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Risk-Cost Tradeoffs in Power Sector Wildfire Prevention

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Abstract

Wildfires ignited by power system infrastructure tend to cause more damage than other ignition sources because they occur during high wind events when fire spreads rapidly. Utilities are exploring a range of approaches to mitigate these wildfire risks. This study evaluates the cost, reliability, and wildfire risk implications of measures recently deployed by the largest utility in the United States – Pacific Gas and Electric. Using detailed data on weather, vegetation, and infrastructure conditions from over twenty-five thousand miles of high-risk distribution lines, we use a prediction model trained on pre-intervention outcomes to estimate highly granular measures of baseline ignition risk. We then compare ignition outcomes in settings with similar baseline risk but different types of wildfire mitigation. We find that undergrounding powerlines, despite the higher investment cost, is more cost-effective than pruning and removing nearby vegetation, primarily because undergrounding fully and permanently eliminates ignition risk. A new strategy that increases the sensitivity of protection equipment – known as "fast-trip" settings – does not completely eliminate risk on circuits but is significantly more cost-effective than undergrounding per avoided ignition and per avoided structure burned, even after accounting for outage impacts to customers. Our analysis underscores the importance of carefully evaluating the social costs and benefits of alternative wildfire risk mitigation measures, particularly in cases where less cost-effective measures may be preferred by utilities due to regulated returns on capital investment and more certain risk reductions.

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Introduction

Wildfire is the fastest growing economic climate risk[1]. Annual losses from natural disasters in recent years have been significantly higher than damages recorded in prior decades[2]. Multiple factors explain this trend, including increased temperatures and aridity caused by climate change[3,4], population growth in the wildland-urban interface[5], and historical fire suppression practices[6].

Although wildfires ignited by electricity infrastructure are infrequent, these ignitions have played an outsized role in determining total acres and structures burned[7]. In 2018, California's Camp Fire, caused by the failure of a worn hook on a transmission line, caused an estimated $15B in capital losses and 85 fatalities[8]. Vegetation contact along a distribution line in Northern California ignited the Dixie Fire, burning nearly one million acres over the course of 104 days in 2021. The 2009 Black Saturday fires in Australia, which were partly caused by powerline failures, resulted in an estimated $4.4B in losses[9]. The devastating 2023 wildfires in Maui were allegedly ignited by falling powerlines in high winds. The disproportionate devastation caused by these and other power grid-related ignitions is partly explained by the positive correlation with wind speed and partly due to the proximity of grid infrastructure to structures at risk[10].

As the climate changes and wildfire risk escalates, utilities around the world are developing strategies to mitigate and manage this risk. This task is complicated by the fact that electrification of transportation, buildings, and industrial applications is an important part of many climate change mitigation policies[11,12]. If utility spending on wildfire risk management puts significant upward pressure on retail electricity rates, it will be harder for households and firms to switch from fuels like gasoline and natural gas to electricity[13]. In addition, wildfire risk mitigation strategies that de-energize lines during high-risk conditions could further slow the pace of electrification by degrading grid reliability. Utility decision-making therefore has important impacts on the balance between societal efforts to adapt to escalating wildfire risk and electrification efforts that rely on low retail rates and reliable electric service.

This paper provides a detailed assessment of how multi-faceted and multi-billion dollar risk mitigation efforts are affecting wildfire outcomes and ratepayer costs. Our aim is to provide an analysis of the tradeoffs between a portfolio of mitigation options with respect to cost and risk. We focus on California, a state that is on the front lines of climate change. In 2023 wildfire mitigation plans, California electric utilities proposed investing over $9B annually to reduce wildfire ignition risk[14–16]. Lessons learned from these efforts in California can inform wildfire risk mitigation investments in other jurisdictions that face similar challenges.

This work contributes to a nascent and growing body of empirical evidence on wildfire risk mitigation efforts and climate change adaptation more broadly. In addition to analysis carried out by utilities, some academic studies have investigated the effects of preventative power shutoffs in California on power supply reliability and climate change attitudes[10,17]. Others have assessed the cost implications of undergrounding[18,19]. Another study finds that a large electric utility's vegetation management program in Connecticut reduced supply outages by 37-66%, but wildfire outcomes were not a focus[20]. We leverage detailed data on powerline-caused ignitions in California, together with granular data on a variety of wildfire risk mitigation measures and interventions.

Our empirical analysis proceeds in three steps. First, we assess the causal impacts of alternative risk mitigation strategies on ignitions. For over twenty five thousand miles of distribution lines located in high wildfire risk areas, we use a prediction model trained on pre-intervention outcomes to estimate highly granular measures of ignition risk. We systematically compare ignition outcomes across locations and times with very similar baseline ignition risk that have received different types of risk mitigation "treatments". This allows us to produce quantitative estimates of the causal effect of risk mitigation treatments on ignition outcomes.

Next, we assess the relative cost effectiveness of risk mitigation treatments, accounting for uncertainty in a range of factors including ignition reduction effectiveness, the cost of service interruptions, discount rates, and climate change-driven increases in ignition risk. We find that undergrounding powerlines, despite the higher investment cost, is more cost-effective than pruning and removing vegetation, primarily because undergrounding fully and permanently eliminates ignition risk well into future periods. However we also find that a new strategy that increases the sensitivity of protection equipment – known as "fast-trip" settings – is significantly more cost effective (in terms of cost per avoided ignition) than other strategies that have been deployed at scale. Though these fast-trip settings degrade reliability and do not fully eliminate risk on treated circuits, they significantly change the cost calculus behind more capital-intensive wildfire risk management strategies. Deploying this relatively cost-effective strategy at scale means that less capital investment in undergrounding will be needed to achieve a given level of risk reduction.

Finally, we expand our analysis to include measures of wildfire damages. We use a wildfire model to map our estimates of avoided ignitions into estimates of avoided damages. Over a limited spatial area, we simulate potential wildfire perimeters and approximate the avoided structure damages of each wildfire mitigation treatment. Across a range of scenarios, we find that costs per unit of damage avoided are significantly lower for fast-trip settings than other strategies such as enhanced vegetation management and undergrounding.

The empirical findings in this paper highlight critical tradeoffs between capital costs, reliability costs, and wildfire risk mitigation. Our analysis underscores the importance of evaluating the cost effectiveness of mitigation measure risk reductions, particularly in cases where less cost-effective measures may be preferred by utilities due to their regulated returns on capital[21,22] and more certain risk reductions. Regulatory oversight has a critical role to play in balancing risk reduction benefits and costs. This paper provides a framework for quantifying these tradeoffs.

Empirical context

Our analysis focuses on the wildfire mitigation activities of Pacific Gas & Electric Company ("PG&E"), the largest electric utility in the United States. The utility's service territory is large and climatologically diverse, which makes wildfire risk management a complex and expensive endeavor. This section provides an overview of powerline-caused ignitions and the strategies that are being deployed to mitigate risk.

Grid-caused ignitions in Northern and Central California

PG&E's overhead distribution grid spans approximately eighty thousand miles, of which twenty five thousand miles (31%) are located in high-fire threat districts ("HFTD"); see Figure 1 for a map and HFTD definition. Distribution lines comprise the last miles of the grid, delivering electricity to retail customers via medium voltage conductors and stepping those voltages down to safe utilization voltages. Importantly, overhead lines are typically uninsulated, and sparks can result from any contact between a line and a grounded object or another line. Our unit of analysis is a distribution "circuit", which connects hundreds to thousands of retail customers to a substation, and is in turn connected to the transmission system. We focus our analysis on 767 distribution circuits that intersect, even partially, PG&E's HFTD service territory. We do not analyze mitigation activities on PG&E's transmission system as these ignitions account for only 5% of the utility's ignitions.

We make extensive use of data on powerline-caused ignitions from the California Public Utilities Commission ("CPUC") and filings made by the utility[23]. On average, circuits with at least one mile in the HFTD cause an ignition once every 3 years; 4.5% of grid-caused ignitions between 2015 and 2022 exceeded 10 acres and 1.3% exceeded 300 acres. Although they are rare, wildfires ignited by electricity infrastructure tend to be more destructive than other types of ignitions. For example, between 2015 and 2020, we find that the average wildfire ignited by powerlines burned roughly twenty structures, whereas the average wildfire ignited by other sources burned less than one structure[24].

Of the 1.3M burned acres associated with PG&E's distribution circuits between 2015 and 2022, 1.2M acres (98%) were ignited by vegetation contact in the HFTD. Our empirical analysis therefore focuses on ignitions caused by vegetation-contact on HFTD distribution circuits.

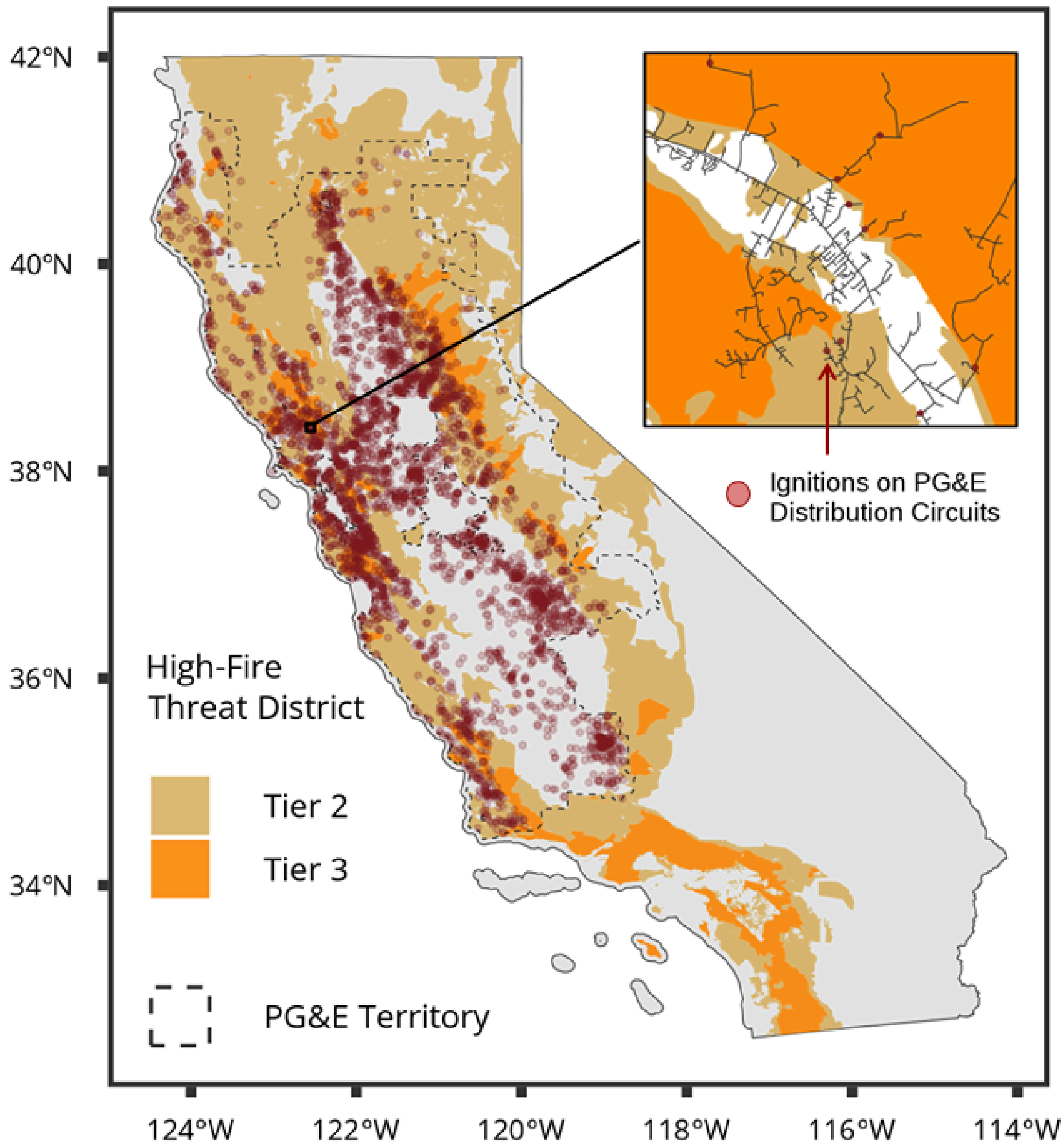

Figure 1 | High-Fire Threat District Map. The map of the high-fire threat district ("HFTD") shows areas where there is an increased risk for utility-associated wildfires to occur, to spread rapidly, and to cause damage to communities. HFTD areas are defined by the California Public Utilities Commission.

Tier 3 features more severe wildfire risk than Tier 2. Overlaid in red are ignitions caused by PG&E distribution circuits between 2014 and 2022. The map inset displays an example distribution circuit and the locations of ignitions associated with the circuit during the study period.

Strategies to reduce grid-caused wildfire ignitions

An electric utility has several approaches that it can use to reduce ignition risk on its distribution grid. These interventions fall into three categories.

System hardening includes measures such as undergrounding overhead powerlines, covering overhead bare conductors with insulated material, and replacing or reinforcing distribution poles. These types of measures require upfront capital investment and take time to deploy. Undergrounding can provide near permanent reductions in ignition risk, but costs are significant. In 2020, PG&E's cost to underground one mile of overhead distribution line was $4.3M[25]. The utility is projecting that these per-mile costs will drop to $2.8M by 2026[26].

Vegetation management can substantially reduce ignitions caused by vegetation contact. In California, "enhanced" vegetation management removes all vegetation within twelve feet of overhead lines, greater than the typical four foot standard. In addition, any vegetation above the line, even at a distance greater than twelve feet, must be removed. The risk reduction benefits of enhanced vegetation management are not as permanent as system hardening investments because vegetation grows back over time. Between 2019 and 2022, PG&E spent an estimated $188K - $293K per mile on enhanced vegetation management work[25].

Operational mitigations, including public safety power shutoffs (PSPS) and "fast-trip" settings, differ from other categories of mitigation activities in that they can be deployed in response to real-time wildfire conditions. PSPS events involve completely de-energizing powerlines during hours of extreme wildfire risk and inspecting those lines for damages before re-energizing them.

Fast trip settings are a simple modification to the configuration of existing protection equipment[27]. This equipment senses when a fault occurs, notably when lines contact an object at a different voltage (such as a tree branch or the ground). When an overhead line is faulted, excess current flows, and protection equipment senses that current and interrupts all current flow on the line. Fast-trip settings work by increasing the sensitivity of protection equipment to these excess currents during periods of high fire risk. By clearing faults more quickly, fast-trip settings reduce the odds that a fault causes an ignition[14]. PG&E's practice is to inspect and repair all portions of de-energized circuits before restoring service to customers. Importantly, both fast trip settings and PSPSs degrade reliability.

Although operational mitigations are inexpensive to enable, they introduce additional costs in the form of power outages (which are unplanned in the case of fast-trip settings) and the deployment of ground patrols and possibly drones and helicopters to inspect the lines for damage before restoring power. For example, in 2022 PG&E spent $149M to patrol fast-trip enabled circuits[28], or approximately $5,600 per mile of HFTD circuit. Between 2019 and 2022, the utility invested an estimated $183M on sectionalizing devices to reduce the size of outages from fast-trip settings and proactive de-energization events (PSPS)[25].

PG&E's approach to wildfire mitigation has been evolving over time. After $30B in wildfire liabilities caused PG&E to file for bankruptcy early 2019[29], the utility began to implement a range of wildfire risk mitigation approaches (see Figure 2). This included enhanced vegetation management and proactively de-energizing (PSPS) tens of thousands of distribution lines during extreme wildfire conditions in the fall of 2019. In July 2021, the utility piloted the use of fast-trip settings on approximately half of its HFTD distribution circuits. In 2022, it expanded fast-trip settings to all HFTD circuits[14]. Fast-trip settings caused approximately 6M customer-hours of outages in 2022[30,31].

In 2023, PG&E announced that it would de-prioritize its enhanced vegetation management program[32]. Over the long-term, the utility plans to underground ten thousand circuit-miles[33], and over the course of 2023-2026, 87% of the underground work is targeted for the top 20% risk-ranked circuits[14]. This proposal is controversial given the high cost that this amount of undergrounding would impose on ratepayers. In 2023, the California Public Utilities Commission refused to approve plans to underground 2,100 miles of distribution lines through 2026 due to the significant impacts these investments would have on ratepayer costs[26]. These deliberations are being closely watched, not just in California but across the country as more utilities weigh the benefits and costs of burying powerlines versus other alternatives[34].

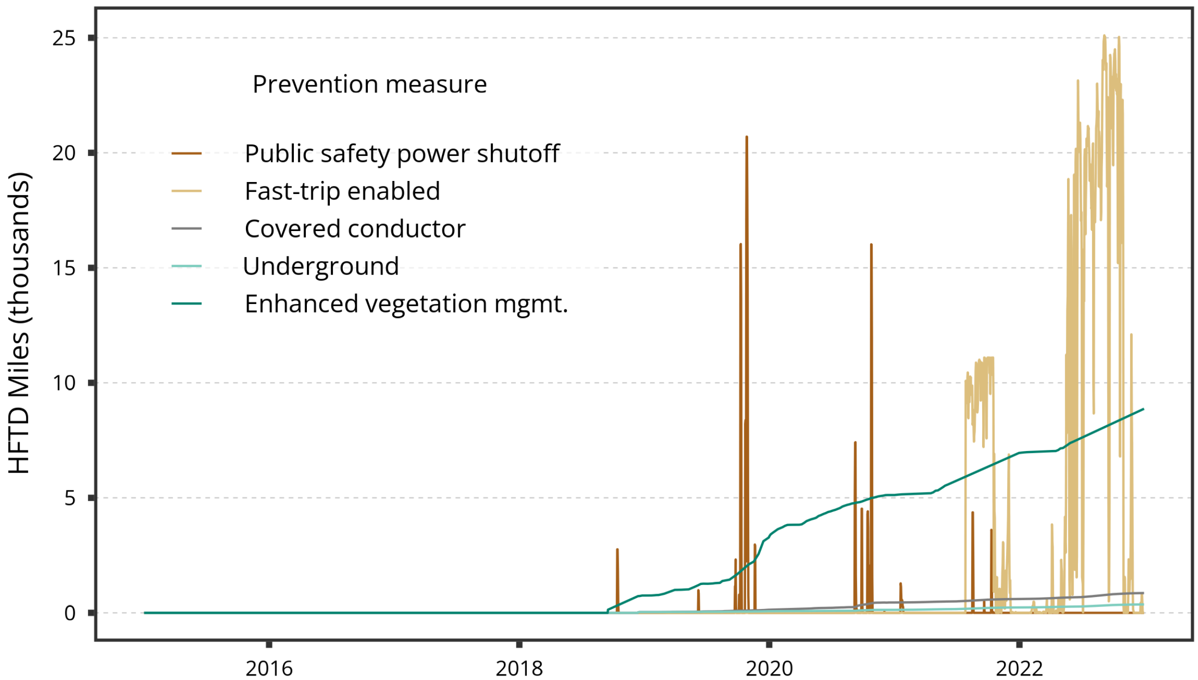

Figure 2 | Deployment of Wildfire Prevention Measures. The vertical axis shows the deployment of select wildfire prevention measures measured in thousands of circuit-miles. The miles deployed of operational mitigations are measured on a daily basis, while grid hardening and vegetation management investments are shown on a cumulative basis. When the utility calls a PSPS de-energization event on a given circuit, we assume all of the circuit's HFTD miles are de-energized, though in reality fewer miles may be de-energized due to grid architecture and installed sectionalizing devices.

Empirical strategy

Measuring the causal impacts of investments in wildfire prevention is complicated by the non-random assignment of risk mitigation "treatments". Presumably, utilities will target these investments at circuits with the greatest combination of ignition and wildfire risk. Thus, a simple comparison of post-treatment ignition outcomes across treated versus untreated circuits will confound the effects of the risk mitigation treatments with differences in baseline risk levels.

The empirical strategy we use to address this selection problem involves two steps. First, we use data from a pre-treatment period to train a machine learning model to predict daily ignitions for all PG&E distribution circuits that overlap the HFTD. We then leverage quasi-experimental variation in the assignment of two risk mitigation strategies, enhanced vegetation management and fast-trip settings. We compare ignition outcomes across circuits that received different risk mitigation treatments but were exposed to nearly identical levels of ignition risk.

For the other two approaches that have been deployed at a significant scale, undergrounding and PSPS events, we do not need to estimate impacts on ignition risk. Proactively de-energizing a line effectively reduces vegetation-contact ignition probability to zero. Similarly, once a circuit has been placed underground, there is no remaining risk of vegetation-caused ignitions. We will control for the utility's deployment of covered conductors, but we cannot estimate the effectiveness of this measure empirically given the low deployment levels (see Figure 2).

Step 1: Estimating Baseline Wildfire Risk

Fire weather variables such as wind speed, fuel moisture, and relative humidity, are highly stochastic and may interact nonlinearly to generate ignition events. Some circuits are twenty miles in length while others span more than two hundred miles. To capture how these factors influence ignition risk, we train a random forest model to predict a circuit's daily ignition risk using time-varying factors like wind speed, fuel moisture, and relative humidity as well as fixed circuit characteristics (see Methods). Importantly, we train and test the model in the pre-treatment period, i.e., 2015-2019 when wildfire mitigation efforts had not yet been deployed at scale. Thus, our predicted measures of ignition risk – even when we evaluate the model with time-varying environmental variables recorded after the training period – serve as baseline measures of location-specific risk.

Overall, our ignition risk model produces an area under the receiver operator characteristic curve (AUC) of 0.84. Prediction models with AUC values between 0.8-0.9 are generally considered excellent[35]. See Methods, Supplementary Figure 3, and the referenced study for more detail on our ignition risk model methods.

Step 2: Matching Procedure

We use ignition risk probability – estimated using our random forest model – to leverage plausibly exogenous variation in risk mitigation interventions. Specifically, we identify circuits that experience similar baseline levels of ignition risk but receive different risk mitigation treatment. Under a conditional unconfoundedness assumption, these comparisons yield unbiased estimates of the causal impact of these wildfire risk mitigation treatments on ignition outcomes.

The unit of observation is a circuit-day, i.e., each day of ignition outcomes and covariates for each of the 767 circuits in our data set. We assume that the ignition outcome y_{it} on circuit *i* in time *t* is determined by ignition risk probability θ^{it} and variables that indicate the level of risk mitigation "treatment" j, denoted D_{ijt} :

$$y_{it} = G(\alpha_0 + \alpha_1\theta_{it} + \sum_j \beta_j D_{ijt}) + \epsilon_{it}.$$

Any factors that play a role in determining ignition probabilities, but are not captured by the deterministic component in parentheses, are included in the error term. To interpret the β parameters as estimates of the causal effects of risk mitigation measures, we must assume that, conditional on θ_{it}, the ϵ_{it} is distributed identically and independently of the risk mitigation treatments. We use a matching algorithm to identify circuits that would have faced the same risk probability over our time period, but received different risk mitigation treatments. Given differences in how vegetation management and fast trip settings were assigned over our study period, we take different approaches to constructing the comparison groups for each.

Enhanced vegetation management (EVM): To identify effects of EVM on ignition outcomes, we leverage some documented "material shortcomings" in PG&E's approach to allocating these EVM efforts. Monitoring inspections reports[36] have found that, as the company rolled out its EVM program, it did not prioritize wildfire risk reduction according to its highest risk circuits[37]. These shortcomings generated variation in EVM treatment across circuits with the same baseline ignition risk.

To isolate this variation, we first calculate average daily ignition risk for each circuit using our random forest model over the period 2015-2022. We then divide the sample into circuits that received the vegetation management treatment ("treated circuits") and circuits that did not ("control circuits"). For each treated circuit, we use caliper matching to identify control circuits within a minimum distance–measured in terms of average daily ignition risk–to a treated circuit as a potential match. This matching process results in a sample of treated and control circuits with nearly identical baseline ignition risk, on average. Supplementary Figures 5 and 6 show how the matching process improves the balance of key ignition risk covariates among treated and control circuits. Prior to matching, the average ignition risk for circuits that received high levels of vegetation management is 2.5 times larger than that of control circuits. After matching, this difference is reduced to zero.

We perform this caliper matching process twice for two levels of the vegetation management treatment. The first comprises circuits that receive high levels of enhanced vegetation management, defined as 50% or more of the circuit's length. Circuits that receive vegetation management between 10 and 50% of circuit length are placed in the second tier of moderately treated circuits. See Methods for a step-by-step guide on the matching technique. Figure 3 displays a scatterplot of successful and unsuccessful matches. Twelve treated circuits, or approximately 5% of all treated circuits, do not find sufficiently close matches. The unmatched circuits tend to be higher risk because the utility generally treats all the highest risk circuits.

Robustness checks produce similar coefficient estimates when we retain the high-risk circuits that are dropped in the matching process (Supplementary Figure 16).

Fast-trip settings: Fast-trip settings are a relatively new innovation in utility wildfire risk mitigation. Because PG&E did not use fast trip settings before 2020, and only partially deployed them in 2021, we can compare similar high-hazard location-days across pre- and post-intervention years to identify the effectiveness of fast-trip settings.

PG&E now uses a wildfire potential index to determine whether fast-trip settings should be enabled on a given day. Our intertemporal comparisons restrict the sample to only those circuit-days when wildfire risk was sufficiently high that the criteria for fast-trip enablement would have been met (see Methods). In other words, we compare days when fast-trip settings are enabled only to days during the pre-period when they would have been enabled. One might be concerned that, among these very-high risk days, risk factors manifested differently in the pre- and post-treatment period. Supplementary Figure 8 compares the conditions we observe on high-fire risk days before and after fast-trip settings were deployed. Along a series of dimensions which are known to increase ignition risk (e.g., wind speed, dead fuel moisture), conditions are similar across the pre- and post-periods. This increases our confidence that differences in ignition outcomes we observe across compared circuits are caused by this risk mitigation intervention versus other confounding factors.

In summary, our identification strategy consists of two overlapping parts. First, we match control circuits with nearly identical baseline ignition risk to circuits treated with enhanced vegetation management. Then, we restrict the sample only to high-fire risk days that meet the criteria for fast-trip settings.

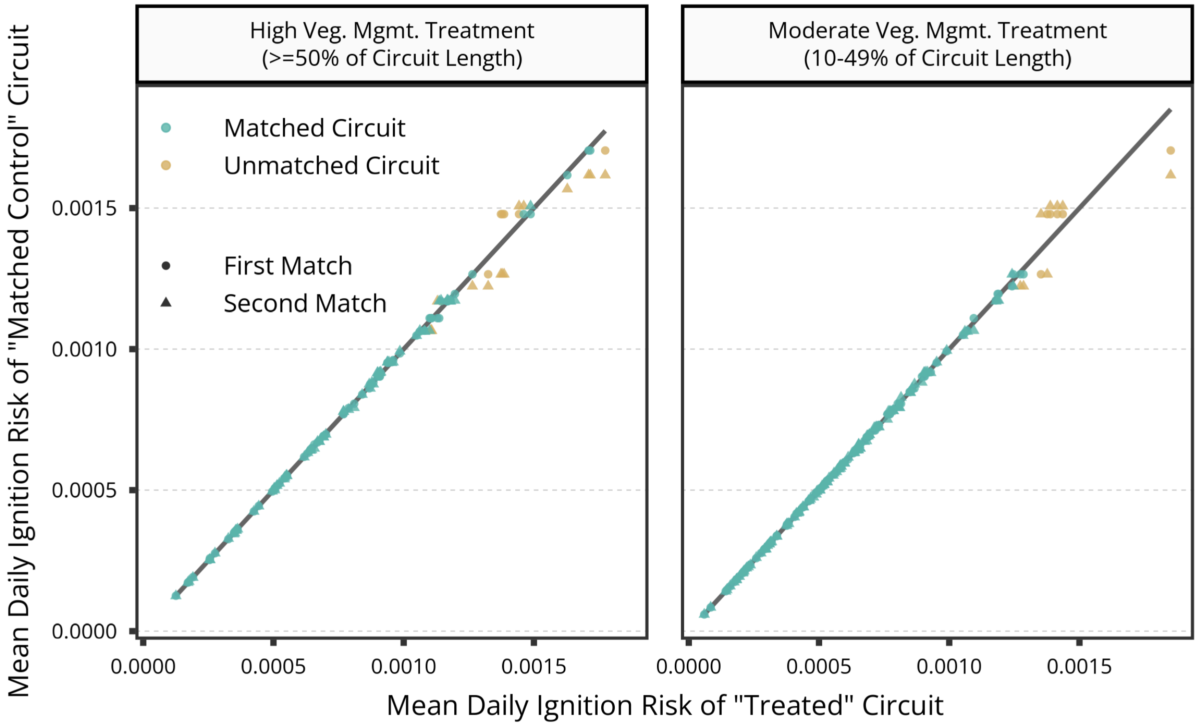

Figure 3 | Scatterplot of Circuits Treated with Enhanced Vegetation Management Against 2-Nearest Neighbor Control Matches. The horizontal axis plots the average daily ignition risk score of each circuit treated with vegetation management. The vertical axis plots the same metric but for the two control 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.

To estimate the impacts of these investments on ignition risk, we specify a logistic regression model of ignition probabilities. We formulate the probability that an ignition occurs at circuit *i* on day *t* as:

$$\textit{\textbf{(1)}} \qquad G(x_{it}\beta) = \frac{exp(x_{it}\beta)}{1+exp(x_{it}\beta)},$$

$$\textit{\textbf{(2)}} \qquad x_{it}\beta = \alpha_0 + \alpha_1\theta^{it} + \beta_1 E^{it}_{EPSS=1} + \beta_2 (D^{i}_{VEG=Hi.} * T^{it}_{Post=1}) + \beta_3(D^{i}_{VEG=Med.} * T^{it}_{Post=1}) + \beta_4 D^{i}_{VEG=Hi.} + \beta_5 D^{i}_{VEG=Med.} + \beta_6 UG^{it} + \beta_7 Z^{it}_{PSPS=1} + \beta_8 CC^{it} +$$

$$\beta_{10}(E^{it}_{EPSS=1} * D^{i}_{VEG=Hi.} * T^{it}_{Post=1}) + \beta_{11}(E^{it}_{EPSS=1} * D^{i}_{VEG=Med.} * T^{it}_{Post=1}) + \varepsilon_{it}$$

Explanatory variables in the model include a binary variable indicating whether fast-trip settings were enabled on a given circuit-day (E^{it}) and a binary variable indicating the circuit-level vegetation management treatment (D^{i}). We interact vegetation management treatment with a time indicator (T^{it}) to capture the effect of the treatment in the post-intervention period. We also include in the model 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). Lastly, we interact vegetation treatment status with fast-trip enablement in the post-intervention period to test the co-benefits of layering these two risk mitigations together.

The α and β coefficient estimates are those that maximize the log-likelihood across all circuits and days in our data. Observations are weighted to reflect the frequency of caliper matching. To accommodate correlation in errors associated with a given circuit over time, standard errors are estimated using a sandwich covariance estimator. Results are robust to alternative specification choices (e.g. negative binomial and quasi-Poisson) and matching techniques. Results are also robust to the inclusion of regional fixed effects (Supplementary Figure 14).

Results

Causal effects of risk mitigation on ignition outcomes

Estimation results are reported in Figure 4. We transform the coefficient estimates to incidence rates for easier interpretation. Coefficient estimates reported in column (1) use the entire data set as opposed to the subset of matched circuits. These coefficients likely confound the effects of risk mitigation treatments with differences in baseline ignition risk across treated and untreated circuits. This is evident by the positive and statistically significant coefficients on high and moderate vegetation management circuits (rows four and five).

The second column reports estimates generated with observations that were identified as matches with our EVM treatment caliper matching strategy, and the third column reports our preferred estimates, which further restricts the sample to high-risk days when fast-trip settings would be (or were) deployed. In the case of fast-trip settings, the estimated incidence rate of -0.72 in column (3) implies that enabling fast-trip settings on a given high-risk circuit-day reduces the circuit's probability of sparking an ignition by 72% (54%-83% confidence interval), on average. Likewise, in column (3) we find that circuits with high levels of vegetation management cause 57% fewer ignitions than similarly risky circuits with zero to minimal amounts of vegetation management.

Our estimating equation also includes interactions between vegetation management and fast-trip indicators. If a utility has cleared significant amounts of vegetation around an overhead line and deployed fast-trip settings, risk reduction may be greater than either measure can deliver independently. Consistent with this intuition, we find that combining enhanced vegetation management with fast-trip settings reduces ignition risk by 92% on average.

	Incidence Rate - Vegetation-Caused Ignitions		
	No Matching	Matching	Matching & High Fire Risk
	(1)	(2)	(3)
Fast-Trip (E_{it}=Enabled)	−0.27	−0.60*	−0.72*
	(−0.58, 0.26)	(−0.75, −0.33)	(−0.83, −0.54)
Veg. Mgmt. (D_i=High x T_{it}=Post)	−0.62*	−0.57*	−0.57*
	(−0.79, −0.29)	(−0.77, −0.20)	(−0.82, −0.02)
Veg. mgmt. (D_i=Moderate x T_{it}=Post)	−0.03	−0.01	0.26
	(−0.27, 0.29)	(−0.27, 0.34)	(−0.14, 0.86)
Veg. mgmt. (D_i=High)	1.18*	0.02	0.12
	(0.77, 1.70)	(−0.17, 0.26)	(−0.12, 0.42)
Veg. mgmt. (D_i=Moderate)	1.23*	0.05	0.05
	(0.87, 1.67)	(−0.11, 0.25)	(−0.17, 0.32)
Combined Effect (D_i=High x E_{it}=Enbld. x T_{it}=Post)	−0.89	−0.87	−0.92
	(−1.00, 1.89)	(−0.99, 2.27)	(−1.00, 1.72)
Combined effect (D_i=Moderate x E_{it}=Enbld. x T_{it}=Post)	−0.77	−0.81	−0.88
	(−0.97, 0.94)	(−0.98, 0.88)	(−0.99, 0.38)
Risk-score matching	No	Yes	Yes
High-fire risk days only	No	No	Yes
Matched control neighbors (N)	-	2	2
Region FEs	No	No	No
Risk-score, undergrounding, PSPS, and covered conductor controls	Yes	Yes	Yes
AUC	0.782	0.798	0.745
Observations	2,400,342	1,890,015	665,868
Log Likelihood	−6,776.30	−8,168.87	−4,610.30

Figure 4 | Effects of Wildfire Prevention Measures on Ignition Probability. 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 coefficients are transformed to incidence rates to ease interpretation. 95% confidence intervals derived using heteroskedasticity-consistent standard errors are shown in parentheses below the incidence rate estimates. Asterisks (*) denote statistical significance at the 95% level. 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 (>=50% circuit length) or moderate (10-49%) 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 (see Methods). Vegetation management effects are shown for both the high and moderate treated groups. 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, and intuitively this group-specific effect is not statistically significant after matching in columns (2) and (3) because the matching process eliminates group-specific differences in baseline risk between treated and control groups. The third and final pair of vegetation management effects describes the combined interaction between vegetation management and fast-trip enablement. For example, comparing the incidence rate estimate of -0.92 for the combined effect with the -0.57 estimate for fast-trip enablement suggests ignitions are 35% less likely when a utility both enables fast-trip settings and deploys high levels of vegetation management. In all three columns, we condition on our ML-derived measure of daily ignition risk. To provide a sense of the regression model's goodness of fit, we report the area under the receiver operating characteristic curve (AUC).

In Figure 5, we use our coefficient estimates from column (3) to predict vegetation-caused ignitions with and without the utility's observed levels of wildfire mitigation efforts. The vertical axis measures the numer of ignitions per month. The top row presents predicted ignitions in the pre-period when no enhanced risk mitigation efforts had been deployed (see Figure 2). The bottom row illustrates the implied risk reductions as risk mitigation efforts increase. Even though undergrounding provides larger risk reductions where deployed, we estimate that fast-trip settings provide larger reductions in ignitions overall. The reason is that fast-trip settings have been applied to all 25K miles of distribution circuits in the HFTD, whereas by the end of 2022, just 1% of HFTD circuit-miles had been moved underground.

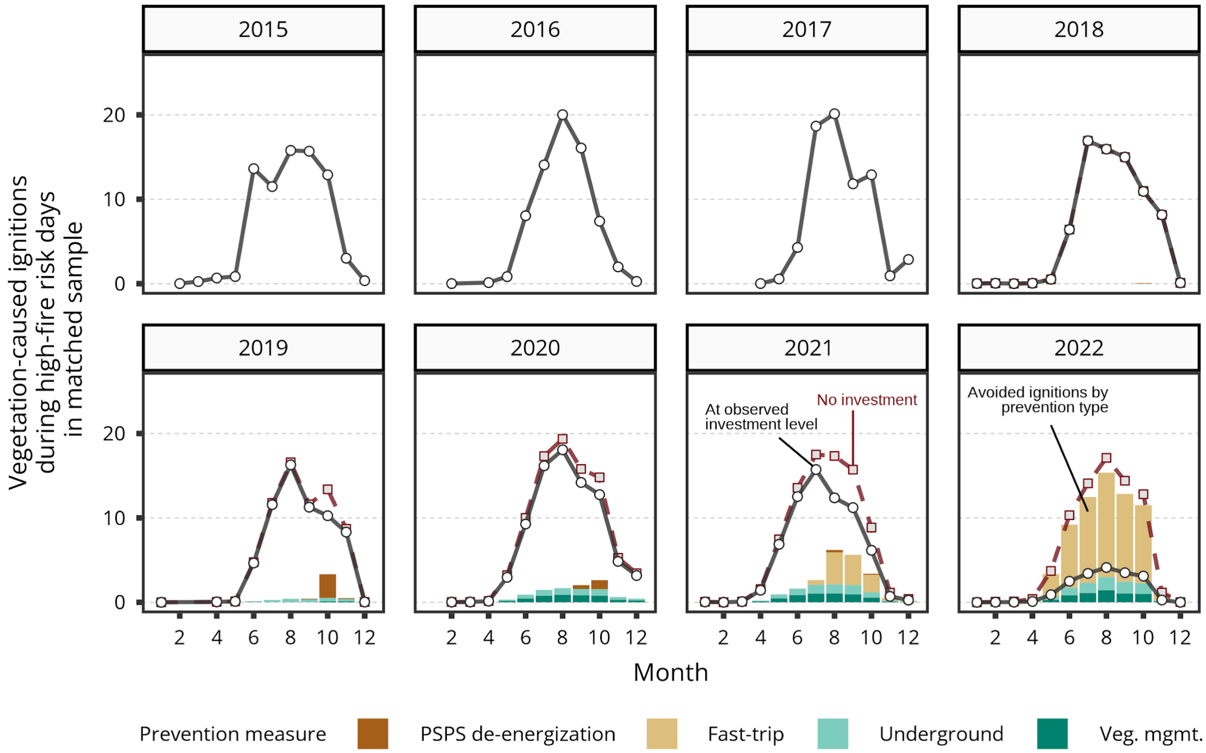

Figure 5 | Ignitions Avoided Due to Wildfire Prevention Investments. The vertical axis shows the number of ignitions predicted by our model on high-fire risk days. The only circuits included in this analysis are ones that received high amounts of vegetation management or control circuits that were matched to these treated circuits based on similar ignition risk. Using the coefficients reported in column (3) of Figure 4, the gray line predicts the number of ignitions in each month assuming the utility invested in wildfire prevention measures at observed levels. The red dashed line plots ignitions if the utility had decided to forgo investment in wildfire prevention. The red dashed line and the gray line began to diverge in October 2019 when the utility called widespread PSPS events. The stacked vertical bars represent the contributions of each key prevention measure to overall ignition reductions. These measure-specific contributions to risk reduction are estimated by deploying each wildfire prevention 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 red dashed line and the gray line. This is because the ignition reductions of each wildfire prevention measure are compared to a baseline of no other wildfire prevention measures. For example, if a circuit may produce 3.0 ignitions over the period without any wildfire prevention measures, then fully undergrounding this circuit would reduce ignitions to zero and enabling fast-trip settings would reduce ignitions to 0.8 [(3 * (100%-72%)] over the period. However, the sum of these two in isolation would produce a total ignition reduction of 3.8, which cannot exceed 3.0 ignitions.

Costs per avoided ignition

In this section, we incorporate data from public utility filings which document the amount that PG&E has spent on each risk mitigation category. We combine these cost data with our ignition risk reduction estimates (reported in column (3) of Figure 4) to assess the average cost per avoided ignition. These calculations implicate multiple sources of uncertainty (e.g., the rate at which wildfire risk will escalate over the life of a capital investment, unit costs, reliability impacts). The Methods section includes a detailed discussion of our cost modeling assumptions. We summarize our most important assumptions and parameter choices below.

Undergrounding: Because undergrounding powerlines eliminates ignition risk completely, we can estimate the implied cost per avoided ignition at a given location by dividing the estimated net costs of undergrounding by the number of ignitions avoided over the life of the investment. We coarsely assume that baseline ignition risk increases at a linear rate in future years, reaching a 50% increase by 2050. See Methods and Figure 6 for more detail. In a subsequent section, we examine how ignition reduction can reduce wildfire damages, which may vary due to changes in climatic factors as well as exogenous policy factors to the utility such as the amount of prescribed burn, fire suppression resources, and home hardening investments to prevent structure loss.

To calibrate the per-mile costs, we use cost numbers reported by PG&E over our study period. Although undergrounding costs surely vary across locations, we use average cost estimates for all locations due to a lack of reporting on location-specific undergrounding costs. A 2021 PG&E rate case reports costs of $4.3M per mile of undergrounding[25], while a 2023 decision cited costs of $3.3M per mile and anticipates $2.8M per mile by 2026. The utility's wildfire mitigation plan cites $3.75M per mile in 2022. Future undergrounding costs are highly uncertain. On the one hand, there will likely be learning by doing. A new pilot program by PG&E wraps conductors in concrete and polymer casings and lays them on the ground, removing the need to excavate beneath the ground and potentially achieving large reductions in ignitions at low-cost. On the other hand, costs could increase if the utility has been deploying less costly projects first.

When a line is moved underground, this will obviate the need for above-ground maintenance such as routine vegetation management, i.e. PG&E's standard vegetation management that it uses on all circuits regardless of wildfire risk. To account for these avoided costs, we use vegetation management cost data that predate the enhanced vegetation management program, which are approximately $400M per year[25]. We then divide PG&E's total reported routine vegetation management costs prior to the EVM program by HFTD circuit-miles to find a per-mile cost for routine vegetation management. This likely over-estimates costs per HFTD mile because the $400M per year routine vegetation management costs were incurred both inside and outside the HFTD.

Finally, in contrast to other risk mitigation strategies, undergrounding power lines requires significant upfront capital investment. We take two alternative approaches to capital cost accounting. The first approach (labeled "social" in Figure 6) simply accounts for capital expenditures, ignoring any costs of allocating this capital to this purpose. This provides a lower bound on capital costs. The second approach (labeled "regulator") counts the regulator-approved rate of return on these capital investments as a cost. This approach captures the costs as incurred by ratepayers. Prior research has documented an economically significant gap between utilities' allowed rate of return and the true cost of capital[22]. When the regulated rate of return exceeds the true market rate, part of the costs reflected in the far right bar represent transfers from consumers to utilities.

Enhanced vegetation management: Estimating the costs per avoided ignition associated with enhanced vegetation management is complicated because the underlying cost structure is more complex and the impacts on ignition risk are more heterogeneous. The effects of vegetation management will attenuate over time as vegetation grows back. We have insufficient data to empirically estimate the rate of decline, so we linearly decline the benefits of vegetation management over a ten-year time horizon. Our sensitivity analysis varies this assumed time horizon between five and fifteen years. As described previously,PG&E spent an estimated $188K - $293K per mile on enhanced vegetation management work between 2019 and 2022[25]. Enhanced vegetation management involves ongoing maintenance and inspection costs, which we further describe in Methods– "Cost analysis."

Operational measures: Fast-trip settings are a relatively new innovation, but PG&E has reported costs for the 2021-2022 period. Costs incurred in a given year will only provide ignition benefits within that year. We assume an annual fast-trip budget of approximately $150M across all 25K HFTD miles based on 2022 cost data. Forecasted costs for 2023-2026 retain this annual budget at approximately the same level. Taken together, vegetation management and fast-trip settings account for approximately $2.1B of risk mitigation investments between 2019 and 2022, which is about 12% of PG&E's total wildfire mitigation expenditure over the same period[14,25].

Fast-trip settings impose additional costs in the form of unplanned electricity outages. In 2022, outages that occurred when fast-trip settings were enabled lasted approximately six hours and caused 2,500 customer-hours of outage impacts, on average. We find that when fast-trip settings were enabled on a circuit there was a 3.5% chance that an unplanned outage occurred. Subsequent Figures 6, 7, and 8 account for the additional economic costs of fast-trip settings by assuming a value of lost load ("VOLL"). In Supplementary Figure 10, we fit an econometric model to quantify potential the co-benefits that vegetation management and undergrounding produce, by lowering the frequency and duration of fast-trip outages.

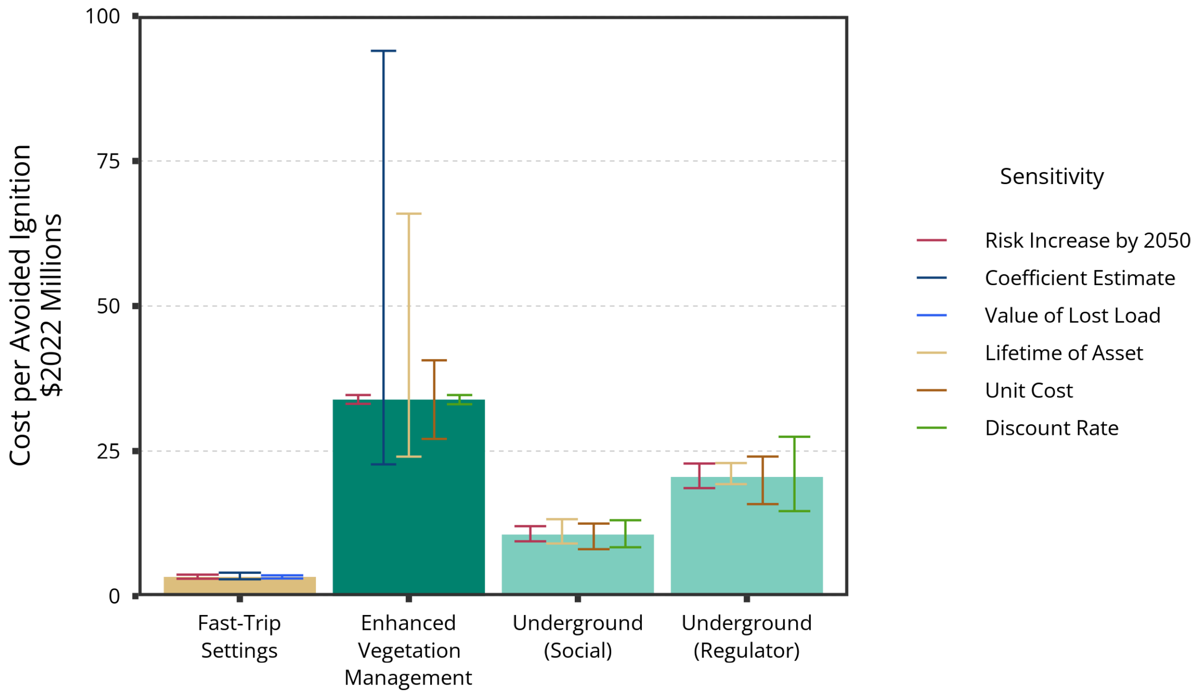

Figure 6 | Cost Efficiency of Wildfire Prevention Measures - Avoided Ignitions. The figure plots estimated electric utility investment costs per avoided ignition for each wildfire mitigation measure deployed across all HFTD circuits. For fast-trip settings, we include estimated reliability costs incurred by customers. For undergrounding, we consider two different cost structures. The first, called the "social" perspective, only considers the per-mile costs of undergrounding and discounts future benefits in terms of avoided ignitions using a real social discount rate. The second, called the "regulator" perspective, adds in the return the utility earns on capital investment under rate of return regulation as a cost. In addition, the per-mile costs of undergrounding are spread out across the lifetime of the undergrounding asset and charged to ratepayers according to a depreciation schedule. Future benefits and costs are discounted using a ratepayer-centric discount rate that is higher than the social discount rate but less than the utility's cost of capital. The real social discount rate in our base case is 2.5% and varies from 1-4%. For the "regulator" perspective, the ratepayer discount rate and cost of capital are 5% and 7.5% in our base case and vary from 2.5%-7.5% and 5%-10%, respectively. When we vary the ratepayer discount rate in the "regulator" perspective, we symmetrically vary the utility's assumed cost of capital. For fast-trip settings and enhanced vegetation management, we derive 95% confidence intervals using the coefficient estimates from the logistic regression model in column (3) of Figure 4. 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 $3.7M per mile in our base case and varies from $2.8M-$4.4M. For fast-trip settings, we rely on 2022 program costs of $149M. 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. Our base case assumes ignition risk increases linearly each year to a 50% increase by 2050, and it continues to increase linearly thereafter. We vary this assumption between 25% and 75%. Varying the increase in ignition risk between 25% and 75% by 2050 has a relatively muted impact on cost per avoided ignition due to discounting in later years. Because the costs of fast-trip settings include reliability impacts borne by customers, we introduce an additional sensitivity that varies the assumed economic value customers place on electric service (value of lost load). In our central case, we assume a constant $5/kW value of lost load. We vary this parameter choice between $2.5/kW and $7.5/kW.

There are three key take-aways from this cost-effectiveness analysis.

First, we find that fast-trip settings reduce ignitions at a much lower cost than vegetation management or undergrounding. Figure 6 shows that the estimated cost to avoid one ignition using fast-trip settings is $3.3M ($2.9M - $3.7M), on average, compared to $37M and $11M per ignition for vegetation management and undergrounding, respectively.

Second, undergrounding powerlines, despite the higher investment costs, is a more cost-effective strategy than vegetation management. This is primarily because undergrounding fully eliminates ignition risk well into the future. Assumptions about the cost per mile of undergrounding, the social or ratepayer-centric discount rate, and the utility's cost of capital are important sources of uncertainty that influence this cost-effectiveness comparison. Using a lower discount rate places a higher weight on future ignition reductions and improves the cost-effectiveness of undergrounding. For vegetation management, the choice of discount rate does not strongly influence cost-effectiveness. The pace at which vegetation grows back over time (i.e. the lifetime of the vegetation management asset) plays a more important role in determining cost-effectiveness.

Third, our estimates of the cost-effectiveness of undergrounding differ significantly across our "social" and "regulator" measures. Using a 5% social discount, the "social" cost per avoided ignition for undergrounding is approximately $15M. Using an equivalent 5% discount rate and accounting for the utility's 7.5% rate of return raises the cost per avoided ignition to $20.5M. To the extent that utilities are authorized to earn a rate of return on capital investments that exceed the true cost of capital, some of the costs passed on to ratepayers accrue as profits for utilities. Excess returns will lead utilities to favor this more capital intensive approach.

Cost implications of a new risk management regime

The cost estimates summarized above are all measured relative to a baseline of routine vegetation management. However, the introduction of fast-trip settings as a viable and highly cost-effective risk mitigation regime provides an updated reference point against which to assess risk mitigation efforts. To explore the implications of this new frame of reference, we assess the costs and benefits of undergrounding against two baselines: one that deploys routine (not enhanced) vegetation management, and one that also includes fast trip settings.

The left panel of Figure 7 illustrates the estimated costs per ignition avoided by undergrounding using these two baselines, respectively. To generate this figure, we order distribution circuits in ascending order of their undergrounding cost per avoided ignition (see Methods). In this analysis, we model the costs of undergrounding from a societal perspective and ignore the return on capital investment the utility earns under rate of return regulation. We then divide each circuit's net present cost of undergrounding by its cumulative total discounted ignitions, as computed from our prediction model estimates of daily circuit-level ignition probability. For reference, the right panel of Figure 7 depicts the cumulative total discounted ignitions associated with the ordering of circuits we constructed in the left panel.

We first estimate the incremental costs of undergrounding miles of distribution lines (in ascending order of ignition risk) relative to a baseline regime that involves only routine vegetation management. The outcome of this calculation is depicted in the solid lines in Figure 7. We then construct a second set of estimates, depicted with dashed lines, which provide costs relative to the current regime in which fast-trip settings are deployed across the HFTD during high-risk days.

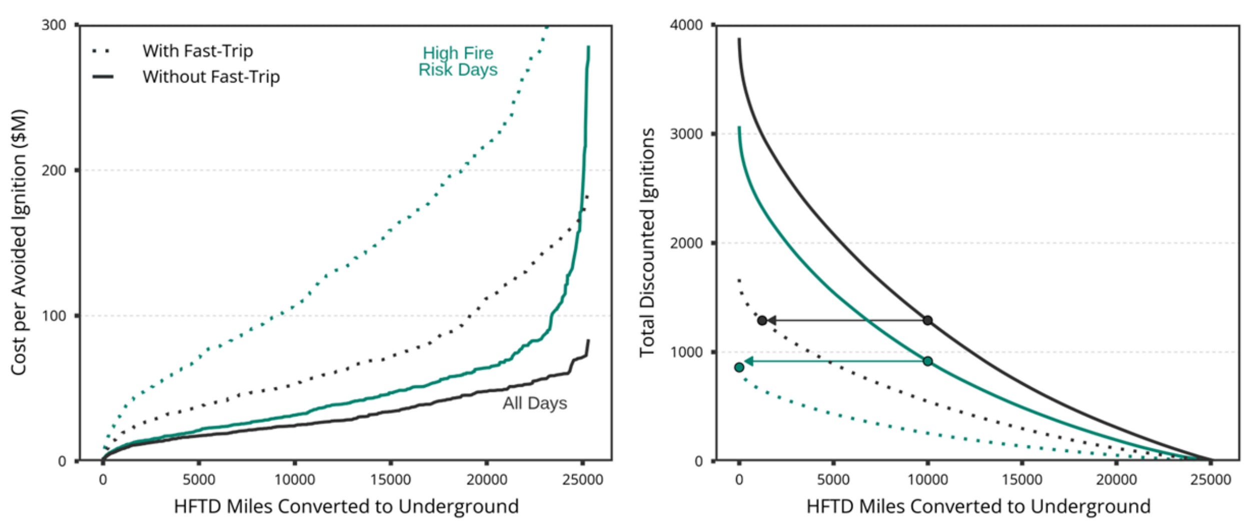

Figure 7 | Estimated Cost per Avoided Ignition of Undergrounding With and Without Fast-Trip Settings. The plot on the left describes how our estimates of the cost per avoided ignition for a given undergrounding investment vary across circuits. Specifically, the horizontal axis corresponds to hypothetical 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 thousand miles of undergrounding (100% of HFTD). Ten thousand miles of undergrounding is used as a reference point, which has been proposed publicly by PG&E. The plot on the left is constructed by ordering circuits in terms of cost-effectiveness. To construct undergrounding cost estimates, we assume an average implementation cost of $3.7M per mile, a project lifetime of 40 years, avoided annual maintenance costs of $16K per mile (see Methods "Cost data"), a real social discount rate of 2.5%, and a linear ignition risk increase of 50% by 2050. The solid line plots cost per avoided ignition for undergrounding under the assumption that no fast-trip settings (or other wildfire mitigation measures) are deployed. However, when we plot the dashed line, we model the impact that fast-trip settings 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 dashed line accounts for cost savings that undergrounding produces in terms of reducing fast-trip program costs, reliability impacts, and routine vegetation management. The plot on the right shows the total discounted ignitions over the lifetime of the undergrounding investment. As 100% of the HFTD is placed underground on the right of the horizontal axis, total discounted ignitions are zero. While there is uncertainty surrounding the specific point estimates due to reasons discussed previously, these figures illustrate that a newly deployed, more cost-effective mitigation measure can significantly alter the amount of investment needed to achieve a desired level of risk reduction.

The analysis in Figure 7 is based on point estimates and average cost measures, so the key implications are more qualitative in nature:

First, undergrounding costs *per avoided ignition* vary significantly across line segments. Intuitively, the higher the ignition risk per circuit-mile absent risk mitigation, then the more cost-effective risk mitigation on that circuit will be.

Second, the implied costs of undergrounding, expressed on a per avoided ignition basis, look quite different when we define the "business as usual" option to be one that assumes fast-trip settings are enabled on all HFTD circuit-miles, versus one that deploys only EVM. Once fast-trip settings are assumed to be part of the business-as-usual regime, undergrounding a line delivers much smaller benefits in terms of avoided ignitions. The costs avoided by undergrounding (i.e., avoided routine vegetation management, fast-trip deployment costs) are relatively small, so the implied costs per avoided ignition increase significantly under the "with fast-trip settings" baseline.

Third, the adoption of fast-trip settings across all HFTD miles significantly reduces the amount of undergrounding needed to achieve a given ignition risk reduction target. The figure on the right summarizes how the total discounted ignitions across the lifetime of the undergrounding investment falls as the number of circuits placed underground increases. Consider, for example, PG&E's ten thousand mile target, which was established before fast-trip settings were deployed. If we assume that the utility is planning to underground the highest risk circuits, we estimate a remaining risk of approximately 1,200 discounted ignitions from the line miles that are not undergrounded. To see how these costs and benefits change with the introduction of the fast trip setting regime, the arrow in the figure shows how many miles should be undergrounded to achieve the same level of ignition risk reduction as ten thousand miles would in the pre-fast-trip regime. This important innovation in operations management reduces the amount of undergrounding required to achieve this level of ignition risk reduction by nearly 100%.

Simulating damages to structures

Thus far we have been focusing on ignitions, which are necessary, but not sufficient, to start a wildfire. The primary objective of wildfire mitigation is to reduce the potential damages from an ignition. In this section, we introduce an additional outcome of interest: the potential quantity of structures burned by a wildfire caused by an electric distribution circuit.

Due to the computational intensity of simulating wildfire growth across numerous ignition points and weather conditions, we focus our modeling efforts on a six thousand mile subset of PG&E distribution circuits. This six thousand mile subset was selected based on two regions of the utility's service territory, roughly comprising (1) the wine-growing region of Napa, Sonoma, and Lake counties and (2) the Central Sierra foothills in Amador, El Dorado, Nevada, Placer, and Yuba counties. Both regions experienced large destructive wildfires caused by powerlines during our study period. We calibrate our simulations of wildfire perimeters using data on the actual acreage of each grid-caused ignition in our data. Importantly, if the perimeter of a wildfire encompasses a given residential or commercial parcel, it does not always lead to structure loss. Fire suppression resources or home hardening investments can protect the structure. As a proxy for the destructive intensity of a wildfire, we vary the proportion of structures burned per parcel encompassed by a wildfire perimeter from 20 to 60%. See Methods for full documentation of our approach to simulating wildfire growth.

This modeling exercise allows us to map our estimates of ignitions avoided into estimates of wildfire damages avoided. In this study, we only consider one form of wildfire damages– residential and commercial structure loss. We acknowledge that structure losses are an incomplete measure of wildfire damages; air pollution, loss of life, carbon emissions, post-debris flows, reductions in ecosystem services, and disruptions to recreation and economic activity likely account for large losses, too[38]. Figure 8 reports our estimates of the cost to avoid one structure burned. For fast-trip settings, we estimate that it costs the utility $260K ($220K - $470K) to avoid burning one residential or commercially-zoned structure, including the measure's impact on reliability. In contrast, we estimate vegetation management and undergrounding investments cost $3.7M and $1.4M, respectively, to avoid one structure lost from a powerline-caused wildfire. Factoring in the nature of rate of return regulation that authorizes the utility to earn a return on capital investment raises the cost of undergrounding to $2.2M per avoided structure burned.

Our estimates of the cost per avoided structure burned are sensitive to the parameter that reflects the destructive intensity of wildfires. Unlike parameters such as the cost of capital and the per-miles costs of each measure, the destructive intensity of wildfires is exogenous to the utility and regulator. The utility and regulator have little influence over how much homeowners will harden their home, the effectiveness of firefighting efforts, or the amount of prescribed burning conducted that reduces the intensity of wildfires. It is worth underscoring that the cost-effectiveness of an electric utility's mitigation efforts depend on these exogenous and uncertain factors that are not explicitly accounted for in regulator-utility proceedings.

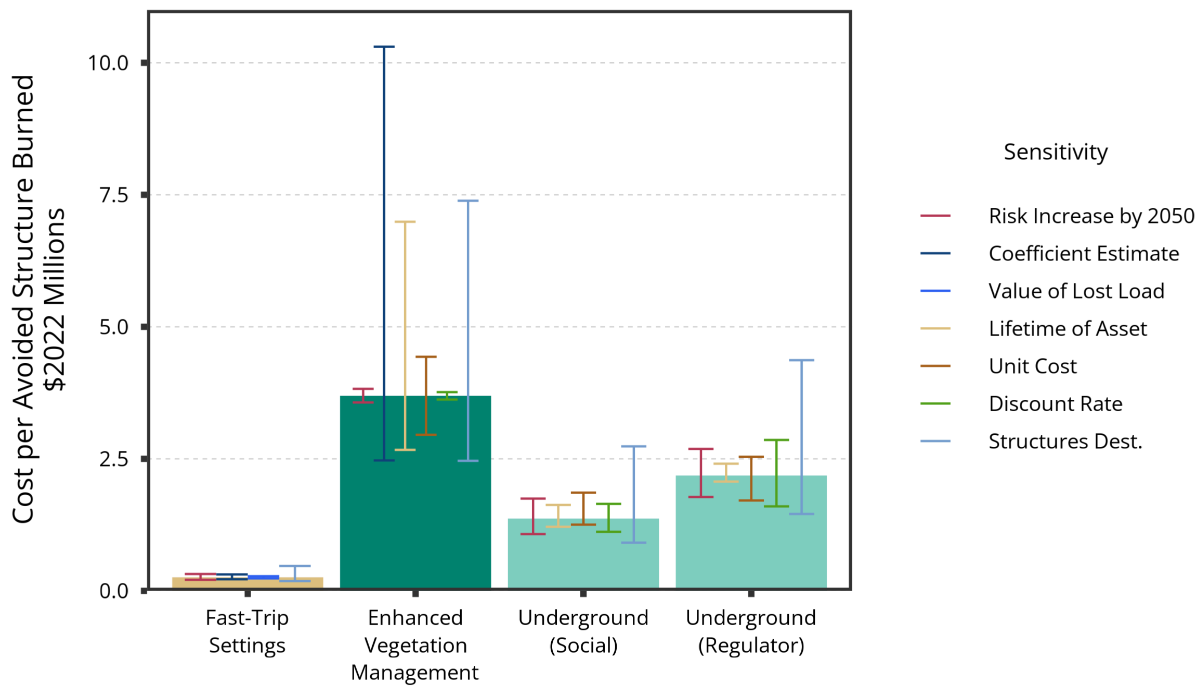

Figure 8 | Cost Efficiency of Wildfire Prevention Measures - Avoided Structures Burned. The figure plots estimated electric utility investment costs per avoided structure burned for each wildfire mitigation measure deployed across a limited sample of HFTD distribution circuits. The limited sample includes six thousand circuit-miles across Amador, El Dorado, Lake, Napa, Nevada, Sonoma, Placer, and Yuba counties. We estimate the potential number of structures burned by an ignition on a given circuit-day by simulating wildfire growth (see Methods). In our base case, we assume 40% of parcels intersected by a wildfire lead to total structure loss and we vary this parameter from 20-60% to reflect uncertainty surrounding the destructive intensity of wildfires and the ability of fire suppression and defensive investments to prevent structure loss. For a discussion of the other sensitivities, see previous discussion in Figure 6 or Methods.

Discussion and conclusion

Electric utilities are experimenting with a variety of measures – including system hardening, operational measures, and vegetation management – to mitigate wildfire risk in their service territories. These investments have massive cost implications for affordability and decarbonization via electrification. There is, therefore, a pressing need to analyze the cost-effectiveness of wildfire mitigation to inform these high-stakes decisions.

Overall, we find that risk mitigation efforts have significantly reduced vegetation-contact ignitions. Absent these efforts, we estimate that ignitions in high-hazard areas would have been four times higher in 2022. Using our measure-specific ignition reduction estimates in combination with utility-reported costs, we find that a new operational innovation – the deployment of fast-trip settings on high-hazard days – is by far the most cost-effective ignition reduction measure. This mitigation strategy can be deployed dynamically in response to evolving wildfire conditions. However, it has the important drawback that it leaves an estimated 28 percent of baseline ignition risk unmitigated, on average. Enhanced vegetation management is less effective at mitigating risk, and significantly more expensive, than fast-trip settings. Consistent with these findings, PG&E has recently stopped using enhanced vegetation management as a key part of its ignition risk reduction strategy. We also find that, although undergrounding fully eliminates risk on treated circuits, it is three to five times more expensive than fast-trip settings in terms of costs per avoided ignition and avoided structures burned. The incentives of rate of return regulation further raise the costs of undergrounding to six to eight more times expensive than fast-trip settings.

Our empirical results should be interpreted in light of some important caveats. There are many sources of uncertainty in our analysis. Our measures of avoided wildfire damages are model-dependent and only reflect potential damages to structures. In addition, we summarize the average cost-effectiveness of each measure where such measures have been deployed to date, but circuit or sub-circuit estimates of cost-effectiveness are needed for a more detailed cost-benefit analysis. These considerations notwithstanding, our results demonstrate how ongoing experimentation with new management strategies has significantly reduced the amount of undergrounding that is needed to deliver a given amount of risk reduction.

The extent to which these – and future - innovations deliver real cost reductions will depend on utility incentives. Under the current regime, if authorized rates of return on capital investment exceed the true costs, utilities will have an incentive to favor more capital intensive mitigation options. Liability rules, public image concerns, and uncertainty surrounding wildfire mitigation outside the power sector strongly incentivize electric utilities to drive power-system ignitions to zero. To the extent that these incentive structures are misaligned with the best interests of consumers and ratepayers, regulatory oversight will have a critical role to play. Striking the right balance between risk reduction benefits and the societal costs of wildfire mitigation is no small task given the multiple sources of significant uncertainty. This paper provides a foundation for thinking more systematically about these risk-cost tradeoffs.

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Methods

Risk-score prediction model

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 the approach in Yao et al[39].

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%, and we address this by under-sampling the data.

In addition, we evaluate models based on the area under the receiver operator characteristic curve (AUC).

We develop the model to characterize a baseline measure of risk, in the absence of wildfire prevention measures, by training it with ignition data occurring between 2015 and 2018, prior to the utility's implementation of PG&E's key wildfire prevention programs. We perform 3-repeat 10-fold cross-validation and split the training and testing data 75/25%. During this process we tune two hyperparameters: the number of decision trees and the number of features considered at each split. Our ignition risk model produces an AUC value of 0.84 when used to predict ignition events in the testing data. The confusion matrix, using a classification threshold of 0.5, and ROC curve are shown in Supplementary Figure 3.

Covariates that are important predictors of ignition risk include vapor pressure deficit, the length of the circuit in HFTD Tier 2 and in Tier 3, the average forest canopy height, wind speed, relative humidity, 1,000 hour dead fuel moisture, and the age of the circuit.

The ultimate output of the risk-score model is the probability of an ignition occurring 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[40], we apply an adjustment to the posterior probability estimates derived by Pozzolo et al. (2015). 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. See Pozzolo et al. (2015) for additional information. After calibrating the probabilities, our ignition risk model predicts 55 ignitions in the test data. The test data includes 45 actual ignitions. The recall of the model in the test data is 84% but the precision of the model is low (0.9%).

Vegetation management matching technique

To identify the effectiveness of vegetation management on ignition outcomes in our econometric model, we match "treated" circuits to "control" circuits based on our prediction of baseline ignition risk. The approach is similar to propensity-score methods, but instead of matching on the propensity score we match on our ignition risk score. Our matching process takes the following 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.

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.

Fast-trip setting enablement

Fast-trip settings are only enabled on circuits and days when the utility's fire potential index exceeds a threshold. To identify the effect of fast-trip settings on ignition outcomes, we need to restrict the sample only to those fast-trip enabled days. However, we do not directly observe the utility's fire potential index on every circuit-day, and therefore we use a historical sample of fire potential index data to train a model that predicts the circuit-days on which fast-trip settings are enabled[41].

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, but we ignore 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[14].

We use a sample of 997 observations of the utility's fire potential index at the circuit-day level[41], 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. See Data Sources for a specific list of variables used. As with the risk-score prediction model discussed earlier, we use 3-repeat 10-fold cross validation and tune hyperparameters. We split the training and testing data 75/25%. We achieve 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. We identify these circuits through incident-specific data on fast-trip outages in 2021[31]. After 2021, all HFTD circuits had fast-trip settings enabled.

Cost data

We obtain cost data for each wildfire prevention measure by reviewing the utility's wildfire mitigation plans and its most recent general rate case (GRC) proceeding filed with the CPUC. For both enhanced vegetation management and undergrounding, we rely on average per mile investment costs. We acknowledge the costs per mile of each measure likely vary substantially across circuits due to differences in topography and other factors correlated with risk. For instance, per mile vegetation management costs are likely higher across circuits located in dense conifer forests compared with circuits located in more populated suburban areas. However, circuit-specific cost data is not publicly available. We address uncertainties in the per mile costs of vegetation management and undergrounding by applying a "low" and "high" unit cost per mile in our cost analysis. See Figure 6 for how this cost uncertainty affects estimated costs per avoided ignition and avoided structures burned.

Enhanced vegetation management: Following Workpaper Table 9-15 from Exhibit PG&E 4, Chapter 9 - Vegetation Management, we find that PG&E recorded average per mile costs of $245K between 2018 and 2020[25]. In addition, the utility cites forecasted per mile costs of $298K from 2021 to 2026. Therefore, our cost analysis assumes a central per mile estimate of $250K per mile and low and high estimates of $200K and $300K, respectively.

We model enhanced vegetation management 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, we are not able to estimate empirically the rate at which these benefits attenuate to zero. In our central case, we assume the ignition benefits of enhanced vegetation management linearly decline to zero over a ten year lifetime. Our sensitivity analysis in Figure 6 varies this assumption between five and fifteen years. Because some of the ignition benefits of enhanced vegetation management work are realized in future years, we discount these avoided ignitions to 2022 terms using a real social discount rate of 2.5%[42]. We vary the discount rate between 1% and 4%.

While the vast majority of enhanced vegetation management costs are incurred at the time the work is performed, we also model 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. We assume annual per mile maintenance costs equal to 1% of the assumed unit cost.

Undergrounding: 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[25]. However, PG&E's wildfire mitigation plan filed in February 2022 cites costs of $3.75M per mile[43]. 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."[26] Our cost analysis uses $3.7M per mile as our central assumption and varies the per mile costs between $2.9M and $4.3M. It is worth noting that it may take more than one mile of undergrounding investment to replace one mile of overhead conductor, due to rerouting underneath the ground to avoid existing underground infrastructure or natural obstacles. One source cites that one mile of undergrounding only replaces 0.64-0.80 miles of overhead conductor[44]. We omit this conversion factor from our cost analysis, but it would decrease our estimates of the cost-effectiveness of undergrounding investments.

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., $3.7M per mile) and the rate of return the utility earns on the newly underground line.

We only model this additional return on capital when we consider the "regulator" perspective in Figures 6 and 8. In the societal perspective, we ignore rate of return regulation and assume the cost of undergrounding consists solely of the per-mile unit cost and ongoing maintenance costs. In practice, there is likely some non-zero cost of financing the capital investment that is less than the utility's authorized return on capital.

To model the utility's return on capital investment, we linearly depreciate the undergrounding asset over its assumed lifetime of 40 years. In each year, we multiply the value of the depreciated undergrounding asset by the utility's cost of capital– 7.5%[46]. We then discount each of these annual returns into 2022 terms using a real discount rate of 2.5% and sum them. Our sensitivity analysis in Figure 6 varies the assumed cost of capital between 5% and 10%.

In the "regulator" perspective, we do 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, we assume 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, we discount them into 2022 terms and sum them. In contrast, in the societal perspective, the per-mile costs of undergrounding are incurred solely in the year the work is completed and not spread out across future years.

Similar to enhanced vegetation management, we account for ongoing maintenance costs associated with the underground lines. We express these ongoing annual maintenance costs as 1% of the per mile capital cost. However, unlike enhanced vegetation management, we assume the undergrounding investment obviates the need for the utility to complete routine vegetation management and tree mortality work on the line. We approximate per mile routine vegetation management costs 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[25]. To calculate per mile costs, we spread 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.

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[47]. 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. We coarsely approximate this increase in future wildfire risk by linearly increasing our measure of baseline ignition probability each year until it reaches a 50% increase by the year 2050. We continue to increase ignition probability at the same linear rate after 2050 until the end of the undergrounding asset's lifetime. Our sensitivity analysis varies this future risk increase between 25% and 75%. We acknowledge that projections of future burned area are not equivalent to projections of powerline ignition risk, however our ignition probability model is strongly influenced by climate and fuel variables such as vapor pressure deficit and dead fuel moistures.

As ignition risk increases in future years, the quantity of high-wildfire risk days may increase similarly. This is especially pertinent to fast-trip settings because fast-trip settings are only enabled when elevated wildfire conditions are identified along a segment of a distribution circuit. This means an increase in ignition risk in future years will likely raise the costs of the fast-trip program because the settings will be enabled more frequently and subsequently increase the number of fast-trip induced outages.

To project an increase in high-fire risk days (when the utility's fire potential index is at R3 or greater), we take the following steps. For each circuit, calculate the average number of high-fire risk days per year during 2015-2022. For example, Circuit A experienced 80 high-risk days per year on average from 2015-2022. Next, for each circuit, calculate the annual increase in ignition risk relative to 2015-2022 as a percentage. For example, in 2023 Circuit A's ignition risk increased by 1% compared to 2015-2022 average, and in 2040, Circuit A's ignition risk increased by 20%. Calculate the number of high-risk days for each circuit based on its cumulative increase in ignition risk. For example, in 2023 Circuit A would have 81 (80 * [1.0+1%]) high-fire risk days, and in 2040, Circuit A would have 96 (80 * [1.0+20%]) high-fire risk days. Round to the nearest whole number. Finally, rank each day in terms of ignition risk and assign the top "X" circuit-days as high-risk days where "X" is the quantity calculated in the previous step. For example, for Circuit A in 2040, the top 96 days in terms of ignition risk would be considered high-risk days.

Fast-trip settings (Enhanced powerline safety settings): Due to the dynamic nature of fast-trip settings, we model their costs 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, we rely on PG&E's forecasted annual budget for the fast-trip program of approximately $150M in 2022[28]. The utility forecasts $151M in fast-trip expenses for 2023, declining to $134M by 2026. We assume the $150M fast-trip budget applies only to the utility's 25K HFTD circuit-miles. In practice, due to the topology of the utility's distribution network, circuit-miles outside of the HFTD may be enabled with fast-trip settings when a circuit-segment within the HFTD is enabled. In addition to the $150M fast-trip budget in 2022, we account for the utility's recorded $18M in fast-trip expenses for the 2021 pilot program[28].

When we evaluate the cost-efficiency of fast-trip settings on reducing structures burned, we do so over a smaller sample of approximately 6K HFTD circuit-miles. We apportion the $150M fast-trip budget to the reduced 6K circuit-mile sample based on the share of fast-trip outages that occurred in the 6K sample relative to the full 25K HFTD sample. The 6K circuit-mile sample accounted for approximately 20% of fast-trip caused outages in terms of customer-hours.

Lastly, when we model the cost-efficiency of the fast-trip program in Figure 6, we do so assuming that no undergrounding and enhanced vegetation management had taken place. A key finding of our reliability model is that these two measures reduce the duration and frequency of fast-trip outages (see Supplementary Figure 10). We adjust the costs of the fast-trip program upwards when no undergrounding and vegetation management efforts are deployed, given more outages would have occurred in their absence. To make this adjustment, we use our reliability model to predict the number of customer-hours of fast-trip outages absent the vegetation management and undergrounding investments. We find that there would have been an additional 700K customer-hours of fast-trip outages in 2022 absent these investments.

Wildfire simulations

To estimate the potential number of structures burned by an ignition at a distribution circuit on a given day, we combine data on the actual acreages of utility-caused wildfires with simulations of wildfire perimeters. We model structures burned (Y_{it}) at distribution circuit *i* on day *t* as a function of (1) the probability that an ignition grows to wildfire size *s*, (2) the number of residential and commercial parcels intersected ($\boldsymbol{\delta}$) by wildfire size *s*, and (3) the proportion of structures burned per residential and commercial parcel intersected by a wildfire ($\boldsymbol{\omega}$).

$$\textbf{\textit{(3)}}\ Y_{it} = \sum_{s}^{S} [Pr_{it}(s|X_{it}, C_i) * \delta_{ist}(\overline{acres_s}, X_{it}, C_i) * \omega]$$

We divide wildfire sizes *s* into four bins:

- "Small" wildfires: <10 acres
- "Medium" wildfires: [10 acres, 300 acres)
- "Large" wildfires: [300 acres, 10,000 acres)
- "Extreme" wildfires: >= 10,000 acres

To estimate the first term of Equation 3, we rely on empirical data on the actual acreages of grid-caused wildfires*.* We train a random forest model using 1,893 ignitions between 2014 and 2022. 94% of the ignitions are considered “small” wildfires. 4% of the ignitions are considered “medium.” 1% are considered “large.” 0.5% are considered “extreme.” We split the training and testing data 75/25%, perform repeated 10-fold cross-validation, and tune hyperparameters. 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 Supplementary Figure 12 for a comparison of actual wildfire sizes and predicted wildfire sizes. Supplementary Figure 13 shows how the distribution of predicted wildfire size probabilities varies across each day of the year.

The second term in Equation 3 reflects the potential number of residential and commercial parcels intersected by an average wildfire in size bin *s* conditional on weather and circuit characteristics*.* In other words, if a “medium”-sized wildfire (10-300 acres) is ignited at a given circuit, how many residential and commercial parcels would we expect that wildfire to intersect, conditional on the prevailing wind direction, dead and live fuel moistures, etc.? Some circuits may be located near major roadways or natural fuel breaks while others may be located in densely forested areas downhill from populated areas. In addition, circuits can span hundreds of miles, and an ignition along one segment of a circuit may produce a wildfire that is more or less likely to intersect a populated area than an ignition along a different circuit segment. A given wildfire size at the same ignition point can produce different structure risk, too, depending on wind direction and the locations of nearby structures. We account for this important variation across circuits, within circuits, and across weather covariates by simulating many wildfire perimeters.

To simulate wildfire perimeters, we implement the Minimum Travel Time (MTT) model using the command line applications developed by the Missoula Fire Sciences Laboratory[48]. We follow a similar approach to Plantinga, Walsh and Wibbenmeyer (2022)[49]. The MTT model serves as the foundation for more complex wildfire simulation applications. Unlike the more complex physical models such as FARSITE and FlamMap, the MTT model’s low computational cost makes it well-suited for running many wildfire simulations[50].

We provide the MTT model with a detailed landscape file from the U.S. Geological Survey’s LANDFIRE program that includes remotely-sensed vegetation and topographic data at a 30m resolution. Our landscape file uses the 40 Scott and Burgan Fire Behavior Fuel Model. For each circuit, we find the nearest RAWS weather station and input corresponding wind speeds and fuel moisture data. For computational efficiency, we do not simulate wildfire perimeters for all days of the year for each circuit. Rather, we sample at most three days per month for each circuit, selecting at most two high-wildfire risk days if available and at least one median day based on fuel moisture levels, wind speeds, and relative humidity. We define a high-risk day based on two of the three conditions being met: peak wind speeds exceeding 22 miles per hour, 10-hour dead fuel moistures being less than 5%, and relative humidity less than 25%. We then randomly create ignition points along each circuit at a density of 1 ignition point every 5 miles, but do not allow fewer than 3 or more than 15 ignition points.

Using the MTT model, we then simulate wildfire perimeters at each ignition point and each weather slice. We allow the MTT model to grow wildfires over a duration of 24 hours and then record the wildfire perimeters at intervals of 1-hour, 8-hours, and 24-hours to generate variation in wildfire sizes. While a 24-hour duration may not seem adequately long relative to some of the extreme wildfires observed in California recently, the lack of fire suppression in the MTT model and the fact that these extreme weather conditions are held constant across the entire 24-hour duration produce sufficiently large wildfire perimeters. The average acreage of a 24-hour wildfire simulated between July and September is 72 thousand acres and the maximum is 340 thousand acres. Supplementary Figure 11 provides example wildfire simulation output for one circuit across two different weather slices, all ignition points along the circuit, and the three duration intervals. Additional assumptions needed to run the simulations include an ember spot probability of 0.01, 300 meter resolution, and use of the Scott-Reinhardt crown fire method[51].

Next, we intersect each wildfire perimeter with the locations of residential and commercial parcels obtained from county GIS services. We exclude non-residential and non commercially-zoned parcels, such as timber production zones, open space areas, and agricultural plots. We exclude these types of parcels to simplify our assessment of the potential number of structures burned, but we acknowledge that wildfires generate significant economic impacts outside of direct structure loss.

At this point, our sample has on average 430 simulated wildfire perimeters for every circuit, taking into account approximately 36 (12x3) weather slices, 3-15 ignition points, and 3 time intervals (1-hour, 8-hours, and 24-hours) that act as a proxy for wildfire size. Because we did not conduct simulations for every day in our dataset, we train a random forest model to predict the number of residential and commercial parcels intersected across all circuit-days. The key variables used to predict parcels intersected are wildfire size in acres, a circuit-specific effect, and detailed weather characteristics. Our prediction model produces an R-squared value of 0.872.

We can then use our prediction model to estimate the number of parcels intersected by an average wildfire in each of our wildfire size bins ("small," "medium", "large," and "extreme") for all of the circuit-days in our sample. The estimated number of parcels intersected for a given wildfire size bin on a circuit-day is captured by $\boldsymbol{\delta}_{ist}$ in the second term of Equation 3. We calculate the expected number of parcels intersected for a given circuit-day by multiplying $\boldsymbol{\delta}$ by the corresponding probability weights of each wildfire size bin *s* (the first term of Equation 3) and summing the results up across each wildfire size bin.

Our wildfire simulations do not account for the effects of fire suppression. However, by deriving wildfire size probability weights using the empirical distribution of grid-caused wildfires, we indirectly account for the ability of fire suppression resources to quickly contain wildfires during the wetter months of the year and to be less effective at containing fires during late summer and early autumn.

Lastly, the third term of Equation 3 provides a more blunt approach to incorporating the effects of fire suppression and possible defensive investments made by residential and commercial parcel owners. $\boldsymbol{\omega}$ is the proportion of structures burned for every residential or commercial parcel intersected by a wildfire. In practice, it is not uncommon for a mapped wildfire perimeter to intersect a parcel boundary and produce no structure damage or only partial structure damage because firefighting resources protected the structure and/or the parcel owner removed fuels in the immediate vicinity of the structure. We assume a value of 0.4 for this parameter based on reviewing incident-specific data from CALFire. Our sensitivity analysis varies this parameter from 0.2 to 0.6.

Due to the computational intensity of the simulations, we only estimate structures burned for two key regions in the utility's service territory. The first region is based on CALFire's Lake-Sonoma-Napa (LNU) administrative unit. The second region is based on two adjacent CALFire administrative units, Nevada-Yuba-Placer (NEU) and Amador-El Dorado (AEU) units. Because circuits or simulated wildfire perimeters in these regions may extend into neighboring counties, we collect parcel data from additional counties such as Mendocino and Marin counties. We selected these two regions based on their recent history of grid-caused wildfires and their differing fire regimes. The Lake-Sonoma-Napa region includes circuits both along the Pacific coast and inland valleys characterized by intense summer heat and oak woodlands. The latter NEU and AEU region is located in the Central Sierra and can feature circuits in dense conifer forests and steep river canyons. The circuits in these regions span approximately six thousand HFTD miles, or about 25% of the utility's total overhead exposure in the HFTD.

Reliability model

The reliability model regresses daily customer-hours of fast-trip outages on the set of wildfire prevention measures, an interaction of each wildfire prevention measure and whether fast-trip settings were enabled or not, and our measure of ignition risk probability. The specification is the following:

(4) $$Y_{it} = \beta_1 E^{it}_{EPSS=1} + \beta_2 D^{it}_{VEG=Hi.} + \beta_3 D^{it}_{VEG=Med.} + \beta_4 (E^{it}_{EPSS=1} * D^{it}_{VEG=Hi.}) + \beta_5 (E^{it}_{EPSS=1} * D^{it}_{VEG=Med.}) + \beta_6 UG^{it} + \beta_7 (E^{it}_{EPSS=1} * UG^{it}) + \beta_8 \theta^{it} + \varepsilon_{it}$$

In the above estimating equation, the dependent variable of interest (Y_{it}) is customer-hours of fast-trip outages on a given day *t* for circuit *i.* The key coefficients of interest are the effects of wildfire prevention measures on fast-trip outages when fast-trip settings are enabled (β_4,β_5, and β_7). These coefficients are of interest because if they are negative and statistically different from zero, they show that system hardening and vegetation management investments can mitigate the outage impacts of dynamic operational measures. In addition, we are interested in estimating β_1 because it captures the average number of customer-hours of fast-trip outages when fast-trip settings are enabled. We estimate Equation 4 using ordinary least squares, in contrast to our logistic regression model in Equation 4, because customer-hours of fast-trip outages is a continuous variable, not a binary response like ignition events.

Only data from 2022 is used in both columns– when fast-trip settings were deployed across the entire HFTD. We estimate Equation 4 over the sample of matched treated and control circuits (see earlier Methods discussion on matching). We do so to ensure circuits in the sample face similar baseline ignition risk on average. Supplementary Figure 10 reports our coefficient estimates for Equation 4. The first column uses the sample where circuits treated with vegetation management are matched to a single control circuit based on ignition risk, and the second column uses the sample where circuits are matched to at most two control circuits. See Supplementary Figure 10 for discussion and interpretation.

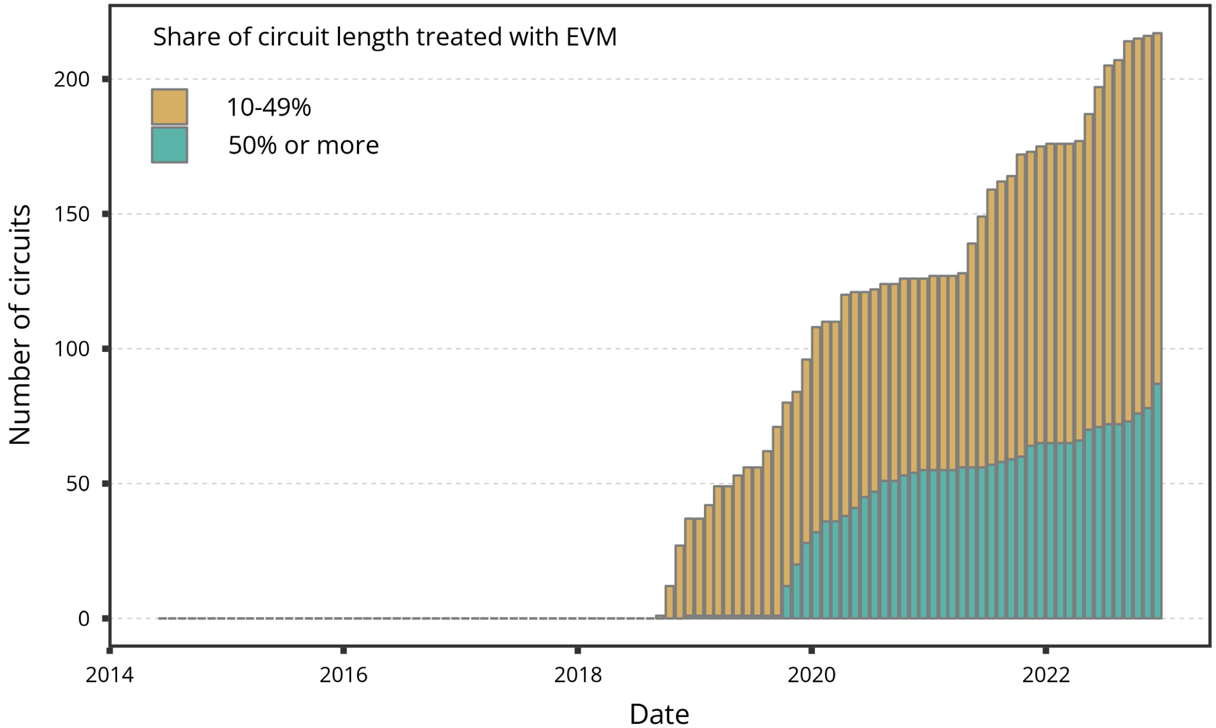
Data Sources

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[52]
Climate	Air temperature, hourly	RAWS weather	Mesowest,

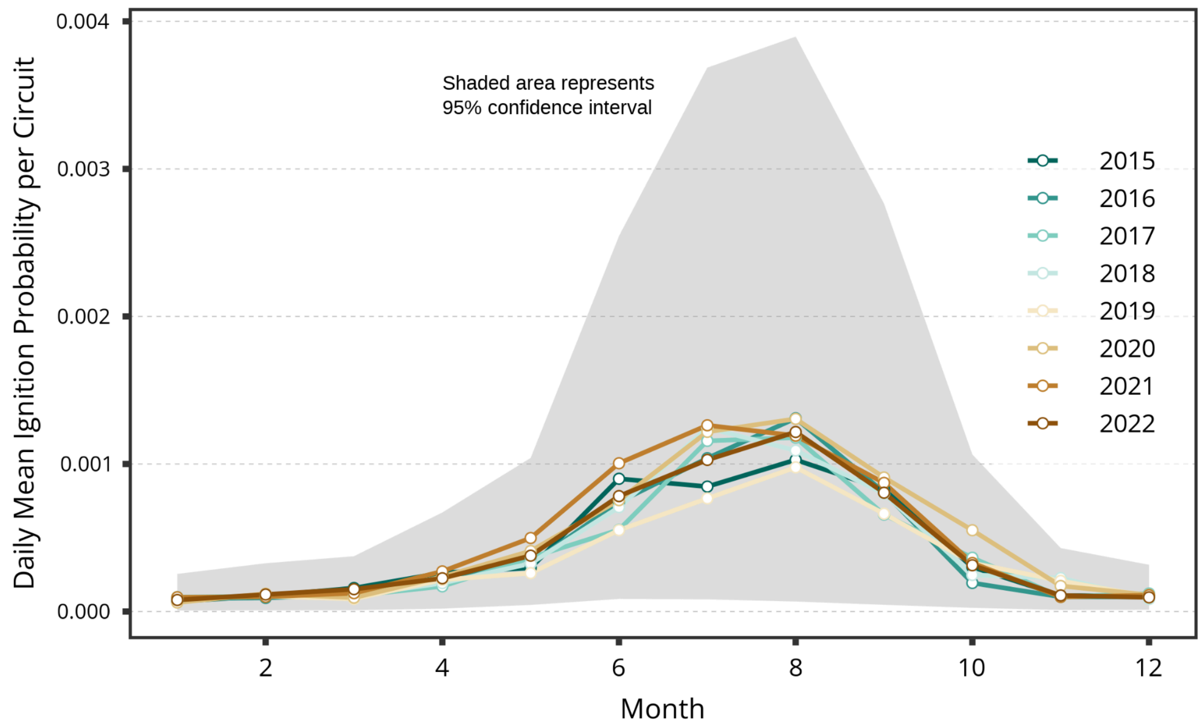
	precipitation, relative humidity, wind speed, wind direction	station	University of Utah[53]
Fuels	100-hour and 1000-hour dead fuel moisture, energy release component	4 km	gridMET, Climatology Lab, University of California, Merced
Fuels	Live fuel moisture	RAWS weather station	Mesowest, University of Utah[53]
Topography	Mean forest canopy height, maximum forest canopy height, elevation above sea-level	30 m	LANDFIRE, USDA and U.S. Department of the Interior[54]
Circuit Characteristics	Installed year, length in HFTD-Tier 2, Tier 3, and non-HFTD	Circuit	PG&E 2020 Wildfire Mitigation Plan[55]
High-Fire Threat District	Perimeters of HFTD Tiers 2 & 3	Spatial polygon	California Public Utilities Commission[56]
Ignitions	Location, voltage, cause, date, time, size, fire potential index	Lat/long position	California Public Utilities Commission[23], PG&E 2023 Wildfire Mitigation Plan[41]
Public Safety Power Shutoffs	Circuit name, date, outage start and end, outage duration, customers impacted	Circuit	California Public Utilities Commission[57]
Fast-Trip Outages	Circuit name, outage start and end, customers impacted, ignitions occurring during fast-trip enablement	Circuit	PG&E 2023 Wildfire Mitigation Plan[30,58], PG&E 2022 Wildfire Mitigation

			Plan[31,59]
Vegetation management & system hardening	Enhanced vegetation management, undergrounding, and covered conductor	Circuit-miles	PG&E 2020, 2021, 2022, and 2023 Wildfire Mitigation Plans[60,61,62,63,64]
Residential and commercial parcels	Perimeters of parcels, zoning classifications	Spatial polygon	County GIS Services
Costs	Undergrounding, enhanced and routine vegetation management, fast-trip settings	Per mile and aggregate	PG&E 2023 General Rate Case[25,26,28]

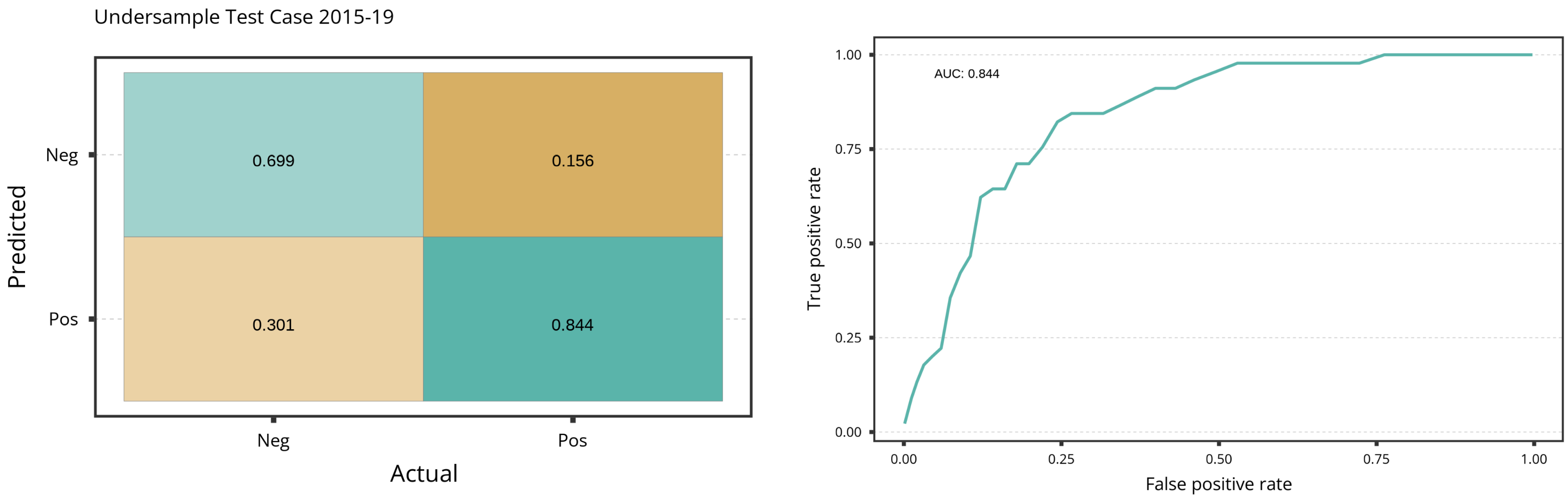
Appendix & supplementary material



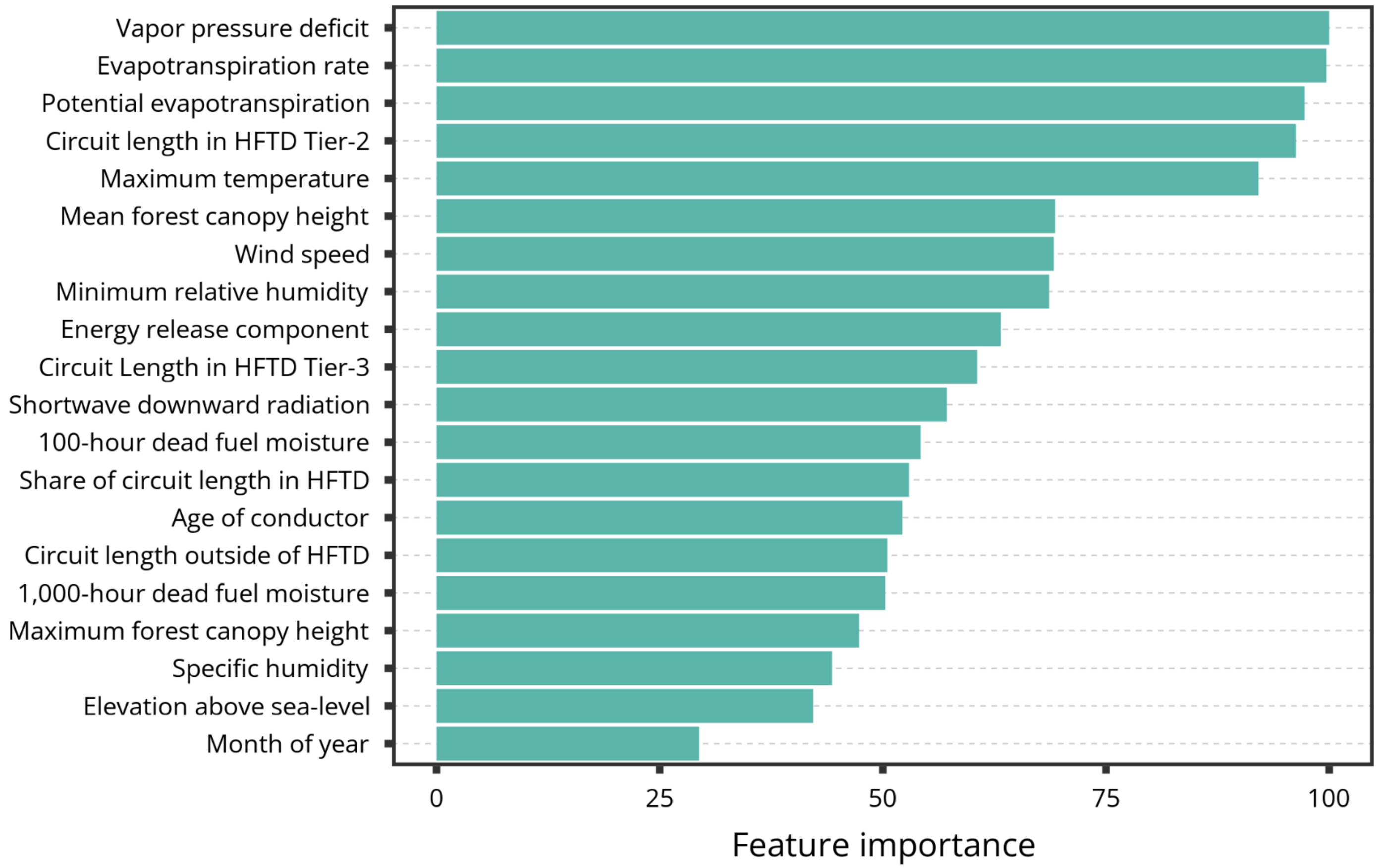
Supplementary Figure 1 | Definitions of High and Moderate Vegetation Management. We consider distribution circuits that have received enhanced vegetation management equal to or greater than 50% of their overhead circuit length to be in the "high" vegetation management treatment group. We define the "moderate" vegetation management treated group as circuits that have received enhanced vegetation management equal to or greater than 10% but less than 50% of total overhead circuit length. The figure above plots the number of circuits that fall into each of these categories over time as PG&E deployed its enhanced vegetation management program.



Supplementary Figure 2 | Distribution of Ignition Risk Probability. The figure plots the output of the ignition risk model (see Methods), which is the probability of an ignition occurring on a given circuit and a given day. To create the figure, we average daily ignition probabilities across all HFTD circuits, months, and years in our sample. In general, powerline ignition risk in Central and Northern California peaks in July and August. However, the figure masks substantial heterogeneity across the utility's service territory due to differences in climate. It is also important to note that the figure plots ignition risk, not wildfire risk. Supplementary Figure 12 shows that wildfire risk from powerline-caused ignitions peaks in September and October.



Supplementary Figure 3 | Ignition Risk Model Confusion Matrix and ROC Curve. The first panel plots the confusion matrix of the ignition risk model on the sample of testing data using a classification threshold of 0.50. The second panel plots the ROC curve, which produces an area under the ROC curve of 0.844.



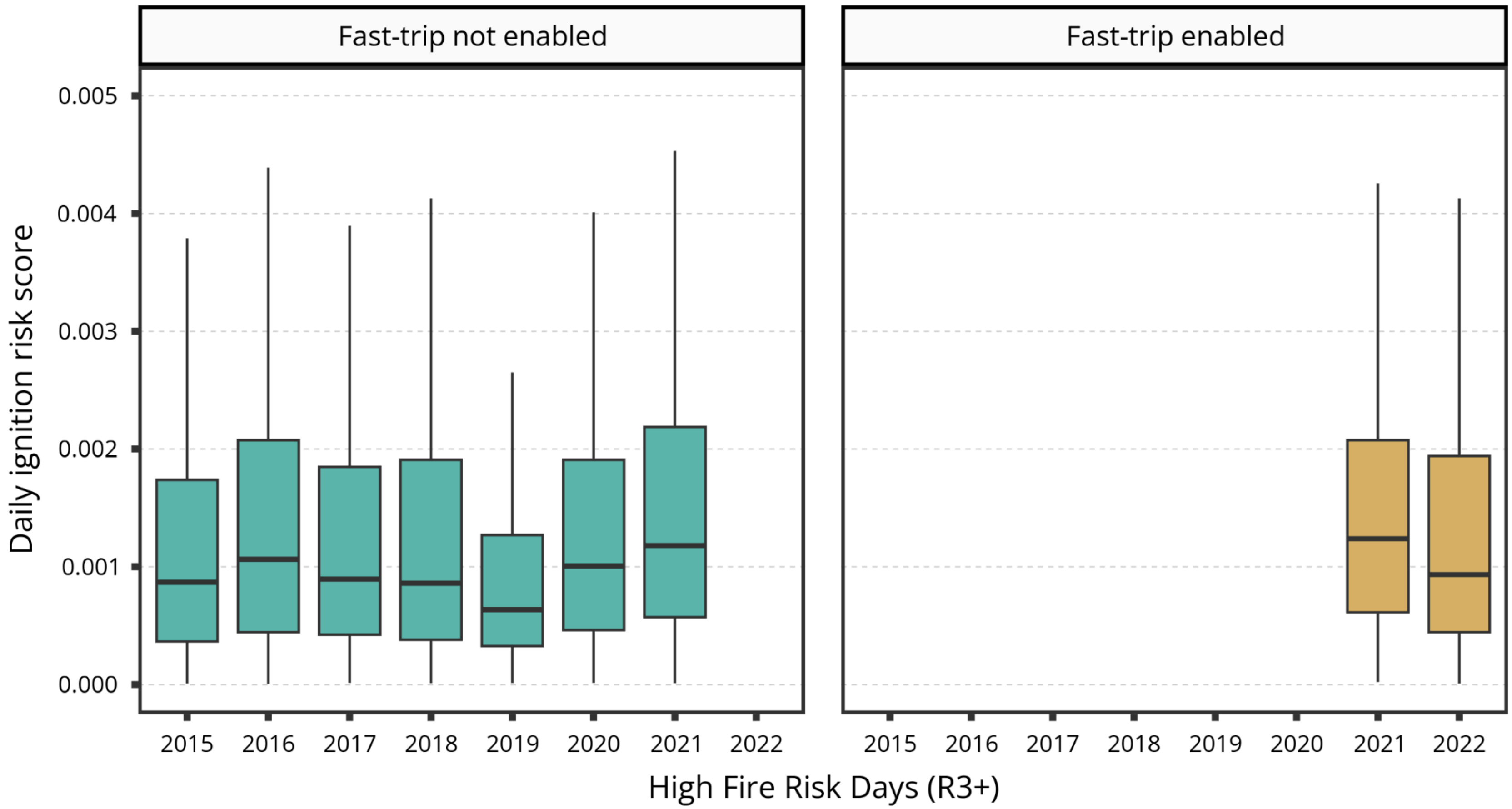
Supplementary Figure 4 | Top 20 Most Important Features in Ignition Risk Prediction Model. The above plot ranks the twenty most important features in the ignition risk model by feature importance. Feature importance reflects the decrease in accuracy of the model when the variable is excluded from training and testing the model. Vapor pressure deficit, which captures how dry the air is and is similar to relative humidity, is shown to be the most important predictor of ignition risk in our model.

Covariate	Units	Controls	Veg. Mgmt.		Matched Controls		Matched Veg. Mgmt.	
		All HFTD <10% Length	High >=50% Length	Moderate [10-50%) Length	High <10% Length	Moderate <10% Length	High >=50% Length	Moderate [10-50%) Length
Ignition Risk Covariates								
Ignition Risk Score	Daily Circuit Probability	0.00034 (0.00028)	0.00084* (0.00039)	0.00064* (0.00033)	0.00079 (0.00034)	0.0006 (0.00028)	0.00079 (0.00037)	0.0006 (0.00028)
Circuit Length	Miles	39.8 (40.9)	91.5* (59.7)	78.6* (60.7)	88.2 (60.5)	62.7 (49.8)	87.7 (58.5)	71.6 (50.4)
Relative Humidity	Daily Minimum (%)	39.0 (7.5)	34.4* (4.7)	37.3* (5.6)	35.3 (5.3)	35.9 (6.0)	34.5 (4.8)	37.5* (5.6)
Vapor Pressure Deficit	kPa	1.0 (0.3)	1.34* (0.25)	1.16* (0.27)	1.24 (0.25)	1.19 (0.28)	1.32* (0.25)	1.15 (0.27)
100 Hr. Dead Fuel Moisture	%	14.3 (2.0)	12.7* (1.6)	13.7* (1.9)	13.3 (1.7)	13.3 (1.9)	12.8* (1.6)	13.8* (1.9)
1,000 Hr. Dead Fuel Moisture	%	15.8 (2.1)	14.3* (1.7)	15.5 (2.1)	14.9 (1.9)	15.0 (2.1)	14.4* (1.7)	15.6* (2.1)
Energy Release Component	Index	38.7 (9.3)	46.0* (7.3)	41.0* (8.8)	43.5 (8.0)	43.1 (8.9)	45.7* (7.4)	40.5* (8.8)
Wind Speed	Meters/Second	3.8 (0.7)	3.3* (0.6)	3.8 (0.9)	3.5 (0.7)	3.6 (0.8)	3.3* (0.6)	3.8* (0.9)
Mean Forest Canopy Height	Meters	7.1 (6.4)	9.1* (5.3)	9.4* (6.3)	10.4 (6.8)	10.1 (7.0)	9.1 (5.4)	9.2 (6.2)
Circuit Age	Years	34.9 (13.0)	31.4* (11.3)	36.6 (13.8)	38 (10.7)	36.7 (11.7)	31.5* (11.6)	37.2 (13.7)
Elevation	Ft. Above Sea-Level	1,068 (1,241)	1,237 (691)	1,313* (934)	1,394 (944)	1,430 (1,084)	1,247 (693)	1,294 (944)
Precipitation	Millimeters/Day	2.0 (0.8)	2.1 (0.7)	2.4* (0.9)	2.3 (0.8)	2.3 (0.8)	2.1 (0.7)	2.4* (0.9)
Mean Absolute Percent Difference		-	25.9%	19.2%	-	-	6.7%	6.4%
Wildfire Prevention Measures (Per Circuit)								
EPSS Fast-Trip	Customer-Hrs/Day	3.3 (8.7)	7.6* (11.9)	6.5* (14.6)	5.9 (10.9)	5.5 (9.8)	7.6 (12.0)	5.1 (10.6)
PSPS De-Energization	Customer-Hrs/Day	37.5 (60.8)	88.1* (78.7)	90.7* (116.8)	79.7 (79.7)	61.3 (66.0)	87.7 (80.2)	80.9* (95.1)
Enhanced Vegetation Mgmt.	Miles Completed ('18-'22)	0.4 (1.7)	66.1* (45.6)	22.5* (23.9)	1.1 (2.4)	0.8 (2.3)	64.9* (46.6)	20.0* (19)
Undergrounding	Miles Completed ('18-'22)	0.9 (2.93)	1.42 (3.76)	1.72* (5.19)	0.46 (0.74)	0.53 (0.88)	1.49* (3.88)	1.73* (5.3)

Supplementary Figure 5 | Covariate balance table–All Days. Asterisks denote statistical significance of a two-sided t-test.

Covariate	Units	Controls All HFTD <10% Length	Veg. Mgmt. High >=50% Length	Veg. Mgmt. Moderate [10-50%) Length	Matched Controls High <10% Length	Matched Controls Moderate <10% Length	Matched Veg. Mgmt. High >=50% Length	Matched Veg. Mgmt. Moderate [10-50%) Length
Ignition Risk Covariates								
Ignition Risk Score	Daily Circuit Probability	0.00067	0.00168*	0.00129*	0.0016	0.00118	0.00158	0.00121
		(0.0006)	(0.00083)	(0.00071)	(0.00076)	(0.00059)	(0.00078)	(0.00059)
Circuit Length	Miles	39.8	91.5*	78.6*	88.2	62.7	87.7	71.6
		(40.9)	(59.7)	(60.7)	(60.5)	(49.8)	(58.5)	(50.4)
Relative Humidity	Daily Minimum (%)	22.3	18.5*	20.2*	19.0	19.6	18.6	20.3
		(5.7)	(3.2)	(4.4)	(4.0)	(4.3)	(3.3)	(4.5)
Vapor Pressure Deficit	kPa	1.8	2.25*	2.03*	2.12	2.04	2.23*	2.02
		(0.41)	(0.34)	(0.38)	(0.34)	(0.38)	(0.35)	(0.38)
100 Hr. Dead Fuel Moisture	%	10.3	8.2*	9.2*	8.6	8.9	8.2	9.3
		(2.6)	(1.9)	(2.4)	(2.0)	(2.3)	(1.9)	(2.4)
1,000 Hr. Dead Fuel Moisture	%	11.3	9.0*	10.1*	9.5	9.8	9.1	10.3
		(2.7)	(1.9)	(2.4)	(2.1)	(2.4)	(1.9)	(2.4)
Energy Release Component	Index	58.5	70.3*	64.4*	67.8	66.4	69.9	63.7*
		(9.3)	(7.3)	(8.8)	(8.0)	(8.9)	(7.4)	(8.8)
Wind Speed	Meters/Second	3.6	3.2*	3.6	3.3	3.4	3.2	3.6*
		(0.8)	(0.7)	(1.0)	(0.8)	(0.7)	(0.7)	(0.9)
Mean Forest Canopy Height	Meters	7.0	9.1*	9.4*	10.4	10.1	9.1	9.2
		(6.4)	(5.3)	(6.3)	(6.8)	(7.0)	(5.4)	(6.2)
Circuit Age	Years	34.9	31.4*	36.6	38	36.7	31.5*	37.2
		(13.0)	(11.3)	(13.8)	(10.7)	(11.7)	(11.6)	(13.7)
Elevation	Ft. Above Sea-Level	1,068	1,237	1,313*	1,394	1,430	1,247	1,294
		(1,241)	(691)	(934)	(944)	(1,084)	(693)	(944)
Precipitation	Millimeters/Day	0.1	0.1	0.1	0.1	0.1	0.1	0.1
		(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
Mean Absolute Percent Difference		-	28.9%	20.1%	-	-	6.0%	6.4%
Wildfire Prevention Measures (Per Circuit)								
EPSS Fast-Trip	Customer-Hrs/Day	12.2	19.4	23.7*	19.2	19.9	19.6	20.6
		(35.8)	(31.3)	(67.5)	(47.1)	(44.4)	(32.0)	(63.9)
PSPS De-Energization	Customer-Hrs/Day	142.5	232.6*	280.5*	227.0	194.9	234.2	257.6*
		(244.2)	(217)	(370.4)	(223.7)	(231.5)	(222.3)	(333.3)
Enhanced Vegetation Mgmt.	Miles Completed ('18-'22)	0.4	66.1*	22.5*	1.1	0.8	64.9*	20.0*
		(1.7)	(45.6)	(23.9)	(2.4)	(2.3)	(46.6)	(19)
Undergrounding	Miles Completed ('18-'22)	0.9	1.42	1.72*	0.46	0.53	1.49*	1.73*
		(2.93)	(3.76)	(5.19)	(0.74)	(0.88)	(3.88)	(5.3)

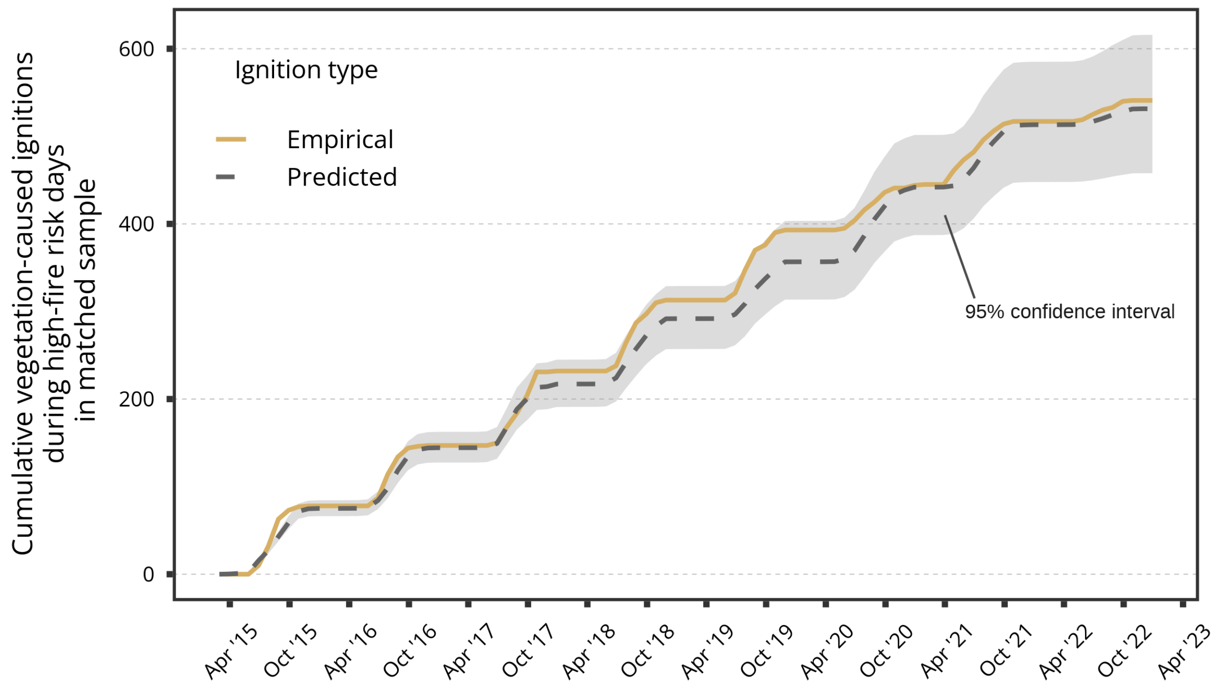
Supplementary Figure 6 | Covariate balance table–High-Fire Risk Days (R3+ Days). Asterisks denote statistical significance of a two-sided t-test.



Supplementary Figure 7 | Intertemporal Comparison of Baseline Ignition Risk Pre- and Post- Fast-Trip Deployment.

Covariate	Units	High-Fire Risk Days Pre Fast-Trip (2015-21)	Post Fast-Trip (2021-22)
Ignition Risk Score	Daily Circuit Probability	0.00133 (0.00070)	0.00137 (0.00071)
Relative Humidity	Daily Minimum (%)	19.1 (3.9)	20.01* (4.75)
Vapor Pressure Deficit	kPa	2.08 (0.36)	2.19* (0.41)
100 Hr. Dead Fuel Moisture	%	8.8 (2.2)	8.8 (2.3)
1,000 Hr. Dead Fuel Moisture	%	9.8 (2.3)	9.8 (2.4)
Energy Release Component	Index	66.5 (12.1)	66.0 (13.2)
Maximum Temperature	Celsius	30.2 (2.1)	31.1* (2.3)
Wind Speed	Meters/Second	3.4 (0.8)	3.5 (0.8)
Precipitation	Millimeters/Day	0.05 (0.04)	0.11* (0.21)

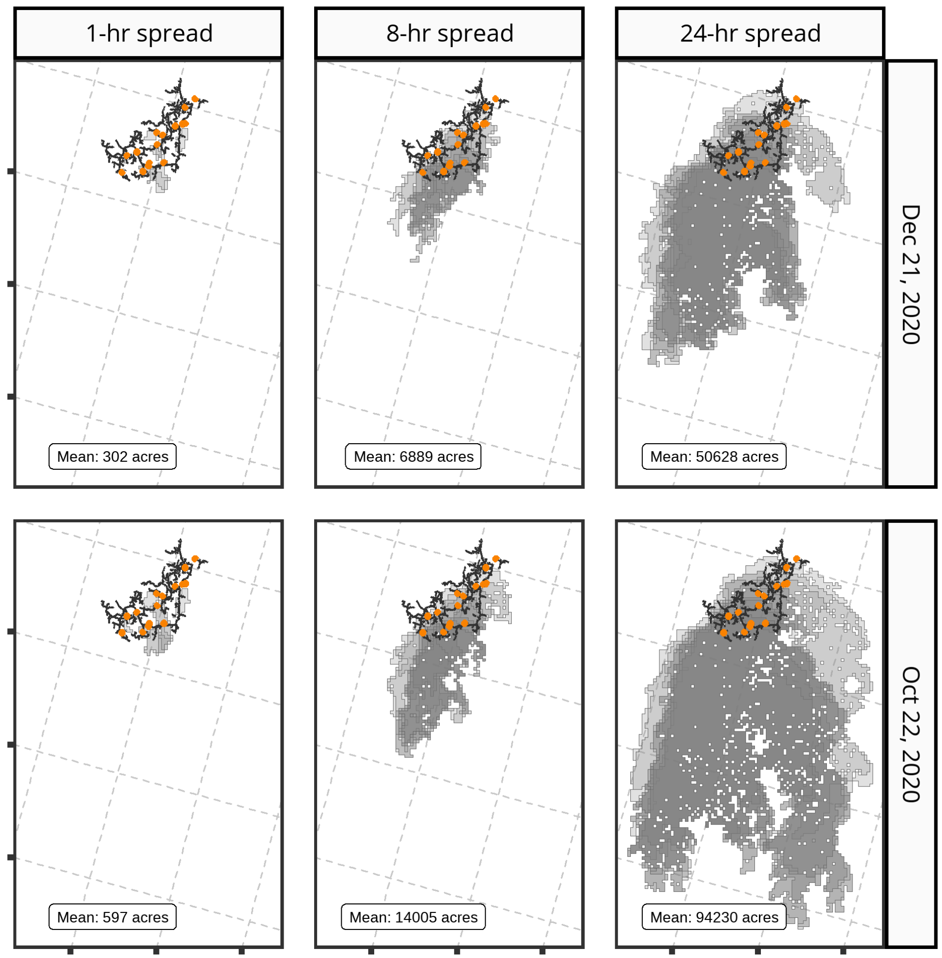
Supplementary Figure 8 | Covariate balance table–High-Fire Risk Days (R3+ Days) before and after fast-trip settings were deployed. Asterisks denote statistical significance of a two-sided t-test.



Supplementary Figure 9 | Comparison of Predicted and Empirical Ignitions. Using our preferred specification in column (3) of Figure 4, 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 Figure 4 of 0.75. Our econometric model tends to underpredict powerline-caused ignitions in 2019 and overpredict 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.

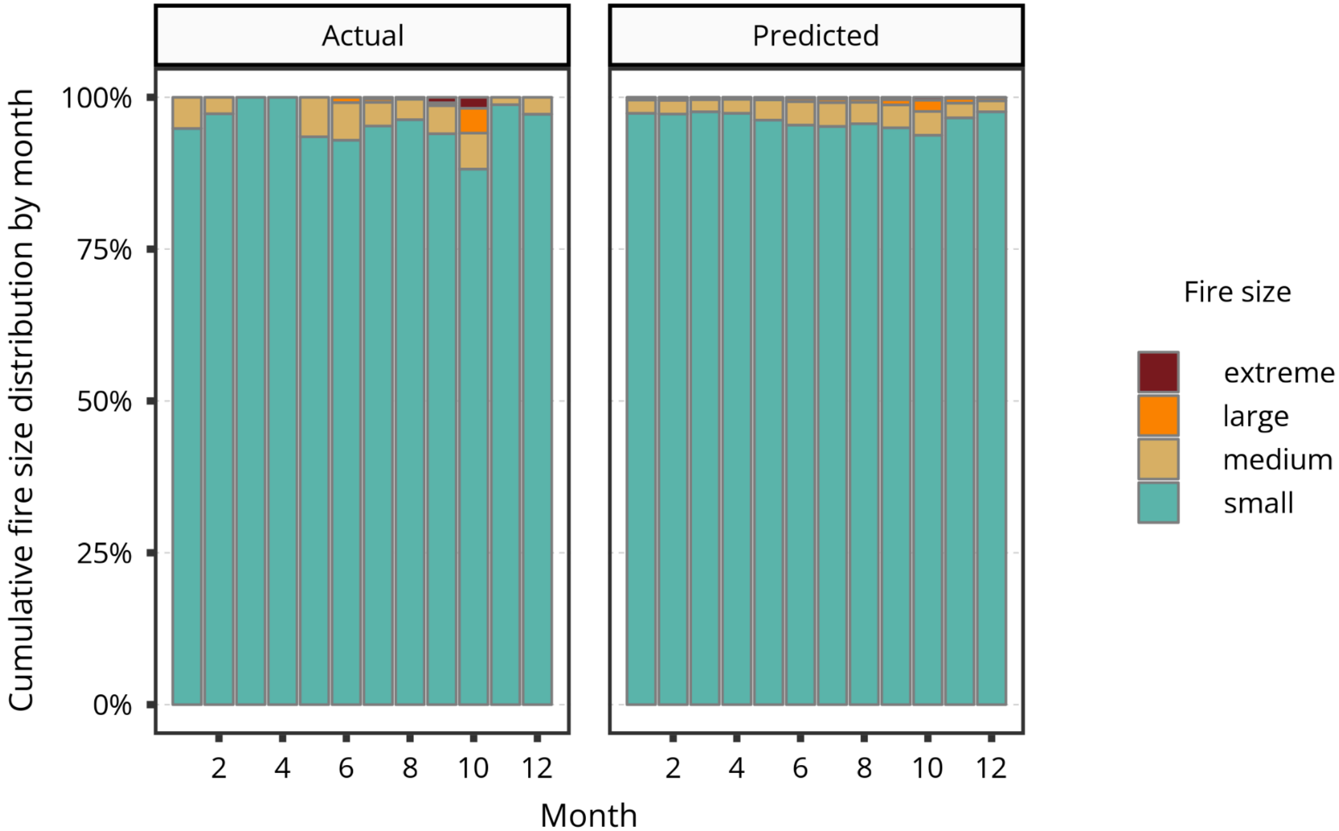
	OLS Model	
	Daily Fast-Trip Customer-Hours	
	(1)	(2)
Fast-trip (E_i=Enabled)	87.8*	74.9*
	(5.0)	(3.7)
Veg. mgmt. (D_i=High)	-0.5	-0.5
	(0.4)	(0.3)
Combined effect (D_i=High x E_i=Enbld.)	−12.8	2.1
	(8.3)	(7.6)
Veg. mgmt. (D_i=Moderate)	-0.6	-0.5
	(0.4)	(0.4)
Combined effect (D_i=Moderate x E_i=Enbld.)	−18.4*	-3.7
	(8.1)	(7.4)
Underground miles (10s mi)	0.03	0.01
	(0.02)	(0.01)
Combined effect (Underground x E_i=Enbld.)	−26.2*	−21.3*
	(6.1)	(5.4)
Ignition risk score (θ)	2,744.2	2,356.8
	(1,924.9)	(1,660.6)
Matched controls	1	2
Observations	149,550	220,324
Adjusted R^2	0.02	0.01

Supplementary Figure 10 | Reliability Model. The reliability model regresses daily customer-hours of fast-trip outages on the set of wildfire prevention measures, an interaction of each wildfire prevention measure and whether fast-trip settings were enabled or not, and our measure of ignition risk probability. Only data from 2022 is used in both columns– when fast-trip settings were deployed across the entire HFTD. The first column uses the sample where circuits treated with vegetation management are matched to a single control circuit based on ignition risk, and the second column uses the sample where circuits are matched to at most two control circuits. We use a linear regression model here, in contrast to the logistic regression model earlier, because customer-hours of fast-trip outages is a continuous variable. We find that when fast-trip settings are enabled on a given day, a circuit will experience 75-88 customer-hours of outages, on average. In the first column, the enhanced vegetation management combined effects show that when fast-trip settings are enabled and a circuit has received high or moderate vegetation management, we expect 13-18 fewer customer-hours of fast-trip outages. This is a 15-21 percent reduction in reliability impacts relative to circuits without enhanced vegetation management. However, as the second column shows, the effect is not robust. Adding a second matched control reduces the magnitudes of the effects and the statistical significance. In contrast, the effect of undergrounding on expected fast-trip customer hours is robust. On days when fast-trip settings are enabled, we find that a circuit with 10 miles of overhead conductor placed underground experiences 21-26 (28-30%) fewer customer-hours of fast-trip outages compared to circuits with zero miles. These results demonstrate that undergrounding and vegetation management can reduce the reliability impact of operational measures that de-energize powerlines.



Supplementary Figure 11 | Example Wildfire Simulation Output. The plot shows pixels burned by wildfires simulated using the Minimum Travel Time (MTT) model. See Methods for assumptions and details of the model. Here we show the wildfires simulated for one distribution circuit across multiple ignition points and two weather slices (October 22, 2020 and December 21, 2020). As described in Methods, ignition points are randomly sampled across each distribution circuit to capture variation in wildfire risk within a distribution circuit. As a proxy for variation in wildfire size, we allow the simulated wildfires to grow for a maximum of 24 hours but record the perimeters of the simulated fires at

1-hour, 8-hour, and 24-hour intervals. The figure shows that for this specific distribution circuit, wildfires tend to move in a southerly direction due to local topography, fuels, and wind direction. We then intersect the perimeters with spatial data on the locations of residential and commercial parcels. In this example, if communities are located south of the distribution circuit, then a wildfire caused by an ignition from this circuit may pose significant structure risk. However, if communities are instead located north of the distribution circuit, then mitigating ignition risk may have less of a benefit in terms of reducing powerline-caused structure risk in this example.



Supplementary Figure 12 | Monthly Distribution of Actual and Predicted Ignition Size from PG&E Distribution Lines. 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 fares 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 wildfires. See Methods for more detail.

Supplementary Figure 13 | Distribution of Predicted Wildfire Sizes. 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. In Supplementary Figure 2, we show that ignition risk peaks typically in July and August. However, this figure (Supplementary Figure 13) shows that the potential for an ignition to grow into a large or extreme wildfire peaks later in the year, in September and October.

	Incidence Rate - Vegetation-Caused Ignitions		
	No Matching	Matching	Matching & High Fire Risk
	(1)	(2)	(3)
Fast-Trip (E_i=Enabled)	-0.25	-0.57^{*}	-0.73^{*}
	(-0.57, 0.31)	(-0.74, -0.29)	(-0.83, -0.55)
Veg. Mgmt. (D_i=High x T_{it}=Post)	-0.62^{*}	-0.59^{*}	-0.59^{*}
	(-0.80, -0.29)	(-0.78, -0.22)	(-0.82, -0.04)
Veg. mgmt. (D_i=Moderate x T_{it}=Post)	-0.01	0.01	0.30
	(-0.25, 0.33)	(-0.25, 0.37)	(-0.12, 0.91)
Veg. mgmt. (D_i=High)	1.04^{*}	0.17	0.28
	(0.63, 1.56)	(-0.06, 0.45)	(-0.003, 0.63)
Veg. mgmt. (D_i=Moderate)	0.75^{*}	-0.12	-0.11
	(0.44, 1.12)	(-0.27, 0.07)	(-0.31, 0.14)
Combined Effect (D_i=High x E_{it}=Enbld. x T_{it}=Post)	-0.89	-0.87	-0.92
	(-1.00, 1.95)	(-0.99, 2.34)	(-1.00, 1.85)
Combined Effect (D_i=Moderate x E_{it}=Enbld. x T_{it}=Post)	-0.75	-0.80	-0.87
	(-0.97, 1.14)	(-0.98, 1.04)	(-0.99, 0.45)
Risk-score matching	No	Yes	Yes
High-fire risk days only	No	No	Yes
Region FEs	Yes	Yes	Yes
Matched control neighbors (N)	-	2	2
Risk-score, undergrounding, PSPS, and covered conductor controls	Yes	Yes	Yes
AUC	0.776	0.757	0.752
Observations	2,400,342	1,890,015	665,868
Log Likelihood	$-6{,}679.31$	$-8{,}039.28$	$-4{,}519.75$

Supplementary Figure 14 | Ignition Model Robustness Tests – Region Fixed Effects.

	Incidence Rate - Vegetation-Caused Ignitions		
	No Matching	Matching	Matching & High Fire Risk
	(1)	(2)	(3)
Fast-Trip (E_{it}=Enabled)	−0.27	−0.36	−0.56*
	(−0.58, 0.26)	(−0.62, 0.05)	(−0.74, −0.27)
Veg. Mgmt. (D_i=High x T_{it}=Post)	−0.62*	−0.59*	−0.58*
	(−0.79, −0.29)	(−0.78, −0.22)	(−0.82, −0.02)
Veg. Mgmt. (D_i=Moderate x T_{it}=Post)	−0.03	−0.03	0.26
	(−0.27, 0.29)	(−0.28, 0.31)	(−0.14, 0.86)
Veg. Mgmt. (D_i=High)	1.18*	−0.11	−0.05
	(0.77, 1.70)	(−0.28, 0.11)	(−0.26, 0.23)
Veg. Mgmt. (D_i=Moderate)	1.23*	−0.10	−0.12
	(0.87, 1.67)	(−0.25, 0.09)	(−0.31, 0.13)
Combined Effect (D_i=High x E_{it}=Enbld. x T_{it}=Post)	−0.89	−0.87	−0.92
	(−1.00, 1.89)	(−1.00, 2.19)	(−1.00, 1.70)
Combined Effect (D_i=Moderate x E_{it}=Enbld. x T_{it}=Post)	−0.77	−0.81	−0.88
	(−0.97, 0.94)	(−0.98, 0.86)	(−0.99, 0.38)
Risk-score matching	No	Yes	Yes
High-fire risk days only	No	No	Yes
Matched control neighbors (N)	-	1	1
Region FEs	No	No	No
Risk-score, undergrounding, PSPS, and covered conductor controls	Yes	Yes	Yes
AUC	0.782	0.785	0.732
Observations	2,400,342	1,282,899	446,254
Log Likelihood	−6,776.30	−5,979.78	−3,397.59

Supplementary Figure 15 | Ignition Model Robustness Tests – One Matched Control Neighbor.

	Incidence Rate - Vegetation-Caused Ignitions		
	No Matching	Matching	Matching & High Fire Risk
	(1)	(2)	(3)
Fast-Trip (E_i=Enabled)	-0.27	-0.55^{*}	-0.72^{*}
	(-0.58, 0.26)	(-0.71, -0.30)	(-0.82, -0.56)
Veg. Mgmt. (D_i=High x T_{it}=Post)	-0.62^{*}	-0.63^{*}	-0.62^{*}
	(-0.79, -0.29)	(-0.80, -0.31)	(-0.83, -0.13)
Veg. mgmt. (D_i=Moderate x T_{it}=Post)	-0.03	-0.03	0.20
	(-0.27, 0.29)	(-0.27, 0.29)	(-0.16, 0.72)
Veg. mgmt. (D_i=High)	1.18^{*}	0.07	0.13
	(0.77, 1.70)	(-0.11, 0.29)	(-0.09, 0.41)
Veg. mgmt. (D_i=Moderate)	1.23^{*}	0.05	0.09
	(0.87, 1.67)	(-0.11, 0.23)	(-0.12, 0.34)
Combined Effect (D_i=High x E_{it}=Enbld. x T_{it}=Post)	-0.89	-0.88	-0.93
	(-1.00, 1.89)	(-0.99, 1.74)	(-1.00, 1.14)
Combined Effect (D_i=Moderate x E_{it}=Enbld. x T_{it}=Post)	-0.77	-0.74	-0.85
	(-0.97, 0.94)	(-0.96, 0.83)	(-0.98, 0.17)
Risk-score matching	No	Yes	Yes
High-fire risk days only	No	No	Yes
Region FEs	No	No	No
Matched control neighbors (N)	-	2	2
Risk-score, undergrounding, PSPS, and covered conductor controls	Yes	Yes	Yes
AUC	0.782	0.794	0.754
Observations	2,400,342	2,037,012	724,765
Log Likelihood	$-6{,}776.30$	$-9{,}491.70$	$-5{,}481.75$

Supplementary Figure 16 | Ignition Model Robustness Tests – High-Risk Unmatched Circuits Included.