ENERGY INSTITUTE AT HAAS

Energy Institute WP 347R

Dynamic Grid Management Technologies Reduce Wildfire Adaptation Costs in the Electric Power Sector

Cody Warner, Duncan Callaway, and Meredith Fowlie

Revised March 2025

Dynamic Grid Management Technologies Reduce Wildfire Adaptation Costs in the Electric Power Sector

Cody Warner[1*], Duncan Callaway[1,2] and Meredith Fowlie[3,4]

[1]Energy and Resources Group, University of California, Berkeley, Berkeley, CA, USA.

[2]Electrical Engineering & Computer Sciences, University of California, Berkeley, Berkeley, CA, USA.

[3]Agricultural and Resource Economics, University of California, Berkeley, Berkeley, CA, USA.

[4]National Bureau of Economic Research, Cambridge, MA, USA.

*Corresponding author(s). E-mail(s): codywarner@berkeley.edu;

Contributing authors: dcal@berkeley.edu; fowlie@berkeley.edu;

Abstract

Wildfire is among the fastest-growing economic risks of climate change, yet strategies to adapt cost-effectively remain under-explored. In the electric power sector, where ignitions have triggered some of the most destructive wildfires on record, utilities are investing heavily to mitigate risk. This study evaluates the cost, reliability, and risk reduction benefits of the largest utility wildfire mitigation program in the U.S. Using detailed weather and vegetation data for 25,000 miles of high-risk powerlines, we develop a prediction model to estimate ignition risk and compare outcomes across locations with similar risk that received different interventions. With this quasi-experimental design, we find that a new strategy that dynamically adjusts protective device sensitivity during elevated wildfire conditions reduces risk more cost-effectively than conventional measures such as burying powerlines underground or trimming vegetation. By combining models of wildfire risk, costs, and electricity outages, we demonstrate that data-driven analysis is critical to guiding adaptation decisions in the electric power sector, especially in cases where utilities face incentives to invest in capital-intensive measures.

Keywords: Climate Adaptation, Wildfire, Electric Grid, Machine-Learning

1 Introduction

As the frequency and intensity of extreme weather events increase, so do the costs of safeguarding communities and infrastructure. Developing effective climate change adaptation strategies will be critical. To date, empirical evidence on the cost-effectiveness of adaptation investments has been limited [1]. A lack of evidence on what works partly explains why there has been significant under-investment in climate change adaptation [2].

This study evaluates the cost effectiveness of a multi-billion dollar, multifaceted wildfire adaptation program in the electric power sector. Wildfire is the fastest growing economic climate risk [3], and mitigating and adapting to the hazards posed by wildfire is a growing priority for policymakers [4, 5]. In recent years, an aging electric grid in the U.S. has ignited some of the most destructive wildfires recorded. In California, where nine of the 20 most destructive wildfires have been ignited by electricity infrastructure [6], risk mitigation spending by electric utilities significantly exceeds state expenditures on forest health [7]. The three largest investor-owned electric utilities in the state are spending \$9 billion annually to reduce wildfire hazards, almost double the amount spent in 2020 [8–10]. A plan by Pacific Gas & Electric (PG&E) to bury 10,000 miles of powerlines could cost utility ratepayers up to \$60 billion.

These large investments, while critical for reducing wildfire risk, could have important implications for climate change mitigation [11]. To reduce greenhouse gas (GHG) emissions, efforts are underway to decarbonize the electricity sector and electrify fossil fuel-dependent sectors [12, 13]. If high costs of wildfire risk mitigation are passed through in higher retail electricity prices, this will slow progress on electrification. In addition, wildfire risk mitigation strategies can involve turning off powerlines, which may further discourage electrification. Thus, wildfire adaptation choices must carefully negotiate trade-offs between risk reduction benefits, utility customer costs, and reliability impacts.

In this paper we aim to contribute to a growing literature on wildfire risk and adaptation. One focus of this literature has been the use of preventative power shutoffs in the power sector, commonly referred to as public safety power shutoffs (PSPS) [14–19]. Other studies have explored costs of alternative approaches to reducing wildfire risk, including burying powerlines [20, 21], vegetation management [22], and electric utility operations and preparedness [23–27]. This paper integrates empirical estimates of risk reductions, deployment costs, and reliability impacts within a single framework for multiple mitigation strategies.

Our approach brings together nearly a decade of data on powerline-caused wildfires, electric-grid infrastructure upgrades, investment costs, electricity outages, and climate and weather variables to evaluate the country's largest utility wildfire risk mitigation program. We leverage a machine-learning model of baseline ignition risk and quasi-experimental variation in the way risk mitigation investments are targeted. This allows us to systematically compare ignition outcomes across distribution circuits that faced the same baseline ignition risk but received different risk mitigation treatments. We use our causal estimates of ignition risk reductions, together with simulation-based estimates of structure damages, to evaluate the costs, avoided damages, and reliability impacts of wildfire risk mitigation strategies.

We find that ignitions caused by vegetation striking powerlines would have been 4.5 times greater in 2022 and 2023 absent the electric utility's risk reduction efforts. A large proportion (80%) of the reduction in ignitions is caused by a new dynamic grid management technology that increases circuit breaker sensitivity and rapidly de-energizes powerlines when a fault is detected. This new technique ("fast-trip settings") was piloted in 2021 before being fully deployed in 2022 and 2023, underscoring the important role of private-sector innovation in driving adaptation outcomes.

Our analysis indicates that, by inexpensively driving down ignition risk, dynamic grid management technologies have the potential to reduce capital spending on measures like undergrounding by tens of billions of dollars. We demonstrate that data-driven analysis of wildfire adaptation decisions is critical to guiding private-sector adaptation, particularly in cases where regulated utilities face incentives that favor capital-intensive adaptation approaches.

2 Wildfire Adaptation Strategies

Ignitions caused by powerline failures differ from other ignition sources because they are correlated with strong winds and dry conditions, when wildfire risk is particularly high [28–30]. Powerlines are also often located in close proximity to communities, so when a wildfire does ignite, it is more likely to impact structures and people living nearby. As a consequence, some of the most destructive wildfires on record were ignited by power system infrastructure (e.g., 2023 Lahaina wildfire, 2018 Camp wildfire, 2009 Black Saturday bushfires [30, 31]).

In this paper, we study the wildfire risk mitigation activities of PG&E, the largest utility in the U.S. Figure 1 shows the utility's service area and the regions that are characterized as high-fire threat districts (HFTD). Since 2019, PG&E has been experimenting with a range of wildfire risk mitigation strategies. These interventions can be classified into three categories.

System hardening includes measures such as burying powerlines, covering overhead conductors with insulated material, and reinforcing support structures. These types of measures require upfront capital investment and take time to deploy. Undergrounding – the main system hardening measure we study – can provide near permanent reductions in vegetation-caused ignition risk, but capital costs are significant.

Vegetation management can reduce ignitions caused by vegetation contact. Under the California Public Resources Code, electric utilities are required to maintain four feet of clearance in high-fire risk areas between distribution powerlines and vegetation [32]. We evaluate PG&E's "enhanced" vegetation management (EVM) strategy, in which the utility removes all vegetation within twelve feet of overhead lines [33]. The risk reduction benefits of vegetation management are not as permanent as system hardening because vegetation grows back over time.

Dynamic grid management technologies differ from other categories because they can be deployed in real-time to respond to evolving wildfire conditions. In this paper we study two of these measures. The first, known as public safety power shutoffs (PSPS), completely de-energizes powerlines during hours of extreme forecasted wildfire risk. The second measure, commonly called "fast-trip settings," modifies the sensitivity of existing protection equipment during periods of high fire risk [34]. This equipment detects when a fault occurs, notably when lines contact an object with a conductive path to ground. Faults lead to excess current flow, and protection equipment detects that current and interrupts all current flow on the line. Dynamic management of fast-trip settings should, in principle, reduce ignitions by quickly clearing faults [8]. However, there is limited empirical evidence on how well these strategies work in practice.

Figure 2 shows how PG&E's use of these adaptation strategies has evolved over time. After $30 billion in wildfire liabilities caused the utility to file for bankruptcy in 2019 [35], the utility began to implement a range of wildfire risk reduction approaches, including EVM, PSPS, covered conductors, and undergrounding. In 2021, the utility piloted fast-trip settings on approximately half of its HFTD service territory, and the next year it expanded fast-trip settings to all of the HFTD [8]. Over the long-term, the utility plans to underground 10,000 circuit-miles, which covers approximately 40% of the utility's HFTD [36]. Given the high capital cost ($4.3 million per mile in 2020 [37], projected to decline to $2.8 million per mile in 2026 [38]), PG&E's plans have raised questions about cost-effectiveness [39].

3 Causal Impacts on Ignition Risk

PG&E's distribution system comprises about 3,000 "circuits," or distinct radial paths connecting a few hundred to a few thousand customers to the transmission system. PG&E's overhead distribution circuits span roughly 80,000 miles, with 25,000 miles in the HFTD. Our analysis focuses on PG&E's risk mitigation efforts on the 767 distribution circuits intersecting the HFTD.

We use data on powerline-caused ignitions from the California Public Utilities Commission (CPUC) and PG&E regulatory filings [40]. From 2015 to 2023, 95 percent of PG&E's 4,266 recorded ignitions occurred along distribution (versus transmission) lines. Because distribution lines are typically uninsulated, contact with another object can readily produce ignitions.

Supplementary Table B7 summarizes these ignition data. Circuits with at least one mile in the HFTD cause an ignition about once every three years. From 2015 to 2023, 4.5% of ignitions led to wildfires exceeding 10 acres. Of the 1.3 million acres burned associated with PG&E's distribution grid, 98% were ignited by vegetation contact in the HFTD. Therefore, our analysis focuses on ignitions from vegetation contact on distribution circuits in PG&E's HFTD service area.

To evaluate the cost-effectiveness of risk mitigation strategies, we need credible estimates of how these interventions impact ignition risk. However, when investments are targeted at the highest-hazard circuits, comparisons between treated and untreated circuits can confound the effects of the risk mitigation with baseline risk differences. An ideal empirical strategy compares ignition outcomes across locations with identical baseline risk.

In pursuit of this ideal, we first estimate baseline ignition risk, defined as the daily probability of a distribution circuit causing a wildfire ignition without the utility's risk management efforts. Next, we leverage aspects of the risk mitigation deployment process that assigned circuits with very similar baseline risk levels to different risk mitigation regimes. Due to differences in how wildfire prevention measures were deployed, comparisons are constructed differently across measure types. In what follows, we introduce the baseline ignition risk model and empirical strategies.

Baseline Ignition Risk. Estimating baseline ignition risk is challenging because fluctuations in fire weather, infrastructure conditions, and vegetation all interact to determine whether an ignition occurs. Building on previous work [41], we train a random forest model with powerline-caused ignitions occurring between 2015 and 2019, prior to PG&E's widespread implementation of its key wildfire programs (AUC value of 0.93 on test data). The models' features include high-resolution weather data, topographic information, and circuit characteristics. We then use the model to construct "counterfactual" baseline ignition risks after extensive treatments began in 2019 (see Methods).

3.1 Constructing Comparison Groups

Enhanced Vegetation Management. To estimate the impacts of enhanced vegetation management (EVM), we leverage "material shortcomings" in PG&E's deployment of these interventions. Monitoring inspection reports [42] found that, as the company rolled out its EVM program, it did not prioritize wildfire risk reduction according to its highest risk circuits [43]. This allows us to compare circuits that received EVM to a control group of circuits with nearly identical baseline ignition risk.

We use caliper matching to match circuits that received EVM to control circuits with similar baseline ignition risk. This is performed over two vegetation management tiers: "high" and "moderate." See Methods and Figure A4 for more detail. Tables A2 and A3 show that, post-matching, baseline ignition risk is distributed nearly identically across treatment and control groups, as are other covariates.

Dynamic Grid Management Technologies. Fast-trip settings were activated on all HFTD circuits in 2022 and 2023 (and half in 2021). To estimate the impact of fast-trip settings on ignition risk, we compare ignition outcomes in deployment years with pre-deployment years. To control for temporal differences in baseline wildfire risk, we restrict the sample to include only days that PG&E considered sufficiently high risk to warrant enabling fast-trip settings.

We observe a limited sample of PG&E's internal characterization of fire risk that is used operationally to enable fast-trip settings. Due to the limited sample, we train a random forest model to predict PG&E's fire risk on all days, and the model achieves a test data AUC of 0.93 (see Methods). In one of the following regression specifications, we restrict the comparison sample to high-risk circuit-days when we predict PG&E has enabled fast-trip settings or would have enabled them historically. Extended Data Table A4 shows how this conditioning strategy eliminates differences in baseline ignition risk between time periods (see Methods).

We do not estimate the causal effects of PSPS events empirically. The probability of vegetation contact causing an ignition when a line is de-energized is plausibly zero. We proceed in the cost-effectiveness analysis under this assumption, and observed ignition outcomes are consistent with this idea.

System Hardening. Very low deployment levels of undergrounding and covered conductor during our study period mean we have limited data to analyze. For undergrounding, we follow a similar approach to PSPS events. The probability of vegetation contact is plausibly zero once a line is placed underground. We apply this assumption in the cost-effectiveness analysis. For covered conductor, we cannot assume the measure is completely effective. Therefore, we exclude it from our empirical estimates of cost-effectiveness.

3.2 Logistic Regression Results

We use the empirical strategies described in the previous section to construct statistical comparisons between circuit-days that face very similar levels of baseline ignition risk but received different risk mitigation interventions. We estimate causal impacts of these interventions on ignition outcomes using a logistic regression model. The Methods section includes a detailed discussion of the model specifications we estimate.

Our results, shown in Table 1, indicate that fast-trip settings are substantially more effective than enhanced vegetation management. On average, enabling a circuit's fast-trip settings on a high-risk day reduces the circuit's probability of causing an ignition by 82% (67%-90%

confidence interval; confidence intervals represent parameter uncertainty, and do not account for misspecification of the ignition risk model). Circuits with enhanced vegetation management cause 48% (3%-73% CI) fewer ignitions on high-risk days as compared to circuits with similar baseline risk treated with standard levels of vegetation management.

The three columns in Table 1 also demonstrate the ability of the matching strategy to balance ignition risk across comparison groups. The first column fits the regression model across all HFTD circuits, and the positive and significant coefficient (β_4) on circuits that were targeted for EVM indicates these circuits have higher baseline ignition risk than circuits that were not targeted. After applying the matching strategy in the second column, the effect is no longer present. This assures us that we are statistically comparing ignition outcomes across circuits that faced nearly identical baseline ignition risk but received different levels of EVM. The same is true in the third column, which represents our preferred specification, as it further filters the sample to high-risk days before and after fast-trip settings deployment (see previous discussion). Our results are robust to different matching techniques and specifications, which are provided in the appendix.

We estimate that ignitions in high-hazard areas would have been 4.5 times higher in 2022 and 2023 without these risk mitigation efforts. By comparing the solid and dashed lines, Figure 3 illustrates these reductions by month and year. To produce these estimates, we combine knowledge of where and when each measure was used along with logistic regression incidence rates and our prior estimates of PSPS and undergrounding effectiveness. Fast-trip settings produce the majority of the ignition reductions due to high effectiveness and widespread deployment.

4 Cost-Effectiveness

We now assess the cost-effectiveness of risk mitigation strategies in two steps.

First, we model deployment costs. This incorporates multiple sources of uncertainty (e.g., wildfire risk escalation in future years, unit costs, outage costs, discount rate), producing cost estimates across a range of scenarios. Costs are estimated as net present values over the adaptation investment's lifetime relative to a baseline that deploys only routine vegetation management.

For undergrounding, we include the upfront capital cost, the regulated rate of return that the utility earns on capital, and maintenance costs net of routine vegetation management costs that are avoided when a line is buried underground. Enhanced vegetation management does not require upfront capital, so we only model operating and maintenance costs. Both undergrounding and EVM generate risk reduction benefits in later years depending on the lifetime of the asset.

Given the longevity of the underground asset, a critical assumption concerns the potential for future changes to ignition and wildfire risk. Relying on 30 different climate models, one study estimates that the vast majority of climate projections lead to at least a 50% annual increase in burned area in the Western U.S. in the period 2021-2050 relative to 1991-2020[44]. However, there is considerable uncertainty surrounding future increases to annual burned area, not only due to uncertain climate projections but also due to feedback effects between burned area and fuel availability. When projecting risk reduction benefits in future years, we assume ignition and extreme wildfire risk will increase due to climate change. (See Methods.)

Dynamic grid management technologies incur some capital expenditures, operating costs, and outage costs. We apply a value of lost load (VoLL) framework to estimate costs associated with observed supply interruptions, differentiating VoLL assumptions by customer class (residential, commercial, industrial, and customers who use electricity to power medical devices). See Methods for details.

Second, we estimate structure losses from utility-caused ignitions. Ignitions vary significantly in terms of the damages they will likely cause. In principle, one should invest more heavily in preventing riskier ignitions. For each day and each circuit in our data, we predict the probability of an ignition spreading into a given wildfire class size (e.g., 0-10 acres, $\geq$10,000 acres). We then use detailed information about structure locations and simulated flame length probabilities to assess structure losses associated with each simulated ignition (see Methods).

We note that this approach captures only one dimension of damages. Other damage dimensions (e.g., smoke exposure, fatalities, ecosystem services, economic disruptions) fall outside our scope. Undergrounding may also provide co-benefits by reducing the costs incurred to replace overhead lines damaged by wildfires, and undergrounding may also lower the rate of unplanned outages from other types of extreme weather events. We discuss the potential magnitude of these co-benefits the Appendix.

Figure 4 summarizes our cost estimates per avoided structure burned for two dynamic grid management technologies as well as undergrounding and EVM. Whiskers on our central estimates indicate the upper and lower ends of our sensitivity analysis.

Our results indicate that fast-trip settings are significantly more cost-effective at reducing wildfire damage to structures as compared to EVM and undergrounding. Because fast-trip settings are not 100% effective, risk managers may want to complement the use of fast-trip settings with preventative power shutoffs (PSPS) during periods of extreme wildfire risk. We estimate that this combined dynamic grid management strategy is more cost-effective than undergrounding (averaged across HFTD circuits). We also find that, despite the significant capital costs, undergrounding powerlines is more cost-effective than vegetation management. This is primarily because undergrounding fully eliminates vegetation-caused ignition risk well into the future.

Undergrounding is capital intensive, making our cost estimates sensitive to cost of capital assumptions. Utilities earn a regulated rate of return on capital, financed by electricity rate increases [45]. While some of this reflects the utility's true cost of capital, previous research shows that the utilities' return on equity is often set 1-5% above their true rate [46]. In Figure 4, we find that lowering the utility's weighted cost of capital (which includes debt and equity) from 7.5% to 5.0% produces a nearly 20% reduction in undergrounding costs (see lower cost of capital whisker for undergrounding in Figure 4). This is on the order of approximately \$1 billion for the 900 miles of undergrounding analyzed through 2023.

Other parameter sensitives are also revealing. Uncertainty in the per-mile capital costs of undergrounding is large – even larger than the total cost of fast-trip settings and PSPS combined. This stresses the importance of identifying strategies to reduce the cost of undergrounding. Furthermore, the cost range associated with uncertainty on the value of lost load for the two dynamic grid management technologies is also large, though nowhere near as large as the range of costs associated with undergrounding.

4.1 Grid Management Innovation Reduces Adaptation Costs

Figure 4 illustrates *average* cost-effectiveness in locations where interventions have been deployed by the utility. However, wildfire risk varies significantly across locations. Next, we expand our cost-effectiveness analysis across all 25,000 miles of high-risk powerlines to simulate the distribution of cost-effectiveness across line segments. We find that, for a given risk level that the utility targets, the introduction of dynamic grid management technologies produces a downward shift in the amount of capital needed to achieve that target. We estimate the downward shift represents approximately $30 billion in avoided adaptation costs from fewer undergrounding costs net of increased outages, dynamic grid management technology costs, and routine vegetation management.

Figure 5 shows how the cost-effectiveness of undergrounding varies across locations in the HFTD. The horizontal axis measures miles of distribution lines in descending order of baseline risk. In panels (a) and (b), the vertical axis measures estimated costs per avoided structure burned and total structures burned, respectively. We assess costs and risk reduction benefits relative to two baseline scenarios. The dashed lines reflect a baseline of only routine vegetation management. The solid lines includes routine vegetation management along with more recent innovations in dynamic grid management (i.e., fast-trip settings, PSPS) in the baseline.

Panel (a) of Figure 5 shows how the undergrounding costs incurred to avoid structure loss vary across line segments. The higher the baseline risk at a location, the lower the cost per avoided structure burned, all else equal. These estimated costs are even lower when measured relative to the baseline that does not include dynamic grid management. This is because the risks eliminated by undergrounding get much smaller once fast-trip settings have been deployed, so the implied costs per avoided structure burned increase. These results indicate that the introduction of fast-trip settings degrades the cost-effectiveness of undergrounding by roughly a factor of four.

Raw measures of cost-effectiveness need to be considered alongside achievable risk reduction. Our results indicate that fast-trip settings have produced the same amount of risk reduction that PG&E would have achieved from undergrounding in the absence of fast-trip settings. Specifically, panel (b) of Figure 5 shows how incorporating dynamic grid management technologies into standard practice has significantly reduced the amount of undergrounding investment needed to achieve a risk reduction target.

Consider, for example, PG&E's 10,000 mile undergrounding target, which would correspond to removal of approximately 8,000 miles of overhead lines (because overhead lines are able to avoid ground-level obstacles and difficult terrain [47]). If we assume that the utility would underground the highest risk circuits, we estimate that the risk remaining along the line miles that are not buried would lead to the loss of approximately 4,500 structures (discounted over the 40-year undergrounding lifetime). Using the alternative baseline that assumes dynamic grid management technologies are deployed, this level of risk reduction can be achieved with minimal to no amount of undergrounding investment (solid line). The arrow denotes this reduction in miles of overhead powerlines buried underground, and it corresponds to savings of approximately $30 billion in undergrounding costs net of additional outages, dynamic grid management technology costs, and routine vegetation management costs.

5 Discussion

Electric utilities are starting to experiment with a variety of measures to adapt to wildfire risk. These are high-stakes experiments with potentially significant implications for power sector costs, reliability, and safety. This study develops an empirically tractable framework for evaluating the effectiveness of these investments and for analyzing trade-offs between wildfire risks and consumer costs.

Dynamic grid management technologies like fast-trip settings can be deployed quickly in response to evolving wildfire conditions at relatively low costs. We find that fast-to-deploy measures have played a vital role in cost-effective adaptation strategies to date. However, we also estimate that the fast-trip protocols that have been demonstrated in California leave an estimated 18% of ignition risk unmitigated, on average. This stands in contrast to capital-intensive measures, like undergrounding, which are slower to deploy, significantly more expensive, but eliminate risk with more assurance in the locations they are deployed. The results do not point to the superiority of one measure over another, however they do elucidate key trade-offs and illustrate how important innovations in wildfire risk adaptation can significantly change the cost-calculus that guides private-sector investment choices.

The analysis comes with some caveats. There are many sources of uncertainty in the cost-effectiveness estimates, and the measures of avoided wildfire damages are model-dependent. Innovative drilling techniques may reduce undergrounding costs greater than forecasted. On the other hand, costs could exceed forecasts if the utility has targeted the most favorable, cost-effective sites first. We do not consider the long-run flexibility of each measure. If wildfire risk changes geographically in ways that are unexpected, the high capital costs associated with burying powerlines underground may not deliver their intended benefits. Dynamic grid management technologies and vegetation management, on the other hand, offer more long-run flexibility and mitigate the issue of legacy utility costs [48].

The deployment of fast-trip settings during the study period represents the utility's initial efforts; dynamic grid management technologies are being refined in ways that could reduce costs and detect faults more effectively. While this analysis estimates that the economic outage costs of fast-trip settings are small compared with the additional investment costs of undergrounding, there are shortcomings when relying on point estimates of the value of lost load to do this quantification. These considerations notwithstanding, the results demonstrate how ongoing experimentation with low-cost grid management technologies can avoid significant capital outlays. These results could be highly relevant for utilities across the globe that face escalating wildfire risk.

The extent to which fast-trip settings– and future grid management technologies– deliver real cost reductions will depend in part on utility incentives. Regulated electric utilities are routinely authorized to earn generous returns on capital investments [46]. These incentives will lead utilities to favor capital-intensive mitigation options. Liability rules and public relations considerations encourage utilities to drive electric power sector ignitions to zero. To the extent that these utility incentives are misaligned with the best interests of consumers, regulatory oversight will be critical in the negotiation of trade-offs between risk reduction benefits and the societal costs of wildfire mitigation. This paper provides a framework for thinking more systematically about these risk-cost trade-offs, and demonstrates how publicly available data and causal inference methods can be used to evaluate the cost-effectiveness of adaptation efforts. In no other sector is the measurement of adaptation impact and cost-effectiveness more critical than in the electric power sector, where adaptation investments, electricity costs, and decarbonization policies are linked so closely.

6 Figures and Tables

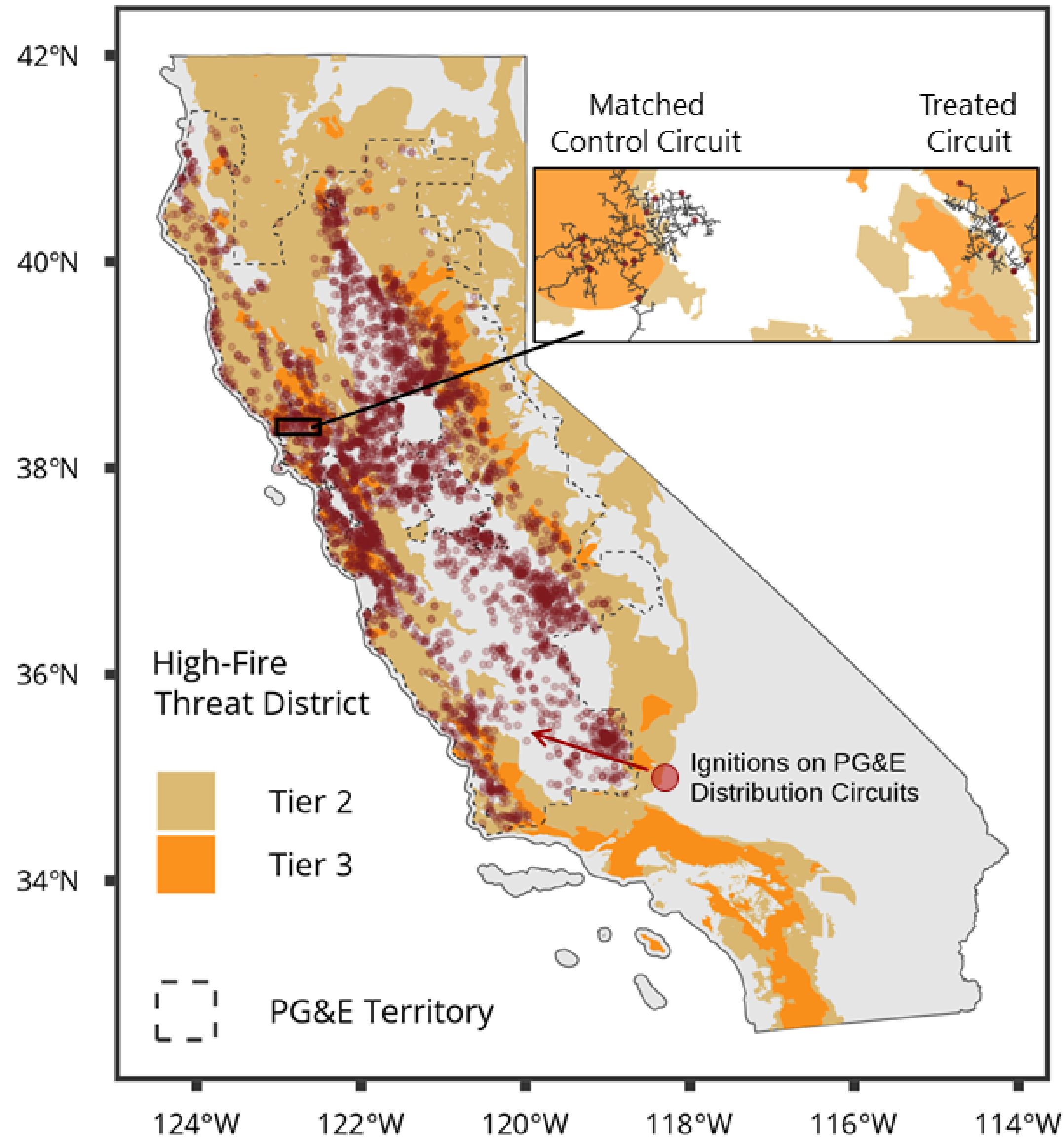


Fig. 1: **High-Fire Threat District Map**. The map of the high-fire threat district ("HFTD") shows areas where there is an increased risk for utility-associated wildfires to occur, to spread rapidly, and to cause damage to communities. HFTD areas were created by the California Public Utilities Commission through a regulatory process. Tier 3 features "extreme" wildfire risk, and Tier 2 features "elevated" risk. Tier 1 (not shown) includes tree mortality zones defined by the U.S. Forest Service and California Department of Forestry and Fire Protection. Tier 1 is not shown because it is predominantly encompassed by either Tier 2 or Tier 3. Overlaid in red are ignitions caused by PG&E distribution circuits between 2015 and 2023. The map inset displays an example distribution circuit that received enhanced vegetation management exceeding 10% of its circuit length. Adjacent to the distribution circuit is a control circuit that both (1) received enhanced vegetation management less than 10% of its length and (2) is matched to the treated circuit on the basis of nearly identical average ignition risk. See Methods for more detail on the matching algorithm.

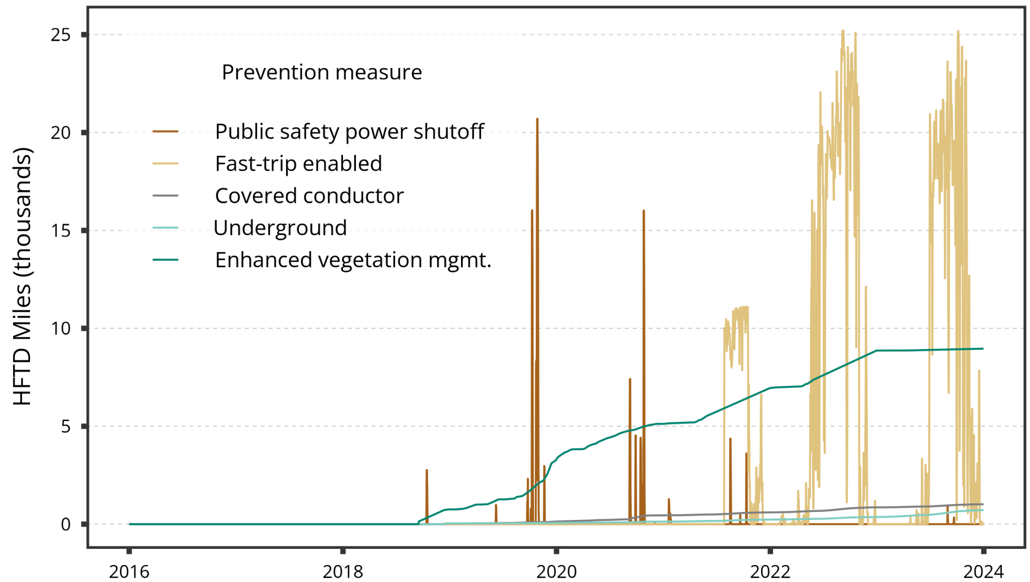


Fig. 2: **Deployment of Wildfire Adaptation Measures**. The vertical axis shows the deployment of wildfire prevention measures measured in thousands of circuit-miles. The miles deployed of dynamic grid management technologies are measured on a daily basis, while system hardening and vegetation management investments are shown on a cumulative basis. When the utility calls a PSPS event on a given circuit, we assume all of the circuit's HFTD miles are de-energized, though in practice fewer miles may be de-energized due to grid architecture and installed sectionalizing devices.

Table 1: Effects of Wildfire Adaptation Investments on Ignition Outcomes

	Incidence Rate - Vegetation-Caused Ignitions		
	All HFTD	High Treatment Tier and Matched Controls	
	All Days	All Days	High Fire Risk
	(1)	(2)	(3)
β_1: Fast-Trip (F_{it})	-0.32	-0.58^*	-0.82^*
	(-0.55, 0.02)	(-0.76, -0.24)	(-0.90, -0.67)
β_2: Veg. Mgmt. (D_i=High x T_{it}=Post)	-0.70^*	-0.64^*	-0.48^*
	(-0.82, -0.50)	(-0.78, -0.39)	(-0.73, -0.03)
β_3: Veg. Mgmt. (D_i=Moderate x T_{it}=Post)	-0.25^*		
	(-0.44, -0.01)		
β_4: Veg. Mgmt. (D_i=High)	1.81^*	-0.13	-0.12
	(1.28, 2.46)	(-0.31, 0.10)	(-0.33, 0.16)
β_5: Veg. Mgmt. (D_i=Moderate)	1.55^*		
	(1.12, 2.07)		
Risk-score (θ) covariate	Yes	Yes	Yes
Mean risk-score (θ)	0.0004	0.0009	0.0021
System hardening (UG, CC) covariates	Yes	Yes	Yes
PSPS (Z) covariate	Yes	Yes	Yes
Risk-score matching	No	Yes	Yes
High-fire risk days only	No	No	Yes
Matched control neighbors (N)	0	2	2
AUC	0.721	0.719	0.738
Observations	2,514,138	810,612	278,048
Log Likelihood	$-6{,}751.84$	$-3{,}991.56$	$-2{,}332.09$

Notes: In all three columns, the dependent variable is a binary variable indicating whether vegetation contact caused an ignition on a given circuit on a given day. The estimated coefficients are transformed to incidence rates for ease of interpretation (see Methods). 95% confidence intervals constructed using heteroskedasticity-consistent standard errors are shown in parentheses below the incidence rate estimates. Asterisks (*) denote statistical significance at the 95% level. Test statistics are based on a two-sided t-test. These confidence intervals reflect parameter uncertainty and do not account for uncertainty from the machine-learning ignition risk model. The sample in column (1) includes all circuits with non-zero HFTD circuit-miles. Column (2) restricts the sample only to circuits that are treated with high ($\geq$50% circuit length) amounts of vegetation management and control circuits that are matched to each treated circuit (see Methods). The sample in column (3) uses the same matched sample in column (2) but further restricts the sample to days when wildfire conditions are elevated. The first pair of vegetation management coefficients estimates the effect of the treatment after the treatment has taken place. The second pair describes a group-specific effect. Circuits with moderate amounts of vegetation management are excluded from columns (2) and (3). Parameter estimates for the moderate treatment tier are reported in Table A5. In all three columns, we condition on our ML-derived measure of daily ignition risk, system hardening covariates, and PSPS events. To provide a sense of the regression model's goodness of fit, we report the area under the receiver operating characteristic curve (AUC).

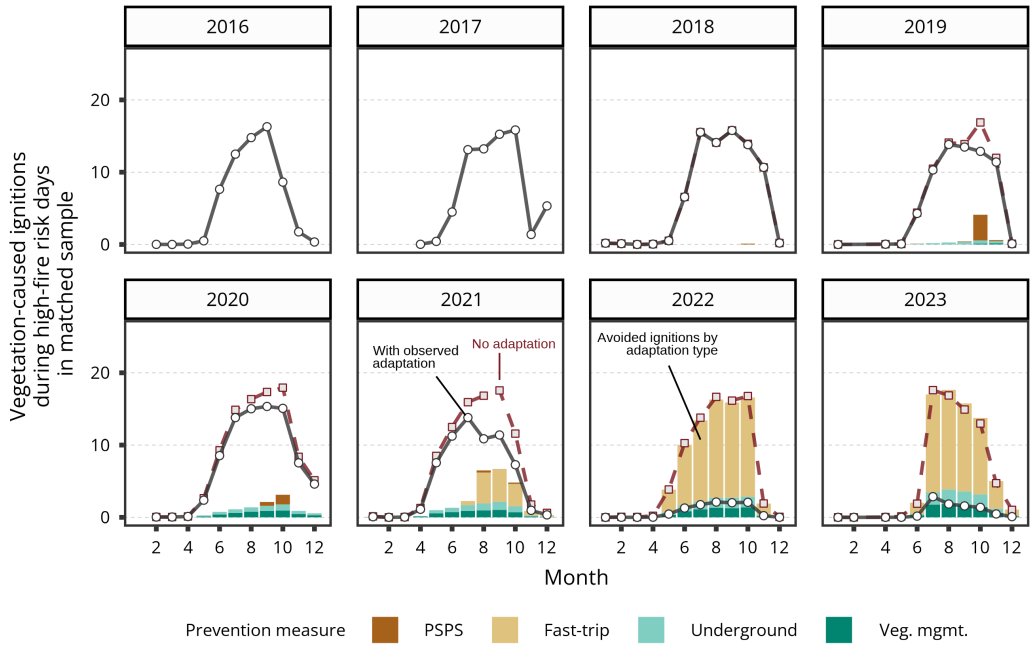


Fig. 3: **Ignitions Avoided by Wildfire Adaptation Investments**. The vertical axis shows the number of ignitions predicted by our logistic regression model on high-fire risk days. The circuits included in this analysis are ones that received high amounts of vegetation management or control circuits that were matched to these treated circuits based on similar ignition risk. Circuits in the "moderate" vegetation management treatment group are excluded because we do not estimate a statistically significant effect (see Table A5). Using the coefficients reported in column (3) of Table 1, and assuming undergrounding is 100% effective at reducing ignitions, the solid line predicts the number of ignitions in each month assuming the utility invested in wildfire adaptation at its observed, historical levels. The dashed line plots a counterfactual scenario, as predicted by the same logistic regression model, in which we assume the utility did not invest in wildfire adaptation. The stacked vertical bars represent the contributions of each adaptation investment to overall ignition reductions. These measure-specific contributions to risk reduction are estimated by deploying each measure in isolation, holding the deployment of all other measures at zero. Note that the sum of the stacked bars may not equal the difference between the dashed line and the solid line. This is because the ignition reductions of each measure are compared to a baseline of no other deployed measures. If a circuit produces 3.0 ignitions over the period without any adaptation, then fully burying this circuit underground would provide an ignition reduction of 3.0, and enabling fast-trip settings would provide an ignition reduction of 2.5 (3 * 82%) over the period. However, the sum of these two in isolation would produce a total ignition reduction of 5.5, which cannot exceed 3.0 ignitions.

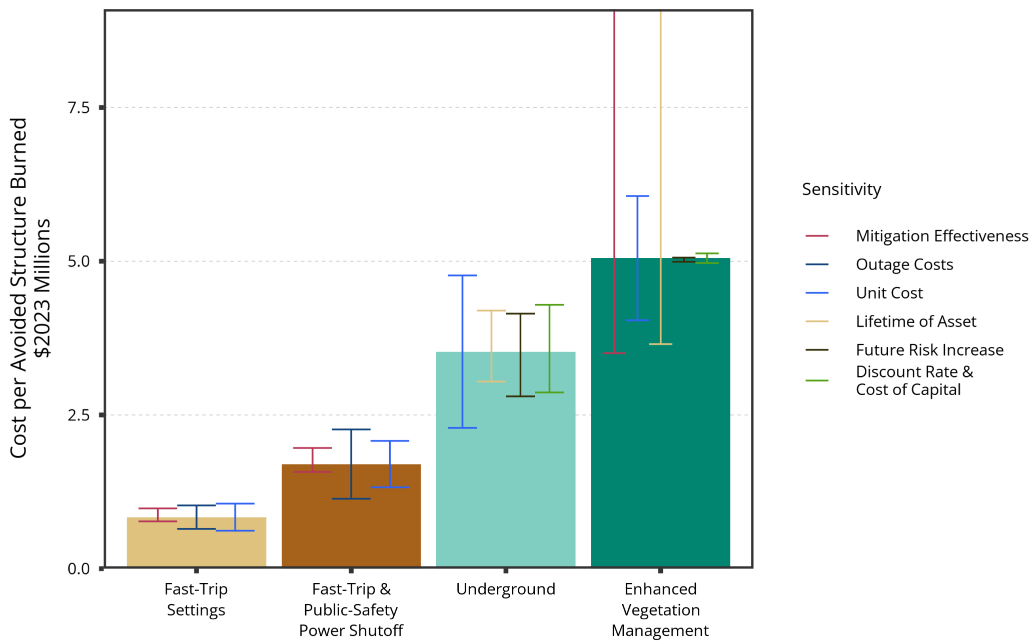
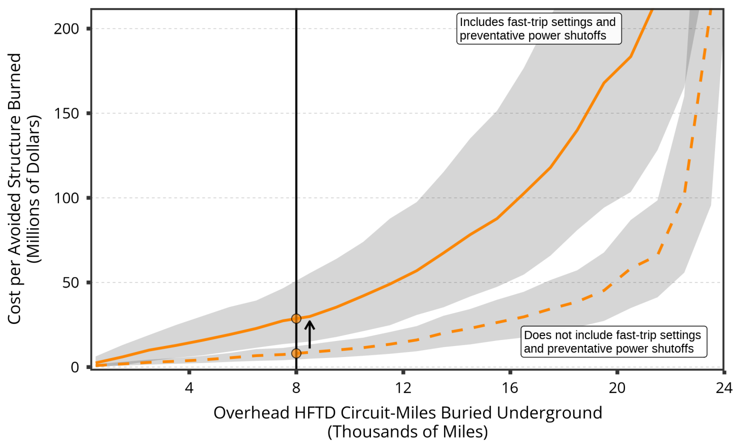
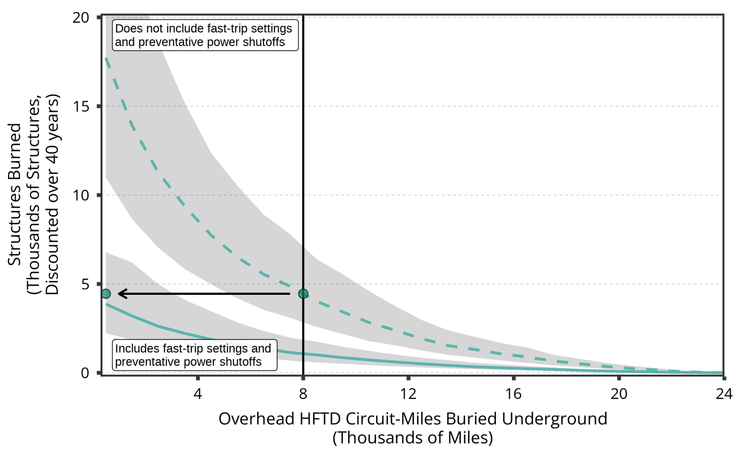


Fig. 4: **Cost Efficiency of Wildfire Adaptation Investments**. The figure plots estimated electric utility investment and outage costs per avoided structure burned for each wildfire mitigation measure at observed deployment levels (i.e., the levels the utility deployed through 2023). We show cost-effectiveness estimates for dynamic grid management strategies in two bars. The first considers only the costs and avoided structures burned of fast-trip settings. The second combines the costs and avoided structures burned from PSPS use with fast-trip settings. In both cases, we apply a value of lost load to estimate outage costs borne by customers. For undergrounding and vegetation management, we project the avoided structures burned that these measures may provide in future years. Hence, these two bars contain additional sensitivities for the lifetime of the asset, future risk increase, and the discount rate. See Methods for detail on the sensitivity analysis.

Fig. 5: **Cost-Efficiency of Undergrounding Capital Investment With and Without Dynamic Grid Management Technologies**



(a) Cost per Avoided Structure Burned



(b) Total Structure Risk Curve

Notes: The horizontal axis in each plot corresponds to hypothetical levels of undergrounding investment across the HFTD, with the left side of the axis corresponding to zero miles of undergrounding (0% of HFTD) and the right side corresponding to 25,000 miles of undergrounding (100% of HFTD). The vertical line corresponds to PG&E's 10,000 mile undergrounding target, which corresponds to approximately 8,000 overhead lines. Underground lines are approximately 25% longer than overhead lines because overhead lines can avoid ground-level obstacles and difficult terrain. (a) describes how our estimates of the cost per avoided structure burned for a given undergrounding investment vary across circuits. (a) is constructed by ordering circuits in terms of cost-effectiveness assuming all miles of the circuit are placed underground. The cost model in (a) uses the low cost of capital sensitivity (5% financing cost). See Methods for additional detail on cost modeling. The dashed line plots costs under the assumption that no dynamic grid management technologies (i.e., fast-trip settings, PSPS) are deployed. However, when we plot the solid line, we model the impact that fast-trip settings and PSPS have on reducing ignition risk during high-fire risk days on circuit-miles that are not placed underground. In addition, the scenario depicted by the solid line accounts for cost savings that undergrounding produces in terms of reducing fast-trip and PSPS program costs, outage impacts, and routine vegetation management. (b) shows the total discounted structures burned over the lifetime of the undergrounding investment. As 100% of the HFTD is placed underground on the right of the horizontal axis, total discounted structures burned are zero. The shaded areas represent 95% confidence intervals from Monte Carlo simulations. See Methods for detail on the distribution of parameters used in Monte Carlo analysis.

7 Data Availability

All raw data used in the analysis are publicly available. Please see Table A1 for detailed documentation. The raw data and processed data will be uploaded in a public repository upon publication and made readily available.

8 Code Availability

The analysis code will be made publicly available via GitHub upon publication.

References

[1] United Nations Environment Programme: Adaptation Gap Report 2023: Underfinanced. Underprepared. Inadequate investment and planning on climate adaptation leaves world exposed. Technical report, United Nations Environment Programme (2023). https://www.unep.org/adaptation-gap-report-2023

[2] Bhandary, R.R., Gallagher, K.S., Zhang, F.: Climate finance policy in practice: a review of the evidence. Climate Policy **21**(4), 529–545 (2021) https://doi.org/10.1080/14693062.2020.1871313 . Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/14693062.2020.1871313. Accessed 2024-06-13

[3] First Street Foundation: The fastest growing economic climate risk - wildfire (2021). https://firststreet.org/research-library/the-fastest-growing-economic-climate-risk---wildfire Accessed 2024-01-05

[4] Balch, J.K., Bradley, B.A., Abatzoglou, J.T., Nagy, R.C., Fusco, E.J., Mahood, A.L.: Human-started wildfires expand the fire niche across the United States. Proceedings of the National Academy of Sciences **114**(11), 2946–2951 (2017) https://doi.org/10.1073/pnas.1617394114 . Publisher: Proceedings of the National Academy of Sciences. Accessed 2024-08-02

[5] Jones, M.W., Kelley, D.I., Burton, C.A., Di Giuseppe, F., Barbosa, M.L.F., Brambleby, E., Hartley, A.J., Lombardi, A., Mataveli, G., McNorton, J.R., Spuler, F.R., Wessel, J.B., Abatzoglou, J.T., Anderson, L.O., Andela, N., Archibald, S., Armenteras, D., Burke, E., Carmenta, R., Chuvieco, E., Clarke, H., Doerr, S.H., Fernandes, P.M., Giglio, L., Hamilton, D.S., Hantson, S., Harris, S., Jain, P., Kolden, C.A., Kurvits, T., Lampe, S., Meier, S., New, S., Parrington, M., Perron, M.M.G., Qu, Y., Ribeiro, N.S., Saharjo, B.H., San-Miguel-Ayanz, J., Shuman, J.K., Tanpipat, V., Werf, G.R., Veraverbeke, S., Xanthopoulos, G.: State of Wildfires 2023–2024. Earth System Science Data **16**(8), 3601–3685 (2024) https://doi.org/10.5194/essd-16-3601-2024 . Publisher: Copernicus GmbH. Accessed 2024-08-14

[6] California Department of Forestry and Fire Protection: Statistics | CAL FIRE (2024). https://www.fire.ca.gov/our-impact/statistics Accessed 2024-06-02

[7] Gabriel Petek: The 2022-23 Budget: Wildfire and Forest Resilience Package. Technical report, Legislative Analyst's Office (LAO) (January 2022)

[8] Pacific Gas and Electric Company: 2023-2025 Wildfire Mitigation Plan R1. Technical report (April 2023)

[9] Southern California Edison: 2023-2025 Wildfire Mitigation Plan. Technical report (March 2023)

[10] San Diego Gas & Electric: 2023-2025 Wildfire Mitigation Plan. Technical report (October 2023)

[11] Michael Wara, Michael Mastrandrea, Eric Macomber: Climate change and utility wildfire risk: A proposal for a federal backstop. Technical report, The Hamilton Project (May 2024). https://www.brookings.edu/articles/climate-change-and-utility-wildfire-risk-a-proposal-for-a-federal-backstop/

[12] Otto, I.M., Donges, J.F., Cremades, R., Bhowmik, A., Hewitt, R.J., Lucht, W., Rockström, J., Allerberger, F., McCaffrey, M., Doe, S.S.P., Lenferna, A., Morán, N., Vuuren, D.P., Schellnhuber, H.J.: Social tipping dynamics for stabilizing Earth's climate by 2050. Proceedings of the National Academy of Sciences **117**(5), 2354–2365 (2020) https://doi.org/10.1073/pnas.1900577117 . Publisher: Proceedings of the National Academy of Sciences. Accessed 2024-06-13

[13] Allen, M.R., Friedlingstein, P., Girardin, C.A.J., Jenkins, S., Malhi, Y., Mitchell-Larson, E., Peters, G.P., Rajamani, L.: Net Zero: Science, Origins, and Implications. Annual Review of Environment and Resources **47**(Volume 47, 2022), 849–887 (2022) https://doi.org/10.1146/annurev-environ-112320-105050 . Publisher: Annual Reviews. Accessed 2024-06-13

[14] Lesage-Landry, A., Pellerin, F., Callaway, D.S., Taylor, J.A.: Optimally Scheduling Public Safety Power Shutoffs. Stochastic Systems **13**(4), 438–456 (2023) https://doi.org/10.1287/stsy.2022.0004 . Publisher: INFORMS

[15] Rhodes, N., Ntaimo, L., Roald, L.: Balancing Wildfire Risk and Power Outages Through Optimized Power Shut-Offs. IEEE Transactions on Power Systems **36**(4), 3118–3128 (2021) https://doi.org/10.1109/TPWRS.2020.3046796 . Conference Name: IEEE Transactions on Power Systems. Accessed 2024-08-12

[16] Taylor, S., Roald, L.A.: A framework for risk assessment and optimal line upgrade selection to mitigate wildfire risk. Electric Power Systems Research **213**, 108592 (2022) https://doi.org/10.1016/j.epsr.2022.108592 . Accessed 2024-08-12

[17] Kody, A., West, A., Molzahn, D.K.: Sharing the Load: Considering Fairness in De-energization Scheduling to Mitigate Wildfire Ignition Risk using Rolling Optimization. arXiv. arXiv:2204.06543 [cs, eess] (2022). https://doi.org/10.48550/arXiv.2204.06543 . http://arxiv.org/abs/2204.06543

[18] Mildenberger, M., Howe, P.D., Trachtman, S., Stokes, L.C., Lubell, M.: The effect of public safety power shut-offs on climate change attitudes and behavioural intentions. Nature Energy **7**(8), 736–743 (2022) https://doi.org/10.1038/s41560-022-01071-0 . Number: 8 Publisher: Nature Publishing Group. Accessed 2023-10-25

[19] Wong-Parodi, G.: When climate change adaptation becomes a "looming threat" to society: Exploring views and responses to California wildfires and public safety power shutoffs. Energy Research & Social Science **70**, 101757 (2020) https://doi.org/10.1016/j.erss.2020.101757 . Accessed 2023-10-25

[20] Wang, Z., Wara, M., Majumdar, A., Rajagopal, R.: Local and utility-wide cost allocations for a more equitable wildfire-resilient distribution grid. Nature Energy **8**(10), 1097–1108 (2023) https://doi.org/10.1038/s41560-023-01306-8 . Number: 10 Publisher: Nature Publishing Group. Accessed 2023-10-25

[21] Larsen, P.H.: A method to estimate the costs and benefits of undergrounding electricity transmission and distribution lines. Energy Economics **60**, 47–61 (2016) https://doi.org/10.1016/j.eneco.2016.09.011 . Accessed 2023-11-27

[22] Taylor, W.O., Watson, P.L., Cerrai, D., Anagnostou, E.: A Statistical Framework for Evaluating the Effectiveness of Vegetation Management in Reducing Power Outages Caused during Storms in Distribution Networks. Sustainability **14**(2), 904 (2022)

https://doi.org/10.3390/su14020904 . Number: 2 Publisher: Multidisciplinary Digital Publishing Institute. Accessed 2023-10-25

[23] Mitchell, J.W.: Analysis of utility wildfire risk assessments and mitigations in California. Fire Safety Journal **140**, 103879 (2023) https://doi.org/10.1016/j.firesaf.2023.103879 . Accessed 2024-06-18

[24] Malloy, C.: The Consequences of Wildfire Liability for Firm Precaution: Evidence from Power Shutoffs in California (2024). https://doi.org/10.2139/ssrn.4780392 . https://www.ssrn.com/abstract=4780392

[25] Eric Macomber, Michael Wara, Michael Mastrandrea: Wildfire: Assessing and Quantifying Risk Exposure and Mitigation Across Western Utilities. Technical report, Woods Institute for the Environment (May 2024)

[26] Vazquez, D.A.Z., Qiu, F., Fan, N., Sharp, K.: Wildfire Mitigation Plans in Power Systems: A Literature Review. IEEE Transactions on Power Systems **37**(5), 3540–3551 (2022) https://doi.org/10.1109/TPWRS.2022.3142086 . Conference Name: IEEE Transactions on Power Systems. Accessed 2024-06-19

[27] Johnson, J.: Quantifying the Economic Risk of Wildfires and Power Lines in San Diego County (2014)

[28] Keeley, J.E., Syphard, A.D., Keeley, J.E., Syphard, A.D.: Historical patterns of wildfire ignition sources in California ecosystems. International Journal of Wildland Fire **27**(12), 781–799 (2018) https://doi.org/10.1071/WF18026 . Publisher: CSIRO PUBLISHING. Accessed 2023-10-25

[29] Abatzoglou, J.T., Smith, C.M., Swain, D.L., Ptak, T., Kolden, C.A.: Population exposure to pre-emptive de-energization aimed at averting wildfires in Northern California. Environmental Research Letters **15**(9), 094046 (2020) https://doi.org/10.1088/1748-9326/aba135 . Publisher: IOP Publishing. Accessed 2023-10-25

[30] Jazebi, S., De Leon, F., Nelson, A.: Review of Wildfire Management Techniques—Part I: Causes, Prevention, Detection, Suppression, and Data Analytics. IEEE Transactions on Power Delivery **35**(1), 430–439 (2020) https://doi.org/10.1109/TPWRD.2019.2930055 . Accessed 2024-04-02

[31] Penn, I.: Utility-Caused Wildfires Are Becoming a National Problem. The New York Times (2024). Chap. Business

[32] Section 4293 - Clearance distances between vegetation and conductors carrying electric current, Cal. Pub. Resources Code § 4293. https://casetext.com/statute/california-codes/california-public-resources-code/division-4-forests-forestry-and-range-and-forage-lands/part-2-protection-of-forest-range-and-forage-lands/chapter-3-mountainous-forest-brush-and-grass-covered-lands/section-4293-clearance-distances-between-vegetation-and-conductors-carrying-electric-current

[33] Pacific Gas and Electric Company: Trees and Powerlines. https://www.pge.com/en/outages-and-safety/safety/vegetation-management.html

[34] California Public Utilities Commission: Protective Equipment and Device

Settings (PEDS). https://www.cpuc.ca.gov/industries-and-topics/wildfires/protective-equipment-device-settings Accessed 2024-01-05

[35] Ivan Penn: PG&E, Troubled California Utility, Emerges From Bankruptcy. The New York Times (2020). Chap. Business. Accessed 2023-11-22

[36] Pacific Gas and Electric Company: System Hardening & Undergrounding. https://www.pge.com/en/outages-and-safety/safety/community-wildfire-safety-program/system-hardening-and-undergrounding.html Accessed 2024-01-05

[37] Pacific Gas and Electric Company: 2023 General Rate Case Exhibit (PG&E-4) Electric Distribution Workpapers Supporting Prepared Testimony Chapters 2-13. Technical Report Application 21-06-021 (June 2021)

[38] California Public Utilities Commission: Decision on Test Year 2023 General Rate Case of Pacific Gas and Electric Company. Technical Report Application 21-06-021 (September 2023)

[39] Blunt, K.: PG&E Wins Approval to Bury More Than 1,200 Miles of Power Lines. Section: US (2023). https://www.wsj.com/us-news/climate-environment/pg-e-wins-approval-to-bury-more-than-1-200-miles-of-power-lines-3ab460d4 Accessed 2024-06-17

[40] California Public Utilities Commission: Fire Ignition Data. https://www.cpuc.ca.gov/industries-and-topics/wildfires Accessed 2023-04-06

[41] Yao, M., Bharadwaj, M., Zhang, Z., Jin, B., Callaway, D.S.: Predicting electricity infrastructure induced wildfire risk in California. Environmental Research Letters **17**(9), 094035 (2022) https://doi.org/10.1088/1748-9326/ac8d18 . Publisher: IOP Publishing. Accessed 2023-10-25

[42] Mark Filip: Re: Information Request Regarding Monitor Team Field Inspections (2020). https://www.courthousenews.com/wp-content/uploads/2020/10/PGEMonitor10202020.pdf Accessed 2024-01-04

[43] California Public Utilities Commission: Resolution M-4852: Placing Pacific Gas and Electric Company Into Step 1 of the "Enhanced Oversight and Enforcement Process" Adopted in Decision 20-05-053. Technical report (April 2021)

[44] Abatzoglou, J.T., Battisti, D.S., Williams, A.P., Hansen, W.D., Harvey, B.J., Kolden, C.A.: Projected increases in western US forest fire despite growing fuel constraints. Communications Earth & Environment **2**(1), 1–8 (2021) https://doi.org/10.1038/s43247-021-00299-0 . Number: 1 Publisher: Nature Publishing Group. Accessed 2024-01-18

[45] Lazar, J., Chernick, P., Marcus, W., LeBel, M.: Electric Cost Allocation for a New Era: A Manual. Technical report, Regulatory Assistance Project (RAP) (January 2020)

[46] Karl Dunkle Werner, Stephen Jarvis: Rate of Return Regulation Revisited. Technical report, Energy Institute at Haas Working Paper (August 2023). https://haas.berkeley.edu/wp-content/uploads/WP329.pdf

[47] Goodson, H., Long, T., Hawiger, M.: Sur-Reply Brief of the Utility Reform Network Regarding the Revised Undergrounding Proposal of Pacific Gas and Electric Company.

Technical report (January 2023)

[48] Davis, L.W., Hausman, C.: Who Will Pay for Legacy Utility Costs? Journal of the Association of Environmental and Resource Economists **9**(6), 1047–1085 (2022) https://doi.org/10.1086/719793 . Publisher: The University of Chicago Press. Accessed 2024-08-01

[49] DW Hosmer, S Lemeshow: Applied Logistic Regression, 2nd edn., New York, NY (2000)

[50] Pozzolo, A.D., Caelen, O., Johnson, R.A., Bontempi, G.: Calibrating Probability with Undersampling for Unbalanced Classification. In: 2015 IEEE Symposium Series on Computational Intelligence, pp. 159–166 (2015). https://doi.org/10.1109/SSCI.2015.33 . http://ieeexplore.ieee.org/document/7376606 Accessed 2024-01-02

[51] Druckenmiller, H., Liao, Y.P., Pesek, S., Walls, M., Zhang, S.: Removing development incentives in risky areas promotes climate adaptation. Nature Climate Change, 1–7 (2024) https://doi.org/10.1038/s41558-024-02082-3 . Publisher: Nature Publishing Group. Accessed 2024-08-05

[52] Pacific Gas and Electric Company: Wildfire Mitigation Tables 1-15 (Q1 2024). Technical report (May 2024)

[53] Pacific Gas and Electric Company: Dynamic Load Profiles. https://www.pge.com/assets/rates/tariffs/energy_use_prices.shtml

[54] Gorman, W.: The quest to quantify the value of lost load: A critical review of the economics of power outages. The Electricity Journal **35**(8), 107187 (2022) https://doi.org/10.1016/j.tej.2022.107187 . Accessed 2023-10-25

[55] Melissa R. Jaffe, Joe H. Scott, Michael N. Callahan, Gregory K. Dillon, Eva C. Karau, Mitchell T. Lazarz: Wildfire Risk to Communities: Spatial datasets of wildfire risk for populated areas in the United States (2nd Edition) (2024). https://doi.org/10.2737/RDS-2020-0060-2 . https://www.fs.usda.gov/rds/archive/catalog/RDS-2020-0060-2 Accessed 2024-07-29

[56] Melissa R. Jaffe, Joe H. Scott, Michael N. Callahan, Gregory K. Dillon, Eva C. Karau, Mitchell T. Lazarz: Wildfire Risk to Communities 2.0: Updated methods for geospatial datasets for populated areas in the United States. Forest Service Research Data Archive, US Department of Agriculture, Fort Collins, Colorado (2024)

[57] Abatzoglou, J.T.: Development of gridded surface meteorological data for ecological applications and modelling. International Journal of Climatology **33**(1), 121–131 (2013) https://doi.org/10.1002/joc.3413 . _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/joc.3413. Accessed 2024-01-12

[58] Mesowest, University of Utah: RAWS Weather Station Network. https://mesowest.utah.edu/ Accessed 2024-01-04

[59] gridMET

[60] U.S. Department of Agriculture, U.S. Department of the Interior: LANDFIRE. https://landfire.gov/index.php Accessed 2024-01-04

[61] Pacific Gas and Electric Company: Attachments to 2020 Wildfire Mitigation Plan ("EDGIS2-12.gdb"). https://www.pge.com/en/outages-and-safety/safety/

community-wildfire-safety-program.html Accessed 2021-10-12

[62] California Public Utilities Commission: Fire-Threat Maps and Fire-Safety Rulemaking. https://www.cpuc.ca.gov/industries-and-topics/wildfires/fire-threat-maps-and-fire-safety-rulemaking Accessed 2024-01-12

[63] Pacific Gas and Electric Company: 2023 Wildfire Mitigation Plan Discovery WMP-Discovery2023_DR_SPD_004-Q001Atch01 (2023)

[64] California Public Utilities Commission: 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 Accessed 2024-01-05

[65] Pacific Gas and Electric Company: 2023 Wildfire Mitigation Plan Appendix D ACI PG&E-22-32_Atch01_Redacted (2023)

[66] Pacific Gas and Electric Company: 2023 Wildfire Mitigation Plan Discovery WMP-Discovery2023_DR_MGRA_002-Q008Atch01 (2023)

[67] Pacific Gas and Electric Company: 2022 Wildfire Mitigation Plan Discovery WMP-Discovery2022_DR_MGRA_002-Q01Atch01 (2022)

[68] Pacific Gas and Electric Company: 2022 Wildfire Mitigation Plan Discovery WMP-Discovery2022_DR_MGRA_002-Q02 (2022)

[69] Pacific Gas and Electric Company: 2020 Wildfire Mitigation Plan Supplemental Data Request 3.4 Table 7 Veg (2020)

[70] Pacific Gas and Electric Company: 2021 Wildfire Mitigation Plan Discovery WildfireMitigationPlans_DR_CalAdvocates_035-Q04-Atch01 (2021)

[71] Pacific Gas and Electric Company: 2022 Wildfire Mitigation Plan Discovery WMP-Discovery2022_DR_MGRA_002-Q16Atch01 (2022)

[72] Pacific Gas and Electric Company: 2023 Wildfire Mitigation Plan Discovery WMP-Discovery2023_DR_CalAdvocates_006-Q003Atch01 (2023)

[73] Pacific Gas and Electric Company: 2023 Wildfire Mitigation Plan Discovery WMP-Discovery2023_DR_CalAdvocates_003-Q001Atch01 (2024)

[74] Pacific Gas and Electric Company: 2023 General Rate Case Exhibit (PG&E-4) Electric Distribution Chapters 1-6. Technical Report Application 21-06-021 (February 2022)

[75] Prest, B., Rennert, K., Newell, R., Pizer, W., Anthoff, D.: Updated Estimates of the Social Cost of Greenhouse Gases for Usage in Regulatory Analysis. Technical report, Resources for the Future (February 2023). https://media.rff.org/documents/EPA_SCC_Report_Comments.pdf

[76] Pacific Gas and Electric Company: 2022 Wildfire Mitigation Plan Update. Technical report (February 2022)

[77] California Public Utilities Commission: Historical Electric Cost Data. https://www.cpuc.ca.gov/industries-and-topics/electrical-energy/electric-costs/historical-electric-cost-data Accessed 2023-11-16

9 Methods

9.1 Ignition risk prediction model

Fire weather variables, such as wind speed, are highly stochastic and may interact nonlinearly to generate ignition events. To develop our measure of a circuit's daily ignition risk, we train a random forest model using high-resolution weather data, topographic information, and circuit characteristics. Our methodology closely follows a previous study that characterized ignition risk in PG&E's territory [41].

In the random forest model, the positive class is an ignition event caused by vegetation contact on a given circuit-day. The ignition data are highly imbalanced, with the proportion of positive events to negative events being only 0.03%, which we address by under-sampling. We evaluate models based on the area under the receiver operator characteristic curve (AUC).

We train the model with ignition data from 2015 to 2019, prior to PG&E's widespread implementation of its key wildfire programs. We perform 3-repeat 10-fold cross-validation and split the training and testing data 75/25%. We tune two hyperparameters: the number of decision trees and features considered at each split. Our ignition risk model produces an AUC value of 0.93 when used to predict ignition events in the testing data. Prediction models with AUC values between 0.8-0.9 are generally considered excellent [49]. The confusion matrix, using a classification threshold of 0.5, ROC curve, and feature importance are shown in Extended Data Figure A2 and Figure A3.

The model outputs the probability of an ignition on a given circuit-day, and in all cases when we use the model to predict ignition counts we use the Bayes classification threshold of 0.5. Because under-sampling creates bias in the posterior probability distribution [50], we apply an adjustment to the posterior probability estimates. The adjustment expresses the posterior probability of the positive class in the original dataset as a function of the posterior probability of the positive class after under-sampling and the proportion of negative class events in the under-sampled dataset. After calibrating the probabilities, our ignition risk model predicts 156 ignitions in the test data. The test data includes 120 actual ignitions. The recall of the model in the test data is 79% but the precision of the model is low (0.1%).

9.2 Enhanced vegetation management matching technique

We use ignition risk probabilities– estimated using our random forest model– to leverage plausibly exogenous variation in risk mitigation interventions. Specifically, we use a matching algorithm to identify circuits that would have had the same risk probability post-intervention but received different treatments.

For each treated circuit, we use caliper matching to identify the two nearest control circuits within a minimum distance – measured in terms of average daily ignition risk – to a treated circuit as potential matches. The caliper size we use to evaluate successful matches is 10% of the sample's ignition risk standard deviation. We perform caliper matching twice for two vegetation management treatment tiers: "high" (50% or more of total circuit length) and "moderate" (10%-50% of total circuit length). Figure A4 depicts this process. For a detailed list of steps, see Appendix.

Extended Data Table A2 and Table A3 show covariate balance tables for vegetation management. In the case of the high vegetation management treatment group (Extended Data Table A2), average ignition risk is 0.34 standardized mean difference (SMD) units higher than

HFTD circuits that received no or minimal amounts of vegetation management. After constructing the matched control group and further filtering to high-risk days, the standardized mean difference between the two groups is 0. While some individual risk covariates show SMDs larger than 0.2 (e.g., energy release component: 0.27, wind speed: -0.20), it is the combination of these individual risk covariates, expressed as the ignition risk probability, that is critical to balance between treatment and control groups.

In addition to creating treatment-control comparisons via our matching technique, we directly control for ignition risk by including the ignition risk score as a covariate in the econometric model. This approach is similar to doubly-robust propensity score methods.

9.3 Fast-trip setting identification

PG&E deployed fast-trip settings to all HFTD circuits in 2022 and 2023, making within-time period matching infeasible for fast-trip settings. To identify effects of fast-trip settings, we rely on an intertemporal comparison. Because PG&E did not use fast-trip settings prior to its partial pilot deployment in 2021, we compare similar high-risk location-days across the pre- and post-intervention periods. Our comparisons restrict the sample only to circuit-days when wildfire risk was sufficiently high that the criteria for fast-trip enablement would have been met, even in the pre-period when fast-trip settings had not been deployed yet.

One might be concerned that risk factors are distributed differently before and after fast-trip settings were deployed. We test for differences and find similar conditions during high-risk days in the pre- and post-period. In the left panel of Extended Data Table A4, we show that average ignition risk is 0.03 SMD units lower after fast-trip settings were deployed compared to before they were deployed, below the commonly-used threshold of 0.1 to assess balance [51]. This increases our confidence that differences in ignition outcomes are caused by the utility's adaptation investments versus confounding factors. For more detail on how the fast-trip dataset is constructed and the criteria the utility uses to enable fast-trip settings, see Appendix text.

9.4 Logistic regression model

We model the conditional probability of a vegetation-caused ignition at location i on day t as a function of variables X_{it} and unknown or unobserved factors ϵ_{it}. We specify a logistic regression model which assumes the ϵ_{it} are drawn from a standard logistic distribution. This yields the following closed form expression for the conditional ignition probabilities:

$$G(X_{it}\beta) = \frac{exp(X_{it}\beta)}{1 + exp(X_{it}\beta)} \tag{1}$$

$$\begin{gathered} X_{it}\beta = \alpha_0 + \alpha_1\theta_{it} + \beta_1 F_{it} + \\ \beta_2(D_{i,\text{Veg=Hi.}} * T_{it,\text{Post=1}}) + \beta_3(D_{i,\text{Veg=Med.}} * T_{it,\text{Post=1}}) + \\ \beta_4 D_{i,\text{Veg=Hi.}} + \beta_5 D_{i,\text{Veg=Med.}} + \beta_6 \text{UG}_{it} + \beta_7 Z_{it,\text{PSPS=1}} + \beta_8 \text{CC}_{it} \end{gathered} \tag{2}$$

Explanatory variables in the model include a binary variable indicating whether fast-trip settings were enabled on a given circuit-day (F_{it}) and binary variables indicating the circuit-level vegetation management treatment (D_i). Vegetation management treatments are defined across two levels, high and moderate. Vegetation management treatments are interacted with a treatment indicator (T_{it}) to capture the effect of the treatment in the post-intervention period. We also include predicted ignition risk probability (θ_{it}), miles of undergrounding (UG_{it}) and covered conductors (CC_{it}), an indicator for PSPS events (Z_{it}), and an intercept term (α_0).

We fit the logistic regression model once over the entire HFTD sample, (the first columns of Table 1 and Extended Table A5). We then separately fit the model for the high vegetation management treatment group and matched controls (Table 1) and the moderate vegetation management treatment group and matched controls (Extended Data Table A5). See Appendix for robustness tests, including the addition of regional fixed effects and adjusting the number of matches for each treated circuit.

When we report parameter estimates in Table 1, we transform the estimates to incidence rates ($\text{IR} = e^{\beta} - 1$) for ease of interpretation. In the case of the coefficient on fast-trip settings (β_1), the incidence rate reflects the change in ignitions on high-risk days when fast-trip settings are enabled versus high-risk days when fast-trip settings are not enabled.

In the sensitivity analysis shown in Figure 4, we show how uncertainty in the coefficient estimates for fast-trip settings and enhanced vegetation management mitigation effectiveness affect cost-effectiveness. The whiskers in Figure 4 reflect 90% confidence intervals, derived using the standard errors obtained from column (3) of Table 1.

9.5 Cost data and modeling

We obtain cost data for each wildfire adaptation measure by reviewing the utility's wildfire mitigation plans and general rate case proceeding documents filed with the CPUC. For enhanced vegetation management and undergrounding, we use average per mile investment costs. These costs likely vary across circuits due to topography and other risk-related factors, but circuit-specific cost data is not publicly available. We address uncertainties in per mile costs by applying a "low" and "high" unit cost per mile in our cost analysis. See Extended Data Table A1 and Appendix for more detail and source material for the cost analysis.

The average unit cost of enhanced vegetation management is $250K per mile in our base case and varies from $200K-$300K. The average unit cost of undergrounding is $3.0M per mile in our base case and varies from $2.0M-$4.0M. For fast-trip settings, we express unit costs as a cost per customer-hour of fast-trip outage. Our central case assumes a unit cost of $25 per customer-hour, approximated using 2022 fast-trip program costs of $150M and total customer-hours of fast-trip outages of six million. To address uncertainty in fast-trip costs, the sensitivity analysis in Figure 4 varies this unit cost between $15 and $35 per customer-hour.

We approach PSPS costs in a similar fashion. Our base case assumes a unit cost of $10 per customer-hour of PSPS outage (varies between $5 and $15), approximated using annual forecasted costs of $100M per year and twelve million customer-hours of PSPS outages per year [52]. Because the utility's use of PSPS in 2019 represents a large outlier and has since been refined (see Extended Data Figure A8), we exclude PSPS costs and their associated avoided structures burned in 2019 when estimating cost-effectiveness in Figure 4.

We assume vegetation management delivers ignition reductions for ten years after it is deployed, and those ignition reductions decline linearly to zero by the end of the ten years. We vary the lifetime of vegetation management from five to fifteen years. We assume the lifetime of undergrounding investments is 40 years and varies from 30-50 years. We assume undergrounding is 100% effective at eliminating ignitions in all years.

To reflect potential increases in risk in future years that impact the economics of long-lived capital investments such as undergrounding, our central case projects a 45% increase in ignition risk and a 50% increase in extreme wildfire probability by 2050, with continued increases thereafter. The high-risk scenario in Figure 4 reaches increases of 83% and 96% by 2050 for ignition risk and extreme wildfire risk, respectively. The low-risk scenario reaches increases of 20% by 2050 for both.

We construct these future risk scenarios by sampling from each circuit's historical climate and weather data on a monthly basis. For the first future year modeled, we draw from each circuit's full historical distribution. By 2050, our central case samples from the 50^{th} percentile and greater, and the low and high risk scenarios sample from the 25^{th} and 75^{th} percentiles, respectively. In the intervening years, the percentile threshold at which we sample from linearly increases each year. After 2050, the percentile threshold continues to increase linearly until a maximum of the 90^{th} percentile. Extended Data Figure A8 shows how these risk scenarios affect the frequency of fast-trip and PSPS in future years.

Under rate of return regulation, capital investments made by electric utilities enter into the customer rate base. Utilities earn an authorized rate of return on these investments, paid through retail electricity rates. Both the return the utility earns on capital investments as well as the associated construction costs are spread out across the lifetime of the asset until the asset is no longer useful. We adopt this approach when modeling the costs of burying powerlines underground. Per-mile costs of undergrounding are spread out across the lifetime of the undergrounding asset and charged to ratepayers according to a straight-line depreciation schedule.

Future benefits (i.e., avoided structures burned, avoided outages) and costs (i.e., regulated rate of return, maintenance costs, avoided routine vegetation management) are discounted using a real social discount rate of 2.5%. The lower and upper whiskers in Figure 4 use a real social discount rate of one and four percent, respectively. When varying the real social discount rate, we symmetrically vary the utility's assumed cost of capital. The cost of capital sensitivity ranges from five to ten percent, with a central scenario at 7.5%.

9.6 Reliability costs

Fast-trip settings and PSPS events create additional costs to customers in the form of unplanned electricity outages. In 2022 and 2023, fast-trip settings caused approximately six to seven million customer-hours of outages per year. Outage data for fast-trip and PSPS events are segmented by customer class, including residential customers, medical baseline customers that rely on electricity to power medical devices, and commercial and industrial customers. Approximately 85% of outage hours are distributed among standard residential customers, 5% among medical baseline, 9% among small commercial and industrial ("C&I"), and 1% among medium and large C&I. We apply a value of lost load (VoLL) framework that varies by customer class to estimate the economic cost of these outages.

We use average load profiles obtained from PG&E to determine that residential customers use 0.8 kWh per hour on average, small C&I use 1.9 kWh per hour, and medium and large C&I use 23 kWh per hour [53]. In our central case, we apply a VoLL of \$3 per kWh for residential customers, \$25 per kWh for small C&I, and \$15 per kWh for medium and large C&I. For medical baseline customers, we assume equivalent average usage per hour as the residential class, but raise the VoLL to \$100 per kWh, assuming customers who use electricity to power medical devices face a high economic cost from service interruptions.

There is not a strong consensus on appropriate VoLL point estimates to use [54]. Moreover, we omit other sources of heterogeneity in VoLL parameter estimates, including the duration of the outage, whether the outage was expected or not, and variation across climate zones. To address uncertainty in the economic costs of outages, the sensitivity analysis in Figure 4 varies the assumed VoLL for each customer class upwards and downwards by 33%.

9.7 Structure risk

The threat of structure loss along circuits can vary considerably due to differences in topography, vegetation type, wind velocity, fuel moisture, structure density, firefighting resources, and structure hardening. The following model takes these factors into consideration when calculating expected structure loss.

Calculation of expected structure loss (Y_{it}) at circuit i on day t takes the following form:

$$Y_{it} = \Pr(I = 1|X_{it}, C_i, Z_{it}) * \sum_{s}^{S} \Pr(s|X_{it}, C_i) * \delta_{is} * \bar{\mathrm{A}}_s \tag{3}$$

The first term of Equation 3 represents the probability of an ignition occurring for a given circuit on a given day (described previously).

The second term of Equation 3, $\Pr(s|X_{it}, C_i)$, reflects the probability of an ignition spreading into a wildfire of size s. The four wildfire class sizes (s) considered are:

1. Small: $<$ 10 acres
2. Medium: [10 acres, 300 acres)
3. Large: [300 acres, 10,000 acres)
4. Extreme: [10,000 acres, ∞)

Wildfire class size probabilities are estimated by training a machine-learning prediction model on 1,893 historical wildfire sizes from PG&E fire ignition data. 95% of the ignitions are considered "small" wildfires, 4% of the ignitions are considered "medium," 1% are considered "large," and 0.5% are considered "extreme."

The training and testing data is split 75/25%. Repeated 10-fold cross-validation is performed, and hyperparameters are tuned. The resulting model produces an AUC value of 0.70. Key weather and environmental variables (X_{it}) and fixed circuit variables (C_i) that influence model performance include average forest canopy height, relative humidity, wind speed, and elevation. See Extended Data Figure A5 for a comparison of actual wildfire sizes and predicted wildfire sizes. Extended Data Figure A6 shows how the distribution of predicted wildfire size probabilities varies across each day of the year.

Fire suppression is not explicitly modeled in this assessment of structure risk. However, fire suppression is implicitly controlled for because we use empirical wildfire sizes when training the machine-learning model.

The third term of Equation 3 (δ_{is}) captures the number of structures burned per acre by a wildfire of size s. Extended Data Figure A7 provides an illustration of how δ_{is} is calculated for an example circuit. Five ignition points are randomly sampled along each distribution circuit because wildfire risk can vary depending on where the ignition occurs along the circuit.

Buffers equal to the average wildfire footprint ($\bar{A}_s$) of each wilfire class size (s) are then drawn around each ignition point. These buffers are shown surrounding each ignition point in Figure A7. Each buffer is then intersected with 30-meter raster data on (1) building counts, (2) conditional risk to potential structures, and (3) the product of the two raster datasets. The raster data comes from the Wildfire Risk to Communities Project, which was developed in collaboration with the U.S. Forest Service and Pyrologix, LLC [55]. The building count data filters out small polygons that may represent sheds or reflect the shadows of rocks, and footprints that overlay uninhabitable land cover such as water and snow are removed.

Conditional risk to potential structures (cRPS) represents the potential consequences of a fire to a structure if both a fire were to occur and a structure was located in that pixel. Its values range from zero to 100, with zero indicating no damage to a structure and 100 indicating complete structure loss. The measure is developed by estimating flame length probability classes across the landscape and assigning response function values based on flame length and vegetation type. Importantly, cRPS reflects the potential risk to a generic residential structure and does not account for actions taken by property owners to protect their homes. See WRC documentation for more details on methods [56].

Across all pixels intersected, δ_{is} is then calculated as the average of the product of building counts (B) and cRPS. δ_{is} is adjusted to a per-acre basis to account for the 30-meter pixel sizes equaling approximately 0.22 acres.

The fourth term of Equation 3 ($\bar{A}_s$) is the average wildfire footprint for a given class size, using historical data from PG&E ignition data. Average wildfire footprint sizes are multiplied by expected structure loss per acre (δ_{is}) to obtain total structure loss for wildfire class size s at circuit i in Equation 3.

1. $\bar{A}_{s=\text{Small}}$: 1 acre
2. $\bar{A}_{s=\text{Medium}}$: 150 acres
3. $\bar{A}_{s=\text{Large}}$: 2,000 acres
4. $\bar{A}_{s=\text{Extreme}}$: 20,000 acres

A limitation of this measure of structure risk is that the circular buffers drawn around each ignition point may not reflect the tendency of wildfires to spread in a prevailing direction around a circuit due to local topography and wind velocity. A second limitation involves small sample bias in the estimation of wildfire class size probabilities. Only 0.5% of wildfires exceed 10,000 acres, but these drive a significant share of structure losses. One wildfire, the Camp Fire, accounts for two-thirds of structure losses attributed to PG&E equipment during the study period. Prediction of wildfire class size probabilities may be improved by including additional non-power sector wildfire observations in the training data that occur in similar locations and under similar weather conditions to powerline-caused fires.

9.8 Monte Carlo analysis

Monte Carlo simulations are used to derive the 95% confidence intervals shown in the shaded areas of Figure 5. For both sub-figures, 200 Monte Carlo draws are performed, once assuming dynamic grid management technologies are enabled and once without. In each draw, key parameters are drawn from a distribution (summarized in Extended Data Table A6), and then the net costs of undergrounding each circuit and avoided structures burned are discounted over a 40-year period. Circuits are ranked in terms of cost-effectiveness to construct each curve in Figure 5.

Extended Data Table A6 shows that we use a median undergrounding unit cost of \$3.75M per mile, higher than the \$3.0M per mile used in Figure 4. We use a higher cost per mile because in the horizontal axis of Figure 5 we are showing the length of overhead lines replaced by underground lines, in contrast to the length of underground lines deployed. The distinction is important because replacing one overhead mile requires more than one underground mile; underground powerlines need to be re-routed more often to avoid difficult terrain and ground or sub-surface obstacles. One mile of undergrounding replaces approximately 0.64-0.80 miles of overhead conductor[47].

Acknowledgements. We thank Ry Andresen, Severin Borenstein, Sam Borgeson, Ed Kahn, Todd Strauss, Alva Svoboda, Mengqi Yao, and seminar participants at UC Berkeley, UC Santa Barbara, and the POWER Conference for helpful discussion. This work received generous financial support from the University of California Office of the President Laboratory Fees Program (LFR-20-652467).

Appendix A Extended Data

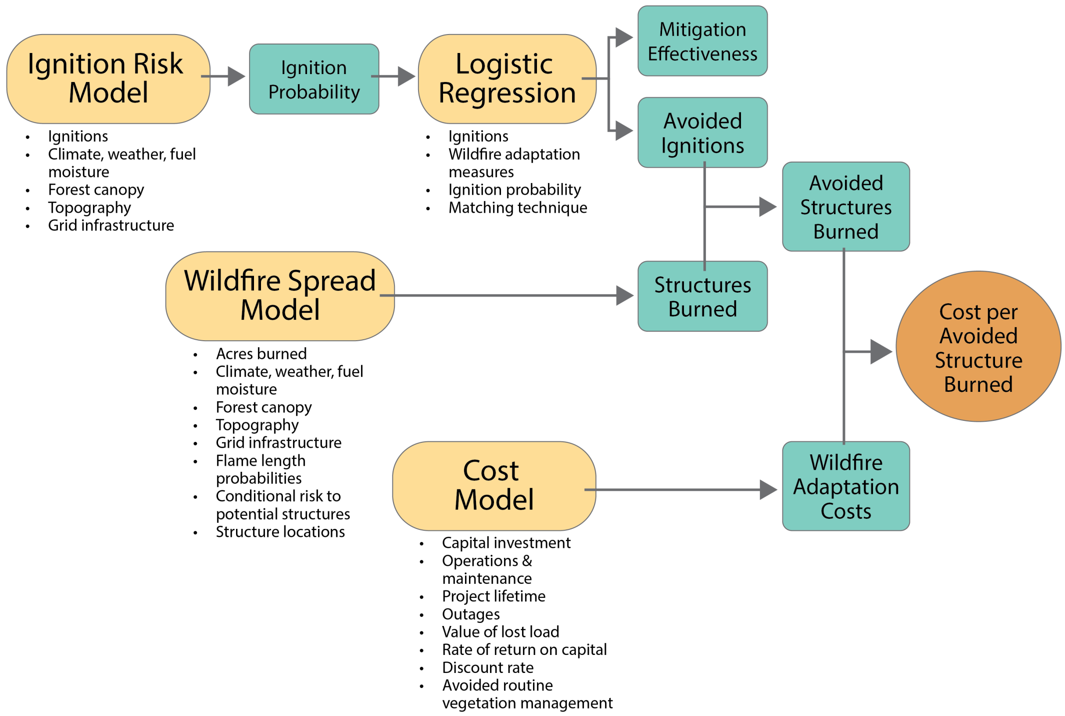
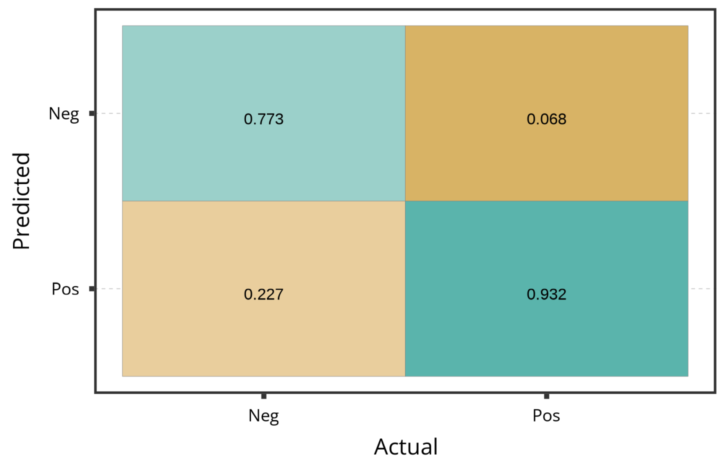


Fig. A1: **Modeling Wildfire Adaptation Costs in the Electric Power Sector.**

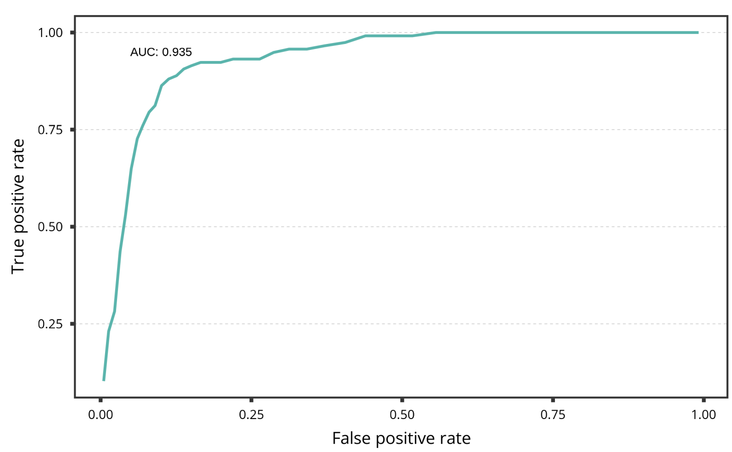
Table A1: Data Availability

Data Type	Variables	Resolution	Source
Climate	Minimum relative humidity, wind velocity, wind direction, accumulated precipitation, maximum temperature, downward surface shortwave radiation, evapotranspiration, vapor pressure deficit	4 km	gridMET, Climatology Lab, University of California, Merced [57]
Climate	Air temperature, hourly precipitation, relative humidity, wind speed, wind direction	RAWS weather station	Mesowest, University of Utah [58]
Fuels	100-hour and 1000-hour dead fuel moisture, energy release component	4 km	gridMET, Climatology Lab, University of California, Merced [59]
Fuels	Live fuel moisture	RAWS weather station	Mesowest, University of Utah [58]
Topography	Mean forest canopy height, maximum forest canopy height, elevation above sea-level	30-meter	LANDFIRE, USDA and U.S. Department of the Interior [60]
Circuit Characteristics	Shapefile, installed year, length in HFTD-Tier 2, Tier 3, and non-HFTD	Circuit	PG&E 2020 Wildfire Mitigation Plan [61]
High-Fire Threat District	Perimeters of HFTD Tiers 2 & 3	Spatial polygon	California Public Utilities Commission [62]
Ignitions	Location, voltage, cause, date, time, acres, fire potential index	Lat/long position	California Public Utilities Commission [40], PG&E 2023 Wildfire Mitigation Plan [63]
Public Safety Power Shutoffs	Circuit name, date, outage start and end, outage duration, customers impacted	Circuit	California Public Utilities Commission [64]
Fast-Trip Outages	Circuit name, outage start and end, customers impacted, ignitions occurring during fast-trip enablement	Circuit	PG&E 2023 Wildfire Mitigation Plan[65, 66], PG&E 2022 Wildfire Mitigation Plan [67, 68], California Public Utilities Commission [34]
Vegetation Management & System Hardening	Enhanced vegetation management, undergrounding, and covered conductor	Circuit-miles	PG&E 2020, 2021, 2022, and 2023 Wildfire Mitigation Plans [69–73]
Costs	Undergrounding, enhanced and routine vegetation management, fast-trip settings, PSPS	Per mile and aggregate	PG&E 2023 General Rate Case [37, 38, 74], PG&E Quarterly Data Reports [52]
Structure Risk	Locations of structures, probability of structure burning	Raster data	U.S. Forest Service, Pyrologix [55]

Fig. A2: Ignition Risk Model, Confusion Matrix, and Receiver Operating Characteristic Curve



(a) Confusion Matrix



(b) Receiver Operating Characteristic Curve

Notes: (a) Plots the confusion matrix of the ignition risk model on the sample of testing data using a classification threshold of 0.50. (b) Plots the receiver operating characteristic (ROC) curve, which produces an area under the ROC curve of 0.935.

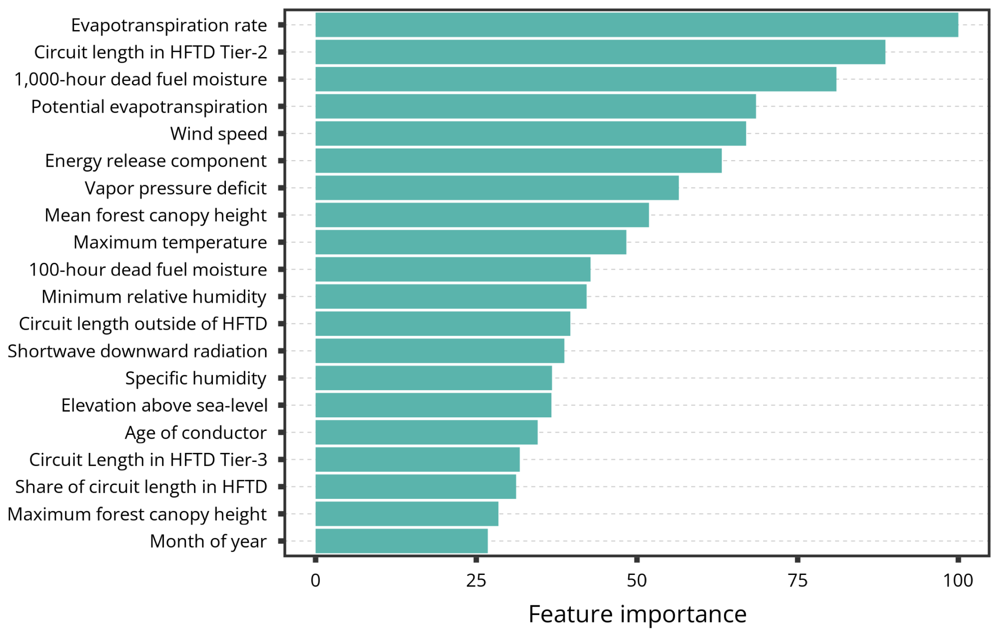


Fig. A3: **Ignition Risk Model Feature Importance**. The figure ranks the twenty most important features in the ignition risk model by feature importance. Feature importance reflects the decrease in accuracy of the model when the variable is excluded from training and testing the model.

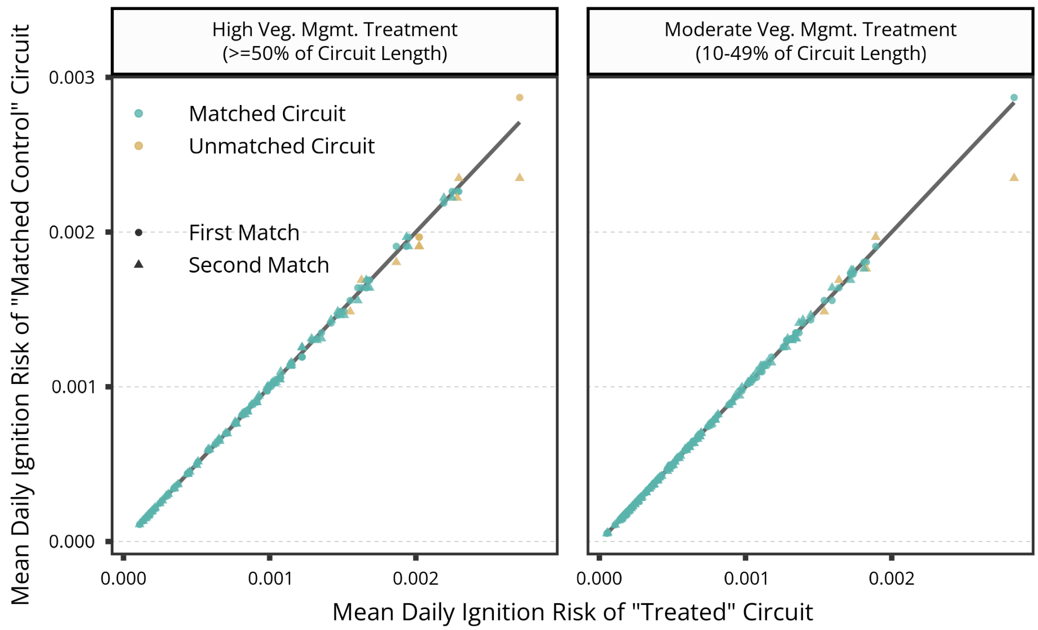


Fig. A4: **Matching on Predicted Ignition Risk**. The horizontal axis plots the average daily ignition risk score of each circuit treated with vegetation management. The vertical axis plots the same metric but for the two control circuits with the nearest average daily ignition risk scores. If treatment and control circuits had identical baseline risk scores, they would fall on the 45 degree line (in gray). The effect of caliper matching is visible in the different color of points that fall sufficiently far off of the 45 degree line. If the absolute difference between a treated and control circuit's average daily ignition risk score is more than 10% of the standard deviation of the sample's risk score, then it is deemed an unsuccessful match. If both of a treated circuit's two nearest neighbors exceed this caliper, then the treated circuit is discarded from the analysis. The plot shows that it is more difficult to find successful matches for higher risk circuits because most high risk circuits receive enhanced vegetation management treatment.

Table A2: Covariate Balance - Circuits Treated With High Levels of Vegetation Management (≥50% Circuit Length)

		All HFTD			Matched Circuits			Matched Circuits and High Risk Days		
	Covariate (Mean)	Control	High Veg. Mgmt.	SMD	Control	High Veg. Mgmt.	SMD	Control	High Veg. Mgmt.	SMD
	Selected Risk Characteristics									
1	Ignition Risk (Daily Probability)	0.0003	0.001	0.34	0.0009	0.0009	0.01	0.0021	0.0021	0
2	Energy Release Component (Index)	37.5	44.4	0.3	41.2	44.3	0.12	67.7	71.5	0.27
3	Wind Speed (Meters/Second)	3.8	3.3	-0.26	3.6	3.3	-0.18	3.3	3.1	-0.2
4	1,000 Hr. Dead Fuel Moisture (%)	16.1	14.7	-0.24	15.5	14.7	-0.11	9.4	8.7	-0.28
5	100 Hr. Dead Fuel Moisture (%)	14.4	12.9	-0.29	13.6	13	-0.12	8.6	7.9	-0.25
6	Precipitation (mm/Day)	2.1	2.2	0.02	2.3	2.2	-0.01	0.1	0.1	0
7	Relative Humidity (Daily Min. %)	39.6	35	-0.24	36	35.1	-0.05	18.9	18.4	-0.05
8	Vapor Pressure Deficit (kPa)	0.99	1.29	0.36	1.16	1.29	0.14	2.1	2.28	0.22
9	Circuit Length (Miles)	40	92	1.09	78	90	0.19	78	90	0.19
10	Forest Canopy Height (Meters)	7	8.9	0.3	9	8.8	-0.04	9	8.8	-0.04
11	Temperature (Daily Max Celsius)	21.3	23.1	0.22	22.3	23.1	0.09	30.4	31.3	0.15
12	Elevation (Feet Above Sea-Level)	1068	1237	0.14	1340	1215	-0.15	1340	1215	-0.15
	Wildfire Adaptation Investments									
13	Fast-Trip (Customer-Hrs/Circuit-Day)	5	12	0.03	12.2	10.4	-0.01	36.9	28.2	-0.02
14	PSPS (Customer-Hrs/Circuit-Day)	35.8	84.2	0.03	64.8	81.8	0.01	196.6	221.8	0.01
15	Enhanced Veg. Mgmt. (Miles/Circuit)	0.5	66.3	3.82	1.4	64.9	2.46	1.4	64.9	2.26
16	Undergrounding (Miles/Circuit)	1.1	3.2	1.25	1	3.3	1.63	0.9	3.1	1.48
17	Number of Circuits	550	87		95	84		95	84	
18	Number of Days	1,801,691	285,383		535,082	275,530		176,409	101,639	

Notes: The table compares the mean values for selected risk characteristics and adaptation investments for the control groups against circuits treated with high levels of vegetation management. We use the standardized mean difference (SMD) to evaluate balance between treatment and control groups. Note that some control circuits are matched multiple times to a treated circuit, which explains the differences between the count of circuits and observations in the matched control and treatment groups.

Table A3: Covariate Balance - Circuits Treated With Moderate Levels of Vegetation Management (≥10% & <50% Circuit Length)

		All HFTD			Matched Circuits			Matched Circuits and High Risk Days		
	Covariate (Mean)	Control	Mod. Veg. Mgmt.	SMD	Control	Mod. Veg. Mgmt.	SMD	Control	Mod. Veg. Mgmt.	SMD
	Selected Risk Characteristics									
1	Ignition Risk (Daily Probability)	0.0003	0.0007	0.2	0.0006	0.0007	0.01	0.0015	0.0016	0.02
2	Energy Release Component (Index)	37.5	39.6	0.09	41.2	39.6	-0.06	68.5	67.8	-0.05
3	Wind Speed (Meters/Second)	3.8	3.8	0.01	3.6	3.8	0.09	3.3	3.4	0.08
4	1,000 Hr. Dead Fuel Moisture (%)	16.1	15.9	-0.04	15.4	15.9	0.07	9.3	9.4	0.06
5	100 Hr. Dead Fuel Moisture (%)	14.4	13.9	-0.09	13.6	13.9	0.06	8.5	8.5	0.03
6	Precipitation (mm/Day)	2.1	2.5	0.06	2.2	2.5	0.04	0.1	0.1	0
7	Relative Humidity (Daily Min. %)	39.6	37.9	-0.08	36.6	37.9	0.07	19	19.3	0.03
8	Vapor Pressure Deficit (kPa)	0.99	1.13	0.16	1.15	1.13	-0.02	2.11	2.13	0.02
9	Circuit Length (Miles)	40	79	0.81	63	79	0.29	63	79	0.28
10	Forest Canopy Height (Meters)	7	9.3	0.36	9.2	9.3	0.02	9.2	9.4	0.02
11	Temperature (Daily Max Celsius)	21.3	22.1	0.09	22.1	22.1	-0.01	30.3	30.5	0.04
12	Elevation (Feet Above Sea-Level)	1,068	1,313	0.21	1,320	1,313	-0.01	1,320	1,313	-0.01
	Wildfire Adaptation Investments									
13	Fast-Trip (Customer-Hrs/Day)	5	8.9	0.02	8.5	8.9	0	26.3	29.1	0.01
14	PSPS (Customer-Hrs/Day)	35.8	86.5	0.03	66.8	86.5	0.01	206.1	283.5	0.02
15	Enhanced Vegetation Mgmt. (Miles)	0.5	22.8	3.13	1.2	22.8	2.32	1.2	22.7	2.21
16	Undergrounding (Miles)	1.1	2.9	0.93	1.4	2.9	0.6	1.4	2.8	0.54
17	Number of Circuits	550	130		161	130		161	130	
18	Number of Days	1,801,691	427,064		837,766	427,064		271,515	130,308	

Notes: The table compares the mean values for selected risk characteristics and adaptation investments for the control groups against circuits treated with moderate levels of vegetation management. We use the standardized mean difference (SMD) to evaluate balance between treatment and control groups.

Table A4: Covariate Balance - Comparison Before and After Fast-Trip Settings Were Deployed - High-Fire Risk Days

		High Veg. Mgmt. Treated and Matched Controls			**Mod. Veg. Mgmt. Treated and Matched Controls**		
	Covariate (Mean)	Pre-Fast Trip	Post-Fast Trip.	SMD	Pre-Fast Trip	Post-Fast Trip.	SMD
	Selected Risk Characteristics						
1	Ignition Risk (Daily Probability)	0.0021	0.002	-0.03	0.0016	0.0014	-0.03
2	Energy Release Component (Index)	69.8	66.5	-0.23	69	65.9	-0.21
3	Wind Speed (Meters/Second)	3.2	3.3	0.03	3.3	3.3	0.01
4	1,000 Hr. Dead Fuel Moisture (%)	9	9.6	0.2	9.2	9.7	0.19
5	100 Hr. Dead Fuel Moisture (%)	8.3	8.8	0.19	8.4	8.9	0.16
6	Precipitation (mm/Day)	0.1	0.1	0.05	0.1	0.1	0.04
7	Relative Humidity (Daily Min. %)	18.3	20.1	0.2	18.7	20.4	0.2
8	Vapor Pressure Deficit (kPa)	2.16	2.18	0.02	2.11	2.13	0.02
9	Circuit Length (Miles)	82	82	0	68	68	0
10	Forest Canopy Height (Meters)	9.2	8.1	-0.2	9.5	8.4	-0.18
11	Temperature (Daily Max Celsius)	30.6	31.1	0.08	30.3	30.7	0.08
12	Elevation (Feet Above Sea-Level)	1,297	1,297	0	1,318	1,318	0
13	Number of Circuits	179	179		291	291	
14	Number of Days	214,272	63,763		312,733	89,074	

Notes: The table compares the mean values for selected risk characteristics on high-fire risk days before and after fast-trip settings were deployed. We use the standardized mean difference (SMD) to evaluate balance before and after fast-trip settings were deployed. We show this covariate balance for circuits treated with high levels of vegetation management ($\geq$ 50% circuit length) and their matched controls, as well as circuits treated with moderate levels of vegetation management ($\geq$10% & $<$50%) and their matched controls.

Table A5: Cost Efficiency of Wildfire Adaptation Investments: Moderate Vegetation Management Treatment Only

	Incidence Rate - Vegetation-Caused Ignitions		
	All HFTD	Moderate Treatment Tier and Matched Controls	
	All Days	All Days	High Fire Risk
	(1)	(2)	(3)
β_1: Fast-Trip (F_{it})	-0.32	-0.47^*	-0.75^*
	(-0.55, 0.02)	(-0.76, -0.24)	(-0.90, -0.67)
β_2: Veg. Mgmt. (D_i=High x T_{it}=Post)	-0.70^*		
	(-0.82, -0.50)		
β_3: Veg. Mgmt. (D_i=Moderate x T_{it}=Post)	-0.25^*	-0.37	-0.20
	(-0.44, -0.01)	(-0.14, 1.12)	(-0.03, 1.63)
β_4: Veg. Mgmt. (D_i=High)	1.81^*		
	(1.28, 2.46)		
β_5: Veg. Mgmt. (D_i=Moderate)	1.55^*	0.62^*	0.63^*
	(1.12, 2.07)	(0.44, 0.81)	(0.38, 0.87)
Risk-score (θ) covariate	Yes	Yes	Yes
System hardening (UG, CC) covariates	Yes	Yes	Yes
PSPS (Z) covariate	Yes	Yes	Yes
Risk-score matching	No	Yes	Yes
High-fire risk days only	No	No	Yes
Matched control neighbors (N)	0	2	2
AUC	0.721	0.719	0.738
Observations	2,514,138	1,264,830	401,823
Log Likelihood	$-6{,}751.84$	$-4{,}603.14$	$-2{,}437.07$

Notes: This table replicates the output of the logistic regression model shown and described in Table 1, however, the model is fit using the moderate vegetation management treatment tier in columns (2) and (3). The main results described previously in Table 1 are estimated using the high vegetation management treatment tier. See Table 1 and Methods for more detail on estimation.

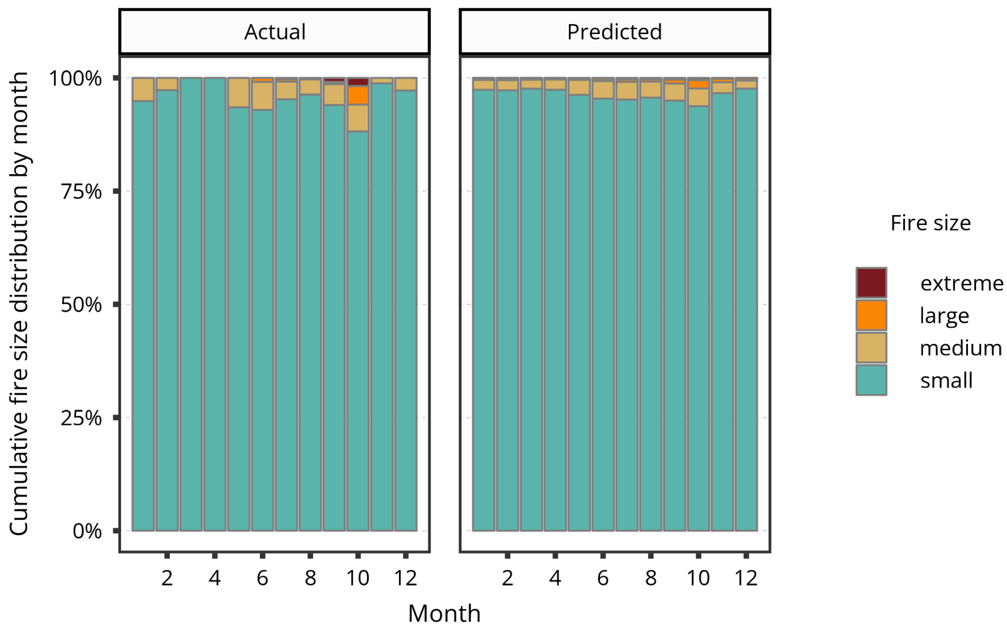
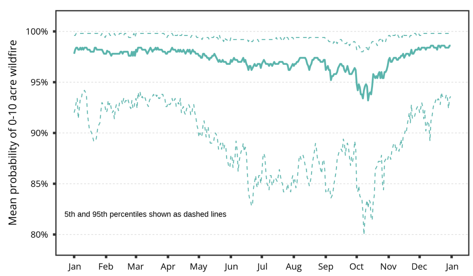
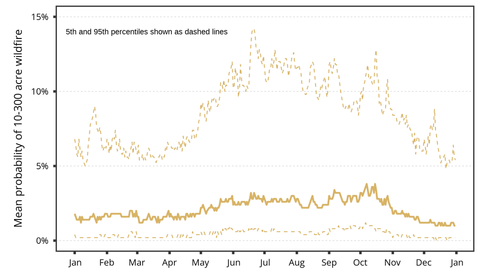


Fig. A5: **Comparison of Predicted and Actual Wildfire Spread Sizes, by Month**. The left panel of the figure plots the distribution of actual wildfires ignited by PG&E distribution lines between 2015 and 2022. Small fires are defined as less than 10 acres. Medium fires are defined as greater than or equal to 10 acres and less than 300 acres in size. Large fires are defined as greater than or equal to 300 acres and less than 10,000 acres. Extreme fires are defined as greater than or equal to 10,000 acres. The plot on the right shows the predicted distribution of wildfire sizes using the random forest model we train on 75% of actual wildfire ignitions by PG&E distribution circuits.

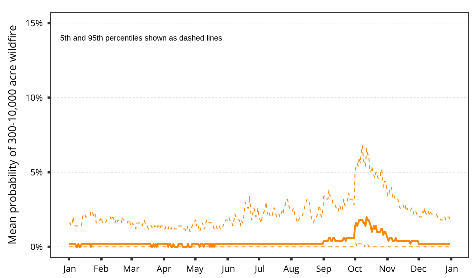
Fig. A6: Predicted Probability of Wildfire Spread Size



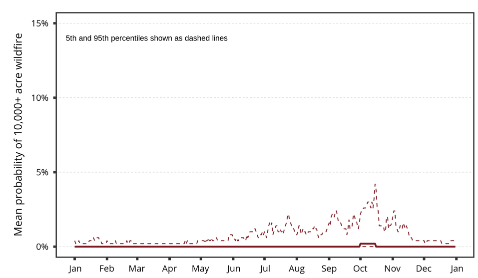
(a) Small (0, 10 acres)



(b) Medium [10, 300 acres)



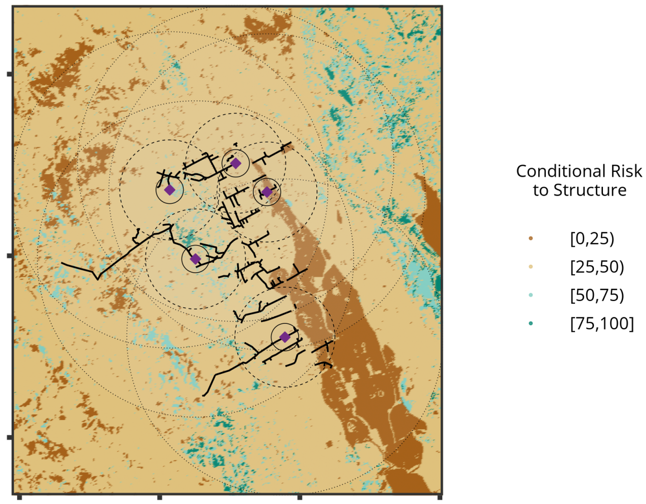
(c) Large [300, 10,000 acres)



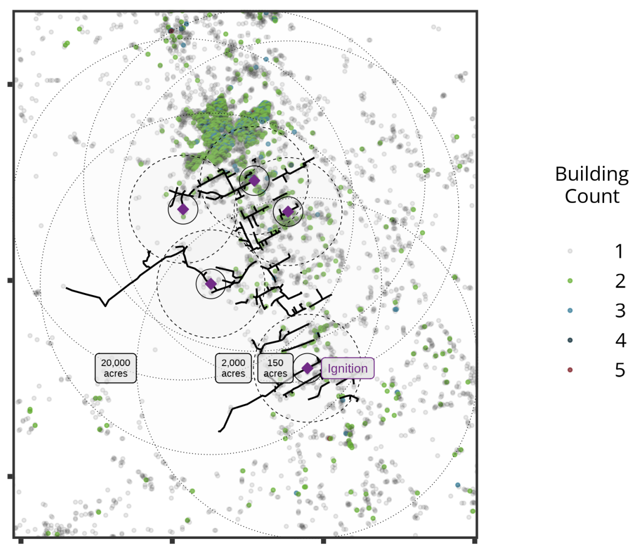
(d) Extreme [10,000, ∞)

Notes: Each plot shows the average predicted probability of a given wildfire size class (e.g., "small": less than 10 acres, "extreme": greater than or equal to 10,000 acres), averaged across each circuit and each day of the year during our study period. In addition to the average, the dashed lines plot the 5th and 95th percentiles.

Fig. A7: Illustration of Structure Risk Methodology



(a) Conditional Risk to Structures



(b) Building Count

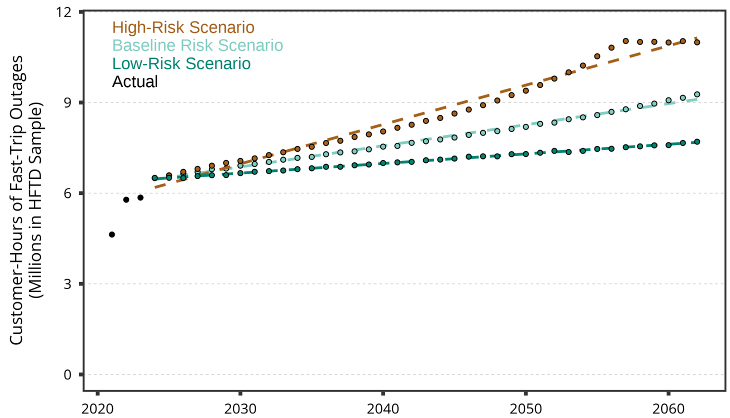
Notes: (a) provides a visual example of the raster data on conditional risk to potential structures (cRPS). cRPS reflects the possible share of damages to a structure if a fire were to occur and a structure located in that pixel. (b) plots the density of building counts in pixels for the same area as (a). The outline of an example distribution circuit is shown in black, and five randomly sampled ignition points are shown in purple. Buffers that represent hypothetical wildfire sizes are drawn around each ignition. See Methods for more detail.

Table A6: Monte Carlo Parameter Distribution

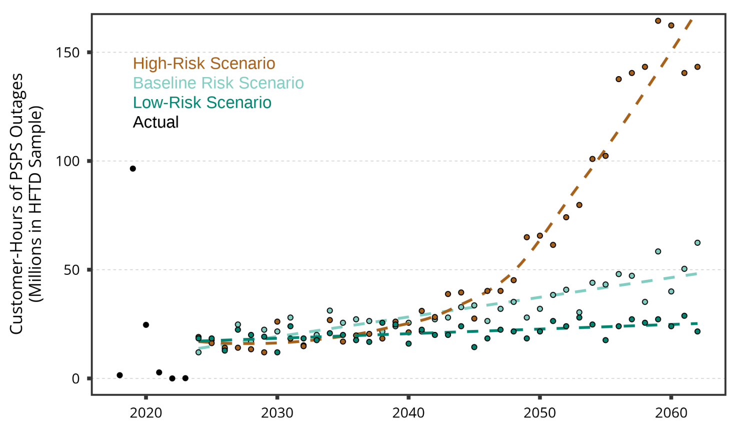
Parameter	Minimum	1st Quartile	Median	3rd Quartile	Maximum
Undergrounding unit cost per mile ($millions)	$2.5	$3.4	$3.8	$4.1	$4.9
Real social discount rate	0.1%	1.8%	2.6%	3.3%	4.6%
Cost of capital	2.5%	4.3%	5.1%	5.8%	7.1%
Effectiveness of fast-trip settings at reducing ignition risk	69%	78%	82%	86%	96%
Utility cost per customer-hour of fast-trip settings	$15	$15	$25	$35	$35
Utility cost per customer-hour of PSPS	$5	$5	$10	$15	$15
Average outage cost across customer classes ($ per customer-hour)	$4.5	$8.7	$10.2	$11.5	$17.5
Ignition risk increase by 2050 (change in daily circuit probability of ignition)	20%	20%	45%	83%	83%
Wildfire risk increase by 2050 (change in probability of "extreme" wildfire)	20%	20%	50%	96%	96%

Notes: The table contains summary statistics for the distribution of key parameters used in the Monte Carlo analysis. The results of the Monte Carlo analysis are used to construct 95% confidence intervals surrounding the curves in Figure 5. 200 draws are used in the Monte Carlo simulations.

Fig. A8: Modeled Increases in Customer Outages Under Future Wildfire Risk Scenarios



(a) Fast-Trip Customer-Hours



(b) PSPS Customer-Hours

Notes: In (a), we model the increase in fast-trip customer-hours due to escalating future wildfire risk increase. (b) shows the equivalent plot for public-safety power shutoffs. These modeled changes in outage hours are used to assess the potential benefits that undergrounding powerlines can provide in future years by avoiding the utility and customer costs associated with dynamic grid management technologies that de-energize powerlines. See Methods for more detail on the modeling approach.

Appendix B Supplementary Information

B.1 Matching Methods

The matching technique follows six steps:

1. Define two groups of vegetation management "treatment." The first group, considered "high" vegetation management, consists of circuits that have received enhanced vegetation management on 50% or more of overall circuit length. The second group, considered "moderate," consists of circuits with vegetation management between 10 and 50% of circuit length. Control circuits are circuits that have received vegetation management equal to less than 10% of circuit length.
2. Calculate the average baseline ignition risk for each treated and control circuit. Calculate the standard deviation of all circuits' average baseline ignition risk.
3. For each "treated" circuit, calculate the absolute difference ("distance") between its average baseline ignition risk and all control circuits' baseline ignition risk.
4. For each "treated" circuit, find the two control circuits with the smallest absolute difference in baseline ignition risk. Consider these two control circuits as potential matches.
5. If the absolute difference ("distance") for either of the potential two treatment-control matches exceeds 10% of the standard deviation ("caliper") recorded previously, discard the potential match as unsuccessful. If the "treated" circuit does not successfully match to any control circuit, then discard the circuit. This ensures that each control circuit's average ignition risk is nearly identical to the treated circuit it is matched to.
6. Repeat the matching process across all circuits in the "high" treated group and "moderate" treated group. Sample from the control circuits with replacement, so a control circuit may be matched to a "treated" circuit multiple times.

B.2 Enhanced Vegetation Management Cost Modeling

Following Workpaper Table 9-15 from Exhibit PG&E 4, Chapter 9 - Vegetation Management, PG&E recorded average per mile costs of $245K between 2018 and 2020[37]. In addition, the utility cites forecasted per mile costs of $298K from 2021 to 2026. Therefore, the cost analysis assumes a central per mile estimate of $250K per mile and low and high estimates of $200K and $300K, respectively.

Enhanced vegetation management is modeled as an operational expense that is incurred in the year the work is performed. However, the benefits of the vegetation management work in terms of risk reduction continue to accrue in subsequent years until the vegetation grows back. Due to data support, the analysis does not estimate empirically the rate at which these benefits attenuate to zero. In the central case, the ignition benefits of enhanced vegetation management are assumed to linearly decline to zero over a ten year lifetime. The sensitivity analysis in Figure 4 varies this assumption between five and fifteen years. Because some of the ignition benefits of enhanced vegetation management work are realized in future years, avoided ignitions are discounted to 2022 terms using a real social discount rate of 2.5%[75]. The discount rate varies in the sensitivity analysis between 1% and 4%.

While the vast majority of enhanced vegetation management costs are incurred at the time the work is performed, there are ongoing maintenance costs that the utility likely incurs. For instance, the utility may need to reinspect segments of the circuit to determine if sufficient clearance still exists between the overhead line and vegetation. The cost analysis assumes annual per mile maintenance costs equal to 1% of the assumed unit cost.

B.3 Undergrounding Cost Modeling

In terms of per mile costs, Workpaper Table 4-23 from Exhibit PG&E 4, Chapter 4, Wildfire Risk Mitigation cites forecasted underground costs of $4.3M per mile in 2022 dollars[37]. However, PG&E's wildfire mitigation plan filed in February 2022 cites costs of $3.75M per mile[76]. A decision on PG&E's general rate case proceeding noted that the utility forecasts $3.3M per mile in 2023 and $2.8M by 2026 for a four-year average of $3M per mile. The decision continued by noting that the utility faces "significant uncertainty and variability associated with wildfire mitigation activities and their associated costs."[38].

The cost analysis uses $3.0M per mile as the central assumption and varies the per mile costs between $2.0M and $4.0M.

Unlike enhanced vegetation management, underground lines are considered capital assets. Under rate of return regulation, the utility earns an authorized rate of return on its rate base, which consists of the utility's total assets net of accumulated depreciation[45]. This rate of return on capital investment enters into the utility's revenue requirement and is recovered by ratepayers via retail electricity rates. Therefore, the cost to underground a line includes both the capital cost (i.e., $3.0M per mile) and the rate of return the utility earns on the newly underground line.

To model the utility's return on capital investment, the cost analysis linearly depreciates the undergrounding asset over its assumed lifetime of 40 years. In each year, the value of the depreciated undergrounding asset is multiplied by the utility's cost of capital– 7.5%[77]. The cost model then discounts each of these annual returns into 2023 terms using a real social discount rate of 2.5% and sums them. The sensitivity analysis in Figure 4 varies the assumed cost of capital between 5% and 10% and varies the real social discount rate symmetrically between 1% and 4%.

The cost analysis does not assume the entire capital cost of the underground work is recovered by the utility in the year the undergrounding work is completed. If this was the case, retail electricity rates would have to adjust significantly in the year the work was completed, rather than adjusting smoothly over the lifetime of the asset. To model this, the cost analysis assumes each year the utility recovers the portion of the undergrounding asset that is depreciated. By the end of the asset's lifetime, it has fully depreciated to zero, and the utility has recovered the full cost of the asset. Because these costs are incurred in future years, they are discounted to 2023 terms and summed.

Similar to enhanced vegetation management, ongoing maintenance costs associated with the underground lines are accounted for. They are expressed as ongoing annual maintenance costs equal to 1% of the per mile capital cost. However, unlike enhanced vegetation management, the analysis assumes the undergrounding investment obviates the need for the utility to complete routine vegetation management and tree mortality work on the line. Per mile routine vegetation management costs are approximated using the utility's recorded costs in 2016 and 2017, prior to the implementation of the enhanced vegetation management program. The utility spent approximately $400M per year on routine vegetation management and tree mortality in 2016 and 2017[37]. To calculate per mile costs, the analysis spreads the $400M per year across the utility's 25K miles in the HFTD to obtain a per mile estimate of $16K. This likely overstates per mile routine vegetation management costs as the $400M annual budget includes circuit-miles outside the HFTD. Discounted across the lifetime of the undergrounding asset, this annual avoided routine vegetation management cost equals approximately 11% of the $3.7M per mile undergrounding capital cost.

The cost model coarsely approximates increases in future wildfire risk due to climate change by increasing ignition and wildfire risk each year. Looking out 40 years, for each circuit and each month, we construct a month of climate and weather data by sampling from the circuit's historical set of climate and weather data for that month. To model the future risk increase, we increasingly restrict the historical set of data from which we sample from to higher-risk days. For the first year in the future period (2024), we sample from the circuit's full historical set. By 2050, we restrict the sample only to days that exceed the circuit's 50^{th} risk percentile. In the intervening years, we increase this risk percentile threshold linearly each year, and it continues to increase in the years after 2050 until reaching a maximum of the 90^{th} percentile. The sensitivity analysis varies 2050 risk percentile threshold between 25% and 75%.

Undergrounding may provide co-benefits that measures like enhanced vegetation management and dynamic grid management technologies do not offer. For example, powerlines buried underground may be protected from damage caused by wildfires and therefore reduce the utility's rebuild costs following a wildfire. To approximate this co-benefit, we intersected all California wildfire perimeters from 2018-2023 with the utility's HFTD distribution grid. We found that 295 HFTD miles were within a wildfire perimeter each year, on average. This equates approximately to 1.1% of the utility's HFTD miles. Assuming this risk escalates by 50% by 2050, a discount rate of 2.5%, that overhead lines are fully damaged when intersected by a wildfire perimeter, and that it costs the utility $600,000 per mile to build an overhead distribution line, we estimate avoided rebuild costs of approximately $220,000 per mile over the lifetime of the undergrounding project. This co-benefit is approximately 7% of the assumed $3 million capital cost per mile of undergrounding.

Our cost model considers how undergrounding can reduce outages from dynamic grid management technologies, but undergrounding may also reduce unplanned outages from extreme weather events such as winter storms. Using data from PG&E's wildfire mitigation plans, we find that the utility experienced approximately 25 million customer-hours of unplanned outages per year, on average, between 2015 and 2022, not due to PSPS or fast-trip settings. We coarsely apportion 8 million customer-hours to the HFTD based on distribution circuit length. Using a 40-year lifetime of the undergrounding asset, a discount rate of 2.5%, an average outage cost of $10 per customer-hour across customer classes, and the assumption that undergrounding fully eliminates unplanned outages, we estimate a co-benefit of approximately $80,000 per mile of undergrounding in terms of reduced unplanned outages. This is roughly 2.5% of the $3 million capital cost per mile of undergrounding.

B.4 Fast-Trip Settings Cost Modeling

Due to the dynamic nature of fast-trip settings, their costs are modeled differently than enhanced vegetation management and undergrounding. Fast-trip settings are inexpensive to deploy, but when they are enabled on a circuit and an outage occurs, the utility must dispatch ground patrols to inspect the circuit for damage before restoring power to customers. In some cases, the utility may dispatch air resources, such as helicopters and drones, to improve restoration times.

To assess the cost-efficiency of fast-trip settings, the cost model relies on PG&E's forecasted annual budget for the fast-trip program of approximately $150M in 2022[74]. The utility forecasts $151M in fast-trip expenses for 2023, declining to $134M by 2026. We express fast-trip costs that the utility incurs on customer-hour basis. Our central case assumes fast-trip costs of $25 per customer-hour, approximated using the total fast-trip budget of $150M and annual customer-hours of fast-trip outages of six million. The sensitivity analysis varies this cost per customer-hour between $15 and $25.

B.5 Modeling the Enablement of Fast-Trip Settings

Fast-trip settings are only enabled on circuits and days when the utility's fire potential index exceeds a threshold. PG&E combines data on weather, fuel moisture, topography, and fuel type to predict the probability of large and catastrophic wildfires, and uses a random forest classifier to predict wildfire risk, which is then summarized into six risk levels: R1, R2, R3, R4, R5, and R5+. R1 and R2 correspond to very little or moderate fire danger. R3 denotes high fire danger, R4 and R5 both denote critical fire danger, and R5+ is the greatest level of fire danger. Fast-trip settings are enabled when the risk level is R3 and above. In rare cases, PG&E enables fast-trip settings at R2, or on an R1 day if it occurs between two high-risk days, but the analysis ignores these rare cases. PSPS events are typically called on R5+ days. For more detail on PG&E's fire potential index, see section 8.3.6 of PG&E's wildfire mitigation plan[8].

To identify the effect of fast-trip settings on ignition outcomes, the analysis restricts the sample only to those fast-trip enabled days (those with fire potential index at and above R3). However, data on the utility's fire potential index is only available for a subset of circuit-days, and therefore we train a model to predict the circuit-days on which the fire potential index was above R3, and therefore fast-trip settings are enabled. Specifically, the model uses a sample of 997 observations of the utility's fire potential index at the circuit-day level[63], along with historical weather, fuel moisture, topography, and fuel type, to train a random forest classifier that predicts when the fire potential index is high enough to enable fast-trip settings, i.e. at R3 or greater on each circuit. As with the risk-score prediction model discussed earlier, the model uses 3-repeat 10-fold cross validation and tunes hyperparameters. Training and testing data are split 75/25%. The model achieves an AUC value of 0.93 with the testing data. Furthermore, PG&E reported that fast-trip settings were enabled on approximately 60% of the circuit-days from May to October in 2022; using a classification threshold of 0.5, our prediction model produces a result of 62%.

Only 11,500 HFTD circuit-miles had fast-trip settings enabled in 2021. These circuits are identified through incident-specific data on fast-trip outages in 2021[67]. After 2021, all HFTD circuits had fast-trip settings enabled.

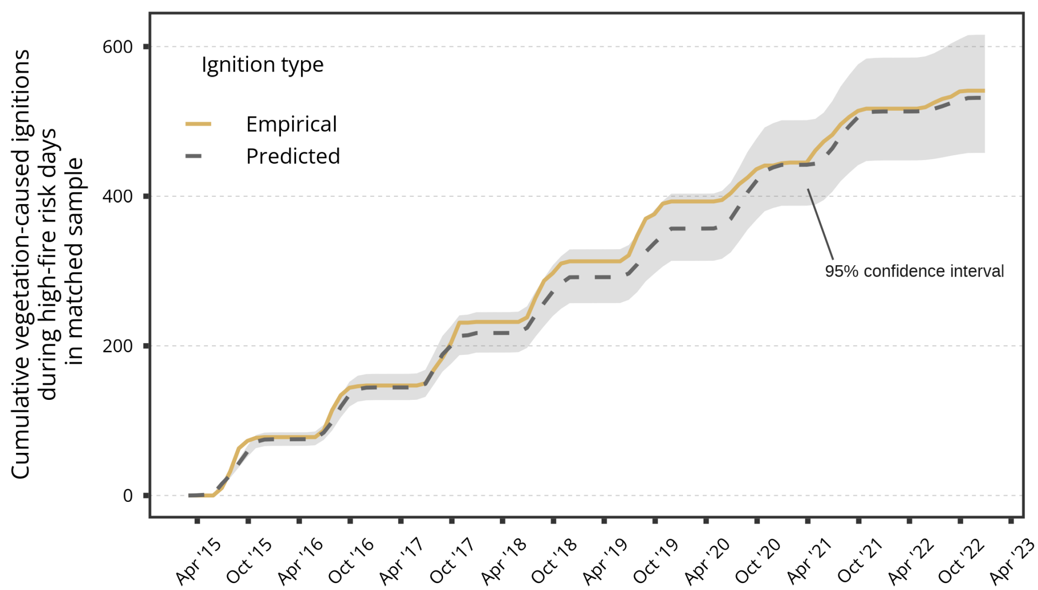
B.6 Supplementary Figures

Table B7: PG&E distribution-grid ignitions (2015-2023)

	Non-HFTD	**HFTD**
Ignitions per circuit-year (mean)	0.10	0.31
Acres burned per ignition (mean)	6	703
Acres burned per ignition (median)	< 1	< 1
Percent of ignitions >10 acres	2.7%	4.5%
Percent of ignitions >300 acres	0.2%	1.2%
Percent of ignitions >5,000 acres	0%	0.5%

Notes: In the raw ignition data, small wildfires are coded as "less than one acre." Hence, the median value in the table is reported as "$<$ 1 acre." When calculating mean acres burned, a value of one-quarter acre is assumed for these observations. The mean value of acres burned in the HFTD substantially differs from the median due to the influence of large wildfires such as the Dixie Fire that burned nearly one million acres.

Fig. B9: Comparison of Predicted and Actual Ignitions



Notes: Comparison of predicted and empirical ignitions. Using our preferred specification in column (3) of Table 1, we compare the number of ignitions predicted by our econometric model against the number of ignitions observed in our matched treatment and control sample on high-fire risk days. We find that the fitted values of our econometric model reasonably predict actual observed ignitions, which is also supported by an AUC value in Table 1 of 0.74. Our econometric model tends to under-predict powerline-caused ignitions in 2019 and over-predict ignitions in 2020. The former period was a relatively low risk year for wildfires given record snowfall totals while the latter period saw a record number of acres burned across the state.

Table B8: Robustness Test - Matching on One Control Circuit - High Levels of Enhanced Vegetation Management

	Incidence Rate - Vegetation-Caused Ignitions		
	All HFTD	High Treatment Tier and Matched Controls	
	All Days	All Days	High Fire Risk
	(1)	(2)	(3)
β_1: Fast-Trip (F_{it})	-0.32	-0.89^*	-0.96^*
	(-0.55, 0.02)	(-0.98, -0.38)	(-0.99, -0.80)
β_2: Veg. Mgmt. (D_i=High x T_{it}=Post)	-0.70^*	-0.59^*	-0.37
	(-0.82, -0.50)	(-0.75, -0.32)	(-0.66, 0.16)
β_3: Veg. Mgmt. (D_i=Moderate x T_{it}=Post)	-0.25^*		
	(-0.44, -0.01)		
β_4: Veg. Mgmt. (D_i=High)	1.81^*	-0.07	-0.10
	(1.28, 2.46)	(-0.29, 0.21)	(-0.34, 0.23)
β_5: Veg. Mgmt. (D_i=Moderate)	1.55^*		
	(1.12, 2.07)		
Risk-score (θ) covariate	Yes	Yes	Yes
System hardening (UG, CC) covariates	Yes	Yes	Yes
PSPS (Z) covariate	Yes	Yes	Yes
Risk-score matching	No	Yes	Yes
High-fire risk days only	No	No	Yes
Matched control neighbors (N)	0	1	1
AUC	0.721	0.747	0.746
Observations	2,514,138	551,433	196,467
Log Likelihood	$-6{,}751.84$	$-2{,}449.19$	$-1{,}553.92$

Notes: This table shows a robustness test of the logistic regression model, described in more detail in Table 1. Here, circuits treated with high levels of enhanced vegetation management are matched to only one control circuit on the basis of ignition risk. In the primary results discussed in Table 1, circuits are matched to at most two control circuits, provided there is a second control circuit with nearly identical ignition risk to the treated circuit.

Table B9: Robustness Test - Matching on One Control Circuit - Moderate Levels of Enhanced Vegetation Management

	Incidence Rate - Vegetation-Caused Ignitions		
	All HFTD	Moderate Treatment Tier and Matched Controls	
	All Days	All Days	High Fire Risk
	(1)	(2)	(3)
β_1: Fast-Trip (F_{it})	-0.32	-0.57^{*}	-0.82^{*}
	(-0.55, 0.02)	(-0.98, -0.38)	(-0.99, -0.80)
β_2: Veg. Mgmt. (D_i=High x T_{it}=Post)	-0.70^{*}		
	(-0.82, -0.50)		
β_3: Veg. Mgmt. (D_i=Moderate x T_{it}=Post)	-0.25^{*}	-0.37	-0.12
	(-0.44, -0.01)	(-0.11, 1.22)	(-0.005, 1.74)
β_4: Veg. Mgmt. (D_i=High)	1.81^{*}		
	(1.28, 2.46)		
β_5: Veg. Mgmt. (D_i=Moderate)	1.55^{*}	0.85^{*}	0.70^{*}
	(1.12, 2.07)	(0.62, 1.07)	(0.42, 0.99)
Risk-score (θ) covariate	Yes	Yes	Yes
System hardening (UG, CC) covariates	Yes	Yes	Yes
PSPS (Z) covariate	Yes	Yes	Yes
Risk-score matching	No	Yes	Yes
High-fire risk days only	No	No	Yes
Matched control neighbors (N)	0	1	1
AUC	0.721	0.747	0.746
Observations	2,514,138	854,138	276,309
Log Likelihood	$-6{,}751.84$	$-3{,}102.10$	$-1{,}721.53$

Notes: This table shows a robustness test of the logistic regression model, described in more detail in Table 1. Here, circuits treated with moderate levels of enhanced vegetation management are matched to only one control circuit on the basis of ignition risk. Results in which circuits are matched to at most two control circuits (provided there is a second control circuit with nearly identical ignition risk to the treated circuit) are shown in Extended Data Table A5.

Table B10: Robustness Test - Regional Fixed Effects - High Levels of Enhanced Vegetation Management

	Incidence Rate - Vegetation-Caused Ignitions		
	All HFTD	High Treatment Tier and Matched Controls	
	All Days	All Days	High Fire Risk
	(1)	(2)	(3)
β_1: Fast-Trip (F_{it})	-0.30	-0.55^*	-0.82^*
	(-0.54, 0.06)	(-0.75, -0.19)	(-0.90, -0.67)
β_2: Veg. Mgmt. (D_i=High x T_{it}=Post)	-0.69^*	-0.63^*	-0.49^*
	(-0.82, -0.49)	(-0.78, -0.38)	(-0.73, -0.02)
β_3: Veg. Mgmt. (D_i=Moderate x T_{it}=Post)	-0.22		
	(-0.41, 0.03)		
β_4: Veg. Mgmt. (D_i=High)	1.41^*	0.11	0.21
	(0.93, 2.01)	(-0.14, 0.44)	(-0.11, 0.63)
β_5: Veg. Mgmt. (D_i=Moderate)	0.88^*		
	(0.54, 1.30)		
Risk-score (θ) covariate	Yes	Yes	Yes
System hardening (UG, CC) covariates	Yes	Yes	Yes
PSPS (Z) covariate	Yes	Yes	Yes
Risk-score matching	No	Yes	Yes
High-fire risk days only	No	No	Yes
Matched control neighbors (N)	0	2	2
Region FEs	Yes	Yes	Yes
AUC	0.719	0.758	0.767
Observations	2,514,138	810,612	278,048
Log Likelihood	$-6,651.01$	$-3,854.10$	$-2,247.11$

Notes: This table shows a robustness test of the logistic regression model, described in more detail in Table 1. Here, regional fixed effects are included in the regression specification.

Table B11: Robustness Test - Inclusion of Unmatched High-Risk Circuits - High Levels of Enhanced Vegetation Management

	Incidence Rate - Vegetation-Caused Ignitions		
	All HFTD	High Treatment Tier and Matched Controls	
	All Days	All Days	High Fire Risk
	(1)	(2)	(3)
β_1: Fast-Trip (F_{it})	-0.32	-0.56^{*}	-0.81^{*}
	(-0.55, 0.02)	(-0.74, -0.23)	(-0.89, -0.66)
β_2: Veg. Mgmt. (D_i=High x T_{it}=Post)	-0.70^{*}	-0.65^{*}	-0.49^{*}
	(-0.82, -0.50)	(-0.79, -0.40)	(-0.73, -0.04)
β_3: Veg. Mgmt. (D_i=Moderate x T_{it}=Post)	-0.25^{*}		
	(-0.44, -0.01)		
β_4: Veg. Mgmt. (D_i=High)	1.81^{*}	-0.15	-0.15
	(1.28, 2.46)	(-0.33, 0.07)	(-0.36, 0.12)
β_5: Veg. Mgmt. (D_i=Moderate)	1.55^{*}		
	(1.12, 2.07)		
Risk-score (θ) covariate	Yes	Yes	Yes
System hardening (UG, CC) covariates	Yes	Yes	Yes
PSPS (Z) covariate	Yes	Yes	Yes
Risk-score matching	No	Yes	Yes
High-fire risk days only	No	No	Yes
Matched control neighbors (N)	0	2	2
Region FEs	No	No	No
AUC	0.721	0.717	0.734
Observations	2,514,138	820,465	282,017
Log Likelihood	$-6{,}751.84$	$-4{,}019.83$	$-2{,}343.97$

Notes: This table shows a robustness test of the logistic regression model, described in more detail in Table 1. Here, we add back in high-risk circuits that are dropped from the matching algorithm because they do not have a control circuit with sufficiently similar average ignition risk.