Economic Impacts of Wildfire Adaptation: Public Safety Power Shutoffs in California

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Abstract

Wildfires pose a significant risk to the state of California, causing capital stock destruction and broader economic impacts. Many of the most destructive fires have been ignited by electricity infrastructure. To reduce ignition risk, electric utilities have begun a program of Public Safety Power Shutoffs in which they cut off customers' power during high wildfire risk weather. These too impose costs on the customers and broader economy, but the impacts are not yet quantified. In this paper, we develop an analytical general equilibrium model to assess the trade-offs between cost of wildfires and that of an adaptation measure used to avoid them. We process novel datasets on wildfire occurrence, power shutoffs, and simulations of wildfires that may have occurred if there had not been shutoffs in 2019 as input to the model. We find that power shutoffs are effective at avoiding wildfire damage but that the net impact to sectoral output and household welfare depends on the economic structure and the magnitude of wildfire risk.

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1 Introduction

Wildfires present a catastrophic risk to the state of California. Fire is a natural, and even beneficial, process for the land and ecosystems but recent trends of inordinate fire and damages demonstrate a departure from the norm. Fifteen out of the 20 most destructive fires have occurred since 2015 and the 2020 fire season shattered records for acres burned; California experienced 9,600 fires that burned an area four times larger than the 2015-2019 average [1], [2]. Losses from these fires exceeded $16 billion and millions of Californians faced weeks of poor air quality from the smoke. The trends of increasing catastrophic fires and losses cannot easily be attributed to one cause. Wildfires need an ignition source to start, fuels to consume, and extreme weather to spread rapidly. Research has linked climate change and extreme weather, such as hot and dry conditions, to the lengthening and worsening of wildfire seasons [3], [4], [5]. Historical fire suppression practices have led to the build-up of fuels in otherwise fire-adapted forests [6]. More recently, significant development in the wildland-urban interface has necessitated a shift back to aggressive suppression to protect people and property in harms way [7]. Meanwhile, this same proximity of people to forests has increased fire ignitions. Over 80% of ignitions are caused by humans, with sources ranging from cars backfiring, to arson, fireworks, and powerlines sparking fires [8].

Actions to both mitigate the occurrence of large fires and adapt to their impacts are necessary. This paper focuses on a specific mitigation strategy used to reduce ignitions by electric utilities: Public Safety Power Shutoffs (PSPS). While powerlines cause only 10% of ignitions, they are responsible for nearly 50% of the most damaging wildfires [1]. This includes the devastating Camp Fire in Paradise, CA in 2018 that led to 85 casualties. These fires are often ignited during high wind events, when powerlines are downed or trees and branches fall on the line, sparking a fire. These same conditions are conducive to fast spread. When found guilty of ignition, utilities are held strictly liable for the damages caused by the wildfire. When Pacific Gas & Electric (PG&E) was found guilty of igniting the deadly Camp Fire, they were liable for an estimated $30 billion, and filed for bankruptcy [9].

To bolster public safety and avoid significant wildfire losses, electric utilities in California have invested heavily in ignition mitigation. In 2019, the three large investor-owned utilities reported approximately $4.7 billion in mitigation such as system hardening, vegetation management, and equipment inspection [10]. However, these costly interventions have not eliminated the risk of ignition and the utilities have turned to a new, additional strategy: Public Safety Power Shutoffs. As the name implies, PSPSs are preventative power shutoffs to promote public safety and reduce the chance of sparking a wildfire during high fire risk weather. This strategy arose in a 2012 ruling by the California Public Utilities Commission (CPUC) finding that San Diego Gas & Electric had the authority to de-energize "in a manner that is consistent with their fundamental statutory obligation to protect the public safety" [11]. In subsequent rulings, this authority has been extended to other utilities and the CPUC set forth rules and requirements for reasonableness, notification, mitigation and reporting [12]. Among other requirements, the utilities must submit post-event reports detailing the factors leading to the decision, customer notifications and outage information. While utilities first conducted PSPSs in 2012, their usage only became widespread in the 2019 and 2020 fire seasons. At times, up to 1 million customers were without power. While this strategy has faced public backlash, it's expected to be a popular strategy with utilities while they undertake more costly long-term mitigation investments. These shutoffs present significant costs to the utility customers and impose indirect effects on the regional economy. However, these costs are currently unknown.

This study seeks to analyze the economic consequences - both costs and benefits - of the PSPSs conducted in 2019 in California using general equilibrium modeling. Research on the costs of electric power disruption fall broadly into two methodological categories: the use of customer surveys to estimate customer interruption costs and regional economic modeling [13]. U.S. utilities have conducted these customer surveys asking industrial and commercial customers about the losses associated with different duration and timing of outages and asking residential customers to estimate their willingness to pay to avoid power interruptions. These costs are used for utility planning, wherein reliability measures are implemented up to the marginal cost of outages, and in research on the costs of historical outages [14]. While widespread, these surveys are not well suited for longer duration outages affecting larger regions. This study joins a growing body of literature on the use of general equilibrium modeling to assess the broader economic consequences of disasters. These models estimate both the direct and indirect economic losses, through supply chains and trade, of shocks to electricity supply. Previous research has looked at the potential impacts of long-duration power outages from hypothetical earthquakes, terror attacks, and other disasters [15].

Regional economic modeling has been used, to a limited degree, to study the impacts of both wildfire and mitigation actions. Wang et al. estimated the economic footprint of the 2018 California wildfires including direct capital losses, health costs from smoke and indirect losses. The direct losses were used as input shocks to an input-output model to assess the output losses of industrial sectors in other regions disrupted by supply-chain links [16]. They found that indirect losses made up a majority of the economic impacts of the wildfires. Butry et al. develop an approach for modeling shocks from a fire in the wildland-urban interface including structure loss, business interruption, and out-migration as well as several risk mitigation actions. The report proposes the framework for the general equilibrium modeling but leaves the actual modeling to future work [17]. This present study could complement this type of work by focusing on the impacts of a specific risk mitigation technique.

Both wildfire destruction and the direct costs imposed by PSPSs on utility customers exert broader effects on the regional economy. In this paper we use analytical general equilibrium modeling of PSPSs and wildfires focusing on California's 2019 fire seasons to elucidate these economic consequences and quantify the tradeoffs between wildfire damages and costly adaptation. The paper's contribution is to enhance understanding of the mechanisms by which wildfires, and the measures to mitigate them, jointly affect the economy, in particular the dependence of mechanisms on the magnitude of capital destruction from wildfire exposure, electricity intensity of sectors' economic activities, and the effectiveness of PSPSs at limiting wildfire damage to the capital stock.

The analysis relies on novel data processing of the PSPS outages, actual wildfires, and simu-

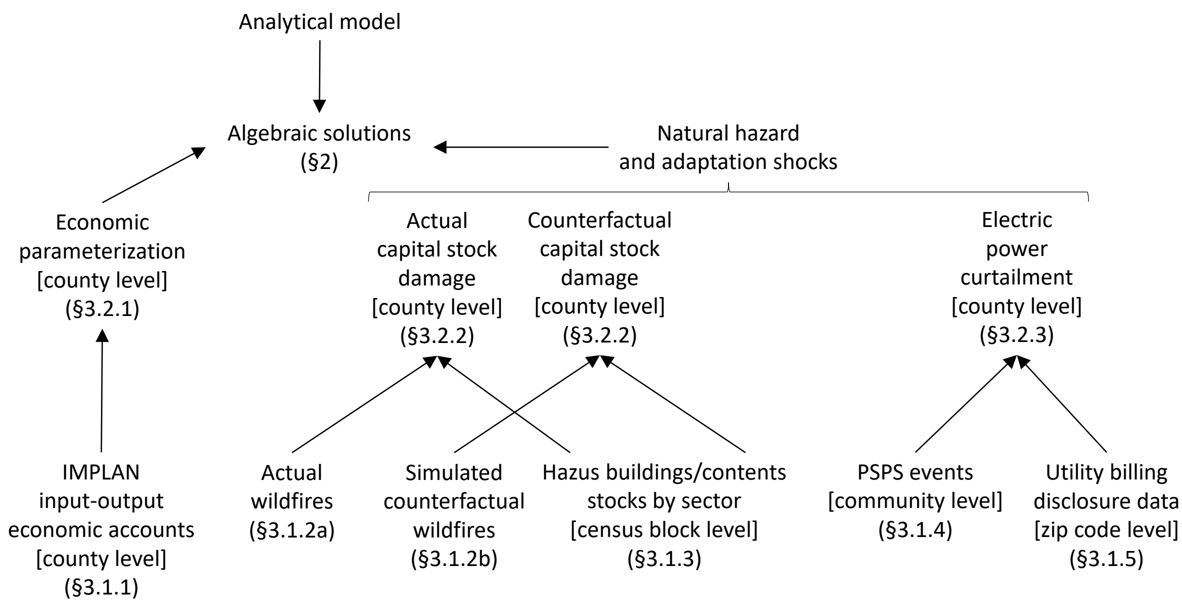


Figure 1: Roadmap of analysis in the paper

lations of counterfactual fires that may have occurred absent the shutoffs. These data, combined with data on economic activity, electricity usage, and capital stock value allow us to model the economic impacts of wildfire, PSPSs and the effectiveness of the latter in limiting the former. Figure 1 shows the structure of the analysis and paper sections. The rest of the paper is organized as follows. Section 2 describes the stylzed analytical model and its algebraic solutions. Section 3.1 walks through the many input datasets. Section 3.2 describes how the data are combined to parameterize the economic model and construct the natural hazard and adaptation shocks. Based on the solutions to the analytical model and numerical parameterization, we compare the economic responses and impacts to the wildfires and PSPSs in Sections 4.2 - 4.3. Finally, we use the historical data and analysis to evaluate the overall effectiveness of PSPSs in limiting wildfire damage (Section 4.4). Implications, limitations and final conclusions are discussed in Section 5.

2 Analytical Model

PSPS outages, along with actual and potential fire damage by county and economic sector were used as inputs to a general equilibrium. To elucidate the mechanisms of economic impact we set up and solve a stylized analytical general equilibrium model of a local economy facing losses from both wildfires and electric power disruptions. Algebraic solutions illustrate the theoretical responses of welfare and the outputs of housing and non-housing sectors to electricity outages as well as wildfire direct losses and indirect disutility (e.g., households' smoke exposure), and how these responses depend on the structure of the economy (sectors' relative sizes, their electricity intensity, elasticities of substitution, the intersectoral distribution of electricity and non-electric inputs) and the PSPSs' mitigation effectiveness.

The stylized analytical model describes a highly simplified world: a closed economy of a single region with one representative agent. There are two producing sectors, housing (H) and non-housing (X) with output quantities q_H and q_X and prices p_H and p_X, respectively. Each sector relies on the same two inputs, electric power (E) and a composite factor (Z), with a constant elasticity of substitution parameterized by shares θ_H and θ_X and elasticities of input substitution σ_H and σ_X. The share of electricity, and the composite factor, consumed by the housing sector are denoted ϵ and ζ, respectively. Households derive utility from consumption of both housing and non-housing, but the occurrence of wildfire diminishes utility (described in more detail below). For simplicity, household utility is defined by CES preferences, with technical coefficient ϕ and elasticity of substitution σ_U.

Wildfire (f) has two channels of impact on our stylized economy. First, it causes capital stock destruction, reducing the supply of the composite factor, Z, resulting in quantity and price effects. Second, we model a direct disutility to households, parameterized by a theoretical coefficient δ. This represents impacts to households such as smoke exposure, evacuation, and emotional distress. Public Safety Power Shutoffs (s) reduce the occurrence of wildfire with modeled effectiveness η. This effect appears in our model as a reduction in electricity supply, resulting in quantity and price impacts, as well as to reduce the impacts of fire (both capital stock losses and direct disutility).

The effects of fire and shutoffs can be seen in Table 1 equations 4a, 4b, and 4i.

As in Fullerton and Metcalf [18], Lanzi and Sue Wing [19], and Sue Wing and Rose [15], the model of the economy is described as a system of log-linear equations. A "hat" over a variable indicates the logarithmic differential, approximating a small fractional change from its equilibrium value (e.g., $\widehat{x} = d \log x = dx/x$). The entire economy is described by the 11 equations in Table 1. Equations 4a and 4b describe market clearance for electricity and the composite factor; that is, any changes in supply are met with an equal change in demand. Equations 4c and 4d describe the sectoral production functions with constant returns to scale. Conditions of zero profit with perfectly competitive supply are described by equations 4e and 4f. Sectoral input substitution and final household demand substitution are defined with eqs. (4g), (4h) and (4j), and finally, household utility is described in (4i). With 11 equations and 11 unknowns (including $\widehat{p_z}$ which is set to zero), we are able to solve the model analytically.

The solutions to each unknown share the following form (for variable ν):

$$\Upsilon_{\nu,F}\widehat{f} + \Upsilon_{\nu,S}\widehat{s} \tag{1}$$

where coefficients, Υ, are functions of the economic parameters:

$$\Upsilon_{\nu,F} = \Psi_{\nu,F}(\epsilon, \zeta, \phi, \theta_H, \theta_X, \sigma_H, \sigma_X, \sigma_U, \delta)/\mathcal{D}(\epsilon, \zeta, \phi, \theta_H, \theta_X, \sigma_H, \sigma_X, \sigma_U) \tag{2}$$

$$\Upsilon_{\nu,S} = \Psi_{\nu,S}(\epsilon, \zeta, \phi, \theta_H, \theta_X, \sigma_H, \sigma_X, \sigma_U, \delta, \eta)/\mathcal{D}(\epsilon, \zeta, \phi, \theta_H, \theta_X, \sigma_H, \sigma_X, \sigma_U) \tag{3}$$

We include the full solutions and detailed explanation in Appendix A.1.

Table 1: Model equations

Electricity mkt. clearance:	$-\widehat{s} = \epsilon \widehat{q}_{E,H} + (1-\epsilon)\widehat{q}_{E,X}$	(4a)
Composite factor mkt. clearance:	$-\widehat{f} + \eta\widehat{s} = \zeta \widehat{q}_{Z,H} + (1-\zeta)\widehat{q}_{Z,X}$	(4b)
Housing production f'n:	$\widehat{q}_H = \theta_H \widehat{q}_{E,H} + (1-\theta_H)\widehat{q}_{Z,H}$	(4c)
Non-housing production f'n:	$\widehat{q}_X = \theta_X \widehat{q}_{E,X} + (1-\theta_X)\widehat{q}_{Z,X}$	(4d)
Housing zero profit:	$\widehat{p}_H + \widehat{q}_H = \theta_H(\widehat{p}_E + \widehat{q}_{E,H}) + (1-\theta_H)(\widehat{p}_Z + \widehat{q}_{Z,H})$	(4e)
Non-housing zero profit:	$\widehat{p}_X + \widehat{q}_X = \theta_X(\widehat{p}_E + \widehat{q}_{E,X}) + (1-\theta_X)(\widehat{p}_Z + \widehat{q}_{Z,X})$	(4f)
Housing input substitution:	$\widehat{q}_{E,H} - \widehat{q}_{Z,H} = -\sigma_H(\widehat{p}_E - \widehat{p}_Z)$	(4g)
Non-housing input substitution:	$\widehat{q}_{E,X} - \widehat{q}_{Z,X} = -\sigma_X(\widehat{p}_E - \widehat{p}_Z)$	(4h)
Utility function	$\widehat{u} = \phi\widehat{q}_H + (1-\phi)\widehat{q}_X - \delta(\widehat{f} - \eta\widehat{s})$	(4i)
Household input substitution:	$\widehat{q}_H - \widehat{q}_X = -\sigma_U(\widehat{p}_H - \widehat{p}_X)$	(4j)
Numeraire:	$\widehat{p}_Z = 0$	(4k)

3 Data and Methods

3.1 Data

3.1.1 Input-output economic accounts

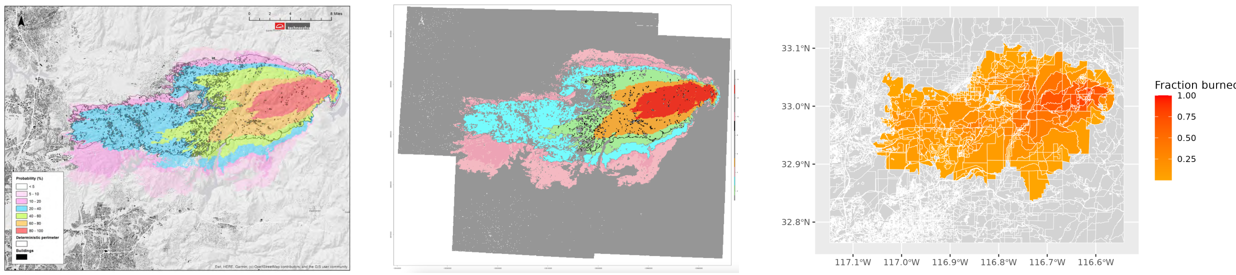
Our analytical model is parameterized using economic accounts data from IMPLAN [20]. IMPLAN gathers data from a variety of sources; key data comes from U.S. Bureau of Economic Analysis, U.S. Department of Agriculture, U.S. Bureau of Labor Statistics, and U.S. Census Bureau. The compiled data captures all economic flows of the economy. This includes the demand for final commodities and the intermediate and primary inputs to production as well as a complete set of industries outputs. The data represent the flows of good and services for a particular benchmark year. We used data available for 2012 and scaled it to a 2019 baseline year by multiplying by the GDP growth rates for the modeled sectors from the US Bureau of Economic Analysis. The data are highly resolved sectorally and spatially and include estimates of inter-county trade flows. Given the aggregate, simplified nature of our model, we aggregate the input-output data to our two sectors for each county. For our model equations in Table 1, $\epsilon, \zeta, \phi, \theta_H, \theta_X$ are parameterized using the IMPLAN data.

3.1.2 Wildfire Occurrence

(a) 2019 and 2020 fire seasons: The California Department of Forestry and Fire Protection, CAL FIRE, together with the United States Forest Service, the Bureau of Land Management, and the National Park Service, maintains a geodatabase of historical fire perimeters [21]. The information includes fires on both public and private lands and is the most complete digital record of fire perimeters in California. We intersected the fire perimeters with census block cartographic boundaries to determine the percent of census block area burned in 2019 and 2020.

(b) Simulated counterfactual 2019 fires: To investigate the effectiveness of the power shutoffs, we make use of simulated fires that model a counterfactual world: what would have happened had there not been shutoffs? The CPUC contracted consulting group, Technosylva, to generate probabilistic fire simulations [22]. Following the PSPS events, the electric utilities reported damage incidents to their powerlines and assessed of the likelihood of these incidents sparking a fire. Technosylva used this information alongside weather forecasts and observational data, an estimate of the most likely time of ignition, and a novel metric to determine which ignitions were likely to escape initial attack, in order to simulate the spread of these would-be wildfires. They produced 5 reports on the 2019 PSPS Events covering over 600 damage incidents.

The fire spread modeling was conducted using their proprietary software which accounts for topographic characteristics (elevation, slope, aspect), weather (temperature, relative humidity and wind fields), surface fuel types and moisture (dead and live), canopy characteristics and foliar moisture content. For this analysis they included updated surface fuels data accounting for recent fires. They simulated each fire for 24 hours. Given uncertainty in exact time and location of ignition, forecasted weather, and model variables, they conducted probabilistic simulations. For this, they simulated each damage incident 100 times with variations to the input parameters, based on ranges from the literature. Of the 600 simulated fires, Technosylva produced probabilistic maps for the most damaging (see Figure 1a for an example). While the reports were made public,



(a) Technosylva map image (b) Processed image (c) Census block burn fraction

Figure 2: Example of georeferencing and resulting probabilistic burned area.

the underlying data were not released nor made available by the CPUC. To make use of these simulations, we used 35 of the map images and converted them to spatial data.

Converting the image files to spatial data broadly required two steps: georeferencing the images and performing an image classification using a clustering algorithm. After extracting the images from the report, this first step, georeferencing, places the image in space. To do so, we manually assigned anchor points, a mapping between the XY coordinates of the image and latitude and longitude of the earth. Each image required 5-6 anchor points (a larger extent would require more, to improve warping to the Earth's curvature). We used GDAL for the georeferencing process to transform the geographic coordinates and then warp the image using spatial interpolation. Then, the second step, image classification, is used to identify and differentiate the probability layers. The image classification algorithm we used is Self-Organizing Map (SOM) [23]. SOM is an artificial neural network algorithm used to reduce data dimensionality and map data similarities within the variable space into two dimensions. After the SOM was fit, k-means was used to separate the data into non-overlapping clusters. The colors on the image were used to cluster the data into raster layers.

In the end, this process yielded rasterized spatial objects with layers corresponding to the probability bands (example shown in Figure 2b). From this, we can find the expectation of area burned by integrating over the bands and performing the census-block spatial intersection as in the previous section (example in Figure 2c).

3.1.3 Hazus general building stocks

In order to estimate the capital stock losses due to fires, we use census-block level data on building value and building content value from the Federal Emergency Management Agency's (FEMA) Hazus Program. The Hazus Program develops a set of tools and data used for estimating risk from natural hazards in the United States. Underlying their modeling is an inventory of building stock by occupancy class. The residential data comes from the U.S. Census American Community Survey and building counts for other occupancy classes come from a variety of primary sources and estimates. Hazus also estimates structure and content replacement values. Structure replacement values are based on survey data and vary by specific occupancy group and region. The building-content value comes from the National Institute of Building Sciences approximation based on a percent of structure value. Details about Hazus underlying data sources can be found in [24].

3.1.4 Public safety power shutoffs

In the last several years, California utilities intentionally caused nearly 5,000 circuit-level outages to mitigate wildfire risk. These outages lasted anywhere from minutes to over 6 six days and at times impacted hundreds of thousands of customers. Event reports and data describing these outages are required by the California Public Utilities Commission; the publicly available information enabled this analysis [25]. The outage event reports thoroughly detail the conditions and considerations that led to the outage decision. This includes information on weather conditions, fire risk, and the utility's assessment of how the benefits of de-energization outweigh the public safety risks. Of relevance to this analysis, the reports provide data on the event time, location, duration and number of customers impacted by customer classification (residential, commercial/industrial, and other). The geographic information includes the circuit name and a description of the communities impacted by each circuit outage (often a census-designated place).

The CPUC also compiles the outage data into an Excel file containing most of the same information as the reports, but notably missing the information identifying the communities impacted. This information is key for relating the customers impacted to their electricity usage (to estimate electricity loss). We scraped the PDF files for this information and joined it to the database. From the names of communities impacted, we were able to estimate the zipcodes affected. To do so, we joined the census-designated places with zipcodes (using online databases and manual searching) and in cases where multiple zipcodes were impacted, we shared out the customers. This information is necessary for estimating losses because utility disclosure data, described in Section 3.1.5, are at the zipcode level. Not all utilities reported the specific communities impacted; for SoCal Edison customers we had to aggregate impacts at the county level.

3.1.5 California electricity usage data

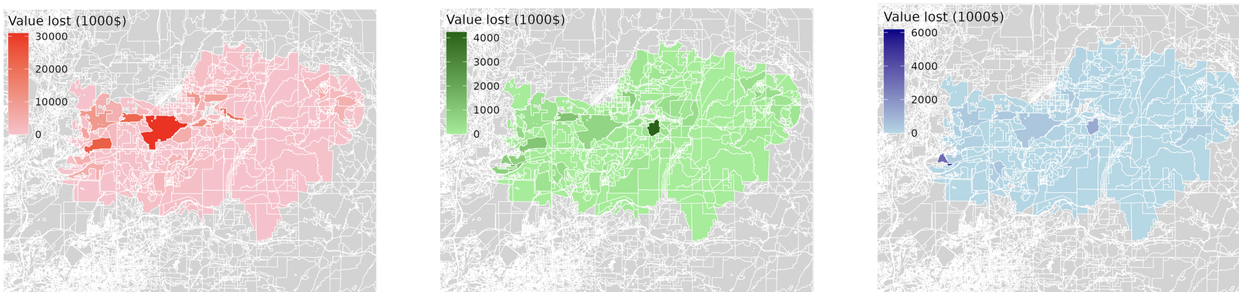
Beginning in 2014, the CPUC required electric utilities to provide access to energy usage data in manner that allows for protection of privacy [26]. Following that decision, the utilities publicly report the total monthly sum and average of customer electricity usage by zip code and by customer class (with some exceptions when it violates anonymity). The customer classes are aggregated to residential, commercial, industrial, and agriculture. These data allow us to estimate the loss of electricity due to power shutoffs (Section 3.2.3) at the zip code and customer class level.

3.2 Methods

3.2.1 Numerical parameterization of the analytical model

In Section 2 we described a stylized model with a closed-form solution. Numerically parameterizing the analytical results enables us to compare the signs and magnitudes of welfare and output elasticities to wildfire and PSPS shocks across county economies, yielding insights into the economic and environmental correlates of vulnerability.

We parameterize the solutions using economic accounts data aggregated to the county and 2-sector level for $\epsilon, \zeta, \phi, \theta_H, \theta_X$ (Section 3.1.1). Electricity and the composite factor are assumed to be necessary inputs to housing and non-housing, and both sectors are necessary for agents' utility. Therefore, $\sigma_H, \sigma_X, \sigma_U \in (0, 1]$. We consider a range of potential values for these elasticities:



(a) Residential (b) Commercial (c) Industrial

Figure 3: Value burned by sector in example probabilistic fire

$(0.005, 0.25, 0.5, 0.75, 1)$ and perform a sensitivity analysis over these uncertain values. δ, the coefficient for the direct disutility of fire, is highly uncertain. While our model framework allows us to consider this parameter and compare its effect to that of capital stock losses, for this initial paper we set δ to 0. η, the parameter describing the effectiveness of power shutoffs in reducing capital stock losses, is estimated by regressing the simulated fire shocks on the power curtailment shocks (Section 4.4). We use a simple linear regression, but incorporate uncertainty in the potential number of, and resulting damages from, the simulated fires.

3.2.2 Natural hazard shocks: capital stock losses due to actual and counterfactual wildfires

Capital stock losses due to actual and simulated wildfires ($\widehat{f}$) are estimated from the geographic fire information (Section 3.1.2) and building stocks data (Section 3.1.3). We multiply the percent of area burned by the Hazus value for building and building-content value at the block level for the fires. This approach makes two key assumptions: that capital stock is uniformly distributed at the block level and that anything inside the fire perimeter is fully damaged. Finally, we aggregate losses to the county-level.

There are a few key differences for the simulated fires. First, they include a probability-adjustment for the area burned based on the uncertain input parameters (Figure 2a). We multiply this value by the percent of area covered by the band to adjust our area burned estimate (Figure 2c). This represents the conditional probability of area burned, given that the damage incident became a large fire. Figure 3 shows the probability-adjusted block areas burned multiplied by the

Hazus values for each sector in an example simulated fire. Depending on the distribution of capital, blocks experience different losses by sector.

Second, we consider the probability that each of these incidents would have sparked a fire. If all counterfactual fires had occurred, the losses would have been an order of magnitude greater than that of the actual fires. This would rival some of the worst fires seen in California. To account for this type of uncertainty, we sample the number of fires (1-35) and which of the fires occurred using a uniform distribution and re-calculate the block level losses. We repeat this process 10,000 times to consider a full distribution of losses. Several of the simulated ignitions occurred in close proximity (and time) and would have burned the same blocks. To avoid double counting capital stock losses, we take the average of losses across the fires for a given block before aggregating to the county level.

3.2.3 Adaptation shocks: electric power curtailment due to PSPSs

In order to estimate the curtailment of electricity, we mapped impacted communities to zip codes, the most granular-level of electricity usage data in public records. Electricity usage data in California is available at the zipcode-month level for several aggregate customer classes. We use average electricity usage data from a non-PSPS year (2017 for PG&E and SCE, 2016 for SDG&E) to estimate the percent curtailed as follows:

$$\text{County shares of outages by use class}(CS_{u,c}) = \frac{\Sigma_{z \in O \text{for each c}} E_{u,z,c}}{\Sigma_{z \in O} E_{u,z,c}} \tag{5}$$

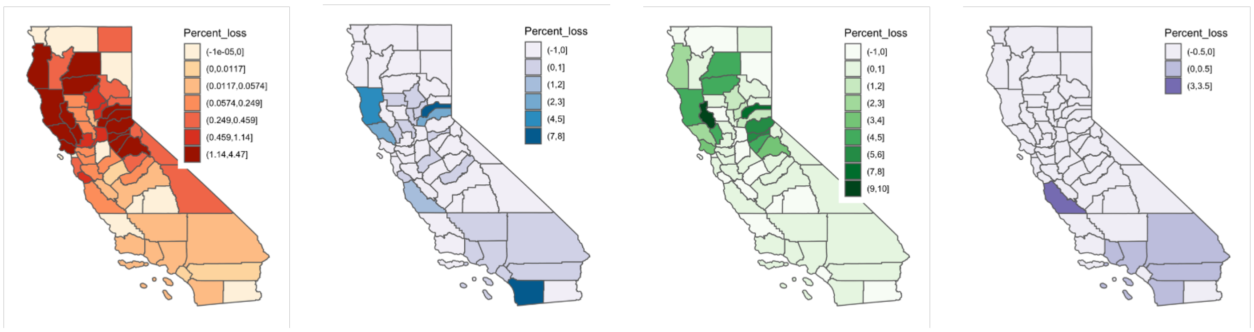
$$\text{Shock (\% reduction in Sept-Dec electric power)} = \frac{A * CS_{u,c} * EI_u}{\Sigma_{z(c)} E_{u,z(c)}} \tag{6}$$

where $E_{u,z(c)}$ = electricity use by all zipcodes in county, A = affected customers (by use class), and EI_u = electricity per capita by use class. This approximation assumes an average electricity intensity for a given customer class and zipcode. Importantly, it also averages over time and does not capture the time-of-day electricity usage effects. In some cases, 1 circuit-level outage affects customers in multiple zipcodes. Here, we chose to share out the losses based on electicity usage across the zipcodes. The use classes are also defined differently across the two datasets, with the outage data reporting commercial and industrial customer losses together. We distribute the outages between these two use classes based on the fraction of customers in the zipcodes covered by that circuit outage. We then aggregate the results up to the county and fire season level. With these data limitations in mind, the end result of this calculation gives us the percent of September to December electricity curtailed for residential, commercial, industrial, and agricultural customers for each county. We compute the shocks for the 2019 and 2020 fire seasons.

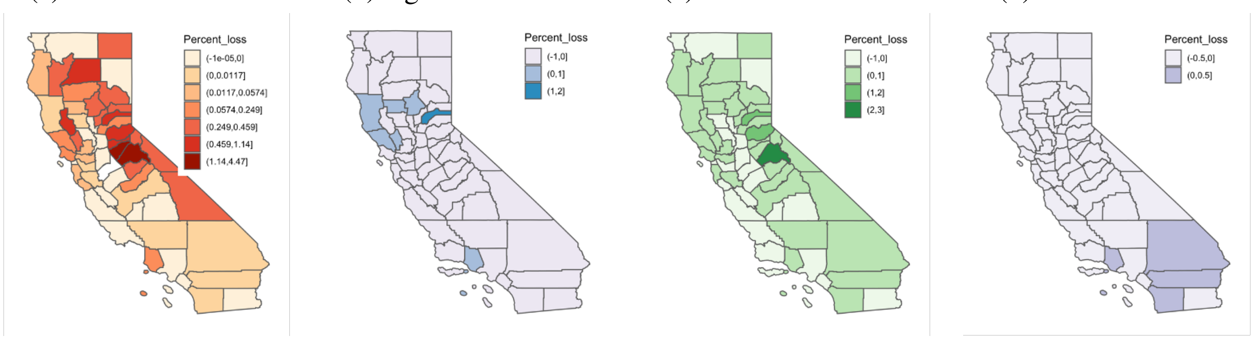
4 Results

4.1 PSPS and Wildfire Shocks

Electricity curtailment is geographically and sectorally heterogeneous. At worst, counties faced up to 10% losses relative to typical September to December power demand. In 2019, shutoffs were generally worse than in 2020, as can be seen by comparing rows in Figure 4, despite the latter season being more severe due to lightning strikes- driven, larger wildfires. This may be attributable to improvements in PSPS planning that allow for more targeted shutoffs or to less problematic fire weather (from the utilities' perspective). Geographically, there are consistently high curtailments in areas of high-risk. Counties such as Mendocino, Lake, Nevada, and El Dorado, all at high wildfire risk, experienced large shutoffs (2-8%) across several sectors in both years. Across sectors, more residential customers experienced outages, but given households' low average seasonal electricity consumption, their fractional curtailment was smaller (0- 4.5% over the Sept-Dec fire season) than commercial and agricultural sectors (0-10% and 0-8%, respectively). On the whole, these represent remarkably high curtailments in several counties. Figure 5a shows the 2019 power curtailments aggregated across sectors.

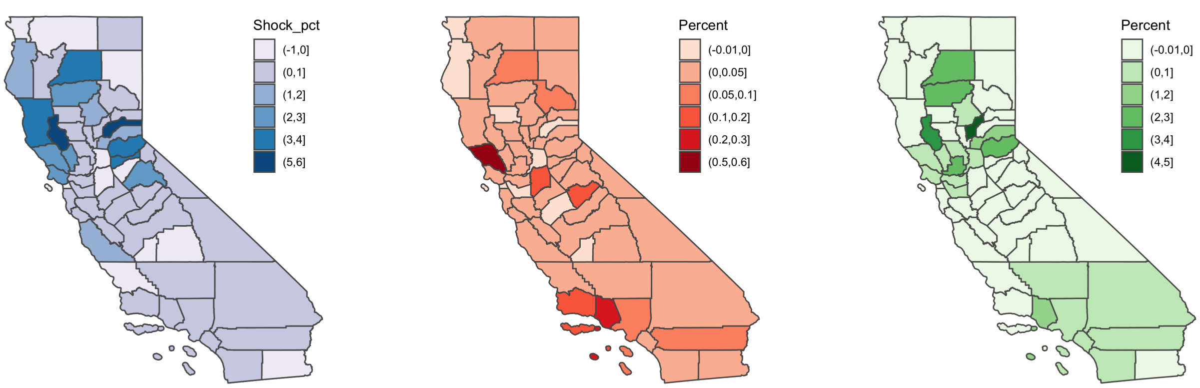


(a) Residential 2019 (b) Agricultural 2019 (c) Commercial 2019 (d) Industrial 2019



(e) Residential 2020 (f) Agricultural 2020 (g) Commercial 2020 (h) Industrial 2020

Figure 4: Percent curtailment of September-December electric power due to PSPS



(a) Aggregate Sept.-Dec. power curtailment: $\widehat{s}$

(b) Capital stock losses from 2019 fires

(c) Capital stock losses from simulated fires

Figure 5: 2019 county-level input shocks aggregated across sectors

The 2019 California fire season was mild compared to other recent years. The most significant fire, the Kincade Fire in Sonoma county, grew to over 77,000 acres and destroyed approximately 375 structures. Figure 5b shows the estimated percent capital stock losses by county based on the method described in Section 3.1.2. Losses range from 0 to 0.5% with the worst impacts in Sonoma, Ventura, San Joaquin and Mariposa Counties. While wildfires cause many other monetary and non-monetary impacts including injury, direct loss of life, health impacts from smoke, psychological impacts, and suppression costs, our shock input is limited to capital stock losses. In the analytical model framework, we could capture these other impact channels through the coefficient δ, which imposes a direct loss to utility.

Figure 5c shows the capital stock losses avoided by the PSPS outages. The median value for each county across the 10,000 simulations of number of fires is shown. Had this counterfactual world occurred, there could have been losses as high as 3-4% of capital stock in some counties (Yuba, Lake) with many other counties also suffering large impacts (greater than 2.5% in El Dorado, Tehama, Solano and Shasta). The losses from the simulated fires were an order of magnitude higher than that of the fires that actually occurred. The fire shocks get implemented in the model following:

$$\widehat{f} = \widehat{f}^{Obs} + \widehat{f}^{Sim}$$

4.2 Economic responses to wildfires and PSPSs

In this section, we illustrate how differences across counties' economies, parameterized by aggregating economic accounts from IMPLAN, yield differences in responses of key economic outcomes to both wildfire and PSPS. We consider the gross cost of shutoffs, assuming $\eta = 0$ as well as the net effect of shutoffs, including an ameliorative effect on capital stock losses. For the latter, we show the coefficients with $\eta = 0.415$ (this value will be further explained in Section 4.4). Figure 4.2 shows the range of values for the coefficients of key variables across the counties and uncertain inputs. The coefficients show the change in each variable for a 1% change in capital stock losses or

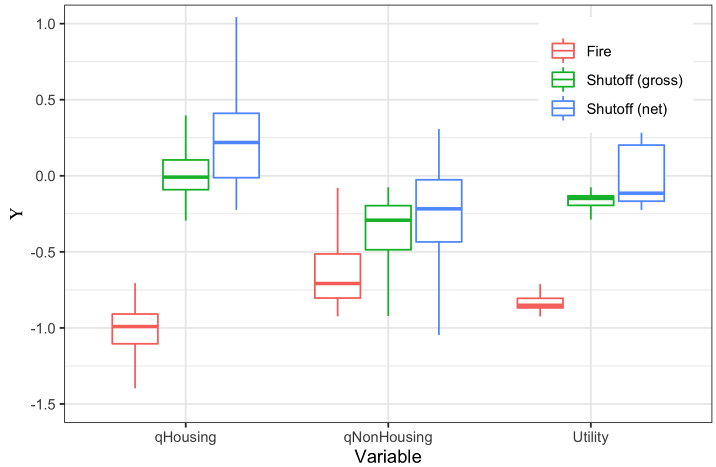


Figure 6: Υ_ν: Economic responses to wildfires and PSPSs for key variables under a range of assumptions. Gross shutoffs: $\eta = 0$, net shutoffs: $\eta = 0.415$

power curtailment, representing the county-level sensitivity to wildfire and shutoffs (coefficients $\Upsilon_{\nu,F}$ and $\Upsilon_{\nu,S}$ in Equation 2). The green boxes show the gross impact of shutoffs while the blue boxes show the net impact including their ameliorating effect on fires.

Housing output declines roughly 1% for every percent change in capital stock destruction. This effect is very consistent across counties but varies in magnitude with σ_H. Gross shutoffs, meanwhile, exhibit a very small magnitude of impact on housing output with an ambiguous sign; under some assumptions of substitution housing output actually increases. The share of electricity input to housing (relative to input of the composite factor) is very small (less than 1%) in all counties, limiting its impact. When the ameliorative effect of shutoffs is included, the shutoffs lead to increased housing output by around 0.25% for every 1% of power curtailment (by reducing the amount of capital burned).

Impacts on the non-housing sector output are uniformly negative and less than unitary for both fires and gross shutoffs. Electricity comprises a sizeable share (10-35%) of the input to non-housing in most counties, leading to some variation across counties but in general, a larger impact of shutoffs on non-housing than on housing output. When $\eta = 0.415$, the net impact of shutoffs on the non-housing sector spans 0, with the sign of effect depending on the counties' economic activity.

Unsurprisingly, the impact of fire on utility is uniformly negative and centered around -0.85. There is not much variation in this effect across counties or across assumptions for σ_U. Without including the ameliorating effect of shutoffs on reducing wildfire damage, shutoffs also cause a negative impact on utility in all counties. The magnitude of the shutoff coefficient on utility is lower than that of the fire, hovering around -0.1 to -0.3 for all counties. This makes intuitive sense, that a 1% curtailment of power is less disruptive to welfare than a 1% loss of capital stock. When including the effectiveness of shutoffs in reducing losses, the net impact of shutoffs on utility is positive in some counties and negative in others. The sign depends on the relative elasticity of the shutoffs and avoided wildfires. A positive coefficient implies that the cost of a shutoff in that county would be outweighed by its benefit in avoiding capital stock losses. The ultimate balance of costs and benefits will depend on both the elasticities and the shocks.

4.3 Economic Impacts of Wildfires—and Power System Adaptation to Them

From the coefficients described in Section 4.2 and the wildfire and PSPS shocks in Section 4.1 we can determine the impacts to welfare and and the net cost or benefit of this adaptation policy. Using the solutions to $\widehat{u}$ in Appendix Equation (reference appendix) we will compare our two scenarios. First, had there not been shutoffs, we would have seen both the observed fires and the simulated counterfactual fires ($\widehat{f} = \widehat{f}^{Obs} + \widehat{f}^{Sim}$ and $\widehat{s} = 0$). Using Appendix Equation (2 - reference this), we can multiply the combined fire shocks (Figures 5b and 5c) by our coefficients on utility ($\Upsilon_{u,\widehat{f}}$). The results are shown in Figure 7d. Wildfire destruction would have caused very significant welfare impacts in many counties, with effects up to 3% of county utility. (Should I put this in dollar terms?).

We can compare this to the world we observed with both power shutoff events and residual wildfires. Since we have information on observed wildfires we can substitute the theoretical impact of shutoffs on fire damage with the observed damage ($-\widehat{f} + \eta\widehat{s} = -\widehat{f}^{Obs}$) in Appendix Eq. (3 - reference). Figure 7a shows the gross impact on utility of the PSPS shutoff events. At worst, counties suffer up to a 1% change in utility (Nevada County), with several others facing losses around 0.5%. The spatial pattern of welfare impacts are generally aligned with the location of the shutoffs. However, there are some counties that are particularly sensitive to shutoff shocks. For example, the welfare impacts in Amador County are slightly higher than that of Mendocino, despite the former having a smaller shutoff. Welfare impacts of wildfires ranged from 0-0.5%. The impacts scale closely with the fires and capital stock losses themselves. Figure 7c shows the sum of panels 7a and 7b. Some counties faced combined impacts from shutoffs and fires but on average the counties' welfare losses did not exceed 1%.

Comparing panels 7c and 7d reveals the potential benefits of the power shutoffs. First, we can see that the worst losses are avoided, considering the several counties with welfare impacts greater than 1% had the shutoffs not happened. However, the effect is heterogeneous and several counties faced mis-targeted shutoffs leading to net costs. On average across counties, there is a net benefit; we find that the welfare impacts are smaller in the shutoffs scenario than if the counterfactual fires had occurred.

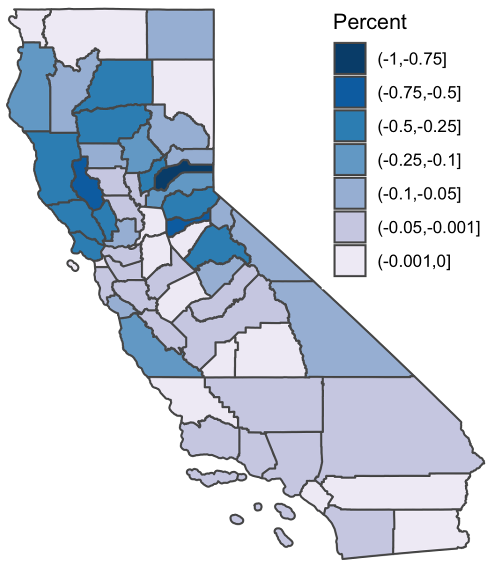
4.4 The Effectiveness of PSPSs

The analysis in Section 4.3 assumes we are looking backwards and have knowledge of the wildfires that occurred, net of adaptation. Looking forward, we may have modeled estimates of fire risk ($\widehat{f}$) and have to make decisions about power shutoffs ($\widehat{s}$) accordingly. Using the historical data, we can learn about the effectiveness of shutoffs more generally and use this to guide future policy-making. This section describes a simple method for estimating effectiveness. Future work should build on this and continue to iterate as more shutoffs and simulated fire data becomes available.

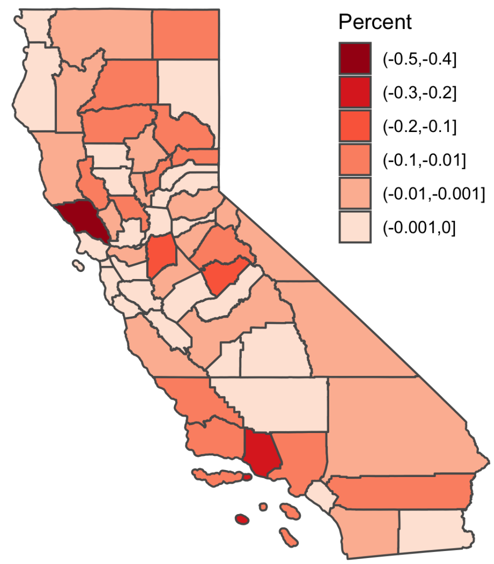
In our model, the effectiveness of shutoffs is represented by parameter η. Using the simulated fires, we estimate eta as:

$$\eta_c = \frac{\text{avoided \% capital stock losses}}{\text{\% reduction in power}} \tag{7}$$

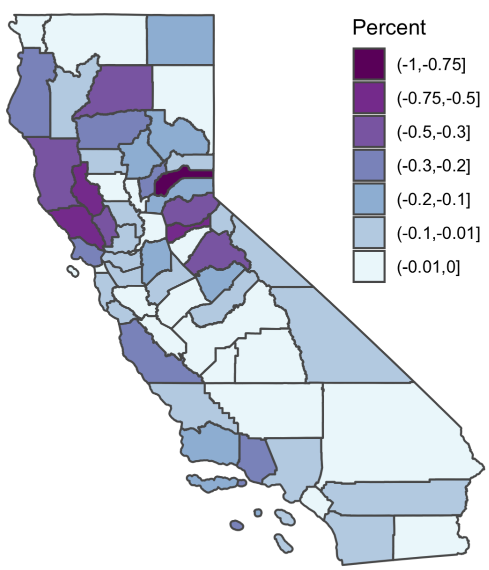
For an initial estimate, we run a county-level linear regression testing the effect of aggregate power



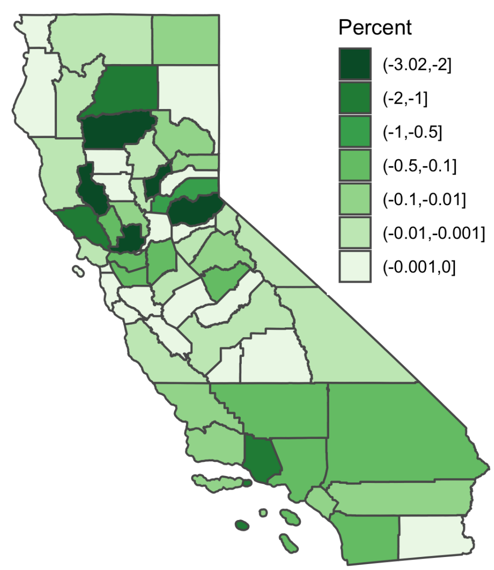
(a) Shutoff impact on utility



(b) Wildfire impact on utility (actual fires)



(c) Net impact on utility - shutoffs and actual fires



(d) Net impact on utility - actual and simulated fires

Figure 7: Welfare impacts of wildfires and shutoffs

curtailments on avoided capital stock losses (Figure A.2). When all 35 fires are included, the regression estimate is 0.5556 and is statistically significant at $\alpha = 0.001$. At the county level, we can see many instances where power was curtailed and no fire would have started (points along the x-axis in Figure A.2) and several outage events that may have prevented significant capital stock loss (points towards the top of Figure A.2). County-level aggregates potentially bias this estimate; in reality there were likely many circuit level outages that would not have resulted in a fire and several small outages that prevented significant damage. In Section 5, we will talk more about this limitation and plans to improve our estimate.

In addition to bias arising from aggregation, there is significant uncertainty in which of the simulated fires would have occurred without the shutoffs. We re-estimate the coefficient for each of the 10,000 simulations described in Section 3.2.2. Figure 8 shows the range of statistically significant values for η based on our uncertainty analysis. The median value is 0.415, close to the estimate when including all 35 fires, with the mean slightly lower at 0.398. The majority of runs yielded estimates between 0.3 and 0.52, indicating that shutoffs are, on the whole, effective at avoiding capital stock losses. However, runs with more fires are more likely to produce statistically significant estimates, so this effect may be an overestimate.

5 Discussion and conclusions

We have developed a stylzed analytical general equilibrium model to explore the economy-wide impacts of wildfires and the power system adaptation to them. The model distills the economy down to 1 region and 2 sectors which allows us to algebraically solve the model and understand the mechanisms underlying the impacts. We numerically parameterize the model using economic accounts data, estimates of the power curtailed in the 2019 shutoffs, capital stock losses from the 2019 wildfires, and simulations of the fires avoided by the shutoffs.

While electric utilities have been conducting PSPS for several years, there is very limited understanding of the balance of costs and benefits of this policy. We find that the impacts depend on

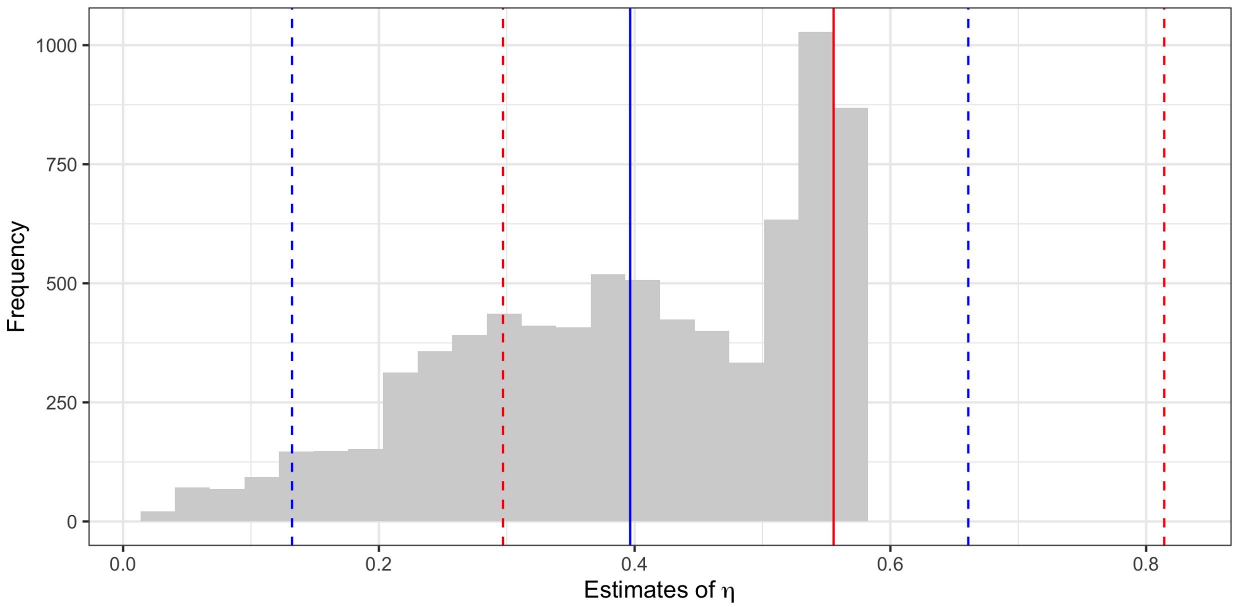


Figure 8: Estimates of the parameter η with linear regression and parametric uncertainty analysis. Red lines show mean and CI for 35 fire estimate. Blue lines show mean and CI across all estimates.

the economic responses to the shutoffs and wildfires as well as the hazard risk and targeting of the shutoffs. We see that the metrics of impact in our simple economy, changes to sectoral output and household welfare, are more sensitive to fire destruction than to power curtailment. Given the data on actual 2019 shutoffs and wildfires, we estimate welfare losses up to 1% in some counties. This is an improvement (on average) over the welfare losses that would have occurred due to additional wildfires without the shutoffs – sometimes as high as 3%. Depending on the hazard and targeting of the shutoffs, some counties fare worse with the shutoffs.

In this paper, we take a first attempt at estimating the effectiveness of the shutoffs in reducing capital stock losses using a linear regression at the county level. We find that for every 1% of power curtailed, approximately 0.4% of capital stock losses are avoided. While the specific value ranges under our uncertainty analysis, the finding is the same: shutoffs are highly effective at limiting wildfire damage. Given that counties' economies are significantly more sensitive to the impacts of wildfire ($\Upsilon_{u,\widehat{f}}$ averaging around 0.85) than that of shutoffs ($\Upsilon_{u,\widehat{s}}$ averaging around 0.15), well targeted shutoffs lead to a net benefit. This information will be very useful for implementing and regulating PSPS policy moving forward.

Our findings, if true, imply that electric utility implementation of PSPS in 2019 avoided significant wildfire damages and led to state-wide benefits. The county level effects varied and better targeting of shutoffs would improve welfare outcomes. However, there were many limitations to our approach that might influence our interpretation. Processing the shutoff and historical wildfire data involved several steps of aggregations and averaging. Despite our granular shutoff data, we estimated power losses using monthly average electricity, losing valuable information about time-of-day electricity use, potentially biasing our shutoff shocks. The assumption of uniform capital stock destruction at the block level likely did not make a large impact on our wildfire impact estimates. However, assuming complete destruction of buildings within a fire footprint may be an overestimate given advances in fire-proof construction.

Data on the counterfactual fires comes from assessments done by the electric utilities. The utilities do not bear the cost of the shutoffs but do face significant consequences if they are found guilty of igniting a wildfire. They would thus be incentivized to take a conservative approach which could have biased their retrospective analysis. If they want to convince regulators to support the shutoffs, they would emphasize the potential harms without them. This is a potentially large source of bias in our analysis. We tried to account for this with our uncertainty analysis but expect that our estimates of counterfactual fires are biased upwards. The limited years of shutoffs and simulation of the counterfactual fires limited the scope of our analysis. Future work should iterate on our findings as more data becomes available. Our estimate of effectiveness can be improved by resolving the data at the event-zipcode level rather than aggregating to the counties. We intend to conduct a robustness check at this more granular level and similarly hope to incorporate more years of data.

More generally, there is uncertainty arising from our choice of model. It is difficult to trust the numbers coming from such a simple, stylized model but this work can complement more detailed modeling work. Similarly, the choice of general equilibrium analysis creates potential limitations. First, it required us to model adjustments to the equilibrium over a several month period. This is a reasonable assumption for long duration and widespread impacts, but may not have been appropriate for the shutoff shocks. A comparison of the cost of the shutoffs found through our general equilibrium approach with a more traditional value of lost load partial equilibrium method may help shed light on the key differences.

While we acknowledge the limitations of our study, we believe this first-of-its-kind analysis contributes important knowledge to the policy evaluation of a wildfire ignition mitigation strategy, PSPS. We provide a retrospective analysis of the net costs and benefits of the use of this policy in 2019 and consider a path forward for prospective decision-making. Both wildfires and power curtailments have real impact on peoples' lives and we hope to improve quantification of these impacts and the potential benefits of adaptation.

References

[1] CalFire (2022). Top 20 Most Destructive California Wildfires.

[2] CAL FIRE (2020). Wildfire Activity Statistics. 2020 Redbook Final.

[3] Goss, M., Swain, D. L., Abatzoglou, J. T., Sarhadi, A., Kolden, C. A., Williams, A. P., & Diffenbaugh, N. S. (2020). Climate change is increasing the likelihood of extreme autumn wildfire conditions across California. Environmental Research Letters, 15(9), 94016. https://doi.org/10.1088/1748-9326/ab83a7

[4] Keeley, J.E., & Syphard, A.D. (2016). Climate Change and Future Fire Regimes: Examples from California. Geosciences, 6, 37. https://doi.org/10.3390/geosciences6030037

[5] Williams, A. P., Abatzoglou, J. T., Gershunov, A., Guzman-Morales, J., Bishop, D. A., Balch, J. K., & Lettenmaier, D. P. (2019). Observed impacts of anthropogenic climate change on wildfire in California. Earth's Future, 7, 892– 910. https://doi.org/10.1029/2019ef001210

[6] Prichard, S.J., Hagmann, K., Hessburg, P. (2021). How years of fighting every wildfire helped fuel the Western megafires of today. The Conversation.

[7] Baylis, P. and Boomhower, J., (2019). Moral Hazard, Wildfires, and the Economic Incidence of Natural Disasters. NBER Working Paper No. w26550, Available at SSRN: https://ssrn.com/abstract=3504434

[8] Chen, B. and Jin, Y. (2022). Spatial patterns and drivers for wildfire ignitions in California. Environ. Res. Lett. 17 055004

[9] Penn, I. (2019). PG&E Bankruptcy Filing Creates 'a Real Mess' for Rival Interests. The New York Times.

[10] California Council on Science and Technology (2020). The Costs of Wildfire in California: An Independent Review of Scientific and Technical Information. Sacramento, CA: California Council on Science and Technology.

[11] CPUC (2012). Decision Granting Petition to Modify Decision 09-09-030 and Adopting Fire Safety Requirements for San Diego Gas & Electric Company. Decision 12-04-024.

[12] CPUC (2018). Resolution Extending De-energization Reasonableness, Notification, Mitigation, and Reporting Requirements in Decision 12-04-024 to All Electric Investor Owned Utilities. Resolution ESRB-8.

[13] Baik, S., Hanus, N. L., Sanstad, A. H., Eto, J. H., Larsen, P. H. (2021). A Hybrid Approach to Estimating the Economic Value of Enhanced Power System Resilience. LBL Report.

[14] Schröder, T. and Kuckshinrichs, W. (2015). Value of Lost Load: An Efficient Economic Indicator for Power Supply Security? A literature Review. Front. Energy Res., 24. https://doi.org/10.3389/fenrg.2015.00055

[15] Sue Wing, I. and A. Rose (2020). Economic consequence analysis of electric power infrastructure disruptions: General equilibrium approaches, Energy Economics 89: 104756.

[16] Wang, D, D Guan, S Zhu, M MacKinnon, G Geng, Q Zhang, H Zheng, T Lei, P Gong and SJ Davis. (2021) Economic footprint of California wildfires in 2018. Nature Sustainability. doi: 10.1038/s41893-020-00646-7

[17] Butry, D. T., Webb, D. H., O'Fallon, C. M., and Cutler, H. (2019). A Framework for Measuring the Impact of Wildland-Urban Interface Fires on a Regional Economy. NIST Technical Note 2026. https://doi.org/10.6028/NIST.TN.2026

[18] Fullerton, D. and G. Metcalf. "Tax Incidence." Handbook of Public Economics Vol. 4 (2002): 1787- 1872.

[19] Lanzi, E. and Sue Wing, I. (2013). "Capital Malleability, Emission Leakage and the Cost of Partial Climate Policies: General Equilibrium Analysis of the European Union Emission Trading System." Environmental and Resource Economics 55: 257-89.

[20] IMPLAN Data Overview and Sources. IMPLAN Group LLC.

[21] CAL Fire Fire Assessment and Resource Program. https://frap.fire.ca.gov/frap-projects/fire-perimeters/

[22] CPUC (2021). 2019 PSPS Event - Wildfire Analysis Report. Prepared by Technosylva Inc. https://www.cpuc.ca.gov/consumer-support/psps/technosylva-2019-psps-event-wildfire-risk-analysis-reports

[23] Kohonen, T. (1990). The Self-Organizing Map. Proceedings of the IEEE, Vol. 78. No. 9, September 1990.

[24] FEMA (2021). Hazus Inventory Technical Manual. Hazus 4.2 Service Pack 3.

[25] CPUC (2022). Utility Company PSPS Reports: Post-Event, Post-Season and Pre-Season. https://www.cpuc.ca.gov/consumer-support/psps/utility-company-psps-reports-post-event-and-post-season

[26] CPUC (2014). Decision Adopting Rules to Provide Access to Energy Usage and Usage-Related Data while Protecting Privacy of Personal Data. Decision 14-05-016.

A Appendix

A.1 Full analytical solution

The solution to analytical model is as follows. The endogenous variables are linear in the forcings, $\widehat{f}$ and $\widehat{s}$, elasticities with respect to which are complicated algebraic functions of the parameters. Endogenous variables have the common denominator:

$$\mathcal{D} = \sigma_U(\theta_H - \theta_X)(\epsilon - \zeta) + \sigma_H(\theta_H \zeta + \epsilon(1 - \theta_H)) + \sigma_X(1 - \theta_X \zeta - (1 - \theta_X)\epsilon) \tag{A.1}$$

The second and third right-hand side terms are unambiguously positive. Positivity of the first term turns on whether $\epsilon \geq \zeta$ and $\theta_H \geq \theta_X$, or $\epsilon \leq \zeta$ and $\theta_H \leq \theta_X$. Housing services production is not particularly electricity intensive (relative to, say, internet services or manufactured goods), so $\theta_H \leq \theta_X$. Also, if housing accounts for a smaller share of the total demand for electricity than it does for the total demand for the composite of all other inputs, then $\epsilon \leq \zeta$. Our baseline assumption is therefore that $\mathcal{D} > 0$.

The welfare impact of wildfire exposure, net of power shutoffs, can be written two ways:

$$\begin{aligned}
\widehat{u} = & \underbrace{\widehat{f}\,\mathcal{D}^{-1}\left[-\sigma_U(\theta_H - \theta_X)(\epsilon - \phi) - \sigma_H(1 - \theta_H)\epsilon - \sigma_X(1 - \theta_X)(1 - \epsilon))\right]}_{\text{Welfare cost of unobserved counterfactual + actually -occurring residual wildfire (D)}} \\
& + \widehat{s}\,\mathcal{D}^{-1}\left[\sigma_U(\theta_H - \theta_X)(\zeta - \phi) - \sigma_H \theta_H \zeta - \sigma_X \theta_X (1 - \zeta)\right. \\
& \qquad \left. + \,\eta(\sigma_U(\theta_H - \theta_X)(\epsilon - \phi) + \sigma_H(1 - \theta_H)\epsilon + \sigma_X(1 - \epsilon)(1 - \theta_X))\right] \qquad \text{(A.2)} \\
= & \underbrace{\underbrace{\left(-\widehat{f} + \eta\widehat{s}\right)}_{\widehat{f}^{Obs}} \mathcal{D}^{-1}\left[\sigma_U(\theta_H - \theta_X)(\epsilon - \phi) + \sigma_H(1 - \theta_H)\epsilon + \sigma_X(1 - \theta_X)(1 - \epsilon))\right]}_{\text{Welfare cost of actually-occurring residual wildfire (B)}} \\
& + \underbrace{\widehat{s}\,\mathcal{D}^{-1}\left[\sigma_U(\theta_H - \theta_X)(\zeta - \phi) - \sigma_H \theta_H \zeta - \sigma_X \theta_X (1 - \zeta)\right]}_{\text{Welfare cost of PSPSs (A)}} \qquad \text{(A.3)}
\end{aligned}$$

Given the sign of $\mathcal{D}$ and the relative magnitudes of the output elasticities ($\theta_H < \theta_X$) the welfare impact of wildfire ($\widehat{f} > 0$) is guaranteed to be negative if $\epsilon \leq \phi$. This is the case for both the capital stock destruction and distutility channels of influence. Power shutoffs ($\widehat{s} > 0$) have an ambiguous impact. Their direct welfare effect is negative if $\zeta \geq \phi$, and their ameliorative effects on capital stock destruction and disutility are positive given the assumed magnitudes of the parameters ($\epsilon \leq \phi \leq \zeta$). The degree to which PSPSs offset the direct welfare consequences of wildfires thus turns on the magnitude of their effectiveness, η.

Housing and non-housing output exhibit responses that are qualitatively similar to utility, but algebraically less complicated:

$$
\begin{aligned}
\widehat{q}_H =& \widehat{f}\,\mathcal{D}^{-1}\left[\sigma_U(\theta_H - \theta_X)(1-\epsilon) - \sigma_H(1-\theta_H)\epsilon - \sigma_X(1-\theta_X)(1-\epsilon))\right] \\
&+ \widehat{s}\,\mathcal{D}^{-1}\left[-\sigma_U(\theta_H - \theta_X)(1-\zeta) - \sigma_H\theta_H\zeta - \sigma_X\theta_X(1-\zeta)\right. \\
&\qquad \left.+\eta(-\sigma_U(\theta_H - \theta_X)(1-\epsilon) + \sigma_H(1-\theta_H)\epsilon + \sigma_X(1-\epsilon)(1-\theta_X))\right] && \text{(A.4)} \\
\widehat{q}_X =& \widehat{f}\,\mathcal{D}^{-1}\left[-\sigma_U(\theta_H - \theta_X)\epsilon - \sigma_H(1-\theta_H)\epsilon - \sigma_X(1-\theta_X)(1-\epsilon))\right] \\
&+ \widehat{s}\,\mathcal{D}^{-1}\left[\sigma_U(\theta_H - \theta_X)\zeta - \sigma_H\theta_H\zeta - \sigma_X\theta_X(1-\zeta)\right. \\
&\qquad \left.+\eta(\sigma_U(\theta_H - \theta_X)\epsilon + \sigma_H(1-\theta_H)\epsilon + \sigma_X(1-\epsilon)(1-\theta_X))\right] && \text{(A.5)}
\end{aligned}
$$

The key difference is the negative first term in η in the expression for $\widehat{q}_X$, which indicates that the efficacy of PSPSs increases utility and housing production, but is associated with declines in non-housing output.

Change in electricity input to housing and non-housing very similar to $\widehat{q}_H$ and $\widehat{q}_X$

$$
\begin{aligned}
\widehat{q}_{EH} =& \widehat{f}\,\mathcal{D}^{-1}\left[\sigma_U(\theta_H-\theta_X)(1-\epsilon)-\sigma_H(1-\theta_H)\epsilon-\sigma_X(1-\theta_X)(1-\epsilon))\right] \\
&+\widehat{s}\,\mathcal{D}^{-1}\left[-\sigma_U(\theta_H-\theta_X)(1-\zeta)-\sigma_H\theta_H\zeta-\sigma_X\theta_X(1-\zeta)\right. \\
&\qquad\left.+\eta(-\sigma_U(\theta_H-\theta_X)(1-\epsilon)+\sigma_H(1-\theta_H)\epsilon+\sigma_X(1-\epsilon)(1-\theta_X))\right] \qquad \text{(A.6)} \\
\widehat{q}_{EX} =& \widehat{f}\,\mathcal{D}^{-1}\left[-\sigma_U(\theta_H-\theta_X)\epsilon-\sigma_H(1-\theta_H)\epsilon-\sigma_X(1-\theta_X)(1-\epsilon))\right] \\
&+\widehat{s}\,\mathcal{D}^{-1}\left[\sigma_U(\theta_H-\theta_X)\zeta-\sigma_H\theta_H\zeta-\sigma_X\theta_X(1-\zeta)\right. \\
&\qquad\left.+\eta(\sigma_U(\theta_H-\theta_X)\epsilon+\sigma_H(1-\theta_H)\epsilon+\sigma_X(1-\epsilon)(1-\theta_X))\right] \qquad \text{(A.7)}
\end{aligned}
$$

The only differences from equations 5 and 6 are the effects on the σ_H terms in $\widehat{q}_{EH}$ (relative to $\widehat{q}_H$) and σ_X terms in $\widehat{q}_{EX}$ (relative to $\widehat{q}_X$).

Change in price of electricity is simply:

$$
\widehat{p}_E = -\widehat{f}\,\mathcal{D}^{-1}+\widehat{s}\,\mathcal{D}^{-1}(1+\eta) \qquad \text{(A.8)}
$$

This implies that the price is reduced by the fire shock, which reduces capital stock (and therefore demand for electricity) but increased by the shutoffs (which reduce supply). The sign of the resultant change depends on the magnitudes of these forces and the effectiveness of shutoffs. (Assuming $\mathcal{D} > 0$, as described above).

A.2 Estimating eta

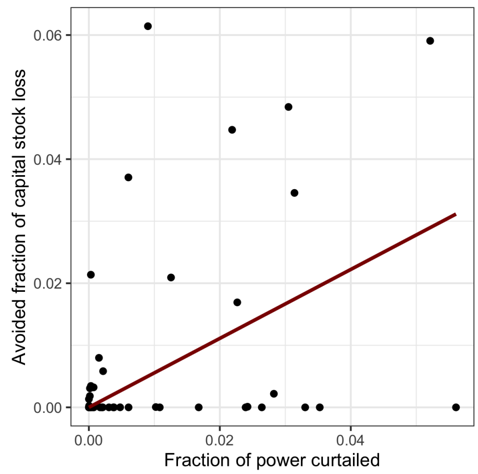


Figure A.2: County-level estimate of η with all 35 simulated fires