Last Resort Insurance: Wildfires and the Regulation of a Crashing Market

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Abstract

An increasing number of households are denied home insurance in the private market and must instead turn to state-sponsored plans known as "Insurers of Last Resort." This paper studies how these residual markets affect the allocation of households under rising disaster risk and regulatory constraints on pricing and coverage supply. We develop a simple model in which regulated insurers cannot freely set premiums across households but can choose who to insure. We bring this framework to the data using California's nonrenewal moratoriums, which temporarily barred insurers from nonrenewing existing policies because of wildfire risk in zip codes affected by, or directly adjacent to, state-of-emergency wildfires. Using quasi-random variation in moratorium coverage, we find that the moratorium reduced company-initiated nonrenewals while active, but did not prevent insurer nonrenewals once the moratoriums expired. We discuss the implications of these results for the design of disaster insurance regulation in segmented markets.

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1 Introduction

Recent growth in damages from natural disasters is increasing the costs of providing property insurance. As expected losses rise, insurers seek to increase premiums to maintain profitability and guarantee solvency, while regulators often aim to limit rate increases to preserve affordability. This tension leaves an increasing number of households unable to find insurance coverage in the private market. In the United States, these households must instead turn to state-sponsored "insurers of last resort" to purchase insurance. Although originally designed as a temporary backstop for the highest-risk properties, insurers of last resort now account for a significant and growing share of coverage in many states. This development raises important questions: which households are served by the insurer of last resort rather than by the private market, how do prices adjust across these market segments under different regulatory regimes, and how does the presence of an insurer of last resort determine the incidence of insurance costs across households and firms?

In this paper, we study how rising disaster-related insurance costs interact with regulatory constraints to determine the allocation of households across market segments. We first develop a simple model of a homeowners insurance market with both a private ("voluntary") market and an insurer of last resort ("residual") market. Under price regulation, private insurers cannot freely set prices, but they can use information about each household's marginal cost to determine whom to insure, and therefore decline to cover households whose expected marginal cost exceeds the regulated price. Because homeowners with mortgages are required to carry insurance, households ceded from the voluntary market have to purchase coverage in the residual market. This makes the relevant margin of adjustment not whether households purchase insurance, but where they obtain it and how much they pay for it. In this setting, the insurer of last resort does not solve any market failure; rather, it is the institutional mechanism that sustains near-universal coverage when price regulation prevents the private market from clearing. The model further shows that when prices cannot adjust in the private market, rising costs are absorbed through both higher residual-market premiums and reallocation of higher-cost households out of the private market. These adjustments have important distributional consequences, as all but the highest-risk households pay premiums above their own marginal cost.

Our framework rationalizes recent dynamics observed in the California homeowners insurance market, the largest in the United States. Following record-setting wildfire seasons in 2017 and 2018, insurers cited restrictive regulations as part of the reason for denying continued coverage to more than 200,000 homeowners, primarily in areas of high wildfire risk, a 61% increase from previous years (Bikales, 2020; California Department of Insurance, 2021). At the same time, take-up of policies offered through the California Fair Access to Insurance Requirements (FAIR) Plan, the state's insurer of last resort, spiked in the same areas. These dynamics are consistent with private firms reducing their exposure by ceding their highest-risk consumers to the insurer of last resort.

We then investigate the effects of the California nonrenewal moratorium, a novel policy implemented by the state legislature and California Department of Insurance to limit insurers' ability to shift high-risk policies from the voluntary market into the FAIR Plan. First enacted in 2019, the moratoriums require insurers to continue supplying insurance through a guaranteed one-time renewal to current policyholders in zip codes affected by, or adjacent to, a wildfire that triggered a declared state of emergency. In the model, when regulated prices cannot fully adjust, private insurers respond to rising costs by changing who they insure, ceding higher-cost households to the residual market. The moratorium directly restricts this margin of adjustment by temporarily preventing insurers from nonrenewing policies in covered areas.

Identifying the effects of insurance regulation is typically challenging because policy interventions are closely tied to underlying risk conditions or affect the entire state at once. We overcome this challenge by exploiting quasi-random spatial variation in moratorium coverage generated by wildfire perimeters and administrative boundaries. Using a generalized difference-in-differences framework, we compare zip codes just inside and outside the moratorium boundaries, which are similar in observable characteristics and exposure to wildfire risk but differ in regulatory treatment, before and after the imposition of a nonrenewal moratorium. To limit potential concerns about within-insurer spillovers, we further refine the control group by excluding zip codes disproportionately served by insurers most affected by the moratorium. This design allows us to isolate the causal effect of the moratorium on insurance market outcomes.

We find that zip codes subject to the moratorium experienced a statistically significant decrease in company-initiated nonrenewals during the year the moratorium was active, with no offsetting increase in customer-initiated nonrenewals, indicating that the regulation was binding for insurers. However, this effect was short-lived; in the year immediately following the expiration of the moratorium, the treated zip codes not only caught up to, but exceeded the number of nonrenewals in control zip codes, representing a 78% increase from baseline annual company-initiated nonrenewals for the treated areas.

These results indicate that the moratoriums did not prevent eventual nonrenewals, but simply delayed and then accelerated insurer nonrenewal activity for higher-risk consumers. Additionally, our results indicate that the majority of nonrenewal customers did not switch to another private insurer, but instead obtained coverage through the FAIR Plan. These findings suggest that the moratoriums did little to slow the retreat of private insurers and may have accelerated insurers' exit from high-risk areas. One year after the moratorium, the number of policies written in the voluntary market had fallen by 3% in treated areas, while the number of FAIR Plan policies had risen by 115% relative to baseline.

This paper first contributes to the literature on property insurance markets (Kunreuther, 1996, 2001; Kousky, 2011; Born and Klimaszewski-Blettner, 2013; Oh et al., 2026; Kousky, 2022). While a growing set of studies examine the pricing of disaster risk (Keys and Mulder, 2024; Sastry et al., 2024; Blonz et al., 2026; Boomhower et al., 2024; Ge et al., 2026; Oh et al., 2026), there is little evidence on how regulation impacts adjustment along the extensive margin of coverage. We provide causal evidence on how regulatory constraints affect insurers' supply decisions in disaster-exposed markets. We show that restrictions on nonrenewals bind in the short run but may lead to intertemporal shifting and the potential acceleration of insurer exit.

In particular, we contribute to the literature on public intervention in disaster insurance markets, both empirically and theoretically. Due to data constraints, most of this literature has focused on the National Flood Insurance Program, which covers most of the flood insurance market (Wagner, 2022; Mulder, 2024; Weill, 2026; Marcoux and Wagner, 2025). Outside of flood insurance, a majority of states now have insurers of last resort, who operate alongside private markets and whose role progressively evolved to provide coverage to properties most exposed to disaster risk. We provide a simple framework to conceptualize the role of insurers of last resort. We show that these residual markets are an institutional feature rendered necessary by the combination of price regulation and insurance mandate requirements for mortgaged homes. We clarify their distributional impacts and estimate how rising costs and regulation determine the allocation of households across market segments.

Finally, this paper adds to the broader literature on climate adaptation (Barreca et al., 2016; Baylis and Boomhower, 2023; Kousky, 2019; Baylis and Boomhower, 2026) and, in particular, to the thinner literature on firm adaptation (Pankratz and Schiller, 2024; Gu and Hale, 2023; Castro-Vincenzi, 2024; Bilal and Rossi-Hansberg, 2023). We provide, to our knowledge, the first causal evidence on the insurance market effects of California's nonrenewal moratoriums, and examine how regulatory constraints interact with insurers' adaptation to climate risk. Particularly relevant to our work, You et al. (2024) study the impacts of the California nonrenewal moratorium on housing markets. While we estimate that the moratorium did not cause in-migration or out-migration, You et al. (2024) find that the moratorium reduced loan applications. Reconciling these findings suggests two possibilities. First, households may have responded to the moratorium by shifting from mortgage-financed purchases to renting or cash purchases. Alternatively, the moratorium may have deterred in-migration of new mortgaged homeowners on the margin, but without meaningfully altering the total flow of homeowners and renters captured in our data.

This paper proceeds as follows. Section 2 provides background on the California moratoriums, while section 3 introduces our conceptual model. Section 4 presents the data used, section 5 introduces the empirical framework, and section 6 presents the results. Section 7 concludes.

2 Institutional background

2.1 Insurance markets

Home insurance pricing in the U.S. is heavily regulated. Since 1945, states have been given the power to regulate insurance and do so with the goals of preventing prices that are (i) unreasonable, (ii) unfairly discriminatory, or (iii) insufficient to guarantee the solvency of firms (McCarran-Ferguson Act, 1945). Price regulation aims to balance fairness objectives with insurance availability; this implies that for subsets of consumers, premiums can diverge from expected costs.

Price regulation takes a variety of forms in practice. In many states, before new insurance rates can be implemented, insurers must first obtain approval from the state's Department of Insurance. This administrative process is often cumbersome and frequently lasts more than 12 months (Oh et al., 2026), with the specifics of the rate approval process varying widely between states. At the time of the initial moratorium regulation, in 2019, insurers in California faced three regulations that explicitly restricted price increases. First, overall rate increases of 7% or higher (calculated over the insurer's entire portfolio) are subject to additional in-depth public scrutiny at the unrecoverable cost of the insurer (California Ballot Propositions and Initiatives, 1988), resulting in an effective rate increase cap (Boomhower et al., 2024).[1] Second, California regulation required the overall rate for natural disasters, known as the catastrophe load, to be justified by historical averages of losses over at least the prior 20 years (California Code of Regulations, 2024). Until 2023, insurers in California were not allowed to incorporate forward-looking catastrophe models or other means of forecasting as justification for higher overall catastrophe loads, exacerbating premium inadequacy when past loss experience poorly reflects future expectations.[2] Finally, California restricted insurers from passing reinsurance costs through to consumer premiums. Recent work documents substantial

[1] Because the 7% regulatory constraint is calculated as the average rate increase over the full portfolio of the insurer, premiums can still increase by more than 7% for some individual homeowners.

[2] While forward-looking catastrophe models could not be used to set the overall rate level, they could be used, if approved, to set rate differentials across policies. Boomhower et al. (2024) shows that there is significant heterogeneity in how firms take catastrophe risk estimates into account, with most of the firms studied failing to capture the difference in wildfire risk across locations.

increases in reinsurance premiums over the past several years, as global reinsurance companies are not subject to the same regulatory oversight and premium approval process as primary insurers (Keys and Mulder, 2024). Together, these various regulations can drive a wedge between the costs faced by insurers and the premium they are able to charge the customer.

State regulation also routinely specifies which observable home and homeowner characteristics are permissible in the underwriting and rating processes, often citing that the use of some variables can be unfairly discriminatory. Banning the use of certain characteristics ("protected classes") that ultimately contain information on expected losses implies that after conditioning on the remaining permissible observables, consumers that are offered the same premium can still vary in their expected costs. As an example, while some characteristics are protected throughout the U.S. (such as gender, race, and religion), California is one of only three U.S. states that ban the use of credit history in homeowners insurance pricing (Blonz et al., 2026).

In addition to stringent regulations, homeowners insurance markets face mounting pressures from losses linked to natural disasters, and wildfires in particular. The 2025 Los Angeles wildfires are the 4th costliest natural disaster in U.S. history, while the 2018 Camp Fire (Paradise, CA) ranks 14th (Hartwig, 2025). Additionally, at least one wildfire has reached the $1 billion damage threshold each year since 2015 (National Centers for Environmental Information, 2025). In California, the value of real estate exposed to wildfire risk is over $500 billion, more than any other natural disaster peril. This exposure is starting to pose a threat to insurance availability: the California Department of Insurance identifies 662 ZIP codes with 1.47 million residential property insurance exposures in distressed areas, defined as zip codes where more than 15% of properties rely on the FAIR Plan for insurance. As of March 2026, the California FAIR Plan has grown to 684,388 policies and $750 billion in total exposure (California Department of Insurance, 2026; CFP Board, 2026).[3]

[3] Although wildfire risk primarily threatens local insurance availability (rather than statewide supply), concerns still exist regarding the stability of the overall market in the state. For instance, State Farm previously stopped accepting new California property-and-casualty applications in 2023, citing rapidly growing catastrophe exposure, while Allstate also paused new California homeowners policies (Gonzalez, 2023; California Department of Insurance, 2023). Another concern is the possibility that wildfires could eventually be treated like floods and earthquakes, which are carved out of the standard homeowners insurance policy (Liao et al., 2024), although increased reinsurance availabil-

2.2 California moratoriums

Following record-breaking losses from wildfires in 2017 and 2018, insurance companies began to increasingly refuse to renew insurance policies in parts of California. Such company-initiated nonrenewals can happen for a wide range of reasons beyond wildfires, but nonrenewal rates are typically low. An increase in the frequency of nonrenewal indicates that homeowners might not be able to purchase insurance in the private market. In order to give "millions of Californians breathing room and hit the pause button on insurance nonrenewals while people recover," the California legislature passed Senate Bill 824 in 2018. This bill prohibits insurance companies from not offering a policy renewal solely on the basis of wildfire risk in any zip code either directly impacted by, or adjacent to, a wildfire that caused a state of emergency (California Department of Insurance, 2019). The moratorium was first applied to fires in Los Angeles and Riverside counties in October 2019. As of January 2025, 25 separate moratorium declarations have been issued and continue to be implemented for new state of emergency fires.

Each moratorium lasts one year from the date of emergency declaration. In the work that follows, we refer to the moratoriums by yearly cohorts: the collection of nonrenewal moratoriums initiated following the 2019 fire season is the "2020 Moratorium," while those initiated after fires in 2020 are referred to as the "2021 Moratorium".[4]

Due to the stochastic nature of wildfire perimeters, zip codes located near each other can be differentially impacted by the moratorium despite being observably similar. This quasi-random spatial variation in moratorium coverage forms the basis of our identification strategy to estimate the causal impacts of the policy on insurance market outcomes. In addition, Senate Bill 824 was a first-of-its-kind legislation nationwide, swiftly enacted within one year, providing firms little to no response time to make any *ex ante* adjustments to their insurance portfolio. As the moratoriums continued each year, firms were able to respond to the changes in the environment by changing for

ity and catastrophe bond backstops lower the risk of a systemic collapse similar to those that preceded the carve-out of flood and earthquake insurance.

[4]The starting dates of the moratoriums vary based on the occurrence of wildfires: for the years examined in our study, the earliest start date for a moratorium is August 18 and the latest start date is November 18.

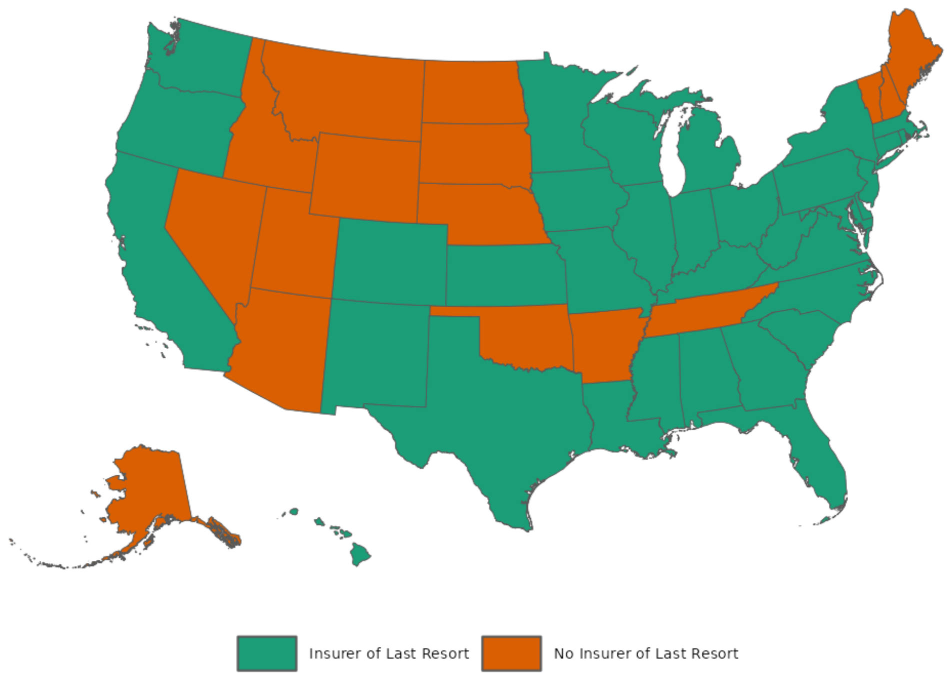
whom they wrote policies, increasing rates, and even completely halting new business operations in the state (Kaufman, 2021). As such, in our empirical study of the regulation, we focus on the short-run effects of the first two years of the moratorium to avoid contamination from endogenous firm anticipatory response in the long run.

2.3 Insurers of Last Resort

Insurers of last resort are state-run (or state-sponsored) plans that provide coverage for properties unable to find insurance in the voluntary market. FAIR Plans were started in 26 states, the District of Columbia, and Puerto Rico in 1968 following the riots and brushfires of the 1960s (Dwyer (1978) offers a discussion of the origin of FAIR Plans). These plans take a variety of forms. Some states have "wind pools" or "beach plans," which cover specific perils with limited geographic coverage, while others operate more broadly (see Kousky (2011) for a discussion of 10 state-sponsored programs and Wallace (2026) for a recent review of the California FAIR Plan). Today, 34 states and the District of Columbia have an insurer of last resort, shown in Figure 1. While insurers of last resort were originally established during the civil rights movement in response to urban unrest and insurance redlining in predominantly minority neighborhoods, their role slowly evolved to address the insurer retreat driven by climate risk and rising costs. Colorado became the latest state to establish a FAIR Plan in 2023, specifically in response to increasing wildfire losses and insurer retreat from high-risk areas.

The California FAIR Plan is a syndicated fire insurance pool, which issues policies on behalf of all companies licensed to write property and casualty insurance in California. Each member company participates in the FAIR Plan's profits, losses, and expenses in direct proportion to its statewide market share and thus is invested in the financial stability of the FAIR Plan. The goal of the FAIR Plan is to provide temporary, basic fire insurance when consumers cannot find insurance in the voluntary market. California FAIR Plan policies are typically more expensive than the voluntary market, have a maximum coverage amount of $3 million for residential properties, and only cover a limited set of perils, requiring customers to obtain an additional difference in coverage

Figure 1: Insurers of last resort in the United States



Note: This map shows which states have an insurer of last resort, or state-sponsored property insurance plan, that provides coverage to individuals who are unable to obtain insurance in the voluntary market.

(DIC) policy in order to replicate the full set of coverages offered in a standard homeowner's insurance policy. Despite these differences, FAIR Plan and voluntary insurance policies can, to some extent, be seen as substitutable, as both can satisfy the requirements of mortgage lenders for homeowners insurance.

3 Conceptual model

Profit-maximizing insurers have an incentive to offer coverage only to consumers whose expected costs are below the premium they are permitted to charge. Regulation that restricts or lowers the permissible price leads firms to reduce the set of consumers they are willing to insure. Similarly, this can occur if expected costs rise faster than the regulated price, all else equal. We formalize this intuition with a simple framework that draws upon standard production theory and models of insurance supply. In particular, we focus on how regulation affects the allocation of consumers across the voluntary and residual markets and the resulting distribution of costs for households and firms. We begin by characterizing supply and demand in the presence of price regulation and use a graphical approach to illustrate how the market equilibrium changes with increasing disaster costs and a forced supply regulation, like the nonrenewal moratorium.

We consider a continuum of homeowners indexed by $i \in [0, 1]$, who each make a discrete purchase decision for a homogeneous full-coverage insurance policy. Consumers purchase their policy from either a private and competitive ("voluntary") market, or from the residual market (the insurer of last resort or FAIR Plan). Homeowners are ordered by their marginal cost to the insurer, $c(i)$, which includes expected disaster losses, non-disaster losses, and other insurer costs.[5] We assume that demand for insurance is highly inelastic, driven by mortgage requirements, and sufficiently high that all homeowners wish to purchase coverage at the prices considered.

The voluntary and residual markets differ in their pricing regime. In the voluntary market, we assume that the regulator sets a fixed price $\hat{P}$. This assumption is meant to capture the complex state-level rate-approval process in a tractable way. In practice, rate regulations can be imposed through many channels such as restrictions on the variables that the insurers can use in pricing to promote fairness (such as gender or race), whether catastrophe loss models are allowed, or how much reinsurance costs can be passed on to homeowners (California Code of Regulations, 2023).[6]

In contrast, we assume that the price can adjust freely in the residual market but must satisfy its zero-profit condition. This assumption reflects the conditions imposed on the California FAIR Plan, which is not subject to Proposition 103 and must charge adequate rates without subsidization per regulation, and is further able to pass through reinsurance costs to policyholders, unlike the private market (California State Assembly, 2023).[7]

Finally, we assume that insurers have full information and observe the marginal cost curve.

[5] These other costs include loss adjustment expenses, underwriting expenses, administrative costs, and reinsurance costs.

[6] Another rationale for regulating prices could be to counteract monopoly power. In California, the homeowners insurance market is thought to be fairly competitive: on average 36 insurers operate in each zip code, with no single company having a statewide market share over 20%.

[7] Although the FAIR Plan is mandated to operate at zero-profit, they are allowed to issue assessments on member firms if funds are insufficient on hand to fully pay out claims. Most recently, the FAIR Plan issued a $1 billion assessment to help pay for claims from the 2025 Los Angeles wildfires (California Department of Insurance, 2025).

This assumption is implausible in the context of health or auto insurance markets, where consumers often hold substantial private information about their expected costs. In homeowners insurance, however, many of the characteristics that impact expected losses are observable to both insurers and policyholders (such as location, building materials, number of floors, or roof structure). Although some drivers of cost, especially disaster risk, remain difficult to measure accurately (Boomhower et al., 2024; Heitfield, 2026), homeowners are unlikely to systematically possess private information about disaster risk that insurers do not also observe. This differentiates our model from the canonical model of selection markets under asymmetric information in Einav et al. (2010). These simplifications allow us to focus on the role of the residual market, abstracting from additional forces related to consumer private information and other informational asymmetries.

3.1 Market segmentation

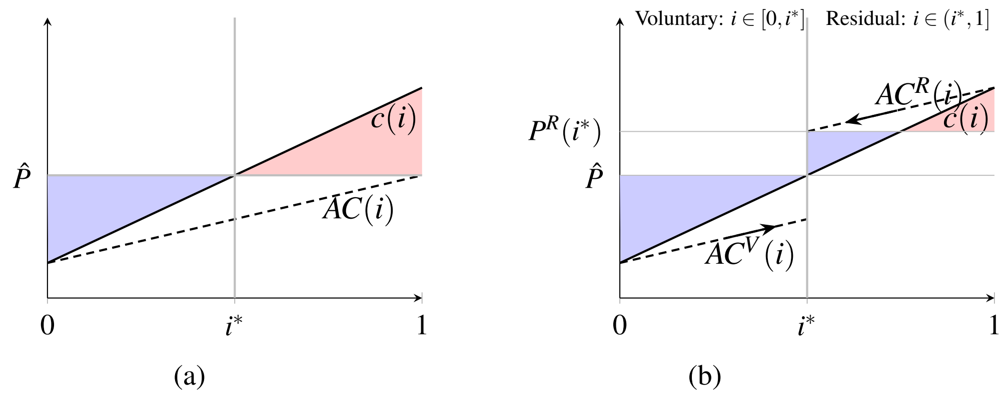
As a benchmark, in a competitive, unregulated market, where insurers have full information, each homeowner is charged a premium equal to their marginal cost. Because demand is assumed to be high, all homeowners purchase insurance in the voluntary market: $p(i) = c(i), \forall i \in [0,1]$. In this case, firms make no profits, but are willing to insure all homeowners with no need for a residual market. Total welfare in the market is captured by homeowners as consumer surplus. If there were a nonrenewal moratorium imposed in this market, both firms and consumers would be unaffected.

When regulation requires insurers in the voluntary market to charge a common premium, $\hat{P}$, to consumers with different observable characteristics (i.e., different marginal costs), competitive insurers will supply coverage only to homeowners whose marginal cost is no greater than $\hat{P}$.[8] Let i^* be the cutoff defined by $c(i^*) = \hat{P}$. The voluntary market then covers homeowners $i \in [0, i^*]$, while the remaining share, $1 - i^*$, is ceded to the residual market. This cutoff arises because insurers have full information and any homeowner $i > i^*$ would generate losses at the regulated premium:

[8] Risk pooling of consumers with differing observable characteristics and expected losses can arise from regulation and insurer pricing granularity. This can vary across states and firms. Our model and accompanying figures depict the effects within one representative tranche of the market, but the logic generalizes to all groups of consumers who must be charged the same regulated price. Overall market effects thus are the sum of the effects across all groups.

if these consumers were served in the voluntary market, insurers would earn negative profits on those policies, as illustrated by the red triangle in Figure 2 (a). In contrast, insurers earn positive profits on the infra-marginal policies they do insure (blue triangle). Total voluntary-market profits are therefore given by $\Pi_V = \int_0^{i^*} \left(\hat{P} - c(i)\right) di$.

Figure 2: Price-regulated insurance market



The figure presents a tranche of the homeowners insurance market where consumers, i, with different marginal costs, $c(i)$, are charged the same price. **(a)** With a regulated premium $\hat{P}$ in the voluntary market, competitive insurers supply only to homeowners with $c(i) \leq \hat{P}$. The blue triangle shows voluntary-market profit $\hat{P} - c(i)$ for $i \leq i^*$, and the red triangle shows negative profits if these consumers were to be insured in the voluntary market. The dashed line is the average cost curve $AC(i) = \mathbb{E}[c(s) \mid s \leq i]$. **(b)** In the presence of an insurer of last resort, insurers in the voluntary market cover $i \in [0, i^*]$ at price $\hat{P}$, while the residual market covers $i \in (i^*, 1]$ at pooled premium $P^R(i^*) = \mathbb{E}\left[c(i) \mid i > i^*\right] = \frac{1}{1-i^*} \int_{i^*}^1 c(s)\, ds$. The average cost curves in the two market segments are defined as $AC^V(i) = \frac{1}{i} \int_0^i c(s)\, ds$ and $AC^R(i) = \frac{1}{1-i} \int_i^1 c(s)\, ds$ before and after i^*, respectively. Arrows indicate the direction in which each market accumulates consumers: from the lowest-cost consumer upward in the voluntary market, and from the highest-cost consumer downward in the residual market.

In the residual market, the FAIR Plan must still charge a single price for the set of consumers, but charges a single pooled premium that equals the average cost over the consumers it serves and is given by the zero-profit condition, $P^R(i^*) = \mathbb{E}\left[c(i) \mid i > i^*\right] = \frac{1}{1-i^*} \int_{i^*}^1 c(s)\, ds$ (Figure 2 (b)). Some policies are still priced below their marginal cost (small red triangle), but these negative profits are now offset by the relatively safer policies in the FAIR Plan, which are priced above their marginal cost.

The two average cost curves in Figure 2b lie on opposite sides of the marginal cost curve because the two markets accumulate consumers from opposite ends of the risk distribution. The voluntary market fills from the lowest-cost consumer upward: $AC^V(i)$ averages marginal costs over $[0,i]$, so it lies weakly below $c(i)$, with equality at $i = 0$, where the pool contains a single consumer. The residual market instead fills from the highest-cost consumer downward: for any cutoff i, it serves the highest-cost homeowners in $(i,1]$, and a lower cutoff extends the pool toward lower-cost homeowners. Its average cost, $AC^R(i)$, therefore averages marginal costs over $[i,1]$, so it lies weakly above $c(i)$, with equality at $i = 1$, where the pool contains a single consumer. The arrows in Figure 2b depict these two directions of aggregation. At the cutoff i^*, the vertical distance between $P^R(i^*) = AC^R(i^*)$ and $\hat{P} = c(i^*)$ shows the pricing wedge faced by the marginal consumer: the first homeowner excluded from the voluntary market pays the pooled residual-market premium rather than a premium equal to her marginal cost.

This stylized example highlights the role of the residual market: it ensures that all consumers can still purchase an insurance contract *despite* (i) the strict price regulation in the voluntary market, and (ii) the requirement that policies with different observable characteristics and marginal costs be priced the same. To see this, note that in the absence of the residual market, consumers with marginal costs above the regulated price cannot buy insurance regardless of how much they are willing to pay, as no firm is willing to insure them. The residual market is an institutional feature rendered necessary by the combination of price regulation and insurance requirements for mortgaged homes.

Relative to the benchmark in which each consumer is charged her marginal cost, the combination of price regulation and a residual market also has important distributional consequences. Consumers who remain in the voluntary market now pay premiums above their marginal cost, with the largest markups borne by the lowest-risk households. Firms capture this loss in consumer surplus and make weakly positive profits. In contrast, consumers in the residual market are pooled at an average cost that necessarily exceeds both the regulated voluntary market price, $\hat{P}$, and the average cost in the market as a whole because the residual market disproportionately serves the highest-risk households. Within the residual market, this pooling implies cross-subsidization: the riskiest consumers pay less than their marginal cost, while the relatively less risky consumers pay more than theirs.

We interpret this allocation as a short-run equilibrium sustained by rate regulation. Because premiums require prior regulatory approval, insurers cannot freely adjust prices in response to profits or losses, and the margin of adjustment becomes the choice of which homeowners to insure. Entrants and incumbents must both charge the regulated premium, so price competition does not push the voluntary market toward the zero-profit allocation in which the premium equals average cost.[9] The next subsection examines the case central to our setting, in which marginal costs rise faster than the regulated premium and short-run profits on previously written policies erode.

3.2 Supply response to wildfires

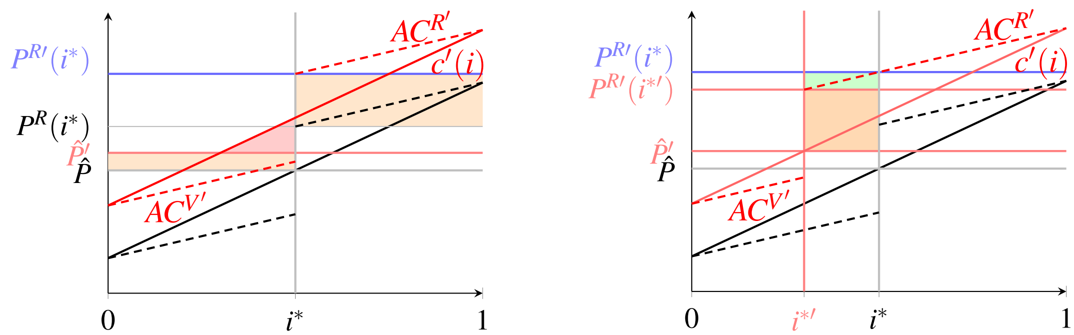
We next consider how this segmented market adjusts following a wildfire. A wildfire can affect the market through three main channels[10]: First, insurers may update their beliefs about wildfire risk upward. Second, claim payments may increase the cost of capital for both primary insurers and reinsurers (Froot and O'Connell, 1999). Both channels would shift the marginal cost curve, and thus the supply curve, outward. Finally, wildfires can lead policymakers to relax the price regulation in the voluntary market, as has been seen in California with the introduction of catastrophe models in rating in 2025, leading to a higher $\hat{P}$.[11]

[9] Over a longer horizon, if costs were constant then sustained underwriting profits would be expected to attract entry and to lead the regulator to revise rates downward. Conditions in California have moved in the opposite direction over our study period with approved rates lagging rising costs, and several major insurers restricting or completely halting new business in the state (Kaufman, 2021).

[10] For tractability, we assume that the wildfire does not meaningfully affect the number of participants in the market. Although this assumption is unlikely to hold at the scale of specific towns or neighborhoods (Wang, 2025), Appendix Figure A8 suggests that it is reasonable for the broader areas affected by a moratorium.

[11] Wildfires could also lead households to update their beliefs about risk, thus leading the demand curve to shift. This case is assumed away here as we already consider a high and inelastic demand curve.

Figure 3: Price-regulated insurance market under increasing costs



(a) (b)

The figure presents a tranche of the homeowners insurance market where consumers, i, with different marginal costs, $c(i)$, are charged the same price. The figure depicts an upward shift in the marginal cost curve from $c(i)$ to $c'(i)$, which is only partially offset in the voluntary market by an increase in the regulated premium, from $\hat{P}$ to $\hat{P}'$, where $\hat{P}' - \hat{P} < c'(i^*) - c(i^*)$. **(a)** The first panel shows the situation under a nonrenewal moratorium, when firms are not allowed to cede policies to the residual market. The shaded orange rectangle shows the increase in voluntary-market revenue on inframarginal policies when the regulated premium rises from $\hat{P}$ to $\hat{P}'$, while the red triangle captures losses on policies between $i^{*\prime}$ and i^* under the shifted cost curve $c'(i)$. **(b)** The second panel shows the situation when the nonrenewal moratorium expires. Under the shifted cost curve and higher regulated premium $\hat{P}'$, the voluntary-market cutoff moves to $i^{*\prime} < i^*$, and the residual-market pooled premium rises to $P^{R\prime}(i^{*\prime})$. The orange rectangle depicts the loss in consumer surplus borne by consumers ceded from the voluntary market to the residual market, while the green rectangle depicts the benefit of having lower-risk consumers enter the residual market.

Both panels of Figure 3 present the situation (in red) where the regulated price adjusts more slowly than costs increase. That is, the regulated price increases from $\hat{P}$ to $\hat{P}'$, with $\hat{P}' - \hat{P} < c'(i^*) - c(i^*)$. Such slow regulatory adjustment is likely to occur because of the length of the rate-filing process. In contrast, the price in the residual market adjusts to yield zero profits.

Panel (a) of Figure 3 depicts the California homeowners market under a nonrenewal moratorium, when firms cannot adjust the set of consumers they serve in the voluntary market (i^* is fixed at the previous level). As the regulated price rises in the voluntary market, consumers experience a loss in consumer surplus equal to the orange rectangles in the voluntary and residual markets. At the same time, firms in the voluntary market face the new, higher marginal cost curve $c'(i)$. They earn negative profits on consumers whose marginal cost exceeds the new regulated price, represented by the red triangle, and would prefer not to insure them absent the regulation. This situation may persist in the short run because firms still earn profits on infra-marginal consumers with costs below the regulated price $\hat{P}'$. But, if the upward shift in marginal costs is not sufficiently matched by a higher regulated price, and firms cannot cede the highest-risk homeowners to the residual market, they may choose to exit the market entirely in the long run.

Panel (b) depicts the market when firms are able to adjust their portfolio given the new regulated price and cost curves (i^* is allowed to adjust to $i^{*'}$). This situation represents the California market at the expiration of the one-year nonrenewal moratorium. Following the shift in the cost curve, the voluntary market cedes all consumers who have a new marginal cost higher than the new regulated price: these consumers are between i^* and $i^{*'}$, where $i^{*'}$ is determined by the intersection of the new marginal cost curve and the new regulated price. Because we consider a demand curve that is sufficiently high, all consumers ceded from the voluntary market purchase insurance in the residual market. These ceded consumers have lower marginal costs than those already participating in the residual market, therefore reducing the residual market price from $P^{R'}(i^*)$ to $P^{R'}(i^{*\prime})$. Relative to the premium that prevailed before the cost shift, $P^R(i^*)$, the net change in the residual-market price is ambiguous: the upward shift in the cost curve raises the pooled premium, while the arrival of lower-cost consumers ceded from the voluntary market lowers it. Figure 3b depicts the case in which the cost shift dominates and the residual-market price rises on net, consistent with the FAIR Plan premium increases we document in Section 4.

The costs of allowing adjustment from i^* to $i^{*'}$ are entirely borne by the group of consumers forced out of the voluntary market. These consumers now pay the higher residual market price and lose the orange area in Figure 3 (b). Consumers already in the residual market experience a benefit, shown by the green rectangle, because the addition of lower-risk consumers to the risk-sharing pool reduces the price.

Our model generates three testable hypotheses: (i) premiums increase in both the residual market and voluntary market in response to wildfires, (ii) the moratorium is effective at stopping the transition from the voluntary market toward the residual market while it is in place, and (iii) the residual market share increases when the moratoriums become inactive. Prediction (i) is unambiguous for the voluntary market, but for the residual market it holds only when the cost-curve shift dominates the compositional change from newly ceded consumers, as depicted in Figure 3b.

We test prediction (i) with descriptive evidence in the Data section and predictions (ii) and (iii) with a difference-in-differences identification strategy, outlined in Section 5.

4 Data

4.1 Insurance data

We obtain homeowners insurance data from the California Department of Insurance (CDI). These data are a combination of two separate products: the Residential Property Experience (RPE) and the Community Service Statement (CSS). The RPE dataset reports the number of new, renewed, and nonrenewed policies at the zip code-year level. We observe whether the decision to not renew the policy was initiated by the insurer or the customer. The data are available yearly from 2015 to 2021.

The CSS contains data on earned exposure units, earned premiums, and average premium at the contract type-company-zip code-year level for all insurance companies licensed to operate in California from 2009 to 2022, including the California FAIR Plan. We construct the total number of policies by dividing exposure units by 12; one exposure unit is one month of coverage for one insurance policy. We construct statistics for the voluntary market by aggregating over private firms, weighting by market share. We aggregate to the market (voluntary or residual)-zip code-year level for dwelling owner-occupied personal fire contracts and homeowner multi-peril policies. We exclude policies that only provide coverage for contents, renters/tenant coverage, and policies covering unoccupied dwellings or mobile homes.

4.2 Wildfire boundaries

We use geolocated fire perimeters from the California Department of Forestry and Fire Protection (CalFire)'s Fire and Rescue Assessment Program (FRAP) to identify the location of wildfires during our sample period. The fire perimeters are developed by CalFire jointly with the U.S. Forest

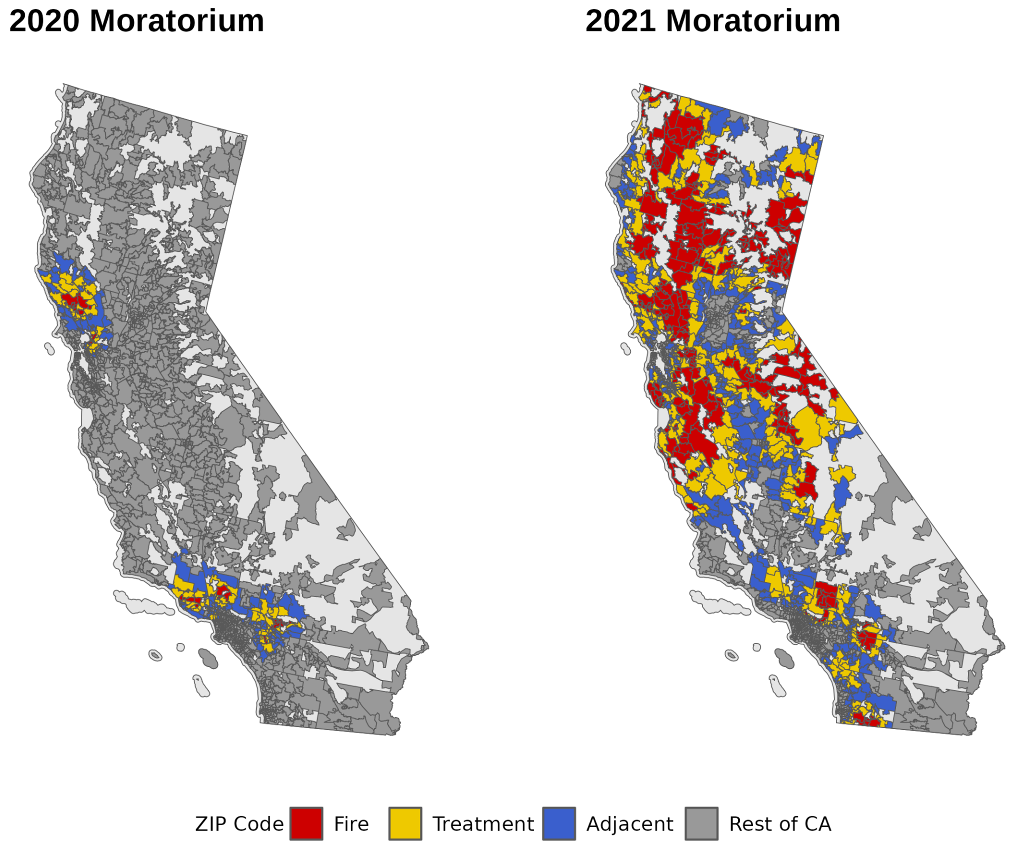
Service, the Bureau of Land Management, the National Park Service, and the Fish and Wildlife Service, covering both public and private lands in California. We exclude prescribed fires from the dataset.

4.3 Nonrenewal moratorium status

We identify zip codes subject to a nonrenewal moratorium in 2020 or 2021 using data from the California Department of Insurance. Under the legislation, zip codes directly affected by a wildfire that triggered a state-of-emergency declaration, along with their immediate neighbors, are covered by the moratorium for one year following the declaration. We classify zip codes into four categories. Two of these groups are subject to the moratorium: "Fire" zip codes are those directly affected by wildfire activity, whereas "Treatment" zip codes are neighboring areas included in the moratorium zone despite not experiencing direct fire impacts.[12] "Adjacent" zip codes are those that directly border the moratorium area, but are not covered by the legislation. "Rest of State" encompasses all other unaffected zip codes further from the moratorium. Figure 4 depicts the designations by zip code for the 2020 and 2021 moratoriums, separately. Of note is the difference in magnitude between the years, with 2021 covering many more zip codes than 2020.

[12]The CDI dataset does not delineate why a zip code was included in the moratorium. We designate moratorium zip codes that border a non-moratorium zip code as being "Treatment". This method most closely aligns with the wording of the legislation. A similar set of "Treatment" zip codes is designated if we instead intersect zip codes with fire perimeter data and designate moratorium zip codes not impacted by fire as "Treatment". We further discuss both methods in Appendix D, where Appendix Figure A6 shows that our main results are unchanged under this alternative definition.

Figure 4: Moratorium classifications by zip code



Note: The nonrenewal moratoriums cover both "Fire" and "Treatment" zip codes. 'Adjacent' zip codes are not covered, but share a border with a zip code covered by a moratorium. 'Rest of CA' are all other unimpacted zip codes. Light gray areas are not assigned a zip code.

4.4 Wildfire risk

Finally, we use the 2014 version of the Risk to Potential Structures (RPS) measure from the U.S. Forest Service to quantify wildfire risk. For each 30x30 meter pixel in California, RPS measures the expected annual structure loss from wildfire to a home, if one were located there. We construct aggregate wildfire risk measures by averaging over pixels within each zip code.[13] RPS captures both the probability of a fire and its expected intensity across the zip code, regardless of actual dwelling locations. One limitation is that RPS represents a snapshot of conditions in 2014

[13]Formally, we use the census Zip Code Tabulation Areas (ZCTA) to construct spatial data to match the level of observation of our insurance data, but employ the more common term "zip code" in the rest of the text.

and does not account for variation in home construction types or heterogeneous changes in risk over time. A newer version of the RPS dataset became available in 2024. This version, however, reflects landscape conditions at the end of 2022, after the fires in our analysis, making the 2014 version more suitable for our use.

4.5 Descriptive evidence

We present the summary statistics for our main variables in Table 1. On average, the FAIR Plan insures only 1.7% of the market during our sample period.[14] The average FAIR Plan premium is not directly comparable to the average voluntary premium, as the FAIR Plan premium reflects only the portion of the policy insured through the FAIR Plan (which covers specific, limited perils and does not include the premium from the difference-in-coverages policy which must be purchased from a third-party company to replicate a complete homeowners policy). In a zip code, the vast majority of policies in a year are either renewed by the insurer or nonrenewed by the customer, with only 2% of policies being nonrenewed by the company, on average. Lastly, we report the average zip-code RPS measure and median household income that are used in the heterogeneity analyses that follow.

Figure 5 shows the evolution of the key insurance outcomes based on the 2020 moratorium classification, expressed relative to their 2015 baseline level.[15] Panel A suggests that the moratorium was binding for firms, as "Fire" and "Treatment" zip codes both experience a decrease in the number of company-initiated nonrenewals the year they were covered by the moratorium, in contrast to the continual increase in "Adjacent" and "Rest of State" zip codes. However, there is a large reversal the following year when the moratorium was lifted for the moratorium groups. While only descriptive, these statistics are consistent with our model predictions: the moratorium appears to be successful at altering firm behavior, but only in the short term.[16]

[14] In Appendix Table A1 and Appendix Table A2, we break out the summary statistics by moratorium designation and cohort. Zip codes eventually covered under a moratorium have moderately higher FAIR Plan market shares.

[15] Appendix Figure A1 presents the same statistics for the 2021 moratorium classification with similar takeaways.

[16] Note that we do not expect insurer-initiated nonrenewals to vanish completely during the moratorium because insurers are still allowed to not renew policies for reasons other than wildfire risk.

Table 1: Summary statistics

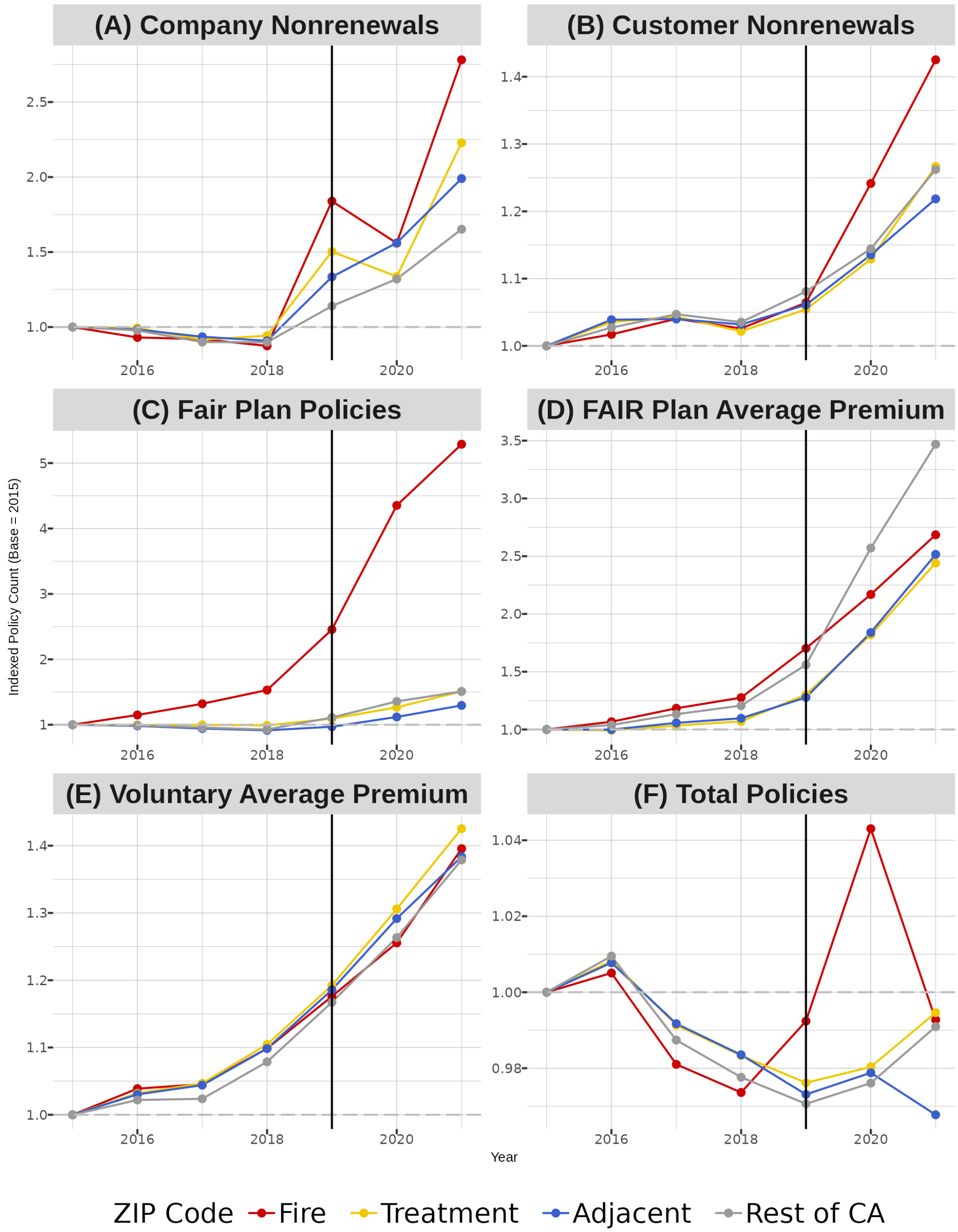
Statistic	Mean	St. Dev.	N	Source
FAIR Plan Policies	62.34	198.81	24,616	CSS
Voluntary Policies	3,622.91	3,749.63	24,616	CSS
Average Premium	1,178.21	757.54	24,616	CSS
Average Voluntary Premium	1,175.52	759.56	24,615	CSS
Average FAIR Plan Premium	1,055.00	1,005.89	20,269	CSS
New Policies	606.63	657.33	12,262	RPE
Renewed Policies	4,342.21	4,321.98	12,262	RPE
Company-Initiated Nonrenewals	121.53	144.76	12,262	RPE
Customer-Initiated Nonrenewals	447.91	483.01	12,262	RPE
RPS	0.27	0.46	24,616	USFS
Median Income	72,888.82	34,014.67	22,694	ACS

A potential concern in our setting is that firms could circumvent the moratorium by disguising a company-initiated nonrenewal as a customer-initiated nonrenewal. This concern does not seem warranted: Panel B shows that customer nonrenewals evolve similarly between "Treatment", "Adjacent", and "Rest of State" zip codes at the time of the moratorium. "Fire" zip codes experience a faster increase in customer nonrenewals, which can be explained by homeowners ending their policy after the destruction of their home or increased insurance shopping behavior following the disaster.

Another takeaway from the conceptual model was that following a shift in the supply curve, premiums in the voluntary market would increase up to the new regulated price, while premiums in the FAIR Plan could either increase or decrease, depending on which effect dominates between the ceding of relatively lower-risk policies from the voluntary market and the upward shift in the cost curves. In panels D and E, we show that across all zip code classifications, premiums begin increasing faster in 2019 for both the voluntary market and the FAIR Plan after the 2017 and 2018 fire seasons. The scale of the increases is significantly larger in the FAIR Plan, climbing 250-350% from 2015-2021. Voluntary market premium increases hover around 7% per year, suggesting that the price increase cap was binding.

Panel C of Figure 5 shows the changes in the number of FAIR Plan policies. By 2021, the

Figure 5: Statistics by 2020 moratorium classification



Notes: Indexed changes, relative to 2015 baseline levels, are shown for variables by 2020 moratorium classification groupings. "Fire" zip codes were directly impacted by a wildfire in 2019 and covered by the nonrenewal moratorium in 2020. "Treatment" zip codes were covered by the nonrenewal moratorium in 2020 but did not experience a wildfire in 2019. "Adjacent" zip codes share a border with zip codes covered by the nonrenewal moratorium in 2020. "Rest of CA" zip codes are the remaining zip codes not covered by the moratorium. Zip codes impacted by the 2021 moratorium are excluded.

number of FAIR Plan policies in "Fire" zip codes had more than doubled from 2019 and more than quadrupled from 2015. Changes in other zip codes are more subtle. In comparison, we see that "Treatment" and "Adjacent" zip codes are comparable before the moratorium, but that there is an increase in FAIR Plan activity in "Treatment" zip codes beginning at the time of the moratorium.

Panel F of Figure 5 shows changes in the total number of policies (voluntary + FAIR Plan) over time. Trends are fairly stable for non-fire zip codes. There is some suggestive evidence that the fire itself drove insurance demand in the short run with "Fire" zip codes experiencing a 6% increase in total policies between 2018 and 2020.

Taken together, this descriptive evidence suggests that the moratorium had significant impacts on the market by reducing nonrenewals in the short term, but that these reductions were concentrated in the year of the moratorium only. In our next section, we formalize the assumptions needed to identify the causal impacts of the moratoriums.

5 Empirical analysis of the nonrenewal moratorium

Our setting involves staggered treatment timing, with two cohorts of treated zip codes receiving treatment in 2020 and 2021. We use quasi-random variation in treatment designation and timing to estimate the average treatment effect on the treated within a generalized difference-in-differences framework. Identification of causal effects in this framework relies on three main assumptions.

First, the parallel trends assumption requires that the potential outcomes in treatment and control areas would have evolved in parallel in the absence of treatment. In our setting, regulation imposes the moratoriums in zip codes that experienced a state of emergency wildfire and the zip codes directly neighboring them. A comparison of all zip codes affected by the moratorium to all other zip codes in California would likely violate the parallel trends assumption for two reasons. First, because some moratorium zip codes are directly impacted by the wildfire, the dynamics of the insurance market in these zip codes are likely to differ substantially from the other zip codes in the months following the fire, and these dynamics will be indistinguishable from the effects of the moratorium. Secondly, spatial and systematic variation in wildfire risk caused by variation in terrain and climate indicates that trends in insurance market outcomes likely differ between regions in California. This difference is likely to intensify as the distance between zip codes grows.

To address both issues, we exclude zip codes that were directly impacted by a wildfire from the treatment group ("Fire" zip codes in Figure 4, in red) and we restrict the control group to zip codes that are adjacent to moratorium-impacted zip codes ("Adjacent" zip codes in Figure 4, in blue). By narrowing our comparison to zip codes on either side of the moratorium border, we strengthen our claim that treatment status is assigned quasi-randomly.[17]

Second, we assume that there is no treatment anticipation. This assumption is plausible for three reasons. First, the legislation was passed for the first time at the end of 2018, without significant prior warning to insurers, allowing very little time to adjust their insurance portfolios before the first moratoriums were enacted in 2019. Second, the exact location and timing of wildfires is unpredictable even after accounting for underlying wildfire risk, so firms offering coverage in wildfire-prone areas are not able to predict *ex ante* which zip code will be impacted by a moratorium. Finally, we limit our analysis to the first two years of moratorium activity to eliminate the possibility that firms learn how to anticipate moratoriums and adapt.

Third, the Stable Unit Treatment Value Assumption (SUTVA) requires the absence of spillover effects onto control units. This assumption could be violated in our context: while insurers were subject to the nonrenewal moratoriums in specific zip codes, they could still adjust their portfolio in non-moratorium zip codes as a direct response to the moratorium. Such potential spillover effects present a challenge for causal identification. To address this, we leverage the data in the CSS to identify the insurance companies *most exposed* to the moratoriums. We define highly impacted firms as the top 50% of firms with the highest percentage of their portfolio (in terms of premium) written in moratorium zip codes at the time of declaration. For each zip code, we then compute the share of total zip code premiums written by these highly exposed firms in the year preceding

[17] In Appendix C, we show that along a panel of baseline census demographics, "Treatment" and "Adjacent" zip codes are observably similar.

the moratorium. Using this statistic, we define highly impacted control zip codes as those that had more than 75% of their total premiums insured by highly impacted firms, corresponding to approximately the top quartile of zip codes.

For our main specification, we exclude "highly exposed" zip codes from the control group. Therefore, the remaining control group is only composed of zip codes where a relatively larger portion of policies is written by insurers that were not highly exposed to the moratoriums, and thus are not likely to react to the treatment in the short run. As a robustness check, we show that our main takeaways are not sensitive to the choice of control group. First, Appendix Figure A4 shows that our main results are not sensitive to the use of the full set of adjacent zip codes, yielding similar estimates as our main results. Secondly, in Appendix E, we use a nearest-neighbor matching approach to compare treatment zip codes to similar zip codes in the "Rest of State" group that never experienced, or were adjacent to, a moratorium. We again find similar results to our main specification, providing support that there are not differential spillovers onto nearby zip codes.

Selective migration is another potential SUTVA violation. If homeowners are more likely, as a result of the fire, to move out of the treatment areas or to relocate from fire-impacted zip codes into treated or control zip codes, this could bias our estimates of insurance market outcomes by driving differential renewal behavior or new policy patterns between treatment and control zip codes. We are able to directly test for differential migration patterns, both inflows and outflows, at the time of the moratorium using our main specification and data from the Federal Reserve Bank of New York/Equifax Consumer Credit Panel. In Appendix F, we document no evidence of differential migration patterns between treatment and control locations before, during, or after the fires and moratoriums.

Formally, we estimate the effect of the moratorium using the following difference-in-differences specification:

$$y_{zt} = \sum_{k=-6}^{1} \beta_k \cdot D_{zt}^k + \delta_t + \sigma_z + \varepsilon_{zt}, \tag{1}$$

where y_{zt} is the outcome of interest in zip code z in year t and D_{zt}^k are event-time indicator variables, which take a value of one if the first year of the moratorium is k years away in year t, with the year prior to the moratorium being the excluded category. We include zip code fixed effects, σ_z, to control for time-invariant heterogeneity correlated with wildfire risk, such as elevation, vegetation, or population density. We also include year fixed effects, δ_t, to account for common annual shocks across all zip codes such as unusually dry years and macroeconomic trends that impacted the demand for insurance, such as the COVID pandemic.

Recent research shows that when treatment timing is staggered, the two-way fixed effects estimator, shown in equation (1), typically does not recover the average treatment effect on the treated if treatment effects are heterogeneous across cohorts (Goodman-Bacon, 2021; Sun and Abraham, 2021; Callaway and Sant'Anna, 2021; de Chaisemartin and D'Haultfoeuille, 2020; Gardner et al., 2024). We expect heterogeneous treatment effects in our setting for two reasons. First, while in 2020 the nonrenewal moratorium was novel in California, over time insurers may adapt their response to the policy and the Department of Insurance may adapt its enforcement role. Second, because of the record-breaking 2020 wildfire season, the 2021 moratorium covered much more territory than the 2020 moratorium, resulting in a higher proportion of insurers' business being subject to compulsory supply. This could cause insurers to respond differently to these two treatments. To address these concerns, we implement the heterogeneity-robust two-stage difference-in-differences estimator from Gardner et al. (2024).

6 Results

We present our main results for the effect of the nonrenewal moratorium on insurance market outcomes in Figure 6. Event time 0 is the year the moratorium is in effect in the treatment zip codes, while event time 1 is the year when the moratorium is lifted and the regulation is no longer in place. For all outcomes, pre-treatment event-time coefficients are small and not significantly different from zero, providing support for the parallel trend assumption and supporting causal interpretation of the effects.

We first present results for the effects of the moratorium on company- and customer-initiated nonrenewals in panels A and B of Figure 6, respectively. During the year of the moratorium, firms greatly decrease their nonrenewals by 42 policies (22% of pre-treatment levels) compared to control zip codes, suggesting that the moratorium was, in part, binding for firms. However, this effect is short-lived; in the year following the moratorium, we estimate a large increase in nonrenewals of approximately 150 policies, representing a 78% increase compared to pre-treatment levels. The cumulative estimates across the event years indicate that firms not only delayed the nonrenewal action to the following contract period, but also accelerated their retreat from moratorium zip codes with more policies being nonrenewed in aggregate across the two years for treated zip codes.

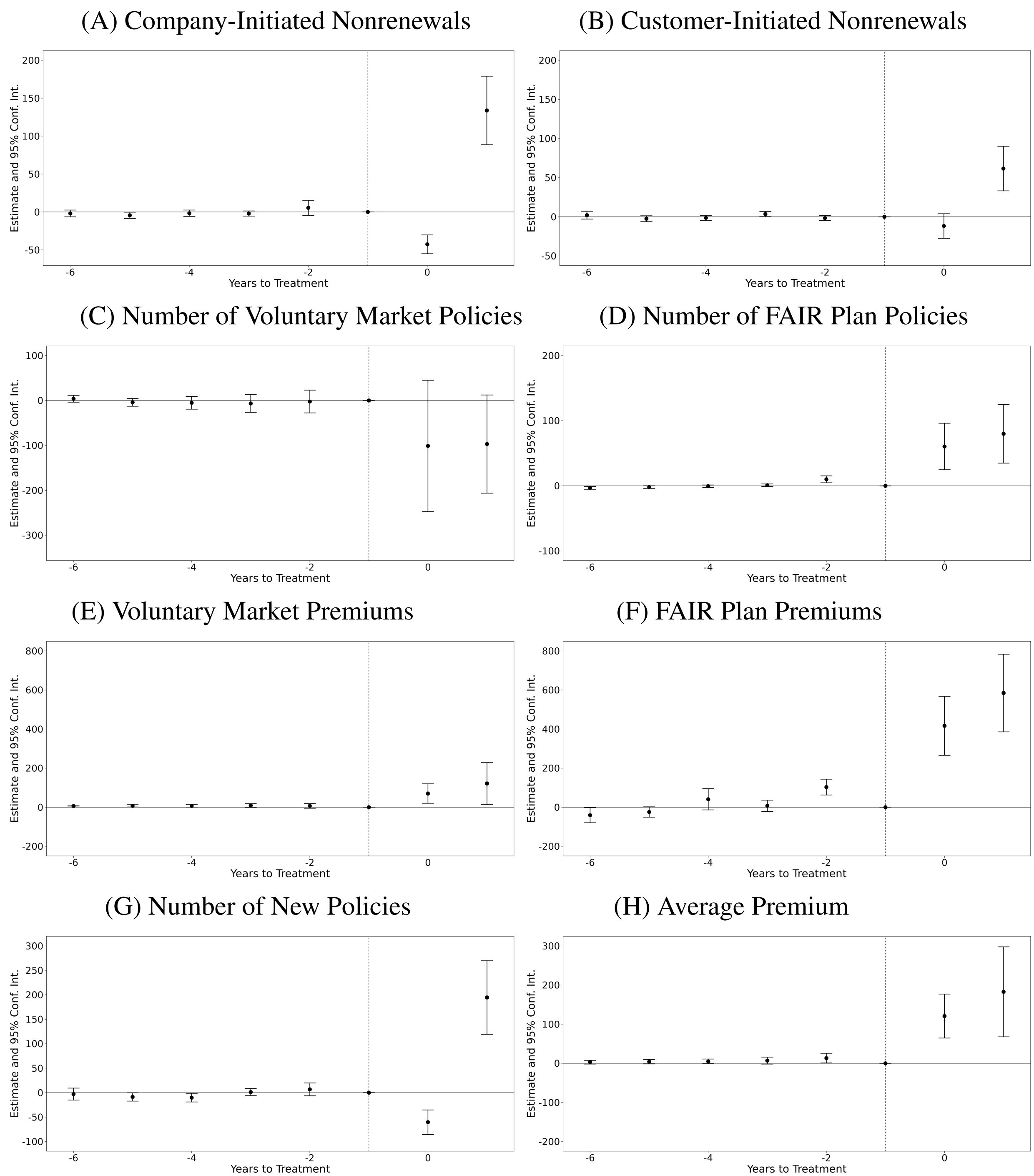
We test for heterogeneous effects by zip code wildfire risk and median income by estimating equation (1) separately by RPS and income quartile in Appendix Figures A2 and A3. The results show that the effect was strongest in zip codes with the highest risk of wildfires and higher levels of income.

In contrast to company-initiated nonrenewals, we find that the moratorium had no significant impact on customer-initiated nonrenewals when the moratorium was in effect, as shown in panel B of Figure 6. This provides further supporting evidence that the moratorium was binding for firms: insurers were not able to drop undesirable contracts by convincing the customer to initiate a nonrenewal or by disguising company-initiated actions during the moratorium, which would lead to a positive coefficient at event-time 0. Panel B also shows that customer-initiated nonrenewals increase by 13% of pre-treatment levels the year after the moratorium is lifted. We hypothesize that this increase is largely driven by the increase in company-initiated nonrenewal activity documented above. In California, company-initiated nonrenewals must be delivered in writing to the policyholder at least 75 days in advance of the policy expiration date (Cal. Ins. Code, 2022). This delay is designed to give the policyholder an opportunity to secure a new policy before their current policy is nonrenewed at the expiration of the contract. If the customer decides to cancel their existing policy before expiration, this is then recorded in the data as a customer-initiated nonrenewal despite the action being driven by the original company-initiated nonrenewal letter. Thus, the true effect of the moratorium being lifted is a combination of the customer- and company-initiated nonrenewals in event-time 1. The sum of these two coefficients represents an upper-bound estimate for the full effect of the moratorium on firm-driven nonrenewal activity, and further supports the conclusion that the moratorium accelerated nonrenewal activity in former moratorium zip codes.

A concern for identification is that there may be higher levels of out-migration in treated zip codes due to the lower insurance availability, leading to the higher observed customer nonrenewal rates. As noted before, we directly test for differential migration patterns in Appendix Figures A8 and A9 which show that there is no difference between treatment and control zip codes. We provide further detail on the analysis, methods, and data used in Appendix F.

Next, we present the effects of the moratoriums on policy counts separately for the voluntary market and the FAIR Plan in panels C and D. In the year of the moratorium, we estimate a positive effect on the number of FAIR Plan policies with an increase of 60 (87%) policies from pre-treatment levels and additional growth of 79 (115%) policies the year after the moratorium is lifted. There is evidence of a reciprocal reduction in the number of policies being insured through the voluntary market, both during the year of the moratorium and in the year following, although the coefficients are imprecisely estimated. These results, when combined with those above, imply that although the moratorium significantly impacted nonrenewals in treated zip codes and likely provided some respite for higher-risk consumers, it did not succeed in slowing the retreat of insurers from high-risk markets and may have even accelerated it. This result is at odds with the second testable hypothesis generated by our model, which says the moratorium is effective at stopping the transition from the voluntary market toward the residual market while it is in place. This discrepancy is likely driven by insurance companies shifting away from writing *new* policies in these areas as a way to reduce their exposure, forcing these new customers toward the FAIR Plan. However, these results do provide clear support for our hypothesis (iii), which states that the residual market share increases when the moratoriums become inactive. Given the overlapping confidence intervals, we cannot statistically rule out that the FAIR Plan absorbed all or a large portion of the policies leaving the voluntary market.

Figure 6: Effect of the nonrenewal moratoriums on insurance market outcomes



Notes: Event study results for the effect of the nonrenewal moratorium using the two-stage DID estimator from Gardner et al. (2024) are shown for various insurance market outcome variables. Treatment zip codes are non-fire areas covered by a nonrenewal moratorium. Control zip codes are adjacent zip codes not covered by a moratorium and are designated as low-impacted. Error bars represent 95% confidence intervals with standard errors clustered at the zip code level.

We next examine the impact of the moratorium on average premiums in the voluntary market and the FAIR Plan (panels E and F). We find that the moratorium has only a small impact ($70) on voluntary market premiums in treated areas. A muted and delayed effect is consistent with the structure of rate regulation in California. Voluntary market firms are constrained in how much and how quickly they can increase premiums, as well as the spatial granularity to which they can apply these increases in the short run.

In contrast, we estimate that the average FAIR Plan premium increases by $416 (28%) during the moratorium and continues to increase by $584 (39%) in the following year. These effects differ sharply from the voluntary market; as outlined in Section 3, the FAIR Plan is not subject to the same strict price regulation, its rates are bound by statute to be actuarially sufficient, and net reinsurance costs can be passed through.

Viewed through the lens of the stylized model, holding all else equal, the dynamics of the FAIR Plan average premium reflect two mechanisms: an increase in the marginal cost curve in the moratorium year (period 0), and a decrease in the average cost in the FAIR Plan when the moratorium expires (period 1), as insurers cede relatively lower-risk policies. The observed premium increase in period 0 is consistent with the first mechanism. The continued increase after the moratorium is lifted, though smaller, is harder to reconcile with the second mechanism alone. The accompanying increase in the number of FAIR Plan policies indicates that other compositional changes are also at work. The results suggest that the new FAIR Plan policies added in period 0, which were not previously insured in the voluntary market, could be riskier on average than the existing FAIR Plan pool.

7 Conclusion

Increasing disaster losses are putting significant strain on home insurance markets. Rising insurance premiums can reduce the risk of insurer bankruptcy, but they can also severely affect household finances. These direct and salient costs to homeowners have led policymakers to enact strict price regulations in most U.S. states.

Our paper highlights the dual role of the insurer of last resort in this setting. By absorbing the highest-risk households that private firms are unwilling to insure at the regulated price, the FAIR Plan sustains universal coverage of mortgaged homes in the state, but reallocates the incidence of rising costs: low-risk households in the voluntary market pay markups above marginal cost, while the highest-risk households pay a higher pooled average cost in the residual market. We then empirically investigate one case of regulation aimed at slowing the retreat of insurers from high-risk markets: the California nonrenewal moratoriums. The moratoriums temporarily disrupted the segmentation between the voluntary and residual markets by forcing insurers to renew policies they otherwise would not have written. We find that the moratoriums were effective in reducing nonrenewals in the short term, but likely accelerated the retreat of insurers as nonrenewals and FAIR Plan policies both rose on net once they expired. This pattern suggests that the policy primarily shifts insurer exit in time rather than preventing it.

For firms to remain in the voluntary market, premiums must better reflect underlying risk. Recent policy changes indicate that California is pursuing two complementary strategies to achieve this goal. First, recent legislation allows firms to use pre-approved forward-looking catastrophe models in rate-making, and to pass through a portion of reinsurance costs to customers (Cal. Code of Regulations, 2022, 2024). In the context of our model, these changes allow the regulated price to track expected marginal cost more closely, expanding voluntary-market supply and reducing reliance on the FAIR Plan. Second, fire-resilient building codes yield meaningful benefits for wildfire-exposed homes (Baylis and Boomhower, 2026). A 2022 California mandate requires insurers to offer discounts for defensible-space and structural mitigation measures (Cal. Code of Regulations, 2022), which could create incentives for homeowners to undertake upgrades and maintenance that lower the marginal cost curve. Evaluating how these policy changes affect the balance between voluntary and residual markets is a promising area for future research.

Recent wildfires in California illustrate the risk posed by a growing insurer of last resort. At the time of the January 2025 Southern California fires, the FAIR Plan insured over $4 billion in the Pacific Palisades fire perimeter and $750 million in the Eaton fire perimeter. Losses from these events vastly exceeded the FAIR Plan's available reserves and reinsurance, triggering a $1 billion assessment on all insurers selling homeowners insurance in the state, falling even on firms with no exposure in fire-prone areas. As FAIR Plan penetration in high-risk areas grows, so does the risk of large assessments for insurers, further reinforcing the incentive for insurers to retreat from the voluntary market.

Finally, while the insurer of last resort allows premiums to remain low in the voluntary market, it is a blunt tool for addressing affordability. Its benefits are geography-based rather than means-tested, accruing to households living in higher-risk areas regardless of ability to pay. Alternative tools are available to policymakers aiming to improve housing affordability, such as targeted insurance subsidies or credits for investments in cost reduction.

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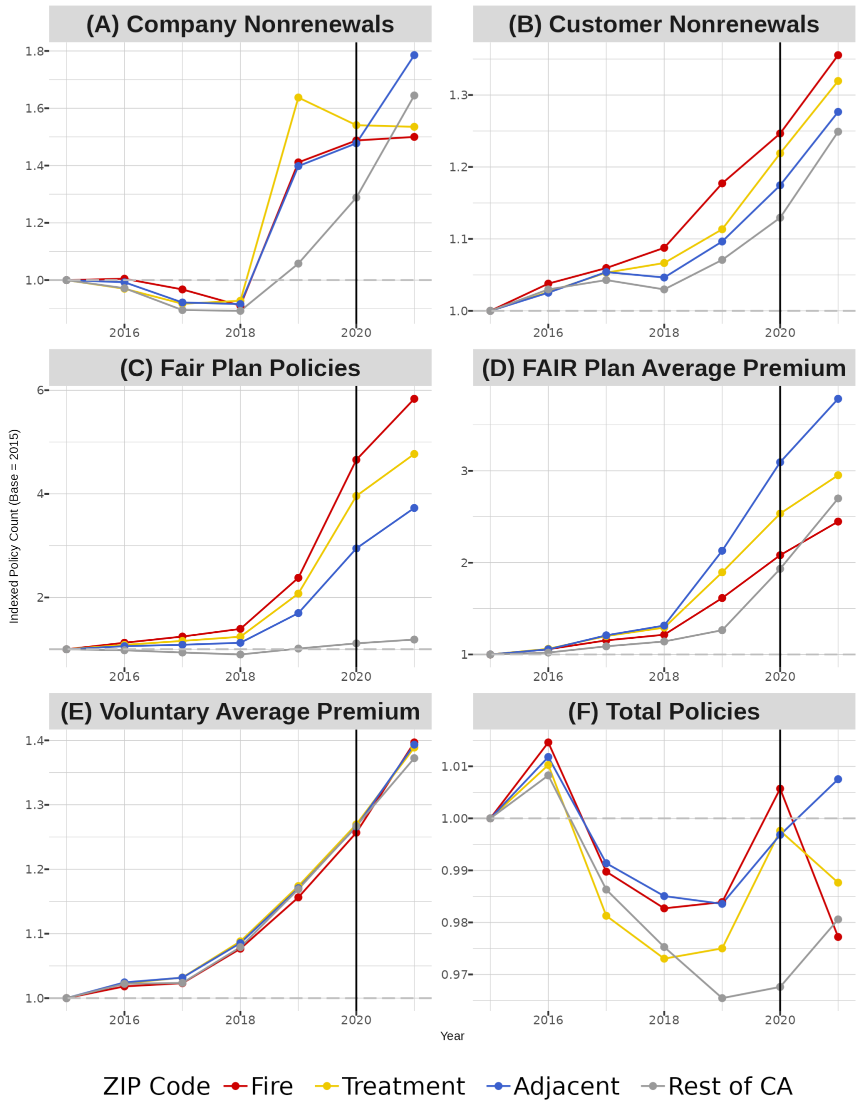
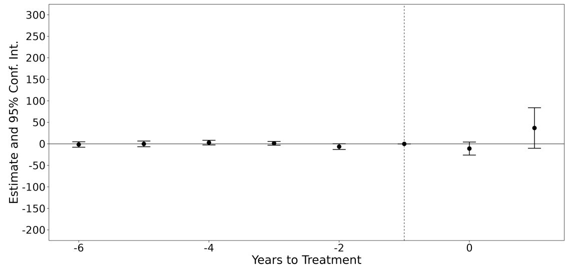
A Additional figures

Appendix Figure A1: Statistics by 2021 moratorium classification



Notes: Zip codes are broken out by moratorium classifications. ‘Fire’ zip codes were directly impacted by a wildfire in 2020 and covered by the nonrenewal moratorium in 2021. ‘Treatment’ zip codes were covered by the nonrenewal moratorium in 2021 but did not experience a wildfire in 2020. ‘Adjacent’ zip codes share a border with zip codes covered by the nonrenewal moratorium in 2021. ‘Rest of State’ zip codes are the remaining zip codes not covered by the moratorium.

Appendix Figure A2: Effect of moratorium on company-initiated nonrenewals by RPS quartile



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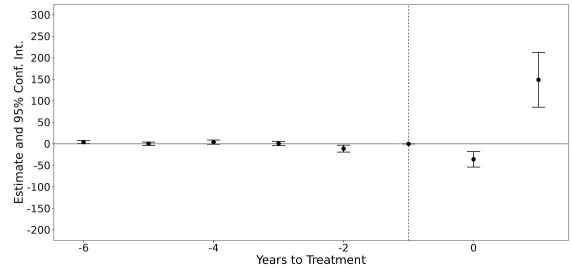

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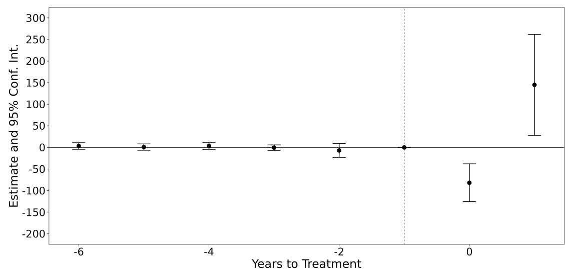
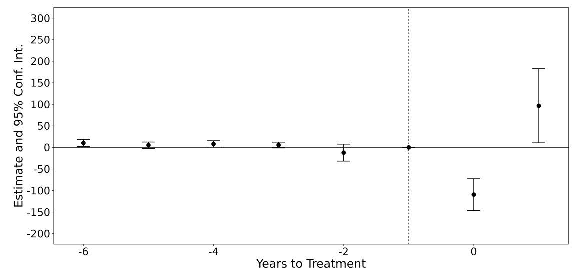


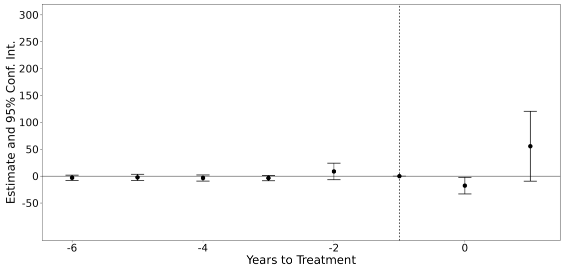
(c) 3rd



(d) 4th

Notes: Event study results for the effect of the nonrenewal moratorium on company-initiated nonrenewals broken out by Risk to Potential Structures quartile are shown using the two-stage DID estimator from Gardner et al. (2024). Treatment zip codes are non-fire areas covered by a nonrenewal moratorium. Control zip codes are adjacent zip codes not covered by a moratorium and are designated as low-impacted. Error bars represent 95% confidence intervals with standard errors clustered at the zip code level.

Appendix Figure A3: Effect of moratorium on company-initiated nonrenewals by income quartile



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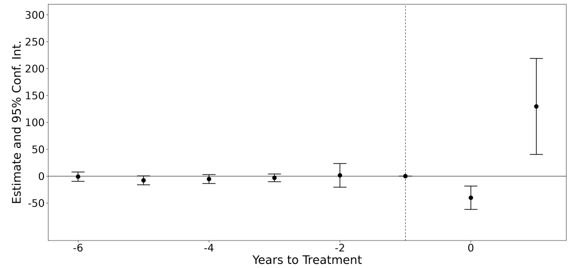

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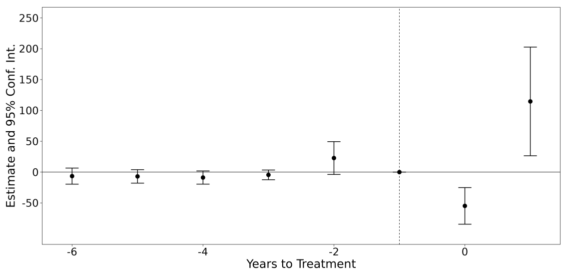

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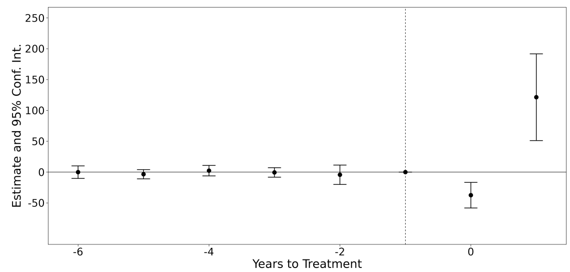
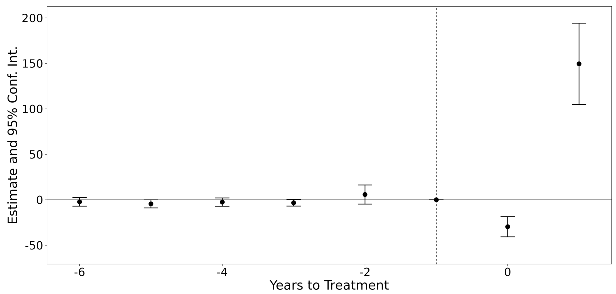


(d) 4th

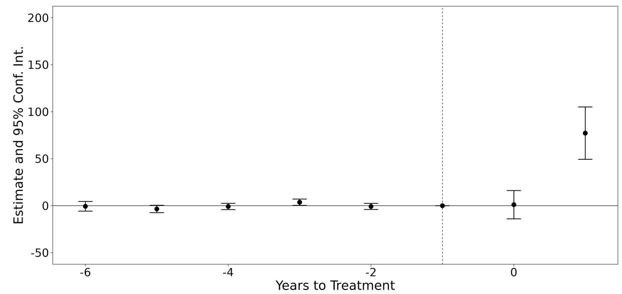
Notes: Event study results for the effect of the nonrenewal moratorium on company-initiated nonrenewals broken out by median household income quartile are shown using the two-stage DID estimator from Gardner et al. (2024). Treatment zip codes are non-fire areas covered by a nonrenewal moratorium. Control zip codes are adjacent zip codes not covered by a moratorium and are designated as low-impacted. Error bars represent 95% confidence intervals with standard errors clustered at the zip code level.

Appendix Figure A4: Effect of the nonrenewal moratorium on insurance market outcomes: all control zip codes

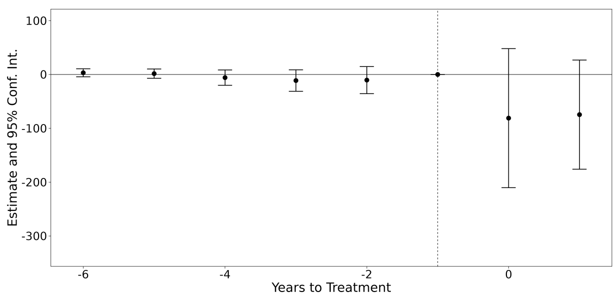
(A) Company-Initiated Nonrenewals



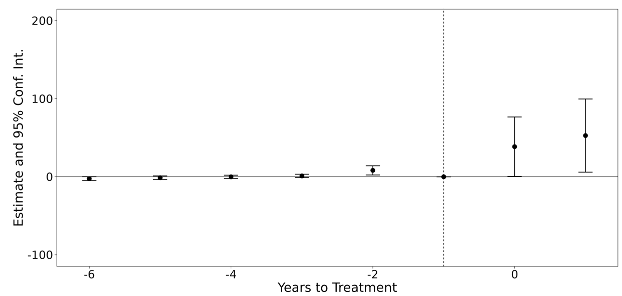
(B) Customer-Initiated Nonrenewals



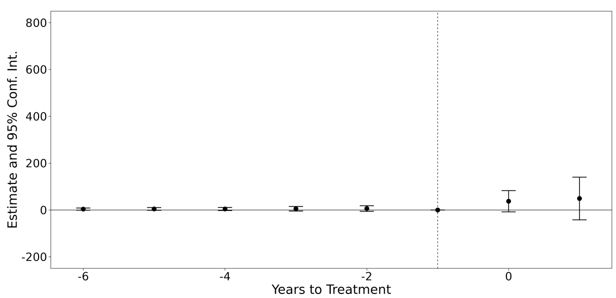
(C) Number of Voluntary Market Policies



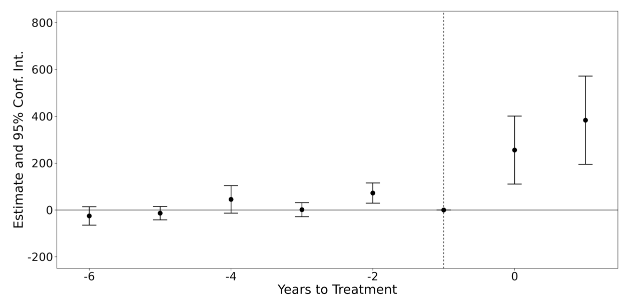
(D) Number of FAIR Plan Policies



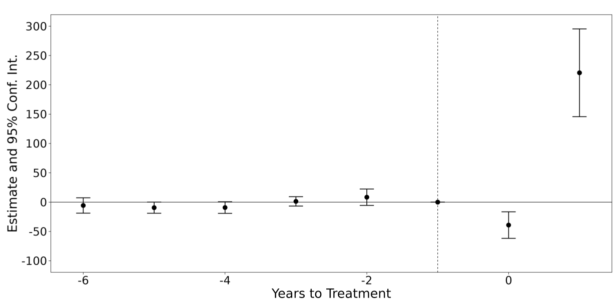
(E) Voluntary Market Premiums



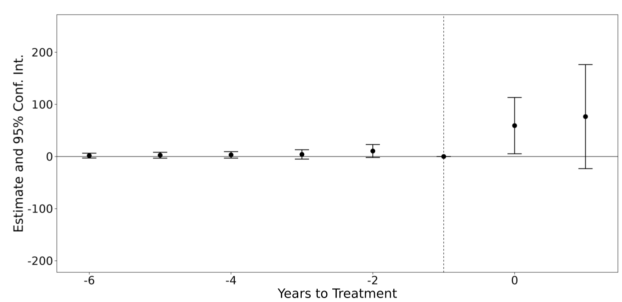
(F) FAIR Plan Premiums



(G) Number of New Policies



(H) Average Premium



Notes: Event study results for the effect of the nonrenewal moratorium using the two-stage DID estimator from Gardner et al. (2024) are shown for various insurance market outcome variables. Treatment zip codes are non-fire areas covered by a nonrenewal moratorium. Control zip codes are all adjacent zip codes not covered by a moratorium. Error bars represent 95% confidence intervals with standard errors clustered at the zip code level.

B Additional tables

Appendix Table A1: Summary statistics by zip code classification (2020 moratorium)

Zip Code Classification	Fire		Treatment		Adjacent		Rest of State	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
FAIR Plan Policies	121.29	428.98	107.76	244.34	83.56	182.80	56.23	186.31
Voluntary Policies	3681.51	3429.57	5561.69	3956.62	4935.17	4107.13	3392.52	3655.09
Average Premium	1232.33	618.31	1333.21	842.48	1332.13	1049.52	1154.21	721.93
Average Voluntary Premium	1243.99	609.05	1346.88	921.64	1345.30	1113.83	1148.80	709.78
Average FAIR Plan Premium	1150.69	1020.65	1162.87	1053.71	964.26	998.84	1053.30	1001.80
New Policies	618.95	601.58	952.10	727.77	867.43	782.59	563.13	630.69
Renewed Policies	4369.29	3949.51	6424.80	4368.08	5807.31	4709.05	4090.54	4234.77
Company-Initiated Nonrenewals	140.64	175.70	215.97	203.11	177.33	182.16	110.56	132.29
Customer-Initiated Nonrenewals	447.43	415.05	679.01	509.36	637.95	566.27	417.70	467.62
RPS	0.54	0.56	0.49	0.55	0.39	0.54	0.24	0.44
Median Income	77412.27	26647.19	83396.07	35170.92	77313.43	31122.73	71685.94	34206.32

Notes: Summary statistics are shown broken out by 2020 moratorium classification. Fire zip codes were directly impacted by a state of emergency declared wildfire in 2019 and covered by a moratorium in 2020. Treatment zip codes are adjacent to Fire zip codes and are also covered by a 2020 moratorium, but experienced no wildfire. Adjacent zip codes are outside the moratorium boundary, but border a moratorium zip code. Rest of State covers all other zip codes.

Appendix Table A2: Summary statistics by zip code classification (2021 moratorium)

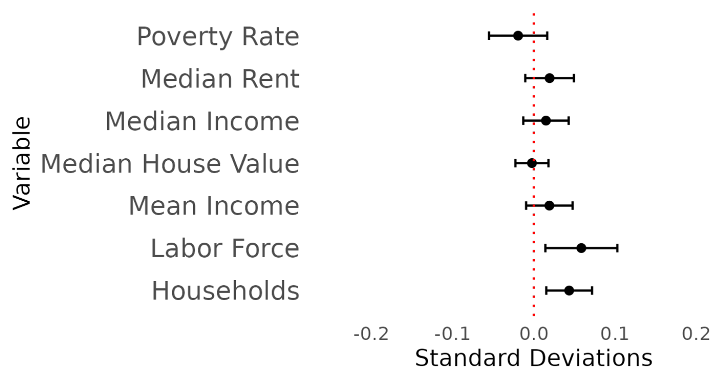
Zip Code Classification	Fire		Treatment		Adjacent		Rest of State	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
FAIR Plan Policies	29.54	114.19	60.86	219.56	41.72	147.46	84.72	232.03
Voluntary Policies	2019.59	3296.00	3446.96	3652.94	3784.56	3835.19	4174.52	3724.79
Average Premium	1232.86	661.84	1171.37	494.37	1135.84	513.98	1181.74	938.50
Average FAIR Plan Premium	1493.91	1168.75	1348.71	1134.40	1125.80	1064.88	781.55	761.14
Average Voluntary Premium	1211.36	639.08	1153.62	444.25	1128.10	490.38	1193.21	961.80
New Policies	347.96	578.23	587.54	675.05	656.38	706.92	681.52	628.64
Renewed Policies	2445.05	3918.52	4109.70	4291.24	4472.08	4368.32	5038.34	4238.74
Company-Initiated Nonrenewals	69.27	112.36	127.17	164.22	132.98	167.18	132.85	131.69
Customer-Initiated Nonrenewals	256.76	435.34	424.19	483.27	480.87	507.90	508.30	468.37
RPS	0.49	0.48	0.48	0.55	0.33	0.55	0.11	0.27
Median Income	65002.82	26293.46	70049.05	32262.89	73040.13	36035.14	76225.26	35207.16

Notes: Summary statistics are shown broken out by 2021 moratorium classification. Fire zip codes were directly impacted by a state of emergency declared wildfire in 2020 and covered by a moratorium in 2021. Treatment zip codes are adjacent to Fire zip codes and are also covered by a 2021 moratorium, but experienced no wildfire. Adjacent zip codes are outside the moratorium boundary, but border a moratorium zip code. Rest of State covers all other zip codes.

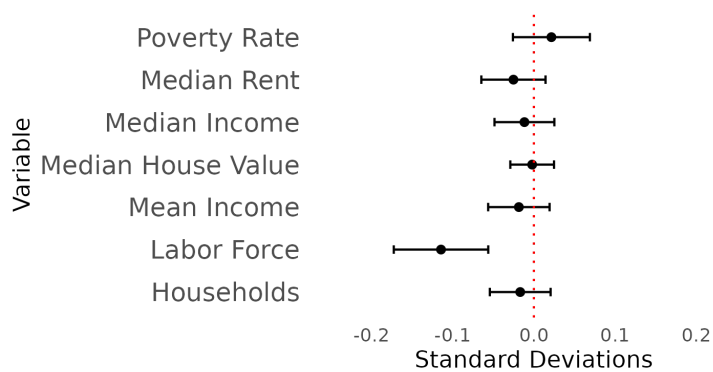
C Baseline demographics

Figure A5 reports the difference in means between the treatment group and the control group of adjacent zip codes for demographic and housing characteristics in the pre-treatment period. We present results broken out by treatment cohort, with the appropriate treatment and control zip codes for the 2020 and 2021 moratorium. The demographic variables have been standardized. The figures show that the treatment and adjacent zip codes are observably similar along most income and housing dimensions in the years prior to the moratorium. The data are sourced from the 2018 American Community Survey 5-year estimates.

Appendix Figure A5: Balance test of baseline demographics by moratorium cohort



(a) 2020 Moratorium



(b) 2021 Moratorium

Notes: Results for balance tests between treatment and adjacent zip codes for the 2020 and 2021 moratoriums are shown. Demographic variables have been standardized. Data are sourced from the 2018 American Community Survey 5-year estimates.

D Treatment designation

Moratorium zip codes are reported from the California Department of Insurance for each fire that reaches state of emergency status. Based on the legislation, zip codes can be included in the moratorium for two reasons: because they directly experienced the fire, or because they neighbor a zip code that experienced the fire. For our identification strategy, we need to separate these two types of zip codes. Inclusion of zip codes that were impacted by the fire directly will conflate the effect of the fire and related recovery with the effects of the moratorium. The data from the CDI, however, does not record the reason why a zip code was included in the moratorium.

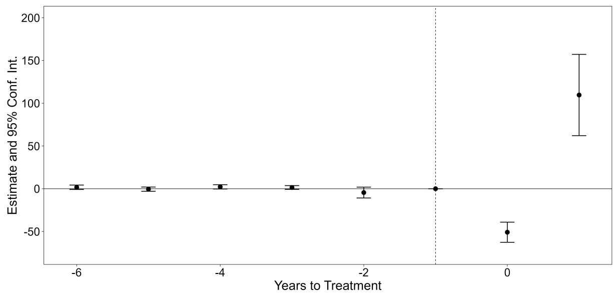
There are multiple methods for determining which zip codes are 'Fire' and which are 'Treatment'. One method is to compare geo-located wildfire perimeters with the set of spatial boundaries for zip codes. We implement this method by spatially merging the CalFire FRAP wildfire perimeter data with the set of moratorium zip codes and removing zip codes that overlap with the fire. The problem with this method is that it results in "Treatment" zip codes that border only other moratorium zip codes that *do not* experience a fire, as well as non-moratorium zip codes. This violates the language of the legislation. This can be caused by incomplete or incorrect fire perimeter data, other fires that occurred in the same fire year, smaller isolated pockets of fire, or a broader definition of direct impact of fire by the CA Department of Insurance than actual burn area.

Our preferred method is to designate any moratorium zip code that shares a border with a non-moratorium zip code as being "Treatment". Given that the legislation states that zip codes impacted by fire and their neighbors are included in the moratorium, the set of moratorium zip codes that border a non-moratorium zip code must not have been impacted by fire. This method most closely matches the wording of the legislation and gives us a more conservative treatment designation. This also has the added benefit of giving us a cleaner match between our treatment and control zip codes as they are direct neighbors and thus likely more similar along unobservable characteristics, making our identification strategy operate like a border discontinuity. When comparing this set of "Treatment" zip codes to the wildfire perimeter data set, only 2% of zip code acreage overlaps with any portion of a wildfire perimeter during the 2019 and 2020 wildfire seasons, suggesting that our definition does in fact isolate zip codes that are largely unimpacted by wildfires.

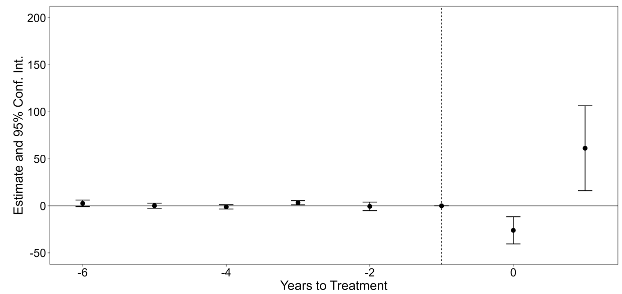
Below, we present the version of our main results (shown in Figure 6 in the main text) where we use the alternative burn-perimeter based method to designate treatment zip codes within the set of moratorium zip codes. Results are consistent across the two methods.

Appendix Figure A6: Alternative treatment definition for the effect of the nonrenewal moratoriums on insurance market outcomes

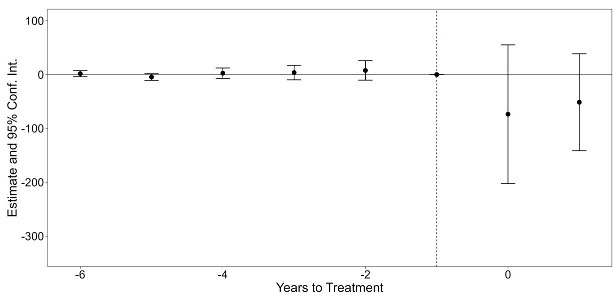
(A) Company-Initiated Nonrenewals



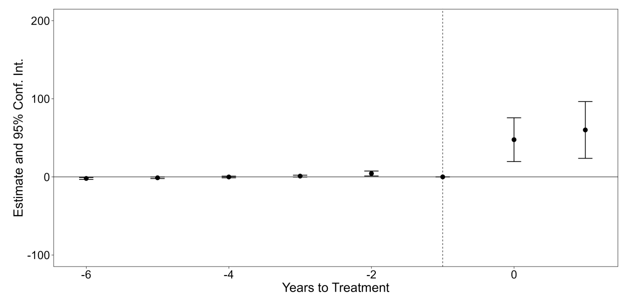
(B) Customer-Initiated Nonrenewals



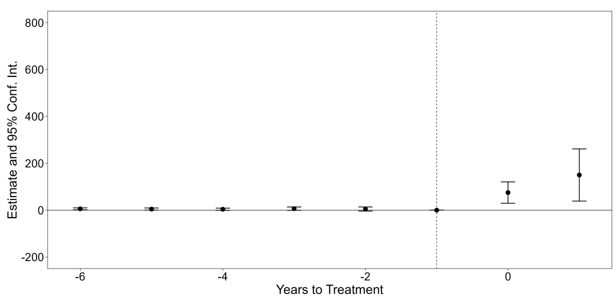
(C) Number of Voluntary Market Policies



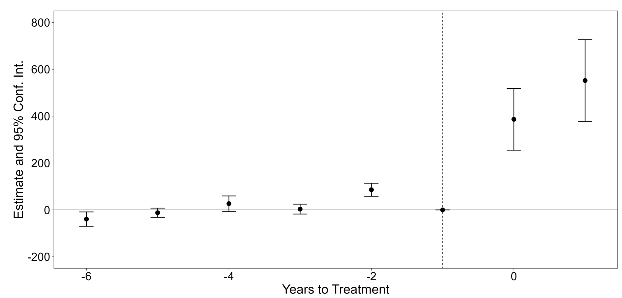
(D) Number of FAIR Plan Policies



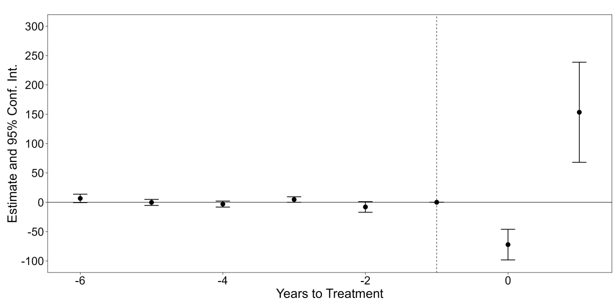
(E) Voluntary Market Premiums



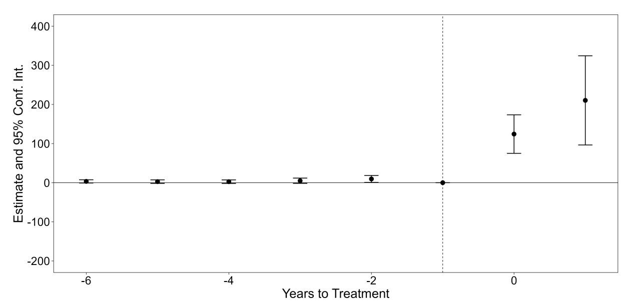
(F) FAIR Plan Premiums



(G) Number of New Policies



(H) Average Premium



Notes: Event study results for the effect of the nonrenewal moratorium using the two-stage DID estimator from Gardner et al. (2024) are shown for various insurance market outcome variables. Treatment zip codes are non-fire nonrenewal moratorium zip codes, identified using burn perimeter data. Control zip codes are adjacent zip codes not covered by a moratorium and are designated as low-impacted. Error bars represent 95% confidence intervals with standard errors clustered at the zip code level.

E Nearest-neighbor matched sample

Our main results make use of the regulatory border of the moratorium, which imposes the moratorium on zip codes that experienced a covered fire and their immediate neighbors, but not those zip codes just outside. Identification of causal estimates of the effect of the moratorium thus relies on two key features. First, that the control zip codes just outside the border represent good counterfactuals for the treated zip codes and were following common trends before the moratorium, and would have done so absent the fire. Second, the SUTVA assumption requires that there is no spillover of treatment onto control units.

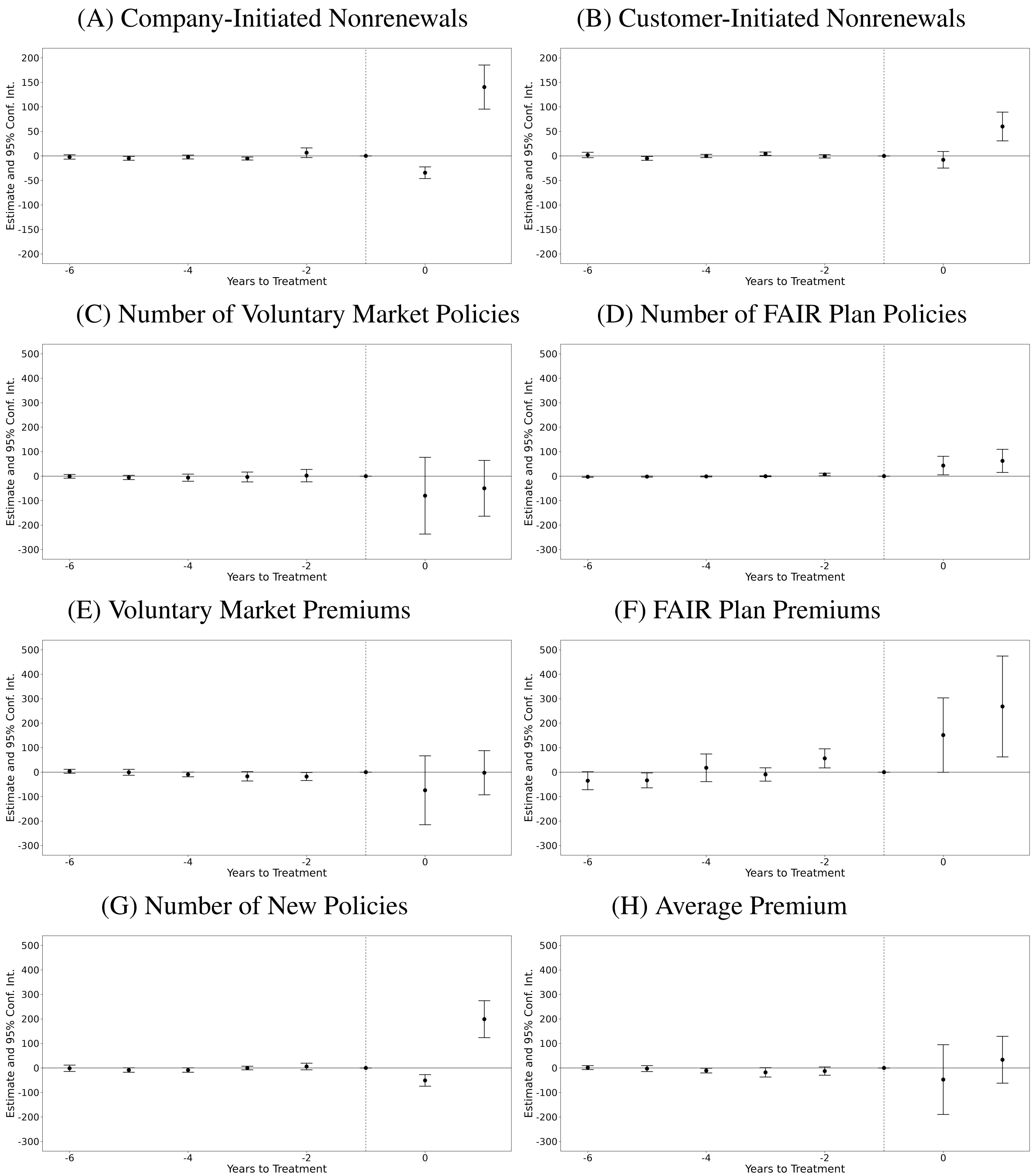
The general location of wildfires is not random. They are more likely to occur on the upslopes of the mountainous portions of the state. Due to the nature of California's geography, it is possible that the moratorium zip codes are on the edge of the foothills, but border zip codes that are located in valleys with a much different wildfire risk profile. Thus, the zip codes that are most similar to the moratorium zip codes may not be located geographically nearby, but are in other parts of the state that have a similar topographical profile and wildfire risk.

In a robustness check of our main results, we can make use of the fact that conditional on wildfire risk, the exact location of a wildfire in a given year is essentially random. We use a nearest-neighbor matching process to identify "control" zip codes from the Rest of State group that were never impacted by a fire, treated, or adjacent to a moratorium. We match to treated zip codes using pre-treatment period trends in the outcome variables, zip code mean RPS, standard deviation of RPS, max RPS value, and median household income following the synthetic control literature.

For the matching process, the outcome variable is first detrended by regressing the variable on a panel of year dummy variables and extracting the residuals. For each zip code, we then use the residual values for years 2019 and prior and regress these values on a simple year variable using OLS. The coefficient on the year variable is the trend in the outcome variable over the pre-treatment period for the zip code. We use the five covariates in a one-to-one nearest neighbor matching process using a logistic regression propensity score to identify control units.

The results limiting to the matched control sample closely match our main results using the adjacent and low-impacted zip codes as controls. This provides evidence that the nearby zip codes represent strong counterfactuals for the treatment zip codes. It also supports the claim that there are no differential geographic spillovers of treatment onto the nearby adjacent zip codes. We cannot rule out, however, that there could be spillovers along characteristic dimensions across the state.

Appendix Figure A7: Direct effect of moratorium using nearest-neighbor matching process



Notes: Event study results for the effect of the nonrenewal moratorium using the two-stage DID estimator from Gardner et al. (2024) are shown for various insurance market outcome variables. Treatment zip codes are non-fire areas covered by a nonrenewal moratorium. Control zip codes are Rest of State zip codes not covered by a moratorium that are matched using the nearest neighbor process. Error bars represent 95% confidence intervals with standard errors clustered at the zip code level.

F Testing for migration effects

In our analyses above, we document changes to policy nonrenewals and insuring patterns impacted by the moratorium. A possible explanation for the changes in the number of policies and customer-initiated nonrenewals is that the moratorium directly affected homeowners' location choices, suggesting that our results may be driven by migration decisions rather than insurance decisions (McConnell et al., 2024). Our identification strategy assumes that there are no other contemporaneous factors with the moratorium that could impact our outcomes of interest. The time period of our study coincides with the COVID-19 pandemic, which led to a large change in where people lived which, if correlated with the moratorium area, could lead to biased estimates.

To test for the impact of the moratoriums on both in-migration and out-migration, we use the Federal Reserve Bank of New York/Equifax Consumer Credit Panel (CCP) between 2003 and 2021. This dataset is a quarterly, individual-level dataset that tracks each individual's residential street address in addition to a set of financial data. The CCP is a nationally representative, random, and anonymized 5% sample of adults with a social security number and a credit report (see Lee and van der Klaauw (2010), for details). We classify individual moves as in-migration the first quarter they are present at a new street address if the zip code for the prior address is different, and an out-migration if their address the following quarter is in a different zip code. We then aggregate total population, in-migration, and out-migration at the zip-code-quarter level for zip codes in California. Lastly, we calculate net outflow, which subtracts in-migration from out-migration. We present summary statistics for the four variables in Table A3.

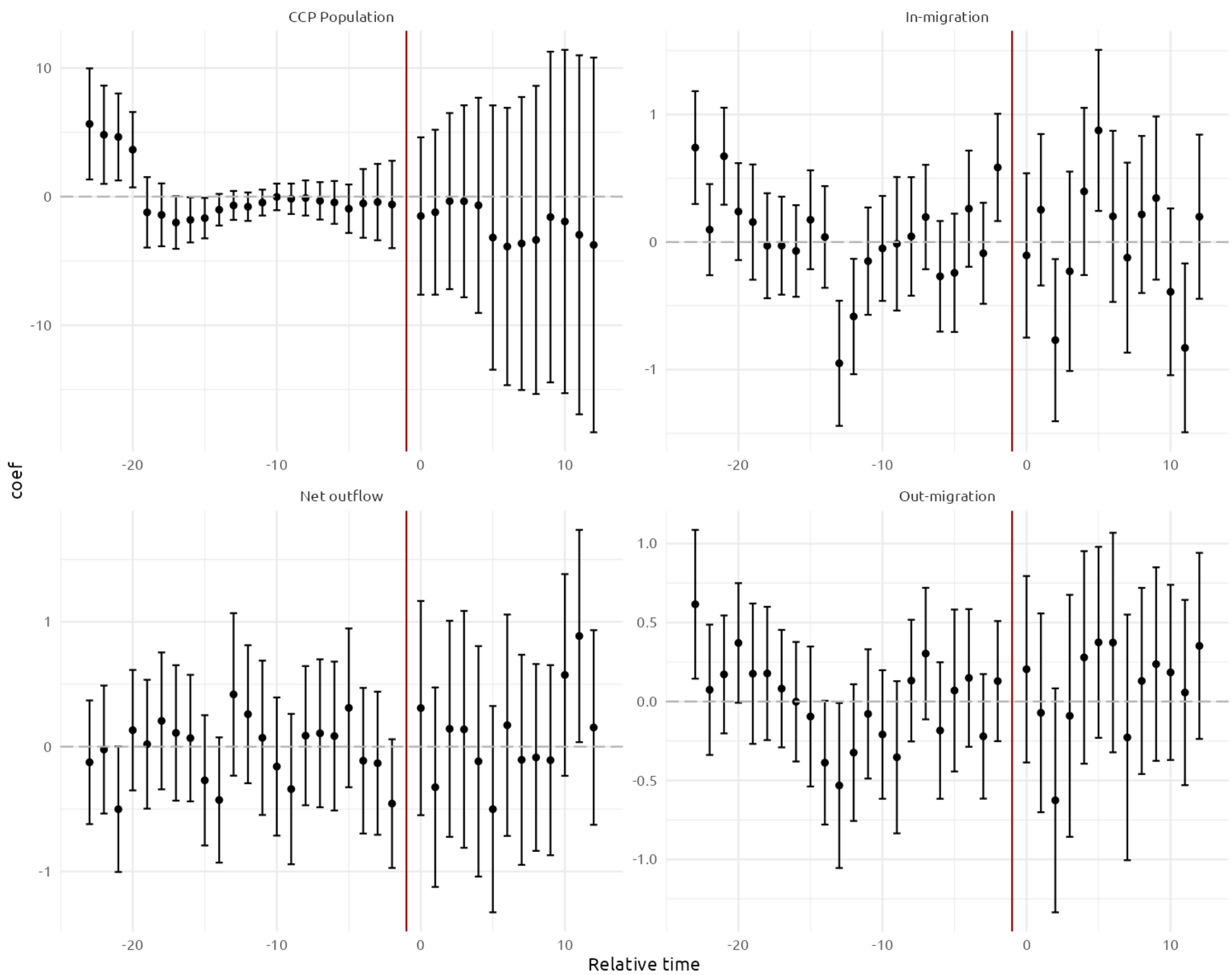
Appendix Table A3: CCP Summary statistics for treated and adjacent zip codes

Variable	Mean	SD
CCP Population	704.9	742.2
In-migration	16.3	19.2
Out-migration	16.9	20.1
Net outflow	0.6	6.8

We estimate the effect of the moratorium on our four outcomes using the two-stage difference-in-differences estimator in Gardner et al. (2024), comparing "treated" to "adjacent" zip codes before and after the staggered treatment timing of the moratoriums. Figure A8 presents the overall effects, while Figure A9 presents heterogeneity effects by wildfire risk quartiles.

Across all outcomes, we do not detect any significant effect of the moratorium on migration patterns. The estimates by fire risk quartiles (Figure A9) suggest some significant effects in the top left panel for the CCP population outcome, but these estimates display some pre-trends and are not detected with any of the subsequent three outcomes. Overall, these estimates do not reject our assumption that the moratoriums had no differential impact on the migration decisions of populations living in treated vs. control zip codes.

Appendix Figure A8: Direct effect of the moratoriums on migration



Two-stage difference-in-differences estimates from Gardner et al. (2024) for the effects of the moratorium on four distinct population outcomes are shown. Time on the x-axis is in quarters. The models compare treated to adjacent zip codes. Standard errors are clustered at the zip code level, and the figure displays 95% confidence intervals.

Appendix Figure A9: Direct effect of the moratoriums on migration by RPS quartile

Two-stage difference-in-differences estimates from Gardner et al. (2024) for the effects of the moratorium on four distinct population outcomes, focusing on heterogeneity by fire risk (RPS variable) are shown. Time on the x-axis is in quarters. The models compare treated to adjacent zip codes. Standard errors are clustered at the zip code level, and the figure displays 95% confidence intervals.