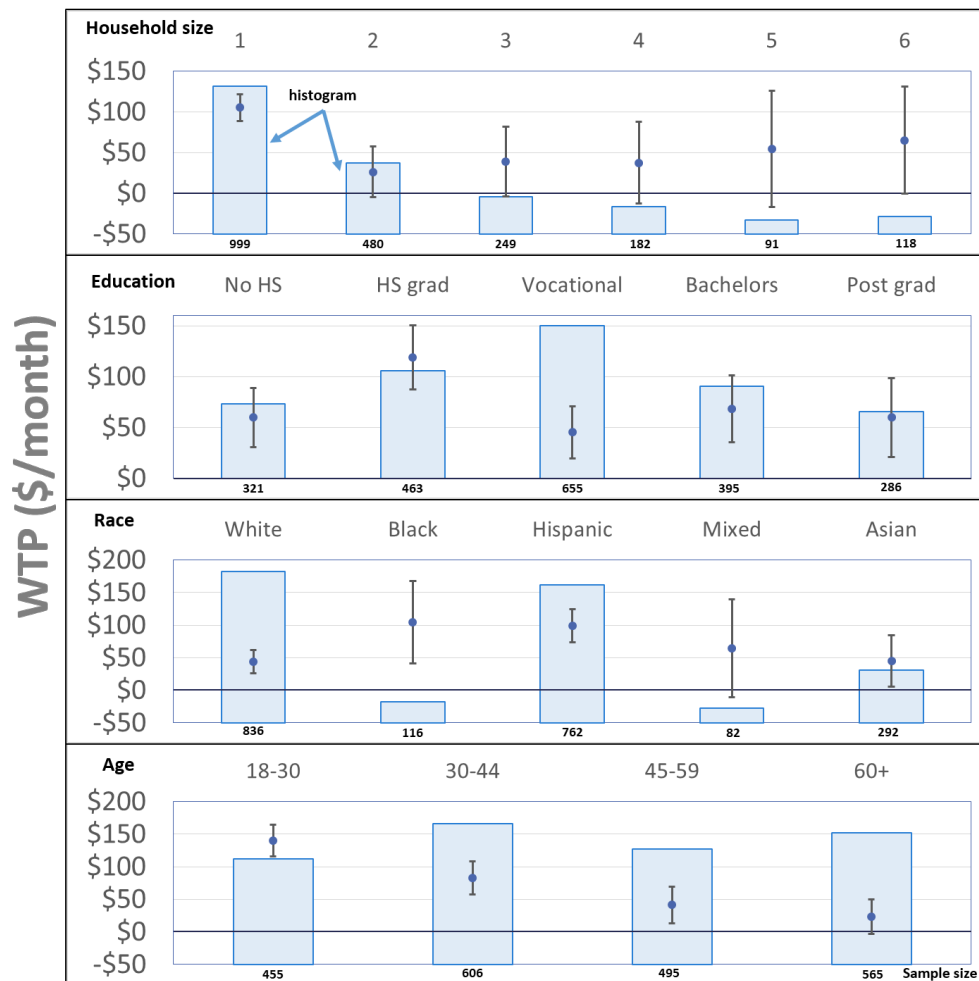


Figure 3.11: Variation on WTP by respondent characteristics (i.e. household size, education, race, and age)

3.4 Conclusions

In the stated-preference experiment, I found positive and statistically significant WTP to avoid power outages, consistent with the expectation that outages are costly to the residential sector. Furthermore, I found that advanced notice of a power outage can reduce the WTP to avoid those power outages, consistent with the hypothesis that notice can allow customers to plan substitution strategies that help mitigate power outage costs. However, the results are not statistically significant. The insignificance of the effect shows that there was no measurable effect of notification on a consumer's power outage cost within our sample, suggesting that notification may not have a central impact on WTP. Still, notification did serve to reduce WTP amounts between 10-20%.

These results were robust over a number of regression specifications that controlled for demographic variables and applied the survey weights provided by NORC. An exploration of heterogeneity suggested that household wealth (proxied using estimated home value) is negatively correlated with WTP, a counter intuitive result if one expects that ability to pay to be positively correlated with WTP outcomes. This relationship, however, is not present with household income, which was not a strong determinant of respondents' WTP. These results have implications for equity analyses which might try to estimate how the distribution of WTP to avoid outages differs between low-income and high-income houses. As mentioned in the introduction, there are limitations to applying the results given the limitations of stated preference methodologies and the lack of any serious budget constraint being applied to the respondents.

On average, respondents did not have high expectations for the number of future outage hours. This result was true even when segmenting out customers who experienced a sustained power outage between 2019-2021. Such a result implies that households in California expect limited impact from future PSPS events. Future researchers could use such a result to study how these expectations may or may not lead to defensive investments that might mitigate power outage costs.

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Chapter 4

A revealed preference estimate of the WTP to avoid power outages: A California case study

4.1 Introduction

As discussed in preceding chapters, electric power outages are costly and negatively impact individuals, businesses, and governments. For individuals, outages result in the loss of food, access to leisure activities, and potentially vital health services such as breathing machines. For businesses, electricity is often critical to serving customers and earning revenues while governments rely on electricity to provide vital public services.

In high-income countries, however, power outages are relatively rare ([Arlet, 2017](#)). This outcome is, in part, the result of regulatory decisions. In the United States, many jurisdictions impose “resource adequacy” requirements on load serving entities (LSEs) which specify that they must procure enough electricity supplies to meet forecasted peak electricity demands plus a 15% planning reserve margin ([Spees et al., 2013](#)). These requirements place a high premium on reliability. Because of the lack of time-varying pricing and the inelastic demand for electricity ([Lijesen, 2007](#)), the resource adequacy requirement means that power plants are built and maintained which may rarely operate, imposing a significant cost on society.

Beyond resource adequacy decisions, grid planners and regulators invest in grid hardening technologies that make the distribution and transmission system more resilient to outages ([Moreno et al., 2020](#)). These investments are important because the distribution network accounts for the majority of power outages in modern electricity systems ([Eto et al., 2019](#)).¹ Though distribution system outages tend to be localized and short in duration, caused by

¹Past research in the United States found that the distribution network incurs between 92-94% of all power interruptions, a breakdown that has been consistent overtime.

vegetation interference at individual circuits ([Graziano et al., 2020](#)),² they can also extend for long periods of time and impact a wide area if large portions of the network are taken offline by extreme weather events ([Forssén et al., 2017](#)). The distribution network, built predominantly with above-ground equipment, is particularly vulnerable to geographic circumstances and ambient weather conditions ([Larsen, 2016](#)).

To choose the optimal level of resource adequacy and grid hardening investments, grid planners need to understand the value of reliable electricity supply to consumers. Investments in resiliency enhancing solutions can be costly and balancing the benefits of avoiding power outages with the cost of electric grid investments is a long-studied and fundamental trade-off in energy economics and electricity system design ([Telson, 1975](#); [Crew and Kleindorfer, 1978](#); [Munasinghe and Gellerson, 1979](#)).

To better evaluate this trade-off, economists and engineers rely on estimates of the value of lost load (VoLL), a monetary indicator expressing the value associated with reducing power outages ([Schröder and Kuckshinrichs, 2015](#)). For long-run planning, the VoLL is a key parameter in decisions to upgrade transmission and distribution infrastructure. The recent actions by California utilities to shutoff power in order to reduce the chance that utility infrastructure ignites fires highlights an important use for the VoLL: making the relevant cost-benefit trade-offs between lowering the probability of wildfires and blacking out households and businesses ([Abatzoglou et al., 2020](#)). In wholesale power market operations, the VoLL is used by market regulators to set price caps and determine which measures a system operator should take during scarcity conditions ([Fraye et al., 2013](#); [Pfeifenberger et al., 2013](#)). When accurately measured, the VoLL supplies electricity system designers with the information needed to decide how much society should invest to improve resiliency and reliability outcomes.

Estimating the VoLL, however, is not straightforward and existing strategies rely mainly on one of two approaches: (1) stated preference measures which ask customers directly how much they value avoiding power outages or (2) production function methods which use macroeconomic input-output datasets for individual firms or entire economies ([Caves et al., 1990](#)). These approaches are especially common in high-income countries where experimental research designs with random assignment of reliability outcomes are infeasible due to equity and access concerns in a system which already maintains a high amount of reliability ([Fowle et al., 2018](#)).

In the stated preferences approach, households and/or firms are typically asked either how much they would be willing to pay (WTP) to avoid a hypothetical power outage or how much they would have to be paid in order to accept (WTA) a hypothetical outage. Many of these studies exist for populations in the United States ([Baik et al., 2020](#); [Chowdhury et al.,](#)

²Or squirrels, see: [cybersquirrel website](#)

2004; Sullivan et al., 2009) and Western Europe (Praktijnjo, 2014; Economics, 2013) and have estimated a wide range between \$1–300/kWh for the VoLL (Schröder and Kuckshinrichs, 2015).

In part, this large range is due to the heterogeneity of contexts studied (i.e. various high-income countries, different customer types, and differing lengths of outages). However, a number of economists have critiqued stated preference approaches, arguing that they are not based on real situations or real behavior and that they can lead to very different answers depending on how the questions are framed (Hausman, 2012). These biases are commonly referred to as hypothetical response bias, where people say different things from what they do, and the embedding/scope problem, where the replies elicited by the research design are not well-defined or stable. Stated preferences shortcomings are oftentimes evidenced by large differences between WTP and WTA estimates for the same underlying decision when, theoretically, the WTP and WTA should be equal (Hartman et al., 1991), and stated preferences estimates have been shown to be quite sensitive to framing and subject to status quo bias (Schröder and Kuckshinrichs, 2015).

Developing production functions is the second method commonly used to estimate the VoLL. In these studies, authors estimate (or, more commonly, calibrate) a representative electricity-using firm’s or economy’s production function using data on outputs, electricity, and other inputs (Shipley et al., 1972). They then calculate the implied effect of a power outage by constructing an estimate of output in the absence of power (Munasinghe and Gellerson, 1979). A similar method is used for households, where researchers estimate either a household income production function or a leisure production function (Becker, 1965). The most recent existing literature using these methods is concentrated in Western Europe, and includes Leahy and Tol (2011) in Ireland; de Nooij et al. (2007) in the Netherlands; Praktijnjo et al. (2011), Growitsch et al. (2015), and Röpke (2013) in Germany. The major downside to these approaches is that they rely heavily on modeling assumptions that are often oversimplified and hard to verify (Sanghvi, 1982).

The reliance on these methodological approaches have posed serious challenges to system designers tasked with making optimal system investments. As electricity systems worldwide incorporate more variable renewable generating sources, such as solar and wind, and the resilience of electricity networks are challenged due to climate change (Chen et al., 2017), regulators and system operators will only be faced with new reliability investment decisions. In the past decade, natural disasters such as Hurricane Maria in Puerto Rico, electricity-induced wildfires in California, and Superstorm Sandy in the Northeast has led to increasing calls for grid hardening (Walton, 2017). However, the fundamental question remains: how much grid hardening is optimal? With the shortcomings of the methods used to estimate the VoLL in high-income countries, there is a need to identify alternative estimating strategies.

In this chapter, we develop a novel, revealed preference VoLL estimation method which relies

on quasi-experimental variation in power outages to estimate the causal effects of blackouts on backup power adoption. We then transform adoption trends into an implied VoLL. To the best of our knowledge, there exists no such evidence from the United States or other high-income countries. In the developing world, there is a burgeoning literature using revealed preference approaches. These include [Allcott et al. \(2016\)](#), who use quasi-random variation in power supply reliability to estimate the effects of blackouts on firm productivity in India; Berkouwer, Puller, and Wolfram (in progress), who study the long-run effects of reliability in Ghana on firms and households by using spatial discontinuities in reliability based on designated “priority feeders”; and [Jha et al. \(2021\)](#), who use high frequency variation in power supply reliability to estimate the effects of outages on small firms with and without backup power in India.

Of course, a limitation of these projects is that they have low external validity in high-income countries: households and firms may behave differently across geographies given differing reliability and income levels ([Arlet, 2017](#)). [Carlsson et al. \(2011\)](#) is perhaps the closest developed-world study to our proposed work: they survey Swedish households about WTP before and after actual power outages. However, many things may confound a simple before-after comparison, and these measures of WTP are still stated preference measurements.

Instead, we study how the adoption of solar and storage technologies was impacted by the more than 2 million power safety public shutoffs (PSPS) that occurred in Northern California in Pacific Gas and Electric’s (PG&E’s) utility service territory in 2019. This large scale power outage event provides an opportunity to study how the adoption of costly resiliency enhancing technologies is driven by individual concern over reliability, leading ultimately to a revealed preference estimate of the willingness-to-pay to avoid power outages. The research design involves a regression discontinuity that estimates the difference in adoption trends between neighbors who experience different amounts of power outages. Our research design takes advantage of PG&E’s differential use of neighboring electrical feeder lines to mitigate wildfire risk.

The chapter proceeds as follows: Sections 2, 3, and 4 describe the PSPS context in California, our empirical strategies, and our data. Section 5 presents impacts of the PSPS in PG&E’s service territory on backup power adoption. Section 6 presents our calculations of the VoLL which uses revealed preference estimates of backup power adoption from section 5. Section 7 discusses challenges and limitations of the research, while section 8 concludes.

4.2 Background: California’s public safety power shutoff program

Wildfire occurrence, total area burned, and average fire size all display an upward trend in California over the last several decades (Feo et al., 2020). Of the top 20 most destructive wildfires in California’s history, 15 have occurred since 2015 (CalFire, 2021). Some of these record-breaking wildfires resulted in serious loss of life and billions of dollars in damages. The 2018 Camp fire destroyed the town of Paradise, burned over 18,000 structures, and resulted in 85 deaths (CalFire), making it the United State’s deadliest fire in a century. Damage estimates for the fire exceed \$16 billion and PG&E, the utility response for the ignition, filed for bankruptcy following the fire citing expected wildfire liabilities of \$30 billion (Johnson, 2019; Westervelt and Schwartz, 2019).

Electric utility equipment is not an uncommon cause of wildfires in California. Estimates from Cal Fire, the state agency tasked with wildfire management, suggest that utility equipment has been responsible for 12, 9, and 10% of wildfire ignitions and 53, 23, and 65% of the resulting burned acreage in the state during the 2017, 2018, and 2019 wildfire seasons, respectively (CalFire, 2019). Though powerlines account for a minority percentage of ignitions, almost half of the 20 most destructive fires in state history were caused by powerlines (CalFire, 2021). This outcome follows from the fact that powerlines and therefore powerline-induced wildfires are often near human development (Abatzoglou et al., 2020).

In 2012, the California Public Utilities Commission (CPUC), the state agency tasked with electric utility regulation, gave electric utilities authority to shut off electricity service in order to prevent wildfires via the Public Safety Power Shutoff (PSPS) Program. As Figure 4.1 shows, this program was used sparingly by the state’s three largest utilities (i.e. San Diego Gas and Electric (SDG&E), Southern California Edison (SCE), and PG&E) until recent years. In July 2018, after the destructive 2017 wildfire season, the CPUC issued Resolution ESRB-8 which increased support for the use of de-energization as a means to mitigate wildfire risks and established key notification and reporting requirements (CPUC, 2021).

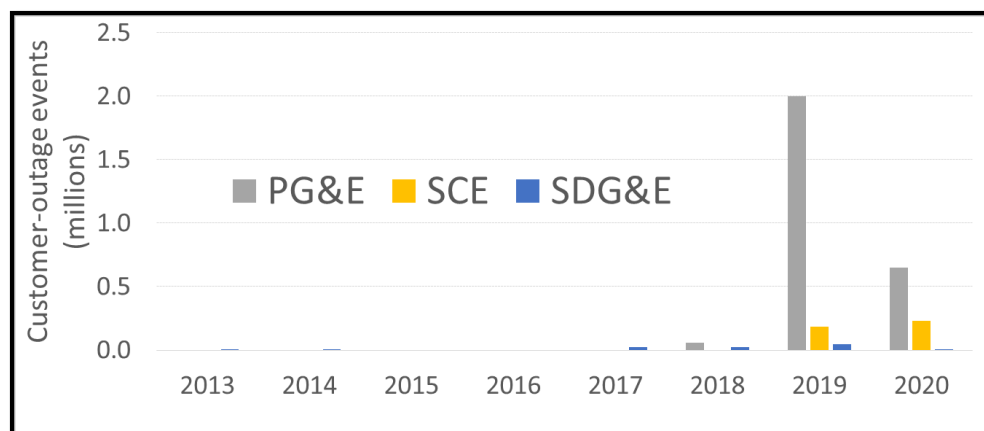


Figure 4.1: Number of customers impacted by power safety public shutoffs in three largest investor owned utilities in California

This ruling led to widespread use of the strategy in PG&E’s service territory. In 2019, PG&E initiated almost 2 million customer-outage events, which compares to only 60,000 customer-outage events in 2018 and 0 customer-outage events in 2017. Figure 4.1 emphasizes the relatively high usage of PSPS events as a mitigation strategy in PG&E’s service territory as compared to the two other large electric utilities in California. PG&E, SCE, and SDG&E deliver power to roughly 4.8, 4.5, and 1.3 million residential households, respectively (EIA, 2021).³

In order to determine whether to implement a PSPS event, PG&E combines weather forecasting, fire risk modeling, and geospatial analysis of its transmission and distribution system footprint. High-risk fire conditions involve the combination of high wind speeds, low fuel moisture, and low relative humidity. Predictions of these weather characteristics are combined with a model of the likelihood of utility equipment failure and the potential for a resulting catastrophic fire. If the high risk conditions are met, PG&E de-energizes individual circuits within the at-risk geographic area, up to a resolution of 4 square kilometers. Further details are outlined in PG&E’s PSPS policies and procedures reference materials (PG&E, 2021a,b).

Importantly, PG&E targets shutoffs in areas where their electrical equipment pose exceptionally high fire ignition risk. Figure 4.2 provides a summary of the circuits PG&E shutoff during the 2019 PSPS as well as wildfire risk zones released by the CPUC. The zoomed in area highlights the alignment between high fire risk areas, which are more commonly in wildland-urban interfaces (WUI), and the circuits that were shutoff (shown in green).

³Though Community Choice Aggregators have become responsible for procuring energy for a subset of customers that historically had been served by these IOUs, the IOUs maintain responsibility for delivery through their transmission and distribution networks.

As evidenced by this figure, not all customers in PG&E were equally impacted by the implementation of the PSPS program (see discontinuity between green and black circuits in Figure 4.2). Distribution feeders are oftentimes the most granular unit of control utilities have over their networks and are often the focus of their PSPS shutoff strategy. Therefore, across-the-street neighbors whom are served by different electricity feeders can be exposed to different levels of PSPS outages, resulting in significant geographic discontinuities in PSPS experience. We rely on these discontinuities to implement our empirical strategy, discussed in greater detail in the next section.

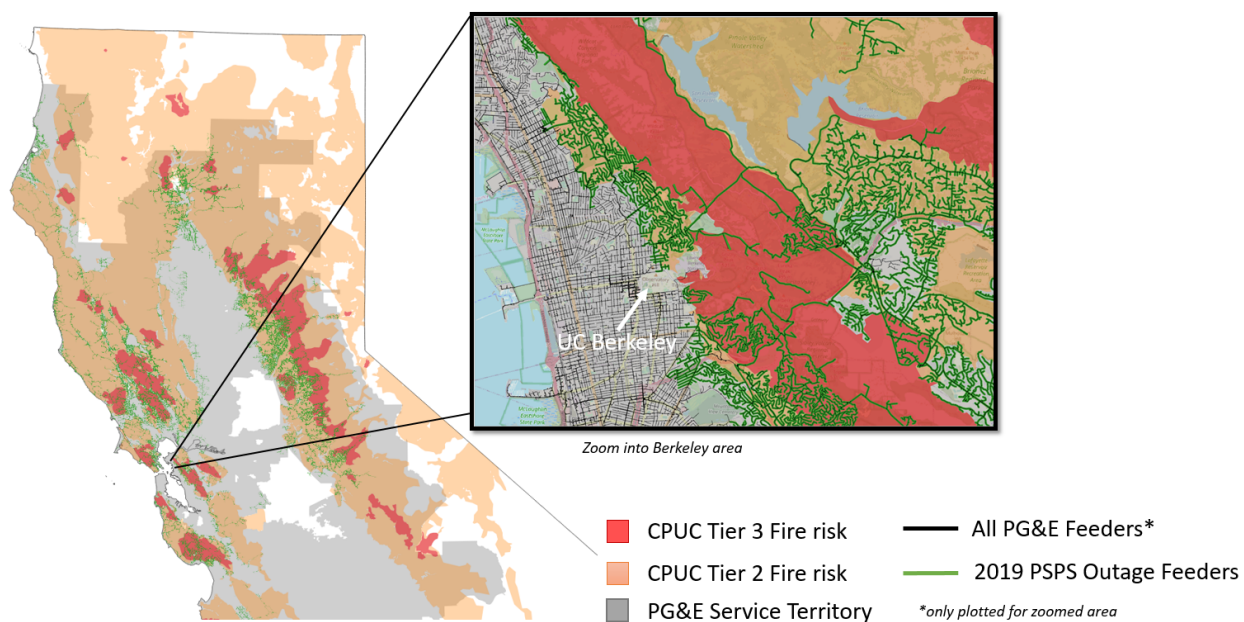


Figure 4.2: Maps of 2019 PSPS outage feeders in PG&E's service territory combined with CPUC's fire risk areas. Tier 3 risk is higher than Tier 2.

California wildfire season typically begins in late summer and can last through December. PSPS shutoffs, therefore, are not implemented year round but occur over the period of a number of months. During the 2019 fire season, PG&E initiated their first PSPS event in June while the two largest PSPS events occurred in October. The second largest event started on October 9th, lasted 3 days, and affected up to 730,000 customers. The largest event started on October 26th, lasted 5 days, and affected 941,000 customers. Given the overlap in wildfire risk areas, many of the customers who were shutoff in the first October event were also shutoff in the second. Figure 4.3 presents all 7 PSPS events that were called in the fall of 2019 in PG&E's service territory and the corresponding amount of customers impacted.

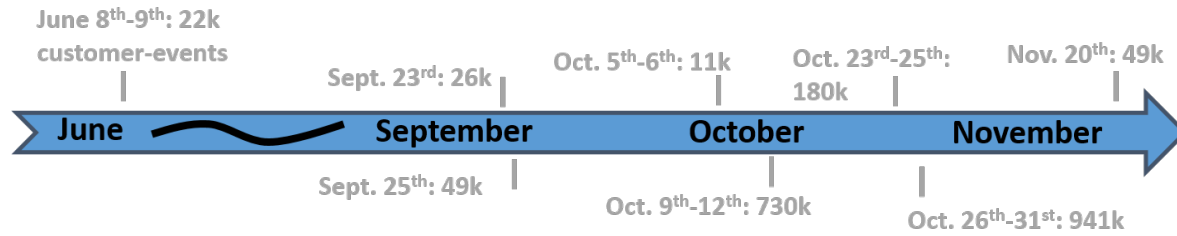


Figure 4.3: Timeline of the various PSPS events called in the fall of 2019

Overall, our focus on the California context affords us the opportunity to study the impact of reliability using a quasi-experimental approach that is relatively uncommon in high-income country contexts.

4.3 Empirical strategy

Geospatial regression discontinuity design

We estimate a sharp geospatial RD design by using the distance a residential PG&E customer is from the border of a neighboring distribution feeder that experienced a different amount of PSPS outage hours. The running variable cutoff point represents the line segment that runs between neighboring feeders (referred to as ‘feeder-pairs’ in this chapter). To conduct this experimental design, we develop a full dataset comprised of 623 distinct feeder-pairs with 440,000 individual residential homes. Our ultimate analyses applied various subsets of this full dataset and are described in greater detail in the data section of this chapter.

There are two main identifying assumption needed for this RD specification. We first have to assume that individuals living within a short geographic distance are indistinguishable across observable and unobservable covariates that might be correlated with our outcome variables of interest. Though we cannot fully test this assumption, we analyze pre-PSPS covariates (i.e. solar and storage adoption, bill amount, monthly electric consumption) across our discontinuity. We are aware of one California public policy choice which specifically targets PSPS exposure and therefore might also be seen as treatment. The CPUC’s Self-Generation Incentive Program (SGIP) offers rebates for installing energy storage technologies. They implement a Equity Resiliency program that fully subsidizes the cost of storage for individuals that either live in a Tier 2 or 3 fire risk area or experienced more than 1 PSPS event. However, to be eligible for the subsidy, the residential customers must also be low-income, eligible for medical baseline, or reliant on electricity well pumps for water supplies.⁴ We test our treatment effects by sub-sampling households that are not likely to qualify for these

⁴More information on the SGIP program can be accessed at: [this link](#).

rebates in order to remove this confounding program impact.⁵

We define our pre-PSPS time period by identifying the date that a specific feeder-pair experienced their first PSPS event. There is a concern that treatment might have occurred before a specific event if customers in PG&E’s territory became aware of the PSPS program before fire season. Analysis of google trends data searching for terms ‘PSPS’ or ‘Public Safety Power Shutoff’, however, reveals that though PG&E had communicated the possibility of PSPS events occurring, the majority of internet activity investigating the program occurred in tandem with the experienced events (See Appendix C Figure C.1). Furthermore, the application and installation process for solar and storage systems can take multiple months, suggesting that our identification of treatment as post-PSPS experience as conservative (i.e. as opposed to a few months after PSPS).

The second identification assumption is that our running variable (i.e. distance to border) is not manipulable around the threshold. This assumption likely holds as feeder boundaries are a technical feature of electric infrastructure that are not easily accessible and interpretable by non-experts. Thus, it would be difficult for residential household selection by such an attribute, especially when compared to other common neighborhood selection decisions such as school district. Furthermore, publicly available maps from the CPUC of at-risk locations indicate different geographic boundaries than our 2019 outage feeders shown in Figure 4.2. Figure 4.4 shows no evidence of bunching around our feeder-pair borders. We use rural-urban commuting area (RUCA) codes to break out our sample between three different land categories.⁶

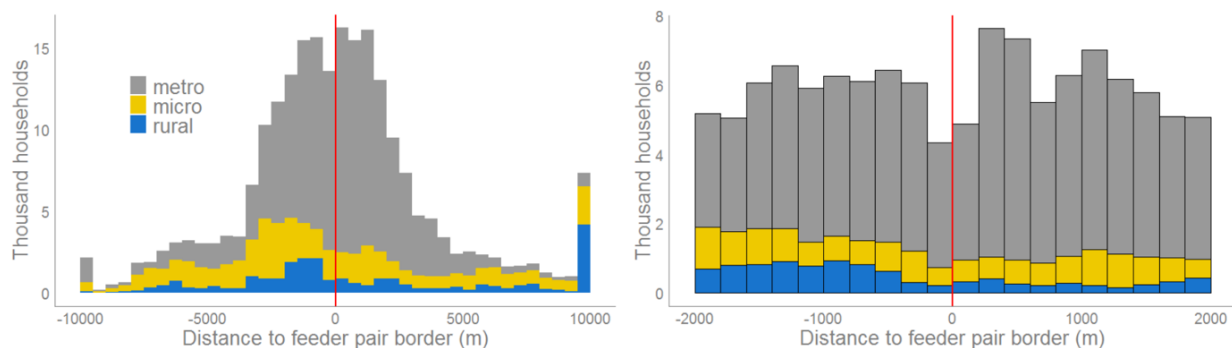


Figure 4.4: Density of RD running variables

⁵Our first sub-sampling approach drops households with low-income rates (i.e. California Alternate Rates for Energy (CARE)). Our second approach uses geospatial data provided by SGIP and the CPUC on regions that likely qualify for enhanced subsidies. Details can be found in the Appendix.

⁶Metro areas represent metropolitan cores, micro areas represent cluster of 10,000 to 49,999 people, and rural represent areas of 10,000 or less people.

Under these assumptions, the following RD specification estimates the causal impact of PSPS outages for people close to feeder boundaries in PG&E’s service territory:

$$Y_{ip} = \beta_0 + \beta_1 Z_{fp} + \beta_2 (D_{ip} - 0) + \beta_3 (D_{ip} - 0) Z_{fp} + \eta_p + \epsilon_f \quad (4.1)$$

for $Y_{ip} \in [0 - h, 0 + h]$, where $Z_{fp} \equiv \mathbf{1}[D_{ip} \geq 0]$

Y_{ip} is the outcome of interest (e.g. battery adoption) for household i on feeder-pair p . D_{ip} represents the customer’s distance to the nearest point along the feeder pair border (the RD running variable), while Z_{fp} represents whether the specific feeder f on a feeder-pair had more ($Z_{fp} = 1$) or less ($Z_{fp} = 0$) PSPS outage hours. We also include feeder-pair fixed effects η_p in order to ensure our comparison of treated and untreated subjects focuses at the neighborhood level. This term allows us to control for the fact that the PSPS borders occur across northern California. We implement Equation 4.1 using the `rdrobust` framework developed by Calonico et al. (2017). Following the standard `rdrobust` procedures, we apply a triangular weighting kernel in distance from the RD cutoff, calculate the MSE-optimal RD bandwidths h , and use heteroskedasticity-robust feeder standard errors.⁷

This sharp RD design estimates the impacts of treatment assigned at the feeder level. Though outage experiences are typically uniform at the feeder level, due to the possibility of feeder sectionalization, we compare our sharp RD estimates to an analogous fuzzy RD design where we instrument for customer-level outages using the feeder specific treatment identifier. This analysis allows us to compare the difference between our intent-to-treat RD estimate to the local average treatment effects (LATEs) of outage experience (See Appendix C Tables C.1 and C.2).⁸

Simulating an implied VoLL

The above empirical strategy provides an estimate of the impact of PSPS outages on customer-decisions such as the adoption of backup power (e.g. battery storage systems). However, it does not estimate the VoLL. The VoLL can be calculated using the mitigation investment framework first developed by Bental and Ravid (1982) and expanded for our specific case in Eq. 4.2 - 4.4. First, we calculate the annualized costs of a backup power investment (A) as shown in Eq. 4.2. Then, Eq 4.3 can be used to calculate the annual operating costs (OC) of operating a backup power system. However, we assume that there are negligible operating costs for solar and storage systems, which differs from traditional backup generators that have ongoing fuel costs. Typically, backup power technologies are solely used to provide energy during a power outage. However, new distributed energy resource technologies, such as solar and storage, also provide financial benefit to end-consumers

⁷The MSE-optimal bandwidth procedure computes a separate h for each outcome variable Y_{ip} , following Calonico et al. (2020).

⁸We implement fuzzy RD using the same `rdrobust` framework.

via bill savings (B) (Barbose et al., 2021a). Those savings offset the costs of owning and operating the backup power system; therefore, the all-in VoLL subtracts any bill savings from the annualized and operating costs as shown in Eq. 4.4. This annualized framework can also be converted to a levelized cost of energy framework shown in equation 4.5, though they produce identical results.

$$A = \frac{(C * r)}{(1 - (1 + r)^Y)} \quad (4.2)$$

$$OC = h * l * f \quad (4.3)$$

$$VOLL = \frac{A + OC - B}{h * l} \quad (4.4)$$

$$VOLL = \frac{\sum_{n=0}^Y \frac{C_y(q_0, \dots, q_Y) + OC - B}{(1+r)^y}}{\sum_{n=1}^Y \frac{l_y * h_y}{(1+r)^y}} \quad (4.5)$$

Where,

A = annualized capital cost (\$/yr)

C = capacity cost (\$)

r = discount rate (%)

Y = operational years (yr)

OC = operating costs (\$/yr)

h = operational hours during outages (hrs/yr)

l = average load lost during outage hours (kW)

f = fuel costs (\$/kWh)

B = bill savings (\$/yr)

Our RD framework generates two key inputs to our VoLL calculation. The first input is the total capacity cost investment (c), which takes the incremental backup power adoption estimated from the RD and multiplies it by recent technology costs. This input comes from running Eq. 4.1 to determine the capacity of solar and storage installed after the 2019 PSPS events. The second key RD input is an estimate of the operational hours of outage which in our case is the treatment effect discontinuity (i.e. discontinuity in the number of outage hours within our feeder-pair sample). This input, which represents the h variable in the above VoLL framework, comes from running Eq. 4.1 with the number of outage hours experienced during the 2019 PSPS events.

The last key empirical input to our VoLL calculation is the amount of kWh of electricity lost (l) as a result of the PSPS events. For this estimate, we implement a difference-in-difference empirical model with the specifications shown below in equation 4.6. We cluster standard errors at the household and month-of-sample level. The beta coefficient in this

model represents the consumption change from an incremental hour of outage due to the PSPS events and represents variable l in Eq. 4.3 - 4.5. We run this model specification on a few different subsamples of our full population for robustness.

$$K_{i,my} = \beta_1 H_{i,my} + \delta_{my} + \gamma_{mi} + \epsilon_{my,mi} \quad (4.6)$$

Where,

K = Billed kWh

H = Hours of Outage

i = SP-ID (i.e. an individual house)

my = month-of-sample (i.e. January 2019)

mi = SP-ID by month-of-year (i.e. household 1 by January)

We have to make two key assumptions when using the above estimates. Expectations around future backup usage is a key input to a customer's decision to install backup power after a PSPS event. However, we do not directly observe these expectations so assume that experiences during 2019 represent future expectations for electricity outages, which we don't observe directly. Second, we assume that the customers expect that their investment could have provided their entire demand during these expected future outage events. Though these are our default assumption, we run a number of scenarios which test the sensitivity of such assumptions on our VoLL estimates.

The last key component to calculating a VoLL via Eq. 4.4 or 4.5 is an estimate of the economic value of the investment in backup from bill savings. If these investments only provided electricity during outage events, we could assume the bill savings (B) would equal \$0. As we will show below, our RD estimates do not show any incremental investment in solar PV, therefore our bill savings solely focus on bill savings from TOU rate arbitrage. To do so, we assume that the battery is fully cycled once per day to shift energy from off to on peak, taking advantage of the TOU price difference. These modeled economic benefits are compared to actual bill savings, where available, from the administrative dataset using a similar difference-in-difference framework introduced above, but replacing billed kWh with billed dollars, replacing the treatment (hours of outage) with installation of a battery, while also controlling for solar co-adoption. The updated specification is shown below in Eq. 4.7, where β_1 represents estimated monthly bill savings due to battery adoption.

$$D_{i,my} = \beta_1 B_{i,my} + \beta_2 S_{i,my} + \delta_{my} + \gamma_{mi} + \epsilon_{my,mi} \quad (4.7)$$

Where,

D = Monthly Bill (\$)

B = Indicator for battery installation

S = Indicator for solar installation

i = SP-ID (i.e. an individual household)

my = month-of-sample (i.e. January 2019)

mi = SP-ID by month-of-year (i.e. household 1 by January)

4.4 Data

Our empirical strategy depends on highly resolved spatial data on both mitigation expenditures in backup power and electric reliability in PG&E’s service territory. For mitigation expenditures, we rely on a spatially resolved dataset of all interconnected solar and storage systems through 2020 in the state of California as collected by Lawrence Berkeley National Lab’s Tracking the Sun project ([Barbose et al., 2021b](#)). This dataset provides address level data for all customers in PG&E, SCE, and SDG&E’s service territories, though we focus exclusively on the PG&E sample. A summary of monthly installations across these three IOUs is produced below in Figure 4.5. A notable uptake in storage installations is observed after PSPS events in PG&E as compared to the other two utilities.

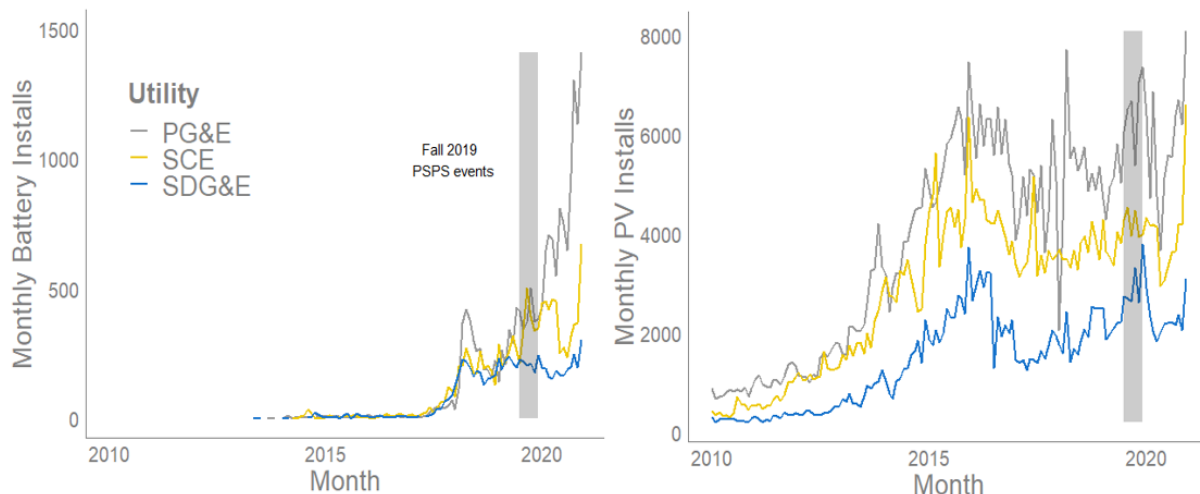


Figure 4.5: Solar and storage interconnections in our data sample

We also collect customer-level electric consumption, PSPS outage, and billing data directly from PG&E for a subsample of the utility’s residential population. These data are also identified at the address level, and the outage and consumption data are resolved at an hourly time scale. Due to regulatory limits on IOU data requests, we could only receive data for 10% of PG&E’s customers.⁹

To identify a robust random sample of PG&E customers, we used a sampling strategy that

⁹We were also only allowed to collect a further subset of hourly Advanced metering infrastructure (AMI) data from our 10% population sample.

focused on residential customers in zip codes with the largest power outages. This sampling strategy involved using two publicly available PG&E circuit maps. The first reports the circuits which experienced outages during the 2019 PSPS events, and the second reports all circuits in PG&E’s service territory. We then calculate the number of outage and non-outage circuits which intersect with a zip code area to generate the percentage of circuits on outage within a given zip code for each PSPS event.¹⁰ To reduce our zip code sample, we first eliminated zip codes where 0% or 100% of the circuits were on outage. These zip codes would not have any geospatial variation in outage experience, thus making them of little use in our research design. Next, we employed a stratified random sample process where we randomly selected between rural and urban zip codes while ensuring that the breakdown in rural and urban households matched before and after the random sampling. More details about this sampling strategy are shared in Appendix C. We then merged the household level interconnection dataset with the PG&E dataset by address. We were able to successfully merge over 95% of the interconnection observations onto the PG&E administrative dataset.

We then construct a feeder-pair dataset in order to generate our RD running variable. To do so, we use an individual feeder’s centroid to identify the five nearest neighboring feeders. These become the individual feeder-pairs, our level of treatment. For all customers on a given feeder-pair, we identify the nearest household on the opposite feeder. The resulting distance between these two customers becomes our running variable, distance to feeder-pair boarder. This process is repeated for all potential feeder-pairs in the dataset. Since we are creating feeder-pairs by identifying the 5 nearest feeders, there is a chance that some feeder-pairs will actually have customers that are not close together. For that reason, we drop any feeder-pair that does not have at least two customers on either side of the feeder-pair border within half a mile. This step results in the 623 feeder-pairs referenced at the beginning of section 4.3.

The final steps to create our subsample aim to ensure a treatment discontinuity and pre-period balance among key variables. First, we calculate the average outage difference between all households on a given feeder-pair and designate that feeder-pairs with more than 1 hr of difference as a treatment feeder-pair. In total, there are 275 treatment feeder-pairs. The remaining 348 non-treatment feeder-pairs are used as placebos in our analysis. Finally, we drop feeder-pairs that are not balanced in key pre-period variables (i.e. PV adoption, battery adoption, June, July, and August 2019 consumption). More details about the creation of our RD dataset can be found in Appendix C.

The last dataset we use comes from a random survey of more than 2,000 California residents undertaken at the end of 2020, and summarized in Chapter 3, asking about both their

¹⁰PG&E circuit maps were taken from the Integration Capacity Analysis (ICA) project and can be located at [this link](#). PG&E outage maps were taken from PG&E’s wildfire planning projects and can be located at [this link](#). Look for Attachment 6 (Part 2): GIS Files for 2019 PSPS events.

experience of historical PSPS outage events and expectations for future events. This survey suggested that the subset of respondents that had prior exposure to a sustained power outage event expected an average of 20 hours of outages in 2022. Furthermore, the majority of respondents did not expect for outage hours to decrease in the next five years and responses were evenly split between beliefs that the outage hours would stay the same or increase. These results are summarized in Figure 4.6, and we use them to inform our sensitivity analyses in our calculation of the VoLL.

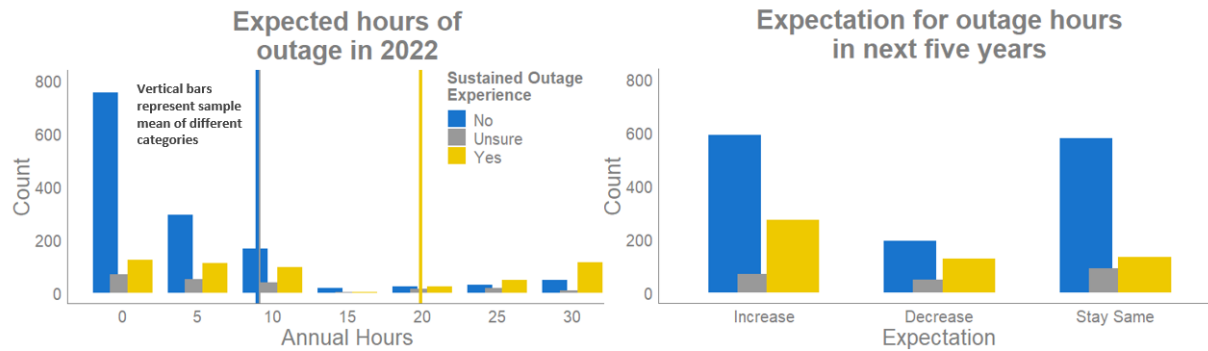


Figure 4.6: Expectations for future power outages for a random sample survey of California residents.

4.5 Regression discontinuity results

First stage: Electricity outages

Using our RD strategy, we first estimate PSPS impact on our treatment discontinuity: total outage hours. Table 4.1 reports these results numerically. We find that PSPS events caused an increase of 14-22 hours of outage hours in households within our sample depending on the RUCA category subsample. For the rural sample, this discontinuity is lowest at 14 hours of outage discontinuity. All of these discontinuities are statistically significant at the 1% level but for the robust result for the rural discontinuity, which is significant at the 5% level.

	Metro discontinuity [1]	Micro discontinuity [2]	Rural discontinuity [3]
Outage hours (Conventional)	22.4*** (2.8)	21.5*** (3.8)	14.0*** (5.2)
Outage hours (Robust)	22.9*** (2.9)	21.6*** (4.2)	13.7** (5.7)
Cluster (feeder)	Yes	Yes	Yes
Feeder-pair FE	Yes	Yes	Yes
Feeder-pair count	52	22	12
Untreated-mean (hrs)	13	85	37
Treated observations	80,421	21,207	13,722
Untreated observations	71,762	30,656	13,203
Note: *p<0.1; **p<0.05; ***p<0.01			

Table 4.1: Outage hour discontinuity by RUCA category

Figure 4.7 presents the corresponding RD plots by RUCA category. Such plots allow us to visualize how the numerical discontinuities in the above table are differentiated as a function of distance to the feeder-pair border.¹¹ In the metro RUCA category, the discontinuity in outage hours is not a significant function of the distance to the feeder-pair border. Such a result implies that our treatment effect is accurately identified at the feeder level, with limited impacts of sectionalization within a feeder that could serve to bias our results if some households on the our treated feeders actually experienced distinct treatment from other households on the same feeder. The rural and micro RUCA categories show more variation in outage hours of our households as a function of distance to the feeder-pair border, suggesting either that the specific impact of treatment within a feeder is differentiated by distance to border or that the sample of households is changing as a function of distance given that some feeder-pairs do not have households within the full range of distances plotted here. This result motivates our use of fuzzy RD techniques, shown in the Appendix of this Chapter.

¹¹Graphs plot the mean outcome within each bin of distance to the border for all households within 1,000 meters of a feeder-pair border. Each feeder-pair is ordered so that the feeder with greater outage hours is on the right (positive distance). Household outage hours are centered before plotting in the following sense: we subtract the mean value within each feeder-pair from each household's observed outage hours and then add the grand mean of outage hours from the entire sample by RUCA. Linear parametric trend lines are plotted separately on each side of the border using local linear regression.

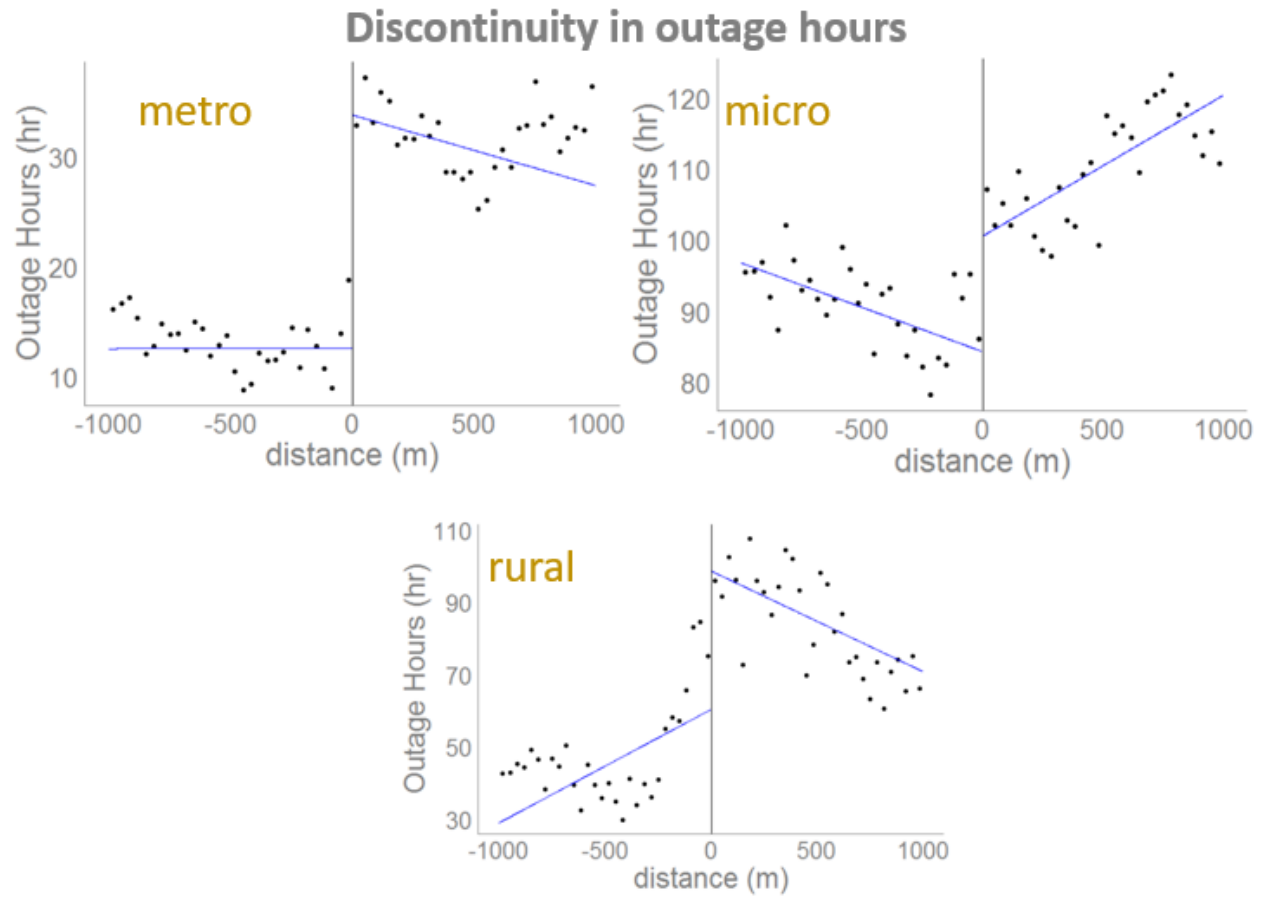


Figure 4.7: Graphical RD results of outages hours by RUCA category

Reduced form: Solar and Battery Adoption

Having established that the PSPS events led to a discontinuity of experience in power outage outcomes, we estimate the corresponding impact on the adoption of solar and battery technologies. Table 4.2 and 4.3 reports these household-level RD results numerically for solar and batteries, respectively. We estimate statistically insignificant increases in the adoption of solar technologies in the metro and rural RUCAs, aligning with the notion that solar, on its own, does not enhance the reliability of a household in the event of a power outage. We find negative adoption rates, however, for the micro category. Correspondingly, though, we estimate statistically insignificant increases in the adoption of battery technologies in the metro and micro RUCA categories. In the rural areas, however, we find that adoption of storage increases by 0.11 kWh, a 360% increase from the untreated rural sample. This result is significant at the 5% level.

	Metro discontinuity	Micro discontinuity	Rural discontinuity
	[1]	[2]	[3]
Solar (kW)	-0.03	-0.09***	0.05
(Conventional)	(0.02)	(0.03)	(0.05)
Solar (kW)	-0.03*	-0.08**	0.05
(Robust)	(0.02)	(0.04)	(0.06)
Cluster (feeder)	Yes	Yes	Yes
Feeder-pair FE	Yes	Yes	Yes
Feeder-pair count	52	22	12
Untreated-mean (kW)	0.1	0.13	0.16
Treated observations	80,421	21,207	13,722
Untreated observations	71,762	30,656	13,203
Note: *p<0.1; **p<0.05; ***p<0.01			

Table 4.2: Solar adoption discontinuity by RUCA category

	Metro discontinuity	Micro discontinuity	Rural discontinuity
	[1]	[2]	[3]
Battery (kWh)	0.00	0.02	0.11**
(Conventional)	(0.02)	(0.03)	(0.05)
Battery (kWh)	0.00	0.02	0.11**
(Robust)	(0.02)	(0.03)	(0.06)
Cluster (feeder)	Yes	Yes	Yes
Feeder-pair FE	Yes	Yes	Yes
Feeder-pair count	52	22	12
Untreated-mean (kWh)	0.06	0.05	0.03
Treated observations	80,421	21,207	13,722
Untreated observations	71,762	30,656	13,203
Note: *p<0.1; **p<0.05; ***p<0.01			

Table 4.3: Battery adoption discontinuity by RUCA category

Estimating a VoLL

To calculate a VoLL with the results observed in the rural RUCA territory, we also need estimates of the amount of lost load that resulted from the 2019 PSPS events. In the left portion of Figure 4.8, we show the estimates from our difference-in-difference analysis of the electricity lost as a result of outages across a variety of subsamples. We find that an additional outage hour led to a reduction of roughly 0.5 kWh of demand. This finding is stable across all of the subsamples we analyzed.¹²

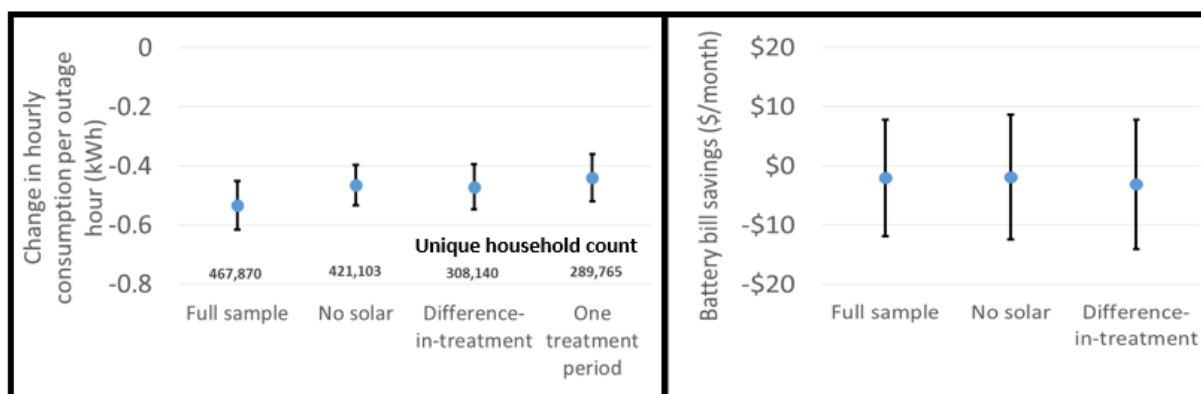


Figure 4.8: Differences-in-differences results showing the effect of a 1 hr increase in 2019 PSPS outages on demand.

We run a similar difference-in-difference calculation on the bill savings that result from installing battery storage. The right portion of Figure 4.8 shows that the addition of battery storage leads to marginal savings of \$3/month in customer bills. These results, however, are statistically insignificant across the variety of subsamples we analyze. Such a result would imply that we should assume \$0 in incremental bill savings as a result of battery adoption. However, customer expectations of bill savings could be different than the empirical reality we document, especially given the relative novelty of battery technologies. Therefore, we also calculate a simple estimate of TOU arbitrage bill savings. To do so, we estimate TOU bill savings by assuming daily battery cycling against a time-of-use rate with an average on-to-off peak price difference of \$0.10/kWh-consumption and a battery efficiency of 90%.¹³ Annual bill savings for 1 kWh of battery would be \$33/kWh-battery.

We can combine the results of the above difference-in-difference models with the increased

¹²The full sample represents the entire population of households collected from PG&E. The no solar sample drops households who have installed solar at any point. The difference-in-treatment sample further drops households that are not within the specific RD treatment sample. Finally, the one treatment period drops additional households if they experienced treatments across multiple months.

¹³The TOU rate assumptions are informed by current PG&E E-TOU-D rate designs.

battery adoption to estimate the VoLL by applying Eq. 4.2 - 4.4. We assume storage costs of \$650/kWh-battery which can be used to estimate the increased capacity cost paid by storage owners (Barbose et al., 2021a). Appendix C figure C.6 shares analysis of the subsidized costs of the batteries we observe in our data sample. With this cost assumption, the annualized cost of the incremental storage installed in rural areas is \$5.49. We assume \$0 operational costs for the battery system. The rural discontinuity in outage hours is 14, which combined with the 0.5 kWh estimate of lost load per outage hour, results in 7 kWh lost across our treatment discontinuity. We estimate a VoLL of \$0.8/kWh when assuming \$0 of bill savings and \$0.30/kWh when applying the bill savings estimate.

4.6 Discussion

Though we found statistically significant increases in the adoption of battery storage in the rural RUCAs, the absolute magnitude of the effects resulted in a small VoLL that is on the lowest end of estimates from the literature (Schröder and Kuckshinrichs, 2015). The relative magnitude of the effect of the PSPS events on battery adoption in the rural subsample, though, was a notable 300+% increase in battery adoption. However, the null results in the metro and micro territories point to serious challenges in the mitigation investment approach to creating a revealed preference estimate of the VoLL.

There are a number of explanations and hypotheses which could drive these small VoLLs. First, and perhaps the most important issue, is that the adoption of battery technology represents just one mitigation option available for our population sample to avoid the impacts of power outages. Other mitigation expenditures include the purchase or rental of fossil fuel based backup power systems, travel costs to friends/family outside of PSPS territory, relocation to alternative housing such as a hotel, and a variety of behavior adjustments that could entail a variety of difficult-to-observe costs (e.g. schedule changes, activity cancellations). Unfortunately, we did not have access to other geospatially resolved datasets that could track these other mitigation investments, which would incrementally each serve to increase our VoLL estimates.

Second, the relative nascence of behind-the-meter battery backup might have affected the salience of the option for battery backup. This novelty, combined with the first issue identified above, could have led our treatment group to focus on other mitigation costs given their prevalence.

A third limitation of the above calculation is that it represents the mean outcome within our sample. The specific individuals who purchased batteries in response to the PSPS events would require higher VoLL to justify such an investment. In our sample, the households which installed battery packs in 2020 had an average of 80 hours of outage hours during the 2019 PSPS events. Using the estimates for the costs of battery packs discussed above, the annualized cost of a 13 kWh battery would be \$650. Combining the 80 hours of outage with

these annual costs suggests that these individuals had a VoLL of at least \$16/kWh when ignoring bill savings, significantly higher than our population weighted estimate shared above. Prior work has shown that residential households have a distribution of VoLLs (Baik et al., 2020). In our analysis, these VoLLs should range from the average marginal cost of electricity (\$0.2-0.3/kWh in California) up to at least the \$16/kWh back-of-the-envelope estimate generated above.¹⁴ However, given the binary nature of the purchase decision, we cannot observe this distribution but rather have to implicitly assume that the portion of our population that does not adopt batteries have a VoLL of \$0/kWh.

In general, the mitigation cost framework is best applied in a situation where a wide variety of mitigation costs are observed or in situations where the mitigation costs are within a more reasonable price range for end-consumers to adopt. However, it is important to note that the corresponding problem would be flipped in such an outcome because the mitigation estimates would not be able to determine the portion of the population distribution with a high VoLL given that they would only reveal their WTP as a function of the available technology set.

A fourth and final limitation is that treatment may not solely be the experience of power outages itself, which we focused on in this Chapter, but also the expectation of increased risk of power outages. Households near feeder-pair boundaries may not be able to distinguish the relative risk of future PSPS outage events between the two feeders, even if they are on a less vulnerable feeder. If this were the case, the particular specification we rely on would result in lower estimates of causal adoption because it would only measure the marginal impact of outage experience while ignoring information spillovers between neighbors who had differential outage experiences.

Our methodology and the above corresponding limitations should provide insights for future researchers aiming to understand how mitigation expenditures can be used to estimate VoLL.

4.7 Conclusion

What is the Value of Lost Load? This chapter complements the prior chapter's stated-preference survey by describing a revealed preference approach to VoLL estimation. To do so, we develop an empirical strategy to estimate the impact of PSPS events in PG&E's service territory in California on the adoption of solar and storage technologies. The research design centers around a regression discontinuity that estimates the difference in adoption trends between neighbors who experience differing amounts of power outages and takes advantage

¹⁴The true VoLL is likely even higher considering the decision to purchase a battery would represent this individual's lower bound for VoLL.

of PG&E’s differential use of nearby electrical feeder lines to mitigate wildfire risk. Then, using administrative data on power consumption, we quantified the willingness-to-pay to avoid power outages. We estimate the VoLL by calculating the incremental costs of battery investments and developing a scenario analysis around a variety of customer expectations for future power outages. Overall, we calculate a VoLL range between \$0.3 - \$0.8 per kWh.

This chapter highlights a novel means by which to estimate the VoLL through a revealed preference rather than stated preference approach, which is quite rare in the literature. However, we were met with a variety of challenges that include: (1) no access to other mitigation investment datasets with the required geospatial granularity, (2) the relative novelty of the behind-the-meter battery technology, (3) the binary nature of mitigation investments when trying to estimate a population distribution, and (4) the focus on power outage experiences rather than beliefs of increased power outage risk. For these reasons, our estimates should be considered a lower bound on the VoLL. Still, our estimates are within the range of estimates shared in the literature, suggesting that the current lower range commonly cited are also lower bound VoLL estimates.

Our results should be used with caution by policymakers wishing to deploy cost-benefit analyses, especially if such analyses are aimed at geographic context outside of our specific setting of wildfire-induced power outages. Nevertheless, our results do suggest that households will make private decisions to enhance their own reliability and such investments exist outside of the typical public provision of electric reliability that has typically existed within electric regulatory institutions.

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Chapter 5

County-level assessment of behind-the-meter solar and storage to mitigate long duration power interruptions for residential customers

5.1 Introduction

The rapid cost declines of solar technologies over the last decade led to significant growth of both utility-scale solar power plants connected to the bulk transmission system as well as smaller “behind-the-meter” (BTM) systems sited at an individual electricity customer (Barbose et al., 2021a; Bolinger et al., 2021; Ritchie and Roser, 2020). Similar cost declines are occurring for battery technologies (Kittner et al., 2017), where there is high interest in utility-scale development, with a significant fraction of proposed battery projects co-located with a renewable power plant (Gorman et al., 2022; Rand et al., 2022). Paired BTM PVESS, however, is still a niche application in most regions, representing less than 5% of all U.S. BTM residential solar systems installed in 2020 (Barbose et al., 2021b).¹

Industry observers note that early adoption of BTM solar-plus-storage (PVESS for remainder of the chapter) has been driven, to a significant degree, by customer concerns over electric system reliability and resilience (EnergySage, 2022). As wildfire, hurricane, and other climate-driven risks to electric grids become more pronounced, those concerns are expected to grow (Brockway and Dunn, 2020). In such scenarios, the vulnerability of transmission and distribution networks could increase and/or become more costly to maintain due to expensive adaptation activities like undergrounding transmission and distribution infrastructure

¹Hawaii is the only region in the United States that has seen significant pairing of BTM storage with solar, where upwards of 80% of new solar systems were paired with a battery in 2020.

(Larsen, 2016). Customer-sited backup power applications, therefore, could provide a key foothold for the BTM solar and storage industry and drive customer-adoption. But, the reliability and resilience benefits of BTM PVESS are poorly understood, owing to lack of data and methodological challenges. Therefore, these benefits are often ignored or estimated in a simplified manner when building customer adoption models (Hoff et al., 2007; O’Shaughnessy et al., 2017). Some customer adoption studies assume PVESS can provide full backup during power outage events, and do not consider heterogeneity across geographies, customer-types, outage durations, and PVESS system sizes (Prasanna et al., 2021).

At the same time, there is active debate on the relative merits of promoting BTM over utility-scale technologies as the electric industry works towards decarbonization (Borenstein, 2022; O’Shaughnessy, 2022). Past research has argued that given the relative expense of BTM compared to utility-scale applications, utility-scale technologies should be promoted to achieve rapid decarbonization of the electric grid in a cost effective manner (Borenstein, 2017; Tsuchida et al., 2015). Counterarguments emphasize that BTM technologies could defer and reduce fixed network costs of the electricity system (Clack et al., 2020). Though the network benefits of BTM solar and storage are notoriously challenging to estimate (Cohen et al., 2016; Cohen and Callaway, 2016), they should be considered in a cost-optimal plan (Carvallo et al., 2020a). The reliability and resilience benefits of BTM technologies for households, though mentioned in these debates, are rarely quantified, in part due to the lack of data and methodological challenges mentioned above.

In this paper, we model the performance of BTM PVESS in providing backup power across a wide range of residential customer types (e.g. single-family, mobile, and multifamily), geography / climate conditions (across the United States), and power outage scenarios (e.g. long-duration outages of varying frequency, timing, and seasonality), considering both whole-building backup and backup of specific critical loads. Our approach provides an assessment of the technical potential of PVESS to enhance customer reliability. We do so by combining novel, disaggregated end-use load profiles across the United States with temporally and geospatially aligned solar generation estimates. We then implement a backup-only PVESS dispatch algorithm to calculate the amount of load served during differing long duration outage events. Such analysis fills a literature gap by providing new information about the conditions PVESS technologies can be relied on to serve load during long-duration outage events, which is useful to both researchers and industry practitioners forecasting future adoption of BTM PVESS systems as well as those evaluating the relative merits of utility-scale and BTM PVESS applications.

We find that PVESS with 10 kWh of storage (at the lower end of sizes currently observed in the market) can meet a limited set of critical loads in most United States counties during any month of the year, though this capability drops to meeting only 86% of critical load, averaged across all counties and months, when heating and cooling are considered critical. A larger PVESS with 30 kWh of storage (at the upper end of sizes currently observed in

the market) would meet an average of 96% of critical load. Backup performance for PVESS with a fixed quantity of storage is generally lower for higher-usage homes. Differences in consumption levels, in turn, reflect a variety of underlying building conditions. For instance, backup performance is lowest in winter months where electric heat is common (southeast and northwest U.S.) and in summer months in places with large cooling loads (southwest and southeast U.S.). Winter backup performance varies by roughly 20% depending on infiltration rates, while summer performance varies by close to 15% depending on the efficiency of the central air-conditioning system. Differences in temperature set-points correspond to a 40% range in winter backup performance and a 20% range in summer performance. Economic calculations show that a customer’s resilience value of PVESS must be high to motivate adoption of these systems.

5.2 Literature review

Past research on the reliability impacts of BTM technologies generally focused either on: (1) development of new optimization and operation methods of PVESS systems, assessing their viability within individual case studies or (2) reliability impacts of PVESS within the distribution system from the perspective of a utility or distribution system operator. Neither of these two approaches lend themselves to significant geographic and building-type heterogeneity, limiting a comprehensive understanding of the scale of applications for BTM PVESS to mitigate power outage events and correspondingly assess future customer adoption trends.

The first area of literature uses case study analyses of particular buildings and locations in order to demonstrate novel methods for optimal PVESS system sizing and/or to show how including reliability/resilience value impacts PVESS cost-effectiveness. For instance, Laws et al explore the economic and resiliency benefits associated with a hybrid system comprising solar PV and energy storage for commercial buildings and critical infrastructure sites (Laws et al., 2018). Anderson et al estimate resiliency value of PVESS plus diesel systems for businesses in New York City, suggesting the potential to reduce \$2.5 billion in business losses (Anderson et al., 2018) while other studies have focused on households during extreme and rare weather events (Wang et al., 2019). These studies are often extended to achieve additional goals, such as determining the storage size to meet a reliability targets (Mitra and Vallem, 2012), to maximize utility bill savings and resiliency benefits (Anderson et al., 2017), to minimize the lifecycle cost of energy (Simpkins et al., 2016), to explore the tradeoffs between outage probability and storage capacity (Yang and Walid, 2013), to consider fuel source vulnerability (Ericson and Olis, 2019), or to incorporate social equity values (Anderson et al., 2022). Work exploring the benefits of introducing load control technologies or controlled electric vehicle charging that increase the value of PV has also been performed (Kaschub et al., 2016; O’Shaughnessy et al., 2018). In general, these studies often rely on stylized scenario analysis (Anderson et al., 2018; Tsianikas et al., 2019) or statistical models and simulations (Simpkins et al., 2016; Wang et al., 2019; Zhou et al., 2019), but such ap-

proaches are tied to the characteristics of reference events and input parameters, which are location-specific.

These studies have improved our understanding of the potential for PVESS-based backup, but their focus makes it challenging to describe variation across regions, outage conditions, customer-types, building stock, and specific end-uses of electricity. Cole et al is perhaps the most geographically expansive analysis, studying PVESS capabilities across 18 different hurricane events in the southeast, but focus on the supply of a constant, flat load (Cole et al., 2020). Furthermore, only a small number of studies in this literature evaluate critical load scenarios. Some of these studies do not specify how they develop a “critical” demand scenario (Chatterji and Bazilian, 2020; Tsianikas et al., 2019) or solely relying on a flat percentage of total load (Dong et al., 2018; Gong and Ionel, 2021; Laws et al., 2018). Manz et al identify refrigeration and lighting as critical loads, but instead of explicitly modeling heating and cooling loads, create a generic ‘baseline’ heating/cooling power consumption (Manz et al., 2008). More recent work has been done to understand how end-customers might prioritize various end-uses (Baik et al., 2018, 2020), but it has remained challenging to implement such sensitivities in PVESS analysis due to the need to have sufficiently disaggregated demand profiles.

A subset of this literature has also evaluated PVESS capability to serve end-consumers with a wider geographic coverage, though the lens of grid defection (Gorman et al., 2020; Hanser et al., 2017; Hittinger and Siddiqui, 2017). Hittinger et al find that grid defection is cost prohibitive when relying on BTM PVESS, results that are corroborated by Gorman et al and Hanser et al under a variety of scenarios. A few studies find that adding BTM fossil-fuel based systems could make grid defection more likely (Peffley and Pearce, 2020). All these studies find that the PVESS system sizes required for grid defection are often quite large due to the constraint to provide year-round electricity service. Given these large sizes, it is difficult to apply results from these studies to understand PVESS capabilities to provide backup during power outage events with smaller system sizes that are currently more commonly adopted (Barbose et al., 2021b).

Compared to the case-study approaches discussed above, the distribution system literature that evaluates the system reliability impacts of BTM PVESS adoption focuses on the electric utility, rather than individual end-consumer, perspective. A wide literature has evaluated the distribution impact of high PV penetrations on distribution feeders, focused on issues of hosting capacity, voltage support, protection coordination, voltage flicker, and short circuiting (Cohen and Callaway, 2016; Leite da Silva et al., 2012). Seguin et al. catalogs major findings from these studies (Seguin et al., 2016). More recent studies have begun evaluating more expansive DER technologies such as electric vehicles and battery storage and their corresponding impacts on the distribution system (Das et al., 2019; Elmallah et al., 2022; Schwarz et al., 2020). Carvallo et al models the capability of BTM PVESS from both the distribution utility and customer perspective. However, their results are focused effects

on system-aggregated metrics such as system average interruption duration index (SAIDI), system average interruption frequency index (SAIFI), and customer average interruption duration index (CAIDI). They find reductions in the SAIDI from 2-12%, depending on PVESS penetration levels but focus on a specific set of locations in Indiana (Carvalho et al., 2021, 2020b).

Given that BTM solar-plus-storage adoption is often driven by end-customer procurement decisions (Willems et al., 2022), it is difficult to take the results from this system-oriented reliability literature and apply them to customer adoption models. Much of the literature studying the adoption of distributed energy resources focuses on cost, demographic and community/network effects (Bollinger and Gillingham, 2012; Rai et al., 2016; Sunter et al., 2019). While these studies are predominantly focused on distributed PV adoption, new methods are being developed to forecast BTM storage adoption (Prasanna et al., 2021; Sigrin et al., 2021). Sigrin et al apply historical co-adoption of PVESS to forecast adoption in the future, citing limited research on distributed storage adoption while Prasanna et al apply an economic model that takes into account the value for backup power based on regionally distributed SAIDI and SAIFI metrics, assuming that a PVESS system could avoid all potential outages (Prasanna et al., 2021).

5.3 Methods

This section is broken up into three subsections which describe our data collection efforts, the implementation of the PVESS dispatch algorithm, and the parameters that we include in our scenario analysis.

Data collection

Our research approach requires three hourly timeseries data: (1) disaggregated end-use load profiles, (2) solar production profiles, and (3) power interruption profiles. Critically, we ensure that these data sets are temporally and geospatially aligned at an hourly interval given the correlation of weather events with likelihood of power outage (Mukherjee et al., 2018). To do so, we rely on a consistent set of typical meteorological year (TMY) and actual meteorological year (AMY) weather data that are used to simulate both end-use load profiles and solar production profiles.

For load profiles, we use a foundational dataset of more than 500,000 residential building models generated by the National Renewable Energy Laboratory’s (NREL) ResStock simulation tool (Wilson et al., 2022). These building models use a wide range of empirical data to inform statistical representations of the United States building stock, covering a variety of residential building types, end-uses, and characteristics. These statistical representations are created by combining Census, Residential energy consumption survey (RECS), and actual

electricity consumption datasets for validation purposes. Often, building characteristics are correlated with different climate zones, such as the DOE building America climate zones (see Figure 5.1). We focus on detached single-family homes for our base case analysis but also assess the capability of PVESS systems to serve mobile homes and multifamily dwellings. Multifamily dwellings are modeled as individual units within ResStock. To create an aggregate building profile, we sum 10 individual unit load profiles within a particular region that have the same HVAC technologies.

The full collection of building models are generated using probabilistic distributions of more than 100 building stock characteristics (e.g. building insulation, HVAC technology type, square footage, heating fuel).² For computational tractability, we select a single building model per county that is closest to the statistical median in terms of annual electricity consumption while ensuring that the selected building has the same end-use characteristics that are most common within that county (e.g. electric heating, air conditioning presence). For counties with fewer than 10 building samples for a given building type, we aggregate the building models into their associated Public Use Microdata Areas (PUMA) region and apply the same selection process as above. In the case of single-family detached homes, this applies primarily to a number of sparsely populated rural counties; for other building types, this aggregation occurs more frequently.

While we focus on the ‘typical’ consumption for building models across the U.S., for a select number of high-population counties, we present a distribution of results across the entire building stock within that county. Such analysis allows us to estimate the range of capabilities of BTM PVESS within a single geographic territory. These focus locations are shared in Figure 5.1.

²To do so, we characterize key end-use characteristics for each region by calculating the percentage of buildings with A/C and percent of buildings with electric space heating.



Figure 5.1: Department of Energy Building America Climate Zones, with indicators for focus locations of analysis in our results section (Seattle, Los Angeles, Phoenix, Houston, Chicago, Boston)

To produce solar generation profiles, we apply the same weather data that are used in the underlying ResStock building simulations in order to ensure geospatial and temporal alignment. In total, 889 weather locations were used, and the corresponding weather data combines both ground based measurement data and solar radiation data from NREL’s National Solar Radiation Data Base (NSRDB) ([Sengupta et al., 2018](#)). Then, we use NREL’s System Advisor Model (SAM), which outputs AC solar production profiles. For these simulations, we use default system losses of 14% and an inverter efficiency of 96% and assume a 1.2 inverter loading ratio, 180 azimuth, fixed-roof system with tilt equal to the latitude of the weather station location.

Finally, we develop two distinct approaches to simulating power interruption profiles: (1) synthetic profiles and (2) historical profiles. Our synthetic profiles are simulated as outage events that occur in every month at a pre-determined start date and start time. These synthetic profiles allow us to assess the capability of PVESS systems to provide power across different seasons and are used solely in tandem with TMY weather conditions. To determine the start day of a synthetic outage within a given month, we calculate the daily net load for each building model and develop scenarios where we choose a specific percentile of net load for the outage window (e.g. 50th percentile or 90th percentile). We default to starting the outage at midnight, though explore a sensitivity where we adjust the start time to different

times throughout the day (e.g. hours 6, 12, 18).

While the synthetic approach allows us to compare our geographies and building models in a consistent way, they are limited in their ability to assess the provision of backup power of BTM PVESS systems during extreme weather events. To complement the synthetic profiles, we identify 10 historical, wide-spread, weather-driven power outages and develop historical outage profiles that align with the empirical experience of outages during those events. We focus on 4 event types: (1) Hurricanes (Harvey (2017), Irma (2017), Florence (2018), Michael (2018), and Isaias (2020)); (2) wildfires (California (2019)); (3) winter storms (Washington state (2019) and Oklahoma (2020)); and (4) thunderstorm (Iowa (2020) and Texas (2020)). For each of these events, we select four representative counties that ensure diversity of experience during the outage event, focusing on the most populous, most vulnerable (based on the U.S. Federal Emergency Management Agency’s social vulnerability index ([FEMA](#))), most impacted rural (using U.S. Department of Housing and Urban Development designations), and longest duration interruption counties. We also limit the selections to counties experiencing a minimum outage duration of 48 hours. The set of counties selected through this process are listed in the Appendix Table [D.1](#).

To determine the start and end-times for each county-event, we use data from Power-outage.us, which tracks the total number of customers who lost power during these extreme weather events by county ([PowerOutage.us](#)). Start and end-times for each event are based on a threshold of 10% of customers experiencing an outage within a specific county. For our analysis of historical extreme weather events, we simulate new building load profiles for a subset of counties and years using the AMY weather data.

PVESS dispatch and evaluation

Since we aim to understand the technical capability of a PVESS to provide backup, we limit the operation of the system to solely provide backup during outage events.³ Figure [5.2](#) shows the decision tree that is used to determine the dispatch of the PVESS system. We assume a 92% one-way battery efficiency and a 2 hour duration battery. We apply constraints on the discharge and charge rates of the battery such that they do not exceed the kW capacity of the battery within the hour, which is determined by dividing the kWh energy limit of the battery by the 2 hour duration. We assume an AC coupled system such that the maximum power of the PVESS is the PV’s AC capacity plus the battery power constraints mentioned above.⁴ The energy limit of the battery is a parameter we adjust, discussed below in the scenario analysis subsection below.

³We do present a scenario analysis which adjusts the beginning state of charge of the battery to explore potential impacts of using the PVESS system for other use cases besides backup power.

⁴We are limited in our capability to model more granular power constraints at the minute-to-minute level given the time scale of the NREL load profiles. We performed a sensitivity analysis using 15-minute data on a subset of our results and found limited implications on the power constraints. We do still observe

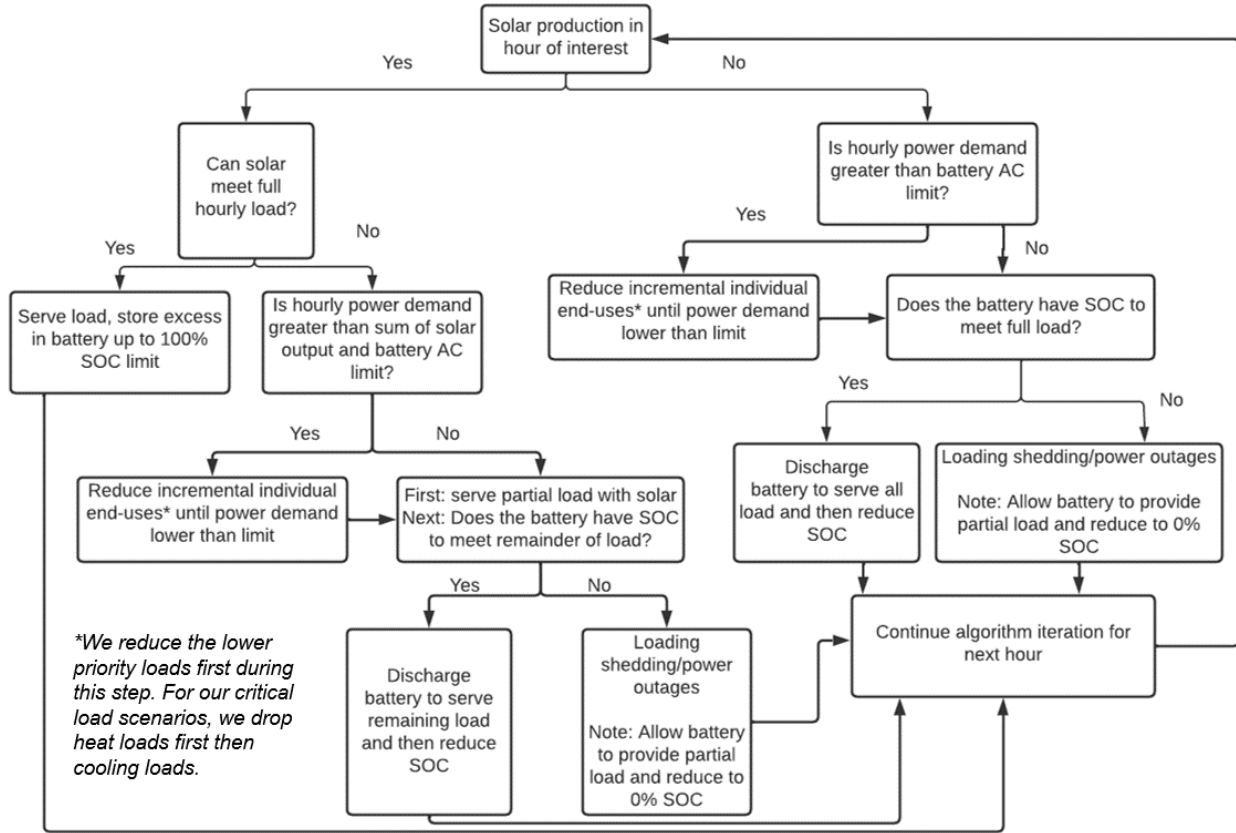


Figure 5.2: Decision tree to control state of charge (SOC) of the battery

In order to describe and compare the performance of the PVESS system across all modeled scenarios, we focus on a simple customer centric metric: percent load met (adjusting for load scenario of interest). This metric is defined by the below equation and is based entirely on dispatch data calculated for our outage events. Importantly, the load demanded and load served vary by our specific load scenario (i.e. full load, critical load, limited critical load) of focus, described in greater detail below.

$$P = \frac{E_s}{E_o} \quad (5.1)$$

Where,

P = percent load met (%)

E_s = load served during outage (kWh)

E_o = load demanded during outage (kWh)

power constraints (rather than just solely energy constraints) binding in our results, especially for electric heating end-use scenarios.

Scenario analysis

Table 5.1 summarizes the adjustable parameters in our analysis. Our baseline scenario is bolded in the below table and involves the single family detached building model, a 3-day synthetic outage event⁵ that starts at 12am on the 50 percentile net-load day, a solar system sized to meet 100% of annual load, and 10 kWh (5 kW) battery size with a 100% beginning battery state of charge. Though we present results with both full load and critical load assumptions, the majority of our results focus on PVESS capabilities to meet critical loads. In our comparison of different residential building types, we update our default PV system sizing assumption to being based on a roof constraint rather than PV sizing based on annual load. This decision relates to the fact that multi-family buildings will be constrained by the space limitations to cite PV. Roof area is provided by meta-data within the ResStock dataset.⁶

⁵Only applies to synthetic events.

⁶Roof constraint calculated as follows: Take square feet of building model and divide by the number of stories of the building model to get roof area. We assume a 160 W/m^2 (0.01486 kW/ft^2) PV panel density and a ground-coverage ratio of 98% for single-family and mobile homes (slanted roofs) and 70% for multi-family (flat roofs).

Scenario	Assumption
Building types	• Single family detached • Mobile home • Multifamily
Outage length (days)	1; 3 ; 7
Load scenario	• Critical load (no heating/cooling) • Critical load (w/ heating/cooling) • Full load
Beginning SOC (% of total kWh of battery)	0%; 50%; 100%
Outage start time	12am ; 6am; 12pm; 6pm
Outage start day(based on net load percentile within month)	worst; median ; best
Solar sizing	Solar generation is 50%; 100% of annual load; roof area constraint
Battery sizing	10 kWh or 30 kWh

Table 5.1: Summary of parameters and scenarios considered for synthetic outage events

Our critical load assumptions are informed by a set prior literature which focused on the Value of Lost Load (VoLL). In particular, Baik et al. survey customers in the northeast asking about load prioritization during outage time periods. The top 7 categories selected by respondents in rough order of prioritization were lighting, refrigeration, chargers, computers, TV, heaters, and air conditioning (Baik et al., 2020, 2018). Informed by this literature, we designate 6 out of 15 disaggregated end-use types in the ResStock building simulations as critical: refrigeration, interior lighting⁷, a limited set of plug loads⁸, well pumps, space heating, and space cooling. End-uses that we deem non-critical are fans (bath, ceiling, range), clothes dryer/washers, pool equipment, cooking ranges, dish washers, water heating, exterior lighting, extra refrigerator/freezer, and full plug loads (other ancillary equipment like televisions, microwaves, humidifiers are unfortunately not disaggregated beyond a generic

⁷Critical lighting load is defined as interior light usage from 5pm to 12am.

⁸The ResStock model does not provide detailed plug load disaggregation. Therefore, we define our critical plug load as a constant 70 W demand, accounting for the typical usage of low demand computer, internet, and phone charger end-uses.

‘plug load’ category in ResStock). We also consider a critical load case without heating and cooling demand.

5.4 Results

Median-building analysis

In the vast majority of counties, the base PVESS configuration can provide full power for our minimum set of critical loads that ignore heating/cooling demand (i.e. include refrigeration, limited interior lighting, computer / internet, and well-pumps). With our largest PV sizing assumption, the entire set of limited critical loads are met in 93% of counties. However, Figure 5.3 shows that the base PVESS configuration cannot provide power for the majority of U.S. counties once including heating and cooling loads are included (maps on the right of Figure 5.3). Across all 12 monthly synthetic outages, greater than 95% of critical load with heating and cooling could only be served in 27% of counties. In our whole-home backup scenario (maps on the left of Figure 5.3), this drops to 0% of counties. There are clear seasonal and regional trends, where performance in summer months is lowest in regions with high cooling loads (i.e. southwest and southeast) while performance in winter months is lowest in regions with electric heating (southeast and northwest, especially in rural counties).

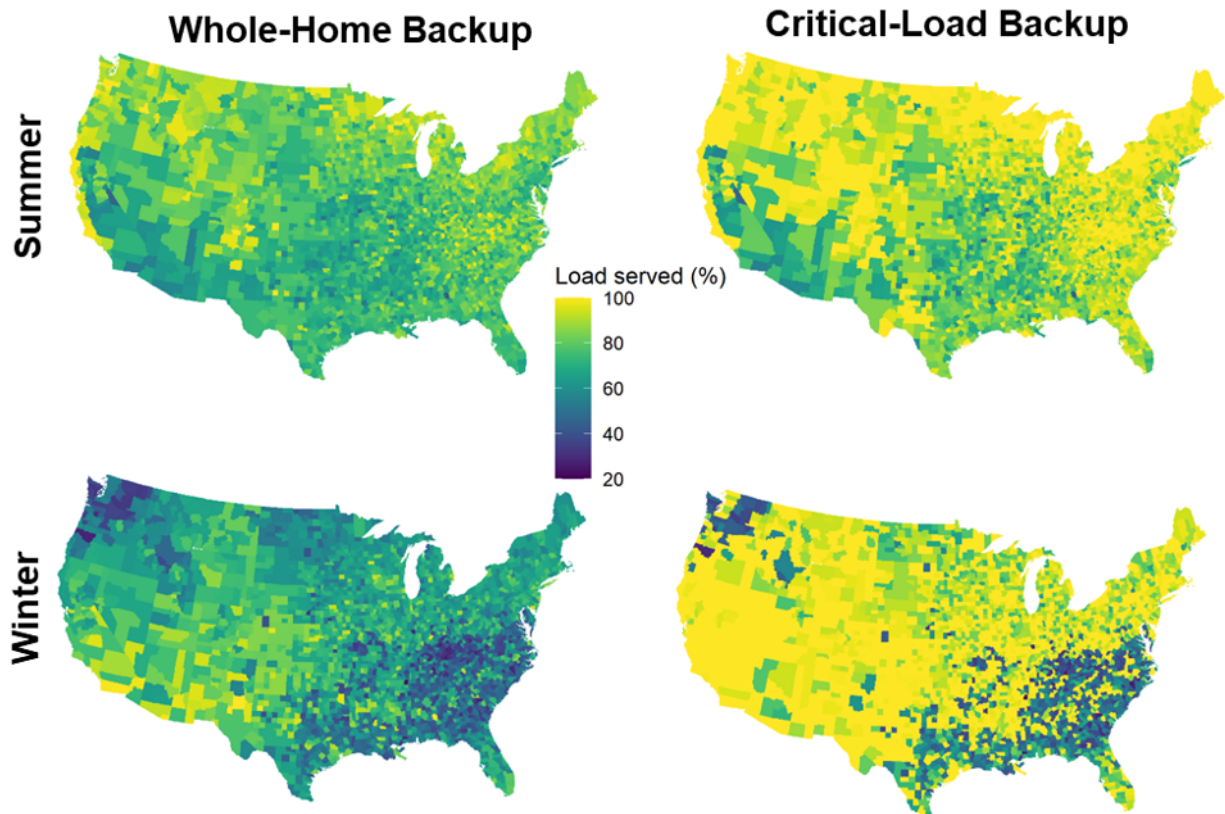


Figure 5.3: Average percent of total load served during the 3-day outages simulated in each month, aggregated to the average of winter and summer seasons for the county-median home. Critical-Load scenario includes heating and cooling. Assumes PV sized to 100% of annual load, 100% beginning SOC, 10 kWh battery.

In order to understand the sensitivity in choice of critical loads, we focus on a set of locations with representative climate/end-use combinations and simulate how our base PVESS configuration can fully backup incremental additions to the critical load profile. Figure 5.4 shows that the base PVESS configuration can fully backup incremental additions of refrigeration, lighting, computer / internet, and well-pump loads for these locations. We also report the key heating and cooling technology used in the representative building model studied. Heating and cooling loads go partially unserved in areas with relatively hot or cold weather. Los Angeles is the only location within this set where all critical load is served. Locations with electric heat have particularly high levels of unserved energy, a result which aligns with the geographic result in Figure 5.3. Unserved heating load can even occur for buildings with fossil-based systems due to the usage of energy by the furnace fan, though these unserved loads are relatively small.

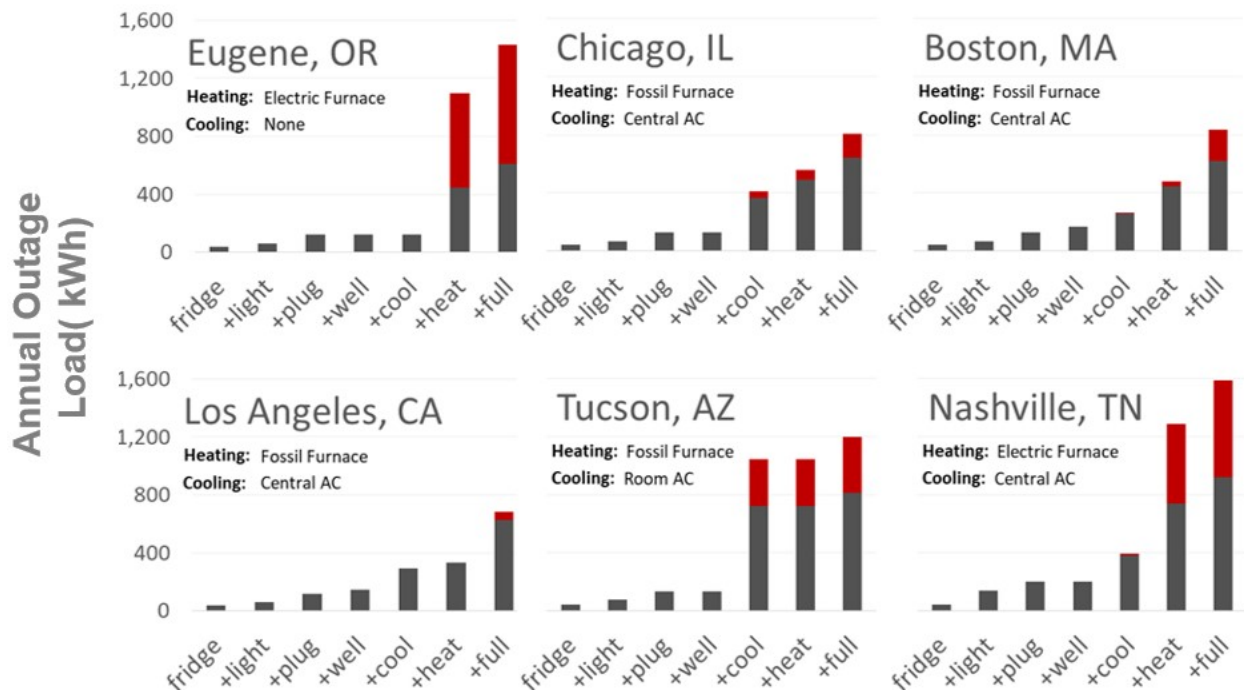


Figure 5.4: Served and unserved load over all 12 3-day monthly outages, as end-uses are incrementally added to the set of critical loads. Assumes PV sized to 100% of annual load, 100% beginning SOC, 10 kWh battery.

Figure 5.5 shares the impact of increasing battery sizes and outage event duration on the capability of the PVESS to meet critical load year-round. The figures above assumed a 10 kWh battery, based on current installation sizes (Barbose et al., 2021b). Systems with larger batteries can naturally better maintain critical loads. Tripling the size from 10 to 30 kWh leads to a 10% increase in the critical load served year-round (86% to 96%). A PVESS system with a 100 kWh battery, which might be more representative of a household with an electric vehicle backup system, could serve 99.5% of critical load across all counties. However, backup performance is limited by PV production, which is shown by the decreasing marginal returns to increased battery sizes in Figure 5.5. Furthermore, we show that as outage duration increases, backup performance declines. The longer duration of the outage, the higher the probability of an especially low solar or high load day. In these cases, the initial stored energy is depleted in the battery and the ability to meet critical load becomes more limited by daily PV generation. These effects are especially pronounced for counties in the lower end of the distribution.

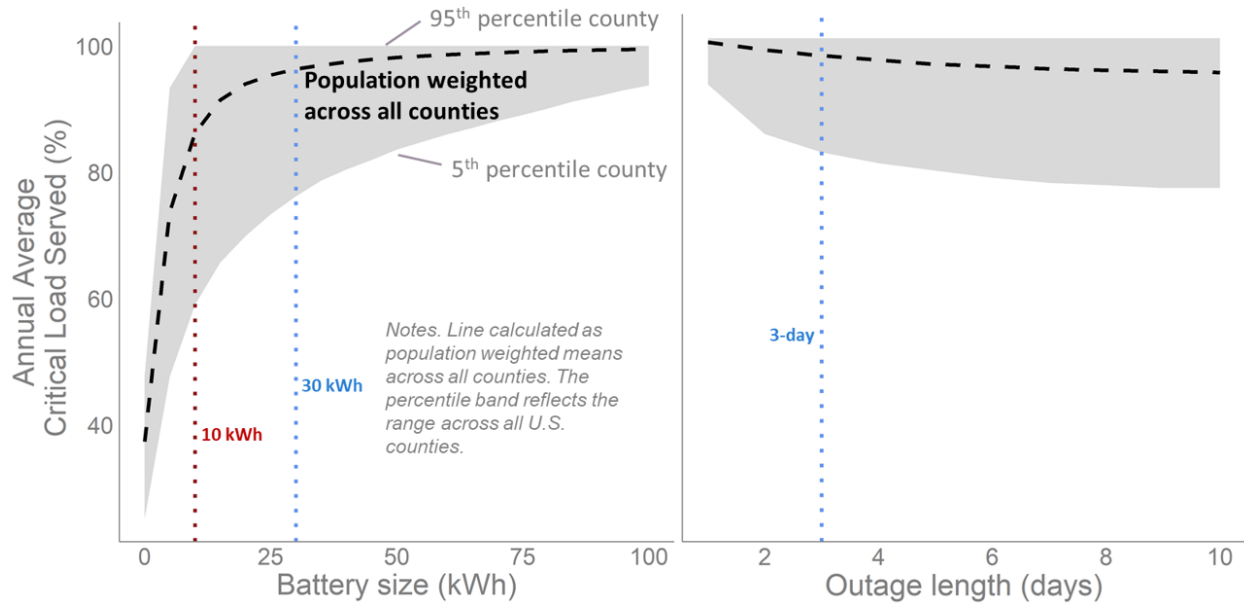


Figure 5.5: Annual average critical load served under varying battery size and event durations. Assumes PV sized to 100% of annual load, 100% beginning SOC.

Given the relatively low ability for a 10-kWh battery system to serve critical load with heating and cooling, we present the remainder of the results with a PVESS incorporating a 30 kWh battery. Figure 5.6 compares results between single-family, mobile, and multi-family homes by climate zone. Load served is generally similar between the three building types. Performance is slightly lower for the multi-family and mobile homes in the cold, marine, and mixed-humid climate zones. In these zones, multifamily and mobile building types were more likely to incorporate electric heating technologies, which is difficult to serve. More information about variation in annual consumption and PV system sizes between these building types can be found in the Appendix (see Figure D.1 and Figure D.2).

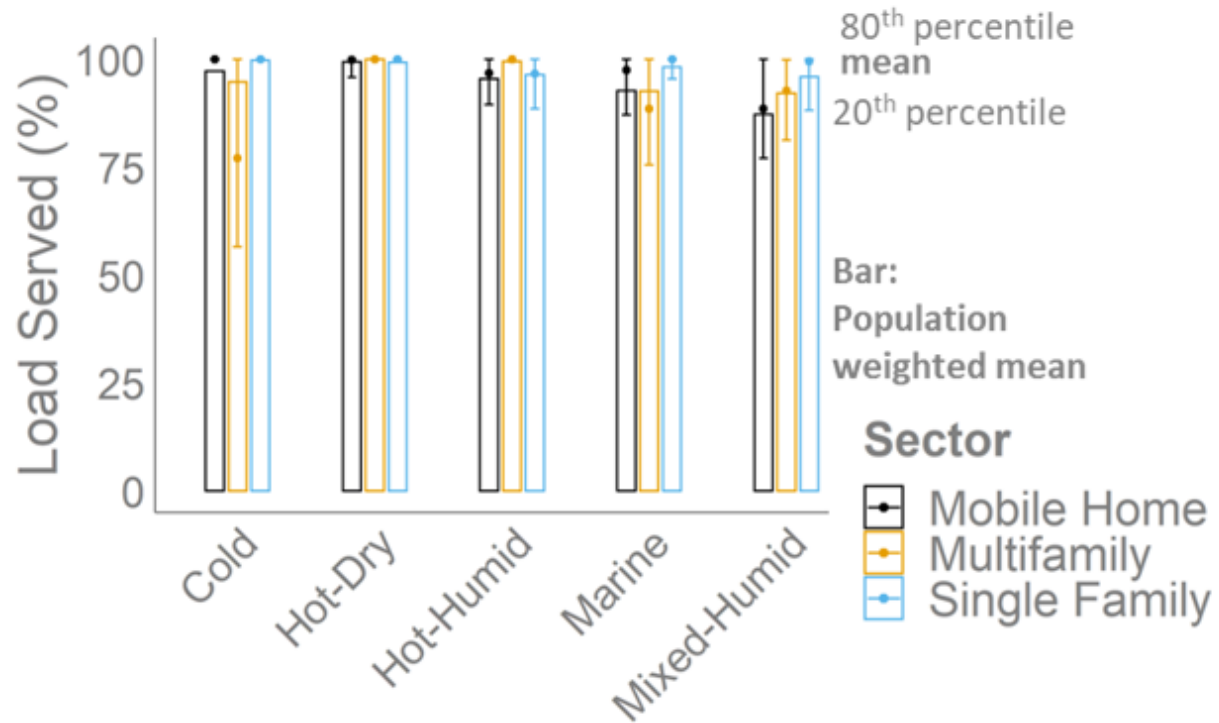


Figure 5.6: Comparison of residential building types. Assumes PV sized based on the roof constraint, 100% beginning SOC, 30 kWh battery per unit.

Distributions within the building stock of select high-population counties

For a subset of high-population counties, we simulate our results for all single-family detached ResStock building models. Figure 5.7 shows that PVESS capability to provide year-round backup of critical load varies significantly across the building stock distribution in Houston and Phoenix, with tighter distributions in Seattle, Los Angeles, Chicago, and Boston. This variability is driven by differences in building and end-use stock conditions as well as behavioral parameters such as occupancy and set-point limits.

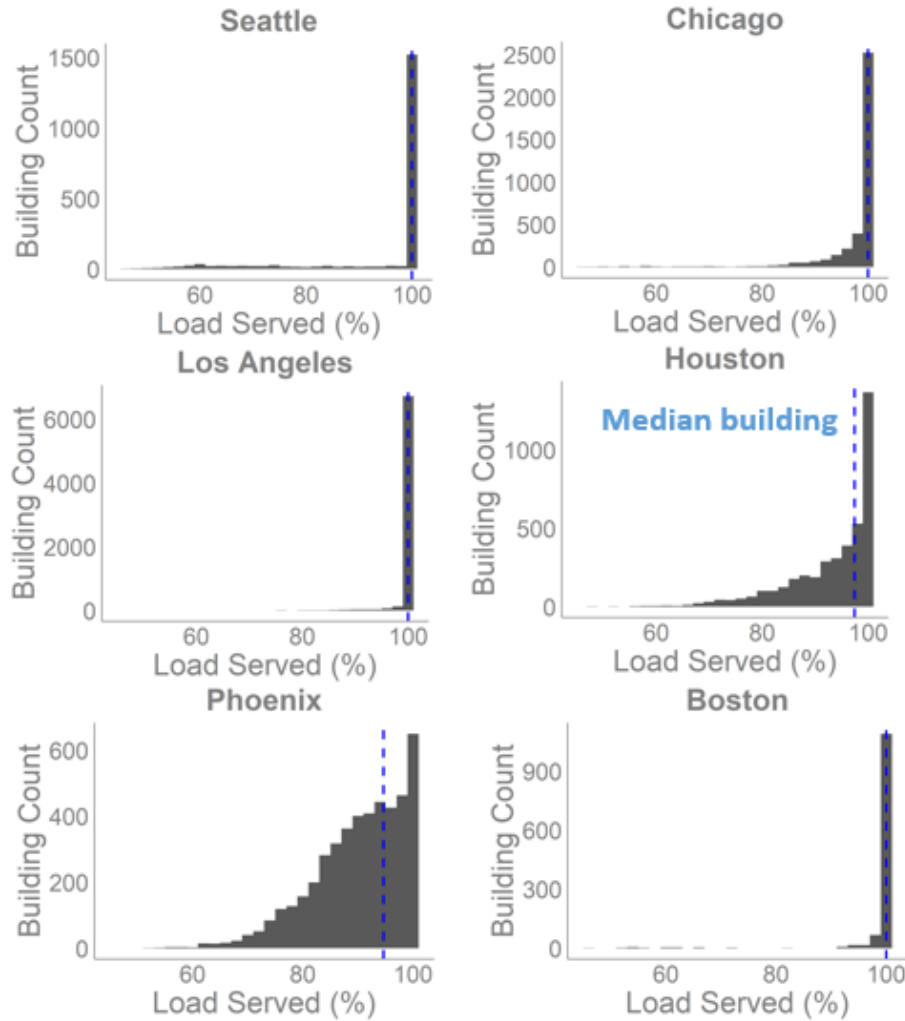


Figure 5.7: Distribution in percent of critical load served across all modeled single-family homes in ResStock with dashed indicating median building results discussed in the above section. Assumes PV sized to 100% of annual load, 100% beginning SOC, 30 kWh battery

Space heating type is one critical driver of these distributions, especially in cold weather climates. Figure 5.8 shares the percentage of critical load served compared to building electricity-use intensity, segmented by heating type. In Chicago, 100% of critical load is served in the median case for homes with fossil-based heating systems compared to 58% in the median case for homes with electric resistance heat. In Boston, the corresponding values are 100% and 56%. In Seattle, we find that backup performance improves with heat pumps vs. electric resistance heating, with 69% of critical load served in the median electric resistance heating case compared to 89% in the median heat pump case. Electricity use intensity captures efficiency broadly, but we find no clear trend in our load served results.

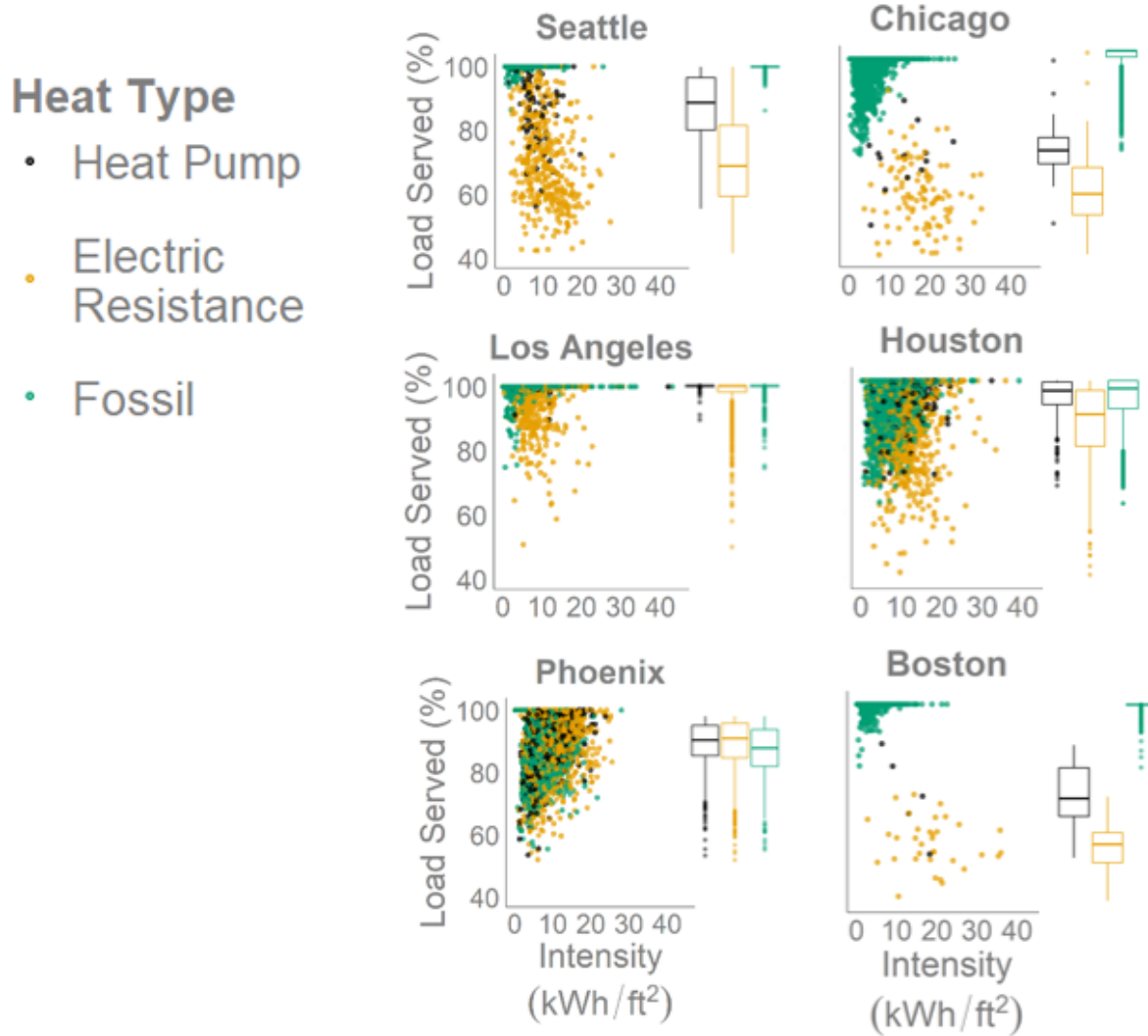


Figure 5.8: Percentage of critical load served versus building energy-use intensity, segmented by heating type, for all single-family building models. Assumes PV sized to 100% of annual load, 100% beginning SOC, 30 kWh battery.

Historical event case study

For historical results, we simulate 500 single-family building models for each county within the sample. Figure 5.9 reports the distribution of results for each event. Each dot represents a distinct county, and the dot's shape corresponds to the criteria by which that county was identified amongst the sample of counties impacted by each historical event. We find that the default system would have supplied full backup for the majority of building models in the Thunderstorm (TX), PSPS (CA), Derecho (IA), and Hurricane Michael events. The worst distributions of load served occur for the two winter storm events and Hurricane Florence.

The large range of experience in Oklahoma is driven by the large portion of electric heating represented in that state (25% of single-family building models), which drives the low end of performance of PVESS during the winter event.

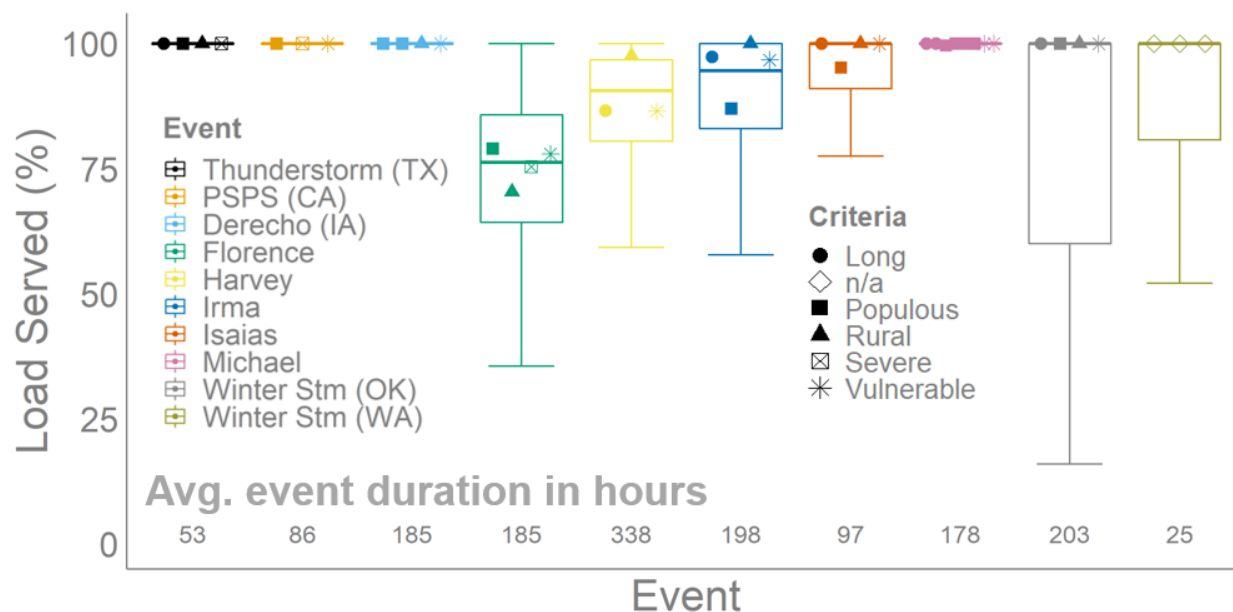


Figure 5.9: Backup power performance across all counties and historical extreme power outage events, assuming 30 kWh battery and critical load scenario. Assumes PV sized to 100% of annual load, 100% beginning SOC, 30 kWh battery.

The relatively poor performance represented by Hurricane Florence is driven by the lack of solar production in the early days of the outage event as shown in Figure 5.10. The lack of solar production results in quick depletion of the 30 kWh beginning state of charge of the battery in order to meet cooling demands. Notably, the PVESS has no difficulty in serving the limited set of critical loads (i.e., no cooling in this event), shown in the bottom portion of Figure 5.10.

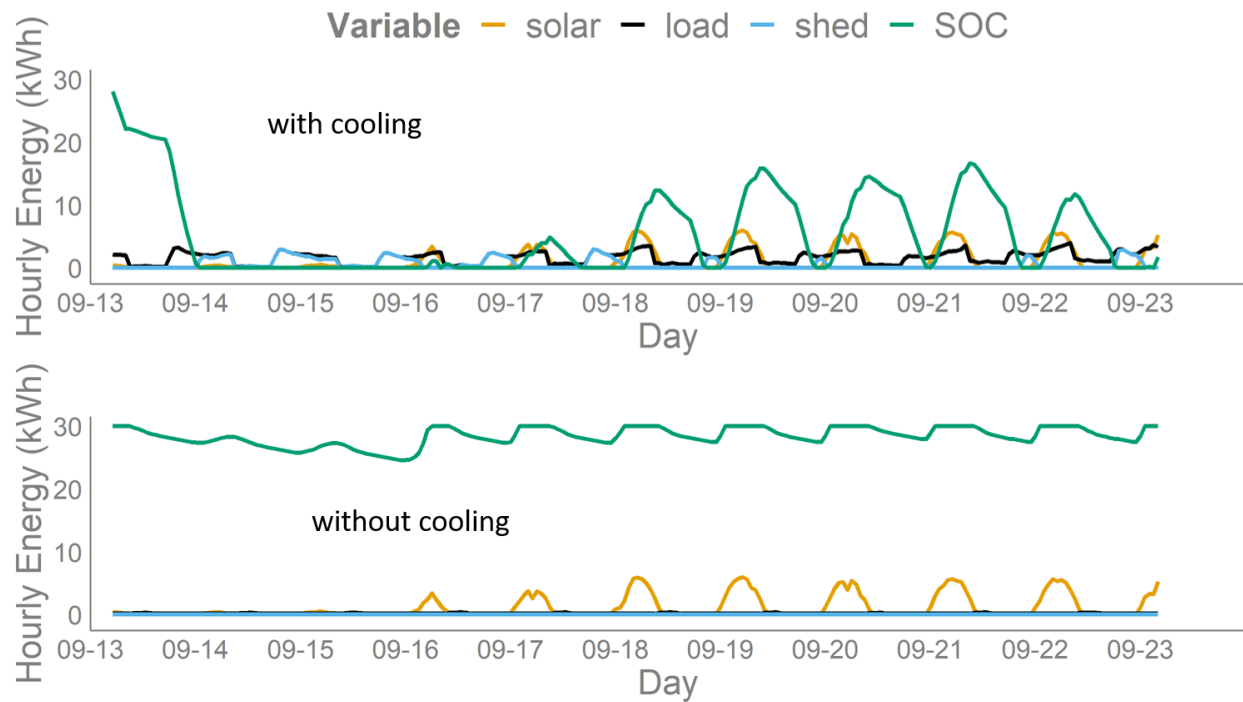


Figure 5.10: Hurricane Florence power outage time series for median home in critical load (with cooling) and limited critical load (without cooling) scenarios. Assumes PV sized to 100% of annual load, 100% beginning SOC, 30 kWh battery

5.5 Discussion

The above results establish a baseline understanding of the capabilities of PVESS to provide backup power across a range of geographies and building stock conditions and have important implications for researchers, analysts, and/or electric system planners trying to forecast the adoption of PVESS for backup. First, assuming that PVESS can fully backup a customer experiencing long-duration outages is incorrect and geographically correlated. Second, we show that the specific electric end-use requirements demanded of a PVESS backup power system will drive the resiliency capability of the system. Across all of our scenarios, PVESS could provide power to refrigeration, nighttime lighting, internet / computer loads, and well-pumps without any shed load. However, heating and cooling demand are much more difficult to backup with a PVESS system and oftentimes cannot be fully served during outage conditions under typical operating conditions. Last, we find that PVESS could mitigate outages for a significant fraction of the building stock during prominent wide-spread outage events over the last 5 years, but customers who adopt PVESS do take on weather risk if the sun is not available during the event, as shown in Hurricane Florence.

We only considered typical operating conditions without load flexibility. In the case of

an outage event, though, households will be able to adjust their thermostat set points to limit the energy demanded. Though deriving the amount of possible flexibility was out of scope for this analysis, we could analyze the relationship between our load served metric and heating and cooling temperature set-points in the select locations where we simulated all building models in ResStock. Figure 5.11 presents this relationship for Houston and Phoenix building models and shows that load served is positively correlated with cooling set-point and negatively correlated with heating set point. Differences in temperature set-points correspond to a 40% range in winter backup performance and a 20% range in summer performance in Houston (10% range in Phoenix for both winter and summer performance).

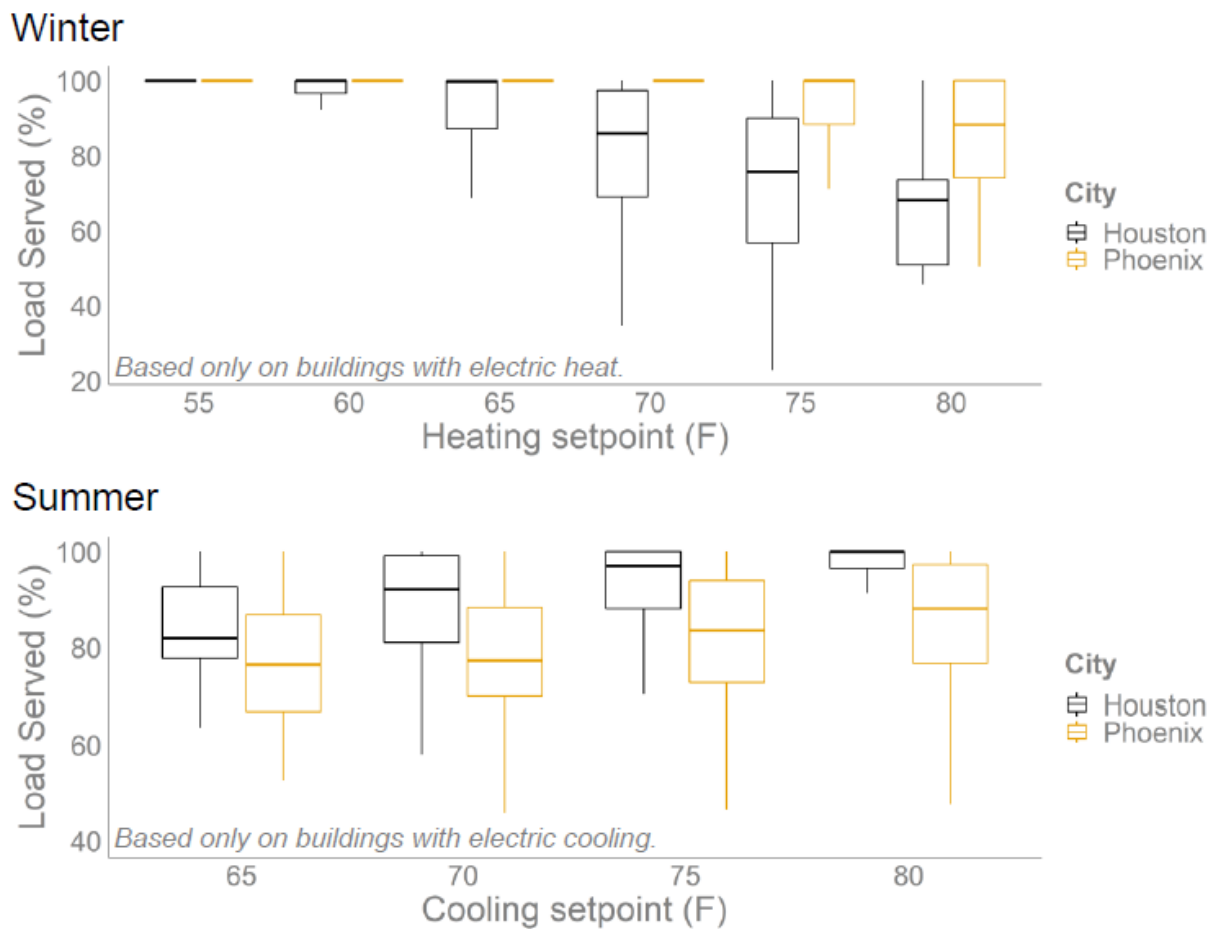


Figure 5.11: Relationship between heating (top) and cooling (bottom) set-point and percent load met by PVESS. Assumes PV sized to 100% of annual load, 100% beginning SOC, 30 kWh battery. Cooling analysis based on summer months; heating analysis based on winter months. Only consider building types with electric heating or electric cooling.

Understanding the capability of PVESS to serve heating and cooling is important because there are situations when our prioritized critical loads (i.e., refrigeration, lighting, internet

/ computer, well pumps) might vary depending on the context of the power outage event. For instance, during the Winter Storm Uri, many homes that rely on electricity to heat their homes might have re-prioritized end-uses towards electric heating given health risks posed by deadly low temperatures (Busby et al., 2021).

Notably, we found that load served is not just limited by energy but also power constraints. Though we were unable to model sub-minute electric demand, we still identified times when the AC power limit of the PVESS reduced the capability to serve load. This limitation is particularly acute for electric heating, which depending on the technology type can draw up to 20 kW or more demand (e.g. electric baseboard). This constraint bound even though we were limited by hourly load data; it is likely that we would find it even more challenging to serve the power component of heating demand, especially in regions where the default heating technology is electric baseboard heat. Future technology solutions that offer modulation of high-power loads might be required if households want to use PVESS to backup electric heating.

In this chapter, we focused on the technical capabilities of PVESS rather than the economic value of such resiliency enhancements to a household. The future adoption of PVESS, however, will be driven by how customers value reliable electric service as well as their expectations of future outage conditions. To provide insight into these values, we can convert our load served metric into a cost of served energy metric using Equation 5.2 below. The cost of served energy metric is an economic indicator which represents the levelized cost of providing energy via PVESS during an outage and is calculated by taking an annualized cost of the PVESS system⁹ net of any bill savings¹⁰ and dividing it by the load served by the PVESS over all outage events for a household in a year. It is important to note that the load served provided in this analysis is based on the portion of total load, rather than critical load, that can be served by the PVESS system.

$$CoSE = \frac{A - B}{E_s + (SAIDI * L)} \quad (5.2)$$

Where,

CoSE = cost of served energy (\$/kWh)

A = annualized capital cost of PVESS system (\$/yr)

B = annual bill savings (\$/yr)

E_s = load served by PVESS during annual outage events for a household, considering total

⁹Annual cost calculated assuming a 5% discount rate, 20-year lifetime, battery cost of \$1,000/kWh and solar cost of \$3,000/kW. We assume a 30 kWh battery and set the PV system size equal to the size assumed in our various historical event case studies (PV sized to meet 100% annual energy consumption). We ignore any upfront capital-cost subsidies in these calculations.

¹⁰Given that the majority of locations in the United States offer limited time-of-use arbitrage rates, we assume a use case where all of the energy generated by the PV system can be used to offset the local utility's retail electric price.

load case (kWh/yr)

SAIDI = 2020 System Average Interruption duration index (hrs)

L = average household consumption (kwh/hr)

This metric can be compared to research measures of the value of lost load (VoLL) assuming that the load served during the annual outage events represents a household's expectation for future annual outage events. For our historical case studies, this assumption is reasonable if these historic events represent the majority of lost energy due to annual outages for a particular household. Such a simplifying assumption is poor for the synthetic outage event analysis; therefore, we do not analyze this metric using those analyses.¹¹ We slightly augment the load served numbers by applying System Average Interruption Duration Index metrics, excluding major event days, provided via EIA 860.¹²

Table 5.2 calculates the median cost of served energy for the 10 historical events we modeled in our analysis. Each row varies the expectation for how frequent such a wide-spread outage event might occur over the course of the assumed 20-year lifetime of the PVESS system. Details of the calculation, including system cost, assumed retail rate, bill savings, SAIDI metrics, and load served are shared in Table D.3 in the Appendix.

Expected Number of events in PVESS lifetime	2020 Thunderstorm (TX)	2019 PSPS (CA)	2020 Derecho (IA)	2018 Florence (NC)	2017 Harvey (TX)	2017 Irma (FL)	2020 Isaias (NY)	2018 Michael (FL)	2020 Winter Stm (OK)	2019 Winter Stm (WA)
2 (1-in-10 years)	\$260	\$135	\$116	\$126	\$41	\$62	\$153	\$154	\$152	\$727
20 (Every year)	\$54	\$17	\$12	\$15	\$4	\$6	\$17	\$17	\$18	\$98
40 (2 times a year)	\$29	\$9	\$6	\$8	\$2	\$3	\$8	\$8	\$9	\$50

Table 5.2: Breakdown of the cost of served energy (\$/kWh) between the historical events with variation depending on assumption of the expected number of events per year

The above numbers can be compared to traditional estimates of the VoLL, which tend to

¹¹A customer's expectation for annual outages is likely not tied to a 3-day outage event occurring every month of the year.

¹²These have a limited impact on the overall results as given SAIDI metrics only represents between 1-4 hours of additional outages per year compared to major event outages between 25 and 380 hours total. However, the relative impact of SAIDI increases when assuming a lower number of expected major events over the lifetime of the PVESS system.

be between \$45-\$1/kWh for the residential customer class (Schröder and Kuckshinrichs, 2015). While some of these events are outside of the VoLL range from the literature (e.g. Washington winter storm) others are much closer, even when assuming that this type of event is relatively infrequent (e.g. Hurricane Harvey). Overall, these economic results suggest that the resilience value of PVESS must be high for a sizable fraction of customers to adopt these systems.

Of course, estimating the likely number of major outage events in the future is challenging, making it difficult to determine which row in Table 5.2 should be used. Serious events like Hurricanes are less likely than PSPS events, for instance, but future researchers could focus on estimating such probabilities regionally to refine the above calculations. Moreover, the risk aversion of PVESS adopters will induce them to pay a premium in case frequencies of events are higher than researchers may estimate. Similarly, these customers may have personal VoLLs that are higher than the average VoLL determined by researchers.

5.6 Conclusions and open research questions

In this paper, we analyzed the performance of BTM PVESS in providing backup power across a wide range of customer types, geography / climate conditions, and power outage scenarios, considering both whole-building backup and backup of a specific set of critical loads. Our approach provides an assessment of the technical potential of PVESS to enhance customer reliability. The synthetic outage analysis showed that that PVESS can meet a limited set of critical loads that includes refrigeration, nighttime lighting, well-pumps, and internet / computer load for 93% of counties if a customer was exposed to a 3-day outage in each month, and had a 10 kWh battery installed with a PV system is sized to meet 100% of annual load. However, we find that providing heating and cooling demand is much more difficult, with only 27% of counties meeting this larger demand scenario. Our results are sensitive to the size of the battery, where increasing the default battery size from 10 to 30 kWh increases the number of counties that can meet critical load with heating and cooling from 27% to 72%.

Our results relied on load profiles which are statistically representative of the current United States building stock. However, deep decarbonization policy goals suggest that the building stock will electrify beyond levels observed in our study. Though we did find signs of how electrification might pose difficulties for PVESS in providing reliable services to end-customers, future research should more precisely consider load profiles which incorporate more electrification. Such electrification might certainly pose challenges to home back-up via increasing electricity demand; however, other electrification trends could support customer resiliency. For instance, our battery size scenario of 100 kWh, which might loosely represent electric vehicle backup, increased the number of counties that can meet critical load to 94%.

Future research would need to consider how electric vehicle transport demands would com-

pete with the household backup power use case in the event of a long duration outage. Future research should also evaluate load flexibility with more detail, especially as it pertains to heating and cooling demand. Finally, our paper was focused exclusively on long-duration outage events, which can be highly costly, but are the least common form of outage experience by customers in the United States. Future work should consider how stochastic, short-term outages may be met by PVESS backup, especially considering economic operations that PVESS might be performing up to a power outage event. Such work could incorporate estimates of the VoLL to provide estimates of the resiliency value of PVESS across short- and long-duration outage events.

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Chapter 6

How rate design impacts the decision to use customer-sited solar and storage for grid defection

6.1 Introduction

As discussed in Chapter 1, solar technology costs have declined significantly in the past decade, more than halving in many parts of the world (Barbose et al., 2018; noa, 2016)¹. This has been accompanied by the rapid deployment of solar capacity through a mixture of large utility-scale projects and smaller customer-sited (or “rooftop”) installations. Most research and industry reports find that, excluding network costs and benefits, residential rooftop solar is significantly more expensive than utility-scale solar (Tsuchida et al., 2015). However, there are now over 1.3 million residential solar systems installed in the United States as of 2017 due to a combination of government subsidies, electric utility rate incentives, and consumer preferences (Barbose et al., 2018). In the coming years the number of rooftop systems is projected to grow (Gagnon et al., 2016).²

When residential households install rooftop solar, they offset their consumption of electricity from the grid, reducing their electricity bills (Darghouth et al., 2016). This process of supplementing a traditional grid connection with customer-owned solar generation has widely been termed “load defection.” When rooftop solar generation displaces grid supplied elec-

¹A version of this chapter was published in the journal, *Applied Energy*, in June 2020. I thank Duncan Callaway and Stephen Jarvis for their collaboration on the project. An individual citation of this work can be made as follows: Will Gorman, Stephen Jarvis, and Duncan Callaway. “Should I Stay Or Should I Go? The importance of electricity rate design for household defection from the power grid.” *Applied Energy*, 2020. doi.org/10.1016/j.enpol.2019.110994

²California recently mandated that all new homes will be required to install residential solar on new construction in 2020 and beyond.

tricity this reduces utility variable costs (mainly wholesale energy procurement), but does not significantly reduce utility fixed costs (mainly capital outlays on network and generation infrastructure) (Cohen et al., 2016). However, the retail rates that residential households pay often fail to reflect this segmentation of costs. Instead utilities across the United States typically have relatively low fixed charges and bundle some portion of their fixed costs into volumetric rates, the charge customers pay per kilowatt-hour consumed (Borenstein, 2016). As a consequence, when a residential household installs solar, utilities often pay more to service these customers than they collect from them (noa, 2013). This has raised concerns about inefficient “load defection”, where mismatched private incentives are such that over-adoption of rooftop solar occurs, leading to non-solar customers covering a disproportionate share of the costs of maintaining the electricity grid (Borenstein and Bushnell, 2021).

One solution that is being actively considered to resolve this issue is to redesign retail electricity rates to more accurately reflect the costs utilities incur to service their customers (Williams, 2018). The first step in such a redesign would likely entail adjusting customer rates such that their volumetric charges equaled, at least on average, utility variable costs (Borenstein and Bushnell, 2021). As a result, customer private marginal costs (PMC) would align with utility marginal costs and the scope for inefficient “load defection” should be reduced.³ However, to ensure cost recovery, utilities would need to match any reduction to volumetric charges with an increase in alternative charges. Fixed per-connection charges are a natural alternative, however if these charges are sufficiently high then some customers may be incentivized to permanently disconnect from the grid and use on-site battery backup for reliability instead – so-called “grid defection” (Costello and Hemphill, 2014). Indeed, the combination of cost declines of solar and storage technologies (Hittinger et al., 2012) and the expectation that retail electricity rates will increase over time has spurred interest in grid defection, both at the residential (Bronski et al., 2014) and commercial/industrial scale (Spector, 2016). In this chapter, we explore the extent of the incentives for both load defection and grid defection in the residential sector, as well as the role of retail rates in determining how efficient these changes will be. Our focus will be on the United States, although our approach and findings are applicable to the issue of load and grid defection more generally.

6.2 Literature review

There is a range of existing research on the economics of standalone customer-sited systems. Some of this research focuses on countries with significant rural off-grid populations (Schnitzer et al., 2014), broadly finding that the cost of decentralized systems can be preferable to the large capital investments required for connecting new customers to the grid (Lee

³This figure is different from total social costs, which would also include the fixed costs required provide electricity as well as the social costs that result from electricity consumption (e.g. environmental pollution).

and Callaway, 2018), both using renewable-only (Chakrabarti and Chakrabarti, 2002) or fossil based hybrid off-grid systems. The literature on grid defection for existing grid customers using solar generation and battery storage (solar/storage off-grid systems) has mixed findings. Early work by the Rocky Mountain Institute (RMI) predicted that these off-grid systems could reach grid parity by 2022 in Hawaii and 2037 in California, partly due to projections of rising utility costs (Bronski et al., 2014). Other modeling in Michigan’s Upper Peninsula suggested grid defection is already economic for some households (Kantamneni et al., 2016) and commercial customers (Peffley and Pearce, 2020), though only with the addition of fossil-fuel based back-up power. Most other work points to low potential for grid defection for solar plus storage systems (Hanser et al., 2017). The general conclusion from these studies is that the relatively high cost of storage (Fares and Webber, 2017), the reliability of the existing grid (Khalilpour and Vassallo, 2015), and opportunities for rate arbitrage of demand and time-of-use rates (Bronski et al., 2015), together, make any significant near term grid defection unlikely in the United States (Hittinger and Siddiqui, 2017).

However, it is critically important to note that none of the above papers investigate the influence of utility cost recovery via fixed charges nor do they consider reliability preferences on defection decisions within a heterogeneous customer population. This is the domain where this research makes its contribution. Fixed charges are relevant to the defection decision because, once a load-defecting solar-plus-storage customer can produce as much electricity as they consume, the central purpose of their grid connection is reliability. If the value of that reliability drops below the cost of the fixed charge, a customer is likely to grid defect. Though some papers have investigated the impact of rate design on solar and storage adoption (Darghouth et al., 2016) and operation (Ratnam et al., 2015; Babacan et al., 2017), these studies do not consider the potential for grid defection. One study investigated grid defection in a German rate design context, but focused on individual case studies rather than a wider range of customer heterogeneity (von Appen and Braun, 2018).

Our research approaches this research gap by using a solar/storage optimization model that minimizes customer electricity costs under a variety of demand and retail rate scenarios. We use the model to answer several key questions: (1) how do residential load defection and grid defection differ by region across the United States, (2) how strongly do fixed charges impact defection decisions, (3) what is the role of differences in consumption across customers, (4) what is the effect of customer standards for off-grid reliability on grid defection decisions, and (5) how much greater is the potential for defection in a plausible future scenario where the cost of solar and storage is significantly reduced.

Specifically, we find that without fixed charges there is very limited incentive for customers to fully defect from the grid and that load defection follows existing patterns. This corroborates prior research. However, grid defection in certain regions is possible if technology costs continue to decline and if utility tariffs are structured so that fixed charges recover a larger fraction of utility costs. Our results indicate strong heterogeneity in defection potential:

under our modeling assumptions, if customers expect perfect reliability, essentially none in the Pacific Northwest, Midwest, and Mid-Atlantic regions of the U.S. will defect. However, in the Southwest and California 3% of customers could defect, and this rises to as much as 7% in Hawaii. We also find that customers with very low electric demand would have the strongest incentive to defect from the grid in a high fixed charge environment. Finally, we show that if customers relax their reliability requirements, more grid defection is possible. In our “flexible” reliability scenario, we find grid defection could increase several-fold across the United States, from 1% to 7% of households. Our results have serious implications for electric utility policy – specifically around rate design. In particular, if utilities seek to limit inefficient load defection by setting variable charges to levels that reflect only marginal costs, those that require high fixed charges to ensure full cost recovery could face significant inefficient grid defection.

The remainder of this chapter is organized as follows. In section 3, we outline a new theoretical framework to describe the interaction between rate design and grid defection, and then describe the mathematical model we use to estimate defection decisions while considering the importance of customer reliability preferences. In section 4, we describe the data used to capture heterogeneity in solar resources, utility tariffs, and customer demand. Section 5 describes our results while highlighting the key drivers of defection. In section 6 we discuss implications for our results and conclude in section 7.

6.3 Research design and methods

Economics of Grid Defection and Utility Rate Design

A household could decide to go “off-grid” and defect from their electric utility for two primary reasons: (1) off grid systems become cheaper than utility service (grid parity), and (2) customers become dissatisfied with their utility’s product when compared to the electricity service provided by an off-grid system (e.g. poor grid reliability, desire for fully “green” electricity, desire for self-reliance). Our research focuses on the core cost and engineering drivers of grid defection and so only considers the first situation. There is, however, some exploration of how preferences for different reliability levels could impact the defection decision. A broader exploration of consumer preferences for electricity service, which could affect willingness-to-defect, is outside the scope of this chapter, but is discussed to some extent in chapters 3 and 4 of this dissertation.

Grid defection due to grid parity is economically intuitive: if electricity can be obtained from cheaper sources than the utility’s network, it is economically rational for a customer to defect from the grid (van der Mei et al., 2019). In this chapter we evaluate solar/storage

systems as the alternative source⁴; as with other work in this area the key drivers we focus on are the costs of solar/storage technology, the customer's electricity consumption needs, the nature of the available solar resource, and the cost of existing electricity provision from the grid. Importantly though, the cost of existing electricity provision from the grid is not just determined by the general level of electric utility rates but also by their structure. Utility rate design can therefore play a critical role in determining the point of solar/storage grid parity.

Electric utilities typically recover their costs from residential customers in the form of a two-part retail tariff comprising a volumetric component (cost per kWh consumed) and a fixed component (monthly or annual fee).⁵ The relative size of these components alters the relative costs faced by customers with differing levels of consumption (Borenstein, 2016). For example, if one holds a utility's total revenue fixed, increasing the fixed component of their retail tariff and reducing the volumetric component will shift costs from customers that consume large volumes of electricity to those that consume low volumes. This in turn alters the point of solar/storage grid parity.

To illustrate this, Figure 6.1 sets out a hypothetical choice faced by two customers over how to meet their electricity needs. Both customers have inelastic demand for electricity, but one customer has low electricity demand and one has high electricity demand (red lines in Figure 6.1). Each customer can either buy grid electricity from their utility, or they can install a solar/storage system and defect from the grid. The cost of a solar/storage system is primarily upfront capital costs, and if the size of the system scaled linearly with a customer's consumption then this results in a flat average cost curve (gold lines in Figure 6.1). On the other hand, grid electricity is paid for according to a simple two-part tariff with a fixed fee (blue dots in Figure 6.1) and a marginal variable charge (blue dashed lines in Figure 6.1). As such grid electricity has a downward sloping average cost curve (blue lines in Figure 6.1). Figure 6.1 depicts two rate designs to illustrate how changing the average cost curve of grid electricity can drive grid defection. The first rate design (on the left) has a low fixed fee and a high variable charge. Under this cost structure the average cost of grid electricity is below the average cost of solar/storage for both customers and so neither defects. The second rate design (on the right) has a high fixed fee and a low variable charge. This means that relative to the first rate design the costs of grid electricity are higher for the low demand customer and lower for the high demand customer. Under this cost structure the average cost of grid electricity is still below the average cost of solar/storage for the high demand customer. However, for the low demand customer the solar/storage system now has the lower average

⁴Grid defection could also occur through other technologies, such as fuel cells or diesel gen sets, and these other distributed technologies could be analyzed using the same framework presented in this chapter.

⁵Residential demand charges have also been proposed to recover utility costs but are out of scope for this research (Hledik, 2014). Rather, we highlight qualitative implications of applying a three-part tariff with demand charges in the discussion section of the chapter.

cost and so this customer defects.

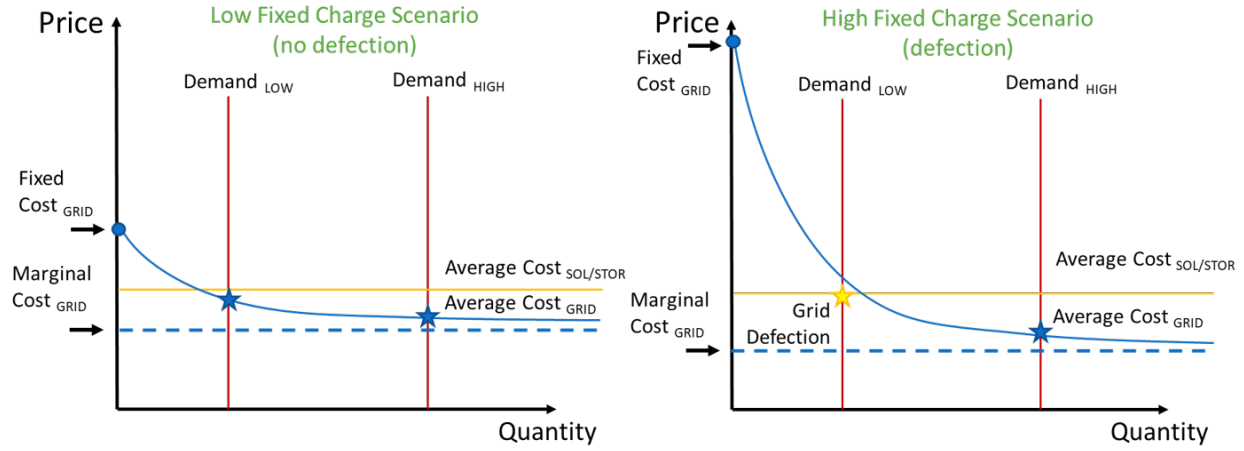


Figure 6.1: Illustration of two-part tariff rate design and corresponding point of grid defection for the low demand customer in high fixed charge scenario

This example demonstrates that the point of grid parity is not solely driven by the costs of a solar/storage system but also by the relationship between retail tariff design and customer consumption levels. Figure 6.2 illustrates this point for a continuum of rate designs ranging from those that recover revenues entirely through variable charges (0% recovery via fixed charge on the x-axis) to those that rely entirely on fixed charges (100% on the x-axis). In this particular example we see that a low-demand customer (green line) would defect at or above a fixed charge recovery percentage greater than 60%, whereas a high-demand customer (red line) would never defect.

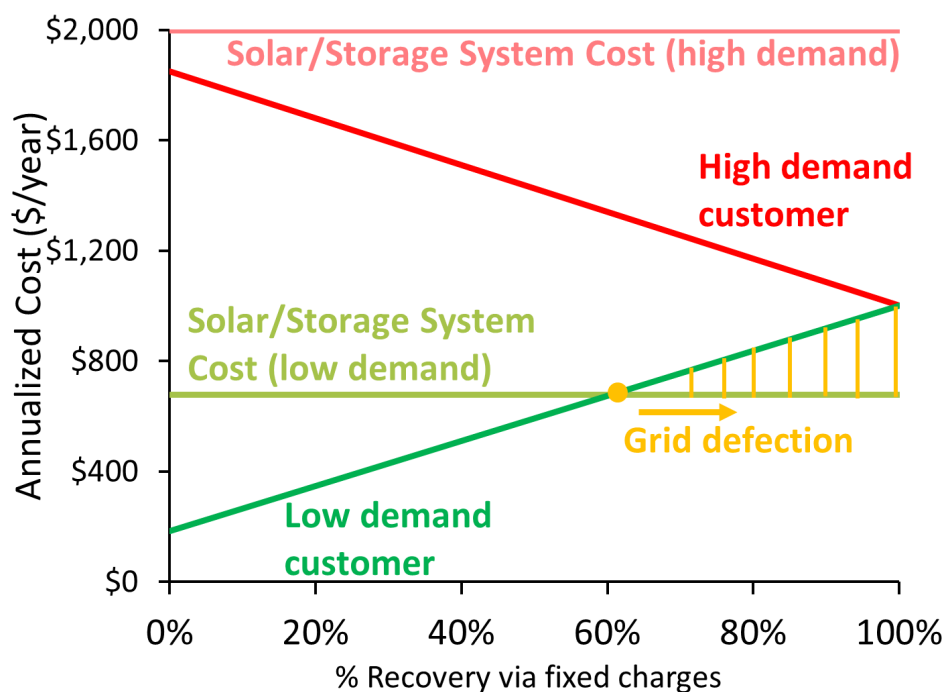


Figure 6.2: Illustration of point of grid defection with varying fixed charge in a two-part rate scheme for the low-demand customer

The point of grid parity, and the extent of grid defection, has important implications for economic efficiency. When a customer defects, their utility will no longer incur marginal supply costs for that customer or customer-specific fixed costs (e.g. metering and billing). If a defecting customer only avoids paying customer-specific costs (marginal supply costs and customer-specific fixed costs such as metering and billing), their decision would not unduly burden any remaining utility customers, and grid defection would be socially efficient. Yet because utilities also recover sunk fixed costs (i.e. legacy generation capacity and network costs that are not reduced when a marginal customer defects from the grid) in their rates, defecting customers also avoid paying these fixed costs; this is economically inefficient because the customer's private economics do not align with social marginal costs (Borenstein, 2018). The scale of these sunk fixed costs (Fares and King, 2017) and the way in which they are being recovered through rate design will determine which kinds of customers choose to defect, and how inefficient this defection will be.

At present it is common for utilities in the U.S. to recover a substantial portion of fixed costs through setting variable charges above true marginal costs (Borenstein and Bushnell, 2021). This has adverse implications for efficiency by under-incentivizing consumption (e.g. electrification of heating or transportation) and over-incentivizing the adoption of technologies that can substitute for grid electricity (e.g. installing rooftop solar). This has led to increasing concerns about inefficient “load defection” where customers, particularly high-demand customers, install solar to reduce their exposure to these variable charges, and in so doing

shift the burden of fixed cost recovery onto other non-solar customers.

There are now growing calls to restructure utility rates to tackle the problem of load defection by shifting revenue collection away from variable charges towards fixed charges. This may indeed reduce load defection, but it will likely increase the potential for “grid defection”, especially amongst low-demand customers as we have illustrated above.⁶ Crucially, this situation of inefficient grid defection can arise even when a utility is setting its fixed and variable charges in a seemingly efficient manner such that they properly reflect the segmentation between the fixed and marginal costs of providing electricity. The critical point is that a shift towards rates with higher fixed charges designed to recover non-customer specific fixed costs could lead to inefficient grid defection. We describe how tax structure, exit fees, and rate design adjustments could offer solutions to this inefficiency in the discussion section of this chapter.

Solar and Storage Optimization Model

Objective function and constraints:

To calculate the cost of solar/storage systems, we develop an optimization model that sizes an off-grid system. The solar/storage optimization model is defined by linear constraints and a linear objective function, and the objective function minimizes the cost of the solar/storage system given a specific electric demand and solar profile (Bordin et al., 2017). The key variables are the size of the solar and storage system, the battery’s state of charge, and power going into or out of the battery in one-time step ($t = 1$ hour). We treat solar array and storage system size (X and Y) as decision variables.⁷ Note that although we account for DC-to-AC inverter costs later, we do not treat inverter size as a decision variable because, for an off-grid system, it is dictated by customer demand – which is an exogenous assumption in our model framework – rather than PV or battery size. The below equations mathematically describe the objective function and constraints on the optimization. The annualized solar and storage capital costs assumptions that are used to parameterize these functions is shown

⁶The shift from load defection to grid defection also has important dynamic consequences. As the number of defectors increase, the utility would potentially have to correspondingly increase fixed charges on other consumers to recover system wide fixed costs which could result in even more grid defection. This process is termed the utility death spiral in the electric industry. Historically the threat of a utility death spiral has been associated with load defection where it is high variable charges rather than high fixed charges that drive the process.

⁷We also place a very small cost on discharging electricity from the storage unit to represent battery degradation due to cycling.

below in Table 6.1.

$$\underset{x, y}{\text{minimize}} \quad X * C_{pv} + Y * C_s + B_d * D \quad (6.1a)$$

$$\text{subject to} \quad SOC_0 = \frac{Y}{2}, \quad (6.1b)$$

$$SOC(k+1) = SOC(k) + \eta B_c(k) - \frac{B_d(k)}{\eta}, \quad (6.1c)$$

$$0 \leq SOC(k) \leq Y, \quad (6.1d)$$

$$0 \leq B_c(k) \leq \frac{Y}{4}, \quad (6.1e)$$

$$0 \leq B_d(k) \leq \frac{Y}{4}, \quad (6.1f)$$

$$L(k) = B_d(k) + B_c(k) + X * S_k(k) + E_l(k) - D_{pv}(k), \quad (6.1g)$$

$$\sum E_l(k) \leq \sum L(k) * R, \quad (6.1h)$$

$$M(k) \leq L(k) - E_l(k) \quad (6.1i)$$

Where,

X = size of solar system (kW)

Y = size of storage system (kWh)

C_{pv} = annualized capital cost of solar panels (\$/kW-year)

C_s = annualized capital cost of storage (\$/kWh-year)

D = Cost of discharging (i.e. degradation cost) (\$/kWh)

SOC_k = state of charge of battery at time step k (kWh)

B_c = battery charging (kWh)

B_d = battery discharging (kWh)

η = battery efficiency (%)

L(k) = demand at time step k (kWh)

$E_l(k)$ = electricity shed from given demand profile at time step k (kWh)

S(k) = power generated from solar, as percentage of installed capacity, at time step k (%)

$D_{pv}(k)$ = curtailed PV production (kWh)

R = demand shed over the year (as a fraction of total)

M = minimum demand served at a given hour (set equal to 300 kW)

Since we are studying grid defection, we do not allow the system to reap payments from energy sent back to the grid from the solar panel. The solar/storage system owner would not be able to sell energy back to other users because they would not be connected to the distribution grid. Therefore, any excess solar production that cannot be stored is curtailed in our model framework.

We implemented a number of operational constraints on the system, shown above in equation 2.1b-f. The main operational constraint placed on the solar/storage system is the demand balancing equation (Eq. 2.1g). This equation sets the rule that the energy consumption has to match the energy production during a given time step. The left-hand side represents household energy use while the right-hand side represents energy production (i.e. positive terms for battery discharging, solar energy production, or avoided consumption due to our reliability constraint) and energy consumption (i.e. negative terms for battery charging or curtailed solar production). The final constraints establish the bound on how much electricity can be shed due to our reliability constraint (Eq. 2.1h, 2.1i).

Reliability scenarios:

It is important to note that we consider two reliability scenarios in the presentation of our results below: (1) a “perfect” reliability case and (2) a “flexible” reliability case. In the first case, the optimization model is not allowed to shed demand in any hour (i.e. $E_l(k)$ is 0 in every hour). In the second case, however, the model can shed a predetermined percentage of a customer’s energy over the time horizon of our model.⁸ This serves to significantly weaken the constraint on the solar/storage system, and therefore significantly reduce the size and thereby cost of the solar/storage system. There are reasonable concerns that such a scenario is unrealistic in that it assumes customers would be willing to forego electricity consumption for long durations of time. We elaborate on these concerns in the discussion section of this chapter.

Notably, this scenario chooses to shed demand in hours that it would be most difficult to provide solar/storage energy rather than the hours that the consumer might be willing to forego electricity. Constraint 1i is used to increase the realism of the “flexible” reliability scenario. Constraint 1i requires that for every hour studied in our time horizon, the solar/storage system has to provide a minimum level of baseload power, which we set to 300 watts in this study.⁹ This constraint, in effect, ensures that such high value electricity services such as refrigeration, lighting, and communications technology remain in service throughout our study period even when allowing the model to shed demand. Furthermore, our “perfect” reliability case is a conservative scenario in that it assumes households have absolutely no ability to shift or reduce consumption relative to the fixed demand profiles we employ. Our “flexible” reliability case allows us to proxy for some of these effects (Bronschi et al., 2015).

In the framework above, we assume that future hourly demand for electricity and future

⁸In the results section, we only run one flexible reliability case where we allow the optimization model to shed 1% of annual demand.

⁹In cases where 300 Watts is larger than the minimum demand throughout our time-horizon, we instead use the minimum demand of that customer as the value for minimum demand constraint (M). This does not substantially affect our results due to the fact that our lowest minimum demand from our 2,700+ load cases is 270 Watts.

hourly solar production is known. Though in practice there will be uncertainty around these quantities, our results show that system sizing is driven by seasonal rather than day-to-day or hour-to-hour input assumptions. Thus, while the dynamic interaction of stochastic solar production and demand preferences would affect the day-to-day operation of the system, it would not significantly affect the overall system sizing decision (Shaner et al., 2018). Since the sizing decision ultimately drives the annual cost of our solar/storage systems, it is the key element in understanding the potential for grid defection.

We use the commercial optimization solver, Gurobi Optimizer (Gurobi). This solver is used for a variety of mathematical programming problems, including linear programming, quadratic programming, and mixed integer linear programming among others. We rely on their linear programming solutions. The implementation of the optimization model is done utilizing the Julia programming language and the package JuMP (Dunning et al., 2017).

Cost Assumptions:

Equation 6.2 below represents the final annualized capital costs of a solar/storage system, where inverter, balance of system, and operations and maintenance costs (which are driven by customer demand, assumed exogenous) are combined with the solar/storage costs from Eq. 2.1.

$$TotalSystemCost = X * C_{pv} + Y * C_s + PL * C_L + PL * OM \quad (6.2)$$

Where,

X = size of solar system (kW)

Y = size of storage system (kWh)

PL = peak load of customer (kW)

C_{pv} = annualized capital cost of solar panels (\$/kW-year)

C_s = annualized capital cost of storage (\$/kWh-year)

C_L = annualized capital cost of inverter and balance of system costs (\$/kW-year)

OM = operation and maintenance costs (\$/kW-year)

Our cost assumptions are included in Table 6.1, and we use these numbers in Equation 2.1 above to compute the final system cost that we compare to the cost of utility prices. Because direct subsidies, such as the 30% Federal investment tax credit (ITC) are set to expire in the near future, we ignore them (Ludt, 2019). We assume a real interest rate of 4% over the life of the assets (10 years for the battery and inverter; 25 years for the solar panels). Interest rate assumption and solar lifetime come from Borenstein (Borenstein, 2008). Battery efficiency and lifetime assumptions based on (Moris, 2018).

In order to capture possible future cost declines in solar/storage we analyze both a current-cost scenario and a future-cost scenario. The current-cost scenario is taken from Lawrence

Financial Category	Assumptions Used
Interest Rates	Both at 4% real
Lifetime	• Solar: 25 years • Storage/inverter: 10 years
Efficiency	Storage: 85% roundtrip
Optimization Capital Costs	• Solar: Current-$\\$1.2/W_{dc}$; Future: $\\$0.6/W_{dc}$ • Storage: Current-$\\$400/kWh$; Future-$\\$100/kWh$
Load-based Capital Costs	• Inverter: Current-$\\$0.3/W_{ac}$; Future-$\\$0.15/W_{ac}$ • Soft Cost/BOS: Current-$\\$1/W_{ac}$; Future-$\\$0.50/W_{ac}$ • O&M: $\\$12/kW_{ac} - year$

Table 6.1: Financial and cost assumptions for solar/storage system under current and future cost scenarios

Berkeley National Laboratory’s Tracking the Sun report and a bottom-up solar cost calculation from NREL for PV (Fu et al., 2018; Barbose et al., 2018) and from NYSERDA for batteries (NYSERDA, 2016), and serves as a current estimate for installed costs for residential systems. Data for the future-cost scenario is taken from Kittner for batteries (Kittner et al., 2017) and the International Renewable Energy Agency for solar (IRENA, 2016) and are meant to represent a future with plausible but aggressive cost declines; these references suggest these declines are possible in the next 5-10 years. In the results section of this chapter, we focus our detailed presentation on the future-cost scenario while outlining the key results from our current-cost scenario. Detailed results of the current-cost scenario can be found in Appendix E.

Determining the decision to defect

Our analysis essentially assumes a customer can decide between three options to meet their electricity needs: (1) remain connected to the grid and do not install solar (i.e. no defection); (2) remain connected to the grid and install a solar system without storage (i.e. load defection); or (3) disconnect from the grid and install an off-grid solar and storage system (i.e. grid defection). To determine which decision customers would make we compare the costs of electricity from these three different outcomes at a range of locations and under a

range of scenarios. The equations used to calculate these costs are shown in Eq. 2.3-2.5.

$$\text{Grid electricity cost: } \text{Cost} = \text{FC} + \text{VC} * Q_f \quad (2.3)$$

$$\text{Load defection cost: } \text{Cost} = \text{FC} + LCOE_{pv} * Q_f \quad (2.4)$$

$$\text{Grid defection cost: } \text{Cost} = \text{Total system cost represented in Eq. 2.2} \quad (2.5)$$

Where,

FC = Fixed charge for grid connection (\$/yr)

VC = Variable charge for electricity consumption (\$/kWh)

Q_f = Annual electricity consumption of customer (kWh)

$LCOE_{pv}$ = unique levelized cost of energy for solar by geographic location (\$/kWh)

In the above framework, we assume customers are rational and choose the cheapest option for electricity service. However, we also constrain the defection decision by the system size required to meet the electricity needs of the consumer. Large system sizes that may result from our optimization analysis might not be practical for many locations due to the physical constraints of adopting large storage and solar systems in a residential context. The median size for residential solar installations in California has been 5 kW, although the largest 1% of residential systems in the state have been in excess of 19kW (CSI). These numbers reflect both the economic considerations as well as the available roof area constraint for residential systems (Barbose et al., 2018). We perform a back of the envelope calculation to better assess roof size limitations. Using an average, two-story home size of 250 m^2 and assumptions from Gagnon, we calculate the median home is physically constrained to 14-19.6 kW solar systems (Gagnon et al., 2016).¹⁰ Therefore, we disallow grid defection in cases where the optimal PV system is larger than 20 kW. Furthermore, we also disallow grid defection if the optimal storage system is larger than 84 kWh. This is equivalent to restricting our grid defection cases to the installation of 6 Tesla Power Walls, which would require roughly 5.6 m^2 of wall space (Lambert, 2016).¹¹ We discuss how often these constraints bind in the discussion section of this chapter.

¹⁰Assumptions include a module power density of 160 W/m^2 , a ratio of module area to roof area of 0.7 for flat roofs, and of 0.98 for tilter roofs. We use average home size of 250 m^2 and that homes are 2 stories resulting in a roof space of 125 m^2

¹¹Tesla powerwall is 1.22 m tall by 0.76 m wide, covering a total of 0.93 m^2 . The powerwall has an energy capacity of 14 kWh.

6.4 Data

Demand and Solar Data

Solar radiation data is taken from NREL’s national solar radiation data base (NSRDB) from 2008-2016 (Sengupta et al., 2018). This gives us 9 years of historic hourly solar generation for almost all counties in the U.S. ($n = 3209$). To create the solar AC generation, we simulated hourly generation from on-site solar systems using the NREL’s System Advisory Model (SAM) (NREL, a). We set the nameplate capacity to 1 kW, with a DC to AC ratio of 1.1, system losses of 14%, and an inverter efficiency of 96%. The optimization model discussed above linearly scales the hourly generation from the SAM simulation based on the optimized nameplate solar size. By utilizing historical data, we can better simulate actual outcomes customers would see over this timeframe.

The demand data is taken from the Department of Energy’s OpenEI database (Wilson). The dataset provides us with annual residential demand profiles for 930 locations in the US. We match these to US counties by finding the demand profile that is nearest to each county centroid. These data are calculated by the National Renewable Energy Laboratory (NREL) using residential building models and the EnergyPlus simulation software (noa). The building models consider electricity end-uses that are dependent on weather (e.g., heating, cooling) and others that are not (miscellaneous plug loads), and these parameters are based on standard building assumptions that vary by geographic region. The building characteristics chosen are significant drivers of the optimization results, as they are used to simulate the household loads used to determine the demand inputs for our optimization model. Furthermore, while NREL made educated guesses for the characteristics of a “generic” household in each geographic location based on climate zone, the model used cannot be generalized for all households in the respective locations. For example, the locations which fall into NREL’s ‘hot-humid’ climate zone will use electric heating. However, NREL assumes households in the other climate zones will use natural gas heating. These differences change the consumption profiles and therefore the size of the required solar/storage system. Furthermore, NREL provides high, base, and low demand cases which are the result of changes in a variety of home characteristic assumptions (NREL, b).¹² We compare the effect of these different demand assumptions in our analysis.

We note that these residential demand profiles use typical meteorological year data (TMY3) as the weather profiles (Wilcox and Marion, 2008). This means we are using TMY3 data for the demand profiles while relying on historic solar radiation data for the solar profiles. Ideally both demand and solar data would be derived from the same weather conditions. However we argue that this does not substantially alter our core findings, because we are

¹²NREL modifies items like total square footage, number of stories, and a variety of energy efficiency assumptions of the appliances.

capturing key seasonal variation which is more important to system sizing in this context, where batteries are sized to have multiple days of storage (Shaner et al., 2018). In future work with a narrower geographic focus we plan on conducting this kind of analysis with a consistent set of demand and solar data in order to fully explore this issue.

Retail Cost Data

In order to compare the costs of our solar/storage systems to the cost of grid electricity we collected utility rate data across the United States. For this we rely on data from Borenstein & Bushnell, although we make a few adjustments to include Alaska and Hawaii (Borenstein and Bushnell, 2021). This gives us annual data on residential retail rates, kilowatt-hour sales, revenues and number of customers for more than two thousand electric utilities in the US between 2014 and 2016. This dataset has complete coverage for more than 95% of the 130 million residential households in the US. Their analysis is primarily based on data from the Energy Information Administration’s Form 861 Survey (EIA, 2015a). This was combined with additional information on residential fixed charges for each utility using OpenEI’s utility rate database (NREL, c). The variable charge was then calculated by subtracting fixed charge revenue from the utility’s collected residential revenue and then dividing the remaining residential revenue by the kWh of residential sales. A more detailed discussion about these data can be found in the referenced paper.

We use the median 2016 rates in each county and the load profiles discussed above to calculate the annual cost of grid electricity for a residential customer under current rates. We then use the annual cost of grid electricity for a residential customer under an alternative rate structure. Here the variable charge is set equal to our estimate of utilities’ private marginal costs (PMC). We do this by calculating the load weighted annual average wholesale price of electricity in each utility’s territory, adjusted for estimated residential distribution losses. Where this new alternative variable charge differs from the existing variable charge, we also calculate the necessary alternative fixed charge that results in revenue neutrality for the utility. These new variable and fixed rates allow us to recalculate the annual cost of grid electricity in a manner that captures how potential changes in rate design might affect customer decisions to defect.

Figure 6.3 maps the fixed and variable electricity rates in each county in the U.S., both for current rates and for our alternative rate structure where variable rates are set equal to utilities’ average private marginal costs. Notably, there is a significant increase in fixed charges when moving to this alternative rate structure. This is because the majority of utility revenue today is collected through variable charges. In the next section, we use these rates to calculate the annualized bill for a given location and demand profile using the three different demand profile assumptions. Overall, by defining these two retail cost of electricity scenarios, we are able to investigate how the change in tariff design impacts defection decisions for a heterogeneous pool of electric consumers.

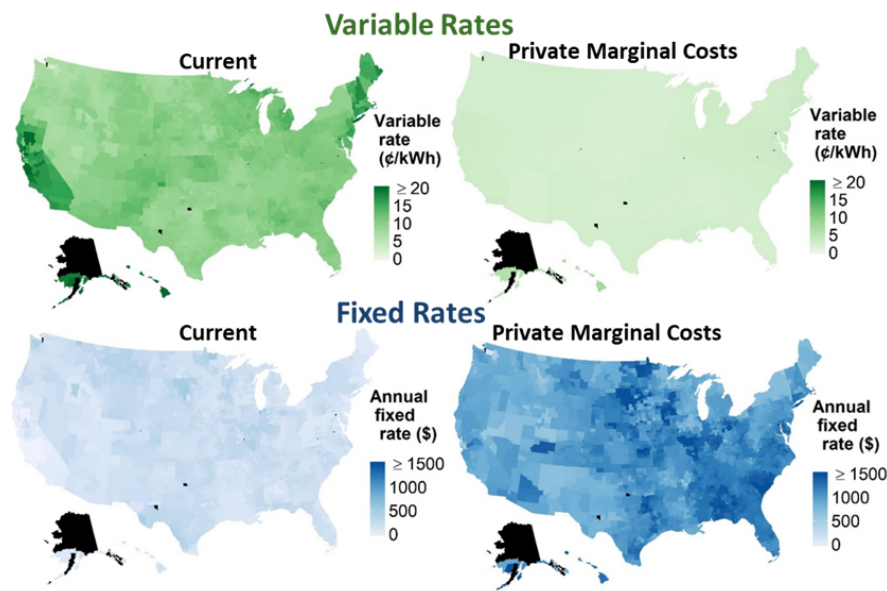


Figure 6.3: United States 2016 current two-part electricity rates (left figure) compared to private marginal cost (PMC) two-part electricity rates based on wholesale market prices (right figures). Note that range of variable rates in PMC scenario (top right graph) is 2.2 - 7.6 cents/kWh

6.5 Results

To examine the scope for grid defection, we explore a wide range of scenarios. These cover two rate design assumptions (current rates vs. private marginal cost “PMC” rates), two different solar/storage cost assumptions (current costs vs. future costs) and two different reliability assumptions (“perfect” vs. “flexible”). For each of the resulting eight scenarios, we estimate which kinds of household would opt for either a) keeping grid utility service, b) load defection by installing solar but remaining connected to the grid, or c) grid defection by installing solar and storage and disconnecting from the grid. For each scenario, the primary variation in household decisions is driven by where in the country a household is (i.e. which county) and how much electricity a household consumes (i.e. whether a household is a low, medium or high demand customer).

Table 6.2 summarizes our estimates of the number of households that choose to defect across our various scenarios. Here we can see that the scope for grid defection is very limited with current technology costs. This result conforms to observed solar and storage adoption patterns, i.e. substantial load defection in some regions, but no significant grid defection. Further detail on the current-cost assumptions can be found in Appendix E. As expected, the current retail rate structure tends to incentivize load defection rather than grid defection, and this is consistent with the extent of solar adoption that has already occurred in states like California and Hawaii. Altering retail rates as in our “PMC” scenarios dramatically

curtails load defection whilst also providing some incentive for grid defection instead. In all cases relaxing the stringency of the reliability that a solar/storage system needs to achieve makes it easier for households to defect.

Scenario			Households (millions)		
Technology Cost	Rate Structure	Reliability	Utility Service	Load Defection	Grid Defection
Current	Current	Perfect	126	9	0
Current	Current	Flexible	126	9	0
Current	PMC	Perfect	134	0	0
Current	PMC	Flexible	134	0	0
Future	Current	Perfect	80	55	0
Future	Current	Flexible	80	54	0.3
Future	PMC	Perfect	133	0	1
Future	PMC	Flexible	123	0	9

Table 6.2: Household defection results in 8 different scenarios considered. Shows no significant grid defection under current cost scenario with potential for grid defection under future cost scenario

Importantly, as set out in the prior methods section we do not actually conduct our solar/storage system optimization for the full distribution of 134 million residential households in the US. Instead, we conduct our analysis for a set of 9306 household cases – a “low”, “base”, and “high” consumption household for 3102 US counties. For each of these cases we produce an estimate of whether the household will choose to defect based on the cost of the required solar/storage system as compared to the local cost of grid electricity service. To appropriately weight the defection results and get an estimate of the total number of households that defect we first calculate the proportion of households in each county that fall into each of the three consumption categories using data from the 2015 EIA Residential Energy Consumption Survey (RECS) (EIA, 2015b). The RECS dataset provides detailed information on a range energy-related issues for a nationally representative sample of almost 6,000 households. We use the distribution of annual household electricity consumption in the RECS to approximate the proportion of households that are “low”, “base”, and “high” demand customers.¹³ Next we use county-level data from the US Census on household counts to appropriately weight the results across each of the 3102 counties. Finally, we draw on additional data in the RECS dataset to limit defection to households that could plausibly

¹³We match the RECS data to counties based on Census Divisions as this is the most granular geographic unit in the RECS database. The proportion for the “low” profile is determined by first counting the number of RECS households with annual electricity consumption less than or equal to the midpoint between the annual electricity consumption for the “low” and “base” profiles. A similar algorithm is used for the “base” and “high” profiles. These three counts of RECS households are then divided by the total number of RECS households in that climate division to get a set of three weights that sum to one.

install a solar/storage system and defect from the grid. For this we assume that a household must be a) a homeowner, and b) live in a single-family house. This generally covers around 50-60% of households in the US. Adding this additional restriction captures the fact that the barriers to defecting are especially high for households that are renters, or that live in multi-family buildings or apartments without suitable roof space for solar.

Drivers of Grid Defection Potential

The results in Table 6.2 clearly highlighted that significant grid defection only occurs when a number of factors have aligned. In particular, grid defection is most likely where low demand customers are willing to accept a more “flexible” level of reliability, are subject to a restructured “PMC” rate design, and have access to lower solar/storage costs. We now explore these various drivers in more detail. Furthermore, given that significant grid defection only occurs in the scenarios with lower solar/storage technology costs the rest of this section focuses on these future cost scenarios.

Figure 6.4 shows the results of our optimization analysis to find the solar/storage system size that satisfies the physical requirements of defecting from the grid. We find there is significant heterogeneity in the size of the system needed for a household to be able to defect from the grid. In general, households with low electricity demand in areas with high solar insolation have the lowest system size requirements, and thereby the lowest solar/storage system costs. We note that the reduced reliability constraint has a significant effect on the solar/storage sizing. For the 1% energy reduction that we use in the “flexible” reliability scenario, the mean solar size across the 3 demand cases is reduced by 43% and the mean storage system size is reduced by 59%.

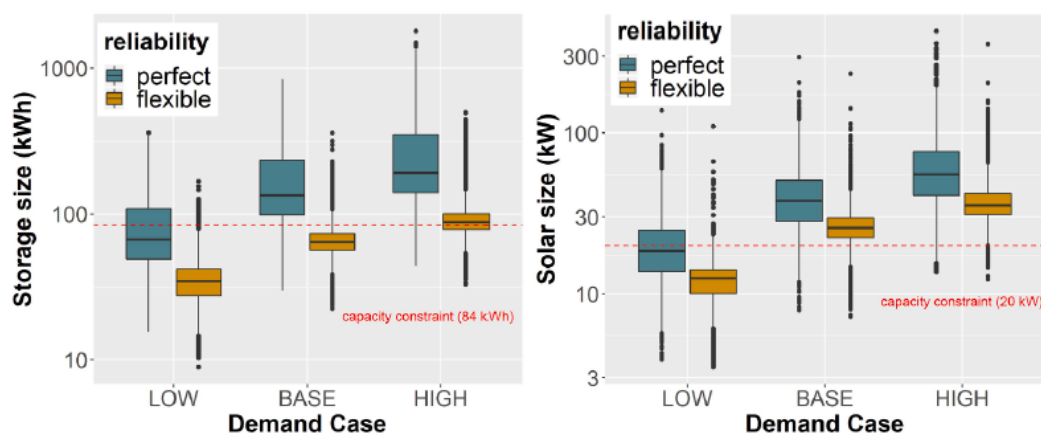


Figure 6.4: Solar and storage system size distribution under different demand cases (low, base, and high) as well as different reliability scenarios (“perfect” and “flexible”). Lower system sizes result in lower solar/storage system costs.

In Figure 6.5, we present the distribution of cost differences between solar/storage system costs and traditional grid service across all counties modeled in the United States. Positive values (to right of black vertical lines) imply that it would be cheaper to supply electricity via a solar/storage system. These distributions show that with the future cost assumptions, at current rates (left graphic) almost no counties, in any demand case, defect. Furthermore, the right graphic shows that even if the utility decided to set rates to wholesale electricity costs, only limited defection would occur, and only by low demand customers.

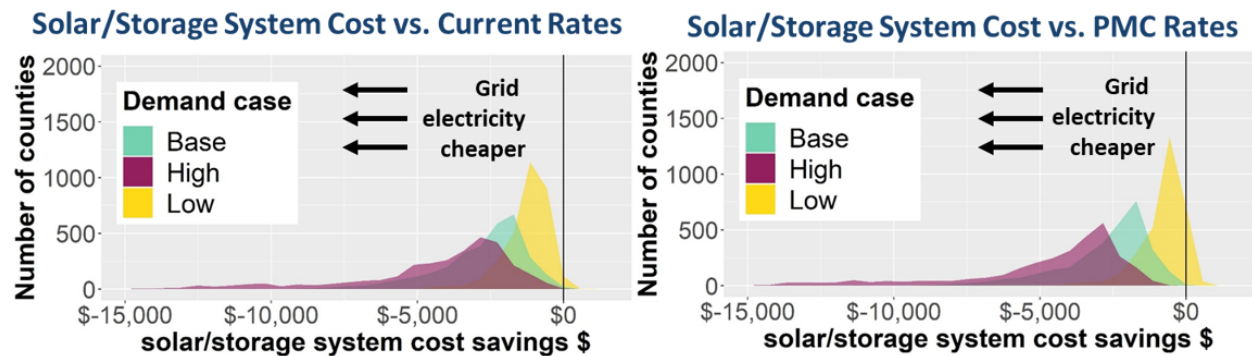


Figure 6.5: Distribution comparing utility costs to solar/storage costs under the “perfect” reliability scenario using future cost assumptions. Negative cost savings result in customer remaining connected to the grid

However, relaxing the reliability constraint has a significant effect on the decision to defect from the grid. Figure 6.6 shows the same distribution but considering the costs with the “flexible” reliability assumptions. Recall that these systems are sized to deliver 99% of the energy in the given demand profile, with the constraint that total demand cannot fall below 300W. In this scenario, there is limited defection under current rate designs (left graphic of Figure 6.6). Moving to the PMC scenario, though, could have serious implications for low demand customers. If customers were willing to accept the “flexible” reliability conditions we outlined above in our optimization framework, a significant portion of the low demand customers would decide to defect and install a solar/storage system.

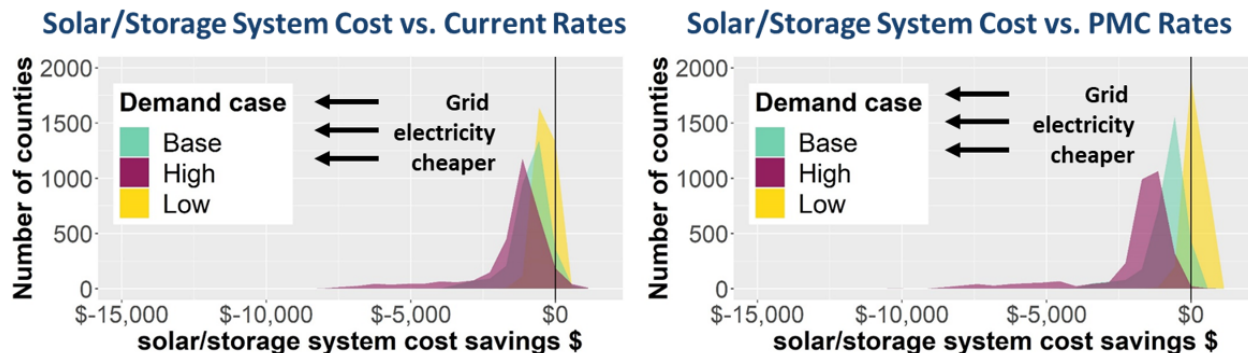


Figure 6.6: Distribution comparing utility costs to solar/storage costs under the “flexible” reliability scenario using future cost assumptions. Negative cost savings result in customer remaining connected to the grid

Our results vary significantly by geographic location. Figure 6.7 shows the same data as presented in Figure 6.6 but mapped to individual counties in the United States. We also show the counties which decide to install solar panels only (i.e. choose to load defect). We first note that shifting to PMC rates results in the elimination of load defection; the leveled cost of energy from rooftop solar, even in the low PV cost scenario, becomes uncompetitive with low variable rates. This is as one would expect, since shifting retail volumetric costs to equal utility private costs is an effective means to limit inefficient load defection.¹⁴

The maps also show that – for the “flexible” reliability case – many regions could experience significant grid defection if rates are shifted to set the retail volumetric charge equal to utility PMC. Furthermore, the rate design implications of grid defection come across strikingly in the top two graphs. For low demand customers, as more of the revenues are collected via fixed fees, the decision to defect becomes more economic while the opposite is true for high demand customers (bottom two graphs).

¹⁴It is important that social cost accounting is more nuanced as some places have significant pollution externalities. Exploring such social marginal costs was out of scope for this analysis. At the same time, as the grid continues to decarbonize, it is expected that these pollution externalities will decrease.

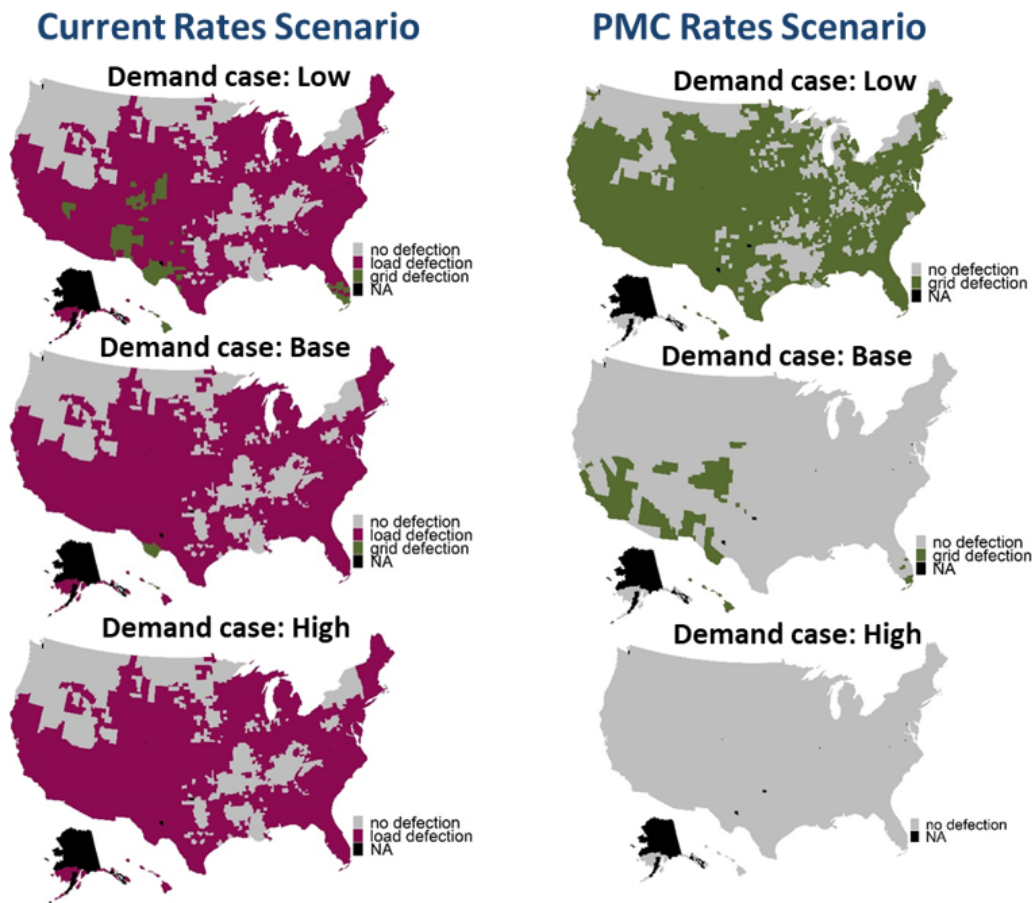


Figure 6.7: Geographic variation in the decision to defect under “flexible” reliability case and future cost assumptions. Breakdown of demand cases showcases how customer electricity consumption is a key driver of grid defection decision in PMC rate scenario

6.6 Discussion

We begin our discussion with commentary on some of the chapter’s key assumptions. This chapter strives to provide a high-level analysis of the potential for grid defection across a range of scenarios. We capture substantial detail on utility rates, spatial and temporal variability in solar irradiance and temporal variability in electricity demand. However, the nature of the analysis – national in scope, with practical constraints on the detail available in the data – forces us to make a number of assumptions, particularly about customer demand patterns and ability to install solar. This section highlights some of the insights we can gather from our analysis but also examines some of the assumptions we are forced to make and their probable impact on the qualitative and quantitative results of this chapter. As we argue below, modifying our assumptions is not likely to alter our key qualitative result that grid defection is probable only for relatively low demand customers with significantly

lower cost solar and storage, and with fixed charges covering all utility revenue requirements except private variable costs.

Our results highlight significant variability in the solar/storage system size necessary to defect from the grid. The observed variability is primarily driven by a location's solar/weather attributes as well as by the different building assumptions that underpin the residential customer demand profiles used here. This suggests that prior research, which focuses on standard demand profiles, without differentiating between low, medium, and high consumers, likely underestimates the potential for grid defection. This is because customers with below average demand are the most likely to defect, particularly when fixed charges comprise a significant portion of customer bills. Indeed, there is certainly far more heterogeneity than the three customer categories we model, suggesting that an analysis which uses a more comprehensive set of customer demand data (e.g. using smart meter data) might reveal that defection is even more favorable for some classes of customers – particularly those with very low demand or with consumption profiles that have a strong positive correlated with seasonal variations in available sunlight.

In addition to making assumptions about customer demand heterogeneity, we also had to make assumptions about the area available on customer premises for a solar/storage system. As explained earlier, we constrained systems to be no larger than 20 kW of solar and 84 kWh of storage to capture the area available for an average customer. We found that this constraint did not bind often. Under the current rate scenario, this constraint never affected the defection decision. Under the PMC scenario, this constraint reduced the number of households that defected by 150,000 (out of 1.6 million) in the “perfect” reliability case and 100,000 (out of 9.5 million) in the “flexible” reliability case. In reality, though, these constraints would need to be considered on a case-by-case basis in order to determine whether a specific building site has the necessary roof space for solar or room space for storage to meet the reliability specifications desired. Without more detailed data correlating demand and building size, we cannot evaluate if and how area constraints might impact the quantitative nature of our results. However, considering the very low number of cases in which area constraints bind as implemented in our analysis, the qualitative nature of our grid defection results would likely hold with more detailed data.

In addition to area constraints, home ownership could change grid defection results. Above, we showed results assuming non-rented single-family homes would be the only households able to defect from the grid. If we relax this constraint and allow multi-family dwellings to grid defect, we estimate that 3 times more households would defect in the future technology cost, “flexible” reliability, and PMC rate scenario, an increase from 7% of households to 23%. Other location- and customer-specific factors would need to be similarly evaluated to better understand a particular home's ability to defect from the grid. Once again though, the qualitative nature of our grid defection results would likely be unchanged by a more detailed analysis in this direction.

We now turn to discussing some of the subtleties of rate design and its impact on our defection results. We do in fact find that a) current rate structures strongly incentivize load defection, and b) changing the balance away from variable charges towards fixed charges could lead to a significant shift from load defection towards grid defection. In California, for instance, under our “flexible” reliability future cost case, the variability in rate design can be the difference between no grid defection and a 20% rate of grid defection. Importantly, ensuring only marginal utility costs are being recovered through variable charges should ensure that any households that load defect are doing so in a socially efficient manner, even for a very low-cost solar scenario. For households engaging in grid defection, however, decisions could still be socially inefficient. Specifically, after a household chooses to disconnect from the grid, utilities must still recover sunk costs from their remaining customer base. This highlights the challenge of designing rates that support full utility cost recovery via customer bills and also provide the correct incentives to customers considering opting for full grid defection.

To understand how grid defection might impact rates for customers that remain connected, we calculated the resulting revenue losses from each region due to defection in the PMC scenario. In the two regions where we find grid defection to be the most significant, California and Hawaii, we find utilities would lose \$2.3 and \$0.24 billion dollars, respectively, in the “flexible” reliability case under PMC rate design. This amounts to 20% and 40% of the baseline fixed charge revenue collection in each state, respectively. If this amount was spread over the remaining connected residential customers, the fixed charge would need increase by \$204 per customer-yr in California and \$738 per customer-yr in Hawaii to maintain the same revenue requirement.

We suggest a few ideas for mitigating the scope for inefficient grid defection. First, governments could reduce or even eliminate the need for utilities to charge fixed fees by providing a fair return to utilities via direct funding from general taxation. This could reduce the risk of distorting a private customer’s decision to defect from the grid with inefficiently designed rates. This use of direct government funding would effectively socialize some portion of non-variable costs on the network, and could be justified on the grounds that the power grid is a public good akin to other socialized services like national parks or national defense. According to our analysis, the Southwest, California, and Hawaii appear most likely to benefit from such a design considering the potential competitiveness of grid defection alternatives. These are areas where load defection is currently a large concern – but also where future grid defection might be significant. Of course, managing a utility’s incentive to overinvest in non-variable capital infrastructure would remain a concern.

A second option could be the implementation of demand charges. These tariffs have been suggested as a means to recover utility costs in a seemingly cost-based approach where customers are charged for their contribution to peak demand which ideally approximates a customer’s cost on the system (Hledik, 2014). However, others have argued that demand

charges do not appropriately represent the underlying utility costs which are largely up-front and sunk investments in the distribution network (Borenstein, 2016). If demand charges are not cost-reflective of marginal utility investment decisions, they would lead to inefficient behavior where customers adopt technologies to avoid private, rather than social costs (Hledik et al., 2018).

A third option would be for the government to require an exit fee when a residential customer wants to disconnect from the utility. This is the approach currently being taken by the public utility commission in California in order to ensure that Community Choice Aggregators, which facilitate a form of “defection” when they acquire customers from the incumbent utilities, pay their fair share of sunk costs that were incurred on their behalf. Ideally, this payment would reflect an individual’s portion of the social cost to building out a networked infrastructure. A challenge with this approach would be determining the correct (and legal) level of such an exit fee. If a customer wishes to reconnect in the future, and their utility incurs costs to do so, it would also be necessary to compute a reconnection fee.

A final issue that we have highlighted is the increased likelihood of grid defection if households are willing to accept lower levels of reliability. Given the strong preference in current grid planning for “perfect” reliability it is unclear how customers might respond to having the option to choose lower levels of reliability in return for a lower electricity cost. In the U.S., the closest analog to these choices is demand response programs. According to the EIA, in 2017 roughly 8 million residential customers participated in a demand response program which required customers to potentially forgo consumption in order to receive a payment from their utility [54]. The increasing prevalence of utility rates with time-of-use or dynamic pricing schemes and the growing adoption of smart home devices also suggests that residential electricity demand may exhibit more price-responsiveness in coming years. We sought to at least partially capture the impact of reliability preferences and demand flexibility using our “flexible” reliability case and found that this increased the likelihood of grid defection.

Our “flexible” reliability case entails making exogenous assumptions about customer behavioral decisions rather than capture them endogenously within the model, which is beyond the scope of this chapter. To further evaluate the significance of the 300W minimum demand requirement, we explored the extent to which this minimum demand constraint was binding in our optimization analysis. We found that the duration of time households were held at the 300 W minimum exceeded 7 days for none of the grid defection households under current rates and for 2 million out of 10 million grid defection households under the PMC rate structure. These results suggest that grid defection in this scenario required 20% of households to go without ancillary electricity usage for longer than a week. This consistently occurs during the winter time when solar output is low and demand for lighting and heating is high as shown in Figure 6.8. Such a behavioral response seems challenging, given that customers may not wish to go without significant heating for this period of time.

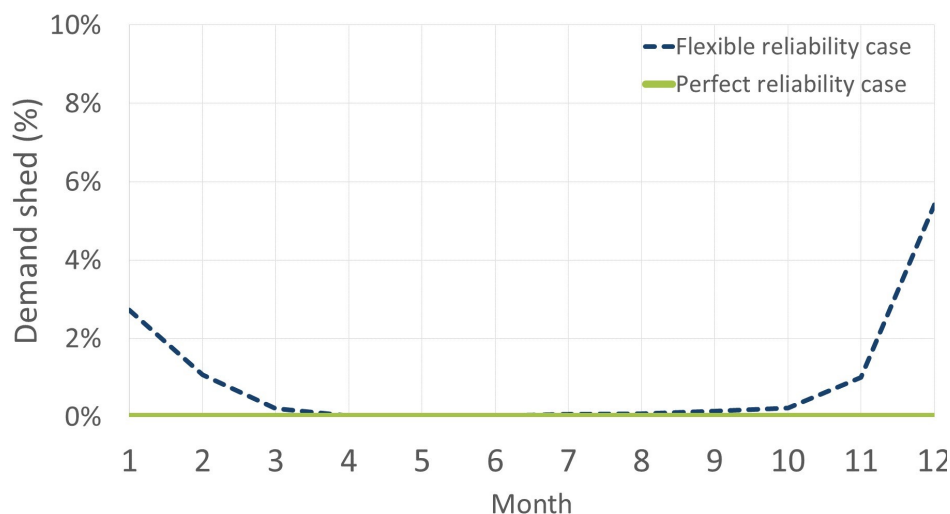


Figure 6.8: Percentage of demand shed by month in “flexible” vs. “perfect” reliability scenarios across all counties modeled in our analysis showing that demand is shed during winter months

Still, the stringency of reliability requirements has serious implications for system cost. Overall, the “perfect” reliability constraint increases solar/storage system costs by around 70% relative to the “flexible” reliability case.

In Section 2 we discussed a range of assumptions in our study. Perhaps the most important is the assumption that consumers make decisions based on monetary costs only, and that reliability levels can be treated as constraints to be met, rather than equated to other economic costs. In practice customer attitudes toward their utility and preferences for reliability could make them more or less likely to grid defect than suggested by the customer decision model in this chapter. In order to do more work in this area it will be necessary to directly observe customer preferences for utility- versus self-supplied service, and to more thoroughly explore customer willingness to pay for reliability. In the absence of these observations we have left more detailed customer models outside the scope of this research. However, we believe it is a critical area for future research.

6.7 Summary

In this chapter, we developed an economic framework to analyze the potential for grid defection considering a range of utility rate designs and solar/storage technology costs. We empirically estimated this potential across the United States using a linear optimization program that calculates the cost of a solar/storage system for a range of scenarios on customer type, location, and minimum reliability. We find that customers will not grid defect without fixed charges. However, if technology costs fall to plausible future levels and utilities shift to using fixed charges to cover all non-variable costs, grid defection could become substantial, and even exceed today’s observed levels of load defection.

In recent years, utilities have considered increasing fixed charges in an effort to bring variable rates closer to their own marginal costs. This would support, among other things, more efficient load defection, where customers adopt solar technologies while still remaining connected to the grid. However, our results show that this tariff redesign could incentivize grid defection, where customers permanently disconnect from the grid, particularly in a future with reduced solar and storage costs. We estimate that grid defection in most regions of the United States would be insignificant. However, our results indicate that regulators and utilities in regions with high utility costs and good solar resources must be mindful of the scope for significant grid defection and ensure it is incorporated into their tariff redesign efforts.

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Chapter 7

Conclusion

7.1 Summarizing remarks and future directions

This dissertation opened with a quote from Neil Chaterjee, the former United States Federal Energy Regulatory Commission (FERC) chairman, about the potential for smaller energy resources, installed within our communities, to provide power locally and revolutionize electricity delivery. The excitement within his quote was likely inflated by Chaterjee's situation. He was marketing a FERC order he had championed and likely saw as an important part of his regulatory legacy. Still, the general themes contained within the quote are supported by the three transformations that broadly motivate my dissertation research and are slowly shifting our electricity industry towards one of more customer engagement: (1) The rapid cost decline and integration of renewable energy and electricity storage technologies into the power system, (2) growth and increased public popularity of distributed, rather than centralized, electricity supply, and (3) increasing concerns about reliability in modern power systems.

The advent of new options for customers to procure and supply electricity closer to their point of consumption leads to many questions for grid planners who aim to understand electric consumption behavior and make informed regulatory choices that minimize electricity costs while achieving decarbonization goals. Though this dissertation did not attempt to address the myriad of questions that customer-sited solar and storage raise, its results highlight various policy tradeoffs in reliability and rate design decision-making while also informing the relative importance of various drivers of distributed resource adoption. Across all chapters, I aimed to answer the following research questions:

1. How do economists define, measure, and quantify the societal benefits of reduced power outages?
2. Does the experience of unreliable electricity supply impact the adoption of behind-the-meter solar and storage systems?

3. What is the backup power potential of solar and storage resources across the United States?
4. How realistic is it for electricity customers to go completely ‘off-grid’ with solar and storage?

Throughout the first half of the dissertation, I provided evidence that power outages have driven customer adoption of battery storage for backup power. Chapter 3 and 4 showed how people’s value of lost load (VoLL) is correlated with backup power adoption. People who have higher VoLLs tended to have higher adoption of backup power. This result, perhaps, is unsurprising given the discussion presented in Chapter 2 which documented the serious costs that can result from power loss. Still, the rise of solar and storage technologies as a novel mitigation investment will present opportunities for future researchers to understand and estimate these costs in novel ways. Mitigation investments provide insight into the underlying costs of power outages because ultimately they serve to offset those costs. Customers will continue to reveal their preferences through future backup power investments, and this dissertation provides methodological advancements towards causal estimation of mitigation investments.

Future researchers should continue to analyze trends in backup power adoption as a means to not only to measure the VoLL but also to inform regulatory decisions on grid reliability that balance public and private investments. Policy makers currently control a substantial subset of electric reliability decision-making. They consider trade-offs between the costs of reliability investments, which can be informed by current costs for labor and materials, and the societal costs of electric power outages, which have been historically difficult to measure. Regulatory institutions acknowledge that electric reliability is a public good and that leaving such reliability investments open to a completely liberalized electricity market without regulatory interventions could result in corresponding market failure and under (or over) investment in reliability. New options for backup power (i.e. solar and storage systems) augment the privatized choice set for electric reliability and thereby raise complex questions about how we plan our grid. How should regulators respond if some customers begin to opt-out of the public procurement of electric reliability? Private opportunities for reliability enhancement need not lead to equitable outcomes across society. Such questions are ripe for exploration by those interested in studying public and private good procurement. This dissertation did not consider such public policy questions in great detail.

The second half of the dissertation focused on evaluating the technical capabilities of solar-plus-storage technologies to mitigate power outages and, in some cases, substitute for grid electricity entirely. In Chapter 5, I used a scenario analysis to show that solar-plus-storage’s

capability to provide backup power is determined by a household's electric consumption context. I found that the end-use electric devices of a particular household have a substantial impact on the capability for solar-plus-storage to provide backup, especially in the case of electric heating and cooling technologies. These findings are influenced by the building stock characteristics which vary by and within regions across the United States. That chapter showed that households will find it particularly challenging to provide full-backup for their typical heating and cooling demand during long-duration power outage events.

In Chapter 6 I found that grid defection using solar-plus-storage might be economically reasonable only for consumers who have relatively low electricity demand. That result, however, was sensitive to the expectations for the ultimate reliability required for an off-grid system. I showed that if customers were willing to more flexibly adjust their demand for electricity, that the overall system size required to defect from the grid could be reduced substantially. Overall, such findings suggest that there are real opportunities for solar and storage to provide power and value to end-consumers locally, even if these distributed technologies do not supplant the bulk power system.

While Chapter 5 showed that solar and storage technologies could provide substitution options for customers to mitigate power outages, Chapter 6 found that they would be less likely to support full grid defection.

Both of these chapters suggest that future work should study interactions between the technical potential of load flexibility within a household and the correlated capabilities of solar-plus-storage to provide backup power and/or facilitate grid defection. Open questions remain about how much customers would be willing to augment temperature set points to increase the length of time a PVESS backup power system could meet critical load demand in a long-duration outage or to lower the cost of an off-grid system. Though I did not study such an adjustment with substantial rigor (i.e. by considering realistic set-points that might be expected to meet minimum health and comfort thresholds), in Chapter 5 I showed that the backup power capability of solar-plus-storage is sensitive to these set points. In Chapter 6, I found that load flexibility could reduce system costs by around 40%.

The likelihood of such flexibility, however, might be particularly questionable for a customer who aims to fully defect from the grid. In such a situation, a customer might need to constantly plan for their electricity consumption decisions on a daily or weekly basis, which would represent a substantial increase in the time a typical electricity consumer today thinks about their own electricity consumption. Future research should aim to corroborate such a hypothesis. How much are customer's willing to engage in day-to-day electricity decision making? The likely behavioral inattention challenges would suggest a need for the integration of automation technology that would support the management of customer electricity demand in the face of solar-plus-storage adoption.

Overall, the research presented within this dissertation focused on unpacking specific reliability, rate design, and customer-demand drivers of the adoption of solar and storage systems. This work highlights key tradeoffs that will impact household decision making in the years to come. The ultimate role for distributed solar-plus-storage in future electricity systems, however, remains up for debate. As outlined in Chapter 5, while some modeling experts suggest that the role for distributed energy should and will increase (Clack et al., 2020; O’Shaughnessy, 2022; O’Shaughnessy et al., 2022), many note serious headwinds to such increases given the corresponding costs and complexity of integrating high levels of distributed energy resources into our distribution systems (Elmallah et al., 2022; Cohen et al., 2016; Borenstein, 2022). While the market for customer sited solar systems has reached a level of maturity (Barbose et al., 2020), the market for pairing storage with those solar systems remains relatively nascent. It is too early to draw definitive conclusions about the direction and overall scale by which these novel systems will ultimately contribute to changes within the electricity system.

Regardless, the continued implementation of the electricity transition in the decades to come will involve complex coordination between regulated electric utilities, policy makers, and the private sector. Hopefully this dissertation research can contribute, in some small part, to the discussion around the role for distributed energy in this transition. Time will tell whether the rise of these systems will truly achieve the vision laid out by Chaterjee in FERC order 2222.

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Appendix A

Chapter 2 appendix on microeconomics of power outages

A.1 Details regarding mitigation cost estimates of the VoLL

I made a number of assumptions to come up with the numbers presented in Table 3. For the gasoline generator, I assume that the 2 kW generator could replace all of the electricity demand of a customer in the case of an outage event. If the generator cannot meet a customer's full demand, then the underlying calculation is focused on the measuring the VoLL for their most valuable load, at the top of their demand curve.

For the standalone battery, I estimate bill savings by assuming daily battery cycling against a time-of-use rate with an average on-to-off peak price difference of \$0.10 and a battery efficiency of 90%. For the solar+storage system, I use the National Renewable Energy Laboratory's ReOpt model for a San Francisco household which cannot export to the grid ([Cutler et al., 2017](#)). The operational dynamics to achieve both economic and reliability performance from storage and solar+storage systems are complicated by competition in use cases during an outage. Such detailed modelling is beyond the scope of these simple calculations. Rather, I assume the most optimistic economic savings potential where both these bill savings and reliability mitigation can be achieved. Nevertheless, more sophisticated models can be used to more precisely estimate the VoLL given that operational decisions in the event of a power outage will cannibalize bill savings. Such impacts would likely be small in the above example since I model at most 4 days of outage while bill savings can be achieved year-round.

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Appendix B

Chapter 3 appendix on VoLL stated-preference survey

B.1 Details of NORC sampling strategy and survey execution

The sample for this study is selected from the AmeriSpeak Panel¹ using sampling strata based on age, race/ethnicity, education, and gender (48 strata in total). AmeriSpeak is designed to be representative of the United States household population, including all 50 states and the District of Columbia. U.S. households are randomly selected with a known, non-zero probability from the NORC National Frame as well as address-based sample (ABS) frames, and then recruited by mail, telephone, and by field interviewers face to face.

The size of the selected sample per sampling stratum is determined by the population distribution for each stratum. In addition, sample selection takes into account expected differential survey completion rates by demographic groups so that the set of panel members with a completed interview for a study is a representative sample of the target population. If panel household has one more than one active adult panel member, only one adult in the household is eligible for selection (random within-household sampling).

The AmeriSpeak panel sample was supplemented with respondents from the Lucid's non-probability online opt-in panel due to the study's focus on a California-only population. To help reduce potential bias in the non-probability sample, Dynata attempted to balance the non-probability respondent sample by age, race and ethnicity, gender, education, and California Census region. TrueNorth is the NORC calibration solution for combining probability and non-probability samples for estimation through small area modeling that leverages data from AmeriSpeak, the American Community Survey, Current Population Survey, and other

¹Find more information on AmeriSpeak online [here](#).

data sources for improved statistical efficiency.²

The online interviews were open from Monday, December 20th, 2021 through Monday, January 3rd, 2022. NORC took the following steps to notify and gain the cooperation of invited Panelists for this survey: (1) invitation emails on Monday, December 20th and Tuesday, December 21st, 2021; (2) reminder emails on Thursday, December 23rd, Tuesday, December 28th, 2021, and Sunday, January 2nd, 2022. Panelists were offered the cash equivalent of \$2 for completing the study. Interviewed respondents took 5 minutes (median) to complete the survey.

Power calculations

The main outcome variables are continuous, and we used power calculations to determine the necessary sample size when comparing any of the individual treatment cases (i.e. 24 hr notification, 1 week notification) to the control case (no notification). For the power calculations, we estimate the relationship between the minimum detectable effect (MDE) and the sample size between each individual treatment group with a control group using the Eq. B.1.

$$MDE = (t_{1-k} + t_{\alpha}) \sqrt{\frac{1}{P * (1 - P)}} \sqrt{\frac{\sigma^2}{N}} \quad (\text{B.1})$$

Where,

MDE = Minimum detectable effect (%)

t = critical values found in a t-table

P = proportion of sample receiving treatment (%)

σ^2 = residual variance

N = sample size

We choose to set P equal to 0.66 in order to result in a 50%, 25%, and 25% breakdown between the one control group and two treatment groups. We use a one-sided t-test, as we expect households will have a lower willingness to pay to avoid outages when they are provided more notice. Prior research into long-duration outages have estimated a VOLL to avoid outages between \$1.4-1.1/kWh with a standard deviation between \$3-1.3/kWh (Baik et al., 2020). We use their estimates to inform the power calculations. Though this prior work did not evaluate how advance notification would affect the VOLL, they provide reasonable guidance on the distribution of values in the control group case. Figure B.1 is the result of the power calculations over a range of sample sizes.

²Find more information on TrueNorth online [here](#).

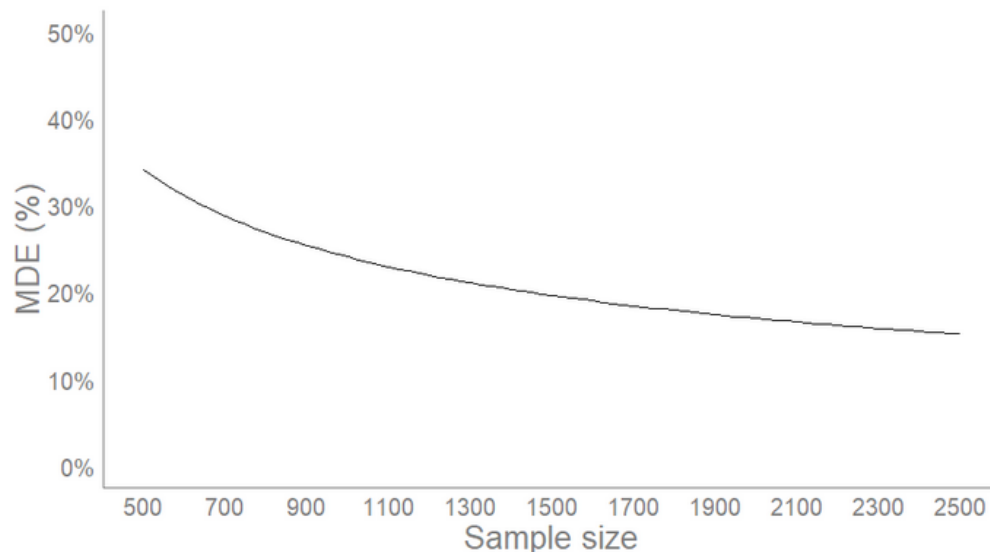


Figure B.1: Minimum detectable effect at various sample sizes considering unequal treatment and control sample sizes.

the total sample size is 2,120. Therefore, we should be able to detect between a 20% effect, making us reasonably well-powered to detect treatment effects. Furthermore, these power calculations are likely to be conservative because we stratify the randomization on responses to early survey questions. This reduces noise and increases statistical power.

B.2 Survey questions

Q1-10 are data gathering questions specific to the research context. They will not be used as inclusion/exclusion criteria. Q6 AND Q7 will be used to do stratified random sampling.

1. How aware are you of wildfire-related power outages carried out by electric utilities (e.g., PG&E, SCE, SDG&E) in California in 2019, 2020, and 2021?
 - a) Very aware
 - b) Mostly aware
 - c) Somewhat aware
 - d) Totally unaware
2. Did you experience a sustained and continuous power outage in 2019, 2020, or 2021 (combined total of 24 hours or more)?
 - a) Yes
 - b) No

- c) Unsure
3. Did anyone in your social network (e.g., friends, neighbors, family, coworkers) experience a sustained and continuous power outage in CA in 2019, 2020, or 2021 (combined total of 24 hours or more)?
- a) Yes
 - b) No
 - c) Unsure
4. In the next year (2022), how many hours of outage do you expect to experience? (A: numeric entry)
5. In the next five years, do you expect the number of outage hours to increase, decrease or stay the same compared to the previous few years?
- a) Increase
 - b) Decrease
 - c) Stay the same
6. If your power went out tomorrow, which of the following would you do? Please select all that apply.
- a) Run an electric generator (back-up power) you had prior to the power outage
 - b) Use solar/batteries you had prior to the power outage for back-up power
 - c) Borrow a generator from a neighbor
 - d) Buy/rent a new generator
 - e) Leave your house
 - f) Turn on flashlight/candles
 - g) Other, please specify: [TEXTBOX]
7. Do you plan to buy a generator or another type of backup power device in the next 6 months?
- a) Yes, a generator
 - b) Yes, another type of backup power device
 - c) No, don't need
 - d) No, already own one
8. **SHOW IF (Q6 = a) OR (Q6 = b) OR (Q7 = d)** When did you purchase your generator or other type of backup power device? (If you've made multiple purchases, choose most recent purchase year and month)

9. **SHOW IF (Q6 = a) OR (Q6 = b) OR (Q7 = d)** How much did you pay in total for your generator and/or solar/battery system? (A: numeric entry)
10. **SHOW IF (Q6 != a) AND (Q6 != b) AND (Q7 != d)** Which category below best indicates why you don't currently own a generator, or another type of backup power? Please select all that apply.
- a) I don't experience outages
 - b) I find other ways to deal with the outage
 - c) Too expensive
 - d) Did not know about them
 - e) Hard to install/use
 - f) Unpleasant scent when operating
 - g) Other, please specify: [TEXTBOX]
11. **** EXPERIMENTAL QUESTION **** For this question, we would like you to imagine the following situation. Your electric utility (e.g., PG&E, SCE, SDG&E) notifies you that in the next year you will experience 2 power outages each lasting 40 hours between the months of September and November, similar to previous wildfire-related outages that resulted from California's Power Safety Shutoff Program (PSPS). Importantly, these 2 outages will be distinct and happen weeks or months apart from each other. You are provided **no/24 hour/ a week's** notice before these two power outages occur at your home. How much would you be willing to pay, per month, to avoid these two outages (it would be added to each monthly utility bill for the entirety of next year)? (A: numeric entry)
12. How much does your household typically pay on their monthly electric power utility bill, on average? (A: numeric entry)

In addition to these questions, the survey implementer (NORC), also collected the below demographic information.

Variable	Values
Gender	1 = Male
	2 = Female
Age	Age in years
Age (7 categories)	1 = 18-24; 2 = 25-34; 3 = 35-44; 4 = 45-54; 5 = 55-64; 6 = 65-74; 7 = 75+
Age (4 categories)	1 = 18-29; 2 = 30-44; 3 = 45-59; 4 = 60+

Education (5 categories)	1 = Less than HS
	2 = HS graduate
	3 = Vocational/tech school/some college/associates
	4 = Bachelor's degree
	5 = Post grad study/professional degree
Race/Ethnicity	1 = White, Non-Hispanic
	2 = Black, Non-Hispanic
	3 = Other, Non-Hispanic
	4 = Hispanic
	5 = 2+ races, Non-Hispanic
	6 = Asian/Pacific Islander, Non-Hispanic
Housing Type	1 = A one-family house detached from any other house
	2 = A one-family house attached to one or more houses
	3 = A building with 2 or more apartments
	4 = A mobile home or trailer
	5 = Boat, RV, van, etc.
Household Income (18 categories)	1 = Less than \$5,000 2 = \$5,000 to \$9,999
	3 = \$10,000 to \$14,999 4 = \$15,000 to \$19,999
	5 = \$20,000 to \$24,999 6 = \$25,000 to \$29,999
	7 = \$30,000 to \$34,999 8 = \$35,000 to \$39,999
	9 = \$40,000 to \$49,999 10 = \$50,000 to \$59,999
	11 = \$60,000 to \$74,999 12 = \$75,000 to \$84,999
	13 = \$85,000 to \$99,999 14 = \$100,000 to \$124,999
	15 = \$125,000 to \$149,999 16 = \$150,000 to \$174,999
	17 = \$175,000 to \$199,999 18 = \$200,000 or more

Household Income (9 categories)	1 = Less than \$10,000
	2 = \$10,000 to \$19,999
	3 = \$20,000 to \$29,999
	4 = \$30,000 to \$39,999
	5 = \$40,000 to \$49,999
	6 = \$50,000 to \$74,999
	7 = \$75,000 to \$99,999
	8 = \$100,000 to \$149,999
	9 = \$150,000 or more
Household Income (4 categories)	1 = Less than \$30,000
	2 = \$30,000 to \$59,999
	3 = \$60,000 to \$99,999
	4 = \$100,000 or more
Marital Status	1 = Married
	2 = Widowed
	3 = Divorced
	4 = Separated
	5 = Never married
	6 = Living with partner
Metropolitan Statistical Area Status	0 = Non-Metro
	11 = Metro (as defined US OMB Core-Based Statistical Area)
Home Internet Access	0 = No
	1 = Yes
Telephone Service	1 = Landline telephone only
	2 = Have a landline, but mostly use cellphone
	3 = Have cellphone, but mostly use landline
	4 = Cellphone only
	5 = No telephone service

Ownership of Living Quarters	1 = Owned or being bought by you or someone in your household
	2 = Rented for cash
	3 = Occupied without payment of cash rent
Region 4 (US Census)	1 = Northeast
	2 = Midwest
	3 = South
	4 = West
Region 9 (US Census)	1 = New England
	2 = Mid-Atlantic
	3 = East-North Central
	4 = West-North Central
	5 = South Atlantic
	6 = East-South Central
	7 = West-South Central
	8 = Mountain
	9 = Pacific
Variable	Values
State	State of residence
Household Size	Total number of members in household
HH members, age 0-1	Number of household members in age group
HH members, age 2-5	Number of household members in age group
HH members, age 6-12	Number of household members in age group
HH members, age 13-17	Number of household members in age group
HH members, age 18+	Number of household members in age group
Current Employment Status	1 = Working - as a paid employee
	2 = Working - self-employed
	3 = Not working - on temporary layoff from a job
	4 = Not working - looking for work
	5 = Not working - retired

	6 = Not working – disabled
	7 = Not working – other
Religion	1 = Protestant (Baptist, Methodist, Non-denominational, Lutheran, Presbyterian, Pentecostal, Episcopalian, Reformed, Church of Christ, Jehovah’s Witness, etc.)
	2 = Roman Catholic (Catholic)
	3 = Mormon (Church of Jesus Christ of Latter-day Saints/LDS)
	4 = Orthodox (Greek, Russian, or some other orthodox church)
	5 = Jewish (Judaism)
	6 = Muslim (Islam)
	7 = Buddhist
	8 = Hindu
	9 = Atheist (do not believe in God)
	10 = Agnostic (not sure if there is a God)
	11 = Nothing in particular
	12 = Just Christian
	13 = Unitarian (Universalist)
	14 = Other, please specify
Religious Attendance	1 = Never
	2 = Less than once per year
	3 = About once or twice a year
	4 = Several times a year
	5 = About once a month
	6 = 2-3 times a month
	7 = Nearly every week
	8 = Every week
	9 = Several times a week
Assets Value	1 = Less than \$50,000

	2 = \$50,000 to \$99,999
	3 = \$100,000 to \$149,999
	4 = \$150,000 to \$249,999
	5 = \$250,000 to \$499,999
	6 = \$500,000 to \$999,999
	7 = \$1,000,000 to \$4,999,999
	8 = \$5,000,000 or more
Home Value	1 = Less than \$50,000
	2 = \$50,001 to \$100,000
	3 = \$100,001 to \$150,000
	4 = \$150,001 to \$200,000
	5 = \$200,001 to \$250,000
	6 = \$250,001 to \$350,000
	7 = \$350,001 to \$500,000
	8 = \$500,001 to \$750,000
	9 = \$750,001 or more
Skill with percentages	1 = Not at all good
	2
	3
	4
	5 = Extremely good

B.3 Bibliography

Sunhee Baik, Alexander L. Davis, Jun Woo Park, Selin Sirinterlikci, and M. Granger Morgan. Estimating what US residential customers are willing to pay for resilience to large electricity outages of long duration. *Nature Energy*, 5(3):250–258, March 2020. ISSN 2058-7546. doi: 10.1038/s41560-020-0581-1. URL <http://www.nature.com/articles/s41560-020-0581-1>.

Appendix C

Chapter 4 appendix on revealed preference estimate on WTP to avoid power outages

In this section, I provide additional details on both the inputs to our regression analysis as well as supporting material to results.

C.1 Additional input summary

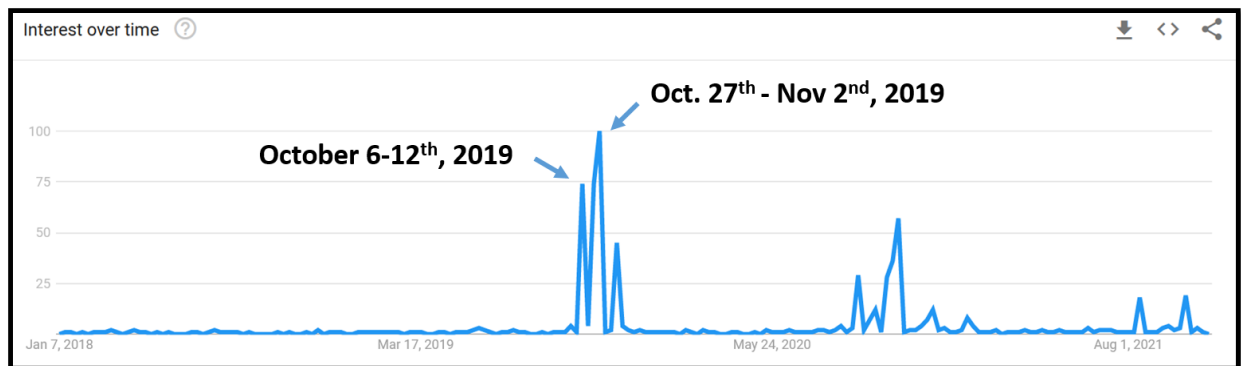


Figure C.1: Google trend analysis on ‘PSPS’ term, showing that popularity of term corresponded with experience of actual PSPS events.

PG&E customer sampling strategy

Selecting ZIP codes withing PG&E’s service territory

We use two publicly available circuit maps provided by PG&E showing: (1) all primary circuits within PG&E’s service territory and (2) primary circuits that PG&E shutoff during

the 2019 PSPS events.¹ We intersect these two maps with publicly available zip code maps to count both the total number of the circuits that appear in a particular zip code as well as the total number of circuits that were on outage during a 2019 PSPS event.² We divide these two counts in order to calculate the percentage of circuits that were on outage for each PSPS outage event within a particular zip code.

Given that we are interested in exploring discontinuities in outage experience, we dropped zip codes from our sample which showed 100% of circuits on outage.³ These zip codes would not provide useful data given their non-existent treatment discontinuities. Figure C.2 shows all of the zip codes that experienced 2019 PSPS outages. The darkest color scale represents zip codes that we drop from our sample which had all of their circuits on outage during their experienced PSPS events. Grayed out zip codes were not exposed to any PSPS events or exist outside of PG&E's service territory. The right figure plots the same data as used in the map but in histogram format for zip codes with varying percentages of circuits on outage.

¹PG&E circuit maps were taken from the Integration Capacity Analysis (ICA) project and can be located at [this link](#). PG&E outage maps were taken from PG&E's wildfire planning projects and can be located at [this link](#). Look for Attachment 6 (Part 2): GIS Files for 2019 PSPS events.

²We identified 502 zip codes that experienced a 2019 PSPS power outage event.

³We also dropped zip codes with fewer than 50 residents according to 2010 census estimates, an additional 9 zip codes.

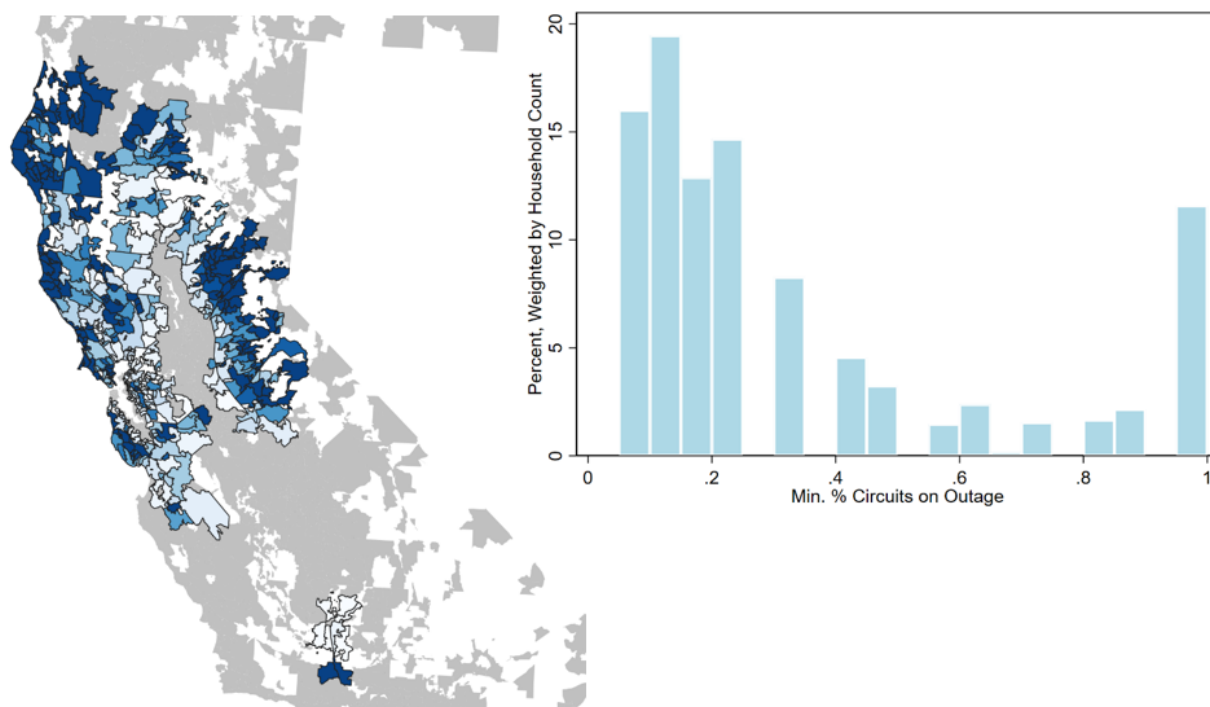


Figure C.2: Zip code percentage of circuits on outage. Colors in map move from darkest blue (100% of circuits on outage) to white (0% of circuits on outage).

Next, we take a stratified random sample of zip codes such that we stay within PG&E's data limits of requesting under a 450,000 resident sample. Our stratification is done to ensure that we maintain balance between urban and rural zip codes. To do so, we first find the actual urban-rural split in the full set of zip codes from the above sampling process, which broke out to 75% urban and 25% rural. We use the RUCA code list to assign urban and rural breakdowns.⁴ Figure C.3 shows the final selection of zip codes resulting from the stratified random sample process. Blue zip codes were dropped from our PG&E data request. We requested PG&E send us PSPS outage information and monthly billing data on all Service Point IDs (SP IDs) from the zip codes colored red, orange, or yellow. The shaded colors represent the total number of outage events that a particular zip code experienced in 2019 with red being the most and yellow being the least. In total, we received data for 480,000 SP IDs from PG&E.

⁴We define urban as 1, 1.1, 2, 3, 4.1, or 10.1 in the RUCA code list.

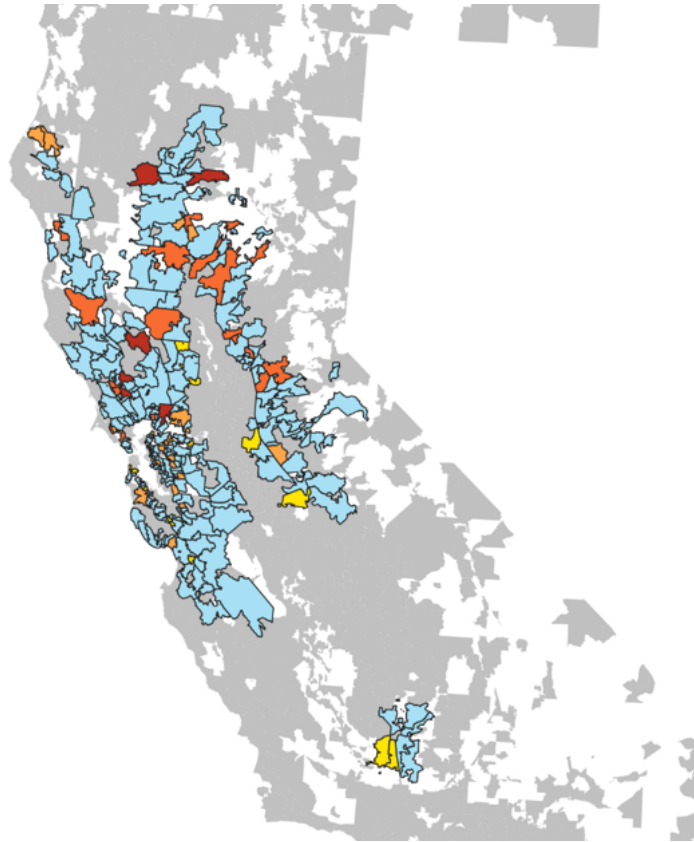


Figure C.3: Final zip code sample sent to PG&E indicated by red, orange, and yellow colors. These colors indicate the total number of PSPS events experienced within the zip with red being the most ($n=4$) and yellow being the least ($n=1$).

Details creating the regression discontinuity dataset and measuring the distance to the feeder-pair borders

The original data sample from PG&E included billing data for Service Account IDs (SA IDs), which are unique by customer account, and Service Point IDs (SP IDs), which are unique by electric meter location. One SP ID can map to multiple SA IDs over time, as people move in and out of a residential household. We will refer to unique SP IDs as “households” throughout the remainder of this section

With the full list of 481,181 households, we first drop geographically erroneous coordinates and feeders from our sample by analyzing the latitude and longitude information provided by PG&E and comparing it to the publicly available geospatial feeder geometries discussed in the above subsection. Missing data leads to 3,676 household drops. Next, we drop households which have the same geographic location (SP ID) but are linked to multiple feeders. This issue can arise because one meter can be connected to multiple electric accounts due to residents moving in and out of a house overtime. Though we cannot confirm the reason for

such assignment, one hypothesis would be that feeder IDs could simply change overtime, and thus when a move occurs, gets updated in our underlying dataset. Alternatively, it could be that the feeders get reconfigured in such a way that households actually get reassigned to new feeders overtime. This assignment of multiple feeders per household impacts our ability to measure the distance to borders, discussed below, therefore we need to drop them from our sample. This error only affects 807 households, a vanishingly small amount compared to our whole sample.

To find erroneous data, for each feeder geometry, which is represented as a multi-linestring object in the R programming language, we created a convex hull shape around it. Then, we imposed a buffer around that convex hull in an attempt to capture the space in which households serviced by the feeder could reasonably be located.⁵ We dropped any feeders for which less than 90% of the households assigned to that feeder by PG&E were located within the buffered feeder geometry. We dropped 66 out of 528 feeders because of these errors. We also dropped any households whose coordinates were *both* more than 10 miles (or 16,090 meters) from their assigned feeder’s centroid *and* did not fall within the buffered feeder geometry. In total, this process drops an additional 8,294 households.

We next created a “feeder-pair” dataset by looping through each individual feeder in our original sample and determining its five closest neighboring feeders. We employed a nearest neighbor algorithm⁶ using the centroid of each feeder geometry. These 5 nearest feeders become the feeder-pairs, a key unit of analysis in our study design. In total, we create 1,498 feeder-pairs from 461 individual feeders. Crucial to a regression discontinuity design is measuring the distance to the discontinuity. Often, discontinuities are easily defined, as is the case with state borders or policy threshold cutoffs. In our case, however, we do not observe a border layer between one feeder and its neighboring feeders. Therefore, we had to measure the distance to the feeder pair border indirectly by assigning each household to its nearest household on that neighboring feeder and measuring the corresponding distance. Therefore, our distance to border metric is defined for each household as the distance to its closest paired household on the neighboring feeder for a specific feeder-pair.

Figure C.4 shows an example map that shows one feeder (in yellow) and the 5 nearest neighboring feeders (in red, green, blue, teal, and purple) that are identified by our nearest neighbor algorithm process. This figure also shows the households along the borders of these various feeder-pairs that are identified using the nearest household on an opposite feeder, showing that this approach is a good substitute for identifying the true feeder border. This process, however, is most accurately identified in urban environments where neighbors live close together.

⁵A 0.008 arc degrees of buffer was chosen, which represents roughly 900 meters.

⁶We rely on the “FNN” package in the R programming language.

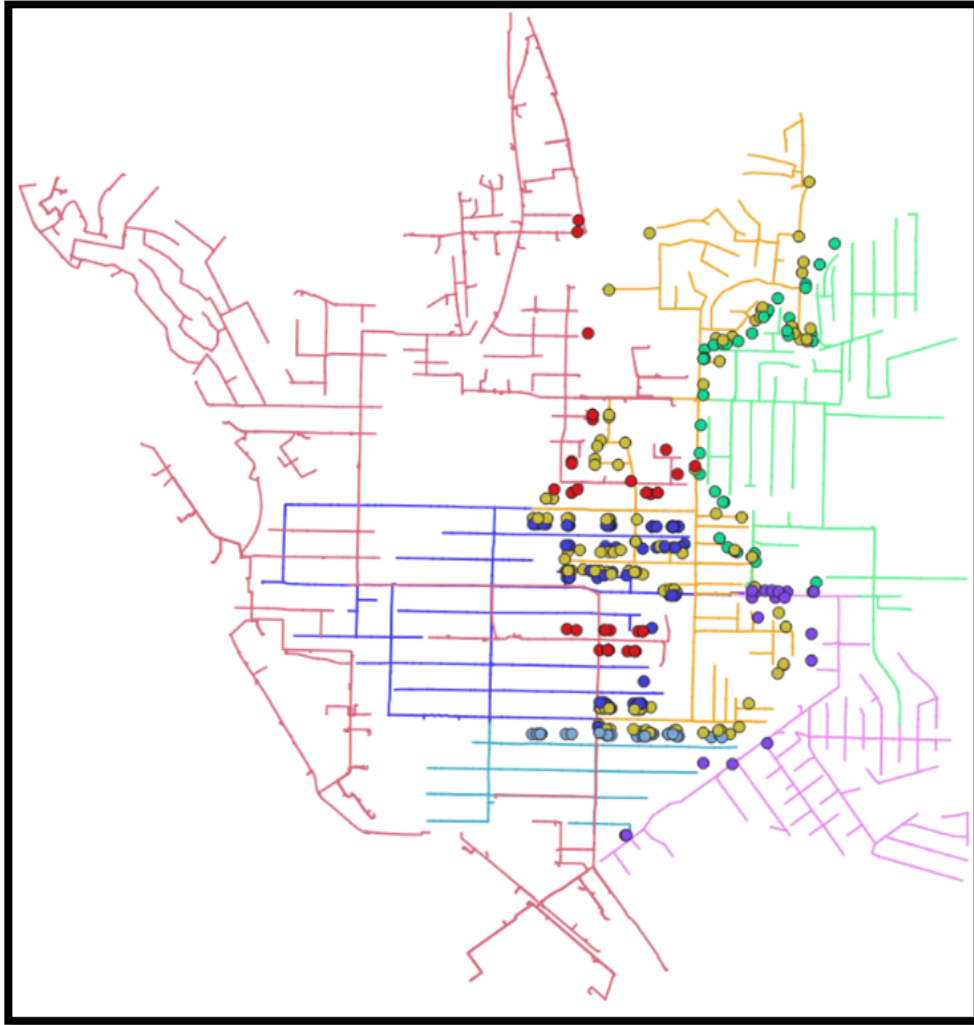


Figure C.4: Feeder-pairs identified by our nearest neighbor algorithm. Colored dots show households that identify the borders of our feeder-pairs. Colors of dots match with feeder color.

After the creation of the feeder-pairs and the calculation of the distance to border metric, we drop feeder pairs where there are less than 2 households within half a mile on both sides of the feeder-pair border. In total, we drop 875 out of the 1,498 feeder pairs. We also drop households which show no distance to the border, suggesting erroneous latitude and longitude information.

In total, unique 440,000 households remain after all of these processes. Next, we determine whether there is a treatment discontinuity across our feeder-pair borders. Since our original sample was taken at the level of a zip code, it is possible that the ultimate feeder-pairs in our sample had the same level of treatment (i.e. the two feeders on a feeder-pair had either no 2019 PSPS outage events or had the same number of 2019 PSPS outage events.) Thus,

we split the resulting dataset into two: one with feeder pairs where there is a difference in treatment between feeders (D), and one with feeder pairs with equal treatment between feeders (ND). To do so, we calculate the total PSPS outage hours by household. Then, we take the average outage hours for all of the households on each feeder. If the feeders on a given feeder pair have more than 1 hr of outage difference, that feeder pair is designated as a difference in treatment feeder pair (D). Otherwise, it is designated as a no difference in treatment (ND) feeder pair. In total, there are 275 treatment feeder-pairs and 348 non-treatment feeder-pairs, which we can use as placebos in our analysis. We merge all SA IDs that are attached to a specific household. This last step allows our dataset to observe billing information across times for our households of interest.

The final step is to subset this final sample to feeder-pairs where there is balance between key pre-period variables. To do so, we apply the following algorithm:

1. Create a loop to filter to all households within 0.5 miles of the border.
2. Generate a randomly assigned binary treatment variable, by feeder. For example, on feeder pair A/B, all observations of feeder A will have $D_{fa} = 1$, and all observations of feeder B will have $D_{fb} = 0$.
3. For each pre-period variable (PV adoption, battery adoption, June, July, and August 2019 consumption), X_i , regress X_i on D_{fa} and record the t-statistic on D_{fa} .
4. If all four t-statistics are less than or equal to 1.6, save feeder pair set to output balanced data set.
5. Move onto next feeder-pair.

In total, this reduced the number of difference-in-treatment feeder pairs from 275 to 98. The number of unique households was reduced from 325,160 to 167,734.

Selecting Households for PG&E AMI Interval Data Sub-sample

We were limited to 300,000 customer-years when requesting advance metering interval (AMI) data from PG&E due to their COVID-19 data policies. Therefore, we developed a sub-sampling strategy to identify 100,000 unique households out of our original sample of 481,181 households. This section outlines our AMI sub-sampling strategy, which is distinct from our RD sampling approach discussed above.

Ultimately, we are interested in studying households that did not move during our treatment time period. To ensure this, we keep the most recent SA IDs *that had PSPS exposure* and also had pre-PSPS bills.⁷ Due to this step, we dropped 24,000 SP IDs, which we will now

⁷The unique SA ID and SP ID combination had to have at least one day of billing after June 7th, 2019 and some billing data before June 8, 2019.

refer to as households throughout the remainder of this section. After this step, we apply the same filter to geographically erroneous household and feeder data described in the above subsection.

A key assumption behind the regression discontinuity design is that the households on either side of our border discontinuity are homogeneous across both observable and unobservable characteristics. Therefore, to further restrict our sub-sample, we tested balance on a number of characteristics we do observe: (1) kWh per day mean consumption, (2) summer kWh per day mean consumption, (3) PG&E service provider mean (fraction of bills in the pre-period that are serviced by PG&E, as opposed to a Community Choice Aggregation (CCA), for example), and (4) a pre-solar indicator (whether or not the household had a solar interconnection established before the 2019 PSPS events).

To do the balance test, we re-create the feeder-pair dataset described above but drop households that do not have at least one bill during July, August, or September of 2018 or before. This step ensures that we observe pre-period summer consumption data for households of interest. In total, 50,000 households were dropped due to this step. We then test balance across the border applying the following algorithm:

1. Filter to all households within 1 mile of the feeder pair border which drops an additional 55,000 households.
2. Generate a randomly assigned binary treatment variable, by feeder. For example, on feeder pair A/B, all observations of feeder A will have $D_{fa} = 1$, and all observations of feeder B will have $D_{fb} = 0$.
3. For each balance characteristic described above, X_i , regress X_i on D_{fa} and record the t-statistic on D_{fa} .
4. If all four t-statistics are less than or equal to 1.96, save feeder pair set to output balanced data set.
5. Otherwise, reduce the distance limit restriction, which begins at 1 mile by 0.1 miles and repeat (b) through (d).

This algorithm tests whether increasingly close sets of households are balanced across our feeder-pair borders. If no balance is found, the feeder pair is dropped from our AMI sub-sampling process. The application of these balance tests dropped an additional 143,000 households.

At the end of the balance test, there are now two balanced feeder-pair sets, one with difference in treatment in feeders and one with equal treatment, as discussed in the above subsection. (i.e. D vs. ND feeder-pairs). To identify the 100,000 unique households for the AMI sub-sample, we take a stratified random sample across these sets, sampling with a 3:1 D to ND

feeder pair ratio and request 2017, 2018 and 2019 (three years) of interval data from PG&E using the resulting SP IDs.

C.2 Additional input analysis

Figure C.5 shows the McCrary test applied to our running variable, signifying no bunching around the discontinuity.

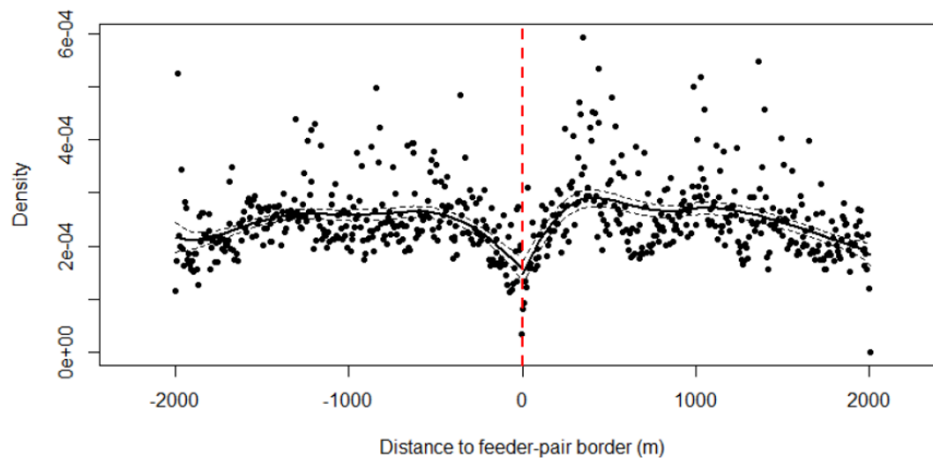


Figure C.5: Implementation of McCrary Test, showing no bunching around our discontinuity.

To identify customers in our sample who were likely eligible for SGIP incentives, we used geospatial data from the aforementioned CPUC website. Using each map provided, we identified whether or not each customer’s household coordinate fell within the various boundaries. Maps identified High Fire Threat Districts (HFTD) Tiers 2 and 3, areas with likely resale restrictions, and areas designated as likely “eligible communities” which included low-income communities, disadvantaged communities, and all Indian country. Another facet of SGIP eligibility is PSPS-exposure (specifically, experiencing 2 or more distinct events) for which we used our household level data. Households were designated as likely “Equity” rebate eligible customers if they were located in at least one of the following areas: “eligible communities” or resale restriction zones. Households were designated as likely “Equity Resilience” rebate eligible customers if they had 1) at least 2 PSPS event exposures OR were in a HFTD zone, and 2) if they are located in a resale restriction zone. Note that we do not have medical data, solar-incentive data, electric pump wells data which also contribute to eligibility, therefore we likely misidentify some SP IDs as non-eligible.

Figure C.6 shows cost information for a portion of the battery sample from our dataset. Costs data comes from reporting by California’s Self-generation incentive program (SGIP). Not all installations qualify for SGIP incentives and therefore do not have cost data reported.

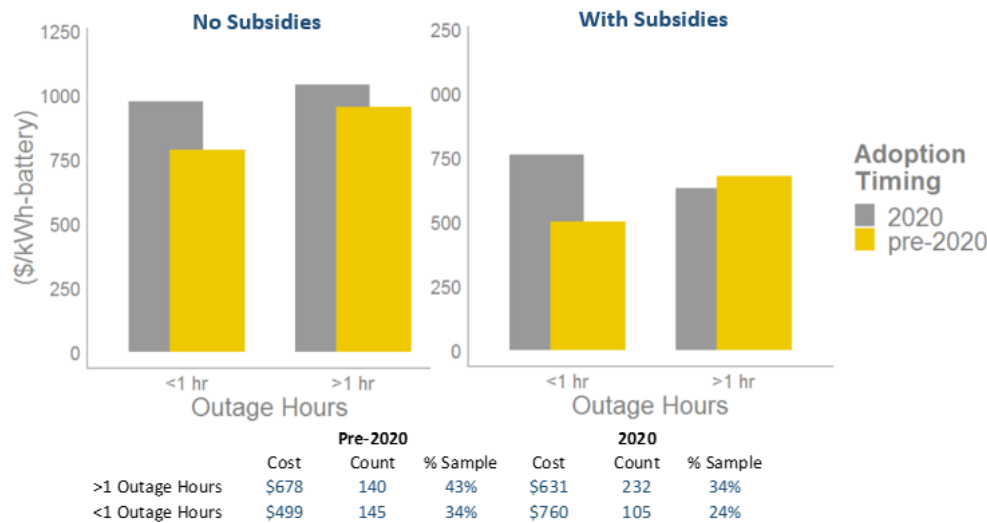


Figure C.6: Comparison of battery costs with and without rebates both before and after PSPS events.

C.3 Additional RD analysis

Table C.1 and C.2 show results of our key treatment effect on solar and storage adoption when using a fuzzy RD approach rather than sharp RD approach.

	Metro discontinuity [1]	Micro discontinuity [2]	Rural discontinuity [3]
Solar (kW) (Conventional)	0.0008 (0.001)	-0.0036** (0.0014)	-0.0036 (0.0039)
Solar (kW) (Robust)	0.0013* (0.0011)	-0.0031* (0.0017)	-0.0060 (0.0047)
Cluster (feeder)	Yes	Yes	Yes
Feeder-pair FE	Yes	Yes	Yes
Feeder-pair count	52	22	12
Untreated-mean (kW)	0.1	0.13	0.16
Treated observations	80,421	21,207	13,722
Untreated observations	71,762	30,656	13,203
Note: *p<0.1; **p<0.05; ***p<0.01			

Table C.1: Solar adoption discontinuity by RUCA category

	Metro discontinuity [1]	Micro discontinuity [2]	Rural discontinuity [3]
Battery (kWh) (Conventional)	0.0026*** (0.001)	0.002 (0.019)	0.0025 (0.0018)
Battery (kWh) (Robust)	0.0031*** (0.0011)	0.0025 (0.0024)	0.0026* (0.0015)
Cluster (feeder)	Yes	Yes	Yes
Feeder-pair FE	Yes	Yes	Yes
Feeder-pair count	52	22	12
Treated observations	80,421	21,207	13,722
Untreated observations	71,762	30,656	13,203
Note: *p<0.1; **p<0.05; ***p<0.01			

Table C.2: Battery adoption discontinuity by RUCA category

Appendix D

Chapter 5 appendix on PVESS backup power

D.1 Historical power outage events

Event	County	State	County Type
Hurricane Harvey	Aransas	Texas	Longest Duration
Hurricane Harvey	Goliad	Texas	Rural
Hurricane Harvey	Nueces	Texas	Populous
Hurricane Harvey	Refugio	Texas	Vulnerable
Hurricane Irma	Bradford	Florida	Rural
Hurricane Irma	Collier	Florida	Longest Duration
Hurricane Irma	Highlands	Florida	Vulnerable
Hurricane Irma	Miami-dade	Florida	Populous
Hurricane Florence	Carteret	North Carolina	Max % Out
Hurricane Florence	New Hanover	North Carolina	Populous
Hurricane Florence	Pamlico	North Carolina	Rural
Hurricane Florence	Robeson	North Carolina	Vulnerable
Hurricane Michael	Bay	Florida	Populous + Long Duration
Hurricane Michael	Leon	Florida	Populous
Hurricane Michael	Liberty	Florida	Longest Duration
Hurricane Michael	Clay	Georgia	Vulnerable
Hurricane Michael	Danville	Virginia	Urban
Hurricane Michael	Guilford	North Carolina	Populous
Hurricane Michael	Lancaster	Virginia	Vulnerable
Hurricane Michael	Pittsylvania	Virginia	Longest Duration

Table D.1: Counties selected for historical long-duration outage events

Event	County	State	County Type
California PSPS	Alameda	California	Populous
California PSPS	Trinity	California	Rural
California PSPS	Lake	California	Vulnerable
California PSPS	Mendocino	California	Highest Avg % Out
Washington Winter Storm	King	Washington	n/a (only 3 impacted counties)
Washington Winter Storm	Pierce	Washington	n/a (only 3 impacted counties)
Washington Winter Storm	Thurston	Washington	n/a (only 3 impacted counties)
Southeast April Storm	Blount	Alabama	Regional diversity
Southeast April Storm	Gregg	Texas	Populous
Southeast April Storm	Marion	Texas	Highest Max % Out
Southeast April Storm	Upshur	Texas	Longest Duration
Derecho	Benton	Iowa	Rural
Derecho	Linn	Iowa	Populous
Derecho	Polk	Iowa	Populous
Derecho	Poweshiek	Iowa	Vulnerable
Hurricane Isaias	Hunterdon	New Jersey	Rural
Hurricane Isaias	Litchfield	Connecticut	Longest Duration
Hurricane Isaias	Passaic	New Jersey	Vulnerable
Hurricane Isaias	Suffolk	New York	Populous
Oklahoma Ice Storm	Caddo	Oklahoma	Rural
Oklahoma Ice Storm	Cleveland	Oklahoma	Populous
Oklahoma Ice Storm	Kiowa	Oklahoma	Vulnerable
Oklahoma Ice Storm	Oklahoma	Oklahoma	Populous/Longest Duration

Table D.2: Continued counties selected for historical long-duration outage events

Variable	Storm (TX)	PSPS (CA)	Derec- ho (IA)	Flore- nce (NC)	Harve- y (TX)	Irma (FL)	Isaias (NY)	Micha- el (FL)	Winte- r Stm (OK)	Winte- r Stm (WA)
Total PVESS System Cost (\$)	\$57971	\$40661	\$46379	\$57268	\$57401	\$56381	\$47128	\$57216	\$51669	\$48924
Annual PVESS Cost (\$/yr)	\$4,652	\$3,263	\$3,722	\$4,595	\$4,606	\$4,524	\$3,782	\$4,591	\$4,146	\$3,926
Utility	SWE-PCO	PG&E	Mid-ameri- can	Duke	Retail Choice	FP&L	LIPA	Gulf	OG&E	SC&L
Variable Retail Rate (\$/kWh)	\$0.09	\$0.35	\$0.10	\$0.09	\$0.12	\$0.13	\$0.20	\$0.12	\$0.09	\$0.13
Annual Con- sumption (kWh/yr)	15,291	6,685	9,194	15,449	16,699	16,357	9,098	15,143	13,483	8,726
Solar Size (kW)	9.3	3.6	5.5	9.1	9.1	8.8	5.7	9.1	7.2	6.3
Annual Bill sav- ings (\$/yr)	\$1,376	\$2,340	\$919	\$1,390	\$2,004	\$2,126	\$1,820	\$1,817	\$1,213	\$1,134
Event Duration (hr)	52	99	191	175	379	216	96	127	242	25
PVESS load served (kWh)	53	51	227	210	579	369	116	166	157	27
2020 SAIDI (hrs)	4.2	2.3	1.5	2.5	2.8	0.8	1.1	0.8	2.3	1.1

Table D.3: Inputs to calculate of the cost of served energy for the historical case analysis

D.2 Additional information on inputs

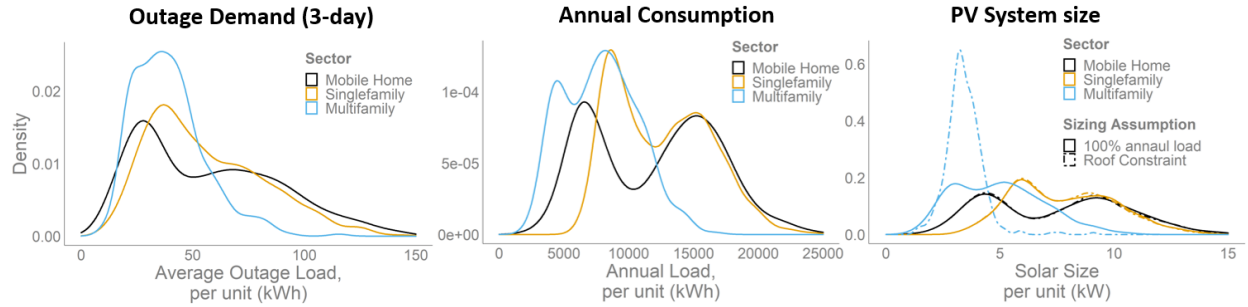


Figure D.1: Outage amount, consumption, and PV size per individual unit across three different residential building types.

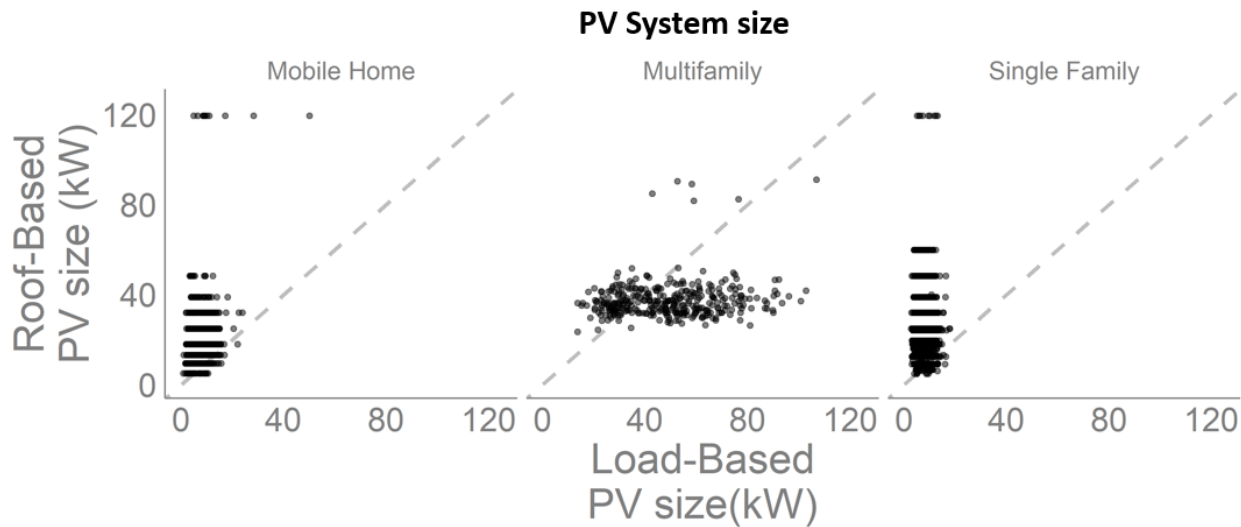


Figure D.2: PV system size in roof-based sizing compared to load-based sizing scenarios for three different residential building types

D.3 Additional results

Most analysis assumes that interruptions begin on the median net load day each month, but loads and solar generation can vary significantly within a month. Below Figure D.3 shows sensitivity where interruptions instead begin on the worst or best days each month (highest/lowest net load). Sensitivity is highly dependent on heating and cooling technology. Across homes with electric heat, avg. performance in winter months drops to 53% of load served on the worst days, compared to 82% for median days and 96% for the best days.

Effects are less pronounced for homes with electric cooling, though still notable in counties at the lower end of the percentile band (in hotter climates).

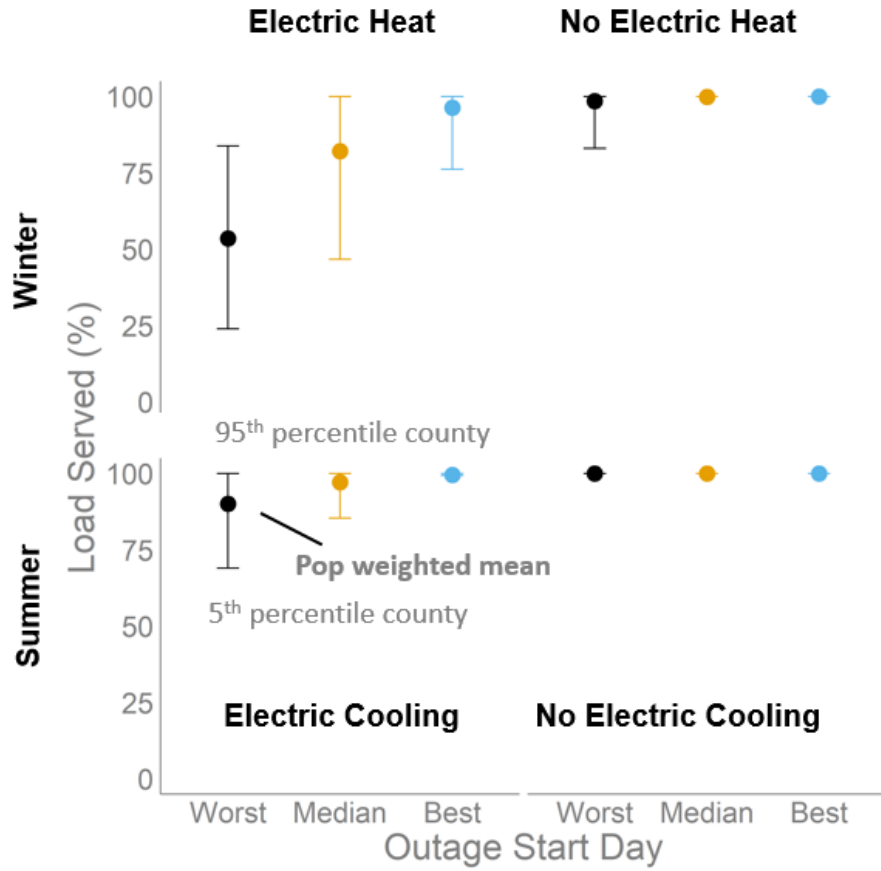


Figure D.3: Annual average critical load served based on monthly outage start-day.

Base-case assumes that interruptions begin at 12 am and that initial SoC is 100%. These two factors are inter-dependent, in terms of how they impact PVESS backup performance, and matter mostly over the first 24 hours of an event (Figure D.4). In the extreme, a 1-day event that starts immediately after the sun sets (hour = 18) will be much harder to meet without any initial SoC (48% of load served vs. 98% if the battery starts fully charged or 94% if it starts with a 50% SoC). These initial conditions become progressively less important over longer duration events, at least terms of average performance over the entire event.

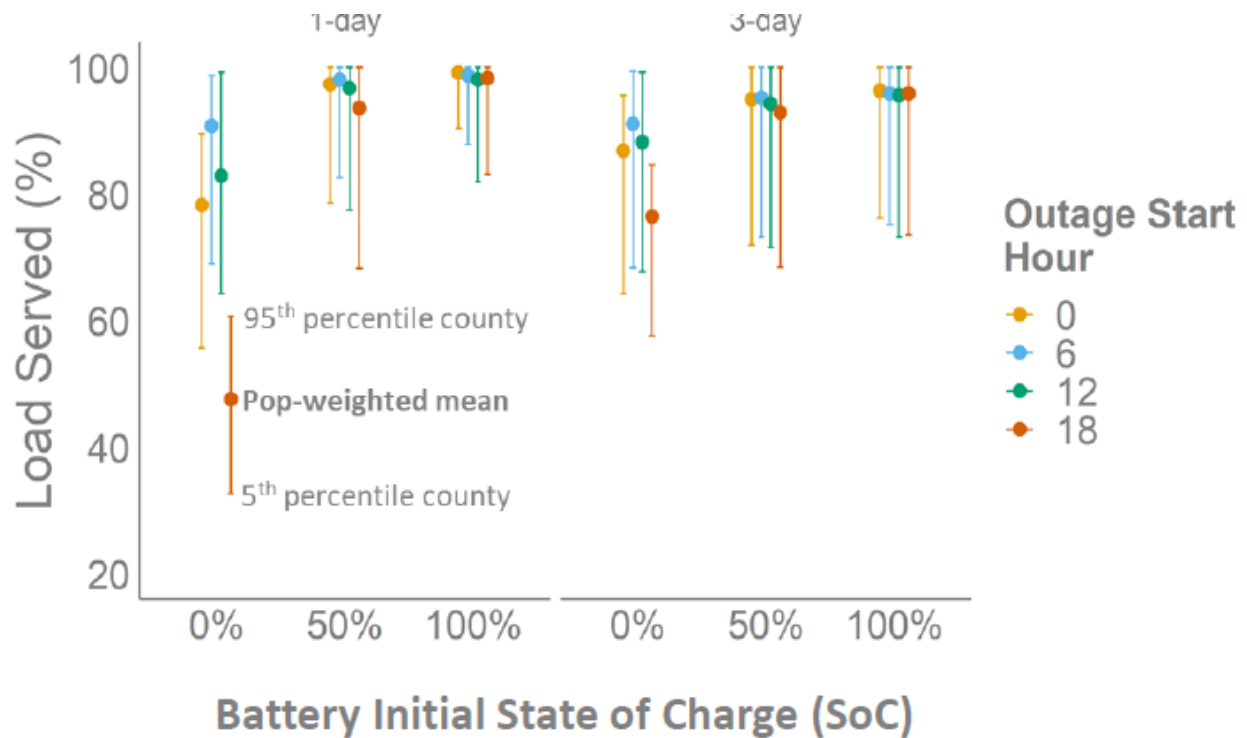


Figure D.4: Annual average critical load served based on monthly outage start-day.

In general, backup performance declines the greater the amount of critical load to serve, given fixed battery sizing (Figure D.5). Scatter around those trends reflects differences in customer load profile shapes, among other factors. Differences in critical load levels reflect a number of fundamental drivers: (1) Building size, (2) Heating and cooling equipment type (especially electric vs. gas heating), (3) Efficiency levels, and (4) Occupant/behavioral factors (e.g., set points).

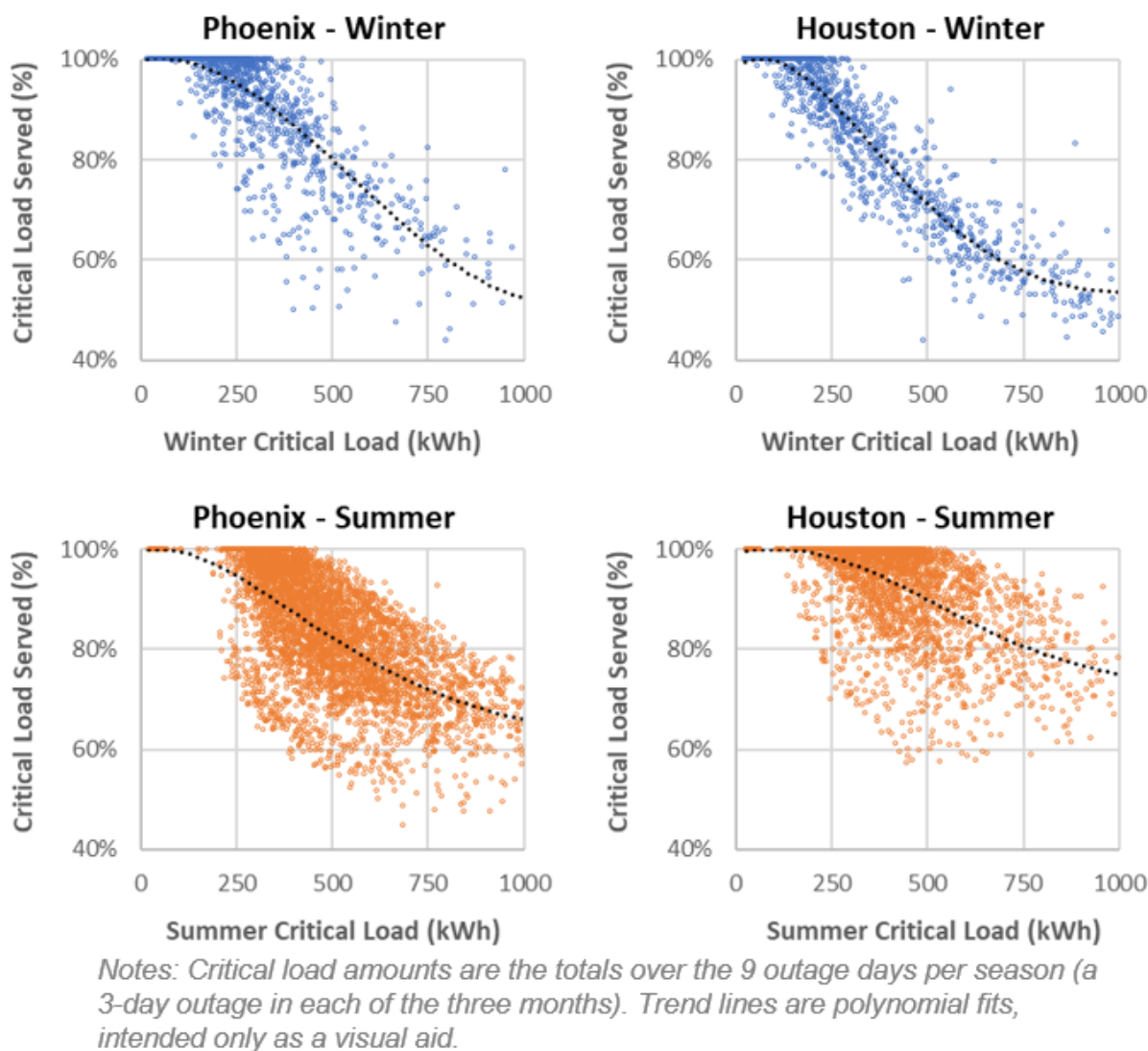


Figure D.5: Percentage of critical load served based on amount of critical load

The top of Figure D.6 compares PVESS backup performance in summer months based on the efficiency of the central air-conditioner (A/C). As shown, backup performance is higher by 10-20% for homes with high efficiency A/C or heat pumps. The bottom figure compares performance in winter months based on infiltration (air leakage) for electric heated homes. As shown, performance is about 20% lower for the leakiest homes; effects would likely be much more pronounced for electric heated homes in cold climates. Both trends illustrate the potential value of improving building and equipment efficiency prior to installing PVESS for backup.

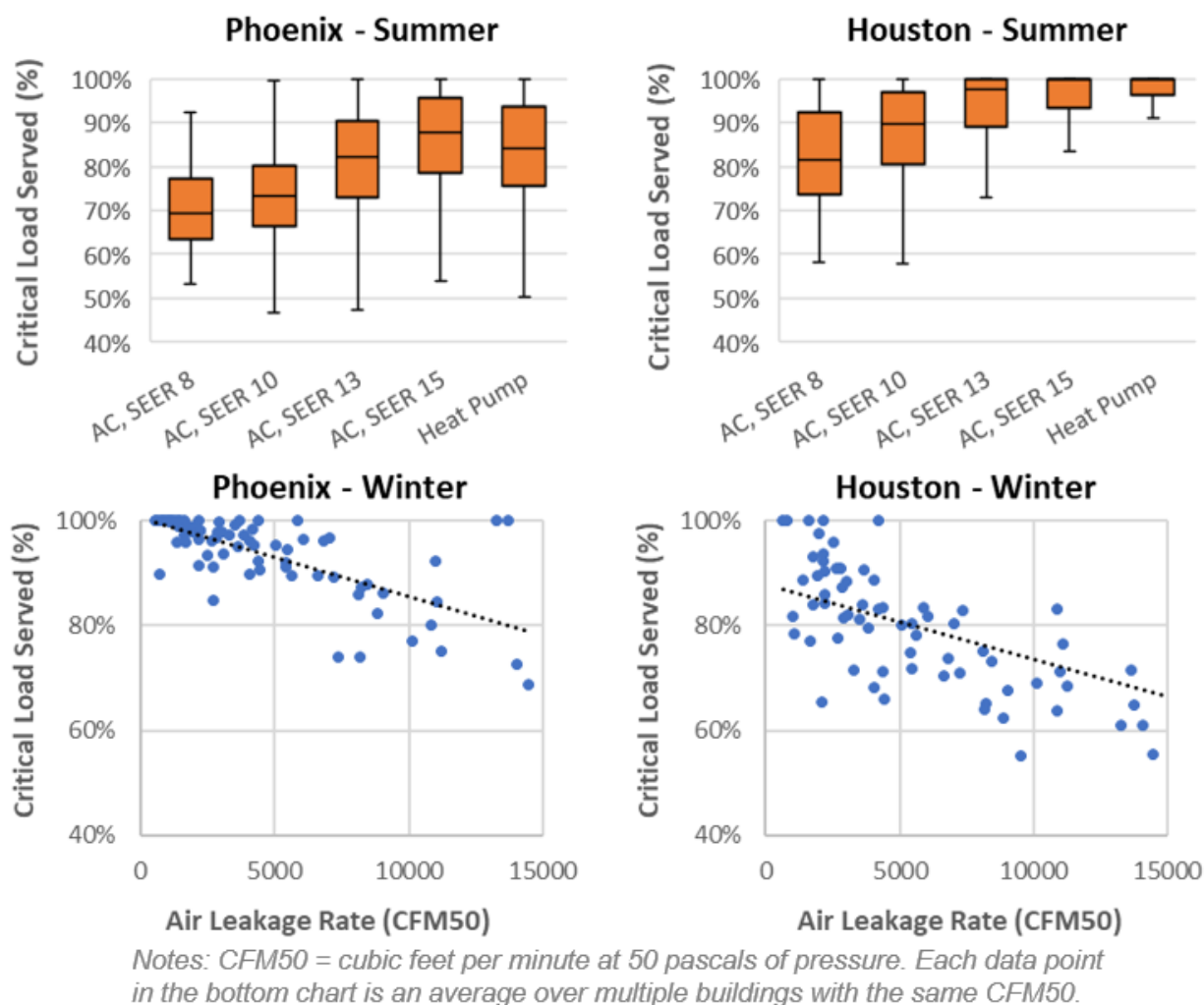


Figure D.6: Percentage of critical load served based on different home efficiency indicators.

Geographic patterns for mobile homes are similar to those shown for single-family homes in the main body of the dissertation; however, multifamily home results are slightly different and show the worst performance in northern climates.

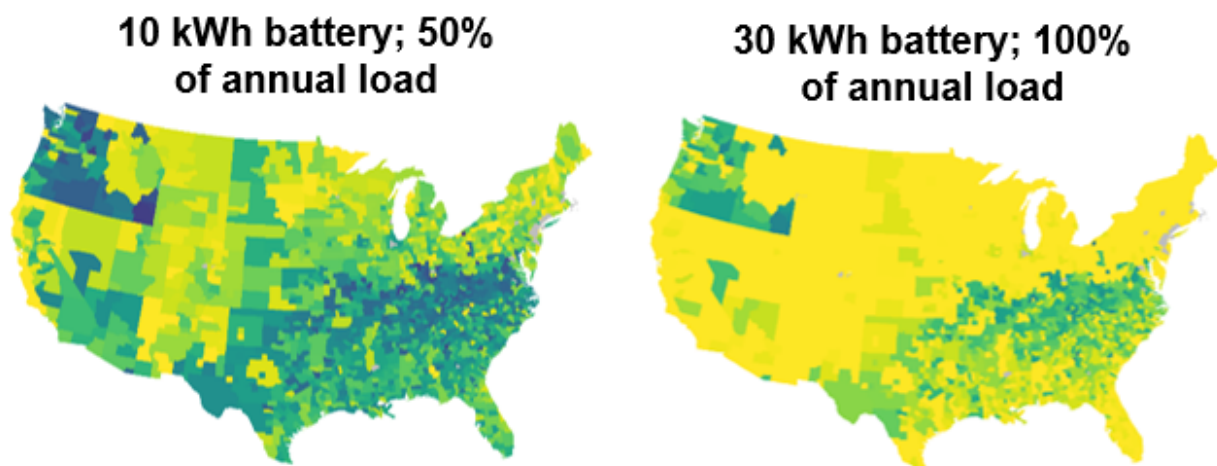


Figure D.7: Average annual critical load served for each county-median mobile home, by PVES size.

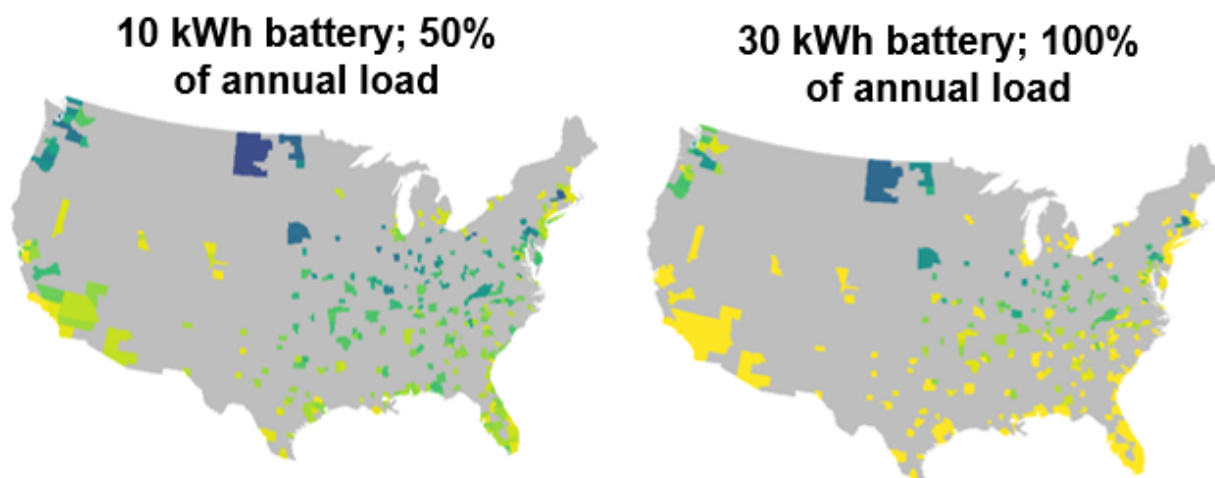


Figure D.8: Average annual critical load served for each county-median multifamily complex, by PVES size.

Appendix E

Chapter 6 appendix on rate design and grid defection

In this section, I provide additional details on both the inputs to the modeling framework as well as results to both the base cases and some sensitivity analyses.

E.1 Additional input summary

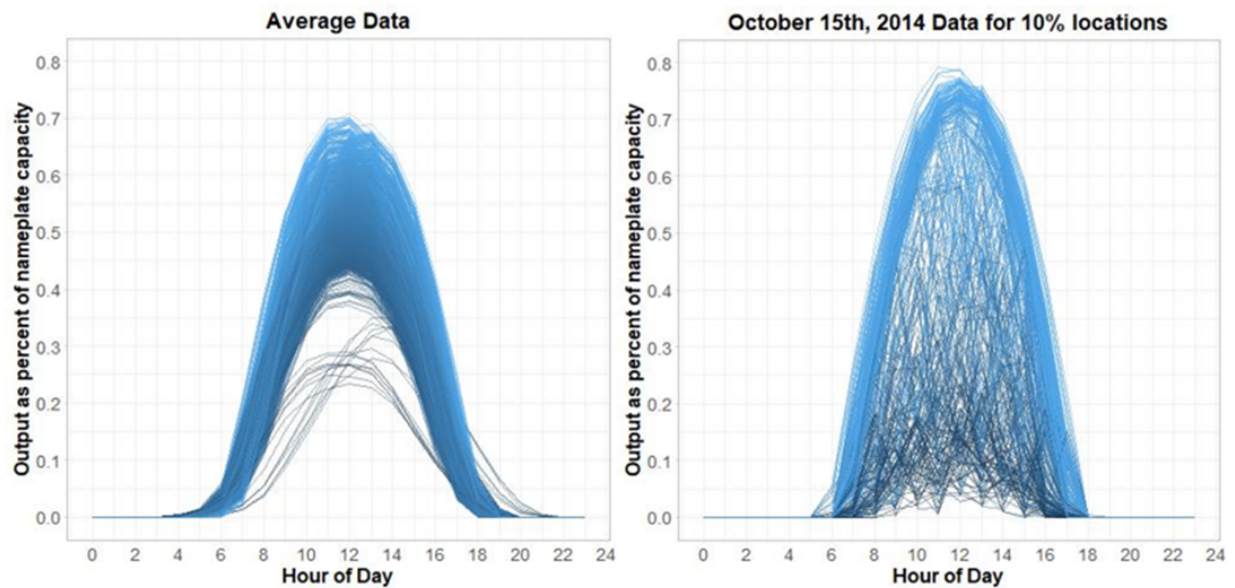


Figure E.1: Solar output multiplier showing the variability of the solar input data to the optimization model. Each line represents a different United States county.

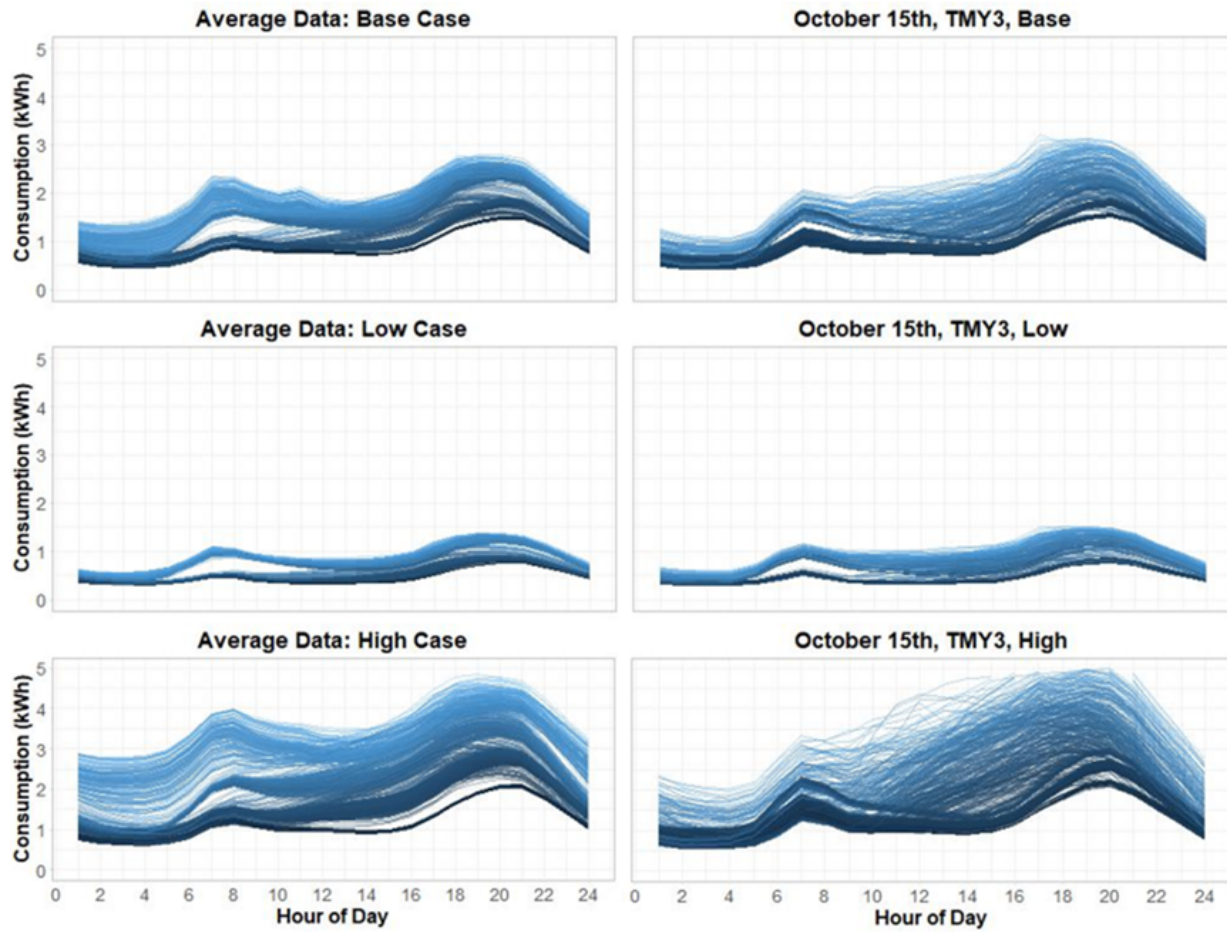


Figure E.2: Demand data used as input to the optimization model. Each line represents a different United States county. The left graphs represent the annual average profile while the right graphs select a unique date.

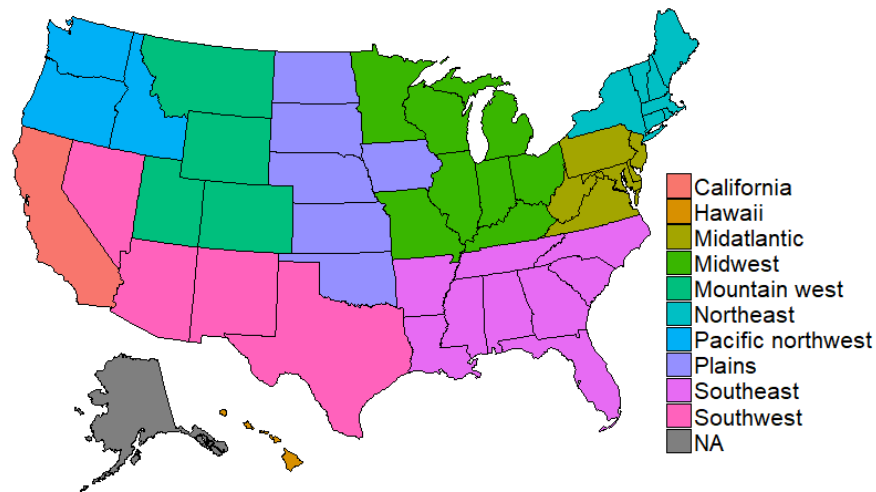


Figure E.3: Region Definition for grid defection tables below in Appendix

E.2 Additional base results

		Solar System Statistics (kW)						Storage System Statistics (kWh)					Median Cost (\$/yr)
Reliability Scenario	Demand Case	Count	Median	Max	Min	10%	90%	Median	Max	Min	10%	90%	
Perfect	Low	3209	18	138	4	11	34	67	360	16	38	157	\$1,817
Flexible		3209	12	110	3	8	16	34	168	9	21	56	\$1,092
Perfect	Base	3209	38	295	8	21	69	134	842	30	77	316	\$3,633
Flexible		3209	26	233	7	17	36	64	358	22	41	94	\$2,117
Perfect	High	3209	55	432	14	32	110	191	1804	44	110	525	\$5,277
Flexible		3209	35	357	12	26	71	88	501	33	64	207	\$3,039

Figure E.4: Summary statistics on system sizing for future cost scenario case

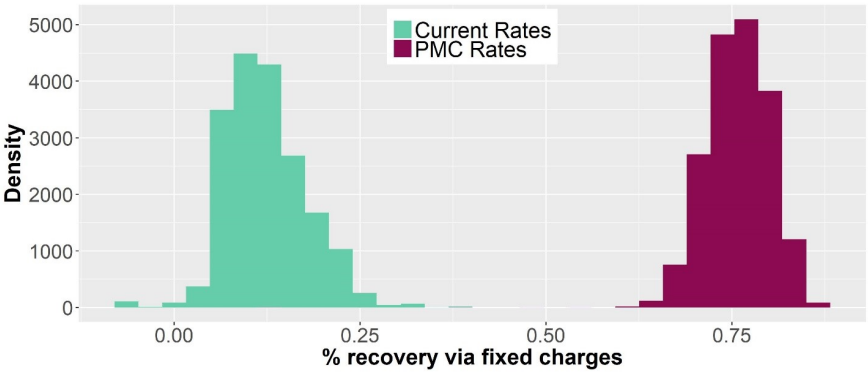


Figure E.5: Breakdown of cost recovery via fixed charge in two rate design scenarios showing the large increase in revenue collection via fixed fees in the private marginal cost scenario

E.3 Sensitivity analyses

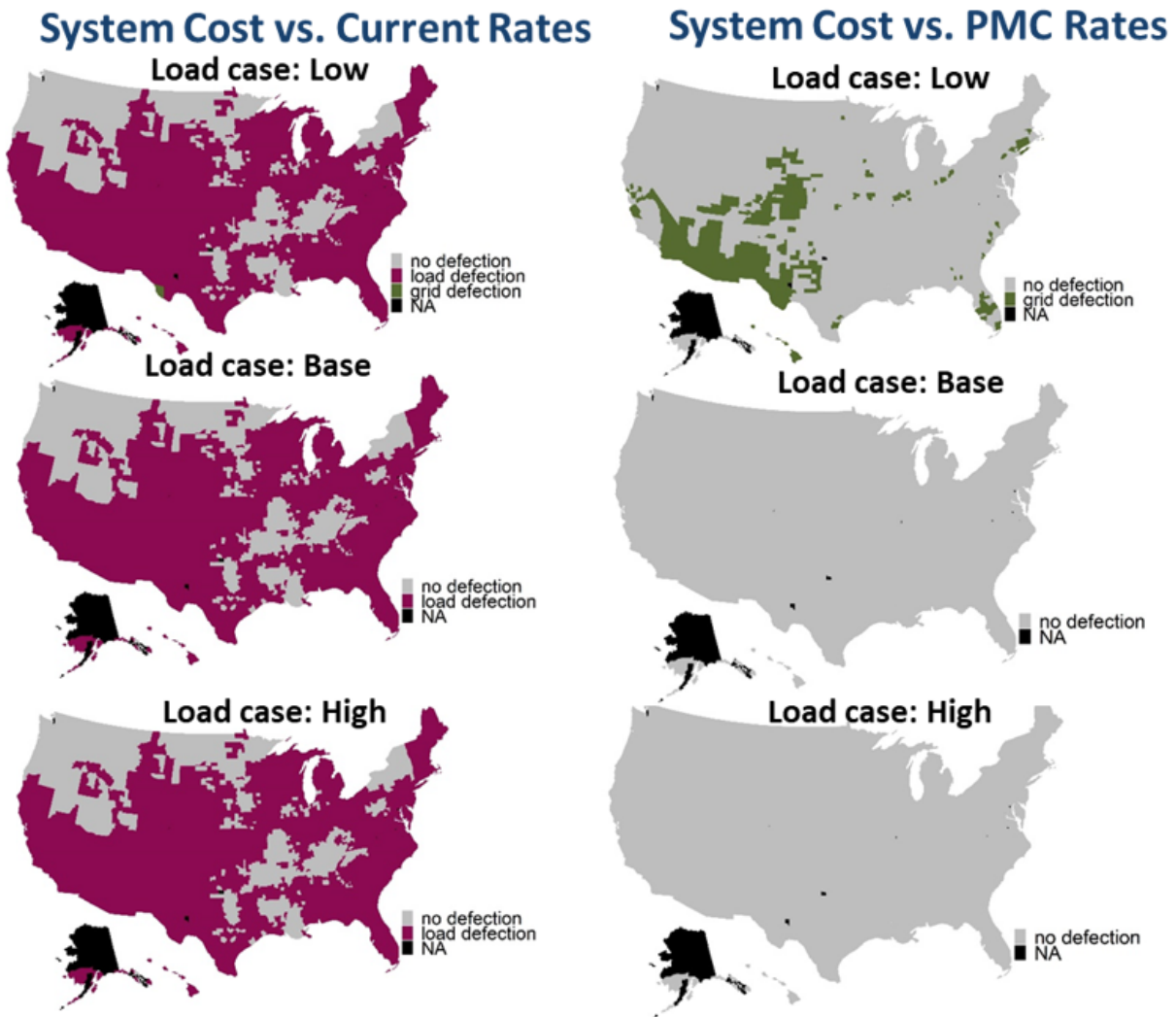


Figure E.6: Geographic variation in the decision to defect under “perfect” reliability case and future cost assumptions. Breakdown of demand cases showcases how customer electricity consumption is a key driver of grid defection decision in PMC rate scenario

Region	Grid Defection					Load Defection			
	2015 Household Total (Millions)	Flexible Reliability		Perfect Reliability		Flexible Reliability		Perfect Reliability	
		PMC defector count	current rate design defector count	PMC defector count	current rate design defector count	PMC defector count	current rate design defector count	PMC defector count	current rate design defector count
Northeast	1.3	1.2	0.0	0.2	0.0	0.0	1.2	0.0	1.2
Southwest	0.9	0.8	0.1	0.4	0.0	0.0	0.6	0.0	0.7
Pacific northwest	0.4	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Mountain west	0.2	0.2	0.0	0.1	0.0	0.0	0.2	0.0	0.2
Plains	0.3	0.3	0.0	0.0	0.0	0.0	0.3	0.0	0.3
Southeast	1.1	0.9	0.1	0.1	0.0	0.0	0.8	0.0	0.9
Midwest	1.5	1.0	0.0	0.0	0.0	0.0	1.3	0.0	1.3
Midatlantic	1.2	1.1	0.0	0.0	0.0	0.0	1.1	0.0	1.1
California	1.1	1.1	0.0	0.4	0.0	0.0	1.1	0.0	1.1
Hawaii	0.1	0.1	0.0	0.0	0.0	0.0	0.1	0.0	0.1
Overall	8.1	6.7	0.3	1.4	0.0	0.0	6.6	0.0	6.9

Figure E.7: Grid defection by region for low demand customers using future cost scenario. We only allow defection for single family households.

Region	Grid Defection					Load Defection			
	2015 Household Total (Millions)	Flexible Reliability		Perfect Reliability		Flexible Reliability		Perfect Reliability	
		PMC defector count	current rate design defector count	PMC defector count	current rate design defector count	PMC defector count	current rate design defector count	PMC defector count	current rate design defector count
Northeast	3.0	0.0	0.0	0.0	0.0	0.0	2.5	0.0	2.5
Southwest	3.3	0.7	0.0	0.0	0.0	0.0	2.5	0.0	2.5
Pacific northwest	1.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.1
Mountain west	0.6	0.2	0.0	0.0	0.0	0.0	0.5	0.0	0.5
Plains	1.0	0.0	0.0	0.0	0.0	0.0	0.8	0.0	0.8
Southeast	5.6	0.2	0.0	0.0	0.0	0.0	4.4	0.0	4.4
Midwest	5.5	0.0	0.0	0.0	0.0	0.0	4.7	0.0	4.7
Midatlantic	2.7	0.0	0.0	0.0	0.0	0.0	2.6	0.0	2.6
California	2.5	1.5	0.0	0.0	0.0	0.0	2.5	0.0	2.5
Hawaii	0.1	0.1	0.0	0.0	0.0	0.0	0.1	0.0	0.1
Overall	25.4	2.7	0.0	0.0	0.0	0.0	20.8	0.0	20.8

Figure E.8: Grid defection by region for base demand customers using future cost scenario. We only allow defection for single family households.

Region	Grid Defection					Load Defection			
	Flexible Reliability		Perfect Reliability			Flexible Reliability		Perfect Reliability	
	2015	current	current	current	current	current	current	current	current
	Household Total (Millions)	PMC defector count	rate design defector count	PMC defector count	rate design defector count	PMC defector count	rate design defector count	PMC defector count	rate design defector count
Northeast	3.0	0.0	0.0	0.0	0.0	0.0	2.3	0.0	2.3
Southwest	3.6	0.0	0.0	0.0	0.0	0.0	2.9	0.0	2.9
Pacific northwest	1.4	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.1
Mountain west	1.2	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0
Plains	1.6	0.0	0.0	0.0	0.0	0.0	1.2	0.0	1.2
Southeast	8.2	0.0	0.0	0.0	0.0	0.0	6.4	0.0	6.4
Midwest	6.7	0.0	0.0	0.0	0.0	0.0	5.7	0.0	5.7
Midatlantic	4.2	0.0	0.0	0.0	0.0	0.0	4.0	0.0	4.0
California	3.3	0.0	0.0	0.0	0.0	0.0	3.3	0.0	3.3
Hawaii	0.1	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.1
Overall	33.4	0.0	0.0	0.0	0.0	0.0	26.9	0.0	26.9

Figure E.9: Grid defection by region for high demand customers using future cost scenario. We only allow defection for single family households.

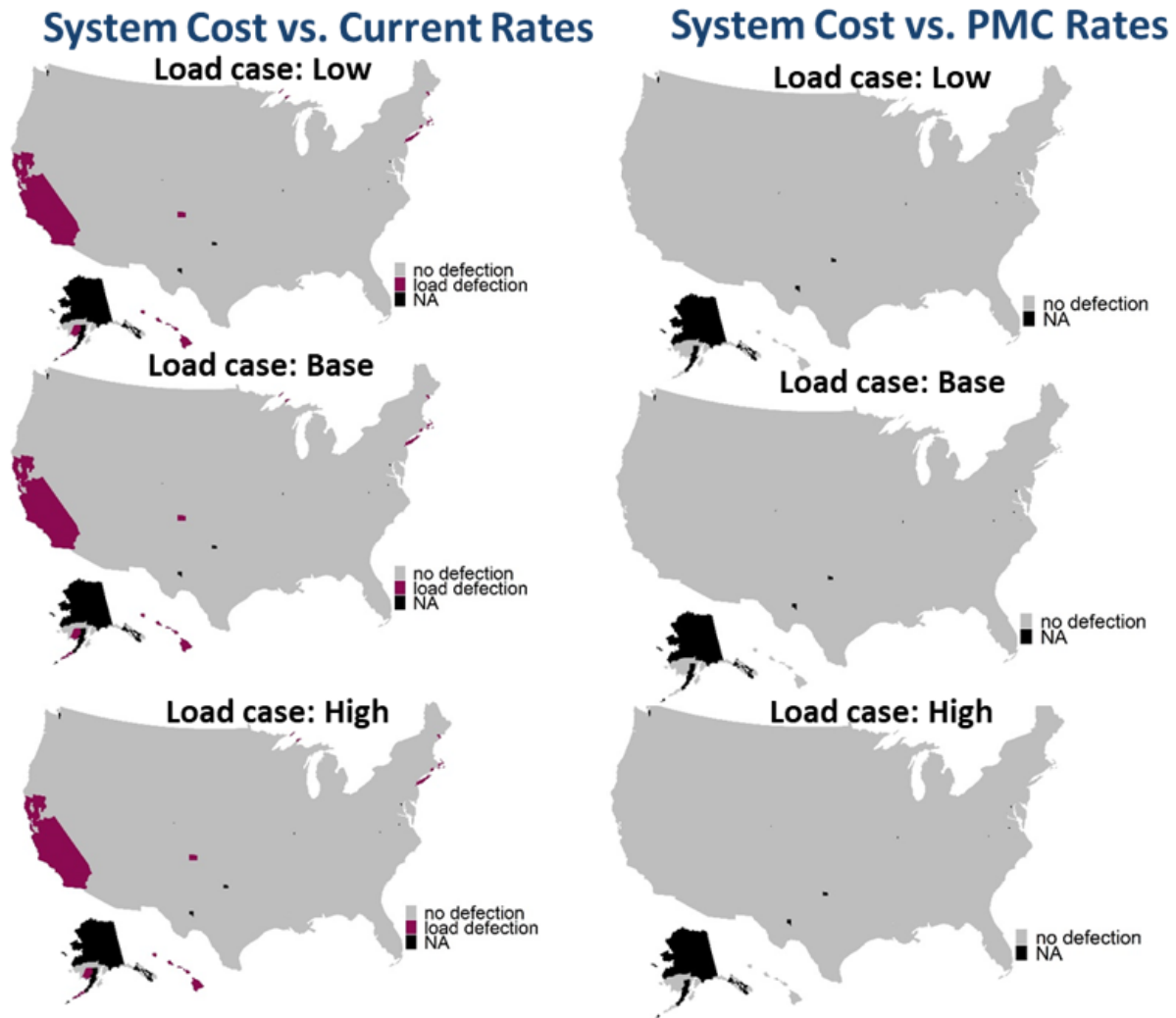


Figure E.10: Defection in the “perfect” reliability case (current cost case) Geographic variation in the decision to defect under “perfect” reliability case and current cost assumptions. Current cost assumptions result in very limited defection

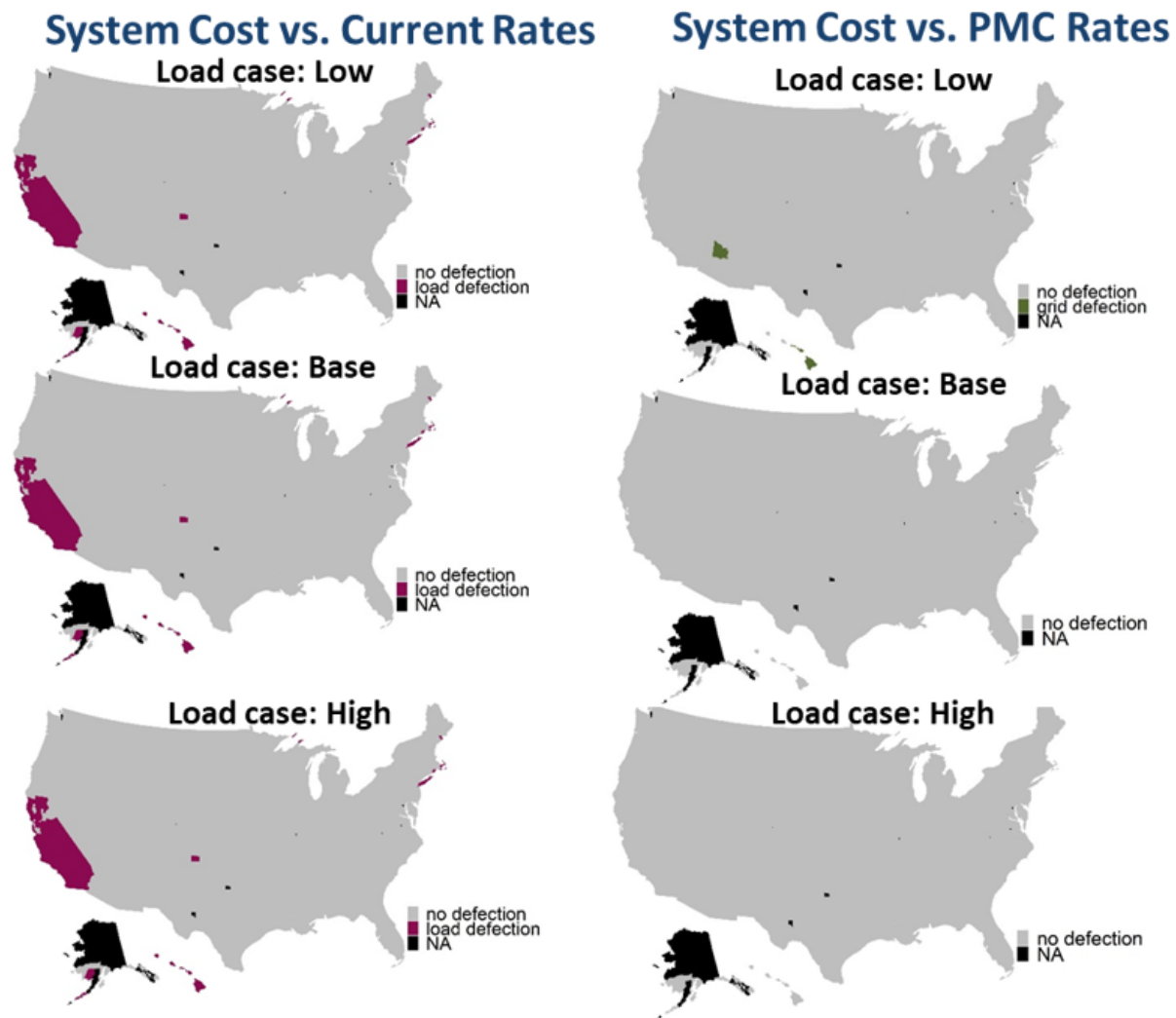


Figure E.11: Geographic variation in the decision to defect under “flexible” reliability case and current cost assumptions. Current cost assumptions result in very limited defection

Region	Grid Defection					Load Defection			
	2015 Household Total (Millions)	Flexible Reliability		Perfect Reliability		Flexible Reliability		Perfect Reliability	
		PMC defector count	current rate design defector count	PMC defector count	current rate design defector count	PMC defector count	current rate design defector count	PMC defector count	current rate design defector count
Northeast	14.8	0.0	0.0	0.0	0.0	0.0	2.4	0.0	2.4
Southwest	15.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Pacific northwest	5.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Mountain west	4.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Plains	5.9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Southeast	30.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Midwest	27.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Midatlantic	16.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
California	14.0	0.0	0.0	0.0	0.0	0.0	6.1	0.0	6.1
Hawaii	0.5	0.0	0.0	0.0	0.0	0.0	0.3	0.0	0.3
Overall	134.2	0.0	0.0	0.0	0.0	0.0	8.7	0.0	8.7

Figure E.12: Grid defection by region for all demand customers using current cost scenario. We only allow defection for single family households.

Region	Grid Defection					Load Defection			
	2015 Household Total (Millions)	Flexible Reliability		Perfect Reliability		Flexible Reliability		Perfect Reliability	
		PMC defector count	current rate design defector count	PMC defector count	current rate design defector count	PMC defector count	current rate design defector count	PMC defector count	current rate design defector count
Northeast	1.3	0.0	0.0	0.0	0.0	0.0	0.6	0.0	0.6
Southwest	0.9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Pacific northwest	0.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Mountain west	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Plains	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Southeast	1.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Midwest	1.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Midatlantic	1.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
California	1.1	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0
Hawaii	0.1	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.1
Overall	8.1	0.0	0.0	0.0	0.0	0.0	1.7	0.0	1.7

Figure E.13: Grid defection by region for low demand customers using current cost scenario. We only allow defection for single family households.

Region	Grid Defection					Load Defection			
	2015 Household Total (Millions)	Flexible Reliability		Perfect Reliability		Flexible Reliability		Perfect Reliability	
		PMC defector count	current rate design defector count	PMC defector count	current rate design defector count	PMC defector count	current rate design defector count	PMC defector count	current rate design defector count
Northeast	3.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0
Southwest	3.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Pacific northwest	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Mountain west	0.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Plains	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Southeast	5.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Midwest	5.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Midatlantic	2.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
California	2.5	0.0	0.0	0.0	0.0	0.0	2.2	0.0	2.2
Hawaii	0.1	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.1
Overall	25.4	0.0	0.0	0.0	0.0	0.0	3.3	0.0	3.3

Figure E.14: Grid defection by region for base demand customers using current cost scenario. We only allow defection for single family households.

Region	Grid Defection					Load Defection			
	2015 Household Total (Millions)	Flexible Reliability		Perfect Reliability		Flexible Reliability		Perfect Reliability	
		PMC defector count	current rate design defector count	PMC defector count	current rate design defector count	PMC defector count	current rate design defector count	PMC defector count	current rate design defector count
Northeast	3.0	0.0	0.0	0.0	0.0	0.0	0.8	0.0	0.8
Southwest	3.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Pacific northwest	1.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Mountain west	1.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Plains	1.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Southeast	8.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Midwest	6.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Midatlantic	4.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
California	3.3	0.0	0.0	0.0	0.0	0.0	2.9	0.0	2.9
Hawaii	0.1	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.1
Overall	33.4	0.0	0.0	0.0	0.0	0.0	3.7	0.0	3.7

Figure E.15: Grid defection by region for high demand customers using current cost scenario. We only allow defection for single family households.