Income and Public Safety Power Shutoff Decisions in California

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Introduction

In the last decade, electric utilities in California have taken many actions to prevent sparking catastrophic wildfire. One adaptation strategy is the Public Safety Power Shutoff (PSPS), where a utility preemptively de-energizes lines that are likely to spark wildfires. Deciding whether to initiate a shutoff is a challenging prediction problem – firms need to decide if a fire is likely to spark and whether it is likely to grow to deadly size once started. Utilities must decide if the concentrated costs of a shutoff outweigh the diffuse benefits of potentially preventing catastrophic wildfire. As with all adaptation to climate change, PSPS decisions could exacerbate inequality if disadvantaged communities bear more of the cost and receive less of the benefit. In this analysis, I study whether disadvantaged communities bear more of the cost of PSPS events.

I examine the extent that PSPS decisions have been equitably targeted, after controlling for the role of weather. Equitable targeting means that communities that experience the same weather variation, but differ in demographics such as socioeconomic status, experience the same rate and duration of shutoffs. Many natural and human factors influence the likelihood of sparking a large wildfire. By controlling for weather variation, I focus on equity among factors that the utility or regulators can influence. If communities with different demographics face different treatment, after controlling for weather factors, this suggests a discrepancy in either the human factors of fire risk or the cost function to utilities. For example, if low-income communities have a lower rate of shutoffs, it could be because lines in those areas are in better condition, or because utilities are less concerned about financial liability from property damages in those areas.

My research question with this analysis is: Does income matter in the decision to shut off power or the duration of a power outage? I approach this question using data from filings of utilities' PSPS decisions, daily historical weather records, and income data. I find that the number of outages and total number of outages correlate with income. After controlling for weather factors, lower-income communities experience a higher degree of PSPS shutoffs, and experience longer outages in some utility service areas.

Setting

Power shutoffs are an especially salient tool in utilities' plan to address growing wildfire risk. Per California law, utilities are responsible for financial damages from utility-sparked wildfires. These fees have grown larger as fires grow larger and more destructive. The last five fire seasons have been the most expensive in California history and included the five largest recorded fires[1]. Utilities are investing in approaches that reduce the long-run risk of catastrophic wildfire, by undergrounding distribution lines in high-risk places or trimming vegetation along lines. PSPS is largely intended as a last-ditch measure to prevent wildfire, to allow utilities more time to develop long-run solutions.

My study focuses on the PSPS actions of California's three largest investor-owned utilities: San Diego Gas and Electric (SDG&E), Pacific Gas and Electric (PG&E), and Southern California Edison (SCE). In 2012, the California Public Utilities Commission (CPUC) first granted approval to SDG&E to conduct PSPS to prevent wildfire. Records of each incident are available from the CPUC, including the time of shutoff and restoration of power, circuit-level location, and number of impacted customers[2]. There have been over 5,000 circuit-level shutoffs, resulting in power outages to over three million customers (not unique customers; many have been impacted repeatedly). SDG&E has used PSPS since 2013, PG&E since 2018, and SCE since 2019. These three utilities account for over 90% of circuit-level outages and 99.8% of all customers.

[1] `https://www.fire.ca.gov/stats-events/`

[2] `https://www.cpuc.ca.gov/consumer-support/psps/utility-company-psps-post-event-reports`

These shutoffs have serious consequences for targeted communities, and may be more severe for lower-income households. Wong-Parodi (2020) shows that shutoffs are traumatic for targeted communities, especially for those with medical conditions who rely on steady access to electricity. Hill et al. (2020) examine the use of PSPS during the 2019 wildfire season and finds that communities were not prepared for PSPS events, including to provide continuous electricity for medical needs. Higher-income households may have alternate sources of electrification, such as backup generators or battery systems. This means that households that are already economically disadvantaged could suffer disproportionate impacts from PSPS events. I am not aware of research examining the equitable targeting of PSPS events.

Utilities publish detailed reports on their strategies to reduce wildfire risk, including how they make PSPS decisions. These reports contain rich detail about the data, statistical analysis, and physical modeling behind PSPS decisions, as well as some details about how health and safety impacts of PSPS are valued relative to wildfire risk reduction (Pacific Gas and Electric, 2021; San Diego Gas and Electric Company, 2021; Southern California Edison, 2021). These decision rules vary considerably among utilities, although all recognize the difficulty of the underlying prediction problem and the importance of minimizing the impacts of PSPS. The primary concern is to mitigate wildfire risk with minimal health and safety interruptions.

Income and PSPS Decisions

For the first stage of my analysis, I examine the relationship between PSPS decisions and community income without controlling for weather factors. This relationship is not evidence of unequal treatment, because lower-income households may locate in locations with inherently higher fire risk.

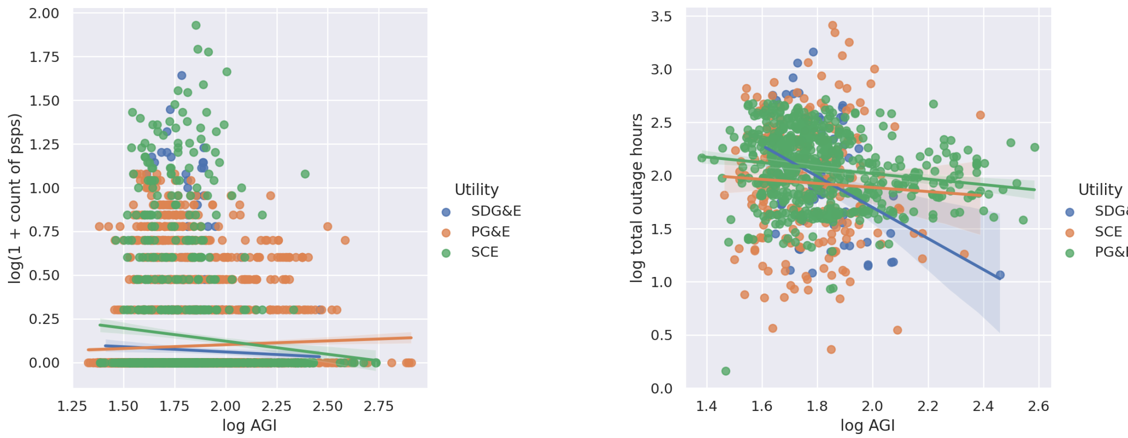
To produce these plots, I construct a database of mean income and PSPS records for each circuit. PSPS records are provided at the circuit level. To merge these with records with income data, I match each string name with a record from Integrated Capacity Analysis maps from each utility. These maps include the GIS shape file of each circuit segment, although some small circuits are excluded to protect privacy. I am able to match 98% of PSPS events from 2013-2021 with a GIS record. I then merge each circuit with mean adjusted gross income from 2010 ZIP-level Internal Revenue Service (IRS) records. I use data from prior to the study period to avoid confounding any possible effect of PSPS decisions on income. When a circuit crosses multiple ZIP codes, I take the weighted average by the length of the circuit in each ZIP code.

The level of disturbance from PSPS events is correlated with income, as visualized in Figure 1. The nature of this correlation varies by utility. There is a negative relationship between mean adjusted gross income (AGI) and the number of PSPS shutoffs for SDG&E and SCE, and a positive relationship between AGI and number of PSPS shutoffs for PG&E. Conditional on having at least one shutoff, there is a negative relationship between duration of shutoff and income for all three utilities.

Income, Weather, and PSPS Decisions

To provide evidence of the extent that non-weather factors related to income shift the exposure to PSPS, I use regression analysis to control for weather variation. This level of analysis is not sufficient to show what channel is responsible, but the findings suggest that it is worth investigating the nature of the relationship in greater detail.

In addition to data used in the previous analysis, I require daily circuit-level weather records. These records are calculated by interpolating from the gridded dataset developed by Abatzoglou (2013). This dataset includes variables such as temperature, precipitation, windspeed, and burn index that are relevant to predicting fire size (Malik et al., 2021). This is a gridded weather dataset; observations are constructed at a 4-km interval using satellite observations, weather stations, and topography. I merge these observations to the circuit level by taking the average of all grid points within $2\sqrt{2}$ km of a circuit.



(a) (b)

Figure 1: Plotting Adjusted Gross Income vs (a) total number of PSPS outages and (b) total hours of PSPS outages, conditional on having at least one outage, experienced from 2013-2021. Income data is from 2010 IRS records; PSPS decision data are from filings to the CPUC. Income, total outage hours, and one plus total number of outages are shown on a log (base 10) scale. Lines indicate best linear fit.

To restrict the scope of my analysis, I only consider circuits with at least one PSPS event and days where a Red Flag warning from the National Weather Service (NWS) is in effect. I am unable to observe many circuit-level determinants of fire risk, such as vegetation trimming or whether electric lines are underground. To coarsely account for these characteristics, I remove circuits where no PSPS outages were ever recorded while conducting these regression analyses. 99% of PSPS outages in my data occurred during a Red Flag warning, and this warning system is incorporated in the decision criteria for most utilities. The only exception I observe is when SCE's private team of meteorologists recognizes a risk of Santa Ana winds.

I use linear regression to predict whether a PSPS decision is initiated, and the duration of an outage conditional on having an outage. As each utility has a separate team making decisions, I model each utility's decision separately. For each prediction problem, I use all observable weather variables from each day and a per-year fixed effect. To assess accuracy of the classification task, I look at specificity[3]. These results are in Table 1; I find that the model correctly classifies about 90% of PSPS decisions. To assess accuracy for predicting outage duration, I look at R Squared; I find that the model is capable of explaining 25-50% of the total variance. These results indicate acceptable model fit, but it may be desirable to consider more flexible specifications, such as debiased machine learning approaches (Chernozhukov et al., 2018; Tan, 2019).

I compute three statistics to compare the significance of income for PSPS decisions:

1. The average derivative of the outcome variable with respect to an increase in AGI. I compute this average derivative by taking a numerical derivative with a symmetric finite difference of 0.1 standard deviations in AGI.
2. The average effect of moving from 2010 median income ($57,700) to the 2010 poverty line for a family of 4 ($22,050). I compute this average effect by taking the average of the difference between predicted values where each circuit-day-observation has median income or poverty-line income, holding all weather features constant.
3. The average effect of moving from 2010 median income ($57,700) to twice the 2010 median income.

[3]Share of positive outcomes the model correctly predicts; true positives / (true positives + false negatives)

	Specificity	Average Derivative	Median to Poverty Line	Median to Twice Median
SCE	0.885	-0.000326	0.0122	-0.0198
		(2.98e-05)	(0.00114)	(0.00174)
PG&E	0.905	-0.000305	0.0129	-0.02
		(7.95e-06)	(0.000366)	(0.000561)
SDG&E	0.914	-0.000235	0.0096	-0.0122
		(6.5e-05)	(0.00264)	(0.0034)

(a) Logistic regression of weather and income covariates on PSPS decision.

	R2	Average Derivative	Median to Poverty Line	Median to Twice Median
SCE	0.212	0.0704	-2.51	4.06
		(0.00413)	(0.147)	(0.238)
PG&E	0.448	-0.0197	0.703	-1.14
		(0.00192)	(0.0685)	(0.111)
SDG&E	0.449	-0.245	8.73	-14.1
		(0.0101)	(0.359)	(0.582)

(b) Linear regression of weather and income covariates on duration of PSPS outage.

Table 1: Results from regression. For each utility and each method, I report an accuracy measure, average derivative, average effect of moving from median income to the poverty line for a family of four, and average effect of moving from median income to twice the median income. Standard errors are in parentheses, and are computed using 30 bootstrap samples.

I conduct inference by computing the target parameter using 30 bootstrap samples and constructing a confidence interval using the observed standard deviation of the statistic.

Results of this analysis show that there is a relationship between income and shutoff decisions, after controlling for weather factors. Results are in Table 1 The model implies that moving from median income to the poverty line would result in roughly 1% more shutoffs among Red Flag warning days for a community, among each utility. Conditional on an outage, there is not a consistent relationship between income and duration of shutoffs; for SCE, the model finds that moving from median income to the poverty would result in 2.51 fewer outage hours, while for SDG&E, the same move would result in 8.73 more outage hours.

Conclusions and Next Steps

Controlling for weather variation, lower-income communities experience a higher degree of PSPS shutoffs, and experience longer outages in some utility service areas. This analysis is not sufficient to specify which channels lead to this discrepancy, and this should be an area of future study. One explanation is that lower-income communities face higher fire risk, as a result of vegetation or infrastructure management decisions around distribution lines in these communities. I plan to study the extent that this objective fire risk influences PSPS decisions, by using an econometric framework to identify prediction mistakes from observational data (Rambachan, 2021).

Regardless of the source of this discrepancy, more attention should be given to the equitable targeting of PSPS events to ensure that their use does not exacerbate inequality.

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