Economic Consequences 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 the cost of wildfires and that of an adaptation measure used to avoid them. We process 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 economic output and household welfare depends on the economic structure, targeting off shutoffs, and magnitude of wildfire risk.

Keywords: wildfire adaptation; public safety power shutoffs; general equilibrium modeling; wildfire impacts

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1 Introduction

Wildfires present a catastrophic risk to the Western United States, and California in particular. Despite being a natural, and even beneficial, process for ecosystems, fires have recently caused inordinate property damage. Fifteen of the 20 most destructive fires have occurred since 2015 and the 2020 fire season broke records for acres burned, with California experiencing 9,600 fires that burned an area four times larger than the 2015-2019 average (CAL FIRE, 2022, 2020). Losses from these fires exceeded $16 billion and millions of Californians faced weeks of poor air quality from the smoke. Multiple factors contribute to the increasing trend of catastrophic fires. Wildfires need an ignition source to start, fuels to consume, and extreme weather to spread rapidly. Climate change and extreme weather, especially hot and dry conditions, have been attributed to the lengthening and intensification of wildfire seasons (Goss et al., 2020; Keeley and Syphard, 2016; Williams et al., 2019). Historical fire suppression practices have led to the build-up of fuels in otherwise fire-adapted forests (Prichard, Hagmann). Increasing population and property development in the wildland-urban interface (WUI) has incentivized aggressive suppression to protect people and property in harm's way (Baylis and Boomhower, 2019). Simultaneously, fire ignitions have increased with the expansion of population in close proximity to forests. Over 80% of ignitions are caused by human a wide range of activity, with sources ranging from cars backfiring, to arson, fireworks, and powerlines sparking fires (Chen and Jin, 2022).

These circumstances have heightened interest in the effectiveness of measures to both mitigate the occurrence of large fires and reduce their impacts on people and property. Here we focus on a specific mitigation strategy for reducing ignitions: public safety power shutoffs (PSPS). Sparking of electric transmission and distribution lines cause only 10% of ignitions, but they are responsible for nearly 50% of the most damaging wildfires (CAL FIRE, 2022)—including the devastating 2018 Camp Fire in Paradise, CA that led to 85 casualties. These types of fires are often ignited during high wind events that can cause powerlines to sway into contact with vegetation, or be brought down entirely, sparking fires. The same weather conditions are conducive to wildfire spread. Utilities are held strictly liable for the damages from wildfires that are found to be caused by their powerlines. Pacific Gas & Electric (PG&E) was found guilty of igniting the deadly Camp Fire, leading to $30 billion in liabilities that prompted the company to file for bankruptcy protection (Penn, 2019).

To bolster public safety and avoid significant wildfire losses, California's electric utilities have invested heavily in ignition mitigation. In 2019, the three large investor-owned utilities reported approximately $4.7 billion in system hardening, vegetation management, and equipment inspection (CCST, 2020). In addition, utilities have recently pursued PSPSs, when high fire risk weather is forecast, pre-emptively de-energizing powerlines to reduce the probability of them sparking, and causing ignitions. The use of PSPSs as a wildfire mitigation intervention stem from a 2012 California Public Utilities Commission (CPUC) finding that San Diego Gas & Electric (SDGE) had the authority to "de-energize powerlines in a manner that is consistent with their fundamental statutory obligation to protect the public safety" (CPUC, 2012). Subsequent CPUC filings extended this authority to other utilities, and codified rules and requirements for reasonableness, notification, mitigation and reporting (CPUC, 2018). Among other requirements, utilities must submit post-event reports detailing the factors leading to the decision, customer notifications and outage information. The use of PSPSs as a wildfire mitigation tool only became widespread in the 2019 and 2020 fire seasons, at times leading to as many as 1 million customers without power. These shutoffs are likely to have significant adverse impacts on affected electricity consumers, and negatively affect economic activity in the regions where electricity service outages occur. However, the associated economic costs are not well understood.

This study analyzes the economic consequences—both costs and benefits—of PSPSs conducted in 2019. Research on the costs of electric power disruption can be broadly classified into two methodological categories: the use of customer surveys to estimate customer interruption costs and regional economic modeling (Baik et al., 2021). Surveys of U.S. electric utilities' customers on their losses incurred due to power outages of varying duration and timing have been used to estimate the willingness to pay to avoid disruptions. The latter are used for planning purposes, whereby reliability measures are implemented up to the marginal cost of outages, and in research on the costs of historical outages (Schröder and Kuckshinrichs, 2015). Although common, these surveys tend not to be well suited for longer-duration outages over large geographic areas. By contrast, the present study is part of a growing body of literature that uses economic 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 large-scale electricity supply disruptions due to hypothetical extreme events such as earthquakes, terrorist attacks, and other disasters (Sue Wing and Rose, 2020; Rose et al., 2015; Wein et al., 2013; Rose et al., 2011). These studies utilize general equilibrium models, which are comprehensive, economy-wide numerical representations of supplies and demands across all sectors, albeit in an aggregate fashion. Following a shock or policy change to supply or demand, the models estimate new equilibrium prices and quantities across all sectors based on market equations and substitution (Baik et al., 2021). The benefit of general equilibrium modeling lies in its economy-wide structure, allowing for quantification of impacts that ripple to downstream sectors.

Distinctly, regional economic modeling has been used to analyze the impacts of both wildfire and mitigation actions. Wang et al. (2021) estimated the economic footprint of the 2018 California wildfires including direct capital losses, health costs from smoke and indirect losses. Direct losses were used as inputs to an input-output model, which was simulated to generate the output losses of industrial sectors in other regions disrupted by supply-chain links. Their key finding was that indirect losses made up the bulk of wildfires' economic impacts. Butry et al. (2019) model several economic consequences of wildfires in the WUI—including capital stock (structure) destruction, business interruption, and out-migration, as well as ameliorating effects of various mitigation measures. They propose an integrating framework using economic concepts of general equilibrium, but defer actual modeling to future work. Our objective is to build on these approaches to characterize the potential economywide cost savings of PSPSs as a specific risk mitigation technique.

Both the destruction of physical capital by wildfire, and the costs of electricity curtailment imposed by PSPSs, exert direct and indirect effects on the affected economy. In this paper we develop an analytical general equilibrium model of the individual and combined impacts of wild-

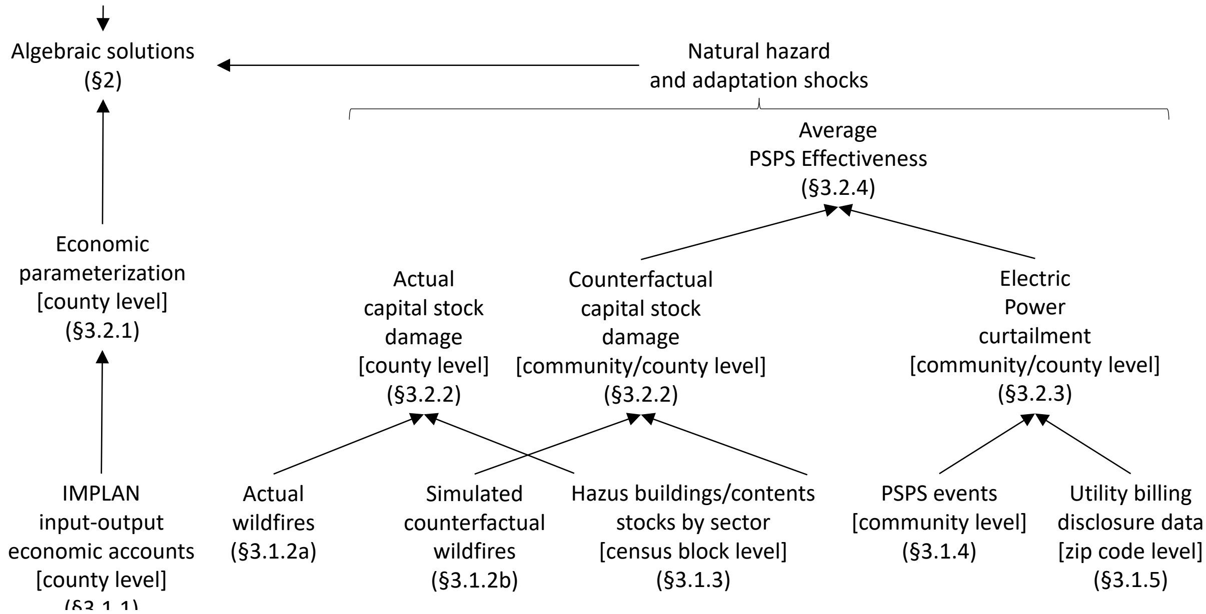


Figure 1: Roadmap of analysis in the paper

fires and their mitigation via PSPSs. 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 simulations 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. §2 describes the stylzed analytical model and its algebraic solutions. §3.1 walks through the many input datasets. §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 4.3 - 4.4. Finally, we use the historical data and analysis to evaluate the overall effectiveness of PSPSs in limiting wildfire damage (§4.2). Implications, limitations and final conclusions are discussed in §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 with a representative consumer household and two representative producer sectors that generate output from inputs of two factors. The supply side of the economy is made up of two sectors, housing (H) and non-housing (X), indexed by $j \in \{H, X\}$, with output quantities q_j and prices p_j. Each sector generates its output from inputs of electric power (E) and a composite factor (Z), indexed by $i \in \{E, Z\}$, with quantities $q_{i,j}$ and prices p_i. Inputs are combined according to the production technology, $\mathcal{F}_j(\cdot)$. On the demand side, the household derives utility from housing and non-housing consumption according to a utility function, $\mathcal{G}_j(\cdot)$. Wildfire (f) has two channels of impact. First, it damages the capital stock, which we model as a secular reduction in the aggregate supply of the composite factor that affects the relative price of electricity, the quantities of sectoral output, and household welfare. Second, we include for completeness its direct disutility to households—e.g., via smoke exposure, evacuation, and/or emotional distress, parameterized by the coefficient δ. Power shutoffs (s) reduce the aforementioned impacts of wildfire, but this benefit comes at the cost of a secular reduction in the aggregate supply of electricity, which impacts the sectors in a manner that is qualitatively similar to reductions in the composite factor supply.

Using $\mathcal{C}_i$ to denote the cost of production, producers' cost minimization problems are

$$\min_{q_{E,j},q_{Z,j}} \{\mathcal{C}_j = p_E q_{E,j} + p_Z q_{Z,j} | q_j \leq \mathcal{G}_j(q_{E,j}, q_{Z,j})\} \tag{1}$$

Simplifying the approach of Fullerton and Metcalf (2002) and Fullerton and Heutel (2010), our characterization of the solution to this problem consists of the production functions

$$q_j = \mathcal{G}_j(q_{E,j}, q_{Z,j}) \tag{2}$$

zero profit conditions that equate each sector's unit cost of production to the price of its output

$$p_j q_j = \mathcal{C}_j \tag{3}$$

and the definition of the elasticity of substitution between E and Z,

$$\sigma_j = -\frac{d(q_{E,j}/q_{Z,j})/(q_{E,j}/q_{Z,j})}{d(p_E/p_Z)/(p_E/p_Z)} \tag{4}$$

Using $\mathcal{E}$ to denote aggregate household expenditure, the household's expenditure minimization problem is

$$\min_{q_H,q_X} \{\mathcal{E} = p_H q_H + p_X q_X | \widetilde{u} \leq \mathcal{U}(p_H, q_X)\} \tag{5}$$

Our characterization of the solution to this problem consists of the utility function

$$\widetilde{u} = \mathcal{U}(q_H, q_X) \tag{6}$$

and the definition of the elasticity of substitution between H and X

$$\sigma_U = -\frac{d(q_H/q_X)/(q_H/q_X)}{d(p_H/p_X)/(p_H/p_X)} \tag{7}$$

Actual utility is modulated by the external effects of wildfires,

$$u = \widetilde{u} \cdot \Delta(\Omega(f, s)) \tag{8}$$

where the function $\Delta(\cdot)$ captures the disutility associated with proximity to fire ($\Delta' < 0$), and $\Omega(\cdot)$ is the net fire exposure function, which is increasing in secular fire occurrence but decreasing in PSPSs. Our maintained assumption is that the household treats their probability of wildfire exposure as random, with the result that neither fire nor power shutoffs directly influence their optimal choices in (5).

The model is closed by supply-demand balance conditions for inputs, in which PSPSs curtail aggregate electricity supply, and net wildfire-induced damage reduces aggregate composite factor supply

$$-s = q_{E,H} + q_{E,X} \tag{9}$$

$$-\Omega(f, s) = q_{Z,H} + q_{Z,X} \tag{10}$$

Eq. (10), and, to a lesser extent, (8), are the channels through which wildfires affect the equlibrium of the economy, while (9) and (10), and, to a lesser extent, (8), are the conduits of PSPS' impact.[1]

We circumvent the need to make further assumptions about the form of the production and utility functions by expressing and solving the model in terms of the logarithmic differentials (Sue Wing and Rose, 2020; Fullerton and Metcalf, 2002; Lanzi and Sue Wing, 2013). The model is specified as a system of log-linear equations, in which "hat" over a variable indicates the logarithmic differential that approximates the fractional change from a benchmark equilibrium value (e.g.,

[1]Eq. (8) is less consequential due to the separability of wildfire or PSPS mitigation effects through the channel external disutility, which exerts no influences on prices or allocation.

Table 1: Equations of the analytical model

Production functions:	$\widehat{q}_j = \theta_j \widehat{q}_{E,j} + (1-\theta_j)\widehat{q}_{Z,j}$	(12a)
Producer zero profit:	$\widehat{p}_j + \widehat{q}_j = \theta_j(\widehat{p}_E + \widehat{q}_{E,j}) + (1-\theta_j)(\widehat{p}_Z + \widehat{q}_{Z,j})$	(12b)
Producer substitution:	$\widehat{q}_{E,j} - \widehat{q}_{Z,j} = -\sigma_j(\widehat{p}_E - \widehat{p}_Z)$	(12c)
Household input substitution:	$\widehat{q}_H - \widehat{q}_X = -\sigma_U(\widehat{p}_H - \widehat{p}_X)$	(12d)
Household net utility:	$\widehat{u} = \phi\widehat{q}_H + (1-\phi)\widehat{q}_X - \delta(\widehat{f} - \eta\widehat{s})$	(12e)
Electricity market clearance:	$-\widehat{s} = \epsilon\widehat{q}_{E,H} + (1-\epsilon)\widehat{q}_{E,X}$	(12f)
Composite factor market clearance:	$-(\widehat{f} - \eta\widehat{s}) = \zeta\widehat{q}_{Z,H} + (1-\zeta)\widehat{q}_{Z,X}$	(12g)
Numeraire:	$\widehat{p}_Z = 0$	(12h)

$\widehat{x} = d\log x = dx/x$). The comparative statics of the economy are described by 10 equations, the log differential analogues of eqs. (2)-(4), (7), (8), (9) and (10), above, summarized as eqs. (12a)-(12g) in Table 1.

Several elements are noteworthy. The parameters $\theta_j, \phi, \epsilon, \zeta \in (0,1)$ express, respectively, electricity's share of sectors' cost of production, the housing sector output's share of household expenditure, and the housing sector's demands for electricity and the composite factor as fractions of these inputs aggregate supplies. In eq. (12e) the parameter δ reflects the elasticity of disutility with respect to net fire exposure. In eqs. (12e) and (12g) our parameterization of net wildfire exposure is deliberately simple:

$$\widehat{\Omega} = \widehat{f} - \eta\widehat{s} \tag{11}$$

Here, η is a key parameter—the PSPS effectiveness elasticity that captures the fractional reduction in baseline fire exposure from a fractional curtailment in electricity supply. Finally, our designation of the composite factor price as the numeraire, (12h), enables us to specify the general equilibrium of the economy as a system of linear equations with as many equations as unknowns, $\{\widehat{q}_j, \widehat{p}_j, \widehat{q}_{i,j}, \widehat{p}_i, u\}$.

The solutions are linear combinations of the fire and PSPS shocks. For each variable, v,

$$\widehat{v} = \Upsilon_{v,F}\widehat{f} + \Upsilon_{v,S}\widehat{s} \tag{13a}$$

where the coefficients, Υ, are functions of the share and elasticity parameters:

$$\Upsilon_{v,F} = \Psi_{v,F}(\epsilon, \zeta, \phi, \boldsymbol{\theta}, \boldsymbol{\sigma}, \delta)/\mathcal{D}(\epsilon, \zeta, \phi, \boldsymbol{\theta}, \boldsymbol{\sigma}) \tag{13b}$$

$$\Upsilon_{v,S} = \Psi_{v,S}(\epsilon, \zeta, \phi, \boldsymbol{\theta}, \boldsymbol{\sigma}, \delta, \eta)/\mathcal{D}(\epsilon, \zeta, \phi, \boldsymbol{\theta}, \boldsymbol{\sigma}) \tag{13c}$$

To conserve space we relegate presentation of the detailed algebraic results, and accompanying explanation, to Appendix A.1. Given wildfires' destructive impact, we expect that $\Psi_{u,F}, \Psi_{q_i,F} < 0$. But in view of the fact that PSPSs simultaneously alleviate this cost and impose opportunity costs of their own, it is not clear whether $\Psi_{u,S}, \Psi_{q_i,S} \gtrless 0$. The outcome depends on the magnitude of the PSPS effectiveness parameter, η, which is thus far unknown. In the rest of the paper, we undertake quasi-empirical analysis that uses the outputs of simulations of hypothetical fires to construct estimates of η. We then use this result in conjunction with values of the parameters derived from regional input-output economic accounts to numerically simulate eq. (13) for California counties.

One final point bears emphasizing. Our algebraic results include components associated with the disutility of wildfire exposure (δ), but this is for the sake of completeness. Developing reduced-form parameterizations based on underlying phenomena such as evacuation or smoke exposure is a herculean task that is well beyond the scope of this study (cf Wang et al., 2021). In more detailed real-world policy analysis, such impacts—appropriately monetized—could be incorporated in broader economic calculations of PSPSs' effectiveness. However, our present rarefied theoretical setting conceptualizes effectiveness in the narrower engineering sense, namely, the magnitude of direct property damage avoided by the reduction of wildfire exposure resulting from a given quantity and distribution of electric power curtailment.

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 (2022). 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. Consistent with the highly stylized nature of our model, we aggregate IMPLAN's detailed industry groupings into an amlgam of private dwellings, real estate and electricity inputs to final consumption (H) and all other sectors (X), and use the resulting accounts to calculate values for the parameters $\epsilon, \zeta, \phi, \theta_H$ and θ_X at the county level.

3.1.2 Wildfire occurrence

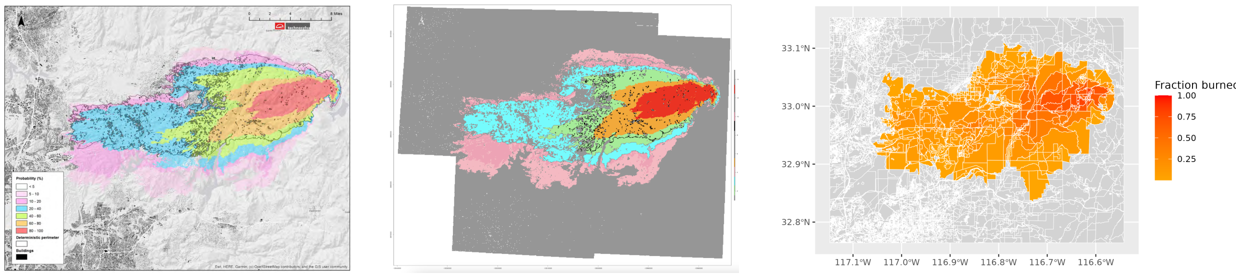
(a) 2019 burned area: The California Department of Forestry and Fire Protection, CAL FIRE, together with the United States Forest Service, the Bureau of Land Management, and the National Park Service, maintains a geodatabase of historical fire perimeters (CAL FIRE, 2022). The information includes fires 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.

(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? For this purpose we use the results of probabilistic fire simulations conducted by a consulting group, Technosylva, for the 2019 fire season (CPUC, 2021). Following PSPS events, electric utilities report damage incidents to their powerlines and assessed of the likelihood of these incidents sparking a fire. Technosylva used this information, along with 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. Their results are summarized in five reports covering more than 600 damage incidents.[2] Of these, Technosylva produced probabilistic maps for the most damaging (see Figure 2a for an example).

While the reports and their constituent map images are publicly available, the underlying data were not released. To make use of these results, we used 35 of the map images and converted them to spatial data. We proceeded in two steps: first georeferencing the images and then performing image classification. After extracting the images from the report, georeferencing locates the image on a map. We began by manually assigned anchor points, creating a mapping between the coordinates of the image and latitude and longitude. Each image required 5-6 anchor points (larger extents required more, to improve warping to the Earth's curvature). The geospatial data abstraction library (GDAL) was then used to transform the geographic coordinates, and warp the image using spatial interpolation. In the second step, image classification, we identify and differentiate the spatial contours corresponding to our images' simulated burn probabilities. We used the self-organizing map (SOM) (Kohonen, 1990), an artificial neural network classification algorithm used to reduce data dimensionality and map data similarities within the variable space into two dimensions. After SOM fitting, k-means clustering was used to separate the resulting image data into non-overlapping clusters. The color values of the original images were used to cluster the data to recover Technosylva's discrete probability classification scheme.

[2] Fire spread modeling was conducted using proprietary software that 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. Additional inputs included updated surface fuels data accounting for recent fires. Given uncertainty in exact time and location of ignition, forecasted weather, and model variables, each damage incident was simulated 100 times with variations to the input parameters, based on ranges from the literature, for a 24 hour period.



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

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

Application of these procedures yielded rasterized spatial objects with layers corresponding to the probability bands (example shown in Figure 2b). From these results, we computed expected area burned by intersecting the burn probability contours with census block polygons and integrating over probabilities (example in Figure 2c).

3.1.3 Hazus general building stocks

In order to estimate the capital stock losses due to fires, we use data on the value of buildings and their contents at the census-block level from the Federal Emergency Management Agency's Hazus expert system's data files FEMA (2021). Block-level building counts for residences are from the U.S. Census American Community Survey, while for other sectors ("occupancy classes") they are drawn from a variety of primary sources and estimates. Hazus provides estimates of structure and content replacement values by occupancy class. Structures are valued at their replacement cost, which varies by occupancy group and region based on survey data. Content values are derived using National Institute of Building Sciences approximations based on percentages of structures' value. Shultz (2017, 2021) provide further details, and in-depth discussions of the limitations of these data.

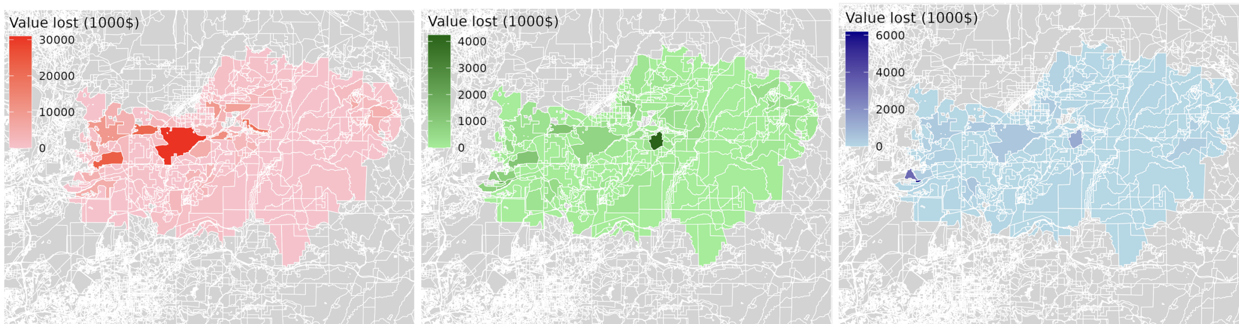
3.1.4 Public safety power shutoffs

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 longer than six days, at times impacting hundreds of thousands of customers. CPUC-mandated PSPS event report filings thoroughly describe the conditions and considerations leading up to the power shutoff decision (e.g., weather conditions, fire probability and risk, and the utility's assessment of the benefits and public safety risks of de-energization) (CPUC, 2022). Reports detail the event time, location, duration and number of customers impacted by customer class (residential, commercial/industrial, and other), and include geographic identifiers such as the circuit name and lists of affected communities (often census-designated places—CDPs) [3]. The latter information was scraped from PDF filing documents and manually matched to CPUC outage summary spreadsheets. Impacted community names were used to impute affected zipcodes via a CDP-to-zipcode crosswalk. Where multiple zipcodes were impacted, affected customers were apportioned among them based on population. The results facilitated estimation of electricity curtailment by matching outages to monthly zipcode-level electricity use data, described in §3.2.3.

3.1.5 California electricity usage data

CPUC mandates that California electric utilities provide access to energy usage data in manner that allows for protection of privacy (CPUC, 2014). Utilities disclose the total and average of customer electricity usage by month and customer class for zipcodes within their service area. We collected records from PGE, SDGE and SCE websites for September-December 2019, aggregating customer classes to residential, commercial, industrial, and agriculture. In §3.2.3 we describe how these data are combined with our PSPS events records (§3.1.4) to impute the fractional loss of electricity service.

[3]Reports provided by Southern California Edison (SCE) lacked this information, requiring us to aggregate outages to the county level and estimate power reductions in §3.2.3 using county-wide electricity intensity data



Residential Commercial Industrial

Figure 3: Value of buildings and their contents destroyed by sector for a representative counterfactual fire

3.2 Methods

3.2.1 Numerical parameterization of the analytical model

Numerical parameterization of the analytical model's closed-form solution in §A.1 requires both the IMPLAN data described in §3.1.1 and values for the elasticities of substitution. Given the highly aggregate character of the model's sectors and factor inputs, we treat electricity and the composite factor as necessary inputs to housing and non-housing production, and the housing and non-housing commodities as necessary inputs to households' consumption, with the upshot that the substitution elasticities are bounded on $(0, 1]$. There is a paucity of information regarding these elasticities generally, to say nothing of values specific to the local scale of individual counties within California. Accordingly, we treat σ_H, σ_X, and σ_U as uncertain parameters, and specify a grid of combinations of potential values for them that we use to compute numerical solutions to the model for California counties.

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

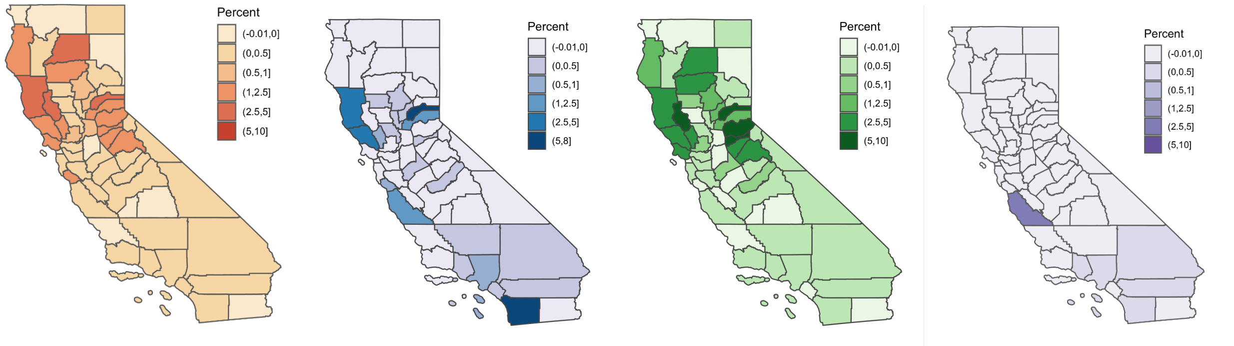
Capital stock losses due to actual and simulated wildfires are estimated from the spatial intersection of geographic fire information (§3.1.2) and building stocks data (§3.1.3). Our approach makes two key assumptions: that capital stock is uniformly distributed at the block level and that anything inside the fire perimeter is fully destroyed. We aggregate both losses and the value of buildings and their contents, sectorally across Hazus occupancy classes, and geographically across census blocks within counties. The ratio of these estimates yields observed fractional capital stock damage from wildfire at the county level, $\widehat{f}^{Obs}$.

Avoided capital stock losses from counterfactual wildfires were also constructed. Using our database of simulated wildfires, we assume that the expected fraction of area burned within each census block is approximately equal to the fraction of building and contents capital destroyed in that block, for all Hazus occupancy classes. Figure 3 illustrates the total building and content losses for aggregate sectoral groupings each sector for a representative simulated fire. Depending on the intersection between each wildfire's spatial probability contours and the distribution of capital across occupancy classes in affected blocks, geographic patterns of losses can vary substantially across different sectors impacted by the same wildfire event.

A critical consideration is the probability that the 35 counterfactual incidents extracted from CPUC (2021) would have progressed to become the actual fires catalogued in that report. In particular, had all 35 fires occurred as simulated, the associated damages to buildings and their contents would be an order of magnitude larger than the losses from actual fires in 2019! Evidence suggests that using this crude total would result in massive overestimation of PSPSs' efficacy: CAL FIRE records indicate an average of 4.5 large, utility-ignited wildfires per year over 2009-2018 (CAL FIRE, 2020). Therefore, to account for uncertainty in fire progression we draw 10,000 samples from the set of counterfactual fires according to a poisson distribution with mean 4.5, as a way of approximating the true distribution of wildfires, and fire-related losses, attributable to utility ignitions.[4]

Aggregating over Hazus block groups yielded, for each draw, the values of building and contents destroyed by counterfactual wildfires likely to have occurred in the absence of each PSPS event. We divide these losses by the total building and content values in both the affected blocks, and the blocks in the surrounding county, to estimate simulated fractional losses, $\widehat{f}^{Sim}$. This en-

[4]Many individual draws selected distinct counterfactual incidents that occurred in close spatial and temporal proximity, and would have likely burned some of the same areas more than once in a given hypothetical fire season. To avoid potential double-counting of capital stock losses, we therefore averaged the losses in a given draw for census-blocks experiencing multiple burns.



Residential Agricultural Commercial Industrial

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

ables the wildfire shock in our analytical model to be expressed as the sum of actual and potential counterfactual fractional losses:

$$\widehat{f} = \widehat{f}^{Obs} + \widehat{f}^{Sim} \tag{14}$$

3.2.3 Adaptation shocks: electric power curtailment due to PSPSs

We estimate the fractional curtailment of electricity ($\widehat{s}$) in three steps. First, we first use our PSPS report dataset (§3.1.4) to estimate de-energized customer-hours by customer class, month and zipcode. Next, we multiply the result by the average electricity use per customer-hour by customer class, month and zipcode, calculated from our utility disclosure dataset (§3.1.5).[5] For this calculation we use average electricity usage data from a non-PSPS year (2017 for PGE and SCE, 2016 for SDGE). The result was an estimate of electricity curtailed by PSPSs. Our final step was to aggregate both curtailed electricity and prior-year estimates of baseline electricity use spatially (over zipcodes corresponding to the communities affected by each individual shutoff event, or their constituent counties) and temporally (over months of the fire season). Dividing aggregate curtailment by aggregate use yields the percent of September-December electricity loss. Figure 4 summarizes losses for residential, commercial, industrial, and agricultural customers at the county level.

[5]Customer classes differed between the two datasets, with outage reports combining commercial and industrial customers. We distribute the outages between these two use classes based on the fraction of customers in the zipcodes covered by each circuit outage.

3.2.4 Estimating PSPSs' effectiveness

Our estimates of simulated losses and electricity curtailment for our 10,000 draws allow us to impute the effectiveness of shutoffs at avoiding capital stock losses, η. We estimate this parameter using a circuit-level univariate regression with electricity curtailed in each 2019 circuit-level outage (n = 2141) as the independent variable, and the draws with probabilistic wildfire-driven losses corresponding to each outage as the dependent variable. For each simulated wildfire, we assign all of the losses to the group of circuits that were de-energized if the fire's start time was within the period of the shutoff and the ignition occurred in the same community.

A crucial limitation is that CPUC (2021) does not report the specific circuit that is the source of ignition of a particular wildfire. We deal with this by apportioning the losses due to each fire equiproportionally among de-energized circuits in the matched space-time window described above. The result is a sparse dataset in which most outages do not avoid any potential losses, while a few outages avoid catastrophic damage. We use these data to empirically estimate PSPS' effectiveness as an elasticity, transforming power curtailment and capital stock losses into approximate percent changes corresponding to each outage, o. We employ three regression specifications. In the first, an inverse hyperbolic sine transformation of f_o^{Sim} and s_o is used to specify the equivalent of a log-log regression that retains the zero-valued observations. The second is a linear model in which losses and electric power curtailment are approximated in fractional terms by dividing simulated wildfire capital losses by the total value of buildings and their contents within the fire perimeter (k_o), and dividing interrupted customer hours by the monthly total customer hours for zipcodes that correspond to affected circuits (e_o). Our third model follows the same strategy as the second, but aggregates fractional wildfire losses and electricity curtailment to the common geographic unit of the encompassing county (losses F_o^{Sim} and capital stock K_o; curtailment S_o and total electricity consumption E_o).

$$asinh(f_o^{Sim}) = \widetilde{\eta}_1 \; asinh(s_o) + \epsilon_1 \tag{15a}$$

$$\frac{f_o^{Sim}}{k_o} = \eta_2 \, \frac{s_o}{e_o} + \epsilon_2 \tag{15b}$$

$$\frac{F_o^{Sim}}{K_o} = \eta_3 \, \frac{S_o}{E_o} + \epsilon_3 \tag{15c}$$

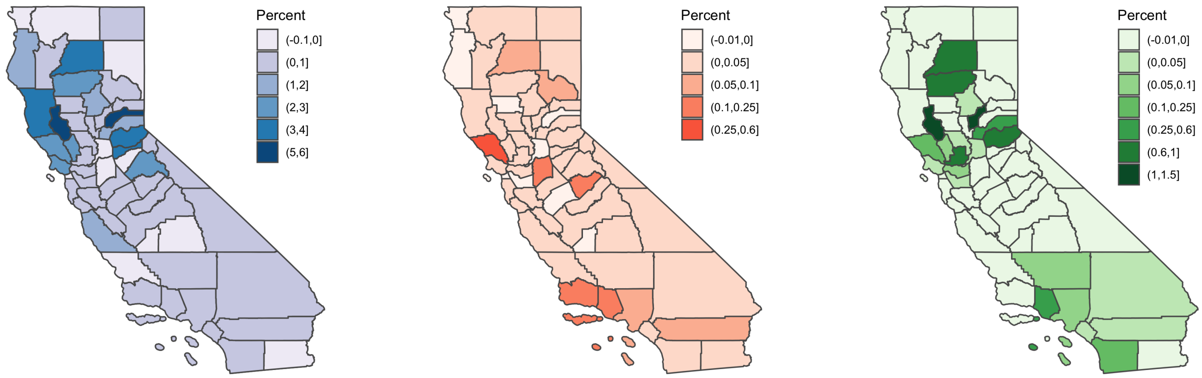
We transform $\widetilde{\eta}_1$ into elasticity values comparable to η_2 and η_3 using formulas provided by Bellemare and Wichman (2020). Given the structure of our probabilistic simulated fire data, we estimate eq. (15) 10,000 times. We run meta-analytic regressions on the resulting datasets of estimated elasticity parameters using the generic inverse variance method (Schwarzer et al, 2015) to obtain the means and corresponding confidence intervals of η_1, η_2 and η_3.

4 Results

4.1 PSPS and Wildfire Shocks

Electricity curtailment is geographically and sectorally heterogeneous (Figure 4). At worst, counties faced up to 10% losses relative to typical September to December power demand. 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.

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



(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 method described in §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 mean 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 1-1.4% of capital stock in some counties (Yuba, Lake) with many other counties also suffering large impacts (greater than 0.6% in El Dorado, Tehama, Solano and Shasta). The losses from the simulated fires were higher than that of the fires that actually occurred. The fire shocks get implemented in the model following:

4.2 The Effectiveness of PSPSs

Figure 6 summarizes the range of empirical estimates of the effectiveness elasticity based on eq. (15). Our preferred specification, (15a), which exhibits the smallest tendency for aggregation bias, yields a mean value of 0.2258. The implication is that each additional percentage point of

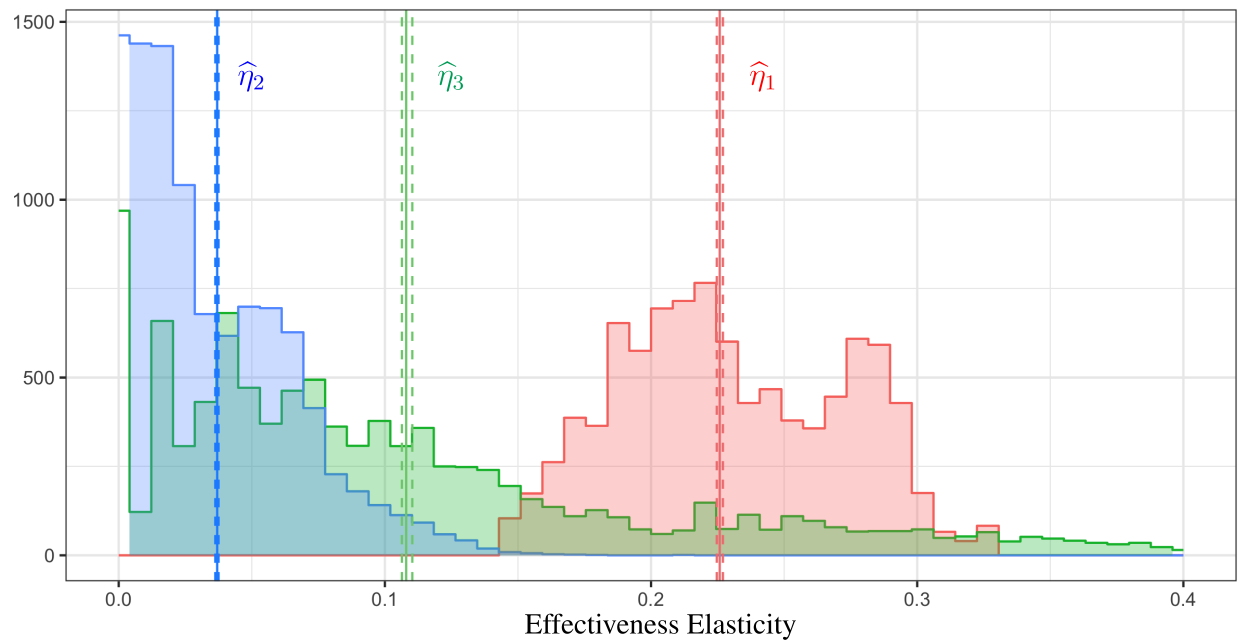


Figure 6: Shaded densities are histograms of 10,000 empirical estimates of the effectiveness elasticity ($\widehat{\eta}$) for the regression specifications (15a) (red), (15b) (blue) and (15c) (green). Vertical solid and dashed lines indicate the corresponding meta-analytic means and 95% confidence intervals.

electricity demand curtailed by shutoffs yields around 0.2% savings in avoided wildfire losses of building capital stocks. While PSPSs are effective at avoiding losses, the small value of our effectiveness elasticity highlights the challenge of precisely targeting shutoffs in space and time to avoid ignitions.

4.3 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 $\eta = 0.226$. Figure 4.3 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 power curtailment, representing the county-level sensitivity to wildfire and shutoffs (coefficients $\Upsilon_{\nu,F}$ and $\Upsilon_{\nu,S}$ in Equation 13). The green

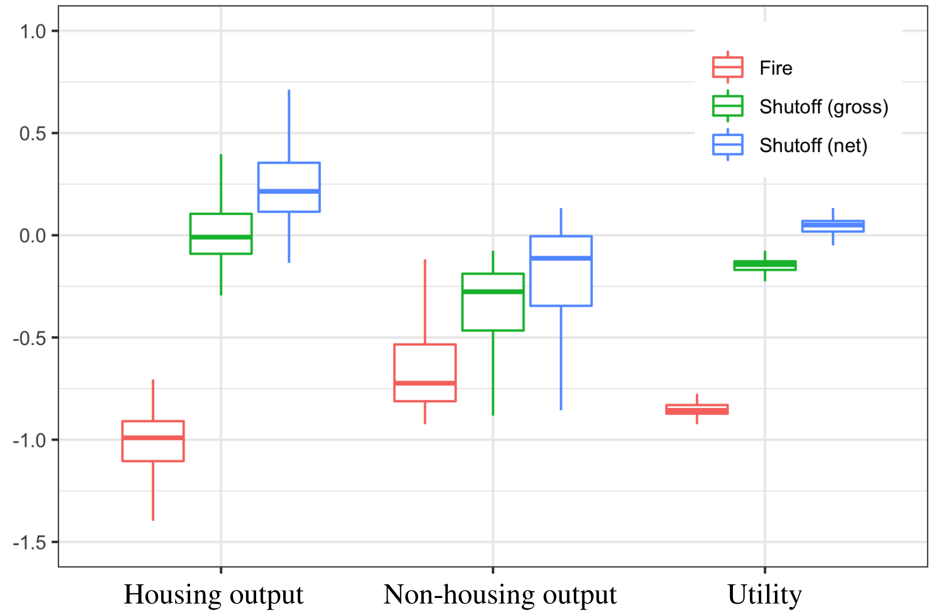


Figure 7: Elasticities of housing output, non-housing output and utility to wildfires and PSPSs for a range of values of the elasticities of substitution. Gross shutoffs: $\eta = 0$, net shutoffs: $\eta = 0.2258$

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 an average 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. The magnitude of fire impact on non-housing is dampened relative to housing. 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.

Unsurprisingly, the impact of fire on utility is uniformly negative, and is 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 dampened but positive. The cost of the shutoff appears to 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.

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

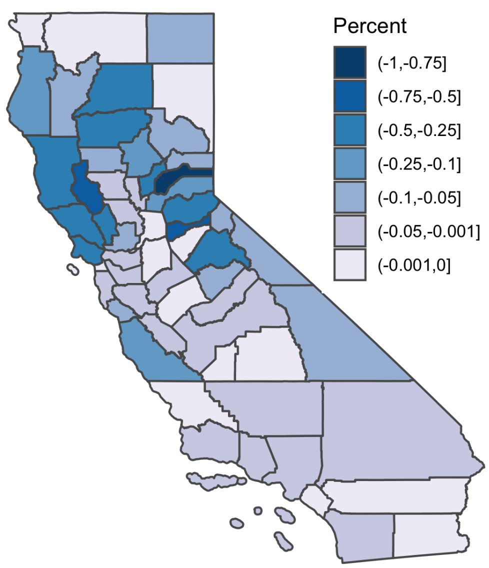
From the coefficients in §4.3 and the wildfire and PSPS shocks in §4.1 we can determine the impacts to welfare and and the net cost or benefit of this adaptation policy. Using the solutions to $\widehat{u}$ in Appendix A.1 we will compare our two scenarios. First, we observed a world with both power 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. A.3. Figure 8a 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 County, despite the former having a smaller shutoff. Welfare impacts from wildfires ranged from 0-0.5%. The impacts scale closely with the fires and capital stock losses themselves. Figure 8c shows the sum of panels 8a and 8b. Some counties faced combined impacts from shutoffs and fires but on average the counties' welfare losses did not exceed 1%.

We can compare this to the unobserved scenario; had there not been shutoffs, we would have seen both the actual fires and the simulated counterfactual fires ($\widehat{f} = \widehat{f}^{Obs} + \widehat{f}^{Sim}$ and $\widehat{s} = 0$). Using Appendix Equation A.2, 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 8d. Wildfire destruction would have caused welfare impacts in many counties, with losses up to 1% of county utility. Comparing panels 8c and 8d reveals the potential net costs or benefits of the power shutoffs. The effects are heterogeneous; some counties fared better due to shutoffs that avoided significant fire losses while others faced mis-targeted shutoffs leading to net costs. On expectation, the state faced a slight net cost due to the shutoff policy. However, this strategy avoided low-probability, high-consequence outcomes; The 95$^{\text{th}}$ percentile of simulated capital stock losses could have resulted in welfare losses up to 5% in some counties. If the decision-maker is risk averse, as is likely the case with the electric utilities under the current liability regime, the shutoff policy may have been well aligned with their goals of minimizing worst-case outcomes.

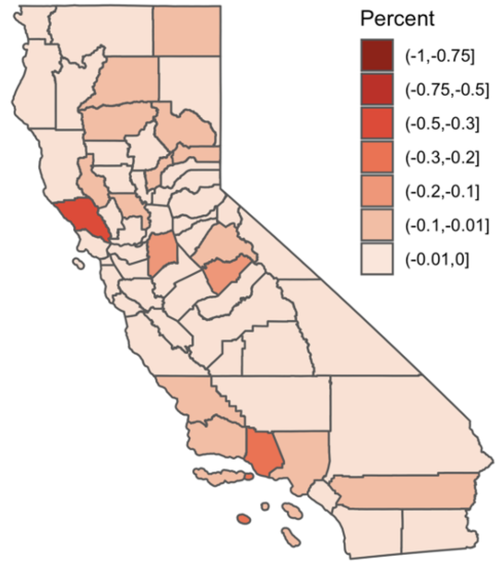
5 Discussion and conclusions

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.

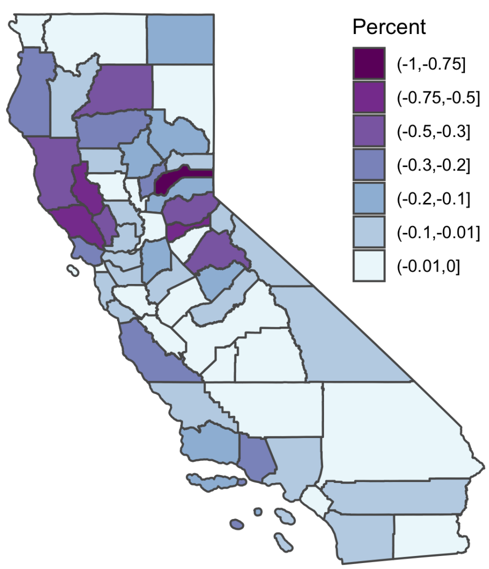
While electric utilities have been conducting PSPS for several years, there is very limited understanding of the balance of costs and benefits of this policy. We find that the impacts depend on the economic responses to the shutoffs and wildfires as well as the hazard risk and targeting of the shutoffs. 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



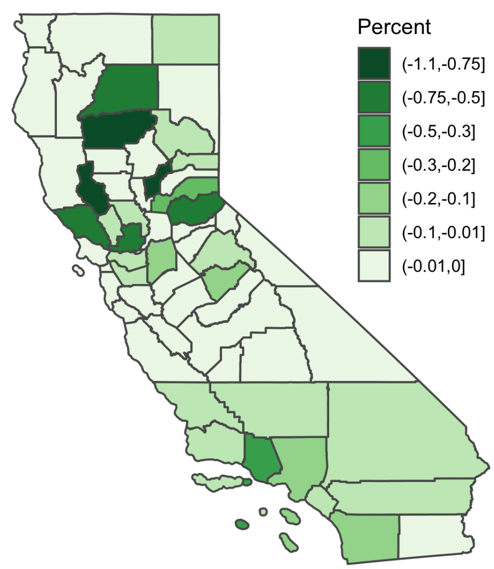
(a) Shutoff impact on utility



(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 8: Welfare impacts of wildfires and shutoffs

is slightly worse (on average) than the welfare losses that would have occurred due to additional wildfires without the shutoffs. Depending on the expectation of fire hazard and targeting of the shutoffs, some counties fare better and some worse with the shutoffs. However, the tail of the fire loss distribution reveals the low-probability potential for very significant welfare impacts, up to 5% in some counties.

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 0.2% of capital stock losses are avoided. While the specific value ranges under our uncertainty analysis, the finding is the same: the shutoffs are effective at limiting wildfire damage. Since 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 can lead to a net benefit but widespread outages may lead to net losses. 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 but led to state-wide net costs. It is important to note that the only wildfire damages considered were capital stock losses and inclusion of other sources of damage may lead to a net benefit. 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 that we try to account for with our uncertainty analysis. The limited years of shutoffs and simulation of the counterfactual fires limited the scope of our analysis. In the years since 2019, utilities have attempted to improve the targeting of shutoffs to impact fewer customers and utilize new technology to de-energize the lines only once they've been impacted. Future work should iterate on our findings as more data becomes available.

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.

Acknowledgements

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A Appendix

A.1 Analytical model solution

The denominator of (13) is

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

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:

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

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 $\widehat{q}_X$

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

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:

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

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 County-level economic accounts data

County	phi	epsilon	zeta	theta$_h$	theta$_x$
Alameda	0.406913963	0.021176859	0.478722412	0.008167707	0.259016681
Amador	0.546738923	0.027017451	0.661376194	0.008930079	0.387924792
Butte	0.51608606	0.046414504	0.576894251	0.010309198	0.225883643
Calaveras	0.612497981	0.044185792	0.706094377	0.010200914	0.348787266
Colusa	0.33103615	0.02384947	0.373380377	0.008727943	0.176775781
ContraCosta	0.290086068	0.037618614	0.310787579	0.00982758	0.102733528
DelNorte	0.614816648	0.027071518	0.764888354	0.008956065	0.513764
ElDorado	0.503474298	0.035858162	0.576951191	0.009671405	0.263680518
Fresno	0.445686206	0.029475065	0.512813536	0.009184882	0.243163856
Glenn	0.440393325	0.028305	0.509762556	0.009260433	0.250181937
Humboldt	0.522026088	0.037099359	0.599154428	0.009752351	0.276447327
Imperial	0.505603175	0.015284086	0.65700399	0.007132017	0.469913569
Kern	0.440403272	0.021917636	0.524008352	0.00828693	0.291038697
Kings	0.473446428	0.015822408	0.600110723	0.007244839	0.405189252
Lake	0.600011718	0.045289316	0.687577681	0.010290614	0.325409173
Lassen	0.653890677	0.015572144	0.928489291	0.007163252	0.855534589
LosAngeles	0.371661353	0.030109126	0.415571738	0.009228598	0.175838546
Madera	0.470900793	0.029302925	0.547036743	0.009150921	0.269792486
Marin	0.399467423	0.031147725	0.449343941	0.00929953	0.192414156
Mendocino	0.488373274	0.036545763	0.556017925	0.009744427	0.245216138
Merced	0.440629677	0.035101784	0.496810482	0.009693382	0.209894948
Monterey	0.477291004	0.020218306	0.584231328	0.008031819	0.355403509

County	phi	epsilon	zeta	theta$_h$	theta$_x$
Napa	0.35598546	0.03077167	0.395323314	0.009327611	0.162398505
Nevada	0.527791426	0.028770155	0.627797624	0.009100391	0.343374729
Orange	0.527791426	0.028770155	0.627797624	0.009100391	0.343374729
Placer	0.456735849	0.025844314	0.535821159	0.008774963	0.278075474
Riverside	0.515420112	0.034403599	0.595996247	0.009576957	0.285900734
Sacramento	0.506678604	0.014599551	0.662934823	0.006944558	0.481415941
SanBenito	0.444267544	0.026513499	0.518519715	0.009006603	0.264364259
SanBernardino	0.472640492	0.027063264	0.55495075	0.008928158	0.287667245
SanDiego	0.45724149	0.015768284	0.5740318	0.007214502	0.379365889
SanFrancisco	0.325983754	0.018894859	0.373760012	0.007803626	0.195971972
SanJoaquin	0.465260572	0.037284696	0.524869671	0.009797079	0.220098919
SanLuisObispo	0.435131229	0.032288572	0.493901	0.009447243	0.218109614
SanMateo	0.316487994	0.018384507	0.362176174	0.007719751	0.190855103
SantaBarbara	0.44111281	0.021368785	0.526801083	0.008212749	0.296861111
SantaClara	0.362192816	0.008213955	0.464840032	0.00509799	0.349554625
SantaCruz	0.479370711	0.032387829	0.551686902	0.009408672	0.25881576
Shasta	0.527795567	0.039829398	0.601815824	0.009939459	0.267820065
Siskiyou	0.539841393	0.035707687	0.626577984	0.009709698	0.307617718
Solano	0.431184007	0.0247332	0.503247129	0.008638457	0.25820826
Sonoma	0.438606082	0.034571414	0.494689082	0.009607377	0.209611343
Stanislaus	0.426195518	0.04052671	0.471724842	0.010040303	0.176556326
Sutter	0.486485975	0.03762829	0.551730362	0.009816077	0.237839696
Tehama	0.545883273	0.046124485	0.615319909	0.010307635	0.256242684
Tulare	0.436810978	0.030710939	0.500308677	0.009506738	0.232718614
Tuolumne	0.577008722	0.03368215	0.683141986	0.009539303	0.373325636
Ventura	0.401270146	0.02560944	0.461076029	0.008765008	0.223507049
Yolo	0.454319849	0.019138364	0.553942464	0.007847048	0.334836506
Yuba	0.600789404	0.014385446	0.837812141	0.006892331	0.710673489
RestOfCA	0.556290014	0.025492191	0.684478711	0.008914133	0.427227622