# The Impact of Wildfires on Home Insurance Market*

Mengfei Zhou Wenjie Zhan Michael R. Springborn

May 17, 2025

**Abstract**

We examine the impact of wildfires on the home insurance market in California. Leveraging the timing and intensity of fire occurrences, we find that wildfires lead to higher average insurance premiums, a decreasing number of insured housing units, and an increase in average insurance coverage for homeowner insurance. We provide suggestive evidence that both increasing insurance demand and declining insurance supply are driving these effects. We also find that some homeowners respond to wildfires by renting out their properties. (JEL G22, Q54)

*Michael R. Springborn (email: mspringborn@ucdavis.edu) is a professor in the Department of Environmental Science and Policy, University of California, Davis. Wenjie Zhan (wjzhan@ucdavis.edu) and Mengfei Zhou (email: mfzhou@ucdavis.edu) are both Ph.D. candidates in the Department of Agricultural and Resource Economics, University of California, Davis.

# 1 Introduction

Over the past few decades, wildfires have become more frequent and severe across the U.S., particularly in the western states (Dennison et al., 2014; Weber and Yadav, 2020), costing the U.S. economy between $394 billion and $893 billion annually (U.S. Congress Joint Economic Committee, 2023). Meanwhile, around 60% of homeowners nationwide are underinsured by about 17% of their home's value (Frazee, 2018). In California alone, roughly 4.5 million homes are at risk of wildfire damage (Martinuzzi et al., 2015), and more than half of homeowners are underinsured (Frazee, 2018). Despite the growing threat, there is surprisingly little causal evidence on how wildfires affect the home insurance market. The few existing studies either face identification challenges (Hazra and Gallagher, 2022) or focus on mitigation strategies rather than the direct effects of wildfires (Liao et al., 2024; Taylor et al., 2025). Quantifying these causal impacts is critical for informing policies that can better protect American households from rising wildfire risks.

This paper studies the impact of wildfires on the home insurance market in California by combining detailed GIS data on historical wildfire burn areas with ZIP-code-level insurance outcomes. While some existing studies rely on the assumption that the timing and intensity of wildfire occurrence are exogenous (Hazra and Gallagher, 2022; Coulombe and Rao, 2025), this approach raises concerns as, over time, fire intensity may be shaped by evolving local factors, such as changes in public funding for fire suppression, that also influence the insurance market. Instead, we follow a similar approach to Walls and Wibbenmeyer (2023) and Liao and Kousky (2022), using a difference-in-differences (DiD) design that compares ZIP codes in California that have experienced a major wildfire event to those that have not. We define a major wildfire as one where the cumulative burned area exceeds 10%, and use ZIP codes where the cumulative burned area have never exceeded 5% as the comparison group. We test the robustness of our findings using alternative definitions for treatment and control groups, and confirm that our results are not driven by the specific thresholds chosen.

Following a major wildfire event, we estimate a 4.0% increase in average premiums, a 2.1% decline in the number of insured units, and a 2.9% increase in average coverage for owner-occupied policies. The effects on premiums and coverage are persistent over the study period, whereas the decline in the number of insured units is transitory. We do not find evidence that wildfires affect the average premium per dollar of coverage. We do find evidence of spillover effects, but the magnitude is much smaller than the direct effects. Lastly, we show that the estimated impacts are primarily driven by homeowner policies, which account for 55% of all contracts, and are much larger in low-income areas.

We provide suggestive evidence for several mechanisms, including information shocks, decreasing insurance supply, shifts toward the FAIR Plan, and migration. First, we observe a sharp increase in Google searches for terms such as "fire insurance", "property insurance", "house insurance", and "home insurance" following a major wildfire. This indicates higher public interest in home insurance, likely reflecting, in part, a shift in perceived risk. Second, we estimate that nonrenewals by insurers rise by 6.7% after a major wildfire, suggesting a declining supply may be contributing to higher average premium and fewer insured housing units. We also estimate that wildfires increase the share of policies issued through the FAIR Plan, California's insurer of last resort, which provides fire coverage to households unable to obtain insurance through traditional carriers. Since premiums under the FAIR Plan are generally higher than those in the private market, the observed increase in average premiums may be partially driven by the growing reliance on the FAIR Plan. Finally, we document evidence of a decreasing share of homeowner-occupied housing units and a corresponding increasing share of renter-occupied units, suggesting that some homeowners respond to rising wildfire risk by renting out their properties.

We make several contributions to the literature. First, this paper adds to the growing body of work on the socioeconomic impacts of wildfires. Wildfires directly affect society in many ways, e.g., they generate smoke and other air pollutants that harm human health (Liu et al., 2015; Sheldon and Sankaran, 2017) and destroy homes, other buildings, and infrastructure (Naser and Kodur, 2025). These direct impacts then have broader effects, e.g., on the labor market (Meier et al., 2023; Walls and Wibbenmeyer, 2023; Borgschulte et al., 2024; Coulombe and Rao, 2025), housing market (Stetler et al., 2010; Athukorala et al., 2016; Huang and Skidmore, 2024), local government budgets (Liao and Kousky, 2022), migration patterns (Winkler and Rouleau, 2021), and household finances (McCoy and Walsh, 2018; Sachdeva et al., 2024). However, less is known about how wildfires affect the home insurance market. One exception is Hazra and Gallagher (2022), who use linear regression and decision trees and find that increasing wildfire frequency is positively correlated with higher premiums and higher premiums per unit of coverage in the Los Angeles area between 2011 and 2018. In contrast we use a difference-in-differences approach to estimate the causal impact of major wildfires on home insurance outcomes in California. We provide new evidence on wildfires' effects on home insurance premiums, coverage, and market participation.

This paper also contributes to the literature on natural disaster insurance. Much of this research focuses on flood insurance and investigates factors that influence insurance uptake, such as flood events (Shao et al., 2022), personal beliefs (Ratnadiwakara and Venugopal, 2023), market frictions (Wagner, 2022), information access (Mulder, 2021; Weill, 2022), income and price sensitivity (Browne and Hoyt, 2000), and social networks (Hu, 2022). In contrast, the wildfire insurance literature is relatively limited and focuses on policies and regulations that address wildfire risk (Boomhower et al., 2023; Liao et al., 2024; Taylor et al., 2025), the effectiveness of insurance in mitigating wildfire hazard (Hazra and Gallagher, 2022), and insurer pricing strategies (Boomhower et al., 2024). Our paper differs from existing literature by focusing on the direct effects of wildfires on the home insurance market.

Finally, this paper contributes to the broader literature on climate adaptation. A wide range of adaptive responses has been studied, including migration (Baez et al., 2017; Chen et al., 2017; Boustan et al., 2012), adjustments in insurance coverage and uptake (Wagner, 2022), adaptation in the agricultural sector (Zappalà, 2024; Yi et al., 2020; Falco et al., 2014; Burke and Emerick, 2016; Chen and Gong, 2021), and policy interventions, such as wildfire building codes (Baylis and Boomhower, 2022) and moratoriums on insurance nonrenewals following wildfire events (Taylor et al., 2025; You et al., 2024). Our paper adds to this literature by providing new evidence on how insurance markets respond to rising wildfire risk, highlighting limitations in how this risk management tool has served to buffer the escalating threat faced by households.

The rest of this paper proceeds as follows. Section 2 describes the home insurance market. Section 3 provides a conceptual framework describing the effect of wildfires on regulated insurance market. Section 4 describes the data. Section 5 introduces the empirical strategy. Section 6 presents estimates of the effect of wildfires on insurance market outcomes. Section 7 discusses the potential mechanisms for estimated effects. Section 8 concludes.

# 2 Background

Unlike other natural disasters, such as floods and earthquakes, wildfire damage is generally covered by standard homeowner/residential insurance. In a typical homeowner insurance contract, there are a number of perils that will be covered, including but not limited to fire. Households can purchase insurance in the admitted market, in the surplus lines market, or from the FAIR Plan. The admitted market provides the vast majority of policies with rate schedules pre-approved by the California Department of Insurance (CDI). Homeowners who cannot find coverage in the admitted market can turn to the surplus lines market. Insurers in the surplus lines market are not subject to rate regulation in California but are supervised by the insurance regulator in their state of domicile. The premium in the surplus lines market is generally higher because the properties that end up in the surplus lines market are those that could not be covered at rates approved for the admitted market (Dixon et al., 2018).

The California FAIR Plan is a fire insurance program created by the state to serve as an insurer of last resort, providing access to fire coverage for households unable to obtain it from a traditional insurer. The FAIR Plan only covers damages caused by fire or lightning, internal explosions, and smoke. Policies offered by the FAIR Plan provide more restricted coverage than those in the admitted market (Dixon et al., 2018). Over the last decade, more people have turned to the FAIR Plan as wildfires have become severe and some insurers have pulled back from insurance markets. While, the FAIR Plan only comprised 1.6% of policies in 2018, this rose to 2.5% by 2020 and 3.7% by 2023 (California Department of Insurance, 2025).

Existing evidence indicates that around 60 percent of homeowners across the United States are underinsured, with coverage falling short by an average of approximately 17% of their home's value (Frazee, 2018). This implies that for many homeowners the rebuilding cost of the structure after perils far exceeds the insurance coverage. More importantly, underinsurance is concentrated in certain areas. In the face of higher premiums, homeowners in high-risk zones tend to purchase less coverage relative to the structure value and have a higher deductible than those in low-risk areas (Dixon et al., 2018; Hazra and Gallagher, 2022).

Higher insurance prices are a likely driver of inadequate coverage. As wildfires continue to grow in intensity and frequency, insurance premiums in California have risen significantly, up to 300-500 percent, which creates affordability problems for some households (Hazra and Gallagher, 2022). A state sanctioned study issued by the California Natural Resources Agency in 2018 found that premiums in high-risk ZIP codes grew significantly faster than in low-risk ZIP codes (Dixon et al., 2018); however, they did not have data to assess whether differences in premiums reflect actual risk differences. Meanwhile, the number of insurer-led, policy nonrenewals has gone up significantly in high-risk areas (Pauls, 2024). Consequently, not only have the number of insurance providers declined, but the available insurance is more expensive (Shrimali, 2019).

# 3 Conceptual Framework

This section introduces a theoretical model that characterizes the effect of wildfires indicating a rising risk on regulated insurance market equilibrium with adverse selection. Our model closely follows Taylor et al. (2025) and Einav et al. (2010). A homeowner $i$ has type $\theta_i$, capturing any factors affecting willingness to pay for insurance. $\theta_i$ is distributed according to a cumulative distribution $F(\cdot)$. Homeowners can choose either to purchase full-coverage insurance or to remain uninsured. While the model can be modified to accommodate cases in which homeowners choose their level of coverage (as in our empirical setting), for simplicity we focus on the dichotomous case.

We assume that households can purchase insurance in the private insurance market, or from a public backstop program, i.e., the FAIR Plan. Following Taylor et al. (2025), we assume that the regulator sets a fixed price $\bar{p}$ in the private market. This assumption is intended to represent the complex rate approval process.[1] In addition, we assume that FAIR Plan can charge a sufficiently high premium to cover expected costs, thereby satisfying the zero-profit condition.

We assume that consumers having a higher willingness to pay are more costly to cover, as typical in a market with adverse selection. This implies that the marginal cost (MC) of policy supply is downward sloping (Einav et al., 2010), which implies that the average cost (AC) curve is also downward sloping and lies above the MC curve. Following Taylor et al. (2025), we assume that insurers can observe the marginal cost curve, which is plausible because most house characteristics that affect expected losses are observable to both the insurer and the homeowner. In addition, insurers are allowed to set prices only based on a limited set of permitted characteristics, such as construction type, roof condition, and home age. As a result, they must offer the same premium to all households that share the same set of permitted characteristics. However, insurers can choose to deny coverage based on other observable factors that influence expected costs but are not legally permitted for use in pricing decisions, i.e., where the policy price, $p$, is greater than MC. This implies that the private insurance market only covers a portion of consumers. Consumers with higher cost and higher willingness to pay may then purchase the FAIR Plan. We assume that the FAIR Plan charges a price sufficient to break even, i.e., $p = AC$.[2]

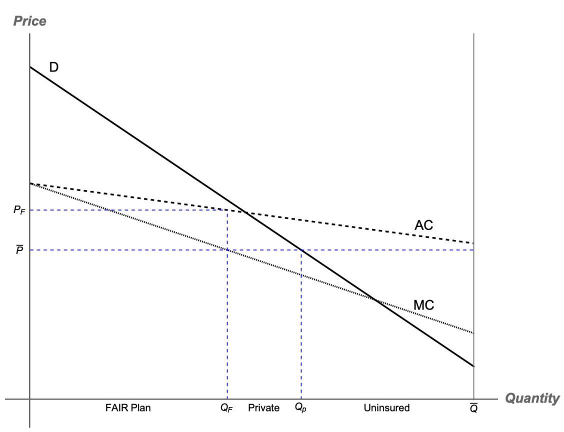
In Figure 1 we show insurance market equilibrium outcomes under price regulation, where private insurers and the FAIR Plan serve different portions of the market. A regulator imposes a fixed price, $\bar{p}$, which is depicted in Figure 1 at a level that remains below the AC curve throughout the entire range of the population, from 0 to $\bar{Q}$. At this

[1] Under Proposition 103, private insurance companies in California must obtain prior approval from the CDI before changing rates. Rates must be based primarily on historical loss data, and consumers have the right to challenge proposed rate changes. Thus, prices in the private market are highly regulated by the CDI. Homeowners who cannot find coverage in the private market can turn to the FAIR Plan, which is the state's insurer of last resort. The FAIR Plan is not directly regulated under Proposition 103, so premiums under the FAIR Plan tend to be higher than those offered by the private insurance market for comparable coverage.

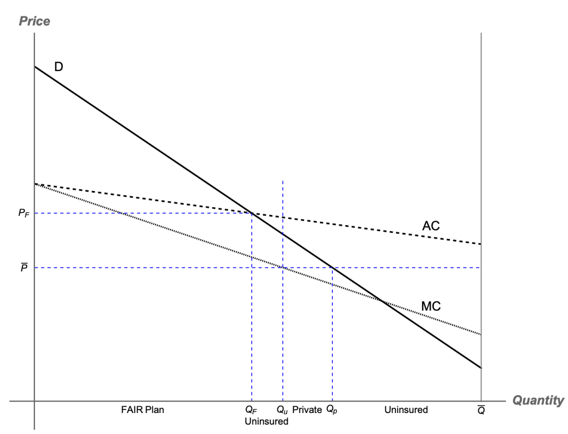
[2] The FAIR Plan is not subject to Proposition 103.

price, profit-maximizing private insurers serve only those consumers whose willingness to pay exceeds the regulated price ($D > \bar{p}$) and for whom the price exceeds marginal cost ($\bar{p} > MC$). This corresponds to the quantity range from $Q_F$ to $Q_p$ in Figure 1a. Consumers above $Q_p$ are uninsured.[3]

Since individuals with high willingness to pay are also typically costly to insure, private insurers choose not to serve them. As a result, these individuals can seek coverage through the FAIR Plan, which charges a higher price. Since the FAIR Plan sets its price ($p^F$) to cover costs, $p^F$ is set equal to the average cost across the quantity it supplies, $Q_F$. In Figure 1a, all consumers who are excluded from the private market (i.e., those between 0 and $Q^F$) have a willingness to pay greater than $p^F$, and are therefore covered by the FAIR Plan. However, this is not the case in the alternative scenario depicted in Figure 1b. Here, at the lower bound of private insurance coverage, labeled $Q_u$, AC is above the demand curve. In this case $p_F$ is given by the intersection of AC and the demand curve, resulting in an *additional* portion of the market remaining uninsured.




(a) Regulated price is high enough to avoid an additional insurance gap.




(b) Regulated price is low enough to create an additional insurance gap.

Figure 1: INSURANCE MARKET EQUILIBRIUM UNDER REGULATED PRICING WITH FAIR PLAN AND PRIVATE MARKET

Figure 2 shows a possible scenario for the insurance market under increasing wildfire risk. $MC^\star$, $AC^\star$, and $D^\star$ represent the new marginal cost, average cost, and demand curves, respectively. Following Taylor et al. (2025), we assume that the regulated price ad-

[3]However, if the regulator does not impose a price floor, the equilibrium may shift, as insurers could lower prices to attract all consumers.

justs more slowly than the increase in costs, i.e., $\bar{p}^\star - \bar{p} < AC^\star - AC$. However, the FAIR Plan is allowed to adjust its price to fully cover the average cost. As costs and demand increase, private insurers raise the price to $\bar{p}^\star$, thereby covering consumers from $Q_F^\star$ to $Q_p^\star$ whose willingness to pay exceeds the new price and for whom $\bar{p}^\star$ is greater than $MC^\star$. In this scenario, private insurers shift their insured pool to include more less-risky consumers who have increased their willingness to pay in response to heightened wildfire risk. For those who cannot obtain a policy in the private market (from 0 to $Q_F^\star$) but have a willingness to pay above the price, they ultimately end up with the FAIR Plan. Figure 2 depicts a case where the demand curve lies above the average cost throughout the range from 0 to $Q_F^\star$. In this case, the FAIR Plan covers consumers from 0 to $Q_F^\star$ and sets the price equal to $p_F^\star$.

Next we consider the equilibrium consequences of an increase in wildfire risk, as manifested in upward shifts of both the demand curve and marginal cost curve. Figure 2 depicts a case in which the demand curve shift, to $D^*$, is stronger than the marginal cost curve shift, to $MC^*$. These shifts result in both a higher prices and an increase in the quantity of coverage. However, depending on the shapes of the demand and cost curves, as well as their sensitivity to increasing risk, it is also possible that the number of units covered decreases while the price increases.

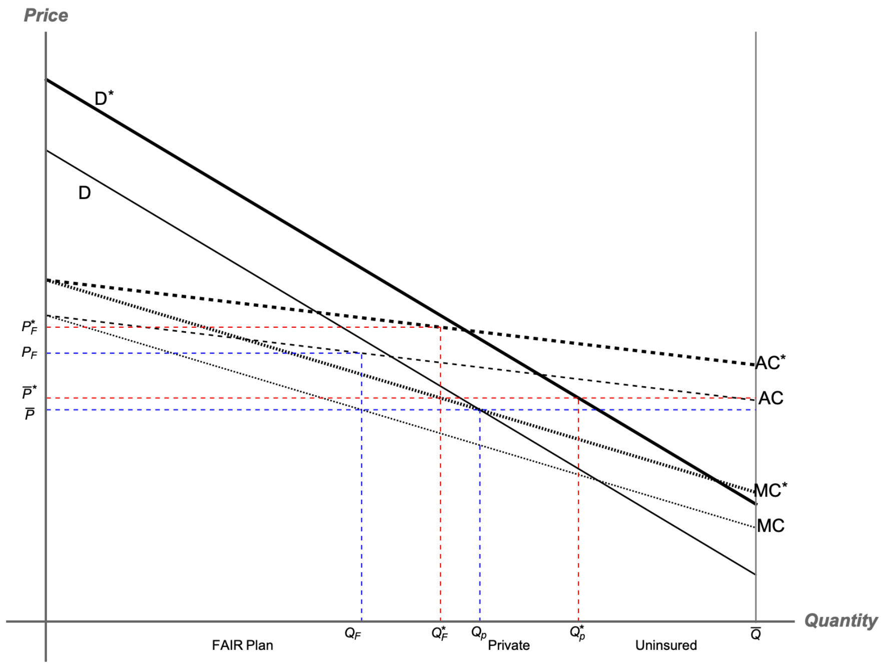



Figure 2: INSURANCE MARKET EQUILIBRIUM UNDER REGULATED PRICING WITH FAIR PLAN AND PRIVATE MARKET (INCREASING RISK)

# 4 Data

## 4.1 Wildfire data

Data on California wildfire events is publicly available on the website of CAL FIRE.[4] Although this data is available going back to 1878, we restrict our attention to 2001 and 2023 since the insurance data is only available from 2009. We assume that any response to wildfires that happened long ago (before 2001) is already complete by 2009. For each fire in the record, the data include a polygon specifying the extent of the fire, ... In addition, we restrict the analysis to high fire hazard areas. CAL FIRE classifies a rural and unincorporated area as a Moderate, High, or Very High fire hazard based on the factors that influence fire likelihood and fire behavior, including fire history, fuel loading, and other factors. The data on fire hazard severity is available on the website of CAL FIRE.

[4]https://frap.fire.ca.gov/mapping/gis-data/.

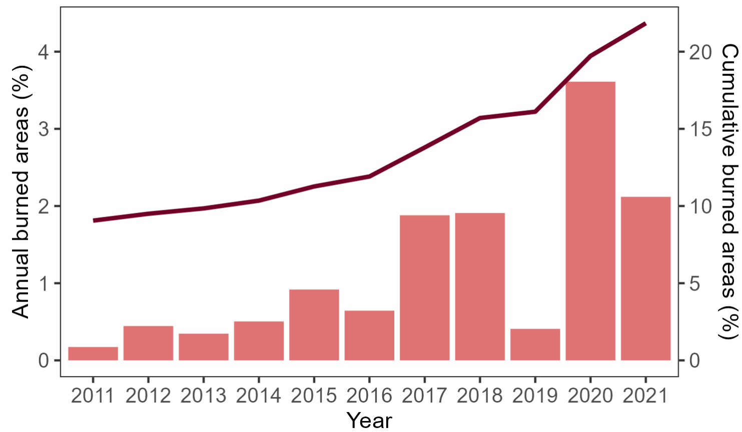



Figure 3: TIME TREND OF BURNED AREAS

## 4.2 Insurance data

We obtained insurance data from the California Department of Insurance (CDI) through Freedom of Information Act requests. The data are recorded by year, ZIP code, and policy forms. The policy form specifies the type of structure and whether the resident is an owner or tenant. We restrict sample to owner-occupied policies[5] and renter-occupied policies.[6]

Our data from CDI comprise three sources of insurance information. First, the Community Service Statement (CSS) Data contains information on the amount of premium earned by insurers and the number of units insured from 2009 to 2022. All insurance companies licensed to operate in California in the voluntary market are required to respond. Second, the Personal Property Experience (PPE) Data provides information on the average amount of coverage (structure and contents) and the average deductible amount. Insurers that wrote $10 million or more in premiums are required to report. The data include the years 2009, 2011, 2013, 2015, and 2017-2021. Third, the Residential Property Experience (RPE) data provides the number of residential policies that were canceled or non-renewed by the insured/consumer and (separately) by the insurer from 2015 to 2021.[7]

[5] Dwelling Owner-Occupied, ...
[6] Dwelling Tenant-Occupied (including Condo units), ...
[7] https://www.insurance.ca.gov/01-consumers/200-wrr/DataAnalysisOnWildfiresAndInsurance.cfm

### 4.3 Google Trends data

Google Trends is a publicly available database that tracks the relative popularity of search terms compared to all searches at the city, designated market area, state, and national levels. The data portal returns an index that normalizes the share of searches relative to the maximum search share within the chosen time frame and region. For 2004-2023, we collect city-by-year-level search data on keywords including “fire insurance”, “property insurance”, “house insurance”, and “home insurance” to capture interests in wildfire-related insurance. We construct an index to represent the aggregated relative popularity of these three keywords by either taking their simple average or weighting them based on their across-term relative popularity following the procedure described in Appendix Section B.

### 4.4 Housing data

We collect annual ZIP code-level housing characteristic data from the United States Census Bureau, American Community Survey (ACS). This data includes the total number of housing units, property values, mortgage status, housing structure type, number of rooms, year built, and the year of move-in. This dataset allows us to explore whether wildfires lead to changes in the composition of housing characteristics at the ZIP code level.

## 5 Methods

We seek to identify the causal effects of wildfires on insurance outcomes. A simple approach—with well-known limitations discussed below—would be to use a two-way fixed effects (TWFE) model:

$$Y_{it} = \beta CBA_{it} + \gamma_i + \lambda_t + \epsilon_{it}, \tag{1}$$

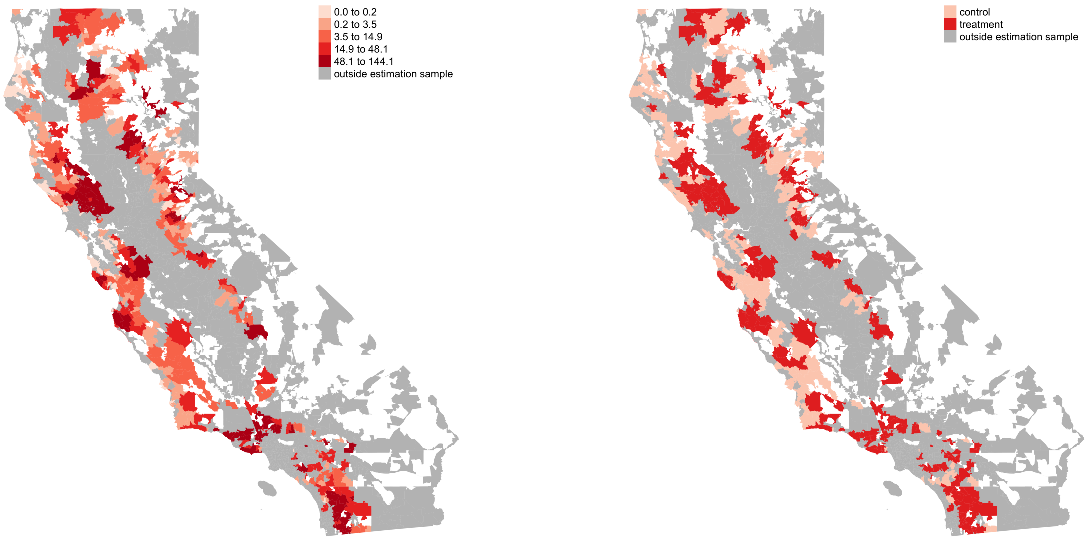
where $Y_{it}$ represents the outcome of interest for ZIP-code $i$ in year $t$, and $CBA_{it}$ represents the total share of land burned by wildfires in $i$ from 2001 up to year $t$, capturing the cumulative zip code exposure to wildfires over time. The term $\gamma_i$ captures ZIP-code fixed effects, $\lambda_t$ accounts for year fixed effects, and $\epsilon_{it}$ is the error term. Since non-prescribed fires are generally unpredictable events, the timing of fire occurrences is plausibly random. However, fire intensity may be endogenous to trends in fire suppression capabilities, such as reduced public funding for fire protection, which could both drive up insurance coverage and premiums while also increasing fire intensity.

To address this concern, we instead use an event-study framework by comparing ZIP-code areas that have experienced major wildfire exposure with those that have not. We define major wildfire exposure as CBA exceeding a given threshold, $CBA_M$, which is 10% in our baseline model. We use CBA to define major wildfire exposure because wildfires often have long-lasting effects. That said, a ZIP code experiencing a wildfire that burns 10% of its area for the first time is likely less exposed to wildfire damage than one that experiences similar fires in two consecutive years. Liao et al. (2024) is another paper that uses cumulative burned area to measure wildfire exposure. Nonetheless, in Section 6.2, we show that using annual burned area instead of CBA to define major wildfire occurrence does not substantially change our main findings.

Another potential concern about this event-study design is that if the treated group experienced a smaller fire earlier or if the control group encountered a smaller fire at any point during the study period, our estimates could be attenuated. To address this while preserving a sufficiently large sample,[8] we take a "doughnut approach" in which we exclude observations for a unit from the sample in periods when the CBA falls between 5% and $CBA_M$. The control group is comprised of zip codes with a CBA less than 5% throughout the study period. Nevertheless, our estimates should be interpreted as a lower bound of wildfire effects. We show that our results are robust to different choices for the threshold $CBA_M$, suggesting that our findings are not driven by arbitrary threshold selection. Figure 4a presents the spatial distribution of CBA levels and Figure 4b shows the distribution of treatment and control groups. These figures show that areas

[8] Refer to Figure A2 for the number of treated ZIP codes under different threshold levels.

with various levels of CBA are distributed throughout the state and not concentrated in one region.




(a) Cumulative fire intensity

(b) Treatment and control

Figure 4: CUMULATIVE FIRE INTENSITY AND TREATMENT STATUS BY ZIP CODE (UNSHADED AREAS INDICATE PLACES WITHOUT ZIP CODES)

Recent literature has shown that the estimand of TWFE specifications can produce misleading estimates if treatment effects are heterogeneous across groups or time, especially in staggered treatment design (Callaway and Sant'Anna, 2021; De Chaisemartin and d'Haultfoeuille, 2020; Sun and Abraham, 2021; Goodman-Bacon, 2021). The estimated treatment effect from a TWFE specification is a weighted sum of several difference-in-differences. TWFE can introduce bias by using already treated units as a "control group" for newly treated units, which can result in negative weights. In such cases, the estimated average treatment effect may be negative even when all individual treatment effects are positive (Roth et al., 2022; De Chaisemartin and d'Haultfoeuille, 2020), leading to a biased estimate. Our main estimation uses the group-time estimator proposed by Callaway and Sant'Anna (2021) to address this issue, hereafter referred to as the CS estimator.

The CS estimator is based on a group-time average treatment effect on the treated

(ATT):

$$ATT(g,t) = E[Y_{g,t}(1) - Y_{g,t}(0)|G = g],$$

where $Y_{g,t}(1)$ and $Y_{g,t}(0)$ represent the potential outcomes under treatment and no treatment, respectively, and $G = g$ denotes the group that first received treatment in period $g$. Following Callaway and Sant'Anna (2021), we aggregate group-time ATTs to obtain overall and dynamic measures of the treatment effect. The overall effect across all treated groups and time periods are given by:

$$ATT^{overall} = \frac{1}{G} \sum_g \frac{1}{T_g} \sum_{t \geq g} ATT(g,t),$$

where $G$ is the number of groups, and $T_g$ represents the number of periods after the group $g$ adopts treatment. Dynamic treatment effects over time—which show how the estimated impact evolves post-treatment—are calculated as:

$$ATT^{dynamic}(t) = \frac{1}{|G_t|} \sum_{g \in G_t} ATT(g,t),$$

where $G_t$ represents the set of groups treated in periods $t$, allowing us to track treatment effects over time and assess potential dynamics of effects of wildfire. Our estimation relies on the parallel trends assumption: in the absence of treatment, the outcome trajectories of treated and untreated groups would have evolved similarly.

In our baseline analysis, we use never-treated areas as the control group. For the dynamic ATTs, we set the period immediately before treatment as the base period to construct pre-treatment estimates. In the appendix, we show that these choices do not affect our results. Finally, we show that TWFE estimators yield results consistent with our main findings using the CS estimator.

CS estimators are consistent under the assumptions of no anticipation and parallel trends. The no anticipation assumption states that the insurance market does not anticipate major fire occurrence. The parallel trends assumption requires that, in the absence of a fire event, insurance outcomes in areas that experience fire events would have evolved similarly to those in areas that do not experience fire events. To strengthen the likelihood of the parallel trends, we restrict our sample to high-hazard areas to enhance the comparability of treated and untreated units.

The validity of our strategy requires the Stable Unit Treatment Value Assumption (SUTVA), i.e., that major wildfire occurrence in one ZIP code does not impact the insurance market in other areas. However, this assumption may not hold in our context, as wildfires in one area may affect how homeowners and insurers behave in surrounding areas. In Section 6.3, we discuss how accounting for wildfire spillover effects could impact our results.

# 6 Results

## 6.1 Effects of wildfires on home insurance outcomes

In Table 1, Panel A presents overall CS estimates for the effects of major wildfire occurrence (CBA exceeding 10%) on *owner*-occupied policies compared to ZIP codes with low CBA (remaining below 5%). We estimate that insurance premiums for owner-occupied homes increase by 4.0%, the number of insured units decreases by 2.1%, and insurance coverage (the average household coverage limit) increases by 2.9%. The estimate for insurance premium per $1000 of coverage (Prem./Cov.) is not statistically significant. Panel B shows the effects of high CBA on *renter*-occupied policies. We do not find precise estimates of effects on home insurance outcomes for renter-occupied insurance.

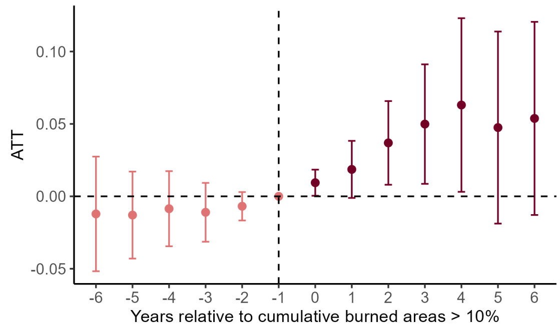
Table 1: Effects of major wildfire occurence on home insurance outcomes

| | log(Premium) (1) | log(#Insured) (2) | log(Coverage) (3) | log(Prem./Cov.) (4) |
|---|---|---|---|---|
| *Panel A: owner-occupied policy* | | | | |
| After major wildfire (CBA $>$ 10%) | 0.0404*** | -0.0205** | 0.0285*** | 0.0062 |
| | (0.0137) | (0.0089) | (0.0094) | (0.0136) |
| Observations | 3,240 | 3,240 | 1,728 | 1,728 |
| Dep. var. mean | 1,141 | 5,401 | 718,712 | 1.5697 |
| *Panel B: renter-occupied policy* | | | | |
| After major wildfire (CBA $>$ 10%) | 0.0122 | 0.0113 | -0.0036 | -0.0072 |
| | (0.0202) | (0.0155) | (0.0344) | (0.0430) |
| Observations | 3,528 | 3,528 | 2,352 | 2,352 |
| Dep. var. mean | 375 | 1,497 | 166,356 | 2.2880 |

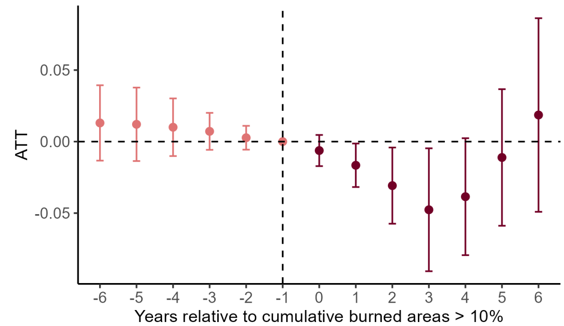
Notes: We report the overall Callaway and Sant'Anna (2021) estimates. Prem./Cov. is premium per $1000 of coverage. We exclude periods when the cumulative burn area (CBA) in a ZIP code falls between 5% and 10% for the treatment group and restrict the control group to ZIP codes where the CBA is less than 5% throughout the study period. Outcomes variables are the log of the ZIP code mean. CS estimates are weighted by the number of housing units in the ZIP code. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels. Reported dependent variable means are weighted by the number of housing units in the ZIP code and are not log-transformed.

In Figure 5 we show dynamic event study estimates for the effect of a major wildfire on owner-occupied policies. We do not find evidence of pretrend issues. Relative to the overall ATT estimates in Table 1, Panel A, the dynamic estimates suggest that these effects ramp up over the first few years after treatment and also that the estimated effect on premiums and coverage is persistent (over the years available) and for number of insured units is transitory.

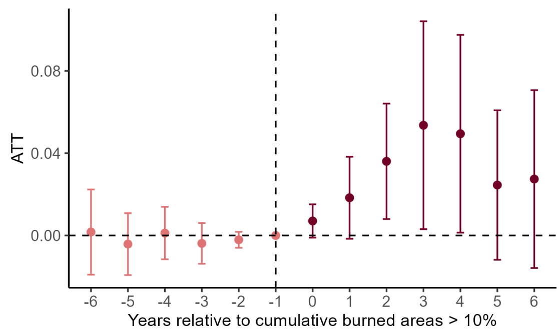
How do our estimates compare to the existing literature? Hazra and Gallagher (2022) find that each additional wildfire is associated with a 0.9–1.2% increase in insurance premiums for policies not under the FAIR plan. Gan et al. (2014) estimate that forestland owners are 1.4% less likely to purchase wildfire insurance if they experienced a wildfire in the past 10 years. Our estimates are moderately larger, as we focus on major wildfire events, but they remain broadly in line with the existing literature.



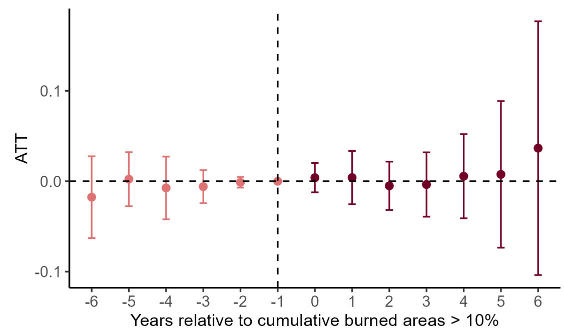

(a) log(Premium)




(b) log(#Insured)




(c) log(Coverage)




(d) log(Prem./Cov.)

Figure 5: DYNAMIC EFFECTS OF WILDFIRES ON HOME INSURANCE OUTCOMES, OWNER-OCCUPIED POLICY

Notes: We report the dynamic Callaway and Sant'Anna (2021) estimators. Prem./Cov. is premium per \$1000 of coverage. ZIP codes are considered treated when the cumulative percentage of wildfire-burned areas exceeds 10%. We exclude periods when the cumulative percentage of wildfire-burned areas falls between 5% and 10% for the treatment group and restrict the control group to ZIP codes where the cumulative percentage of wildfire-burned areas is less than 5% throughout the study period. CS estimates are weighted by the number of housing units in the ZIP code. Whiskers represent 95% confidence intervals.

## 6.2 Robustness

We begin by assessing sensitivity of our results to our baseline treatment group threshold ($CBA_M$ = 10%) by re-estimating effects under alternative levels (5%, 15%, 20%, 25%, or 30%) while keeping the control group unchanged. Separately, we also assess sensitivity to our baseline control group threshold (5%) to alternative levels (1% or 10%) while keeping the treatment group threshold unchanged. Appendix Figure A5 shows the DD estimates of the effect of a major fire on insurance outcomes across different definitions of treatment and control groups. Our conclusions are robust across these specifications, indicating that our findings are not driven by arbitrary threshold choices.

Second, we present the results for the TWFE estimator, Callaway and Sant'Anna (2021) approach with different control groups, and the imputation method proposed by Borusyak et al. (2024) in Appendix Figure A6. Overall, the results are consistent with our baseline model, suggest that our conclusions are not driven by the choice of estimation method. Event-study estimates using the Borusyak et al. (2024) estimator do show evidence of pre-trends, suggesting that the parallel trends assumption is problematic under that approach. Third, in Appendix Figure A7 we show that changing the definition of hazard areas does not substantially change our results.

Finally, we present results using annual burned area (ABA) instead of cumulative burned area to define major wildfire occurrence. Panel A of Appendix Table A1 shows estimates where the treatment group includes ZIP codes that have ever experienced an ABA exceeding 10%, while the control group includes ZIP codes where cumulative burned area has never exceeded 5%. The results are consistent with our main findings. Since a given ZIP code may experience multiple major wildfires over time, Panel B of Table A1 restricts the sample to periods corresponding to the first major wildfire. The results remain robust under this restriction.

## 6.3 Spillover effects

The effects of wildfires in one ZIP code may extend beyond its boundaries, as insurance firms update their approach to the market and people update their risk perceptions based on news coverage or visible smoke from nearby fires. To test the sensitivity of our estimates to spillover effects, we control for major wildfires in neighboring ZIP codes. Since the CS estimator does not allow for control variables and since TWFE estimates were very similar to our CS estimates (see Appendix Figure A6), we report TWFE estimates with additional controls for neighboring fire instead. In Appendix Table A2, we first present TWFE estimates of our main results (Panel A), followed by estimates that account for major wildfires in adjacent ZIP codes (Panel B). We define neighboring major wildfire occurrence as CBA across all neighboring ZIP codes exceeding 10%. We find that the estimated effect of neighboring major wildfire occurrence have the same sign as main (within-ZIP code fire) effects, but is smaller in magnitude. Moreover, adding this neighboring fire effect results in attenuation of the main estimated effect of within-ZIP code major wildfire occurrence by 13-26%. However, we cannot fully disentangle spillover effects from collinearity, as wildfires often span multiple ZIP codes. To explore this, in Panel C of Appendix Table A2, we introduce indicators for major wildfires in neighboring ZIP codes by distance bands. The estimated effect of neighboring wildfires occurring within 30 miles is not statistically significant for premium or number insured but is for coverage. For the 30 and 60 mile distance band we find the opposite. For average insurance coverage, the results in Panel C suggest that the coefficients for neighboring wildfires in Panel B may reflect collinearity rather than true spillover effects.

## 6.4 Heterogeneity

### 6.4.1 Policy form

We further break down our sample by six policy forms: homeowner policies (HO, 55.36%), condominium unit owner policies (HC, 7.68%), dwelling owner-occupied policies (DO, 4.38%),[9] mobile home policies (MO, 2.73%), tenant/renter policies (HT, 18.23%), and dwelling tenant-occupied policies (DT, 11.62%).[10] Appendix Figure A8 shows CS estimates for the effect of major wildfire occurrence on insurance outcomes across different policy forms. The results suggest that our main results are primarily driven by homeowner policies, which constitute the majority of home insurance coverage. Estimated effects on premiums for other policy types are not statistically significant (though all are positive). For the number of insured homes, the estimated effect for mobile homes is positive for this small share of the market, in contrast to our baseline result. Consistent with our baseline results, we also find an estimated increase in average coverage for homeowner, dwelling owner-occupied and tenant/renter policies. We do not find any statistically significant estimates for premium per $1,000 of coverage for any policy form.

[9] DO also includes Lender/Forced Placed and Real Estate Owned (REO) type policies covering an Occupied Dwelling.

[10] DT also includes any policies covering an Unoccupied Dwelling/Vacant Dwelling.

#### 6.4.2 Income

Appendix Table A3 presents estimates for the heterogeneous effects of major wildfire occurrence across low-income versus high-income areas. We find that the magnitudes of estimated effects for low-income areas are roughly double those for high-income areas (except for prem./cov. for which both groups lack statistically significant estimates). This pattern aligns with the intuition that houses in low-income areas are more vulnerable to wildfire risk, in part due to limited access to fire protection services (Auer, 2021; Meldrum et al., 2024; Reining et al., 2025).

# 7 Potential Mechanisms

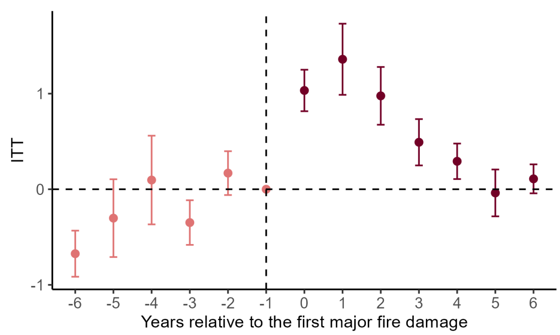
## 7.1 Increasing demand following an information shock: evidence from Google Trends

We provide suggestive evidence that information shock may be one reason the insurance market responds to wildfires, using data from Google Trends. We match the timing of major wildfire incidents with search activity for terms such as "fire insurance," "property insurance," "house insurance," and "home insurance" between 2004 and 2023. Our results show that, after major wildfire occurrence, searches for these keywords rise by 0.53 to 0.8 standard deviations, depending on how the search index is constructed (see Table 2 and Figure 6). There are multiple reasons why individuals might search such terms after major wildfire occurrence, including navigating existing insurance claims and pursuing new or additional coverage. While this search metric is broad, it is consistent with higher consumer interest, and thus greater demand, for home insurance following wildfire events.

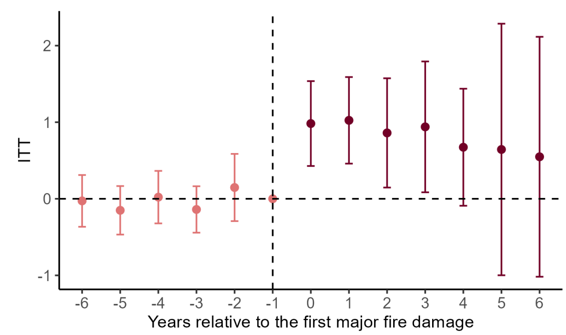
Table 2: Overall effects of wildfire on relative popularity of searching for insurance-related search term use on Google

| | Normalized relative popularity of searches for "fire insurance", "property insurance", "house insurance", and "home insurance" | |
|---|---|---|
| | (1) | (2) |
| After a major wildfire (CBA > 10%) | 0.5257*** | 0.7955*** |
| | (0.0708) | (0.1825) |
| Observations | 3760 | 19,296 |
| Dep. var. mean | 1.1784 | 1.2494 |
| Aggregation approach | Simple average | Weighted average |

Notes: We report the Callaway and Sant'Anna (2021) estimates of the overall ATT of major wildfire occurrence on insurance-related relative search term use on Google. The search terms include: "fire insurance", "property insurance", "home insurance" and "house insurance". The treated group is the cities where wildfire damage has exceeded 10%, while the control group is the cities where wildfire damage has never exceeded 5%. Regressions and dependent variable mean are weighted by city population. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels.




(a) Simple average




(b) Weighted average

Figure 6: Dynamic effects of wildfire on relative popularity of searching for "fire insurance", "property insurance", "house insurance", and "home insurance" on Google

Notes: We report the Callaway and Sant'Anna (2021) estimators with the never treated as control group. The treated group is the cities where wildfire damage has exceeded 10%, while the control group is the cities where wildfire damage has never exceeded 5%. We control for city and year fixed effects. Regressions are weighted by city population. Standard errors are clustered at city level.

## 7.2 Declining supply: evidence from nonrenewal by insurers

A declining supply of home insurance may also contribute to rising premiums and a reduction in insured housing units. We link the timing of major wildfire events to ZIP-code-level data on new policies, renewals, nonrenewals by the insured, and nonrenewals by insurers. In 2018, the California legislature passed Senate Bill 824, which prohibits insurers from canceling or not renewing policies solely due to wildfire risk in ZIP codes directly affected by, or adjacent to, areas impacted by a wildfire that triggered a state of emergency (California Department of Insurance, 2019). The moratorium was first implemented for wildfires in Los Angeles and Riverside counties in October 2019. To account for this policy change, we examine nonrenewals by insurers separately, through 2018 versus thereafter.

Table 3 shows estimates of the effect of major wildfire occurrence on new policies, renewals, and nonrenewals. Following major wildfire occurrence, we estimate that the number of new policies declines by 6.6%, and nonrenewals by the insured fall by 2.9%. These results are consistent with the observed decline in the number of insured housing units in our main results. Nonrenewals by insurers increase by an estimated 6.7% before the moratorium (up to 2018), suggesting that a shrinking supply of insurance may be one of the underlying mechanisms. After 2018, the estimated effect is still positive, but smaller and very noisy, consistent with the expected effect of the moratorium.

Table 3: EFFECTS OF MAJOR WILDFIRE OCCURRENCE ON NEW POLICIES, RENEWALS, AND NONRENEWALS

| | log(#new policies) | log(#renewals) | log(#NRs by the insured) | log(#NRs by the insurer to 2018) | log(#NRs by the insurer after 2018) |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| After a major wildfire (CBA $>$ 10%) | -0.0659*** | -0.0035 | -0.0287* | 0.0667*** | 0.0353 |
| | (0.0227) | (0.0069) | (0.0160) | (0.0271) | (0.1563) |
| Observations | 1,897 | 1,904 | 1,890 | 1,164 | 726 |
| Dep. var. mean | 748 | 5,757 | 561 | 135 | 187 |

Notes: We report the Callaway and Sant'Anna (2021) estimates. We exclude periods when the cumulative burn area (CBA) in a ZIP code falls between 5% and 10% for the treatment group and restrict the control group to ZIP codes where the CBA is less than 5% throughout the study period. Regressions and dependent variable mean are weighted by total housing units. The mean of the dependent variable is the average value before applying the log transformation. Standard errors are clustered at ZIP-code level. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels.

## 7.3 Composition change in housing characteristics

One potential driver of changes in home insurance costs—coverage overall and/or premium per unit of coverage—is a change in housing characteristics in ZIP codes affected by wildfire. Certain characteristics, such as higher property values and older homes, are associated with higher insurance coverage or premiums. If the share of such homes is increasing at the same time as a wildfire occurs, this could confound our results. Appendix Table A4 shows the effects of wildfires on housing characteristics. We fail to find a statistically significant estimate of the effect of major wildfire occurrence on the total number of housing units, average housing value, mortgage status, unit structure, number of rooms, and year built. However, our estimate of the decrease in the share of owner-occupied housing and increase in the share of renter-occupied housing are both statistically significant, which suggests that some homeowners may rent out their properties following major wildfire occurrence. We also find that wildfires significantly increase the share of households that moved in during or after 2010, further supporting the idea of migration in response to wildfires.

## 7.4 Increasing share of FAIR Plan

Table 4 presents estimates of the effect of major wildfire occurrence on the share of housing units covered by the FAIR Plan as well as on average premiums and total number insured for both the FAIR Plan and private market. The results show that the estimated share of units covered by the FAIR Plan increases following a major wildfire. Since FAIR Plan premiums are generally higher than those in the private market, the post-wildfire increase in average premiums may be partially driven by the growing reliance on the FAIR Plan. In addition, we find that the estimated effect on premiums is positive, but while this is statistically significant for the private market, the FAIR Plan estimate is very small and imprecisely estimated, which may be due to the fact that the FAIR Plan already charges relatively high premiums in high-risk areas.

Table 4: EFFECTS OF WILDFIRES ON FAIR PLAN AND PRIVATE MARKET INSURANCE

| | %FAIR Plan | | FAIR Plan | | Private Market | |
|---|---|---|---|---|---|---|
| | $\leq$ 2018 | >2018 | log(Premium) | log(#Insured) | log(Premium) | log(#Insured) |
| After a major wildfire (CBA > 10%) | 0.0505 | -0.4431 | 0.0091 | -0.0832 | 0.0394*** | -0.0220 |
| | (0.1064) | (1.2385) | (0.0614) | (0.1507) | (0.0105) | (0.0142) |
| Observations | 2,088 | 848 | 2,028 | 2,028 | 2,856 | 2,856 |
| Dep. var. mean | 0.4530 | 5.0186 | 1,280 | 19.1956 | 1,071 | 5,007 |

Notes: We report the Callaway and Sant'Anna (2021) estimates. We exclude periods when the cumulative burn area (CBA) in a ZIP code falls between 5% and 10% for the treatment group and restrict the control group to ZIP codes where the CBA is less than 5% throughout the study period. Regressions and dependent variable mean are weighted by total housing units. The mean of the dependent variable is the average value before applying the log transformation. Standard errors are clustered at ZIP-code level. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels.

# 8 Conclusion and Discussion

We examine the impact of wildfires on the home insurance market in California. By combining data on the timing and severity of wildfires with home insurance records, we analyze how key insurance outcomes respond to major wildfire events. We find that, following a major wildfire incident, average insurance premiums rise, the number of insured housing units declines, and average insurance coverage increases.

We explore two potential mechanisms driving these changes: rising demand and declining supply for home insurance. First, we use Google Trends data to capture shifts in demand, assuming that searches by suppliers and researchers constitute only a small portion of the total search activity. Our analysis reveals a significant increase in searches for home insurance-related keywords after a wildfire, suggesting a rise in consumer interest. Second, we examine insurer non-renewal rates and find that non-renewals increase following major wildfire incidents, indicating a decline in supply. Finally, we observe that some homeowners rent out their properties in response to wildfire events.

We find that, even as demand for home insurance increases, premiums are rising and the number of insured housing units is decreasing, especially in low-income communities. This pattern suggests that wildfires may worsen financial vulnerability by reducing access to insurance in the places that need it most. From a policy perspective, these findings highlight the need for targeted strategies that address the growing demand for disaster insurance while acknowledging that private insurers often reduce their exposure in high-risk areas. As wildfires and other climate-related disasters become more frequent, depending solely on private insurance markets may not be enough to ensure broad, affordable coverage. For example, Taylor et al. (2025) provides early evidence that California's insurance moratorium reduced non-renewals by insurers after wildfires, showing that government policies can help protect coverage in vulnerable areas.

Still, more evidence is needed to understand how well these policies work and what their long-term effects might be (Bayham et al., 2022). Future research should look at how different approaches, such as temporary moratoriums, public insurance programs, or government support for insurers, can keep insurance available without creating unintended consequences. Policymakers will need to weigh the benefits of protecting homeowners against the risks of overburdening the system or discouraging private insurers from staying in the market.

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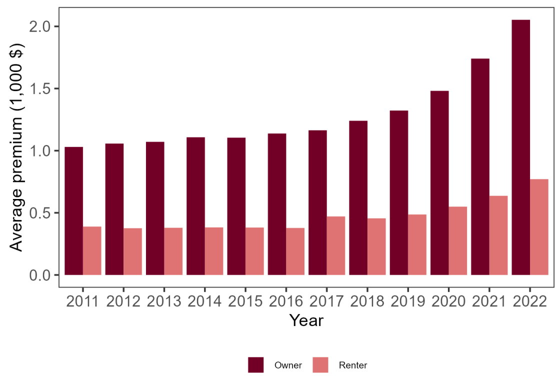
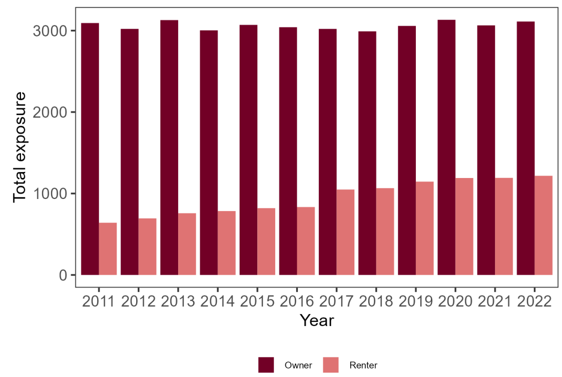
# Appendix

## A Additional results

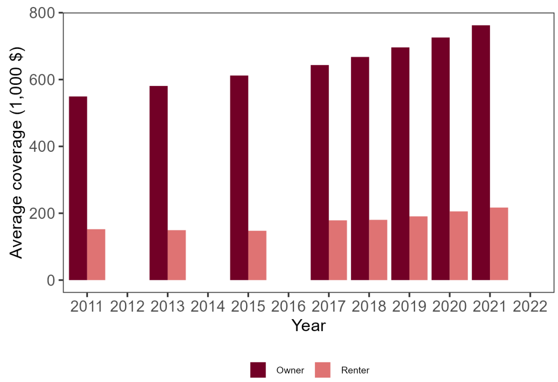
Figure A1: AVERAGE ANNUAL INSURANCE OUTCOMES FOR OWNER-OCCUPIED VERSUS RENTAL UNITS ACROSS SAMPLE ZIP CODES



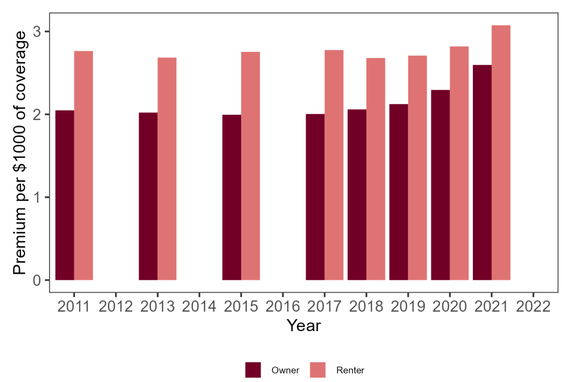

(a) Premium




(b) Total number insured



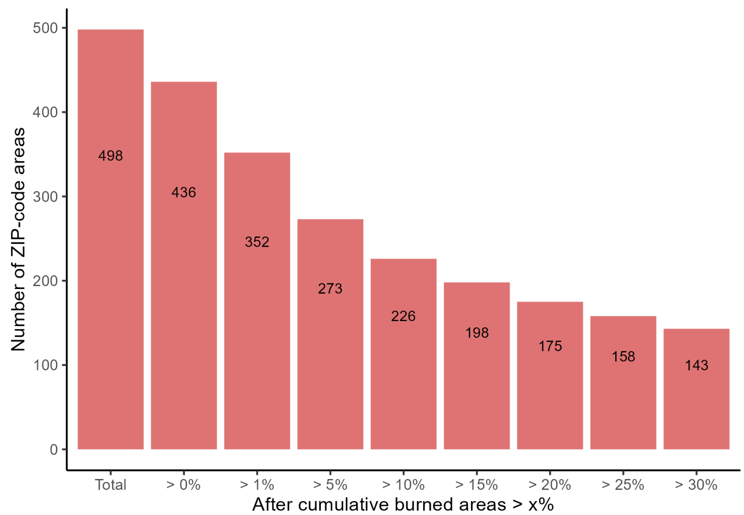

(c) Coverage




(d) Premium per $1000 of coverage

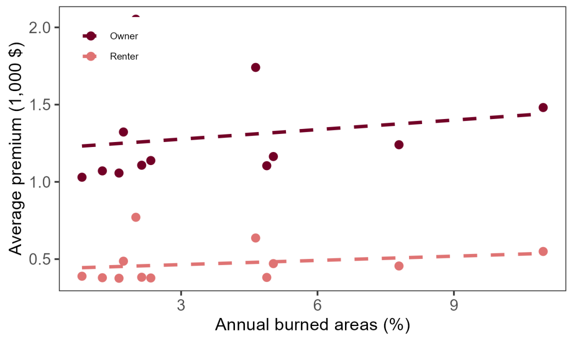
Notes: Figures are in levels, not log-transformed.

Figure A2: NUMBER OF TREATED ZIP-CODE AREAS BY MAJOR FIRE OCCURRENCE THRESHOLD

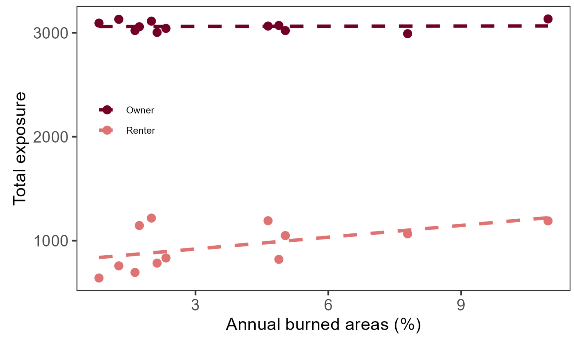



Notes: The "Total" bar indicates the total number of counties in sample, regardless of burned area history. Cumulative burned area is calculated over years 2001-2022.

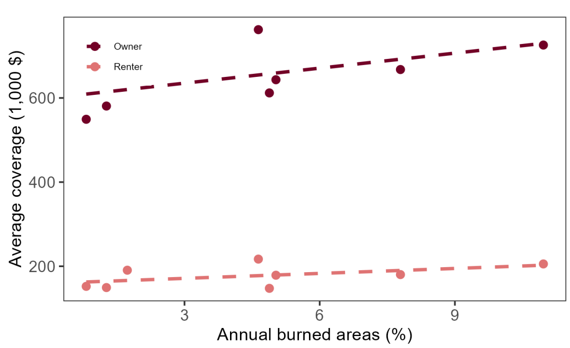
Figure A3: Correlation between annual burned areas and annual average insurance outcomes for owner-occupied versus rental units across sample ZIP codes for 20XX-20XX



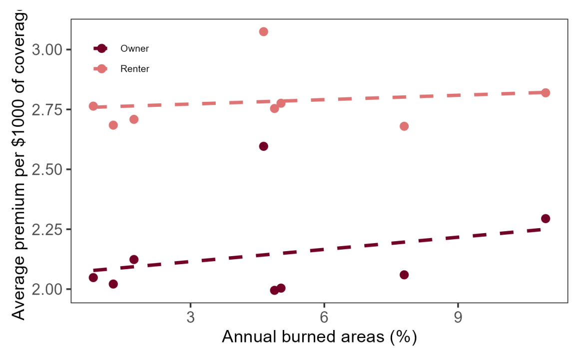

(a) Average premium versus annual burned areas




(b) Total number insured versus annual burned areas

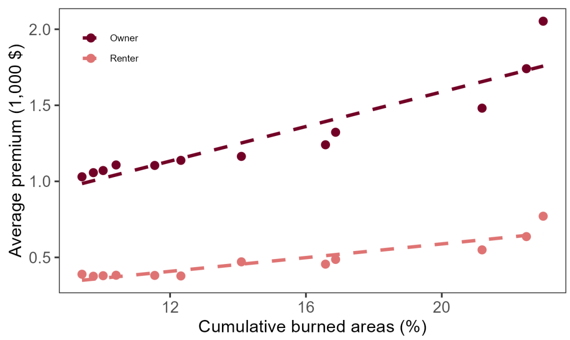



(c) Average coverage versus annual burned areas

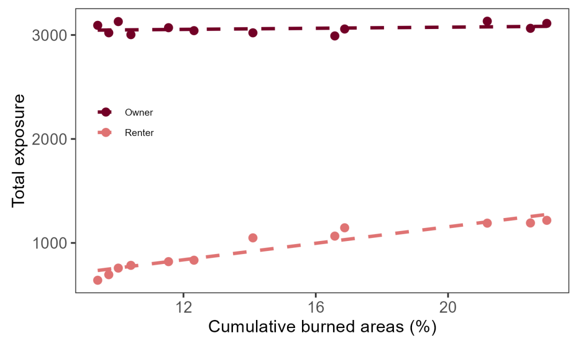



(d) Premium per $1000 of coverage versus annual burned areas

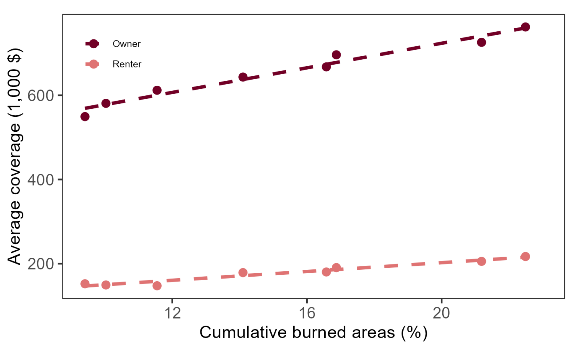
Figure A4: Correlation between cumulative burned areas and annual average insurance outcomes



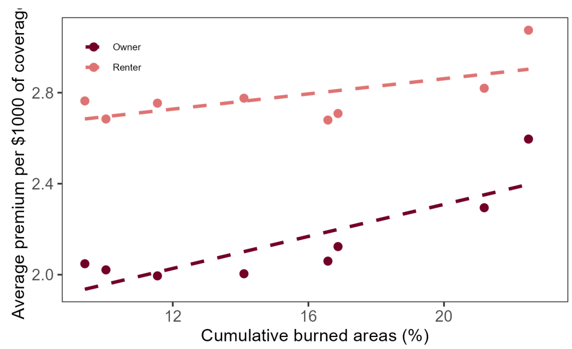

(a) Average premium v.s. cumulative burned areas




(b) Total #insured v.s. cumulative burned areas

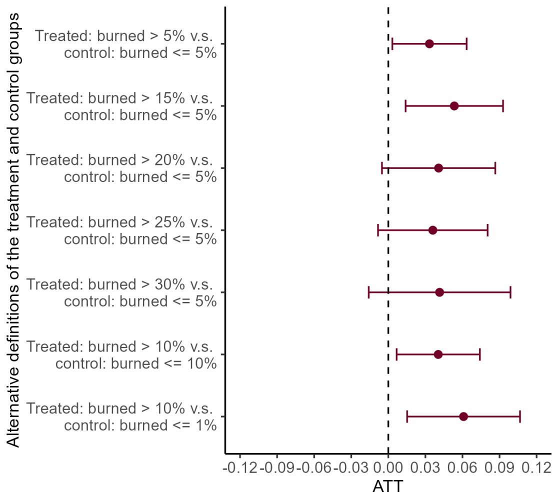



(c) Average coverage v.s. cumulative burned areas

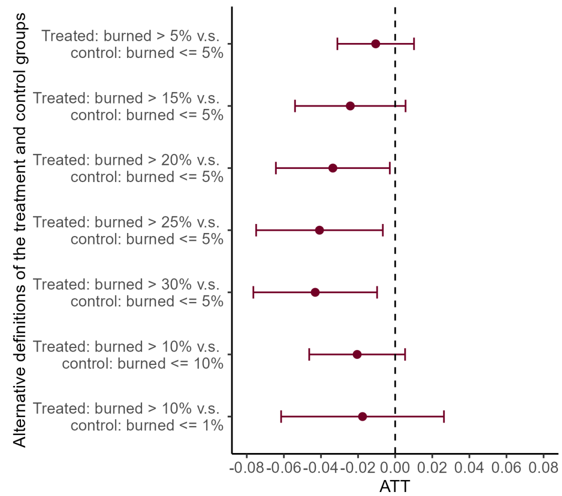



(d) Premium per \$1000 of coverage v.s. cumulative burned areas

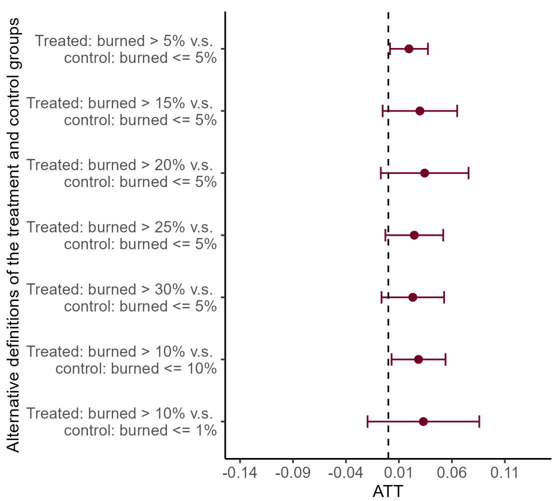
Figure A5: ROBUSTNESS TO DIFFERENT DEFINITIONS OF TREATMENT AND CONTROL GROUPS



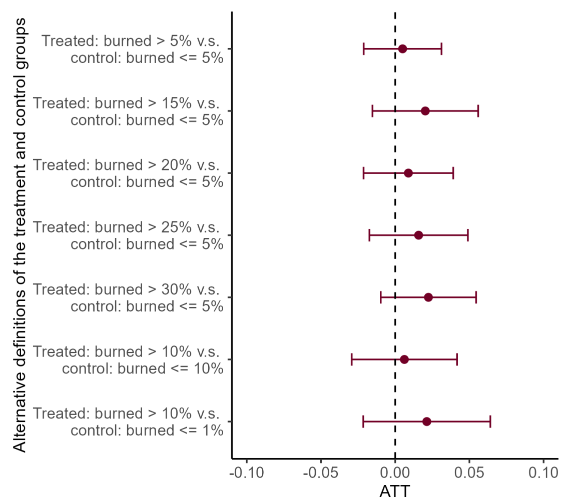

(a) log(Premium)




(b) log(#Insured)



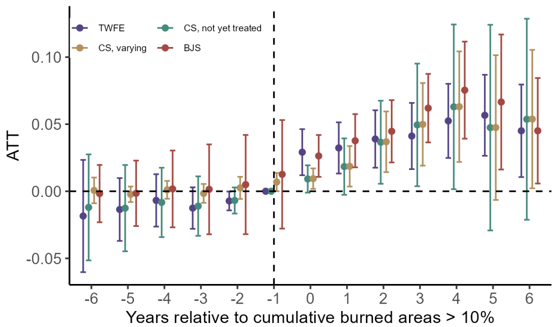

(c) log(Coverage)



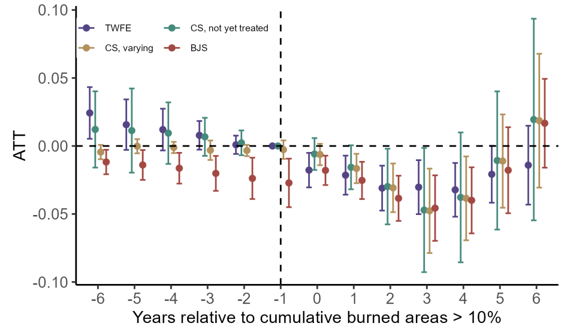

(d) log(Prem./Cov.)

Notes: We report the Callaway and Sant'Anna (2021) estimators for overall ATT. Prem./Cov. is premium per $1000 of coverage. Regressions and dependent variable mean are weighted by total housing units. Whiskers represent 95% confidence intervals.

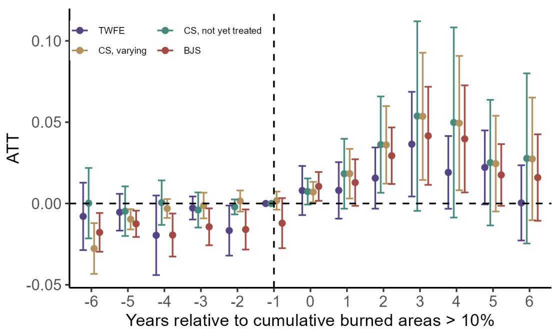
Figure A6: EVENT-STUDY ESTIMATE ROBUSTNESS TO ESTIMATION METHODS



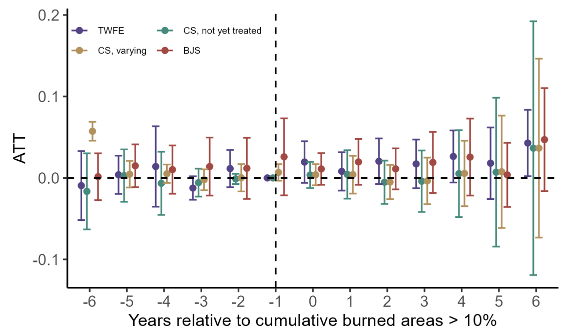

(a) log(Premium)




(b) log(#Insured)



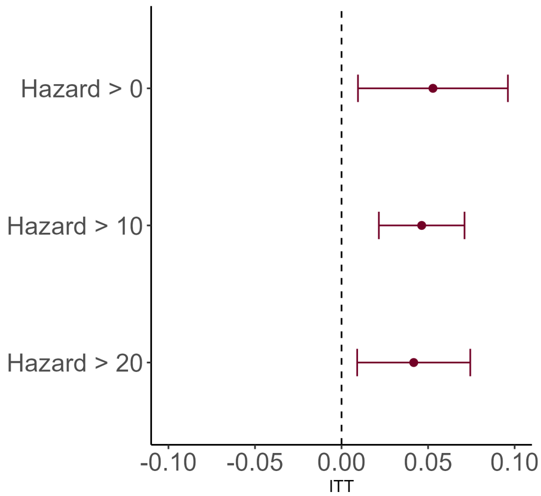

(c) log(Coverage)



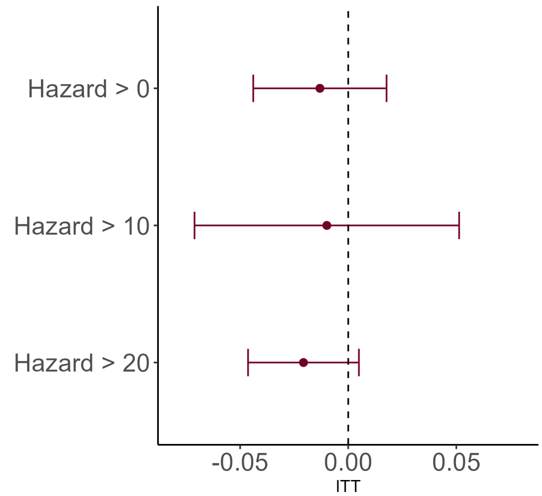

(d) log(Prem./Cov.)

Notes: We report dynamic event-study estimates for ATT. Prem./Cov. is premium per $1000 of coverage. "TWFE" denotes two-way fixed-effects estimators. "CS, not yet treated" refers to the Callaway and Sant'Anna (2021) estimator, using the not-yet-treated group as the control (and dropping all ZIP codes that never meet the treatment threshold). "CS, varying" represents the Callaway and Sant'Anna (2021) estimator with the never-treated group as the control and $t-1$ as the base period for pre-period coefficients (the default in the *did* package). "BJS" denotes the imputation estimator proposed by Borusyak et al. (2024). The treated group is ZIP-code areas where cumulative burned areas has exceeded 10%, while the control group is the ZIP-code areas where cumulative burned areas has never exceeded 5%. We control for ZIP-code and year fixed effects. Regressions and dependent variable mean are weighted by total housing units.

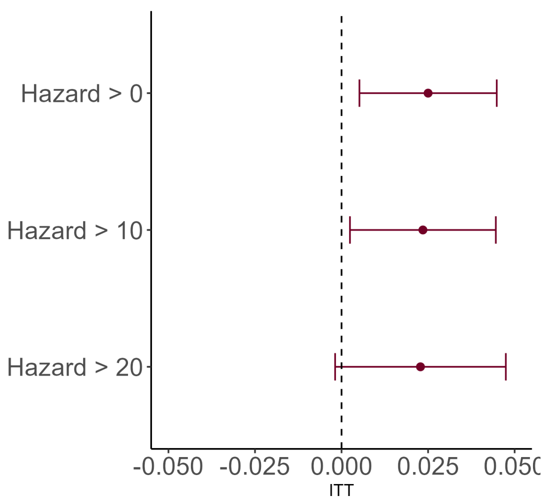
Figure A7: ROBUSTNESS TO DIFFERENT DEFINITIONS OF HAZARD AREAS



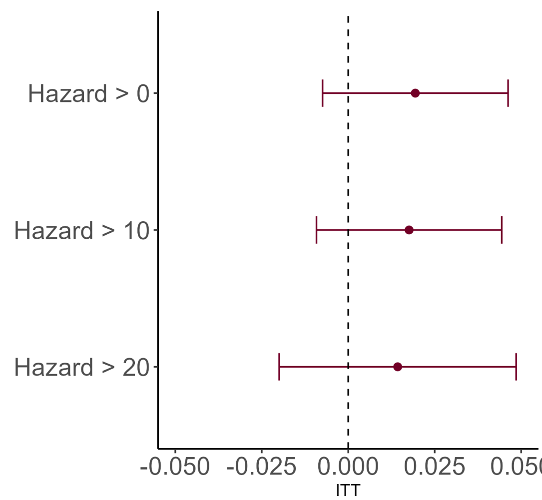

(a) log(Premium)




(b) log(#Insured)




(c) log(Coverage)




(d) log(Prem./Cov.)

Notes: We report the Callaway and Sant'Anna (2021) estimates of overall ATT for different insurance outcome variables. Prem./Cov. is premium per $1000 of coverage. Regressions and dependent variable mean are weighted by total housing units.

Table A1: EFFECTS OF WILDFIRES ON HOME INSURANCE OUTCOMES UNDER AN ALTERNATIVE DEFINITION OF TREATMENT GROUP BASED ON ANNUAL BURNED AREA

| | log(Premium) | log(#Insured) | log(Coverage) | log(Prem./Cov.) |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Panel A: multiple treated periods included* | | | | |
| After a major wildfire (ABA > 10%) | 0.0433*** | -0.0219** | 0.0270** | 0.0094 |
| | (0.0134) | (0.0103) | (0.0110) | (0.0145) |
| Observations | 3,192 | 3,192 | 1,680 | 1,680 |
| Dep. var. mean | 1,142 | 5,412 | 719,941 | 1.5686 |
| *Panel B: multiple treated periods excluded* | | | | |
| After a major wildfire (ABA > 10%) | 0.0310** | -0.0242** | 0.0105* | 0.0263** |
| | (0.0136) | (0.0111) | (0.0068) | (0.0120) |
| Observations | 3,024 | 3,024 | 1,600 | 1,600 |
| Dep. var. mean | 1,140 | 5,414 | 716,500 | 1.5757 |

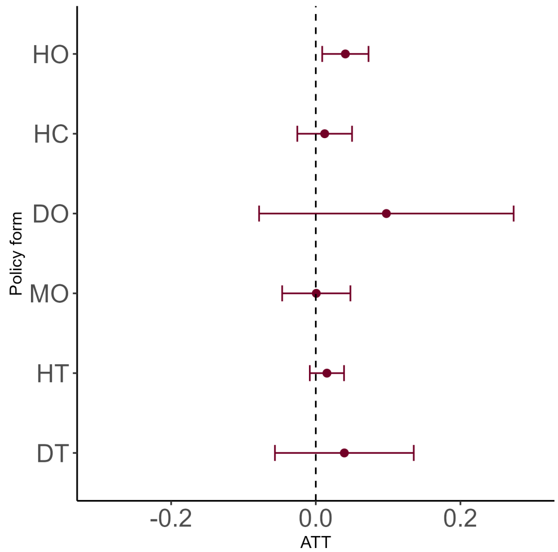
Notes: We report the Callaway and Sant'Anna (2021) estimates. Prem./Cov. is premium per $1000 of coverage. A ZIP code is treated if annual burned area (ABA) is larger than 10%. We exclude periods when the cumulative burn area (CBA) in a ZIP code falls between 5% and 10% and restrict the control group to ZIP codes where the CBA is less than 5% throughout the study period. Regressions and dependent variable mean are weighted by total housing units. The mean of the dependent variable is the average value before applying the log transformation. Standard errors are clustered at ZIP-code level. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels.

Table A2: EFFECTS OF WILDFIRES ON HOME INSURANCE OUTCOMES, CONTROLLING FOR WILDFIRES IN NEIGHBOR ZIP CODES

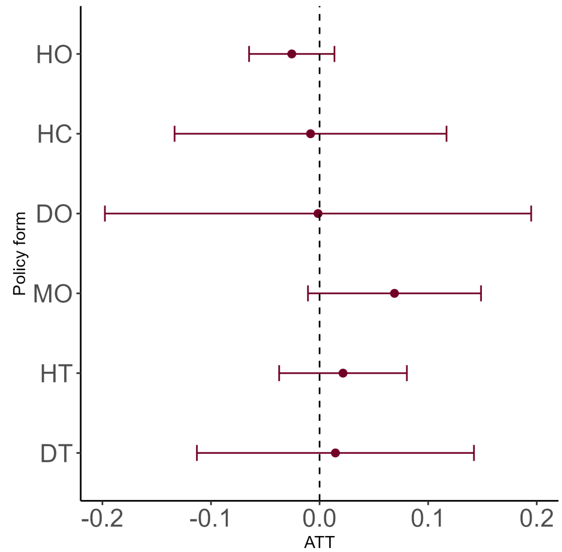
| | log(Premium) (1) | log(#Insured) (2) | log(Coverage) (3) | log(Prem./Cov.) (4) |
|---|---|---|---|---|
| *Panel A: baseline estimates* | | | | |
| After a major wildfire (CBA > 10%) | 0.0504*** | -0.0356*** | 0.0300*** | 0.0114 |
| | (0.0128) | (0.0094) | (0.0083) | (0.0137) |
| Observations | 5,366 | 5,366 | 3,383 | 3,383 |
| Dep. var. mean | 1,202 | 7,890 | 733,609 | 1.6970 |
| *Panel B: accounting for spillover effects* | | | | |
| After a major wildfire (CBA > 10%) | 0.0388*** | -0.0309*** | 0.0221*** | 0.0112 |
| | (0.0137) | (0.0098) | (0.0082) | (0.0148) |
| After a major wildfire in neighboring | 0.0223** | -0.0092 | 0.0151** | 0.0003 |
| ZIP codes (CBAN > 10%) | (0.0104) | (0.0085) | (0.0064) | (0.0120) |
| Observations | 5,366 | 5,366 | 3,383 | 3,383 |
| Dep. var. mean | 1,202 | 7,890 | 733,609 | 1.6970 |
| *Panel C: accounting for spillover effects by distance* | | | | |
| After a major wildfire (CBA > 10%) | 0.0446*** | -0.0315*** | 0.0271*** | 0.0101 |
| | (0.0127) | (0.0099) | (0.0076) | (0.0140) |
| After a major wildfire in neighboring | 0.0131 | -0.0152 | 0.0124** | -0.0025 |
| ZIP codes within 30 miles | (0.0082) | (0.0094) | (0.0054) | (0.0092) |
| After a major wildfire in neighboring | 0.0263*** | -0.0196** | 0.0027 | 0.0182** |
| ZIP codes from 30-60 miles | (0.0085) | (0.0080) | (0.0051) | (0.0087) |
| After a major wildfire in neighboring | 0.0179** | 0.0014 | -0.0001 | 0.0111 |
| ZIP codes from 60-100 miles | (0.0088) | (0.0072) | (0.0052) | (0.0090) |
| Observations | 5,366 | 5,366 | 3,383 | 3,383 |
| Dep. var. mean | 1,202 | 7,890 | 733,609 | 1.6970 |

Notes: We report the TWFE estimators. Prem./Cov. is premium per $1000 of coverage. We exclude periods when the cumulative percentage of own wildfire-burned areas falls between 5% and 10%. We control for ZIP-code and year fixed effects. Standard errors are clustered at ZIP-code level. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels.

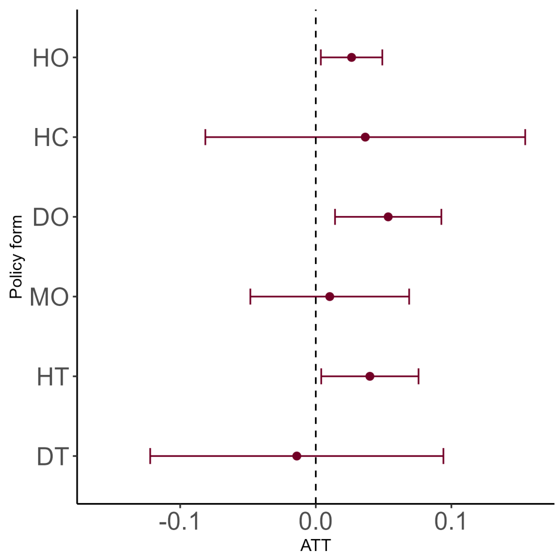
Figure A8: HETEROGENEOUS EFFECTS BY POLICY FORMS



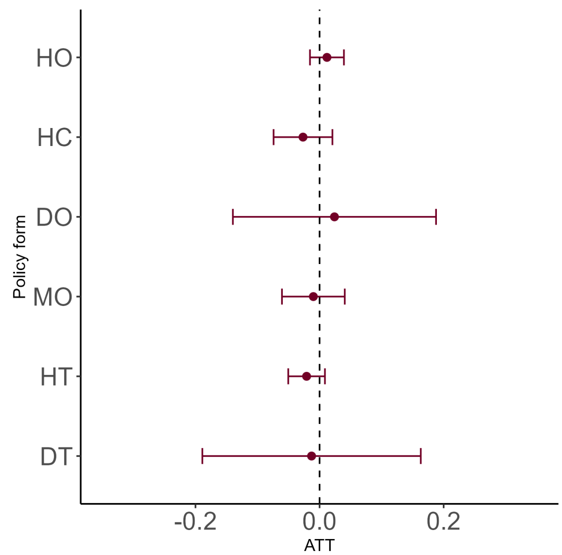

(a) log(Premium)




(b) log(#Insured)




(c) log(Coverage)




(d) log(Prem./Cov.)

Notes: We report the Callaway and Sant'Anna (2021) estimators for overall ATT by policy form. Prem./Cov. is premium per $1000 of coverage. Regressions and dependent variable mean are weighted by total housing units. Policy forms include homeowner (HO), condominium unit owner (HC), welling owner-occupied (DO), mobile home (MO), tenant/renter (HT); and dwelling tenant-occupied (DT, including Condo units).

Table A3: HETEROGENEOUS EFFECTS BY INCOME

| | log(Premium) (1) | log(#Insured) (2) | log(Coverage) (3) | log(Prem./Cov.) (4) |
|---|---|---|---|---|
| *Panel A: low-income ZIP codes* | | | | |
| After a major wildfire (CBA > 10%) | 0.0700*** | -0.0412** | 0.0425*** | 0.0114 |
| | (0.0183) | (0.0210) | (0.0114) | (0.0167) |
| Observations | 1,608 | 1,608 | 816 | 816 |
| Dep. var. mean | 1,012 | 3,621 | 548,274 | 1.8105 |
| *Panel B: high-income ZIP codes* | | | | |
| After a major wildfire (CBA > 10%) | 0.0336** | -0.0165 | 0.0214* | 0.0100 |
| | (0.0160) | (0.0104) | (0.0120) | (0.0172) |
| Observations | 1,584 | 1,584 | 896 | 896 |
| Dep. var. mean | 1,212 | 6,625 | 811,760 | 1.4721 |

Notes: We report the Callaway and Sant'Anna (2021) estimators with the never treated as control group. Prem./Cov. is premium per $1000 of coverage. The treated group is ZIP-code areas where cumulative burned areas has exceeded 10%, while the control group is the ZIP-code areas where cumulative burned areas has never exceeded 5%. We control for ZIP-code and year fixed effects. Regressions and dependent variable mean are weighted by total housing units. Standard errors are clustered at ZIP-code level. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels.

Table A4: EFFECTS OF MAJOR WILDFIRE OCCURRENCE ON HOUSING CHARACTERISTICS

| | log(Total housing units) (1) | log(Median housing value) (2) | %Mortgage (3) | %Occupied (4) | %Owner-occupied (5) | %Renter-occupied (6) | %Built after 2010 (7) | %Built between 2000-2009 (8) |
|---|---|---|---|---|---|---|---|---|
| After a major wildfire (CBA > 10%) | -0.0135 | 0.0047 | -0.4311 | 0.3193 | -0.8638** | 0.8640** | 0.1176 | -0.4491 |
| | (0.0120) | (0.0128) | (0.4260) | (0.2913) | (0.3955) | (0.3941) | (0.5891) | (0.4865) |
| Observations | 3926 | 3926 | 3926 | 3926 | 3926 | 3926 | 3926 | 3926 |
| Dep. var. mean | 9.0859 | 13.0530 | 69.7295 | 88.8924 | 67.4254 | 32.5747 | 2.4920 | 13.3349 |

| | %Built between 1990-1999 (1) | %Built between 1980-1989 (2) | %Built between 1970-1979 (3) | %Built between 1960-1969 (4) | %Built before 1959 (5) | %Moved in after 2010 (6) | %Moved in between 2000-2009 (7) | %Moved in between 1990-1999 (8) |
|---|---|---|---|---|---|---|---|---|
| After a major wildfire (CBA > 10%) | 0.0780 | 0.0774 | -0.0446 | -0.1619 | 0.3791 | 1.1623** | -2.1907** | -0.1549 |
| | (0.2471) | (0.3760) | (0.3467) | (0.2696) | (0.3209) | (0.4765) | (0.9065) | (0.3638) |
| Observations | 3926 | 3926 | 3926 | 3926 | 3926 | 3926 | 3926 | 3926 |
| Dep. var. mean | 12.9842 | 19.4360 | 21.5000 | 12.5313 | 17.7241 | 27.3095 | 33.4007 | 15.6095 |

| | %Moved in before 1989 (1) | %1 unit (2) | %2-4 units (3) | %5-19 units (4) | %≥ 20 units (5) | %1 room (6) | %2-4 rooms (7) | %≥ 5 rooms (8) |
|---|---|---|---|---|---|---|---|---|
| After a major wildfire (CBA > 10%) | 0.5680 | 0.2542 | 0.1621 | -0.1664 | -0.2232 | -0.0010 | 0.6215 | -0.6205 |
| | (0.3754) | (0.3210) | (0.1994) | (0.2458) | (0.2879) | (0.1331) | (0.6543) | (0.6492) |
| Observations | 3926 | 3926 | 3926 | 3926 | 3926 | 3926 | 3926 | 3926 |
| Dep. var. mean | 14.5548 | 76.4094 | 5.3052 | 6.3332 | 5.1369 | 1.9199 | 27.7437 | 70.3365 |

Notes: We report the Callaway and Sant'Anna (2021) estimates for overall ATT. The treated group is ZIP-code areas where cumulative burned areas has exceeded 10%, while the control group is the ZIP-code areas where cumulative burned areas has never exceeded 5%. Regressions and dependent variable mean are weighted by total housing units. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels.

## B Aggregate Google Trends data

The raw data downloaded from Google Trends data portal represent the relative popularity of a search term within a city-year (city-year relative popularity) (Burchardi et al., 2019):

$$G(i,d,t) = \left[ \frac{share(i,d,t)}{max_d\{share(i,d,t)\}} \cdot 100 \right],$$

where $share(i,d,t)$ is the share of searches for term $i$ among total searches made in city $d$ at time $t$, $max_d\{share(i,d,t)\}$ is the maximum of $share(i,d,t)$ across all cities at time $t$, and $T$ is the reporting threshold.

We collect search data on keywords like "fire insurance," "property insurance," and "house insurance" to gauge interest in wildfire-related insurance. However, due to Google Trends' reporting threshold, these terms alone do not generate enough search volume to provide sufficient data for sensible results. To address this, we aggregate their search data. A common approach, as seen in previous studies (Burchardi et al., 2019; Alsan and Yang, 2022), is to take a simple average of these terms. However, since each term is normalized based on a different maximum search share, this method does not fully account for variations in search volume across terms. We propose an alternative aggregation method using Google Trends data on their cross-term relative popularity for the entire period from 2004 to 2021:

$$C(i,t) = \left[\frac{share(i,t)}{max_{i,t}\{share(i,t)\}} \cdot 100\right],$$

where $share(i,t)$ is the share of searches for term $i$ among total searches nationwide at time $t$ and $max_{i,t}\{share(i,t)\}$ is the maximum of $share(i,t)$ across the three selected terms over entire 2004-2023 period. The share of searches for term $i$ in city $d$ at time $t$ can be represented as:

$$\begin{aligned}\widetilde{share}(i,d,t) &= \frac{G(i,d,t)}{\sum_d w_{pop}(d)G(i,d,t)} \cdot C(i,t) \\ &= \frac{share(i,d,t)}{\sum_d w_{pop}(d)share(i,d,t)} \cdot \frac{share(i,t)}{max_{i,t}\{share(i,t)\}}.\end{aligned}$$

Since we do not have direct data on the share of searches for term $i$ in city $d$ relative to the entire U.S., we use the population share $w_{pop}(d)$ as a proxy. If $w_{pop}(d)$ reasonably approximates the share of searches for term $i$ in city $d$ relative to the entire U.S., then $share(i,t) \approx \sum_d w_{pop}(d)share(i,d,t)$ leading to simplification $\widetilde{share}(i,d,t) = \frac{share(i,d,t)}{max_{i,t}\{share(i,t)\}}$. Finally, the aggregated search index for city $d$ at time $t$ is computed as:

$$share_{aggregated}(d,t) = \sum_i \widetilde{share}(i,d,t).$$

This allows a more accurate representation of search interest across different WIC-related terms. We impute raw relative popularity values of "$< 1$" as 0.5 and null values as 0.