The Consequences of Wildfire Liability for Firm Precaution: Evidence from Power Shutoffs in California*

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Abstract

Across all sectors of the U.S. economy, regulators use liability regulations to encourage firms to take actions that reduce the costs associated with low probability, high severity events such as oil spills and production defects. Despite the widespread use of these regulations, there is limited evidence of their effectiveness in influencing firms' tradeoff between expected liability cost and incentives for precautions. This study provides causal evidence of firm responses to the entire distribution of potential liability and quantifies the distribution of liability costs between firms and the public by studying power line-ignited fires in California's electric utility sector. In this setting, when a power line-ignited fire damages a structure, the owner of the power line assumes the cost. Using exogenous variation in the replacement cost of structures that lie downwind of power lines, I find that firms increase their precaution by 130% in response to a $680 million increase in liability. In the short run, the estimates from this study imply that the implemented liability regulation had welfare costs up to $7 billion.

JEL Codes: D22, Q40, L51, K13

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1 Introduction

Low probability, high severity events such as oil spills or product defects characterize many sectors of the U.S. economy. A popular approach to mitigate the frequency of such events is to make firms liable for potential damages in part to incentivize precaution. To understand the effectiveness of liability regulation we need to know how firms' precautions respond to: (1) the application of liability and (2) changes in the amount of damages they are liable for.

In settings where a firm faces large potential liabilities from an accident, its liability cannot exceed its asset value because it may use bankruptcy to avoid further damages. This discrete drop in firms' incentives for precautions at their asset value is commonly termed the judgment-proof problem (Shavell (1986)). One common solution used to solve the judgment proof problem is to cap firms' level of potential liability. However, determining the liability cap level is a difficult task for a regulator: higher caps induce firms to undertake greater precautions as they bear a larger share of liability costs, but setting too high a cap may cause the firm to declare bankruptcy, shifting liability costs onto the public. This creates ambiguity about a fundamental question in public economics: What are the efficiency tradeoffs associated with capping liability?

Motivated by this gap in the literature on liability regulation, this paper provides the first causal evidence of how firms' precautions responds to the imposition of a negligence standard in California's electric utility sector. Between 1999 and 2017, firms faced with covering liabilities due to power line fires were allowed to recoup these costs through increases in retail electricity prices. However, since November 2017, utilities have borne liability costs whenever the regulator found that their imprudence led to an ignition. Using this setting, I estimate an empirical model that shows how firms' use of one type of precaution, called a Public Safety Power Shutoff event (PSPS), changed following the policy shift. Furthermore, I develop an empirical model which uses daily variation in the replacement cost of structures that are downwind of power lines to estimate how firms' use of power shutoffs respond to the entire distribution of potential liability. Since firms in this setting are responsible for the replacement cost of structures damaged by power line-ignited fires, variation in downwind regions across days creates exogenous changes in potential liability.

Firms use Public Safety Power Shutoff events to prevent fire ignitions along their power lines. During a power shutoff, utilities turn the power off on sections of their energy infrastructure when forecasted climate conditions suggest an ignition is likely to occur. Because electricity must be running through a power line for an ignition to happen, power shutoffs significantly reduce the likelihood of fire and potential liabilities that a firm faces. In contrast, other types of precaution available to firms such as clearing vegetation away from power lines do not provide the same assurance because an ignition could still occur.

This is an important setting to study liability regulation. Climate change is increasing the severity of power line-ignited fires in the western U.S., making it important to understand how to incentivize firms to prevent ignitions in this setting (Syphard and Keeley (2015)). Furthermore, power line-ignited fires are more damaging than fires from other ignition sources because they typically occur during high wind speed events when the wind carries vegetation into the line. Since fires are also more likely to spread rapidly and grow out of control during windy conditions, power line-ignited fires tend to cause more damage than fires from other sources (Keeley et al. (2018)). For example, one privately owned utility, Pacific Gas and Electric, faced over $30 billion dollars in liability from several fires ignited in 2017 and 2018.[1] Figure 1 plots total damages in billions of 2021 dollars by source of fire ignition and shows that, although power line-ignited fires make up less than one percent of ignitions historically, they account for most of the damage from fires in California between 2008 and 2019.

My setting also has a key advantage: it allows me to causally estimate the relationship between the level of liability a firm faces and its precaution using exogenous changes in the direction that the wind is blowing across days.[2] Prior work has typically relied on regulatory changes that cap the level of liability a firm faces to study this relationship, but in this setting I am able to measure firms' responses across the full distribution of potential liabilities that they face.

Using administrative data on precautionary measures taken by the three largest privately owned utilities in California, I find three results. First, I show that firms dramatically increase their use of power shutoffs following the 2017 policy change. Prior to the reform, power shutoffs occurred on 0.1 percent of days when the ignition risk was elevated and, on average, created 2 lost customer hours of power. After the reform, power shutoffs happened on 4 percent of days with heightened

[1] Los Angleles Times "Pacific Gas and Electric to file for bankruptcy as wildfire costs hit $30 billion. Its stock plunges 52%", January 14, 2019.

[2] The privately owned utilities in California's electric utility industry that I study are representative of most electric utilities in the United States. In fact, in 2017 privately owned utilities supplied 72% of electricity customers in the United States (EIA Annual Electric Power Industry Report).

ignition risk and the number of customer hours without power increased by 734 customer hours, on average. Using lower and upper bounds on consumers' value of electricity use from the literature, I find that this increase in power shutoffs translates to between $150 and $51,000 of lost consumer surplus at the average distribution circuit.[3] I also show that although firms increase shutoffs most in the regions of greatest *ex ante* ignition risk, these are more likely to be areas with high shares of customers that rely on electricity for their medical needs, making the shutoffs particularly costly.[4]

Second, I show that firms' precaution is positively related to the level of liability that they face. Since utilities are liable for the cost of replacing structures damaged by fires that their power lines ignite, I measure liability using this value. In most settings, causal estimation of the relationship between the level of liability that firms face and precaution is difficult because liability is likely to be endogenous. My setting allows me to remove this endogeneity by using daily variation in the replacement cost of structures that lie downwind of each firm's power lines between 2018 and 2020 to generate daily variation in each utility's potential liability. I estimate that power shutoffs increase by 130 percent relative to the average likelihood of a shutoff when the total replacement cost of structures in downwind areas increases by 10 percent ($680 million).

Third, I estimate that the short-run welfare impact of the 2017 liability rule change is negative and large. Depending on the chosen estimate of consumer's value of electricity from the literature, the policy resulted in a welfare loss of between $7 billion ($76.11 per kilowatt hour valuation of electricity use) and $17 million ($0.22 per kilowatt hour). From the social planner's perspective, this suggests that utilities have overused shutoffs as a precautionary measure in the short term. I also develop a conceptual framework that suggests this increase in shutoffs reduced utilities' use of other types of precautionary measures such as vegetation management or infrastructure upgrading.

These results have several policy relevant implications. I provide an empirical framework to estimate how firms' precautionary behaviors change across the distribution of potential liabilities, a key parameter for determining the liability cap level. Current and past policy proposals have

[3]The lower bound of consumers' value of electricity is the average retail price of electricity in California as of August 2022 ($0.22 per kWh) and the upper bound is $76.11, the largest residential value of electricity use from Collins et al. (2019). The upper bound of consumers' electricity use may be much higher however, because the shutoffs left commercial and industrial consumers, who have higher use values of electricity, without power as well.

[4]Customers relying on electricity for their medical needs may require reliable energy to power respirators, electric wheelchairs, and other devices. Because these customers have an above average use value of electricity, this result implies that using an average value of consumers' value of lost load would systematically underestimate the welfare consequences of power shutoffs.

included limits on the amount of damages homeowners can recover from electric utilities.[5] However, such policy proposals note that it is unclear what level liability should be limited at and how such limits would distribute costs between homeowners, electricity consumers, and utility shareholders.

Furthermore, I estimate how economic incentives influence the reliability of electricity supply using a novel dataset of distribution power lines. This is relevant for regulators across the U.S. who want to incentivize utilities to make investments that improve the reliability of electricity supply and upgrade aging infrastructure. Because of the projected growth of renewable energy generation in the United States, the federal government has made upgrades of energy infrastructure a cornerstone of its energy platform.[6] My work in this paper underscores that having detailed administrative data on distribution networks across the U.S. will be important for effectively upgrading energy infrastructure.

This paper makes three contributions to the literature in public economics. First, it poses a new channel, expected damages, through which liability regulations impact firms' decisions and quantifies how the burden of precautionary costs is distributed between firms and electricity consumers. I show that, when firms bear liability costs, they direct more precautionary effort to areas with high levels of expected liability. Since power shutoffs are socially costly, utilities' increased reliance on shutoffs to prevent ignitions causes electricity consumers to bear a greater share of costs associated with ignition prevention. This adds to previous work documenting other determinants of firms' choice of precaution such as bankruptcy (Shavell (1986)), subjective firm beliefs (Currie and MacLeod (2013)), risk aversion (Shavell (1982)), and market structure (Chen and Hua (2017)). Furthermore, this result contributes to a growing literature that examines the determinants of wildfire suppression (Plantinga, Walsh and Wibbenmeyer (2022), Baylis and Boomhower (2022)).

Second, I show how precaution varies across the distribution of potential liabilities that firms face. Previous research has estimated how capping medical liability impacts doctors' prescribing behavior (Helland et al. (2021)), medical outcomes (Danzon (1985), Kessler and McClellan (1996), Currie and MacLeod (2008), Frakes (2013)), and the labor supply of doctors (Malani and Reif (2015), Kessler, Sage and Becker (2005), Klick and Stratmann (2007), Matsa (2007)). Another

[5] "Allocating Utility Wildfire Costs: Options and Issues for Consideration", California Legislative Analysts Office, 2019.

[6] See here.

related literature examines how changes in liability impact toxic waste discharges and abatement technology adoption (Akey and Appel (2021), Alberini and Austin (2002), Stafford (2002)). Many of these studies estimate how precaution responds to the level of liability a firm faces at one point in the liability distribution because their variation comes from caps on liability at a particular value. The empirical strategy in this paper allows me to estimate how precaution changes across the entire distribution of liability that firms face in practice.

Previous work on the judgment-proof problem by Boomhower (2019) shows that requiring firms to purchase insurance which covers damages beyond their own assets encouraged greater production by larger firms with better environmental outcomes in Texas' oil and gas sector. This paper complements Boomhower (2019) by directly estimating how firms' precautions change across the distribution of potential liability they face. Since requirements to cover damages beyond firm assets may not be feasible in settings with concentrated market power, such as the electric utility sector, the estimates in this paper provide relevant information that can be used to implement other solutions to the judgment-proof problem such as capping liability.

This paper also makes important contributions to a recent literature in environmental economics and engineering. I show that liability considerations drive firms' decision to declare power shutoffs. Previous work by Abatzoglou et al. (2020) applied one utility's publicly stated climate thresholds for declaring power shutoffs to observed weather data during 2019, finding that the utility used shutoffs more than would be predicted by its own decision rules. I provide an economic explanation for this overuse of power shutoffs by documenting the role of liability in determining firms' precaution.

I also provide evidence that utilities' use of power shutoffs are costly. This adds to a recent literature that estimates the costs and benefits of public safety power shutoffs in California (Sotolongo, Bolon and Baker (2020), Wong-Parodi (2020), Zanocco et al. (2021), Mildenberger et al. (2022)). I provide the first causal estimates of power shutoffs' impact on customers that rely on electricity for their medical needs, finding results consistent with the descriptive analysis performed by Sotolongo, Bolon and Baker (2020).

Finally, I provide the first evidence of fire liability's impact on firms in the electric utility industry. Yoder (2008) shows that the number of fires escaping from private landowners' property during a prescribed burn declines following the implementation of strict liability regulations. I add to this evidence by causally showing that electric utilities increase precautionary actions to prevent fire ignitions along their power lines in response to greater liability for fire damages.

The rest of this paper proceeds as follows: section 2 provides background on liability regulation for power line-ignited fires in California and utilities' ignition prevention decision environment. Section 3 presents a simple theoretical model with testable predictions of liability regulation's effect on utility's precautionary effort. In section 4, I develop an empirical framework to study how the application of liability impacts precaution, describe the data used in this analysis, and present results. Section 5 develops an empirical strategy to causally estimate the relationship between liability and shutoffs, describes the data sources used in this analysis, and presents results. Section 6 discusses the results and outlines opportunities for future research.

2 Background

2.1 Institutional Background

This paper focuses on electricity distribution to residential and commercial consumers, the final link in the U.S. electricity supply chain which consists of generation, transmission, and distribution. Electric distribution utilities are generally considered natural monopolies and most are regulated by Public Utility Commissions (PUCs). The California Public Utility Commission (CPUC) mandate states that its goal is to provide "...access to safe, clean, and affordable utility services and infrastructure."

PUCs' primary regulatory tool to influence utilities' actions is called a rate case. CPUC defines rate cases as quasi-judicial "proceedings used to address the costs of operating and maintaining the utility system and the allocation of those costs among customer classes." At each rate case proceeding, the PUC determines the fixed electricity price which a utility can charge customers until its next rate case proceeding. The three largest Investor Owned Utilities (IOUs) in California each have their own separate rate cases every three years. In this way, utilities in the U.S. face price cap regulation with periodic adjustment of the cap. The PUC adjusts the price cap so that each utility earns a fair rate of return on its capital and recovers its operating expenses. However, the PUC may disallow a capital investment if it does not meet a standard of being "used and useful."

Importantly, in California utilities could request to recover uninsured costs associated with fires ignited by their distribution infrastructure during rate cases between 1999 and 2017. Thus, while utilities paid for residential damages and suppression costs associated with fires ignited by their equipment, the expectation was that these costs could be recovered through an increase in the electricity price cap. After a 2017 ruling in a rate case proceeding that rejected San Diego Gas and Electric's application to recover fire-related costs through electricity rates, utilities faced a greater likelihood that they would be financially accountable for such costs, increasing their liability. The next section discusses the history of fire liability for utilities in California.

2.2 Liability Regulation in California

Liability regulations impact the incentives for individuals and firms to take risk and exert precaution. In the case of fire ignited by utility-operated infrastructure, utilities may adjust their level of precaution according to the proportion of fire-related damages they would be held accountable for if an ignition occurs. Similarly, individual homeowners may increase effort to reduce the probability of wildfire-related damage to their property when a firms' share of liability from a power line ignited wildfire is low. Regulators choose the degree of liability that a firm faces by choosing from two types of regulations: strict liability and a negligence rule. Under strict liability, the firm is fully liable for the resulting damages of a fire ignited by their equipment. In contrast, the negligence rule sets a minimum threshold of precaution that firms must meet in order to avoid financial responsibility for damages. In the simplest model, the firm will take the highest level of precaution under strict liability and reduce its level of ignition prevention to just meet the threshold when subject to the negligence rule (Kaplow and Shavell (1999)).

Since the California Supreme Court held Southern California Edison liable for damages resulting from a fire ignited by its equipment in the case *Barham v. Southern California Edison Company (1999)*, IOUs have been held to a strict liability standard for fire damages. A key factor in the Court's decision was the fact that, just as a government can raise revenue through taxes, IOUs can raise revenue through retail electricity rates in California.[7] The Court reasoned that since the state government is strictly liable for damages it causes under the Takings clause of the California constitution, IOUs could be held strictly liable for damages related to power line-ignited fires. As a result, IOUs faced strict liability for fire damages in excess of their insurance coverage, but could

[7]The Court's decision argues that IOUs' ability to raise electricity rates is akin to a government's ability to levy taxes. IOUs are currently challenging this logic in court by pointing out that their ability to raise electricity rates is subject to approval by the CPUC.

recover these costs through increases in the retail price of electricity. IOUs continued to challenge the Court's ruling in *Barham* as recently as 2012, arguing that they could not have the same liability status as a government because their ability to raise rates is subject to the approval of the CPUC.[8] The Court continued to maintain, however, that because there was no evidence CPUC would not allow IOUs to recover costs through electricity rate increases, strict liability would continue to apply.

Although IOUs faced strict liability, the precedent established by *Barham* ensured that their liability net of revenue increases from raised electricity rates would be low. The precedent that IOUs could recover liability costs through increased electricity rates was not tested until several damaging fires ignited by power lines operated by San Diego Gas and Electric in 2007. The 2007 fires were the first time since the *Barham* decision that the liability costs associated with power line-ignited fires exceeded an IOU's liability insurance coverage (Hafez (2020)). As a result, San Diego Gas and Electric's application to recover uninsured liability costs through electricity rate increases was a novel test of the strict liability standard. Ultimately, CPUC rejected San Diego Gas and Electric's application to recover liability costs through electricity rates in December 2017, citing San Diego Gas and Electric's lack of precaution in preventing the 2007 fires as the deciding factor.[9] Because IOUs could no longer expect to automatically recover costs through electricity rate increases following the 2017 CPUC decision, their liability for fire damages increased dramatically. CPUC's decision states that "If the preponderance of the evidence shows that the utility acted prudently, the Commission will allow the utility to recover costs from the ratepayers." While CPUC declined to define a precise negligence threshold in its decision, the decision dramatically increased the share of liability that each IOU is responsible for.

The "prudent manager" standard remained in effect until SB 901 added section 451.1 to the Public Utilities Commission Code which took effect for all fires ignited after January 1, 2019. Section 451.1 replaced the "prudent manager" standard with twelve non-exclusive criteria that CPUC uses to determine whether an IOU can recover costs associated with fire liabilities through electricity rates. The criteria take into account the IOU's design, maintenance, and operation of

[8] Pacific Bell Telephone Co. v. Southern California Edison Co., 208 Cal. App. 4th 1400, 1403 (2012).

[9] Application of San Diego Gas Electric Company (U 902 E) for Authorization to Recover Costs Related to the 2007 Southern California Wildfires Recorded in the wildfire Expense Memorandum Account, filed Sept. 25, 2015. Decided Dec. 26, 2017.

assets in addition to the severity and unpredictability of the weather event which caused the ignition. While, section 451.1 clarified the standard used to judge each utility's negligence it still significantly increased the share of costs associated with fire damages utilities expected to bear relative to the pre-2017 regulatory environment. If the reader is interested in learning more about the history of liability law and IOUs in California, Hafez (2020) provides a complete and succinct description. The next section describes utilities' allocation of ignition prevention effort and demonstrates how increasing the share of damages born by IOUs changes this allocation.

2.3 The ignition prevention decision environment

This section draws largely from Wildfire Mitigation Plans submitted by Southern California Edison, Pacific Gas and Electric, and San Diego Gas and Electric to CPUC in 2019, 2020, and 2021. IOUs face a complex decision making environment as they determine how and where to invest in strategies that lower the risk of fire ignited by their electrical infrastructure. Despite accounting for 1-5% of total fire ignitions in Southern California, utility-operated equipment accounts for 20-30% of total area burned by wildfires (Syphard and Keeley (2015)). Ignitions by power lines typically occur between July and December and their two leading causes are wind-blown vegetation and equipment failure. Much of the transmission and distribution infrastructure operated by IOUs in California is quite old (in 2017 Pacific Gas and Electric estimated that the average age of its transmission towers was 68 years old). As climate change has increased vegetative aridity and the severity of weather events in IOU service territories, the risk of fire ignition has also risen. In determining which areas to prioritize for ignition mitigation activities, utilities weigh the benefits of providing electricity to their residential, industrial, and commercial customers with the cost of each activity and the ignition risk associated with each section of their distribution and transmission infrastructure.

To determine the ignition risk of a section of power line, utilities consider historical and forecasted weather conditions, infrastructure age, vegetative growth, presence of outdated equipment with known ignition risk, and the value of electricity demanded by customers on that section. After determining the baseline risk of a power line segment, a team at each utility then chooses an ignition mitigation activity which reduces the risk at least cost. Utilities perform a range of ignition prevention activities including vegetation management, installation of weather stations along power lines, burying power lines underground, upgrading equipment, inspecting power lines, and turning off the power to targeted sections of the grid when weather conditions elevate the probability of ignition. Use of ignition prevention activities differs across utilities and over time as conditions change and utilities learn more about the effectiveness of each action. For example, Pacific Gas and Electric primarily deployed shutoff events and infrastructure upgrades in 2019 to reduce the probability of ignition, while Southern California Edison focused on installing covered conductors that reduce the probability of ignition on high risk assets. Recently, each IOU has increased efforts to bury sections of high-risk assets underground.

Historically, utilities in California have not relied on power shutoffs to reduce the likelihood of ignition because they disrupt the service of electricity to customers, proving costly. The California Public Utilities Commission (CPUC) defines Public Safety Power Shutoff events as actions taken by utilities to temporarily turn off power to specific areas in order to reduce the risk of fires caused by electric infrastructure. Of the three largest IOUs in California, only San Diego Gas and Electric utilized shutoffs to prevent ignitions prior to 2017.[10] Because shutoff events require the utility to interrupt service to customers it is seen as a measure of last resort to mitigate fire ignitions. As a result, each IOU has invested in devices which further segment high-risk areas of their transmission and distribution networks, allowing more targeted blackouts that affect fewer customers.

CPUC approves the use of power shutoff events by IOUs, first granting approval to San Diego Gas and Electric (San Diego Gas and Electric) in 2012, Pacific Gas and Electric in 2018, and Southern California Edison (Southern California Edison) in 2018. Figure 2 plots the total number of customer hours impacted by shutoff events over time separately for each of the 3 largest California IOUs. The most affected customer hours occurred during 2019 in Pacific Gas and Electric's service territory. A similar pattern exists for the number of commercial customer hours and medically vulnerable customer hours affected by power shutoffs.

IOUs consider climatic conditions, the condition of electrical infrastructure, and the value of lost electricity load in potentially impacted areas to determine when and where to declare power shutoffs. Figure 3 shows the criteria Pacific Gas and Electric uses to declare shutoff events as reported in their 2021 Wildfire Mitigation Plan. The minimum criteria for deciding a shutoff in

[10]San Diego Gas and Electric sought and received approval from CPUC to initiate power shutoffs in its service territory starting in 2013.

a high fire threat area are sustained wind speeds greater than 20 MPH, dead fuel moisture below 9%, relative humidity below 30%, and a fire potential index (FPI) greater than 0.2.[11] Despite these criteria, utilities have discretion in declaring power shutoffs–Abatzoglou et al. (2020) provide evidence that shutoff events are used more frequently by Pacific Gas and Electric than would be implied by their minimum climate criteria.[12]

According to the standard economic model of liability regulation, the increase in the share of liability born by IOUs following CPUC's 2017 decision should increase the level of ignition prevention effort (Kaplow and Shavell (1999)). Furthermore, increasing the liability born by IOUs should also increase their use of more costly prevention activities such as shutoff events. Finally, the increase in IOU liability should cause IOUs to direct ignition prevention efforts to regions of their service area with a high property values. Since destroyed property values make up a significant portion of liability damages born by IOUs when their equipment ignites a fire, IOUs have an incentive to direct ignition prevention activities to these regions.

The next section develops a simple model of liability in the context of the electric utility industry, presents several testable hypotheses, and derives a sufficient condition for estimating the welfare change from an increase in the share of liability born by firms.

3 Conceptual Framework

The goal of the model is to demonstrate three points: (1) Decreasing the return on defensive capital investment increases utilities' use of blackouts, crowding out defensive investment that mitigates ignitions along power lines. (2) Increasing the level of potential liabilities leads firms to use more power shutoffs. (3) Utilities use more shutoffs when ignitions are likely.

The model in this paper is adapted from Lim and Yurukoglu (2018) who show that a regulator's inability to commit to a predictable path of capital returns leads utilities to systematically underinvest in capital. Here, I consider a simplified version of the model with no strategic interaction between the regulator and the utility. In this model, the utility takes the regulator's choice of capital return as given rather than as an output from a negotiation process.

[11] The FPI measures the likelihood of an ignition causing a catastrophic wildfire using wind speeds, temperature, humidity, dead and live fuel moisture, and vegetative cover types.

[12] Abatzoglou et al. (2020) note that this could be due to differences in climate modelling between their study and Pacific Gas and Electric's internal methods.

For simplicity, I model a single utility's decision to make defensive capital investments and supply electricity to one distribution circuit. If the utility supplies electricity, it receives future net revenue and faces expected liability damages from a potential ignition along its power lines. However, if the utility declares a power shutoff it receives no revenue and faces no expected damages. The utility self protects against expected damages by making defensive capital investments that reduce the probability of ignition.[13] In making its decisions, the firm compares the marginal reduction in damages from self insurance to total expected damages. Whenever expected damages exceed the marginal benefit of self insurance, the firm shuts off the power.

I make several important assumptions in this model. First, because the model only considers one distribution circuit, the firm will never make additional defensive capital investments if it shuts off the power. In practice, defensive investments may complement power shutoffs because utilities could self insure against damages on days when the ignition risk is low. Second, in a departure from reality, I do not allow for strategic interaction between the firm and the regulator. The results from Lim and Yurukoglu (2018) suggest that allowing for such interaction would cause firms to increase shutoff use more and invest in defensive capital less. Third, I do not model the firm's non-defensive capital investment decisions. Finally, the model assumes that consumers value their homes at the structure replacement cost. This simplifying assumption does not affect the framework's predictions, but it would increase the benefit of shutoffs for households in the welfare effect of the liability regulation.

3.1 Firm's Problem

The regulator sets a per unit output price p that allows the utility to recoup a reasonable return on defensive capital (γk) and per-unit liability costs (ν).

$$p = \frac{\gamma k + \nu}{Q} \tag{1}$$

Where k represents the stock of firm defensive investment which it uses to self insure against damages from a potential fire ignition and ν is the exogenous rate of return on defensive investment that is set by the regulator. The firm inelastically supplies Q units of electricity to consumers who

[13] I define self protection in the same way as Ehrlich and Becker (1972), where defensive investments reduce the probability of ignition rather than total damages.

purchase a quantity Q of electricity up to a "choke" price ($\bar{p}$) above which they are no longer willing to pay.

$$D(p) = \begin{cases} Q & \text{if } p \leq \bar{p} \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

The utility earns revenue by supplying electricity to retail consumers and reduces expected liability costs by renting defensive capital that reduces damages from a potential ignition from households at the prevailing interest rate (r). The utility can also prevent ignitions by supplying no electricity to consumers.

$$\max\{\pi_1, \pi_0\}$$

Where

$$\pi_1(k) = \max_{k'}\{-r(k' - (1-\delta)k) + \beta(\phi p Q)\}$$

$$\pi_0(k) = \max_{k'}\{-r(k' - (1-\delta)k) + \beta(pQ - \theta(k')\bar{d})\}$$

Where the utility earns π_1 in profits if it shuts off the power and π_0 in profits if it supplies power, δ is the capital depreciation rate, and $\bar{d}$ is the dollar amount of expected liability damages if an ignition occurs. In the empirical analysis later in this paper, $\bar{d}$ is the total replacement cost of structures threatened by a power line ignition. The utility can self protect against liability costs by investing in defensive capital (k') which reduces the probability of ignition ($\theta(k')$). The utility chooses whether to declare a blackout and investment in capital subject to an uncertain probability of ignition ($\theta(k')$). When the utility shuts off the power it recoups a fraction $\phi \in (0, 1)$ of its revenues by exerting market power in wholesale electricity markets. β is the per-period discount factor. Substituting the price of electricity from equation 1, allows us to rewrite the utility's profit functions.

$$\pi_1 = \max_{k'}\{-r(k' - (1-\delta)k) + \phi\beta(\gamma k + \nu)\}$$

$$\pi_0 = \max_{k'}\{-r(k' - (1-\delta)k) + \beta(\gamma k + \nu - \theta(k')\bar{d})\}$$

Intuitively, when the firm supplies electricity (π_0) it pays defensive capital rental costs today and receives future net revenues (pQ) while facing expected liability costs from a potential ignition ($\theta(k')\bar{d}$). When the firm chooses to shutoff the power (π_1), it pays capital rental costs today and receives only a fraction of its revenue in the future, but since an ignition cannot occur it also faces no expected damages.

Figure 4 presents a simplified version of the firm's shutdown decision to demonstrate its incentive to use a power shutoff. Both graphs show example demand (red) and supply (blue) curves for electricity when the utility supplies electricity (left) and shuts off the power (right). For simplicity, I am showing the case where the utility does not recoup any revenue when it declares a blackout ($\phi = 0$). When the utility shuts off the power, the supply curve shifts all the way to the left, creating lost producer and consumer surplus. Intuitively, the utility incurs a private cost from shutoffs through lost producer surplus and benefits from shutoffs because it faces no expected liability cost. So the utility's privately optimal choice of shutoffs depends on the relative magnitude of producer surplus and expected liability costs. Importantly, the utility does not internalize the loss in consumer surplus when it turns off the power, causing the utility's privately optimal choice of shutoffs to exceed the socially optimal level.

Assuming without loss of generality that the utility starts with no defensive capital ($k = 0$), solving the firm's problem when it does not declare a blackout is trivial. When the firm shuts off the power, its profit is constant regardless of defensive capital investment made by the firm.

$$\pi_1^* = \beta\phi\nu \quad \forall \quad k_1'^*$$

In the state of the world where it does not declare a blackout (π_0) the firm invests in defensive capital such that the marginal benefit of investment (reduction in expected damages and increased revenue) equals the marginal cost of investment (the rental rate paid to households).

$$-\beta\theta'(k')\bar{d} + \beta\gamma = r \tag{3}$$

Where $-\beta\theta'(k')\bar{d}$ is the reduction in expected liability costs from increasing defensive investment, $\beta\gamma$ is the increase in revenue the firm receives by increasing its defensive capital stock, and r is the rental rate of capital. The utility then chooses whether or not to declare a shutoff by comparing its optimized profit when it declares a shutoff (π_1^*) to when it supplies electricity (π_0^*). Figure 5 presents the utility's decision rule for declaring a shutoff. Whenever the firm can earn greater profits by supplying electricity, it does not shut off the power.

This paper empirically studies how two changes impact utilities' use of power shutoffs. First, I use a difference in differences research design to study how a policy which effectively reduced the rate at which utilities pass liability costs on to consumers. In the model, the policy is akin to reducing the rate of pass through (ν). As a result of the policy, we expect the firms' profit function when it supplies electricity (π_0) to decrease by more than its shutoff profit function (π_1) decreases. As a result, if the firm supplies electricity prior to the policy, it is unclear whether it will increase or decrease blackouts following the change. I test this ambiguous prediction and show that utilities increase their use of shutoffs following the policy change.

Second, I use exogenous variation in wind direction and speed across days to estimate how utilities' use of shutoffs changes when they face higher total expected liability costs. In the model, firms face higher liability costs when the total replacement cost of structures threatened by a potential ignition ($\bar{d}$) is large. Increasing $\bar{d}$ in the model shifts π_0 down, but leaves π_1 unchanged. Depending on how large the drop in π_0 is, the firm may use more shutoffs or keep supplying electricity. I show that firms increase their use of shutoffs when areas with higher total structure replacement cost are threatened by a potential ignition. Finally, utilities should utilize blackouts more when they face high realizations of the probability of ignition ($\theta(k')$). As a result, we expect there to be more blackouts on days when the weather is conducive to fire ignitions along power lines (prediction (3)).

4 How does firms' precautions change when they face any liability?

4.1 Empirical Framework

I estimate the overall effect of the regulatory change on one utility's power shutoff use in a two way fixed effects empirical strategy. As explained in section 2, a 2017 regulatory change made by the California Public Utility Commission shifted the burden for liability costs from consumers of electricity to utilities in California. Several factors make estimation of the causal effect of the regulatory change on utilities' shutoff use difficult. First, due to stronger winds and an ever-drier climate over time, the likelihood of fire ignited by power lines has increased over time. As a result, a pre-post regulatory change comparison of shutoff use may reflect this increasing trend in ignition probability. Second, the regulatory change affected all utilities at the same time, making it difficult to separate the policy effect from annual changes in firms' investment behavior.

I overcome these difficulties by using a two way fixed effects research design that compares the pre/post regulatory change in shutoff use at circuits with high ex ante ignition risk to their counterparts with low ex ante ignition risk. Low ignition risk circuits are a valid control group because the regulatory change was unlikely to impact firms' behavior in regions with low fire risk. Indeed, in section 3 changing the amount of liability born by the firm does not impact its behavior if there is no chance of an ignition occurring at a circuit. Importantly, I control for daily weather conditions at each circuit such as wind speed, humidity, temperature, and relative humidity which are significant determinants of ignition risk.

Equation 4 models shutoff use (y_{it}) at each circuit i on day t as a function of daily weather conditions, infrastructure age, ex ante ignition risk, and the regulatory change.

$$y_{it} = \beta_0 + \beta_1 Treated_i \times Post_t + \beta_2 X_{it} + \gamma_i + \delta_t + \varepsilon_{it} \tag{4}$$

Where y_{it} is either equal to one when there is an active shutoff at circuit i on day t or the total number of customer hours of lost power at circuit i on day t. $Treated_i$ is one for all circuits with positive ex post ignition risk, and $Post_t$ equals one for all days following the regulatory change in December 2017. I determine ex post ignition risk at each circuit using San Diego Gas and Electric's modeled measure of ignition risk which they included in their 2021 Wildfire Mitigation Plan that was submitted to the California Public Utility Commission.[14] The ignition risk reflects the annual likelihood and consequence of fire risk at each circuit as of 2021.

The vector X_{it} contains daily wind speed, temperature, humidity, and precipitation binned into septiles as well as the average age of infrastructure in circuit i. The circuit fixed effects account for characteristics of each circuit, such as the slope of the land, which do not change over time. The calendar day fixed effects control for seasonality in the ignition threat across all circuits. The coefficient of interest ($\beta_1 \times 100$) measures how the likelihood of a shutoff changes, on average, at high risk circuits relative to low risk circuits after the policy shift. I cluster standard errors at the high fire threat district by week level to allow for correlation in shutoff use in areas with similar ignition risk during a calendar week.[15]

The two way fixed effects research design relies on a conditional parallel trends assumption which states that, conditional on the covariates, the trend in shutoff use would have been the same at high and low ignition risk circuits. I provide suggestive evidence of this assumption by estimating the following event-study model.

$$y_{it} = \alpha + \sum_{j=-3}^{2} \nu_j Treated_{i,t-j} + \psi X_{it} + \gamma_i + \delta_t + \varepsilon_{it} \tag{5}$$

Where the event time end points are binned at $t = -3, 2$ following Schmidheiny and Siegloch (2020).[16] The variable $Treated_{i,t}$ again takes a value of one if circuit i has a non-zero probability of ignition at post regulatory change calendar day t. Just as in equation 4, X_{it} includes nonlinear controls for daily changes in temperature, precipitation, humidity, wind speed, and infrastructure age. I cluster standard errors at the high fire threat district by calendar week level. Figure 6 shows the event study results.

Each coefficient represents the cumulative annual effect of the 2017 rule change on power shutoff declaration in percentage points for years leading up to and following 2017. All coefficients are interpreted as the effect relative to the year prior to the rule change. For example, shutoff events were used around 0.025 percentage points more one year after the rule change than they were used

[14] See San Diego Gas and Electric's 2021 Wildfire Mitigation Plan. Modeled ignition risk is included in the attachment "2021 WMP CalPA-SDGE-DR1 02-11-2021".

[15] High fire threat districts were determined by the California Public Utility Commission in 2012. They are designed to show the areas which represent elevated risk for power line-ignited wildfires.

[16] Using binned end points in this way assumes that the treatment effect is constant more than 3 periods prior to treatment or 2 periods after treatment.

one year prior to the rule change. The pre-treatment coefficients in Figure 6 demonstrate that there are no anticipatory effects or underlying time trends in shutoff use that drive the estimated effect in Table 4. All pre-period coefficients are statistically indistinguishable from zero and economically insignificant, providing support for the parallel trends assumption.

4.2 Data Used in Extensive Margin Analysis

Power Shutoff Events I obtain the date, duration, location, and number of impacted customers from power shutoff post-event reports for the period 2013-2020 from the California Public Utilities Commission.[17] Since Pacific Gas and Electric, Southern California Edison, and San Diego Gas and Electric serve the majority of electricity consumers in California and account for the largest share of power shutoffs since its' first use in 2012, I restrict the sample to events initiated by one of these utilities. Furthermore, I exclude publicly owned utilities from this analysis because they have not been granted the authority to conduct power shutoff events by the regulator. Since San Diego Gas and Electric was the only utility to receive permission to use power shutoff events prior to 2018, I use exclude Pacific Gas and Electric and Southern California Edison when estimating how the 2017 liability rule change influenced utilities' use of shutoffs. The intensive margin analysis of the relationship between replacement costs and power shutoff use between 2018 and 2020 uses data from all three of California's largest private utilities.

Energy Infrastructure Information on the geographic location of distribution and transmission lines operated by Pacific Gas and Electric, Southern California Edison, and San Diego Gas and Electric is collected from publicly available GIS files submitted to the California Office of Infrastructure Safety in 2020. The GIS data shows the location of each transmission and distribution line within a circuit and exclude critical energy infrastructure. Since the California Public Utility Commission reports shutoff events at the circuit level, I aggregate the line level data to the circuit level before string matching events to circuits by circuit name. On average across the three utilities, I match 97 percent of events to circuits using string matching.[18]

Climate Data I obtain wind speed and direction at ten minute intervals from the 3,041 weather

[17] Utilities are required to submit under Ordering Paragraph 1 of California Public Utilities Commission (CPUC) Decision (D.) 19-05-042.

[18] For only 2019, events are geocoded at the line level. In the future I will conduct a robustness analysis that verify the property value results using line level data.

stations operated by Pacific Gas and Electric, Southern California Edison, and San Diego Gas and Electric along their energy infrastructure and temperature, relative humidity, and precipitation from the 892 weather stations operated by the National Weather Service and Remote Automatic Weather Stations in California.[19] For each station, I compute daily average and maximum temperature, humidity, precipitation, and wind speed. Then, for each circuit I compute the inverse distance weighted average for each climate variable across all stations within 20 kilometers the circuit, generating daily average and maximum temperature, relative humidity, precipitation, and wind speed for each distribution circuit operated by Pacific Gas and Electric, Southern California Edison, and San Diego Gas and Electric in California.

Replacement Cost of Structures Since electric utilities are liable for the cost of replacing structures damaged by power line-ignited fires, I use parcel-level structure replacement costs to measure potential damages rather than the market value of each property. I obtain parcel level replacement costs of each property in California in the year that it is assessed from the Zillow Transaction and Assessment Database (ZTRAX) which contains parcel-level assessed values and transaction information for most counties in the U.S. Zillow computes the replacement cost by taking the difference between the market value of the property and the market value of the land in the year of assessment. I adjust replacement costs to 2021 dollars using the consumer price index.[20]

Expected Damages Because the welfare calculation in equation 10 requires a measure of expected damages at each distribution circuit ($D(m_i, z_i)$), I obtain parcel level replacement costs and a measure of the fire risk faced by each structure. To compute the expected damages at each circuit if an ignition were to occur, I multiply the replacement cost of each parcel by a measure of fire risk. First, I compute the total replacement cost of structures within 5 kilometers of a circuit using the ZTRAX data described above. Second, I use the Risk to Potential Structures (RPS) index created by Scott et al. (2020) to capture the likelihood that each structure in the ZTRAX database would be damaged by a fire. The RPS index ranges from 0 (no damage) to 12 (fully destroyed) at the 30 meter pixel level and answers the question: "What would be the relative risk to a house if one existed here?" Since the RPS uses data from 2014, it reflects the risk to structures based on 2014 vegetation conditions. I compute expected damages at each circuit by multiplying

[19] I accessed the weather station data through the Mesonet API.

[20] https://fred.stlouisfed.org/series/CPALTT01USA659N.

the property value at each parcel by the inverse of its RPS index and summing to the circuit level.

Likelihood of Ignition at Each Circuit Since the welfare calculation in 10 requires knowledge of the ignition probability at each circuit (θ), I collect circuit level wildfire risk scores from publicly available data files submitted by San Diego Gas and Electric as part of its 2021 Wildfire Mitigation Plan.[21] The circuit level ignition probabilities are raw wildfire risk scores from San Diego Gas and Electric's internal fire risk model called the Wildfire Next Generation System. Each risk score represents the probability of ignition adjusted for wind patterns, vegetation, and infrastructure hardening at a circuit. Since San Diego Gas and Electric only applied the model to its circuits in areas with elevated ignition risk, the probability of ignition is assumed to be zero at circuits that were not modelled.

Energy Usage The final information necessary for the welfare calculation in equation 10 is a measure of energy usage at each circuit. For now, I use publicly available energy usage data reported by San Diego Gas and Electric at the zip code level for each quarter of the year. For each zip code, I compute the average energy use between 2013 and 2017. Then, I assign energy use to each circuit in a zip code in proportion to its share of total circuit miles in that zip code. For example, if there are two circuits in a zip code that have the same total length of power lines, then I would assign half of the total zip code energy use to each circuit. In the future, I hope to replace this approximation with the actual reported circuit level energy use.[22]

Summary Statistics Table 1 reports summary characteristics for the daily panel of distribution circuits operated by San Diego Gas and Electric between 2013 and 2020. At the daily level shutoff events are rare, occurring on 0.002 percent of circuit-days, on average.[23] The average maximum daily wind speed across all circuits between 2013 and 2020 is 7.4 meters per second, but there is substantial variation with some circuits experiencing wind speeds as high as 96 meters per second. Across San Diego Gas and Electric's service territory, 88 distribution circuits ever experience a shutoff event between 2013 and 2020, reflecting San Diego Gas and Electric's efforts to target only the highest risk circuits.

[21] See San Diego Gas and Electric's response to data request CALPA-SDGE-01 questions 4 and 5 here.

[22] I have a pending application with San Diego Gas and Electric to access this data.

[23] However, shutoff events become much more prevalent conditional on high wind speeds. In particular, conditional on a circuit having wind speeds greater than 9 m/s the average likelihood of a power shutoff event increases to 0.3 percent.

4.3 Results

Since prior theoretical work shows that applying liability to firms may be ineffective, I first estimate how San Diego Gas and Electric's use of power shutoffs changes when they fully bear liability costs. Table 4 presents results from the model presented in equation 4. The reported estimates reflect how San Diego Gas and Electric's use of shutoffs changes at *ex ante* high ignition risk circuits relative to low risk circuits following the 2017 policy change which increased their expected liability. Column 1 displays the effect of applying liability on the likelihood of a shutoff and column 2 presents the same effect, but for the number of customer hours without power. Both specifications include weather controls, circuit fixed effects, and calendar fixed effects.

The estimated effect suggests that the rule change led to a 5.6 percentage point increase in power shutoffs. Relative to the average probability of a shutoff prior to the 2017 reform, this amounts to more than an 80-fold increase in shutoff use. The estimate in column 2 implies that, on average, the number of customer hours impacted by shutoff events increased by 923 customer hours following the rule change (a 6-fold increase relative to the pre-treatment mean). Assuming each of the 923 customer hours of lost power would have had average energy use as reported by the Energy Information Administration in 2020, this estimate implies that the policy led to between \$150 and \$51,000 in lost consumer surplus at the average distribution circuit. Together these results suggest that the liability regulation effectively encouraged ignition prevention behavior in this setting.

Although shifting fire liability costs onto electric utilities effectively increased their precautionary behavior, the greater reliance on shutoffs may have burdened consumers if they affected individuals with a high value of electricity use. Since consumers whose medical or life-supporting devices rely on electricity likely have a high value of their electricity use, I estimate how San Diego Gas and Electric's use of shutoffs changes by the share of total customers that rely on electricity for medical needs. San Diego Gas and Electric publicly reports the number of customers with medical devices that rely on electricity by census tract, so I estimate an aggregated version of equation 4 on a daily panel of census tracts in California. The results of this analysis are reported in figure 9 and figure 10. These estimates suggest that shutoff use increased the most in census tracts with the highest share of customers relying on electricity for their medical needs and for life support. Because these customers have a high value of energy use, San Diego Gas and Electric's increased use of shutoffs following the policy change was likely costly for consumers.

To validate the empirical model above, I estimate the effect of increasing electric utilities' share of liability costs by circuit-level ignition risk and daily weather conditions in Appendix A. The utilities' stated criteria for power shutoffs suggest wind speed and humidity are two prominent drivers of ignition risk. As expected, I find that shutoff use increased almost 200-fold at the circuits with the highest risk of ignition. Furthermore, I find that wind speed and humidity are also significant predictors of shutoff use. These results help to provide confidence that the empirical model above is correctly specified and captures utilities' ignition prevention behavior.

5 How does the level of liability that a firm faces affect precaution?

5.1 Empirical Framework

Precaution and Threatened Property Values

According to the theory developed in section 3, utilities' use of shutoffs should respond (either positively or negatively) to the liability cost they bear. One way to test this hypothesis would be to estimate a linear model that relates the probability of a shutoff at circuit i on day t (y_{it}) to the total replacement cost of structures near circuit i ($Value_i$).

$$y_{it} = \nu Value_i + \varepsilon_{it} \tag{6}$$

Under the conditional independence assumption, ν identifies the effect of liability on firms' use of shutoffs. However, the conditional independence assumption is unlikely to hold in this example because unobserved determinants of shutoffs such as the moisture content of vegetation, regional weather conditions, and the presence of critical energy infrastructure are likely correlated with structure replacement costs. To overcome this challenge and isolate the effect of structure replacement cost on shutoffs, I use daily changes in wind direction to create exogenous variation in structure replacement costs that would be threatened by an ignition, if it occurred. Since fires ignited by electrical infrastructure are more likely to occur during periods of extreme wind speeds (Syphard and Keeley (2015)), wind direction is likely to be a relevant determinant of whether a region is threatened by a wildfire on any given day, t. Furthermore, since, on average, daily variation in wind direction is unlikely to be correlated with both power shutoffs and property values the conditional independence likely holds.

Following a procedure implemented by Missirian (2020) in a different context, I use reported wind conditions from stations operated by Pacific Gas and Electric, Southern California Edison, and San Diego Gas and Electric to determine which zip codes are downwind of each circuit. Figure 7 displays this process. I compute the horizontal ("U-wind") and vertical ("V-wind") wind vectors by multiplying the wind speed by the sine or cosine of the wind direction (in radians). After converting the horizontal and vertical wind vectors from meters per second to degrees latitude or longitude per second, I can compute how far away an object would travel if it could remain airborne for one second (the end of the blue arrow in Figure 7). Finally, I scale the horizontal and vertical wind vectors up by an estimate of how long a lit ember could remain airborne if picked up by the wind from Albini et al. (2012).[24]

I use circuit level changes in wind direction across days to assign which zip codes lie downwind of a utility's power lines. I choose to use zip codes as the unit of analysis for several reasons. First, it uses borders which are determined by the California government, rather than boundaries that I have chosen myself. Second, using zip codes allows me to control for other characteristics that are important determinants of utilities' shutoff use such as population and total energy use which are not available at finer geographic scales using publicly available data. Finally, the data on structure replacement costs is available for the universe of parcels in California at the zip code level, but may be missing at more granular levels of aggregation. In a robustness analysis, I re-estimate the relationship between structure replacement cost and shutoff use using only variation in wind direction within twenty kilometers of power lines, finding similar results to the aggregate zip code analysis.

Figure 8 shows how I determine downwind structure replacement cost in the empirical analysis using an example of 13 zip codes from San Diego County in California. The tan zip code in the center of both panels contains three distribution circuits and the black circles represent the centroid of each circuit. In my empirical framework, I define each tan zip code in my sample as an "origin"

[24] Albini et al. (2012) estimate that the maximum spotting distance for a wind driven fire is 10 kilometers. Assuming that wind speeds are at the third quartile observed across my sample between 2018 and 2020 (6.7 meters per second), the 10 kilometer estimate implies that an ember could remain airborne for up to 24 minutes. Estimates are robust to other assumptions of how long a lit ember could remain airborne (such as 5 minutes).

zip code. All of the white and yellow zip codes lie downwind of the origin zip code at some point during 2018 and 2020. I define these zip codes as "destination" zip codes because they are the set of possible destinations where an ember could land if picked up at a circuit in the origin zip code. Each black line points in the direction that the wind is blowing, and its end point is how far away from each circuit a lit ember could travel given observed wind speed and direction. When the black line intersects with a zip code, I define the zip code as downwind of the origin zip code. Therefore, in panel (a) the three yellow destination zip codes to the north of the origin are downwind, while the following day (shown in panel (b)) the three destination zip codes to the west are downwind. I estimate the relationship between the total replacement cost in the downwind zip codes and shutoff use at circuits in the origin zip code. As a result, this strategy uses daily variation in liability that is driven by exogenous changes in wind speed and direction. Equation 7 formally presents this research design.

Since there may be underlying static characteristics about each zip code, such as geography, that correlate with shutoff declaration and threatened property values, I construct a paired data set of origin and destination zip codes and control for a pair fixed effect following Kuhn et al. (2011). For each day t and origin zip code o the data file contains a set $(N(o))$ of neighboring destination zip codes indexed by d which are ever downwind of zip code o between 2018 and 2020. By including pair fixed effects, ν_{od}, this strategy accounts for time invariant characteristics of pairs that may be correlated with structure replacement cost and power shutoffs, such as vegetation moisture. Furthermore, I include a calendar day fixed effect which accounts for day-specific unobserved heterogeneity which impacts all zip code pairs, such as seasonality or statewide climatic factors.

$$y_{jodt} = \beta_1 Value_{jd} \times DW_{jodt} + \beta_2 Value_d + \beta_3 DW_{jodt} + \beta_3 X_{jot} + \beta_4 X_{jdt} + \nu_{od} + \delta_t + \gamma_{jt} + \varepsilon_{odt} \quad (7)$$

Where y_{odt} is a binary variable indicating whether a shutoff is in effect in zip code o which is ever upwind of zip code d on day t. $Value_d$ is the logged and de-meaned total (or average) structure replacement cost in zip code d and DW_{odt} is equal to one if zip code d is downwind of zip code o on day t. The model includes time-varying covariates (X_{ot}, X_{dt}) which are specific to zip codes o and d respectively and include average daily wind speed, temperature, specific humidity, and maximum wind speed. In order to allow the effect of the climatic controls to non-linearly impact the outcome, I bin each control variable into septiles. I also control for the 2020 wildfire hazard potential interacted with the downwind indicator and the share of 2010 zip code population living in the wildland-urban interface interacted with the downwind indicator to control for day-to-day variation in characteristics of the downwind landscape such as vegetation and slope. Finally, I include utility by year fixed effects (γ_{jt}) which account for annual changes in utilities' plans to prevent ignitions.

Since I de-mean the structure replacement cost in equation 7, β_3 is the change in shutoff likelihood when a zip code with average structure replacement cost is downwind. The coefficient of interest β_1 measures the average percentage point change in the likelihood of a power shutoff with respect to a one percent increase in downwind structure replacement cost. Furthermore note that while the coefficient β_2 captures the effect of non-threatened property values, it is not estimated because the replacement cost is collinear with the pair fixed effects. Under the conditional independence assumption, β_1 and β_3 identify the causal effect of down wind structure replacement cost on the probability of a shutoff.

Causal identification of the relationship between potential liability and power shutoffs in equation 7 relies on exogenous changes in wind speed and direction across days. To provide suggestive evidence that the daily variation in wind conditions is as good as randomly assigned, I compare average socioeconomic and demographic characteristics of destination zip codes by downwind status in 3. The average characteristics for not-downwind and downwind zip codes are shown in columns 1 and 2 while the difference in means as a percent of a standard deviation is presented in column 3. While downwind and not-downwind zip codes are statistically different across nearly all characteristics, all differences are small, accounting for less than 8% of a standard deviation for all observed variables. For example, although the median replacement cost of structures in downwind zip codes is around \$1,000 more than in non-downwind zip codes, this is less than 2% of the average replacement cost. Furthermore, the empirical framework in equation 7 includes a pair fixed effect which controls for all time-invariant characteristics about zip codes.

Model 7 estimates how threatened property values impact the probability of shutoff declaration, but does not explore how this effect is distributed across each zip code's socioeconomic status. The next part of the analysis addresses this question by separately interacting threatened property values with an indicator variable equal to one if a non-zero share of each zip code o's (or d's) 2010 population lives in a census tract designated as a disadvantaged community by the California government (denoted by DAC_o and DAC_d respectively).

$$
\begin{aligned}
y_{odt} = {} & \gamma_1 DAC_o Value_d DW_{odt} + \gamma_2 DAC_d Value_d DW_{odt} + \gamma_3 Value_d DW_{odt} \\
& + \gamma_4 DAC_o DW_{odt} + \gamma_5 DAC_d DW_{odt} + \gamma_6 DW_{odt} + \gamma_7 X_{ot} + \gamma_8 X_{dt} + \nu_{od} + \delta_t + \varepsilon_{odt} \qquad (8)
\end{aligned}
$$

The parameters of interest γ_1 and γ_2 measure the percentage point impact of threatened property values relative to days when they are not threatened and on days when zip code o is disadvantaged or zip code d is disadvantaged respectively. A positive estimate of γ_1 would suggest that higher threatened property values in non-disadvantaged zip codes increase the probability of a power shutoff in disadvantaged zip codes. Similarly, a positive estimate of γ_2 would imply that higher threatened property values in disadvantaged zip codes increase the probability of shutoff declaration in non-disadvantaged zip codes. Standard errors are again clustered at the calendar week level to allow for correlation in shutoff use across circuits within a week.

5.2 Additional Data Used in Intensive Margin Analysis

Replacement Cost I use the same parcel-level replacement costs from Zillow ZTRAX to compute the total and median replacement cost in each zip code. Table 2 reports that the average total replacement cost across all zip codes in the sample is nearly \$7 billion dollars, while the average of the zip code-level median replacement cost is \$53 thousand dollars.

Vegetative Cover I use the discrete Wildfire Hazard Potential index to capture underlying vegetative conditions in the areas surrounding distribution circuits in California.[25] Values of the WHP index indicate wildfire risk and range from 1 (very low) to 5 (very high). The WHP index is intended to guide strategic long-term management of vegetation and is based on vegetation and fuels data from LANDFIRE 2014. As a result, the WHP reflect vegetative conditions at the end of 2014. Future work will utilize vegetation data from more recent products such as LANDFIRE

[25] Dillon, Gregory K; Gilbertson-Day, Julie W. 2020. Wildfire Hazard Potential for the United States (270-m), version 2020. 3rd Edition. Fort Collins, CO: Forest Service Research Data Archive. https://doi.org/10.2737/RDS-2015-0047-3

2018.

Wildland Urban Interface Since utilities' decision to declare a shutoff event could be impacted by whether a circuit is located in an area that is high fire risk, I obtain the boundaries of the Wildland Urban Interface (WUI) from the California Department of Forestry and Fire Protection's Fire and Resource Assessment Program. The WUI is defined as an area with dense housing adjacent to vegetation that can burn in a wildfire.[26] Because the property value analysis is estimated at the zip code level, I compute the share of total 2010 zip code population living within the WUI.

Potential Liabilities In order to identify structures that would be threatened by a potential ignition, I use daily variation in wind direction at the centroid of the area where each distribution circuit operated by Pacific Gas and Electric, Southern California Edison, or San Diego Gas and Electric in California overlaps with a zip code. In the dataset construction I refer to zip codes with a distribution circuit as "origin" zip codes and zip codes that lie downwind of the origin zip code on any given day as "destination" zip codes. Using data on the daily average wind direction and maximum wind speed described above, I assign destination zip codes to each origin zip code for each day of the sample. I describe this process in detail below.

As shown in figure 7, I use two results from trigonometry to calculate the vertical and horizontal wind vectors in degrees of latitude or longitude per second.[27] After converting the vertical and horizontal wind vectors to degrees of longitude per second and latitude per second respectively, I multiply each vector by a measure of how many seconds a lit ember can stay airborne from Albini et al. (2012).[28] I then use the scaled-up vertical and horizontal wind vectors to compute where an ember would land if it were picked up by the wind at each distribution circuit. Finally, I connect the start and end points with a line and assign a zip code as downwind if it intersects with that line. As shown in table 2, the daily wind speeds across distribution circuits during the sample period range between 24 and 88 miles per hour.

Disadvantaged Community Definition I use the California Office of Environmental Health Hazard Assessment's definition of a disadvantaged community in the CalEnviroscreen 2018 update

[26] Specific housing density and vegetation thresholds for WUI classification can be found here.

[27] The vertical wind vector is given by $x \sin\theta$ and the horizontal wind vector is given by $x \cos\theta$, where x is the wind speed in meters per second and θ is wind direction measured from the x-axis in radians.

[28] Albini et al. (2012) report a maximum spotting distance of 10 kilometers for wind driven fires. To convert this estimate to seconds that an ember is airborne, I multiply 10,000 meters by the inverse of the third quartile of wind speed in the sample yielding an estimate of about 18 minutes. This estimate means that at it would take a lit ember 18 minutes to travel 10 kilometers at the third quartile of wind speed in the sample.

to assign disadvantaged status to each zip code. This definition classifies the census tracts with CalEnviroScreen 3.0 scores in the top 25% of all tracts in California as disadvantaged communities. The CalEnviroScreen score accounts for pollution exposure, environmental conditions, health factors, and socioeconomic factors which could magnify the negative effects of pollution exposure. Since disadvantaged status is assigned at the census tract level, I compute the share of total 2010 population in each zip code that lives in a disadvantaged tract. For the main analysis I assign disadvantaged status to any zip code with more than 50 percent of its population living in a census tract designated as disadvantaged.

Summary Statistics Table 2 reports the summary statistics for relevant variables that I use in this analysis. On the most active day of power shutoffs in my sample there were 80 concurrent power shutoffs. However, shutoff events are very infrequent at the daily level, occurring on average 0.8% percent of total zip code-days in the sample. The last row of table 2 shows that there are 539 zip codes in California that ever experience an event between 2018 and 2020. The average replacement cost is substantial at around $6.8 billion and there is significant variation across zip codes with a standard deviation of $6.6 billion.

I construct the final sample by dropping all days that do not fall under the minimum criteria for a shutoff event used by Pacific Gas and Electric in 2021 as shown in figure 3.[29] I make this sample restriction based on the reported wind speeds and humidity in origin zip codes rather than destination zip codes because this reflects climate conditions around the power lines themselves. I further drop months where no shutoff events occur between 2018 and 2020 since these months do not help identify the coefficient of interest from model 7. The final sample consists of a daily panel of 13,039 unique origin-destination zip code pairs.

5.3 Results

In settings where firms' assets are significantly less than their liability costs from an accident, it may be optimal for firms to declare bankruptcy (Shavell (1986)). A common solution to this problem posed by regulators is to cap the liability firms face, providing incentives for precaution without leading to bankruptcy. However, because prior estimates of firms' precautionary response to liability

[29]The minimum criteria are wind speeds greater than 20 mph and relative humidity less than 30%. Pacific Gas and Electric has many other criteria for declaring a shutoff, but these are the minimum criteria that I can observe using the publicly available climate data.

are from one point in the distribution of potential liabilities, regulators have limited information about which level to place the cap on damages. The estimates in this section leverage firms' full distribution of potential liabilities from power line-ignited fires, allowing me to non-parametrically estimate their precautionary response to liability.

Table 5 reports the main results from regression model 7. The coefficient of interest is reported in row 1 and is interpreted as the percentage point change in power shutoff declaration probability that results from a 1 percent increase in the replacement cost of downwind structures relative to days when the properties are not downwind. Since I de-mean the replacement cost of structures, the estimate in row 2 reflects the change in shutoff likelihood when a zip code with average total (or mean) replacement cost lies downwind. Columns 1 and 2 report the estimate of firms' precautionary response to liability with total and mean zip code replacement cost as the independent variable of interest. Both specifications include controls for daily maximum wind speed, maximum temperature, average relative humidity, and cumulative precipitation in the origin and destination zip codes. In addition, both specifications include origin-destination zip code pair fixed effects and calendar day fixed effects.

The estimate in column 1 suggests that, on average, utilities' are 0.02 percentage points (100%) more likely to use a power shutoff when a region with 10% higher total zip code replacement cost lies downwind. Assuming that baseline total replacement cost is at the average level I observe in the sample ($6.8 billion) implies that shutoff use increases by 100% when potential liabilities increase by $680 million. However, the positive relationship between total liability and shutoff use could reflect utilities' increased willingness to undertake precaution when densely populated regions lie downwind. The estimate in column 2 shows that firms consider liabilities independently of population, suggesting that utilities use shutoffs 160% more when the mean downwind zip code structure replacement cost is about $6,000 higher.[30]

Although prior work suggests that the relationship between liability and precaution should be nonlinear, the estimates in table 5 assume a linear relationship. I relax this linearity assumption by binning total (or mean) zip code replacement cost by decile and re-estimating equation 7. Figures 11 and 12 report the resulting estimates of downwind total and mean replacement cost on power shutoff

[30] In Appendix A, I estimate robustness specifications that explicitly control for population. While I find that downwind population is a relevant determinant of shutoff use, it does not alter the estimates in table 5.

use. The estimates in figure 11 suggests that shutoff use increases in total structure replacement cost until liability exceeds \$10 billion (the eighth decile of total replacement cost), after which it begins to decrease. Similarly, the response of shutoffs to average zip code replacement costs in figure 12 is increasing until mean liability cost exceeds \$85 thousand (the eighth decile of mean replacement cost). Shavell (1986) posits that as the ratio of liability to assets increases, the firm will eventually begin to take fewer precautions to prevent an accident. The estimates I report above are consistent with this prediction. Utilities take greater precautions until their total liability from a potential ignition exceeds \$10 billion and then begin to take less precautions.

Because utilities direct shutoffs to areas with higher structure replacement costs, there may be systematically more precaution taken in high socioeconomic status communities that tend to have greater property values. I explore this possibility in Appendix A and find that because low socioeconomic status communities tend to live in low ignition risk areas in this setting, there is not relationship between firms' response to liability and socioeconomic status. In other settings where high and low socioeconomic status communities live in high risk areas at similar rates, there may be systematic distributional consequences of liability regulation.

5.4 Robustness

Factors such as vegetation conditions near power lines, extent of interaction between housing and wilderness, and energy consumption patterns could drive utilities' use of shutoffs. If these factors are also correlated with structure replacement costs, then the estimated relationship between shutoffs and potential liability could be biased. In table 6, I estimate several modifications of regression model 7 to test the robustness of the main result in table 5. Column 1 replicates the main estimate from table 5. Column 2 adds a control for the share of total population in destination zip code d living in the WUI interacted with the downwind indicator, DW_{odt}. This covariate captures daily changes in the number of structures near vegetation that is likely to burn in the event of a fire. In column 2 I also control for the average WHP index in each destination zip code interacted with the downwind indicator. This covariate measures the conduciveness of vegetation in the downwind zip code to spreading fire. Column 3 adds separate controls for monthly electricity usage in zip codes o and d respectively. These additional covariates capture patterns in electricity usage that are relevant to firms' shutoff decision making process.

The empirical model in equation 7 uses daily changes in downwind structure costs to estimate the relationship between shutoffs and liability. However, evidence suggests that utilities monitor forecasted wind conditions in addition to current conditions. As a result, utilities may base their shutoff decisions on their expectation of which regions will be downwind in the upcoming days. To account for this behavior, define a destination zip code as downwind if it lies downwind of the origin zip code at any time in the next five days. For example, the downwind indicator, DW_{odt}, is set equal to one if a destination zip code is downwind anytime over the next five days (between day t and day $t+5$). I report the results from this specification in column 4 of table 6. The main estimate of interest is positive, significant, and of a similar magnitude in all specifications.

Since the empirical framework in equation 7 is specified at the zip code level, it may include properties that are located far away from high-ignition risk circuits. If utilities only consider structures that are very close to high-risk power lines (and therefore very likely to be destroyed if an ignition occurs), then the zip code analysis could be misspecified. In appendix A, I address this by estimating 7 at the circuit level. I do this by using daily variation in the replacement cost of structures that lie downwind of power lines and are located within 20 kilometers of a circuit. Using this local variation, I estimate similar effects to the main result from table 5.

6 Discussion and Conclusion

6.1 Short Run Welfare

In this section I derive the short run welfare change resulting from a decrease in the pass through rate of liability costs. Consumer surplus is the sum of the value of electricity consumption, total payments to the utility, and rental payments from the utility to the household.

$$CS = \bar{p}Q(1-L) - \beta\theta(k')(\gamma k' + \nu) + rk' \tag{9}$$

Where the first term is the consumer's dollar valuation of their electricity consumption, term two is the consumer's payment to the utility, and term three is the utility's rental payment to the household. Producer surplus is denoted by the utility's profit function. Since total welfare is the sum of consumer and producer surplus, I can write the change in welfare from a change in the rate of capital return as the sum of the change in consumer and producer surplus. Since this model has a constant marginal cost, producer surplus is zero. By including producer surplus in the welfare derivation, I therefore obtain an upper bound on the short-run welfare change.

$$WF(\nu') - WF(\nu) = PS(\nu') - PS(\nu) + CS(\nu') - CS(\nu) \tag{10}$$

$$WF(\nu') - WF(\nu) = \beta[\theta(k')\bar{d} - (\bar{p} - p)\mathrm{Q}][P(L = 1 \mid \nu') - P(L = 1 \mid \nu)] + \tag{11}$$

$$\beta\bar{d}[\theta(k'(\nu')) - \theta(k'(v))](1 - P(L = 1 \mid \nu) \tag{12}$$

Where $\bar{p}$ is the consumers' maximum willingness to pay per kilowatt hour and $\nu' < \nu$ is the capital return after the 2017 CPUC rate case decision. Since this study estimates the short-run response of firms to the change in the share of liability cost they bear, I assume that the third term is zero so that the welfare estimates reflect short run variation. There are three parameters that characterize the short run welfare change from an increase in the share of liability born by firms in equation 10: (1) the change in probability of shutoff event following an increase in the share of liability born by firms ($P(L = 1 \mid \nu') - P(L = 1 \mid \nu)$), (2) expected damages ($\theta(k')\bar{d}$), and (3) consumers' maximum willingness to pay for electricity ($\bar{p}$).

There are several important caveats to the welfare change represented in 10. In the model, consumers value their home at its replacement cost and receive a payment from the utility equal to the home replacement cost if the structure burns down. As a result, consumers in this model do not care whether their home burns down. In practice, consumers may have a value of their home which exceeds the replacement cost, causing consumer surplus to potentially increase when firms use more shutoffs. Thus, the welfare change in equation 10 is likely larger (in absolute terms) than a more detailed model that incorporates intrinsic home values.

Another caveat to keep in mind is that I am assuming the adjustment of defensive capital cannot occur in the short term (making term three in equation 10 zero. Since the sample includes three post-policy years and the utilities have extensive networks of power lines, the extent of defensive capital investment is limited in this setting. However, future analyses of defensive capital's impact on the likelihood of ignition would be very useful.

In order to compute (1), I use the estimates by ignition risk presented in Figure A1. This strategy assigns the same probability change to all circuits that are in the same decile of ignition risk. Then, I use parcel-level assessed values from the Zillow ZTRAX dataset and the Risk to Potential Structures index created by Scott et al. (2020) to compute (2) as described in the data section. To account for the likelihood that an ignition occurs at each circuit, I obtain modeled ignition probabilities from San Diego Gas and Electric's data filing as part of its 2021 Wildfire mitigation plan. Multiplying damages by the likelihood of ignition yields expected damages (2). In order to compute (3), I multiply the average historic energy use at each circuit (described in the data section) by estimates of the value of lost load per kilowatt hour of energy use from a 2019 value of service study conducted by Southern California Edison.

Since the empirical literature on the value of lost load is still young, I first estimate the per kilowatt hour value of lost load required for there to be a welfare change of zero at each circuit. Figure 13 plots the number of circuits by the value of lost load necessary for welfare to remain the same following the policy. For most circuits in the sample, the maximum value of lost load required for a non-negative welfare change is less than \$3 per kWh. The average value of lost load necessary for welfare to remain unchanged across all circuits is \$0.3 per kWh and the median is \$0.01 per kWh. The smallest estimate of the value of lost load conducted for Southern California Edison customers is \$1.90 for residential customers, implying that the observed change in liability likely leads to a reduction in welfare.

To calculate a conservative estimate of the short run welfare change at each circuit, I assume that consumers' value of electricity is \$0.22 per kilowatt hour, the average retail price of electricity in California. Figure 14 plots a histogram of the estimated welfare change at each circuit in millions of dollars. The short run welfare effect is negative at nearly every circuit in the sample, suggesting that the value of lost electricity use at each circuit during power shutoffs outweighs the reduction in expected damages. In the next section I provide a short discussion of the results, explore policy implications, and suggest directions for future research.

6.2 Conclusion

In summary, I find that utilities increase their use of shutoff events following an increase in the share of liability for power line-ignited fire damages and that this policy change reduced welfare in the short term by leading utilities to over-utilize shutoff events. The theoretical framework outlined in section 3 suggests that the observed increase in blackouts crowds out other types of ignition prevention, such as burying power lines underground. I further provide evidence that utilities increase shutoff event use at the circuits with the highest likelihood of fire ignition and on days when threatened downwind property values are higher. There are several key implications for policymakers from this paper: First, these results suggest that policymakers can increase utilities' ignition prevention effort by increasing the share of liability for fire-related damages that they bear. Second, the policymaker can influence which ignition prevention efforts the utility undertakes by clearly defining which strategies will allow the utility to avoid a negligence ruling. In the California context, the 2017 rule change and subsequent rule amendments did not clearly specify what utility actions (or lack thereof) would lead them to be negligible for fire damages. This lack of clarity may have led utilities to use shutoff events as a signal that they are not acting negligently, leading to an overuse of blackouts at the expense of longer term mitigation investments. Third, since utilities appear to direct precautionary effort towards regions with higher threatened property values, policymakers should be wary of potential distributional consequences of liability regulations.

There are several areas where future research can extend this analysis to further inform our knowledge of liability regulations and how they impact firm precaution in the power line-ignited fire setting. First, future research should explore whether the circuits with the highest welfare loss from an increase in liability are located in areas with a large share of disadvantaged community members. For example, if expected damages are low and the VOLL is high in disadvantaged communities, then this implies that increasing the share of liability on firms is regressive in this setting. Second, future studies should take a longer term view of the impact of liability regulation on utilities' ignition prevention behavior. Researchers could do this by collecting data on other measures of ignition prevention, such as burying power lines, which utilities can take in the long term. Although liability regulation has a negative welfare impact in the short term, it could be beneficial in the long term if it encourages precautionary activities that both reduce the likelihood of ignition and the probability that a power shutoff occurs. Finally, more work is needed to identify which ignition prevention strategies most effectively reduce the likelihood of a fire caused by power lines. In particular, cost benefit analyses may need to be revised to account for the fact that capital investments both reduce the probability of ignitions *and* blackouts in the future.

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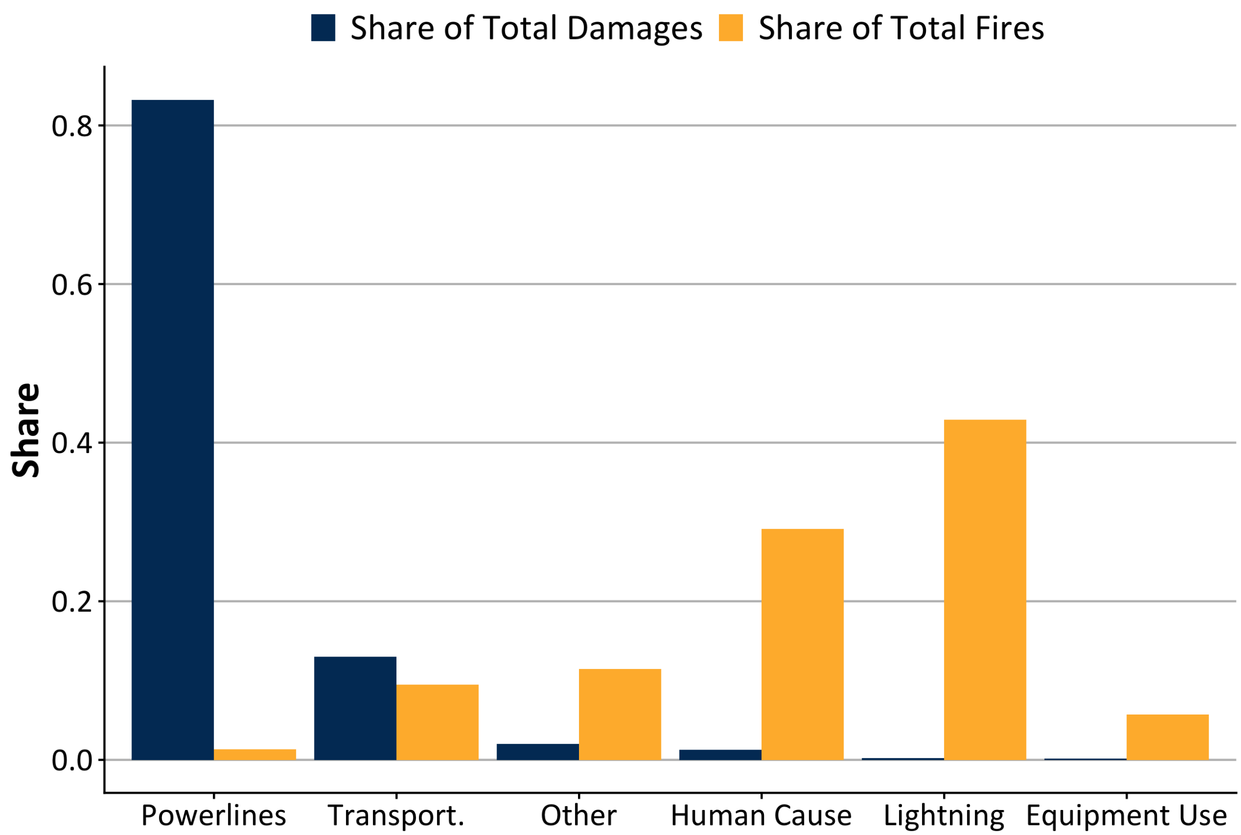
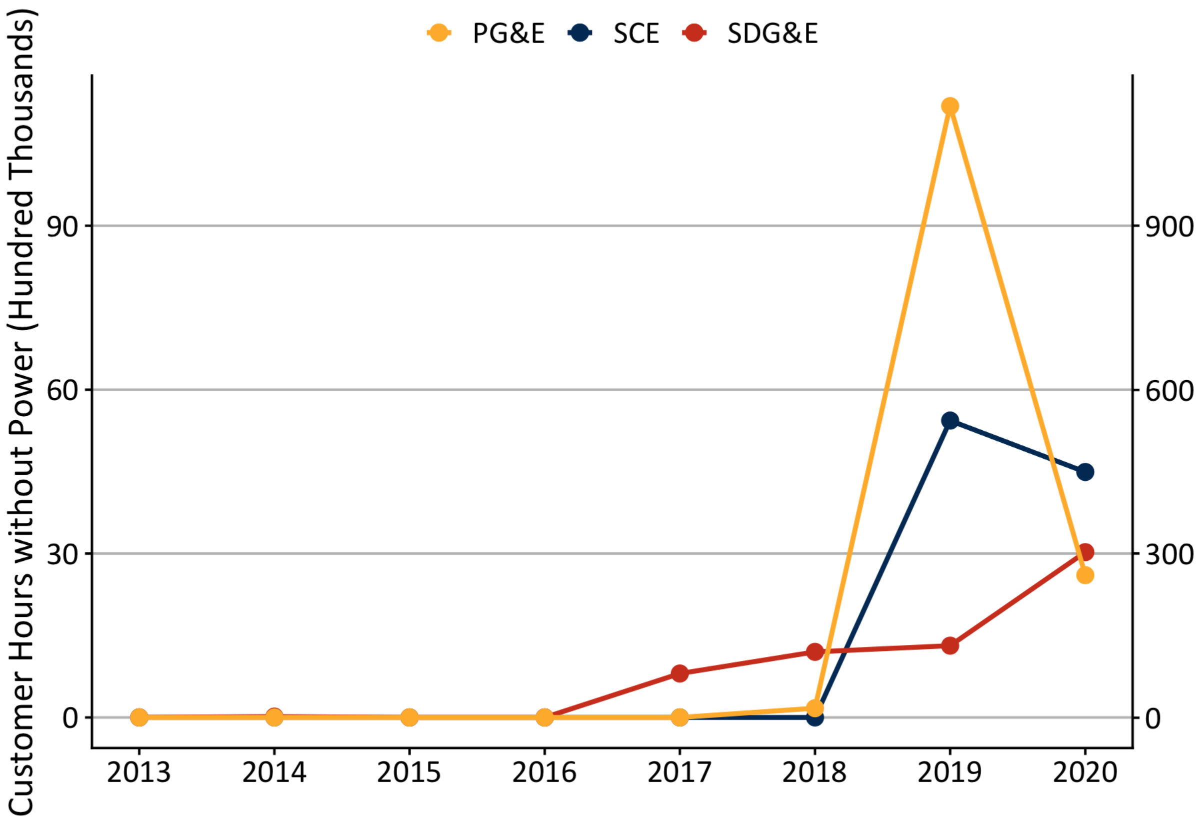
7 Figures

Figure 1: Share of Wildfire Ignitions (1910-2016) and Damages (2008-2019) by Source



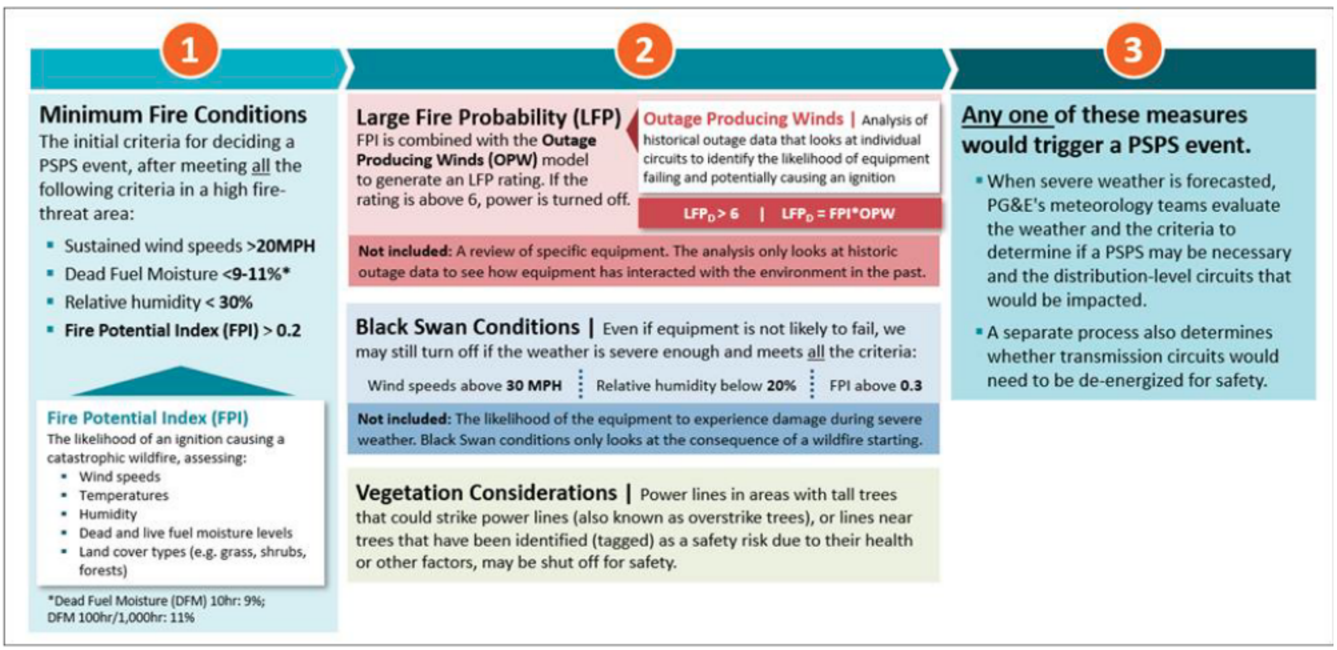
Notes: Share of total wildfire ignitions in California by cause of ignition between 1910 and 2016 are shown in yellow. The "Other" category includes fires caused by arson, debris, smoking, camping, playing with fire, railroads, lumber, equipment, and vehicles. Data are from Keeley et al. (2018). Share of total wildfire damages by ignition cause between 2008 and 2019 in California are shown in blue. Damages are defined as the replacement cost of homes destroyed by wildfire. The "Other" category includes fires caused by arson, debris, smoking, camping, playing with fire, railroads, lumber, equipment, and undefined cause. Data were collected by the author from CalFire historical wildfire activity data, also referred to as "redbooks."

Figure 2: Total Customer Hours Impacted by Shutoff Events



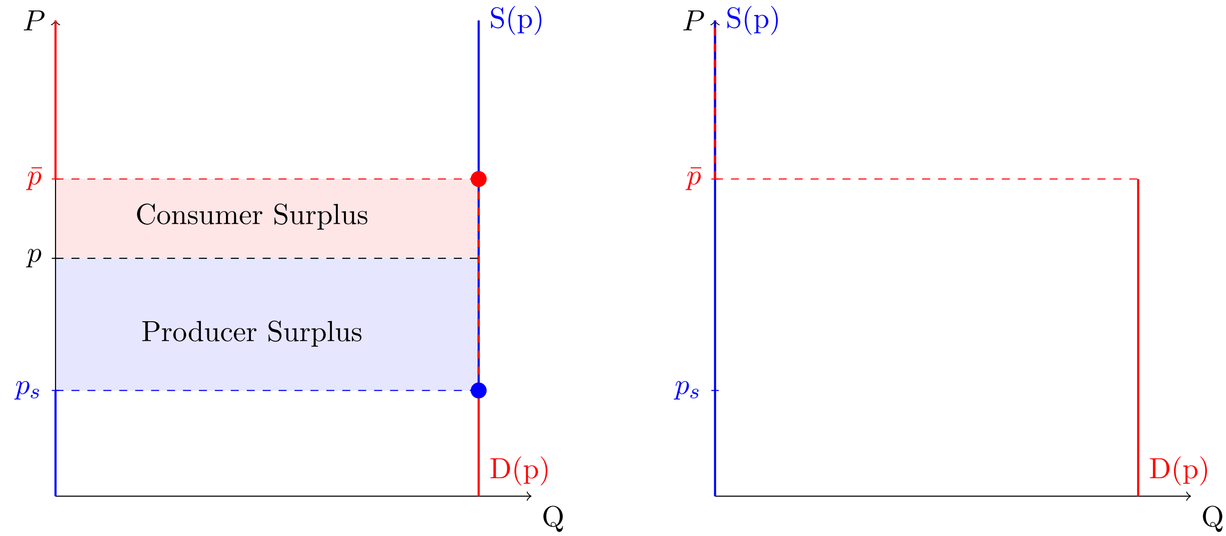
Notes: Total customer hours computed by the author from public safety power shutoff post event reports. Customer hours include commercial and residential customers served by California's three largest privately-owned utilities, Pacific Gas and Electric, Southern California Edison, and San Diego Gas and Electric. Reports are available from the California Public Utility Commission.

Figure 3: Pacific Gas and Electric Power Shutoff Criteria



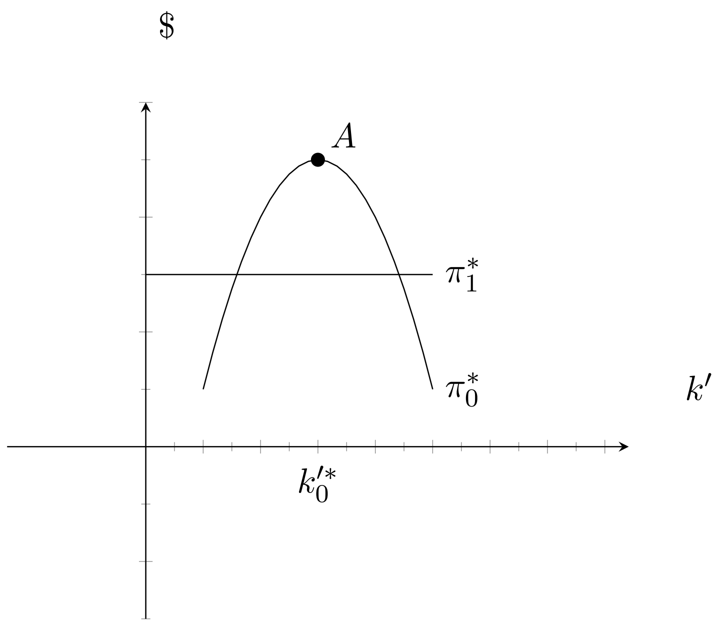
Notes: Minimum criteria for declaring a power shutoff as reported by Pacific Gas and Electric in their 2021 Wildfire Mitigation Plan.

Figure 4: Demand, Supply, and the Shutoff Decision for an Example Firm



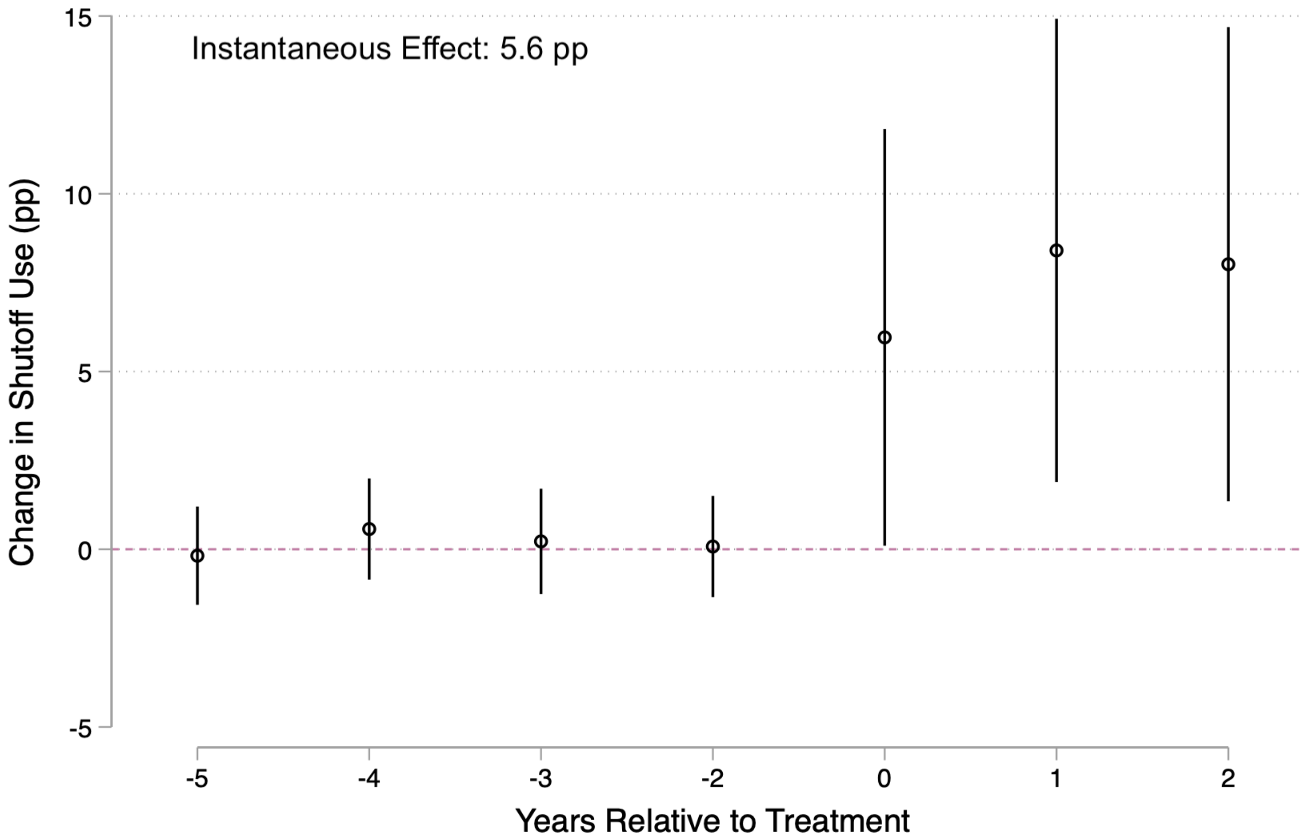
Notes: Supply and demand curve for an example firm when the firm provides electricity (left) and uses a power shutoff (right). Consumers' maximum willingness to pay for electricity is $\bar{p}$ and the firm's shutdown price is p_s.

Figure 5: Firms supply electricity when $\pi_0 > \pi_1$



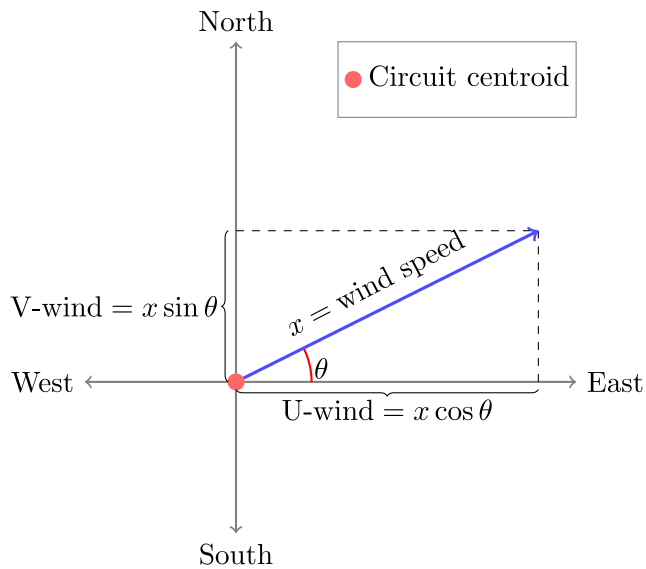
Notes: Solution to the firm's problem. Defensive capital investment is on the x-axis and dollars of profit is on the y-axis. The firm does not use a shutoff whenever its earns higher expected from supplying electricity (π_0) than from using a shutoff (π_1).

Figure 6: Effect of 2017 Rule Change on Power Shutoff Use



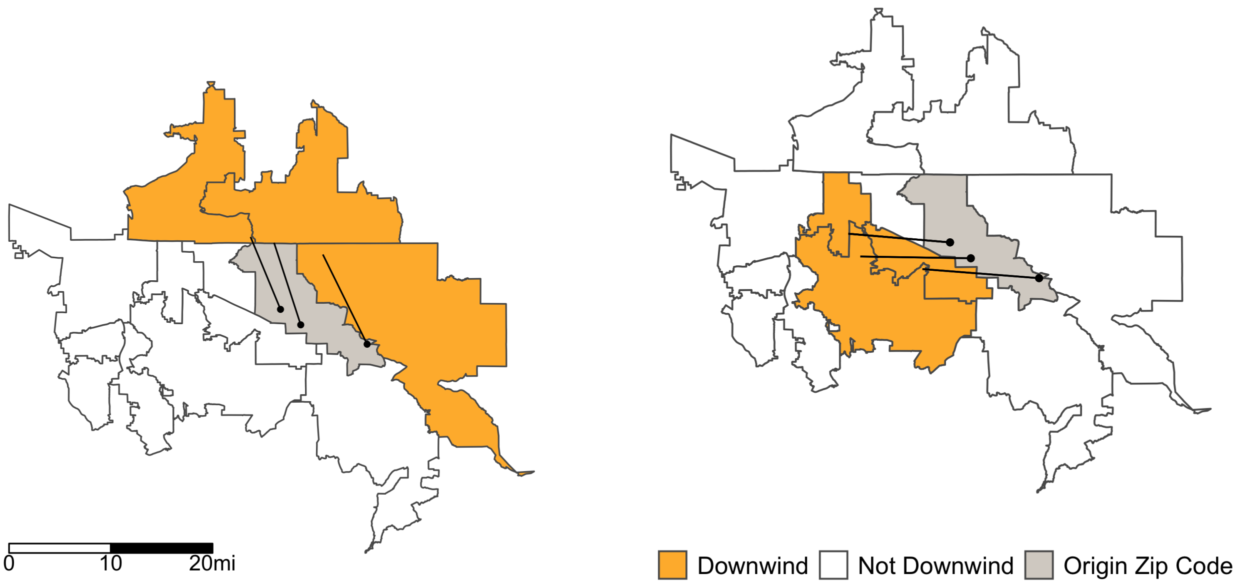
Notes: Estimated effect on shutoff use (in percentage points) of shifting liability for power line-ignited fire damages from electricity consumers to utilities. The x-axis plots event time in years relative to the 2017 liability rule change. The coefficient for period "-1" is excluded in this figure because it is zero by construction. Coefficient estimates are plotted with their 95% confidence intervals. The figure is created by estimating an event study version of regression model 7 on a daily panel of distribution circuits operated by San Diego Gas and Electric between 2013 and 2020. Standard errors are clustered at the high fire threat district by calendar week level to allow for correlation in Shutoff use across circuits with similar ignition risk during the same week.

Figure 7: Description of Downwind Assignment



Notes: Figure shows how to compute U and V wind vectors from station-level wind speed (x) in meters per second and direction (θ) in radians. U and V wind vectors are scaled up by 18 minutes, the amount of time it takes for a lit ember to travel 10 km at wind speeds of 9.5 meters per second, and converted to degrees latitude and longitude to compute where a lit ember would land if picked up by the wind at the circuit centroid.

Figure 8: Example of Regions that are Downwind of Power Lines Across Days

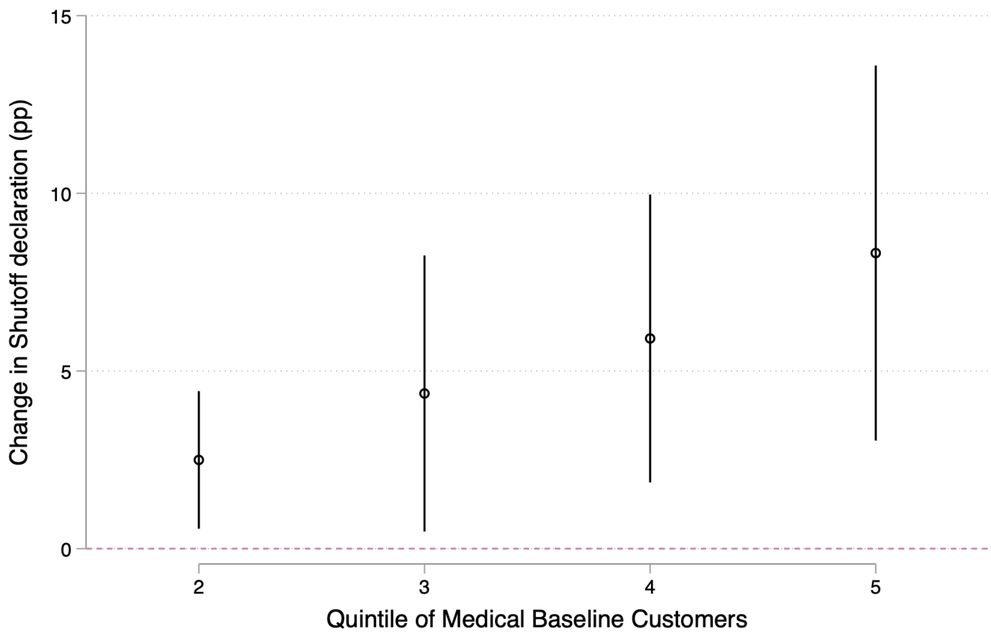


(a) Oct. 10, 2019

(b) Oct. 11, 2019

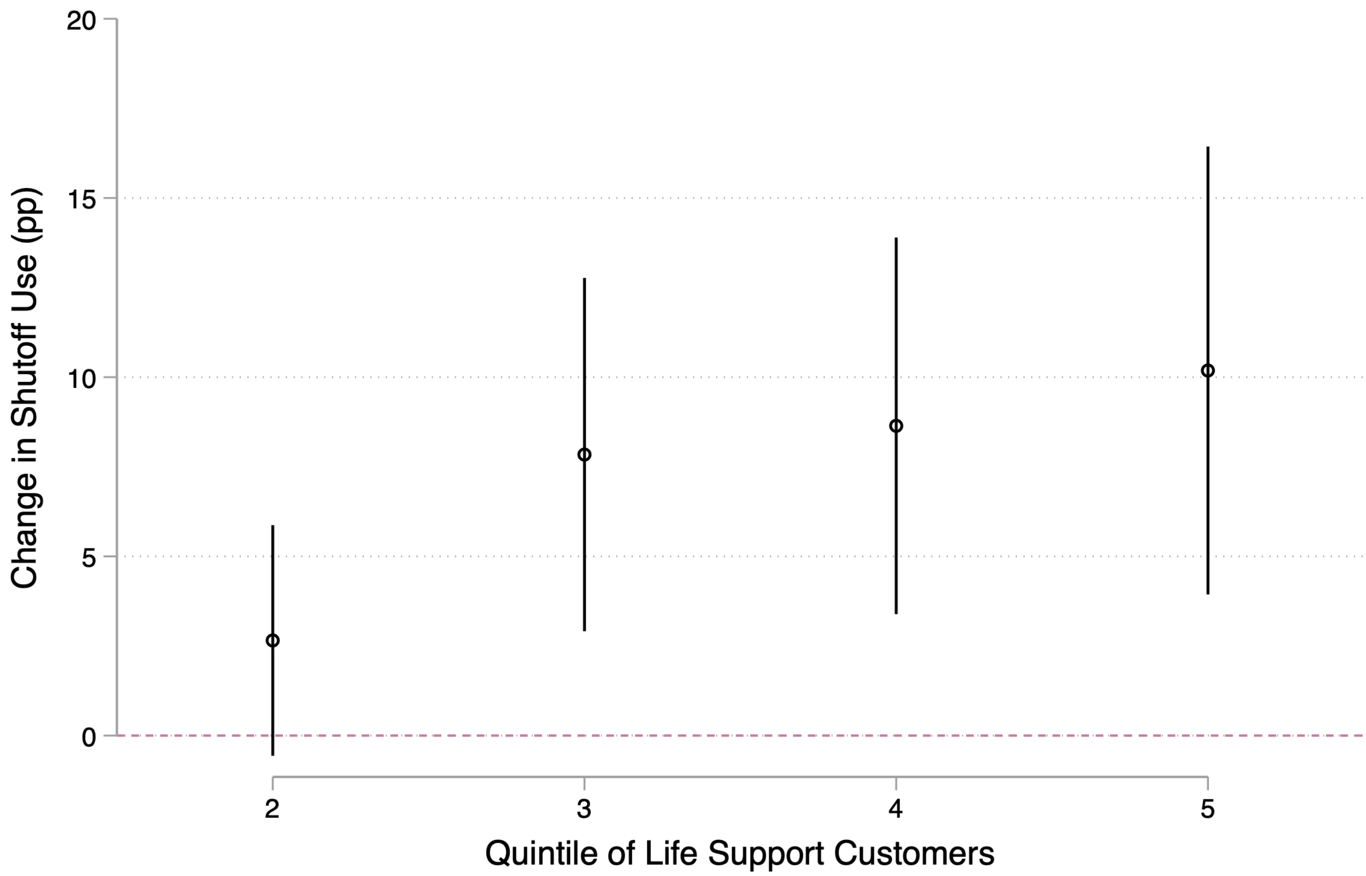
Notes: Daily variation in which zip codes are downwind of zip code 95917 (shown in tan) on October 10 and 11, 2019. The yellow and white shaded zip codes are the set of zip codes that are downwind of 95917 on any day between 2018 and 2020. The yellow zip codes are downwind of 95917 on a given day and the white zip codes are not downwind on the day shown. The black dot is the centroid of an electrical distribution circuit in zip code 95917 and the black line indicates the maximum daily wind direction and speed at the circuit on the day shown. The black line is using maximum daily wind speed and direction, an estimate of how far the wind can carry a lit ember from Albini et al. (2012), and several trigonometric identities. I calculate the total structure replacement cost for the yellow and white zip codes and changes in liability are generated by variation in wind direction and speed across days.

Figure 9: Effect of 2017 Rule Change on Shutoff Declaration by Share of Medical Baseline Customers



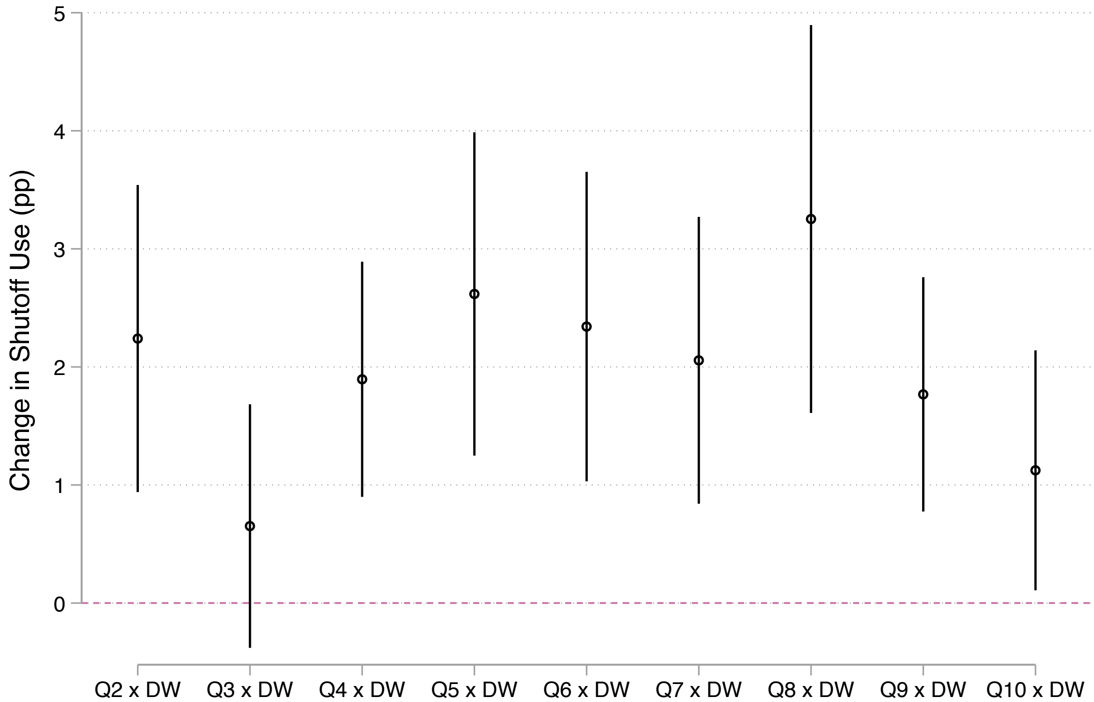
Notes: Estimated effect on shutoff use (in percentage points) of shifting liability for power line-ignited fire damages from electricity consumers to utilities by quintile of medical baseline customer share. A customer self selects into medical baseline status by notifying San Diego Gas and Electric of a qualifying medical condition or device. The share is calculated as the Coefficient estimates are plotted with their 95% confidence intervals. Each coefficient is interpreted relative to the estimated effect on days in the lowest septile of each climate condition. The figure is created by estimating a version of regression model 7 where treatment is interacted with binned climate conditions on a daily panel of on a daily panel of census tracts containing distribution circuits operated by San Diego Gas and Electric between 2013 and 2020. Daily climate conditions are from weather stations operated by San Diego Gas and Electric along their power lines. Standard errors are clustered at the high fire threat district by calendar week level to allow for correlation in shutoff use across circuits with similar ignition risk during the same week.

Figure 10: Effect of 2017 Rule Change on Shutoff Declaration by Share of Life Support Customers



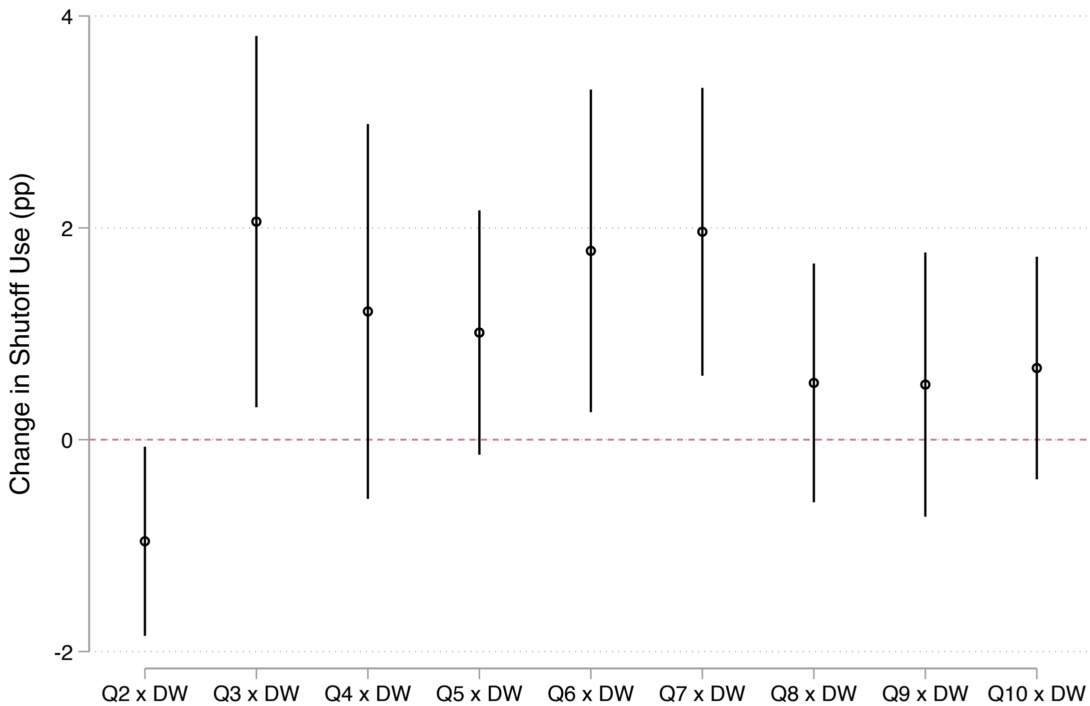
Notes: Estimated effect on shutoff use (in percentage points) of shifting liability for power line-ignited fire damages from electricity consumers to utilities by quintile of life support customer share. A customer self selects into medical baseline status by notifying San Diego Gas and Electric of a qualifying medical condition or device. The share is calculated as the Coefficient estimates are plotted with their 95% confidence intervals. Each coefficient is interpreted relative to the estimated effect on days in the lowest septile of each climate condition. The figure is created by estimating a version of regression model 7 where treatment is interacted with binned climate conditions on a daily panel of census tracts containing distribution circuits operated by San Diego Gas and Electric between 2013 and 2020. Daily climate conditions are from weather stations operated by San Diego Gas and Electric along their power lines. Standard errors are clustered at the high fire threat district by calendar week level to allow for correlation in shutoff use across circuits with similar ignition risk during the same week.

Figure 11: Results by Decile of Total Zip Code Replacement Cost



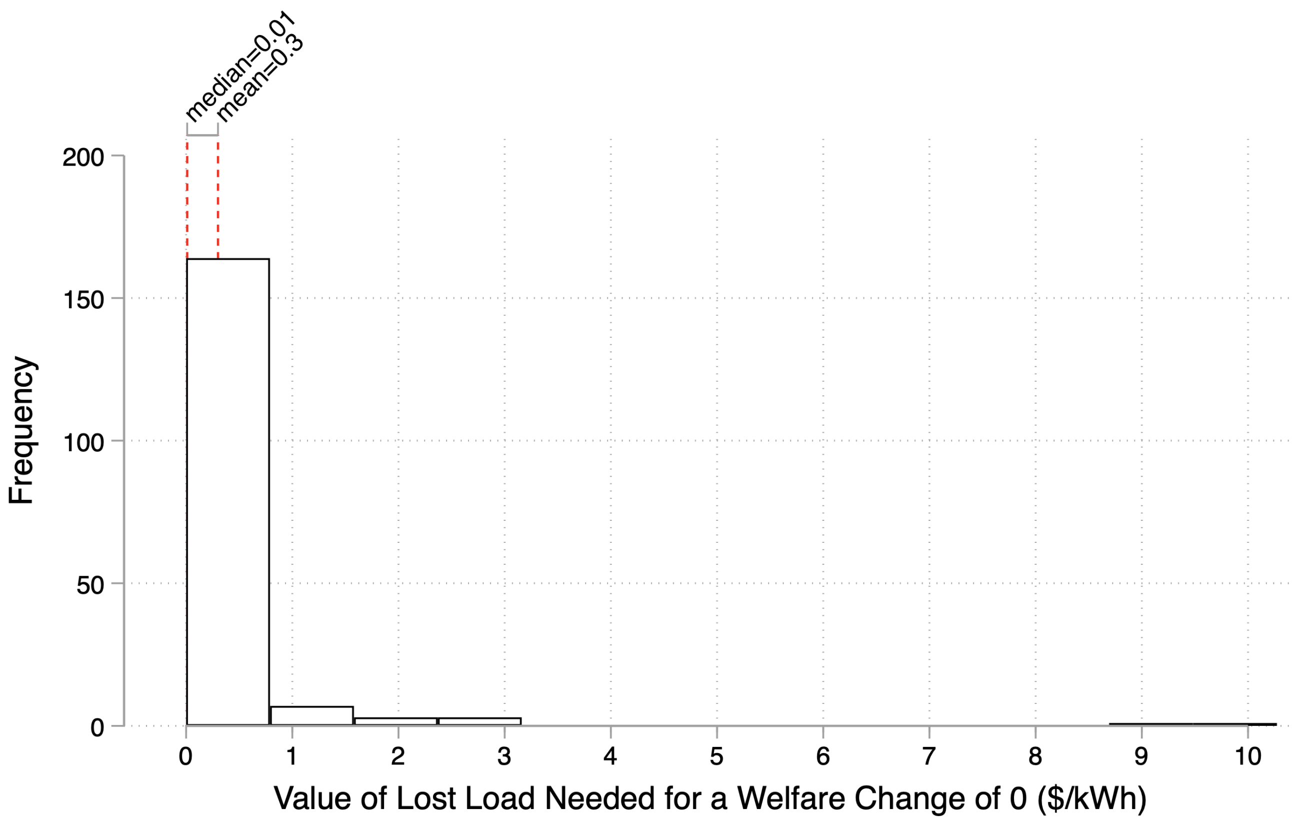
Notes: Wind and climate data is taken from weather stations operated by utilities in California and interpolated to each distribution circuit centroid using inverse distance weighting. Replacement costs are taken from the Zillow ZTRAX dataset. The underlying data consists of pairs of upwind, ever-downwind zip codes for selected days during January and April-December 2018-2020. Only days with wind speeds greater than 20 mph and relative humidity less than 30% are included in the sample. The outcome is a binary variable equal to 1 if there is an active shutoff in origin zip code o. The variables of interest are indicator variables for whether the total replacement cost in each destination zip code d is in one of ten bins on days when it lies downwind of zip code o. The excluded category is decile one, so all estimates represent the impact of threatened property values in each decile relative to the first decile. Controls include daily average temperature, wind speed, humidity, and maximum wind speed binned by septiles for each origin zip code o and destination zip code d. Standard errors are clustered at the high fire threat district by calendar week level.

Figure 12: Results by Decile of Mean Zip Code Replacement Cost



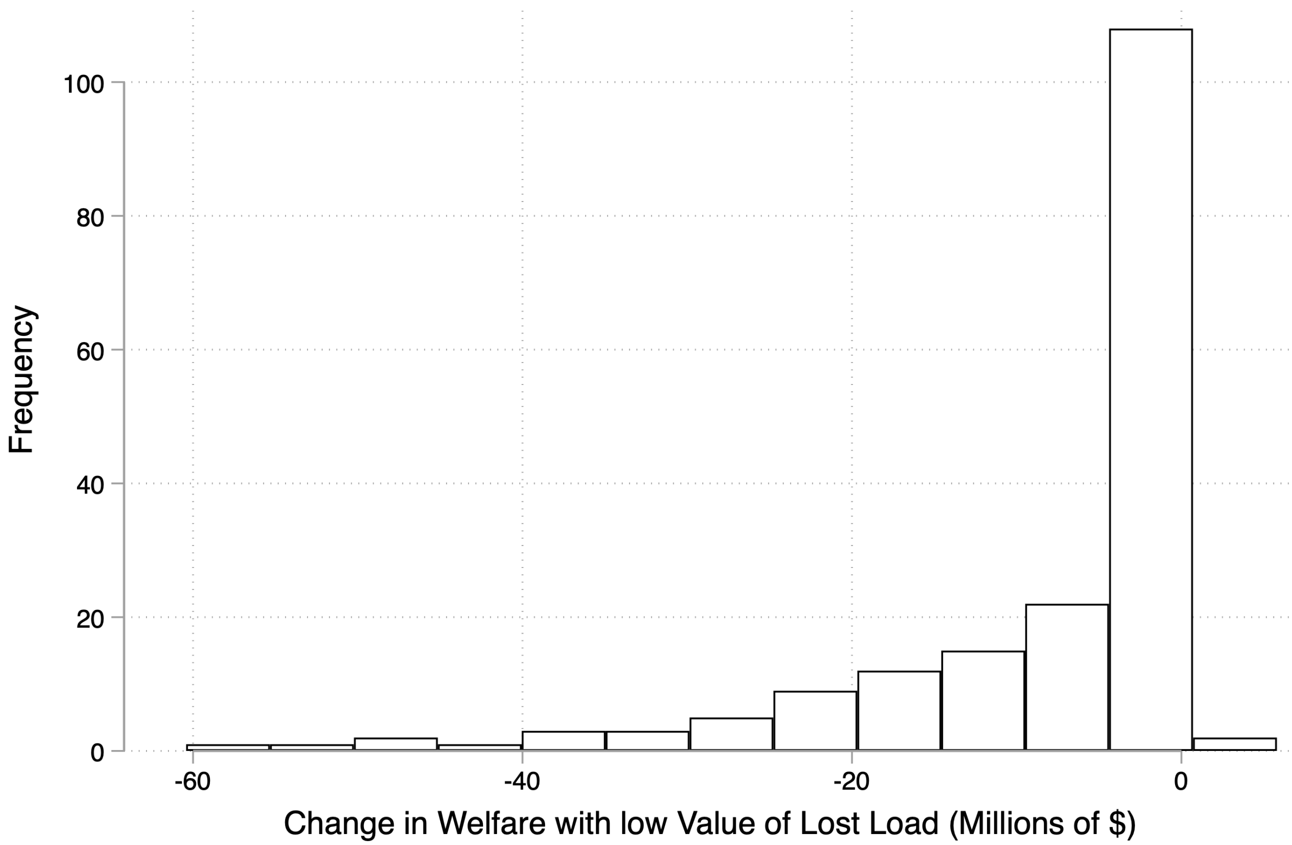
Notes: Wind and weather data is taken from weather stations operated by utilities in California and interpolated to each distribution circuit centroid using inverse distance weighting. Mean replacement costs are computed from the Zillow ZTRAX dataset for each zip code. The underlying data consists of pairs of upwind, ever-downwind zip codes for selected days during January and April-December 2018-2020. Only days with wind speeds greater than 20 mph and relative humidity less than 30% are included in the sample. The outcome is a binary variable equal to 1 if there is an active shutoff in origin zip code o. The variables of interest are indicator variables for whether the median replacement cost in each destination zip code d is in one of ten bins on days when it lies downwind of zip code o. The excluded category is decile one, so all estimates represent the impact of threatened property values in each decile relative to the first decile. Controls include daily average temperature, wind speed, humidity, and maximum wind speed binned by septiles for each origin zip code o and destination zip code d. Standard errors are clustered at the high fire threat district by calendar week level

Figure 13: Value of Lost Load Needed for a Welfare Change of 0 at Each Circuit



Notes: This figure plots the value of lost load, or consumer's maximum willingness to pay for electricity, required for the observed shift of liability onto utilities to be welfare neutral. Values are computed by computing equation 10 for each circuit operated by San Diego Gas and Electric between 2013 and 2020. The change in the likelihood of shutoff use at each circuit is taken from the estimated coefficients in figure A1. Ignition probabilities at each circuit are from San Diego Gas and Electric's internal model of circuit-level ignition risk. Energy usage at each circuit is computed from zip code level energy usage statistics reported by San Diego Gas and Electric. The author assigns energy usage to each circuit based on its share of total power line length in a given zip code. Future versions of this paper will use restricted access circuit-level energy use data. Damages are computed as the total commercial and residential property value within 20 kilometers of a circuit.

Figure 14: Short Run Welfare Change at Each Circuit with a Low Value of Lost Load



Notes: This figure plots the short run welfare change for San Diego Gas and Electric customers following a 2017 policy change which increased utilities' share of liability costs from power line-ignited fires. Values are computed by computing equation 10 for each circuit operated by San Diego Gas and Electric between 2013 and 2020. The change in the likelihood of shutoff use at each circuit is taken from the estimated coefficients in figure A1. Ignition probabilities at each circuit are from San Diego Gas and Electric's internal model of circuit-level ignition risk. Energy usage at each circuit is computed from zip code level energy usage statistics reported by San Diego Gas and Electric. The author assigns energy usage to each circuit based on its share of total power line length in a given zip code. Future versions of this paper will use restricted access circuit-level energy use data. Damages are computed as the total commercial and residential property value within 20 kilometers of a circuit.

Table 1: Circuit by Day Panel Summary Statistics

	Mean (SD)	Min	Max	N
PSPS Likelihood (%)	0.02	0	100	2,960,650
	(1.43)			
Temperature (C)	23.74	0	46	2,960,650
	(5.11)			
Precipitation (mm)	0.71	0	165	2,960,650
	(3.56)			
Humidity (%)	64.74	3	100	2,960,650
	(16.44)			
Max Wind Speed (m/s)	7.43	0	96	2,960,650
	(1.86)			
Energy Usage (Millions kWh)	1.04	0	6	2,960,650
	(0.90)			
Property Value (Billions of $)	5.03	0	52	2,960,650
	(2.99)			
Expected Damages (Millions of $)	2.02	0	20	2,960,650
	(3.30)			
Probability of Ignition (%)	0.01	0	2	2,960,650
	(0.09)			
Installation Year	1969.24	1928	2019	2,815,192
	(20.15)			
N Circuits	88.00			

Notes: Statistics are computed for a daily panel of distribution circuits operated by San Diego Gas and Electric between 2013 and 2020. Shutoff event use data was collected from post-event reports submitted to the California Public Utility Commission. Daily temperature, humidity, and maximum wind speed are collected at 10 minute intervals from weather stations operated by San Diego Gas and Electric along their power lines. Energy usage data was collected from zip code level reports published on the San Diego Gas and Electric website. Property values were collected from the Zillow ZTRAX database. The probability of ignition was collected from a public data submission by San Diego Gas and Electric to the California Public Utility Commission in their wildfire management plan. Expected damages is the product of circuit-level ignition probabilities and property values at each circuit. "N Circuits" refers to the number of circuits that ever experience a shutoff event between 2013 and 2020.

Table 2: Zip Code Panel Summary Statistics

	Mean (SD)	Min	Max	N
N PSPS	0.167	0	44	325,211
	(1.16)			
PSPS(0/1)	0.046	0	1	325,211
	(0.21)			
Replacement Cost (Billions)	6.799	0	37	325,211
	(6.64)			
Median Replace Cost (Thousands)	53.384	0	223	325,211
	(27.73)			
DAC Status	0.158	0	1	325,211
	(0.36)			
DW DAC Status	0.166	0	1	325,211
	(0.37)			
Temperature(F)	41.458	31	109	325,211
	(12.95)			
Humidity(%)	10.651	0	30	325,211
	(8.02)			
Wind Speed (mph)	24.496	20	88	325,211
	(4.52)			
Downwind Temp. (F)	45.030	30	113	324,965
	(14.48)			
Downwind Humid. (%)	14.517	0	100	324,965
	(12.49)			
Downwind Wind Speed (mph)	21.210	0	56	177,615
	(6.67)			
Downwind WHP Share	3.054	0	5	325,211
	(0.99)			
Downwind WUI Pop Share	0.006	0	1	325,211
	(0.04)			
Energy Use (GWh)	6.644	0	833	318,485
	(30.39)			
Downwind Energy Use (GWh)	6.880	0	833	320,130
	(31.81)			
N Zip Codes	562.000			

Notes: Wind and weather data is taken from weather stations operated by utilities in California and interpolated to each distribution circuit centroid using inverse distance weighting. Total replacement costs are taken from the Zillow ZTRAX dataset and converted to 2021 dollars. Median replacement costs are computed for each zip code from the parcel-level Zillow data. Disadvantaged community (DAC) status comes from the CalEnviroScreen 3.0 update and is computed as the share of total 2010 zip code population living in a census tract categorized as a DAC. The number of zip codes denotes the total number of zip codes that ever experience a shutoff during 2018-2020.

Table 3: Zip Code Characteristics by Downwind Status

	Mean (Not Downwind)	Mean (Downwind)	Difference (% of SD)
Replacement Cost (Billions)	5.4	5.6	-2.8***
Median Replace Cost (Thousands)	47.3	48.4	-4.1***
Share Disadvantaged	0.5	0.4	7.7***
Wildfire Hazard Potential	3.1	3.1	-0.9
Pop. Living in WUI (% of Total)	0.6	0.4	5.9***
Avgerage kWh Consumed	4,182.6	3,889.9	1.4***
N Houses	7,345.2	7,305.8	0.5
Total Population	20,039.4	19,705.6	1.6***
% White	58.8	60.2	-5.9***
% Black	3.2	3.1	1.0*
% Asian	6.1	5.6	4.9***
% Other Race	4.2	4.4	-4.8***
% Hispanic	27.7	26.7	5.0***
Employment	5,715.0	5,376.3	3.9***
Annual Payroll (Thousands)	264,031.3	253,718.2	1.7***
N Establishments	432.4	416.3	3.1***
N Medicare Beneficiaries	2,992.5	2,967.2	0.9*
N Medical Devices	111.1	113.4	-1.9***
Temperature(F)	38.1	38.4	-6.1***
Relative Humidity (%)	12.8	13.1	-3.2***

Notes: Wind and weather data is taken from weather stations operated by utilities in California and interpolated to each distribution circuit centroid using inverse distance weighting. Total replacement costs are taken from the Zillow ZTRAX dataset and converted to 2021 dollars. Median replacement costs are computed for each zip code from the parcel-level Zillow data. Disadvantaged community (DAC) status comes from the CalEnviroScreen 3.0 update and is computed as the share of total 2010 zip code population living in a census tract categorized as a DAC. Wildfire hazard potential is an index varying from 1 (low) to 5 (very high) which quantifies the relative potential for wildfire that may be difficult to control (Dillon and Gilbertson-Day (2020)). The share of 2010 population living within the wildland urban interface is computed using data from Radelof et al. (2017). All population data is from the California Department of Finance. Employment, payroll, and the number of establishments are collected from the 2013 Census zip code business patterns database. Medicare beneficiaries and the number of medical devices that rely on electricity are collected from the U.S. Department of Health and Human Services emPOWER Map 3.0.

Table 4: Effect of Liability Regulation on Shutoff Probability and Customer Hours without Power

	Shutoff Indicator (1)	Customer Hours (2)
Treated x Post 2017	5.64***	923.47***
	(1.56)	(245.21)
Controls	x	x
Circuit FE	x	x
Month FE	x	x
Mean of Dep. Var	0.07	1.33
Bootstrap 95% CI	[1.9,9.4]	[376.3,1,506.5]
Observations	50,809	50,809

Notes: All columns estimate the change in shutoff use following a reform that increased the share of liability born by firms. The outcome is a binary variable equal to 1 when there is an active shutoff event at circuit i on day t. Column 1 reports the estimate from a regression with no controls. Column 2 adds nonlinear controls for daily climate conditions at circuit i. Column 3 adds circuit fixed effects and column 4 adds month fixed effects. Post 2017 is a binary variable that takes a value of 1 for all days following November 30, 2017. Standard errors are clustered at the calendar week level to allow correlation in shutoff declaration across circuits within a week. The average value of the outcome conditional on wind speeds being in the highest septile observed during the sample period is also reported.

Table 5: Effect of Total Zip Code Replacement Cost on the Probability of a Shutoff

	Total Value (1)	Mean Value (2)
Value x DW	0.02***	0.04**
	(0.01)	(0.02)
DW	0.04**	0.04**
	(0.02)	(0.02)
Controls	x	x
Pair FE	x	x
Day FE	x	x
Mean of Dep. Var	0.025	0.025
1 SD Effect	0.286	0.224
Bootstrap 95% CI	[0.005,0.038]	[0.004,0.078]
Observations	505,656	505,656

Notes: Wind and weather data is taken from weather stations operated by utilities in California and interpolated to each distribution circuit centroid using inverse distance weighting. Total replacement costs are taken from the Zillow ZTRAX dataset and converted to 2021 dollars. The underlying data consists of pairs of upwind, ever-downwind zip codes for every day during January and April-December 2018-2020. The outcome is a binary variable equal to 1 if a shutoff event is active in origin zip code o. Value measures the total cost of replacing structures in each destination zip code d and DW is a binary variable equal to 1 when zip code d is downwind of zip code o on day t. Controls include daily average temperature, relative humidity, precipitation, and maximum wind speed binned by septiles for each origin zip code o and destination zip code d. Standard errors are clustered at the high fire threat district by calendar week level.

Table 6: Robustness Analysis Estimates

	Main Model (1)	WUI Controls (2)	Usage Controls (3)	5 Day Treatment (4)
Value x DW	0.02***	0.02**	0.02**	0.02**
	(0.01)	(0.01)	(0.01)	(0.01)
DW	0.04**	0.09**	0.10**	0.02
	(0.02)	(0.04)	(0.05)	(0.01)
Controls	x	x	x	x
Pair FE	x	x	x	x
Day FE	x	x	x	x
Mean of Dep. Var	0.025	0.025	0.025	0.025
1 SD Effect	0.286	0.224	0.264	0.198
Observations	505,656	505,656	498,324	505,563

Notes: Column 1 replicates the main estimate from column 4 of table 5. Column 2 adds controls for the share of total population in zip code d living in the Wildland Urban Interface. Column 3 adds controls for monthly zip code electricity usage in zip codes o and d separately. Column 4 assigns a destination zip code (d) as downwind if it is downwind anytime in the next 5 days (from t to $t+5$). Wind and weather data is taken from weather stations operated by utilities in California and interpolated to each distribution circuit centroid using inverse distance weighting. Total replacement costs are taken from the Zillow ZTRAX dataset and converted to 2021 dollars. The underlying data consists of pairs of upwind, ever-downwind zip codes for every day during September-December 2019-2020. The outcome is a binary variable equal to 1 if a shutoff is active in origin zip code o. Value measures the total structure replacement cost in each destination zip code d and DW is a binary variable equal to 1 when zip code d is downwind of zip code o on day t. Standard errors are clustered at the high fire threat district by calendar week level.

Appendix A: Further Results and Robustness Checks

A.1 Extensive Margin

Estimates by Ignition Risk

For this analysis, I measure ignition risk using San Diego Gas and Electric's modelled probability of ignition at each circuit as reported in its 2020 Wilfire Mitigation Plan. This measure captures the likelihood of ignition at each circuit operated by San Diego Gas and Electric as of 2020. Unlike the measure of ignition risk used in the main analysis, the modelled probabilities are *ex-post* because they reflect conditions after the 2017 policy change.

I bin the circuits by ignition probability into 11 categories: one category for circuits with an ignition probability of 0 and one category for each decile of the ignition probability conditional on it being positive. Figure A1 plots the coefficients from a modified version of equation 4 where treatment is interacted with the 11 mutually exclusive indicator variables representing different risk percentiles. Since the 0 ignition probability category is excluded, each coefficient reflects the treatment effect at a specified decile of ignition risk relative to the treatment effect at circuits with no ignition risk. The coefficients in figure A1 increase with wildfire risk, suggesting that San Diego Gas and Electric's increase in precaution following the policy was largely concentrated at circuits with high ignition risk. At the highest risk circuits, power shutoffs increased (on average) by around 12 percentage points, a more than 170-fold increase relative to the pre-period mean.

Precaution and Climatic Conditions

In order to test how changes in daily climate conditions influence precautionary activity, I use the daily panel of distribution circuits operated by San Diego Gas and Electric between 2013 and 2020. I examine how the change in shutoff use following the 2017 rule change differs by daily maximum wind speed, relative humidity, temperature, and cumulative precipitation. Based on the IOUs' explanation of ignition risk in their Wildfire Mitigation Plans, maximum wind speed and humidity should be particularly important predictors of power shutoff use because fire risk is elevated during periods of high wind speed and low humidity. Equation 13 presents how I model the relationship between shutoff declaration (y_{imt}) and climate characteristics using a fixed effects framework with climate variables binned into septiles.

$$y_{imt} = \beta_0 + \sum_{k=1}^{7} \beta_{2k} X_{kimt} + \sum_{k=1}^{7} \beta_{3k} X_{kimt} Post_{mt} + \gamma_i + \delta_m + \nu_t + \varepsilon_{imt} \tag{13}$$

Where X_{kimt} is a vector of climate variables including maximum daily wind speed, daily average relative humidity, cumulative precipitation, and temperature each binned into septiles. The model conditions on fixed effects for each circuit (γ_i), month (δ_m), and calendar day (ν_t). Finally, the coefficients of interest, β_{3k}, capture how the percentage point change in power shutoff declaration following the 2017 rule change varies by daily climate conditions. Standard errors are clustered at the week by high fire threat district zone level to allow for correlation in utility decision making across all circuits with similar ignition risk during the same week.

Estimates by Daily Weather Conditions

Figure A2 plots the estimates from Equation 13 by septile for each of the four daily climate variables (maximum wind speed, relative humidity, temperature, and cumulative precipitation). In Panel (a) the coefficients imply that the increase in shutoff declaration following the 2017 rule change is increasing in maximum daily wind speed, with power shutoffs increasing by approximately 0.6 percentage points on days with wind speeds in the top septile. Panel (b) shows that San Diego Gas and Electric's increase in shutoff event use following the 2017 rule change was also decreasing in relative humidity. These results are reassuring, since utilities present wind speed and humidity as two primary drivers of ignition risk in documents submitted to the regulator. Panel (c) provides evidence that San Diego Gas and Electric's power shutoff event use increased more on cooler days following the 2017 rule change. Finally, Panel (d) shows that there is no clear relationship between daily cumulative precipitation and shutoffs.

A.2 Intensive Margin

Analysis Using Local Variation in Replacement Cost

To alleviate the concern that the estimates of potential liability's effect on shutoff use may be spuriously driven by the replacement cost of structures that are not close to a distribution circuit, I estimate a modified version of equation 7 which uses local variation in wind direction around each circuit. Figure A4 provides an example of the methodology for this circuit-level analysis. As shown in figure, A4, I create 10 and 20 kilometer buffers around each circuit, and divide each buffer into quarters to create 8 potentially downwind regions around each circuit. I then compute the total and median structure replacement cost in each region and use daily variation in wind direction and speed to generate changes in potential liabilities across days just as in the zip code analysis. Finally, I estimate a modified version of 7 at the circuit level that controls for daily weather conditions at each circuit, circuit-region fixed effects, utility-year fixed effects, and calendar day fixed effects.

Table A1 reports the results of this analysis. The coefficient in column 2 implies that the likelihood of a shutoff increases by 0.05 pp (208% relative to the mean) when the median downwind structure replacement cost increases by 10%. Reassuringly, this effect is very similar to the effect of potential liability on precaution from the zip code analysis.[31]

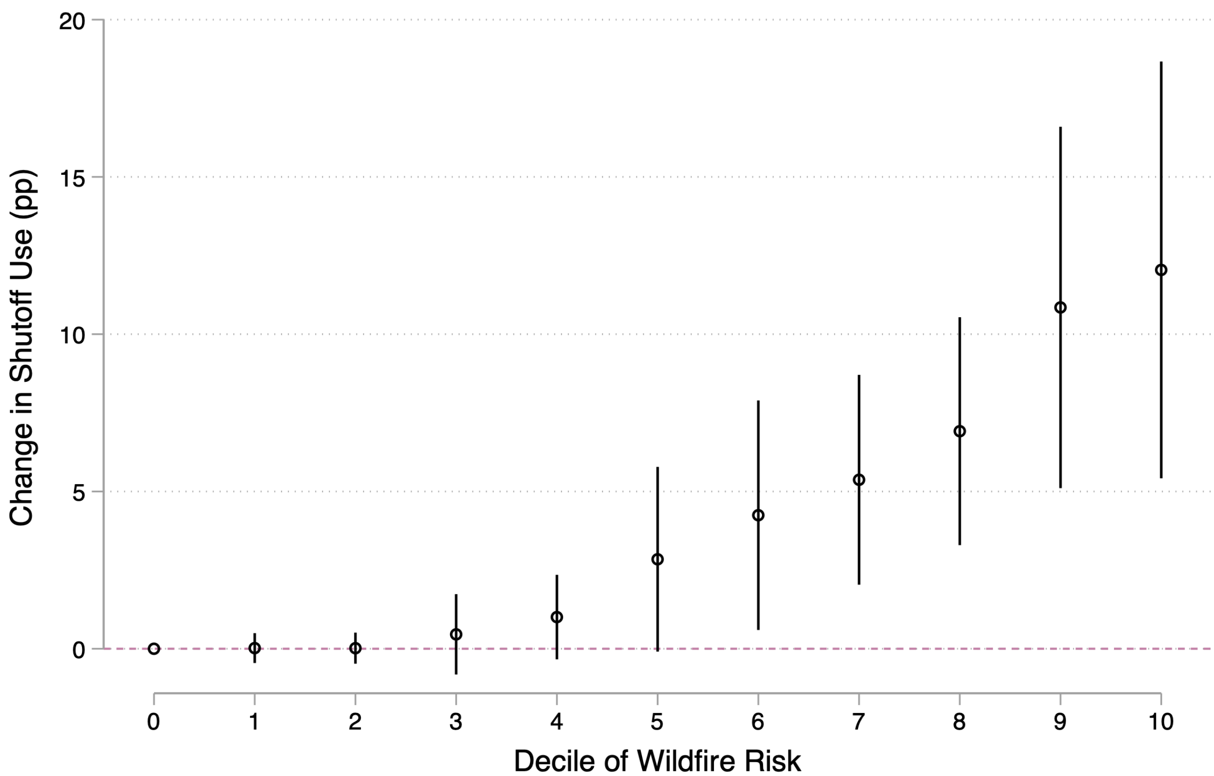
Estimates by Zip Code Socioeconomic Status

Since I find that utilities use shutoffs more in regions with higher structure replacement cost, which is positively correlated with socioeconomic status, there could be distributional consequences associated with liability regulation. For example, utilities may be more likely to use a shutoff in a low socioeconomic status community in response to higher potential liability in a downwind high socioeconomic status community. To test for distributional impacts, I re-estimate equation 7 and decompose the effect by whether the origin or destination zip code has an above-average share of its 2010 population living in a census tract defined as a disadvantaged community by the California state government.

Table A2 reports the estimated relationship between potential liability and shutoff use by socioeconomic status. Row 1 reports the effect when a high socioeconomic status community lies downwind of a low socioeconomic status community, while row 2 reports how shutoffs respond to potential liability when a low socioeconomic status community lies downwind of a high socioeconomic status community. The estimates in rows 3 and 4 reflect the relationship between shutoffs and liability when both the upwind or downwind zip codes are high socioeconomic status. The results suggest that the relationship between potential liability and shutoff use is driven by zip codes of high socioeconomic status, providing no evidence of distributional consequences in this setting.

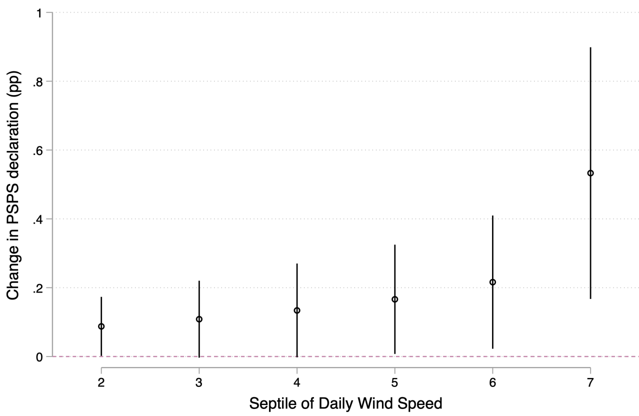
[31] The effect in column 1 is no longer significant, but this is unsurprising because I had to drop all of the parcels in the ZTRAX data that did not have geocoordinates or that were geocoded to zip code centroids. As a result, the total replacement cost is no longer accurate. I am in the process of manually geocoding these parcels.

Figure A1: Effect of 2017 Rule Change on Shutoffs by Circuit Ignition Risk

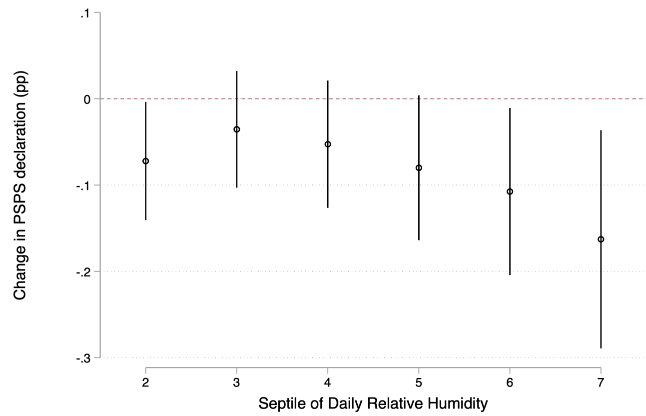


Notes: Estimated effect on shutoff use (in percentage points) of shifting liability for power line-ignited fire damages from electricity consumers to utilities by decile of circuit ignition risk. Coefficient estimates are plotted with their 95% confidence intervals. Each coefficient is interpreted relative to the estimated effect at circuits with no ignition risk. The figure is created by estimating a version of regression model 7 where treatment is interacted with binned circuit ignition risk on a daily panel of distribution circuits operated by San Diego Gas and Electric between 2013 and 2020. Ignition risk is from an internal model created by San Diego Gas and Electric. Standard errors are clustered at the high fire threat district by calendar week level to allow for correlation in shutoff use across circuits with similar ignition risk during the same week.

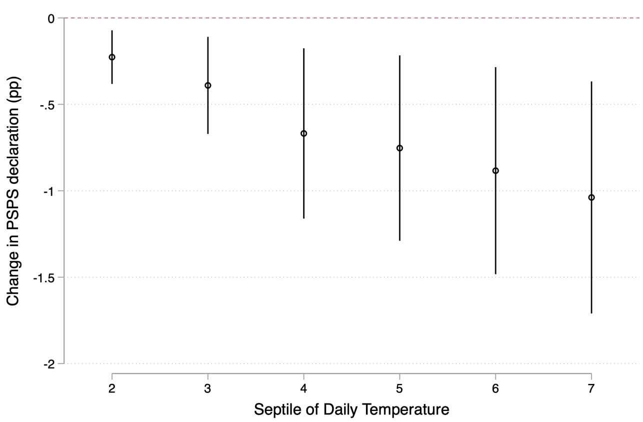
Figure A2: Effect of 2017 Rule Change on Shutoff Declaration by Daily Weather Conditions



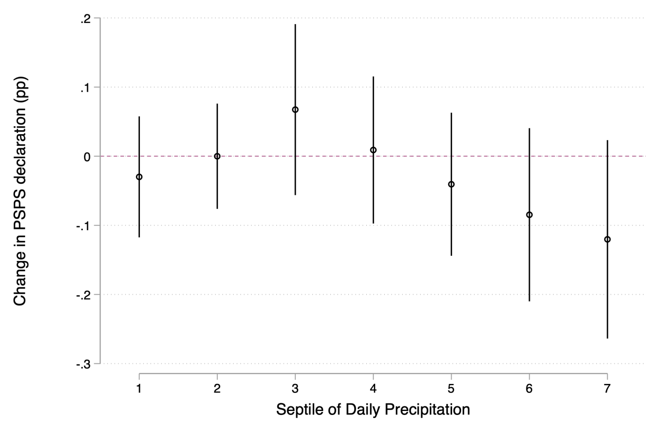
(a) Maximum Wind Speed



(b) Relative Humidity



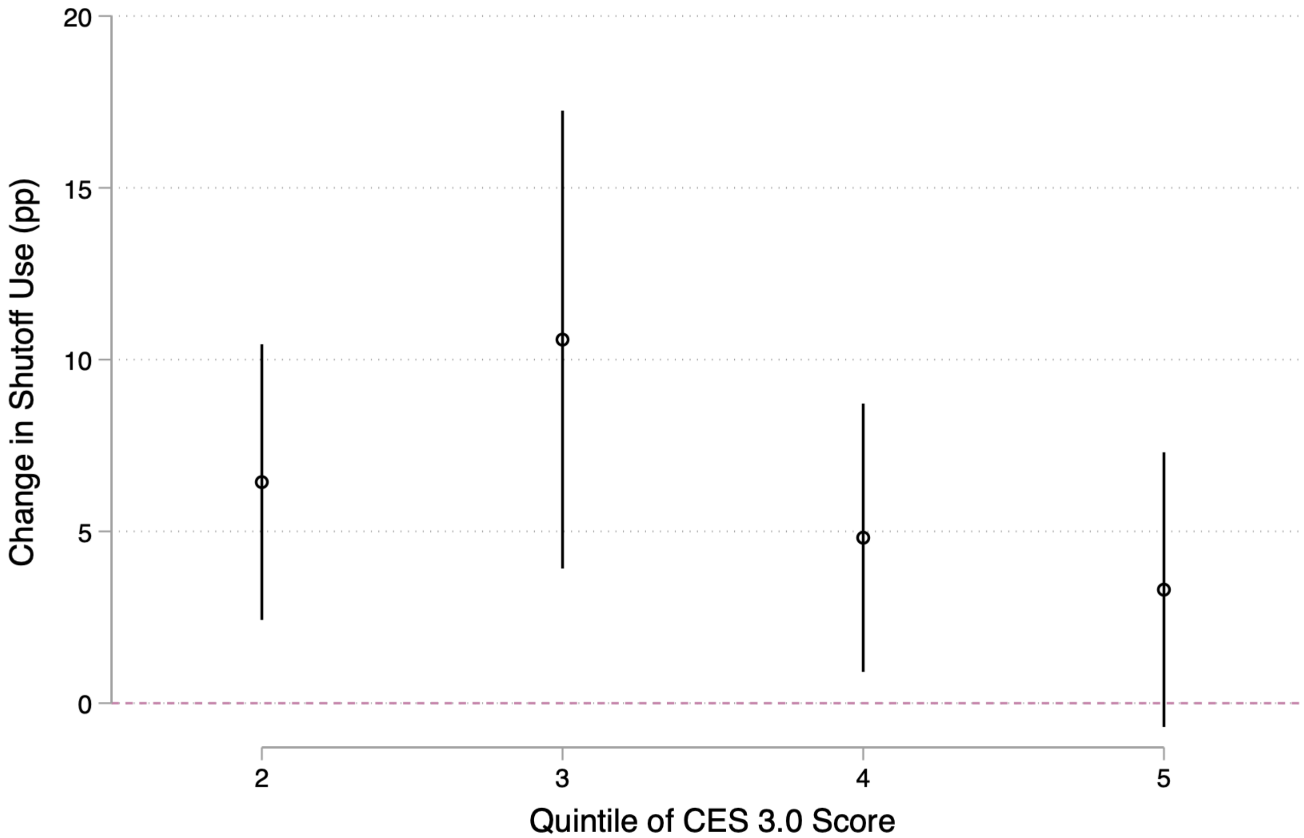
(c) Temperature



(d) Cumulative Precipitation

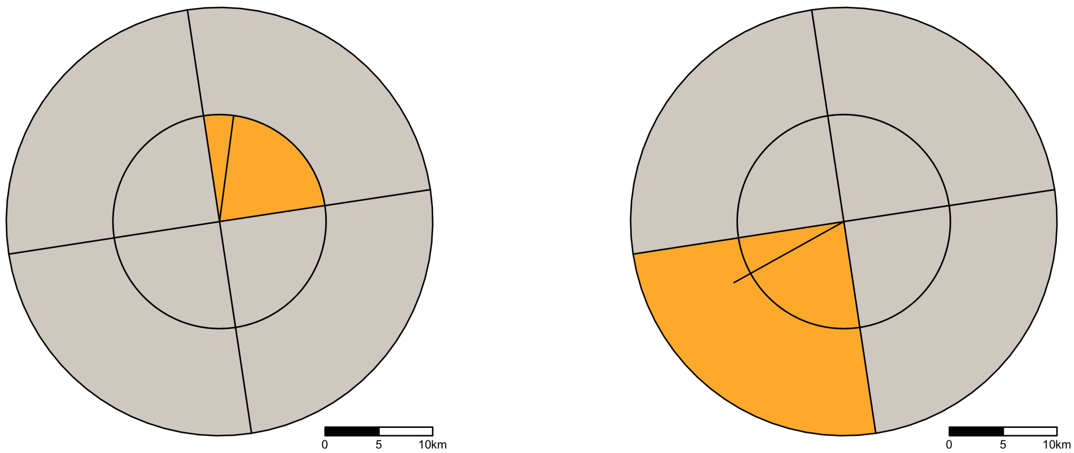
Notes: Estimated effect on shutoff use (in percentage points) of shifting liability for power line-ignited fire damages from electricity consumers to utilities by septile of daily climate conditions. Coefficient estimates are plotted with their 95% confidence intervals. Each coefficient is interpreted relative to the estimated effect on days in the lowest septile of each climate condition. The figure is created by estimating a version of regression model 7 where treatment is interacted with binned climate conditions on a daily panel of distribution circuits operated by San Diego Gas and Electric between 2013 and 2020. Daily climate conditions are from weather stations operated by San Diego Gas and Electric along their power lines. Standard errors are clustered at the high fire threat district by calendar week level to allow for correlation in shutoff use across circuits with similar ignition risk during the same week.

Figure A3: Effect of 2017 Rule Change on Shutoff Declaration by Socioeconomic Status



Notes: Estimated effect on shutoff use (in percentage points) of shifting liability for power line-ignited fire damages from electricity consumers to utilities by quintile CalEnviroscreen (CES) 3.0 score. The CES score is a composite index used by the California state government to rank census tracts by pollution exposure, demographic characteristics, and socioeconomic characteristics. The top 25% of census tracts based on the CES 3.0 score are defined as disadvantaged. Coefficient estimates are plotted with their 95% confidence intervals. Each coefficient is interpreted relative to the estimated effect at circuits in census tracts that are the least disadvantaged (lowest CES score). The figure is created by estimating a version of regression model 7 where treatment is interacted with binned CES scores on a daily panel of census tracts containing distribution circuits operated by San Diego Gas and Electric between 2013 and 2020. Daily climate conditions are from weather stations operated by San Diego Gas and Electric along their power lines. Standard errors are clustered at the high fire threat district by calendar week level to allow for correlation in shutoff use across circuits with similar ignition risk during the same week.

Figure A4: Example of Daily Variation in Replacement Cost at the Circuit Level



(a) Sep. 23, 2019 **(b)** Sep. 24, 2019

Notes: Daily variation in which regions are downwind of a circuit operated by Pacific Gas and Electric on September 23 and 24, 2019. The centroid of the circuit is the center of the circle, and it is encircled by 10 and 20 kilometer buffers. Each buffer is divided into 4 regions, creating 8 possible downwind regions for each day between 2018-2020. Yellow shaded regions are downwind of the circuit on each day, while the tan regions are not downwind. The black line indicates which direction the wind is blowing and its length indicates how strongly the wind is blowing. The black line is created using maximum daily wind speed and direction, an estimate of how far the wind can carry a lit ember from Albini et al. (2012), and several trigonometric identities.

Table A1: Effect of Replacement Costs on Shutoff Probability at the Circuit Level

	Shutoff Indicator (1)	Customer Hours (2)
Value x DW	0.05**	269.25*
	(0.02)	(142.88)
Controls	x	x
Pair FE	x	x
Day FE	x	x
Mean of Dep. Var	0.024	450.459
1 SD Effect	1.788	9,646.735
Observations	105,273	105,273

Notes: Estimates are from a regression of a binary variable equal to one if there is an active shutoff event at circuit i on day t on the total (column 1) or median (column 2) replacement cost in regions that are downwind of circuit i on day t. Both regressions control for septiles of maximum wind speed, maximum temperature, average relative humidity, and cumulative precipitation at circuit i on day t. Furthermore, both regressions include calendar day and circuit-downwind region pair fixed effects. Each circuit has 8 potentially downwind regions as shown in figure A4. Standard errors are clustered at the high fire threat district by calendar week level.

Table A2: Effect of Total Replacement Cost on the Probability of a Shutoff by Socioeconomic Status

	Total Value
	(1)
DAC_o x Value x DW	-0.015
	(0.015)
DAC_d x Value x DW	-0.004
	(0.019)
DW	0.041**
	(0.018)
Value x DW	0.024***
	(0.009)
Controls	x
Pair FE	x
Day FE	x
Mean of Dep. Var	0.025
1 SD Effect	-0.191
Observations	505,656

Notes: Wind and weather data is taken from weather stations operated by utilities in California and interpolated to each distribution circuit centroid using inverse distance weighting. Total replacement costs are taken from the Zillow ZTRAX dataset and converted to 2021 dollars. Disadvantaged community status is taken from the CalEnviroScreen 2018 data release. The underlying data consists of pairs of upwind, ever-downwind zip codes for every day during January and April-December 2018-2020. The outcome is a binary variable equal to 1 if a shutoff event is active in origin zip code o. Value measures the total cost of replacing structures in each destination zip code d and DW is a binary variable equal to 1 when zip code d is downwind of zip code o on day t. I code an origin zip code as a disadvantaged community if more than 50% of its population lives in a census tract designated as a DAC by the California government. Controls include daily average temperature, relative humidity, precipitation, and maximum wind speed binned by septiles for each origin zip code o and destination zip code d. Standard errors are clustered at the high fire threat district by calendar week level.

Appendix B: Heterogeneous Treatment Effects

I use observed data on power shutoff use from three large investor owned utilities in California called Pacific Gas and Electric, Southern California Edison, and San Diego Gas and Electric to estimate the relationship between potential liability and precaution. Because each utility has different exposure to ignition risk in its service territory and varying experience with ignition prevention historically, there are likely heterogeneous treatment effects across firms in the sample. For example, over half of Pacific Gas and Electric's service territory lies within regions of heightened ignition risk while 35% of San Diego Gas and Electric's service territory is in high risk areas.[32]

Recent econometric research has shown that in settings with heterogeneous treatment effects (like in the case of the California's electric utility industry), two-way fixed effects or difference in differences estimators identify a weighted average of treatment effect parameters which may not correspond to the overall average treatment effect on the treated (Sun and Abraham (2020), de Chaisemartin and D'Haultfœuille (2020), Borusyak and Jaravel (2017), Goodman-Bacon (2021)). Furthermore, recent work has pointed out that many environmental policies have different effects across units and over time (Steigerwald, Vazquez-Bare and Maier (2021)).

Since heterogeneity across firms is the primary source of treatment effect heterogeneity in this setting, I re-estimate equation 7 by firm. As a result, the regression model identifies three parameters of interest: the response of shutoffs to liability for Pacific Gas and Electric, San Diego Gas and Electric, and Southern California Edison. Following Steigerwald, Vazquez-Bare and Maier (2021), the overall effect of liability on shutoff use can be estimated by taking a weighted average of the three coefficients of interest, where each weight is the group's proportion of the sample.

$$\hat{\beta_\lambda} = \sum_g \lambda_g \beta_{FE}^{\hat{g}}$$

Where λ_g is the fraction of observations in the sample that are part of group g.[33] Since the cluster-robust variance estimator is sensitive to heterogeneity in between-cluster variation (Carter, Schnepel and Steigerwald (2017)), I compute the effective number of clusters using the *summclust*

[32]See Pacific Gas and Electric and San Diego Gas and Electric's 2020 wildfire mitigation plans for a detailed breakdown of their service territories by ignition risk.

[33]In this setting the weights are 0.39 (Pacific Gas and Electric), 0.39 (San Diego Gas and Electric), and 0.22 (Southern California Edison).

Stata command. There are 20 effective clusters in this setting, suggesting that using the wild cluster bootstrap procedure recommended by Cameron, Gelbach and Miller (2008) is warranted. I report the bootstrapped 95% confidence interval for the overall effect of potential liability on shutoff use in table B1.

The results of the heterogeneity analysis are presented in table B1. Columns 1 and 2 report estimates for the effect of total and average structure replacement costs on the likelihood of a power shutoff. The coefficients of interest in columns 1 through 3 suggest that most of the relationship between potential liability and shutoff use is driven by San Diego Gas and Electric and (to a lesser extent) Pacific Gas and Electric. The overall effect of structure replacement cost on shutoffs is reported as the "Pooled Estimate". Reassuringly, the pooled estimates are of a similar magnitude as the main estimates in table 5 and both are statistically different from zero at the 95 percent confidence level.

Table B1: Effect of Structure Replacement Cost on Shutoffs by Firm

	Total Value (1)	Mean Value (2)
Value x DW x PGE	0.01	0.01
	(0.01)	(0.02)
Value x DW x SDGE	0.04***	0.15***
	(0.01)	(0.04)
Value x DW x SCE	-0.01	-0.06
	(0.02)	(0.04)
DW x PGE	-0.01	-0.01
	(0.02)	(0.02)
DW x SDGE	0.07**	0.09**
	(0.03)	(0.03)
DW x SCE	0.04	0.03
	(0.03)	(0.03)
Controls	x	x
Pair FE	x	x
Day FE	x	x
Mean of Dep. Var	0.025	0.025
Pooled Estimate	0.016	0.048
Bootstrap 95% CI of Pooled Estimate	[0.0002,0.0304]	[0.0039,0.0922]
Observations	505,656	505,656

Notes: Wind and weather data is taken from weather stations operated by utilities in California and interpolated to each distribution circuit centroid using inverse distance weighting. Total replacement costs are taken from the Zillow ZTRAX dataset and converted to 2021 dollars. The underlying data consists of pairs of upwind, ever-downwind zip codes for every day during January and April-December 2018-2020. The outcome is a binary variable equal to 1 if a shutoff event is active in origin zip code o. Value measures the total cost of replacing structures in each destination zip code d and DW is a binary variable equal to 1 when zip code d is downwind of zip code o on day t. The variables PGE, SDGE, and *Southern California Edison* equal one for observations from Pacific Gas and Electric, San Diego Gas and Electric, and Southern California Edison. Controls include daily average temperature, relative humidity, precipitation, and maximum wind speed binned by septiles for each origin zip code o and destination zip code d. Standard errors are clustered at the high fire threat district by calendar week level. The "Pooled Estimate" is a weighted average of the estimates in rows 1, 2, and 3 where the weights are the utility's proportion of observations in the sample. Since there are 20 effective clusters in this analysis, I construct a bootstrapped 95% confidence interval for the pooled estimate following Cameron, Gelbach and Miller (2008).