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

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Abstract

An increasing number of people are denied home insurance coverage in the private market, and must instead turn to state-sponsored plans known as "Insurers of Last Resort". This paper examines how insurers of last resort interact with the private market under increasing disaster risks. We first present a simple model of an adversely selected insurance market, highlighting that the insurer of last resort allows strict price regulation to be compatible with full insurance. We then empirically study the California non-renewal moratoriums, a regulation that forced insurers to supply insurance to current customers following wildfires in 2019 and 2020. Using quasi-random geographic variation in regulatory borders and a difference-in-differences strategy, we find that the moratoriums successfully reduced company-initiated non-renewals and cancellations in the short run. The effects only lasted for one year, with insurers dropping policies as soon as the moratorium lapsed. The moratoriums had no discernible effect on participation in the State's insurer of last resort.

JEL Codes: D22, G22, L10, Q54

Keywords: Insurance, natural disasters, wildfire

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1 Introduction

Natural disasters pose substantial financial risks to households, firms, and communities, highlighting the urgent need for well-functioning insurance markets. However, escalating disaster risks and the increasing costs of natural disasters present new challenges for insurers. In the United States, "insurers of last resort" offer coverage to households unable to purchase insurance from the private market. Originally intended to provide temporary coverage for the highest-risk properties, state-run insurers of last resort have come to hold significant market share. This shift introduces financial risks for state governments and a puzzle for insurance market regulators: why is the reliance on insurers of last resort growing, and which public policies can help prevent private insurance markets from unraveling?

In this paper, we examine how regulation and increasing disaster risks can result in the unraveling of the private insurance market. We first present a simple model of a disaster insurance market featuring both a private (or "voluntary") market and an insurer of last resort operating in the "residual market." Although private insurers cannot freely set prices, they can use information on the marginal cost of consumers to decide *who* to insure. Profit-maximizing firms rationally choose not to offer insurance to those who have an expected marginal cost above the regulated price, leading the riskiest consumers to receive coverage from the insurer of last resort in the residual market. In our framework, the insurer of last resort does not solve any market failure but is necessary to guarantee full market coverage under strict price regulation.

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 suggest private firms reduced their exposure by ceding the highest risk policies to the insurer of last resort as expected costs increased faster than the regulated price.

We then empirically estimate the effects of the California nonrenewal moratorium, a novel policy implemented by the California Department of Insurance to curb the growth of the FAIR plan. The moratoriums (first enacted in 2019) force insurers to continue supplying insurance through a guaranteed renewal for at least one year to current policyholders in zip codes affected by, or adjacent to, a declared 'state of emergency' wildfire. We exploit the quasi-random variation generated by the regulatory boundaries of the moratoriums to study the causal impact of the policy on insurance market outcomes. Our treatment group consists of moratorium zip codes adjacent to, but not directly affected by, the wildfires. This avoids confounding the treatment effect of the moratorium with the direct effects of the fire, which are likely correlated with our insurance market outcomes of interest. Our control group comprises non-moratorium zip codes directly adjacent to those impacted by the regulation. These zip codes offer a credible counterfactual, as they closely resemble the treatment zip codes while not being subject to the restrictions of the moratorium; the quasi-random occurrence of wildfire ignition sites and zip code boundaries suggests their exemption from regulation was purely coincidental. We further refine our control group by excluding zip codes with high levels of premium written by the insurers most impacted by the moratorium to account for the potential of spillover effects within firms.

We find that, relative to the control group, zip codes impacted by the moratorium experienced a decrease in company-initiated nonrenewals during the year the moratorium was active, indicating that the regulation was binding for insurers. However, this effect was short lived; insurers increased nonrenewals by at least 80% in the year immediately following the expiration of the moratorium.

Further, we estimate that the moratorium did not slow the retreat of private firms from high-risk areas and may have even accelerated it. The number of policies written by the voluntary market declined by 200 in treated areas one year after the moratorium, and the number of policies written by the FAIR Plan increased by 100. Our results are robust to using an alternative control group constructed by nearest-neighbor matching between treatment zip codes and untreated zip codes in the rest of the state (detailed in Appendix D).

While the nonrenewal moratoriums are designed to target the actions of firms in specific zip codes, firms may respond in non-moratorium zip codes, impacting the effectiveness of the moratorium. We assess whether such unintended spillover effects are at play by leveraging variation in firms' exposure to the moratorium. Focusing on all zip codes never subject to a moratorium, we compare those primarily serviced by firms that are highly exposed to the moratorium ("spillover-treated") to those serviced by firms with low exposure to the moratoriums ("spillover-control").

We find that, in spillover-treated zip codes, firms were more likely to stop writing policies and to retain their current customers by reducing nonrenewals. In addition, spillover-treated zip codes experienced a sharp increase in the the number of policies insured through the California FAIR plan. These spillover results highlight the unintended costs of incomplete regulation; the California moratorium only acted as a short-term band-aid in areas directly targeted by the policy but ultimately backfired by increasing reliance on the state's insurer of last resort in the rest of the state. Overall, deeper changes of the rate-setting guidelines are required to avoid an unraveling of the market.

This paper first contributes to a growing literature on natural disaster insurance markets (Kunreuther, 1996, 2001; Kousky, 2011; Born and Klimaszewski-Blettner, 2013; Oh et al., 2023; Kousky, 2022; Wagner, 2022; Mulder, 2022; Weill, 2023; Marcoux and Wagner, 2024). Because of a lack of publicly available data on private homeowners insurance policies, the literature on non-flood homeowners insurance is emerging. Recent papers explore the role of reinsurance costs (Keys and Mulder, 2024), the pricing of disaster risks (Blonz et al., 2024), the impacts of premiums on mortgage delinquencies (Ge et al., 2025), and the magnitude of under-insurance (Sastry et al., 2024). Closely related to our paper, Boomhower et al. (2023) uses similar insurer data from California to examine wildfire risk estimation across insurers. In contrast, our paper focuses on the interaction between private insurance markets and the state insurer of last resort, with an application to the California nonrenewal moratoriums.

This paper also contributes to the literature on insurance regulation, both theoretically and empirically. We develop a model of adverse selection in a segmented market under price regulation and rapidly changing risk that extends the canonical model of Einav et al. (2010), which has been used broadly to study adverse selection in insurance and lending markets (Spinnewijn, 2017; Cabral and Cullen, 2019; Boyer et al., 2020).[1] A majority of states are now operating residual markets or an insurer of last resort (Kousky, 2011). We provide a simple framework to investigate how these markets interact with private markets. Our paper also shows how regulating both price and risk selection, as is the case with the California nonrenewal moratoriums, can lead to long-run firm exit and unravelling of the private market. Our work expands on the natural disaster insurance regulation literature (Born and Viscusi, 2006; Born and Klimaszewski-Blettner, 2013; Oh et al., 2023) and the smaller set of studies focused on regulatory effectiveness and efficiency in California's insurance market (Liao et al., 2022).

Finally, this work fits into a broader literature on climate adaptation (Barreca et al., 2016; Baylis and Boomhower, 2019; Kousky, 2019; Botzen et al., 2019; Kahn, 2021; Sastry, 2021; Boomhower and Baylis, 2024) and, in particular, firm adaptation (Prankatz and Schiller, 2021; Gu and Hale, 2022; Castro-Vincenzi, 2022; Bilal and Rossi-Hansberg, 2023). A large literature focuses on the links between climate change, insurance pricing, and real estate (Nyce et al., 2015; Issler et al., 2024; Biswas et al., 2023; Xudong et al., 2024). Particularly relevant to our work, You et al. (2024) studies the impacts of the California nonrenewal moratorium on housing markets. While we estimate that the moratorium did not cause out-migration, You et al. (2024) finds that the moratorium acted as a risk signal to potential home buyers and reduced loan application. These results suggest that the moratorium potentially changed the demographics but not the number of Californians living in moratorium-exposed zip codes.

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.

[1] See Einav and Finkelstein (2023) for a review of literature that makes use of the framework from Einav et al. (2010).

2 Institutional Background

2.1 Insurance markets

Home insurance pricing is heavily regulated. Since 1945, U.S. 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 many states, before new insurance rates can be implemented, insurers must first obtain approval from the state Department of Insurance. This administrative process is cumbersome and frequently lasts more than 12 months (Oh et al., 2023) 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 entire insurer 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., 2023).[2] Second, California regulation requires the overall rate for natural disasters, known as the catastrophe load, to be justified by historical averages of losses over at least the past 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 catastrophe loads, exacerbating premium inadequacy when past loss experience does not reflect future expectations. Finally, California restricted insurers from passing reinsurance costs through to consumer premiums. Recent work highlights large increases in reinsurance premiums in recent years, with global reinsurance companies not subject to the same regulatory oversight and premium approval process as primary insurers (Keys and Mulder, 2024).

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

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 such variables are unfairly discriminatory. While the classic case of adverse selection relies on consumers having private information unobserved by the firm, adverse selection can also arise from regulation restricting the set of permissible characteristics used in pricing (Finkelstein and Poterba, 2014). Banning the use of certain characteristics ("protected classes") implies that after conditioning on the remaining permissible observables, consumers that are offered the same premium can still vary in their expected costs and willingness to pay. While some characteristics are protected throughout the U.S. (such as gender, race, and religion), California is also one of only three U.S. states that ban the use of credit history in homeowners insurance pricing (Blonz et al., 2024).

2.2 California moratoriums

Following large losses from record breaking wildfires in 2017 and 2018, insurance companies began to increasingly refuse to renew insurance policies in parts of California. Insurer-initiated nonrenewals can happen for a wide range of reasons, but nonrenewal rates are typically low – increases in these rates indicate 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 renewing a policy solely because 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 is referred to as the "2021 Moratorium."[3]

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, the passing of 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 to 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 of endogenous policy response in the long run.

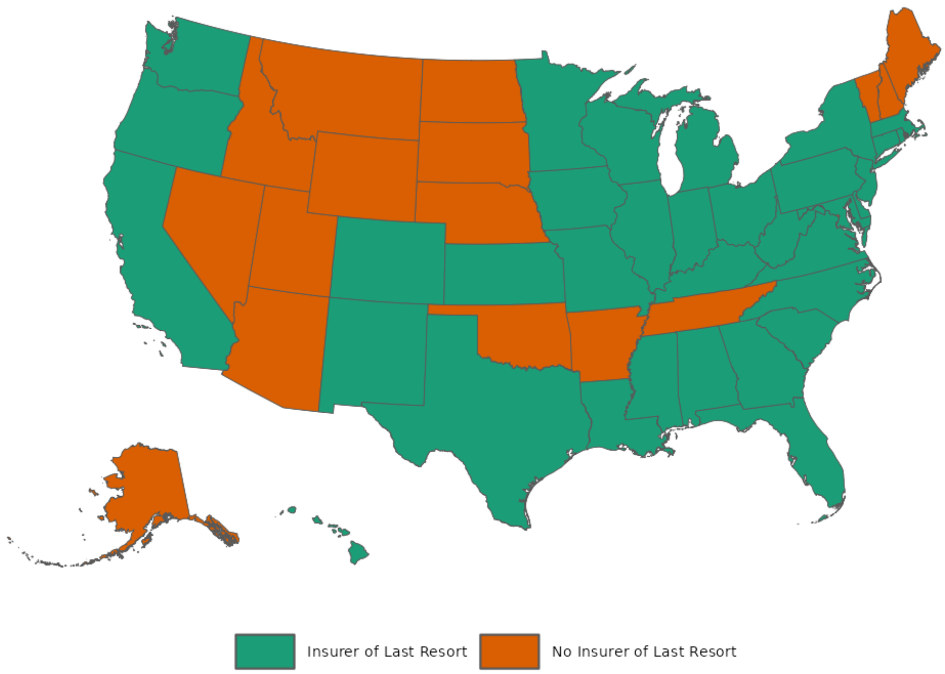
2.3 Insurers of Last Resort

Insurers of last resort are state-run (or state-sponsored) plans that provide coverage for properties unable to find insurance in the voluntary market. These plans take a variety of forms; FAIR plans were started in 26 states, the District of Columbia, and Puerto Rico in 1968 following the riots and bushfires of the 1960s (Dwyer (1978) offers a discussion of the FAIR Plans' origin). Some states have "wind pools" or "beach plans," which cover specific perils with limited geographic coverage (see Kousky (2011) for a discussion of 10 state-sponsored programs). Today, 34 states and the District of Columbia have an insurer of last resort (shown on Figure 1). While insurers of last resort were originally established in response to insurer retreat from racial tensions in inner cities, their operations slowly evolved to address the insurer retreat from the climate crisis: Colorado became the latest state to establish a FAIR Plan in 2023 in response to increasing wildfire

[3]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.

losses.

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 private market.

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 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 (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

This section presents a simple framework to clarify the role of the insurer of last resort in a market with adverse selection. 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 wildfire risk.

Our framework closely follows Einav et al. (2010); consumers make a discrete purchase decision for a homogeneous full-coverage insurance policy, which they buy at the lowest price available from profit-maximizing firms competing in the market. Consumers purchase their policy from either the private ("voluntary") market or the residual market (the insurer of last resort).

We focus on three distinct pricing regulations. First, the regulator decides on a permissible set of observable property and homeowner characteristics $\{c_i\}$ that are allowed for pricing. For example, gender, race, and estimates of risk from catastrophe models were not allowed to be used to set household-level insurance premiums in California at the time of the moratorium regulation, as discussed above (California Code of Regulations, 2023). Second, conditional on this set of characteristics $\{c_i\}$, we assume that the regulator sets a fixed price $\hat{P}$ in the voluntary market. This assumption is meant to capture the complex state-level rate-approval process in a tractable way. Finally, we assume that prices can move freely in the residual market but must satisfy a zero-profit condition. This assumption reflects the conditions commonly imposed in the California FAIR Plan, which is not subject to Proposition 103, must charge adequate rates without subsidization, and is able to pass through reinsurance costs to policyholders, unlike the private market (California FAIR Plan, 2023).

Restricting the observable characteristics $\{c_i\}$ permitted for rate-making results in what Finkelstein and Poterba (2014) call "asymmetrically used information"; consumers with the same permissible characteristics are facing the same price, *despite* otherwise observable differences in their expected costs. This information asymmetry leads to adverse selection, characterized by downward sloping marginal and average cost curves (Einav et al., 2010). Boomhower et al. (2023)

shows that there is heterogeneity in the granularity of variables used by insurers in the rating process. For tractability, in our conceptual setting, we make no distinction between which voluntary market firm insures the customer.

We make two additional assumptions to close the model. For simplicity, we assume that demand is higher than average cost at every point, implying that, at actuarially fair prices, every consumer prefers to purchase insurance than to go without.[4] Second, we assume that insurers observe the marginal cost curve. This assumption is implausible in the context of health or auto insurance markets, where consumers typically have private information about their expected losses. However, in the context of home insurance, most characteristics that impact expected losses are observable to both homeowners and insurers (such as location, building materials, number of floors, or roof structure). Both assumptions can be relaxed without impacting the core conclusions of the model.

3.1 Market segmentation

In what follows, we depict one tranche of the market where all consumers have the same set of permissible rating characteristics $\{c_i\}$ (and are therefore charged the same premium) but vary in their expected losses and willingness to pay, leading to adverse selection. In Panel (a) of Figure 2, we consider the case where the regulator imposes an exogenous price $\hat{P}$ below the average cost curve AC at every point. While all consumers would opt to buy insurance at this price, insuring the entire market (Q^{max}) would lead to negative expected profits for firms, shown in red.

Because firms can observe the marginal cost curve MC, they can select which consumers they want to offer a contract at price $\hat{P}$. Panel (b) shows that firms only offer coverage to consumers who are profitable (such that $\hat{P} \geq MC$). This results in only a portion of the market receiving insurance coverage from the voluntary market, shown as consumers from Q^R to Q^{max}. The remainder of the market (Q^0 to Q^R) is forced to purchase insurance from the residual market or go uninsured. The zero-profit condition imposed on the residual market results in the price being set at the average

[4] According to the National Association of Insurance Commissioners, about 90% of homeowners have insurance, largely because of mortgage lender requirements.

cost, calculated over the customers that purchase from the residual insurer: $P^R = AC^R(Q^R)$. By construction of the demand curve, all customers ceded from the voluntary market will purchase a policy from the residual insurer because their willingness-to-pay is greater than the average cost curve at every point.[5] Positive profits (shown in blue) in the short run are possible in the voluntary market because firms take as given the fixed regulated prices when deciding whom to insure.[6]

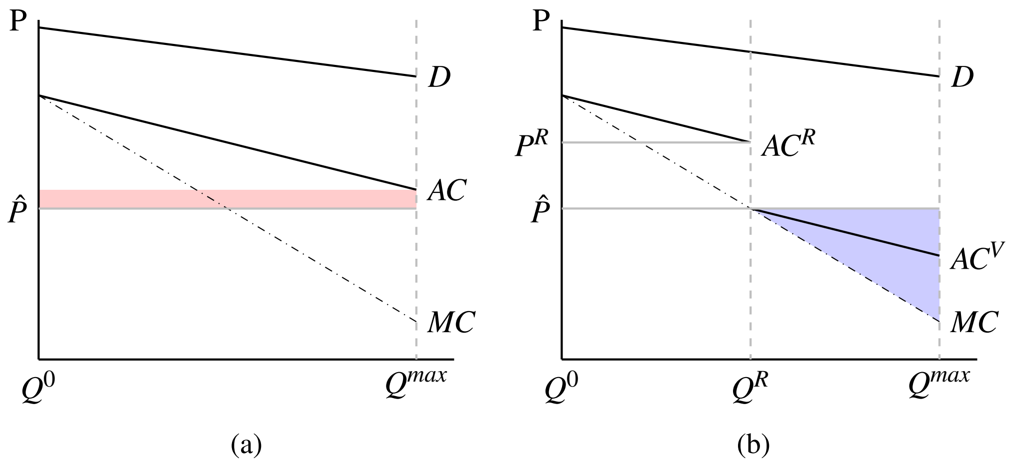
This stylized example highlights the crucial role played by the residual market; it ensures that all consumers can purchase an insurance contract *despite* strict price regulation in the private market. To see this, note than in the absence of the residual market, consumers with marginal costs above the regulated price cannot buy insurance *regardless of how much they are willing to pay* as no firm would be willing to insure them. In contrast, in the absence of regulation, competitive firms would incorporate the unused information in to their rating process, resulting in each consumer being charged a price equal to their marginal cost. The residual market thus allows price-suppressing regulation to be sustainable in the voluntary market.

Relative to the benchmark where the price for each customer is equal to their marginal cost, the scenario with a residual market and price regulation entails clear distributional consequences. All consumers that purchase a policy in the voluntary market are charged more than their marginal costs, with the lowest risk consumers paying the highest markups. Consumers buying in the residual market are charged an average cost necessarily greater than both the regulated price of the voluntary market ($\hat{P}$) and the average cost pooled across the total market, as the risk pooling is concentrated on only the highest risk consumers. Again, the riskiest consumers are charged less than their marginal cost, while the least risky consumers in the residual insurance pool are charged more than their marginal cost.

[5] In an alternate scenario, if the demand curve were steep enough, consumers that are marginally ceded from the voluntary market will not purchase from the residual market as the pooled price from the residual insurer is higher than their willingness-to-pay.

[6] Characterization of the dynamic rate setting negotiations and long-run equilibria is beyond the scope of this paper.

Figure 2: Price-Regulated Insurance Market



(a) Regulated price ($\hat{p}$) is below average cost (AC) at every point. All consumers buy insurance (Q^{max}) and insurers have negative profits, shown in red. **(b)** Insurers choose customers with marginal cost (MC) below $\hat{p}$. Profits are shown in blue. The residual insurer covers the highest risk consumers, Q^0 to Q^R, and charges P^R.

3.2 Increasing expectations of wildfire risk

Next, consider the changes to the market under increasing disaster risk. In Figure 3, MC' and AC' represent the new cost curves, reflecting an increase in wildfire risk. For simplicity, we assume these curves are a parallel outward shift in expected costs for each consumer.[7]

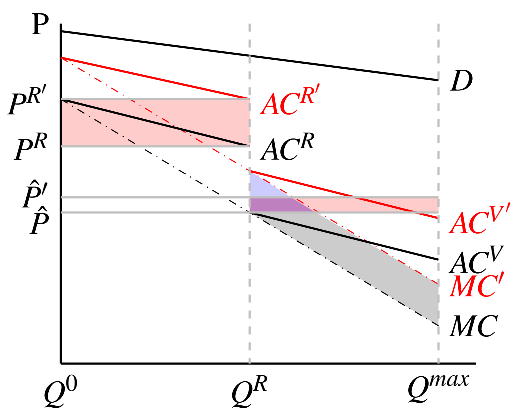
Figure 3 presents a situation where the regulated price adjusts more slowly than costs increase. That is, the regulated price increases from $\hat{P}$ to $\hat{P}'$, with $\hat{P}' - \hat{P} < AC' - AC$. Such situations can occur because of specific regulatory constraints, or more generally because of the length of the rate-filing process. In contrast, because the price in the residual market is not constrained by the regulated price, price adjusts to the average cost over customers already insured in the residual market, $P^{R'} = AC^{R'}(Q^R)$, keeping economic profits equal to zero in the residual market.

Panel (a) of Figure 3 represents the California homeowners market under the nonrenewal moratoriums–i.e., when firms are not allowed to further adjust which consumers they serve in the voluntary market (Q^R is held constant). As premiums increase, consumers suffer a reduction in wealth represented by the red rectangle in the residual market and the red and purple areas in the

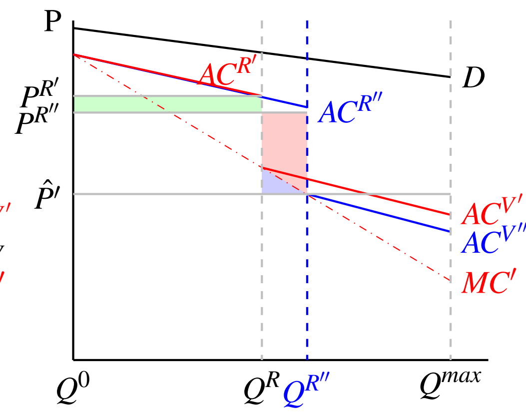
[7] We assume that disaster costs themselves are increasing. However, similar results hold if instead true costs remain constant, but insurers update their expectations of these costs.

voluntary market. Firms in the voluntary market incur higher expected costs, shown by the gray, purple, and blue areas, which are only partially offset by the increase in the regulated price. In this situation, firms generate negative economic profits on consumers with marginal cost greater than the new regulated price, shown by the blue triangle: firms would prefer to not offer these contracts. In the extreme scenario, if the increase in costs is high enough so that the average cost over consumers from Q^R to Q^{max} is above the regulated price ($\hat{P}'$), firms will choose to exit the voluntary market in the long run and the voluntary market would collapse.

Figure 3: Increasing Expected Costs



(a) No Residual Market Adjustment



(b) Residual Market Adjustment

Panel (b) depicts the market if firms are able to adjust their portfolio given the new regulated price and cost curves, meaning that Q^R is allowed to adjust. This situation represents the California market at the expiration of the one-year nonrenewal moratorium. Following the increase in wildfire risk, the voluntary market cedes all consumers who have a new marginal cost higher than the new regulated price (these consumers are between Q^R and $Q^{R''}$, where $Q^{R''}$ is determined by the intersection of the new marginal cost curve and the new regulated price). Because we consider a demand curve that is always above the residual market's average cost curve, the consumers dropped from the voluntary market will purchase insurance in the residual market. Given that the consumers dropped from the voluntary market have lower marginal costs than those already participating in the residual market, the residual market price drops to $P^{R''}$.

The costs of allowing adjustment from Q^R to $Q^{R''}$ are entirely borne by the group of consumers forced out of the voluntary market as a result of the adjustment. These consumers lose the red and blue areas in Figure 3 (b) due to the higher price $P^{R''}$. The firms capture the blue portion of the welfare loss because of the reduction in expected losses. Customers 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 increasing risk, (ii) the moratorium is effective at stopping the transition from the voluntary market towards the residual market while it is in place, and (iii) the residual market share increases when the moratoriums become inactive. We test prediction (i) with descriptive evidence in the Data section and predictions (ii) and (iii) with a difference-in-difference identification strategy, outlined in section 5.

4 Data

4.1 Insurance data

We obtain homeowners insurance data from the California Department of Insurance (DOI). 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 or condo owner multi-peril policies. We exclude policies that only provide coverage for contents, renters/tenant coverage, and policies covering unoccupied dwellings and mobile homes.

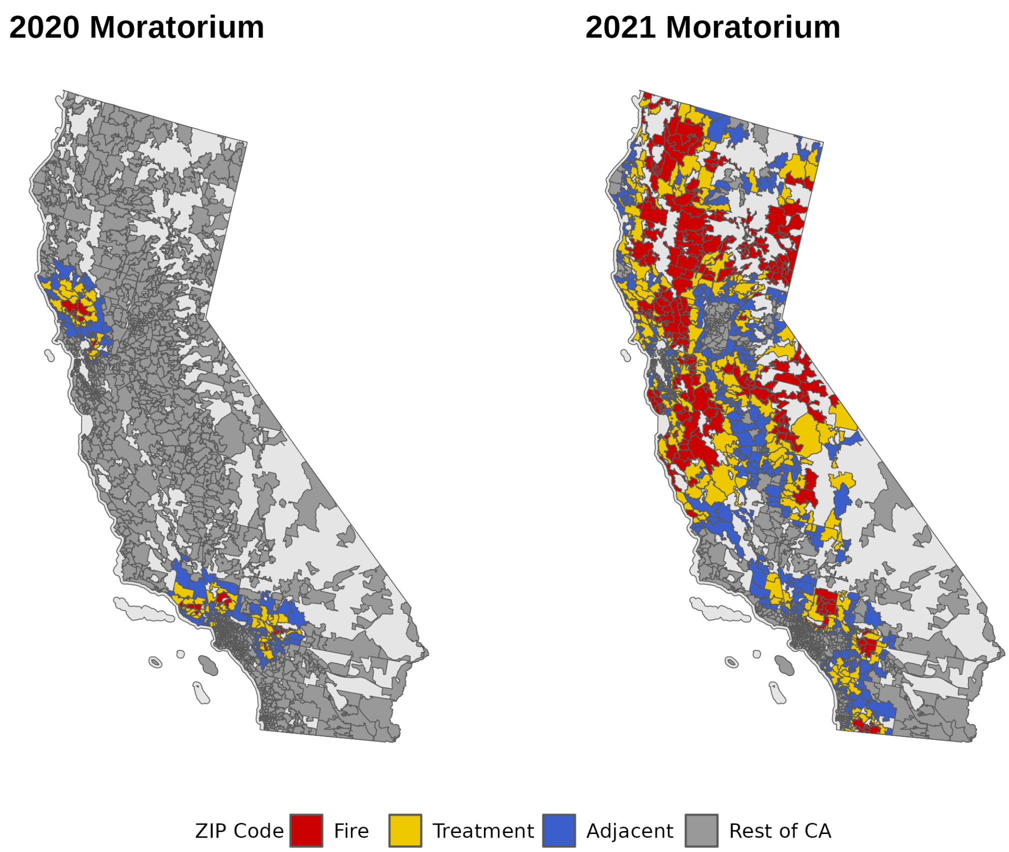
4.2 Wildfire boundaries

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. We classify zip codes into four categories. 'Fire' zip codes are those that were included in the moratorium because they directly experienced a fire that was declared a state of emergency. 'Treatment' zip codes are included in the moratorium by regulation because of their proximity to a burned area but did not directly experience the fire causing the declaration. These zip codes form the basis of our identification strategy discussed in the following sections. 'Adjacent' zip codes are zip codes that are not included in the moratorium, but share a border with a zip code covered under a moratorium. 'Rest of State' encompasses all other unimpacted zip codes. The California Department of Insurance reports all zip codes subject to a moratorium without distinction, thus we use fire perimeter data to differentiate the 'Fire' and 'Treatment' zip codes, excluding from the 'Treatment' group any zip code that experienced a wildfire that year. Figure 4 depicts the locations for the various moratorium classifications in 2020 and 2021, separately. Of note is the relative scale of the two moratoriums, with 2021 covering many more zip codes than 2020.

Figure 4: Moratorium Classifications by Zip Code



Note: The nonrenewal moratoriums cover both 'Fire' and 'Treatment' zip codes. 'Fire' zip codes are directly impacted by a wildfire. '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 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 annual probability of a fire capable of causing damage to a building if one were located there. We construct aggregate wildfire risk measures by averaging over pixels within each zip code.[8] RPS captures both the probability of a fire and its expected intensity evenly across the zip code, regardless of actual

[8]We use the census Zip Code Tabulation Areas (ZCTA) to construct all geographic level 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.

dwelling locations. One limitation is that RPS represents a snapshot of conditions in 2014 and does not account for variation in home construction types or heterogeneous changes in risk over time.

4.5 Descriptive evidence

We present the summary statistics for our main variables in Table 1. On average, the FAIR plan insures only 2% of the market during our sample period. We show in Appendix Tables A1 and Table A2 that this varies between moratorium and non-moratorium zip codes, with moratorium having a higher FAIR plan market share. 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 perils and does not include the difference-in-coverages policy, which must be purchased from a third-party company to replicate a homeowners policy). In a zip code, most policies in a year are either renewed by the insurer or nonrenewed by a customer, with only 2% of policies being nonrenewed by the company on average. Lastly, we report the average risk to potential structures (RPS) measure and median household income that are used in the heterogeneity analyses that follows.

Table 1: Summary Statistics

Statistic	Mean	St. Dev.	N	Source
Fair Plan Policies	92.85	294.08	24,740	CSS
Voluntary Policies	4,454.71	4,500.07	24,740	CSS
Average Premium	1,056.03	666.71	24,740	CSS
Average Voluntary Premium	1,053.54	670.30	24,735	CSS
Average Fair Plan Premium	968.44	910.27	21,292	CSS
New Policies	603.29	657.05	12,330	RPE
Renewed Policies	4,318.27	4,322.01	12,330	RPE
Company-Initiated Nonrenewals	120.86	144.64	12,330	RPE
Customer-Initiated Nonrenewals	445.44	482.82	12,330	RPE
RPS	0.27	0.46	24,740	USFS
Median Income	72,894.35	34,025.01	22,708	ACS

Figure 5 shows the evolution of the key insurance outcomes based on the 2020 moratorium classification, expressed relative to their 2015 baseline level (Appendix Figure A1 presents similar statistics for the 2021 moratorium with similar takeaways). 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, we also see a large reversal in the following year after 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.[9]

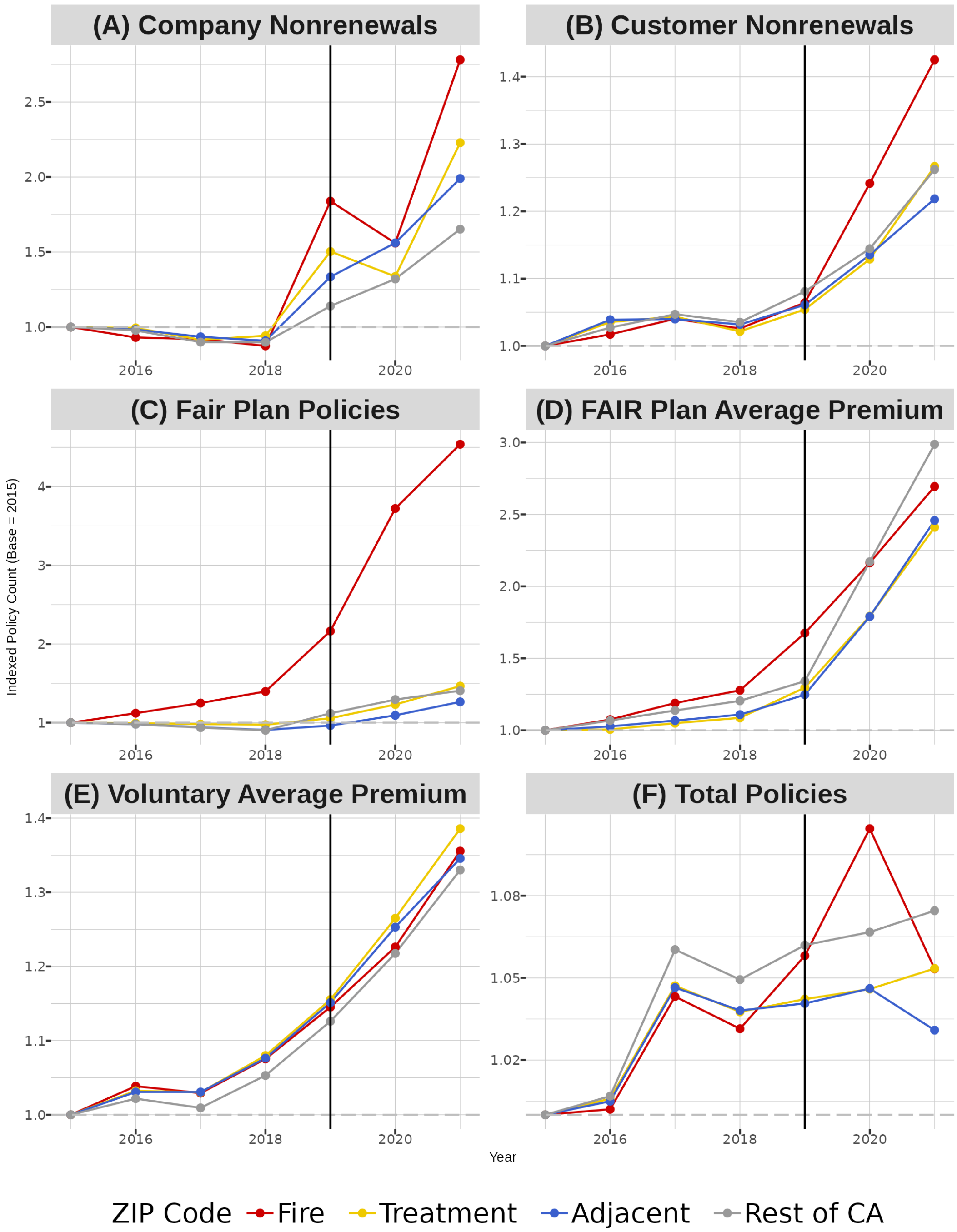
A potential concern in our setting is that firms could circumvent the moratorium by disguising a company-initiated nonrenewal as a customer-initiated nonrenewal. This concern does not seem warranted: Panel B shows 'Treatment' zip codes see an increase in customer nonrenewals similar to that observed in adjacent and "Rest of State" zip codes. The '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 premiums in both the voluntary market and the FAIR plan should increase in response to increased risk. 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 costly 2017 and 2018 fire seasons. However, the scale of the increases is significantly larger in the FAIR plan. Voluntary market premium increases hover around 7% per year, supporting the theory of a binding 7% price increase cap. The premium increases, on a percentage basis, are similar for all zip code groups in the voluntary market.

Panel C of Figure 5 shows the changes in FAIR Plan market share. By 2021 in 'Fire' zip codes, FAIR Plan market share had more than doubled from 2019 and more than quadrupled from 2015. In comparison, changes in FAIR Plan market share in other zip codes is more subtle, but, we can see that increases are larger for 'Treatment' zip codes than for 'Adjacent' zip codes following the expiration of the moratorium.

[9]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.

Figure 5: Statistics by 2020 Moratorium Classification



Notes: Indexed changes, relative to 2015 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.

Panel F of Figure 5 shows changes in the total number of policies over time. Trends are fairly stable for non-fire zip codes. There is some suggestive evidence that the fire itself drove insurance demand with 'Fire' zip codes experiencing a 10% 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 to 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 non-renewal moratorium

5.1 Identification strategy

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

To begin with, 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 trend 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 is 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. In addition, spatial and systematic variation in wildfire risk caused by variation in terrain and climate indicate 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).

Second, we assume that there is no treatment anticipation. This assumption is plausible for two reasons. First, the legislation was passed for the first time at the end of 2018, without prior warning to insurers, allowing very little time to adjust before the first moratoriums were enacted. 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 be able to predict *ex ante* which zip code could 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.

Third, the Stable Unit Treatment Value Assumption (SUTVA) requires the absence of spillover effects. This assumption could be be violated in our context: while insurers were subject to the nonrenewal moratoriums in specific zip codes, they could still adjust their portfolio in other zip codes as a direct response to the moratorium. Such potential spillover effects present a challenge for causal identification. To address it, we leverage the data in the CSS to identify the insurance companies *most exposed* to the moratoriums, defined as the top 50% of firms by percent of firm state-wide premiums written in moratorium designated zip codes at the time of declaration. For each zip code, we then compute the share of premiums written by these highly exposed firms in the year preceding the moratorium. Using this statistic, we define highly impacted control zip codes as those that had more than 75% of their premiums insured by highly impacted firms which corresponds to approximately the top quartile of zip codes – these zip codes are shown in Figure A2.

For our main specification, we exclude from the control group (adjacent zip codes) all zip codes that are designated as "highly exposed." 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. In robustness checks, we show that our main takeaways are not sensitive to the choice of control group, with the full set of adjacent zip codes yielding similar estimates (Figure A5).

5.2 Estimating equation

We estimate,

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

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. 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 estimator from Gardner et al. (2024).

6 Results

6.1 Direct effects of the moratorium

We present our main results for the direct 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 code, while event time 1 is the year when the moratorium is lifted and the regulation is no longer in place. For all outcomes except voluntary market policies, pre-treatment event-time coefficients are small and not significantly different from zero, providing support for the parallel trend assumption.

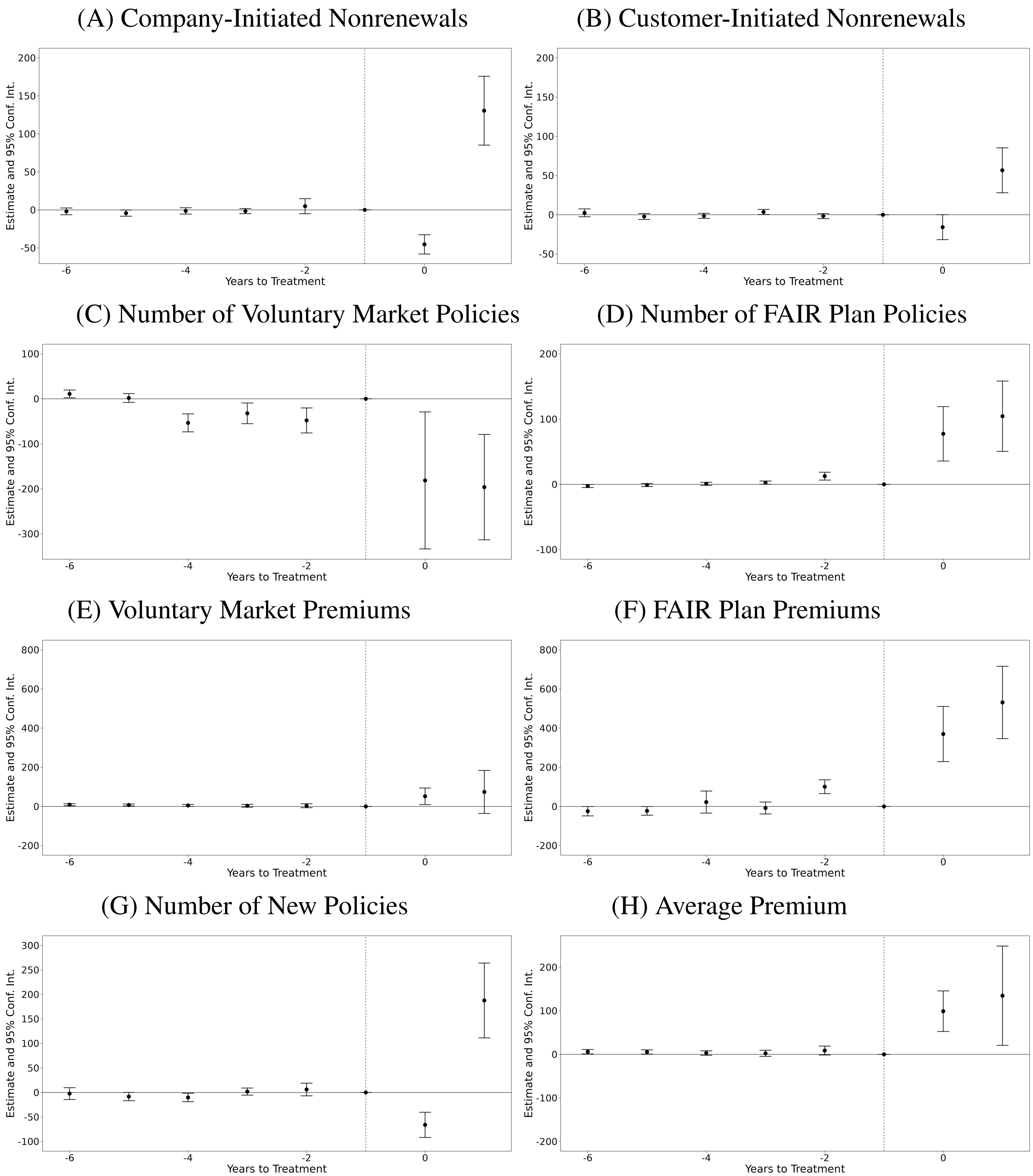
Panels A and B of Figure 6 show the effects of the moratorium on company- and customer-initiated nonrenewals, respectively. During the period of the moratorium, firms decrease their nonrenewals by approximately 50 policies (26% of pre-treatment levels) compared with the control zip codes, suggesting that the moratorium was 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 (80% of pre-treatment levels) compared with the control zip codes. These estimates indicate that firms not only delayed the nonrenewal action to the following contract period, but also accelerated their retreat from moratorium areas with more policies being nonrenewed in aggregate across the two years.

Appendix Figures A3 and A4 explore the effects of heterogeneity in wildfire risk and income by estimating equation (1) separately by RPS and income quartile. The results show that the effect was largely contained to zip codes with the highest risk of wildfires and the higher levels of income.

In contrast to company-initiated nonrenewals, we find that the moratorium had no impact on customer-initiated nonrenewals (Figure 6 panel B) when the moratorium was in effect. 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 during the moratorium, which would lead to a positive coefficient at time 0. Panel B also shows that customer-initiated nonrenewals increase by 10% 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 nonrenewals, which must be delivered in writing to the policy holder 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 shop for a new policy and cancel their existing policy before it expires, which is then recorded as a customer-initiated nonrenewal in the data. Thus, the true effect of the moratorium being lifted is a combination of the customer- and company-initiated nonrenewals in event time 1. The addition of these two coefficients is an upper-bound estimate of the effect of the moratorium on firm-driven nonrenewal activity.

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 a 100% increase in policies from pre-treatment levels and additional growth of 100 policies the year after the moratorium is lifted. There is 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. These results, when combined with those above, imply that although the moratorium significantly impacted nonrenewals in treated zip codes and 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. 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: Direct 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 had no impact on voluntary market premiums. Such null 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 contrast, we estimate that the average FAIR Plan premium increases by around \$400 (29%) during the moratorium and continues to increase 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 and its rates are bound by statute to be actuarily sufficient and net reinsurance costs can be passed through.

In the stylized model, holding all else equal, as insurance companies cede more policies to the FAIR plan, the pooled price in the FAIR plan declines as the additionally ceded risks are less risky than those already in the FAIR plan. Applying this to the empirical setting, the model would predict treatment areas to have higher FAIR plan prices the year of the moratorium as the control areas cede relatively lower risks into the FAIR plan, as seen in our results. However, in practice, even if marginal customers are of lower risk it will take time for their better loss experience to impact the rate the FAIR plan will charge due to regulatory lag and the backwards looking structure of ratemaking. Thus, another plausible explanation for the increasing FAIR plan premium result found both in time 0 and the post period is due to the composition of the homes being moved between the voluntary market and the FAIR plan; if firms nonrenew higher valued homes, their introduction to the FAIR plan can increase the average premium, as premiums are an increasing function of the amount of coverage provided, which we do not observe.

6.2 Spillover effects

Next, we directly test for the existence of spillover effects to areas outside the moratorium boundary by restricting the estimation sample to the set of zip codes that were not subject to either moratorium ('Adjacent' and 'Rest of State'). Within this sample, we compare the highly impacted zip codes, as described earlier, to low impacted zip codes (shown in Figure A2). This allows us to estimate *differential* spillover effects between the two groups. Firms with a large portion of their portfolio impacted by the moratorium are more likely to make adjustments outside of moratorium boundaries, so any spillover effects are most likely to be concentrated in highly impacted zip codes. Note that it is possible for the 'low impacted zip codes' to experience some treatment effects in the absence of a pure control group. Testing for differential spillover effects estimation is more common in the geographic context, where spillover effects are assumed to decline with distance from the treated areas (Butts, 2023). In our setting, there can be spillovers through both geographic distance and attribute similarity.

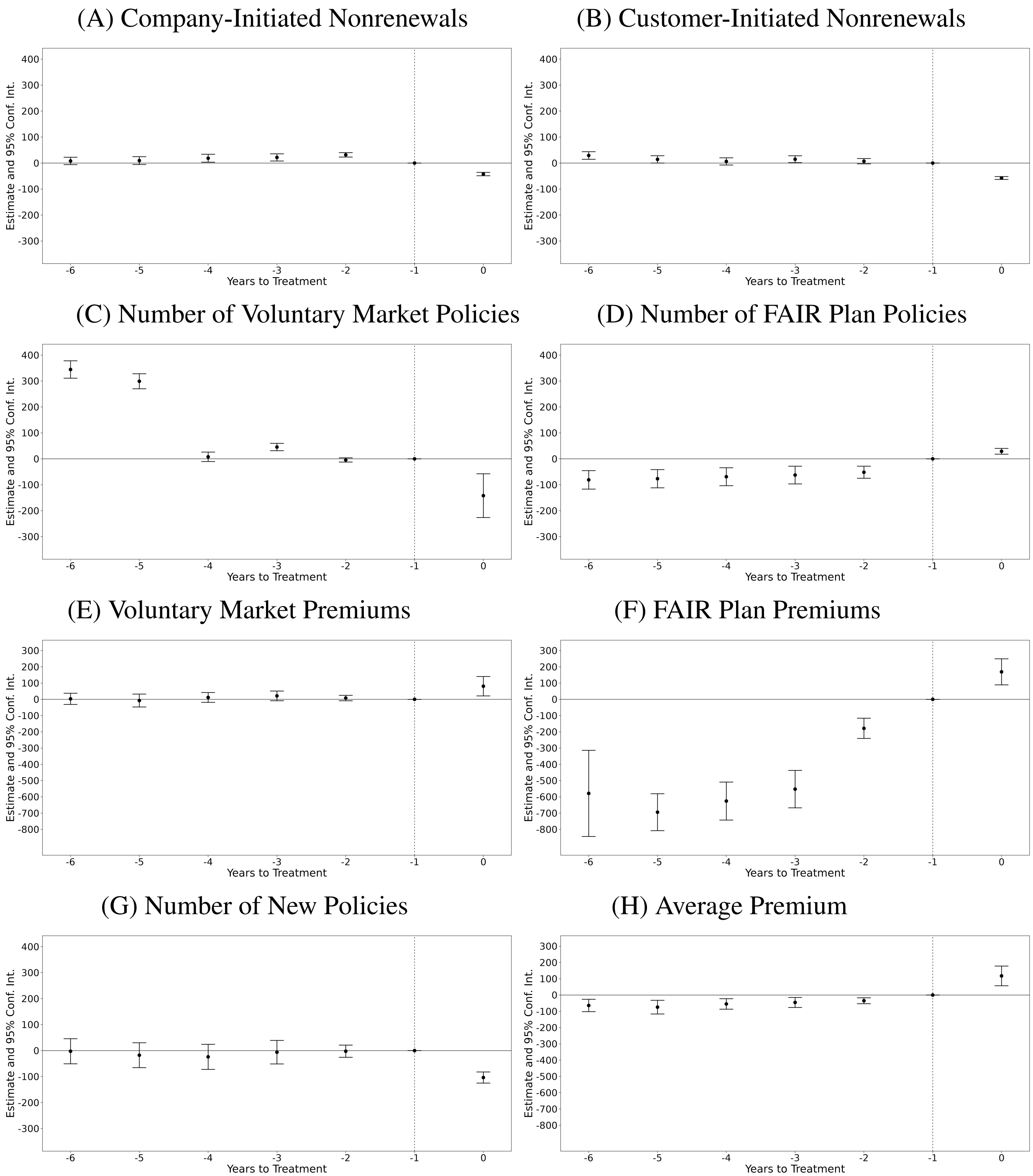
Figure 7 presents our main spillover results. We focus on the larger moratorium to estimate the effects of spillovers as the impact to the statewide portfolio of insurers from the first moratorium was minimal (the first moratorium resulted in very few highly impacted zip codes, even when using a substantially lower threshold). Although pre-trends for most insurance outcomes are flat and not significantly different from zero, the pre-trends for FAIR plan market outcomes are large and statistically significant, indicating that enrollment in the FAIR plan and average prices for FAIR plan policies were already relatively increasing in highly impacted zip codes prior to the moratorium. These pre-trends suggest that our estimates for FAIR plan outcomes in this setting cannot be interpreted as causal. Our discussion focuses on the voluntary market outcomes, and we return to the FAIR plan outcomes using additional methods below.

We find that the number of new policies fell by around 100 policies in the year of the moratorium, (Figure 7 panel G), suggesting that the moratorium led highly impacted firms to reduce the issuance of *new* policies across the state. Similarly, panels A and B show that both company- and customer-initiated nonrenewals also declined by around 50 policies each per zip code. Together, these declines imply that firms were retaining more of their existing portfolio, rather than selling new policies, while customers were more likely to stay with the same insurer and therefore less likely to nonrenew.

Finally, panel G shows that average premiums in the voluntary market increased more in highly impacted zip codes relative to low impacted zip codes by about $100. This could be the case if highly-impacted zip codes are exposed to higher wildfire risk. To account for potential differences in wildfire risk, as well as to address the pre-trend concerns for the FAIR plan outcomes, we present two additional approaches in Appendix Figure A6 and Appendix Figure A7. In Appendix Figure A6 we restrict the low impacted control group to only those that border a highly impacted zip code and implement the aforementioned nearest neighbor matching procedure, matching highly impacted zip codes to observably similar low impacted zip codes. Results show a muted effect on voluntary market premiums, including 0 in the confidence interval when using the adjacent control group. For the FAIR plan policy outcome, these additional approaches drastically improve the pre-trend, and we now estimate a precise null effect for highly impacted zip codes. FAIR plan premium still exhibit differential pre-trends, although improved. Importantly, our other spillover results are robust to the use of these other approaches.

Overall, these results are consistent with a state-wide "market freeze" effect in the zip codes where firms were highly impacted by the moratorium: firms issued fewer new policies and retained more of their existing portfolio, while customers were more likely to renew with the same insurer, and premiums slightly increased. This market freeze effect likely reflects the uncertainty associated with future wildfire risks and insurance regulation.

Figure 7: Spillover Effect of the Nonrenewal Moratoriums on Insurance Market Outcomes



Notes: Event study results for the spillover effect of the 2021 nonrenewal moratorium Gardner et al. (2024) are shown for various insurance market outcome variables. The sample consists of zip codes never covered by a moratorium. Treatment zip codes are those designated as highly impacted by the moratorium and control zip codes are low impacted as measured by the percent of zip codes premiums insured by highly impacted firms. Error bars represent 95% confidence intervals with standard errors clustered at the zip code level.

7 Conclusion

Increasing disaster losses are putting significant strain on the stability of home insurance markets. Rising insurance premiums can reduce the risk of insurer bankruptcy, but they can also severely affect household finances (Ge et al., 2025). These direct and salient costs to homeowners have led policymakers to enact strict price regulations in most U.S. states (Oh et al., 2023). Without the insurer of last resort, strict price regulation would lead to an unraveling of the market as prices and risk diverge. Our paper highlights how the insurer of last resort stabilizes private insurance markets by capturing the highest risk households that would otherwise be unprofitable for the private market under price regulation. 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 disrupted the market stabilizing role of the insurer of last resort by forcing insurers to provide policies they otherwise would not have. We find that the moratoriums were effective in the short term at reducing nonrenewals, but the strong rebound effect suggests this policy is not an effective long-term solution, and even resulted in a net increase in policy nonrenewals and FAIR Plan policies, accelerating the retreat of insurers from high-risk markets.

In order for firms to remain in the market in the long run, premiums must be reflective of the underlying risks. This can be achieved by either relaxing regulation, or investing in climate adaptation. Recent policy changes indicate that both strategies are being pursued in California. First, recent legislation has taken steps to bring rates in line with the risk level, allowing firms to begin using filed and approved forward-looking catastrophe models in their rate-making and to pass through some reinsurance costs to customers (Cal. Code of Regulations, 2022, 2024). In the context of our model, these regulations allow the regulated price to approach the expected marginal cost curve, expanding the supply of insurance in the voluntary market. In addition, allowing firms to incorporate new rating variables results in a flatter marginal cost curve, and reduced reliance on the FAIR plan.

Another way to control the growth in premiums and to prevent unraveling of the market is to promote the adaptation of buildings and communities to growing disaster risk. In California, fire-resilient building codes have been shown to yield benefits for homes faced by wildfire (Boomhower and Baylis, 2024). Expanding these measures and creating incentive programs for builders and homeowners could further lower the expected marginal cost curve. Additionally, an effort to promote adaptation was passed in 2022 by the California Department of Insurance, requiring firms to file discounts which rewarded adaptation measures undertaken by homeowners, such as clearing defensible space or installing a fire resistant building material (Cal. Code of Regulations, 2022).

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 entire FAIR Plan's available reserves and reinsurance. Consequently, the FAIR Plan was granted a $1 billion assessment from all insurers selling homeowners insurance in the state, proportional to their market share, including from firms that had no exposure in fire-prone areas. As FAIR plan penetration in high-risk areas increases, the risk of assessment to firms also increases, furthering insurers' incentive to reduce their exposure in the state.

While the insurer of last resort allows premiums to remain below their actuarially fair level, its distributional consequences are unclear. Rather than being means-tested, the benefits afforded by the FAIR plan are geography-based, and accrue to individuals living in higher risk areas. 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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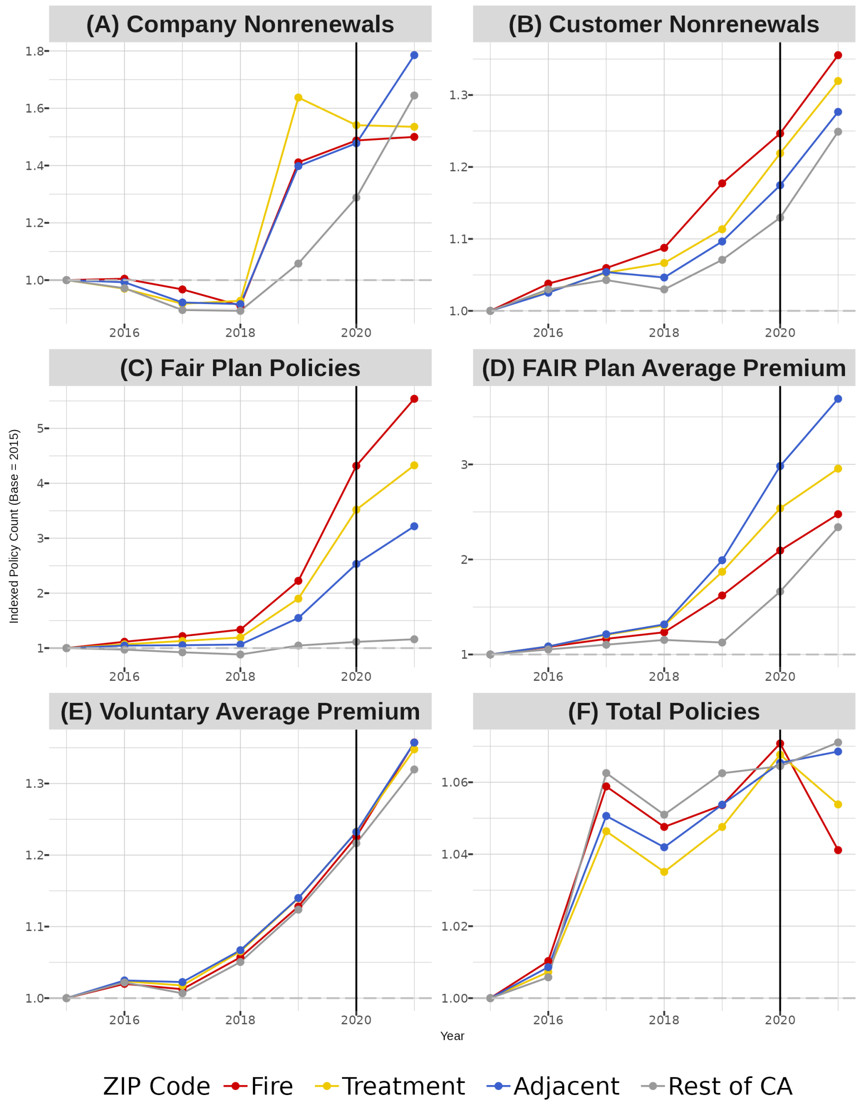
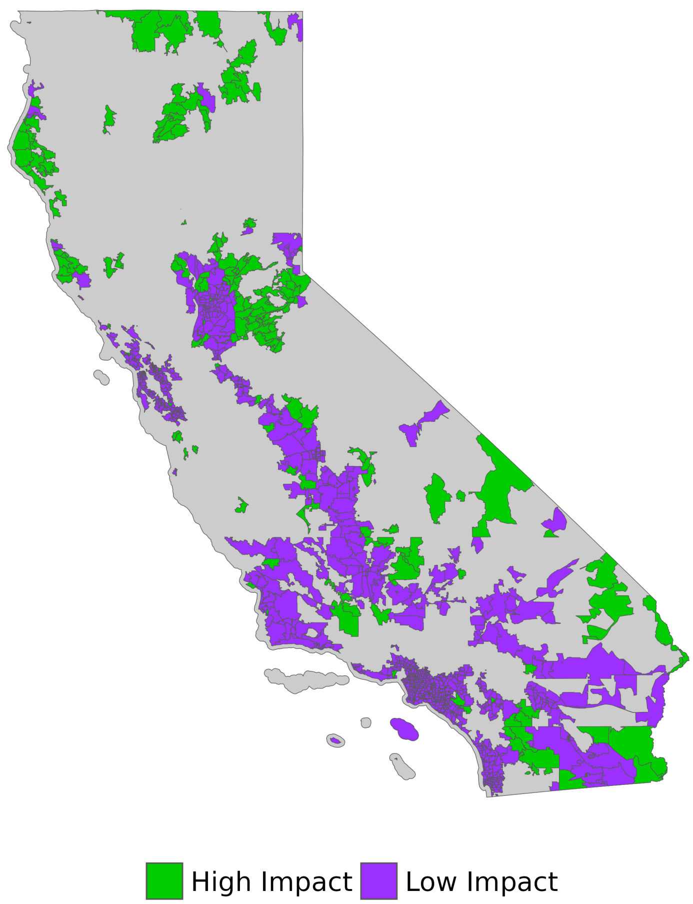
A Additional Figures

Appendix Figure A1: Statistics by 2021 Moratorium Classification



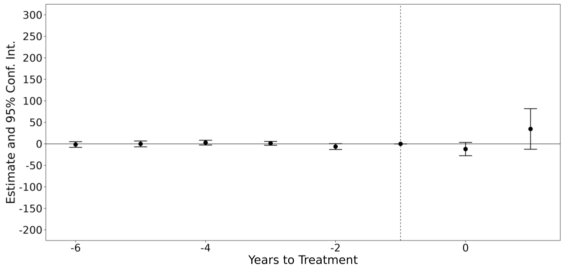
Notes: Zip codes are broken out by moratorium classifications. 'Fire' zip codes were directly impacted by a wildfire in 2020 and covered by the non-renewal moratorium in 2021. 'Treatment' zip codes were covered by the non-renewal moratorium in 2021 but did not experience a wildfire in 2020. 'Adjacent'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

Appendix Figure A2: High vs. Low Impact Zip Codes for Non-Moratorium Areas

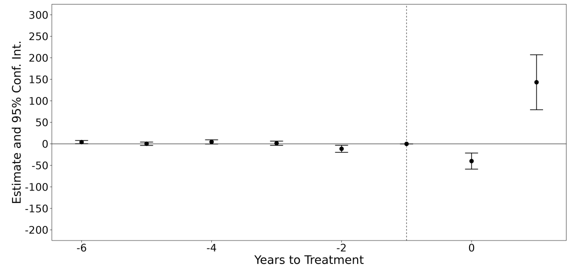


Notes: Zip codes not covered by the either the 2020 or 2021 nonrenewal moratorium are shown by their level of potential impact. High impact zip codes had more than 75% of their premiums insured by firms highly impacted by the 2021 moratorium.

Appendix Figure A3: Effect of Moratorium on Company-Initiated Nonrenewals by RPS Quartile



(a) 1st



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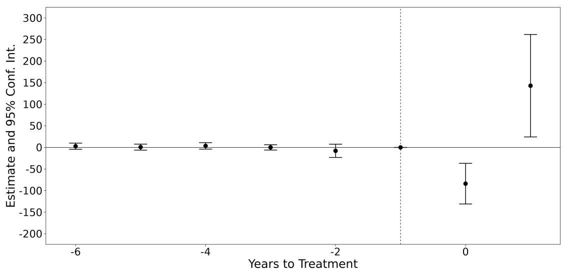
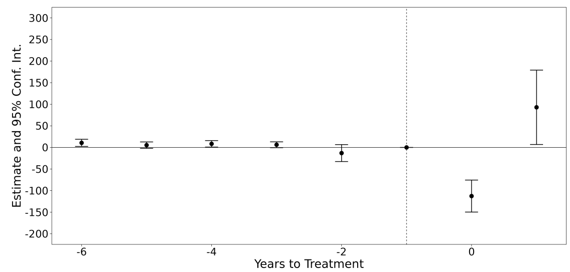


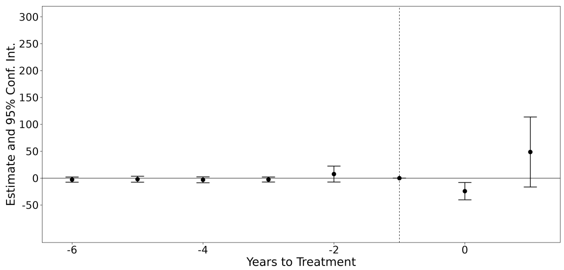
(c) 3rd



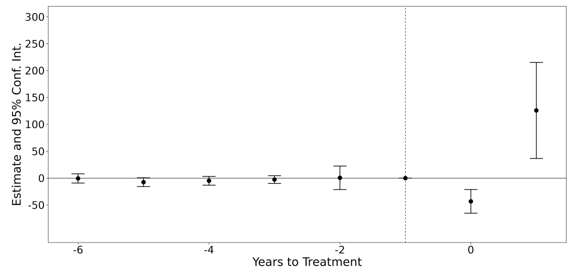
(d) 4th

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 A4: Effect of Moratorium on Company-Initiated Nonrenewals by Income Quartile



(a) 1st



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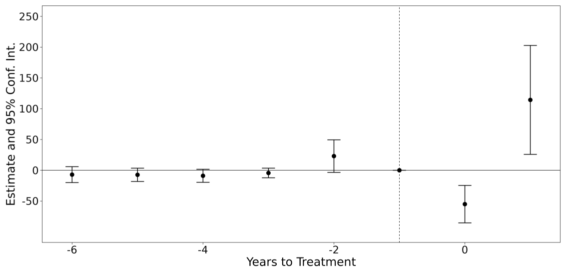
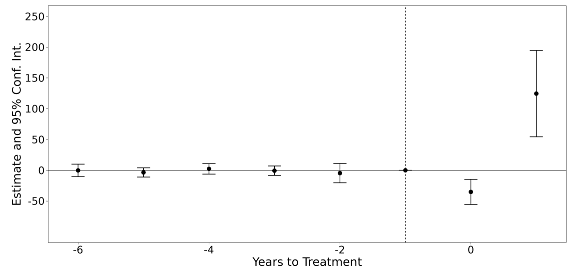


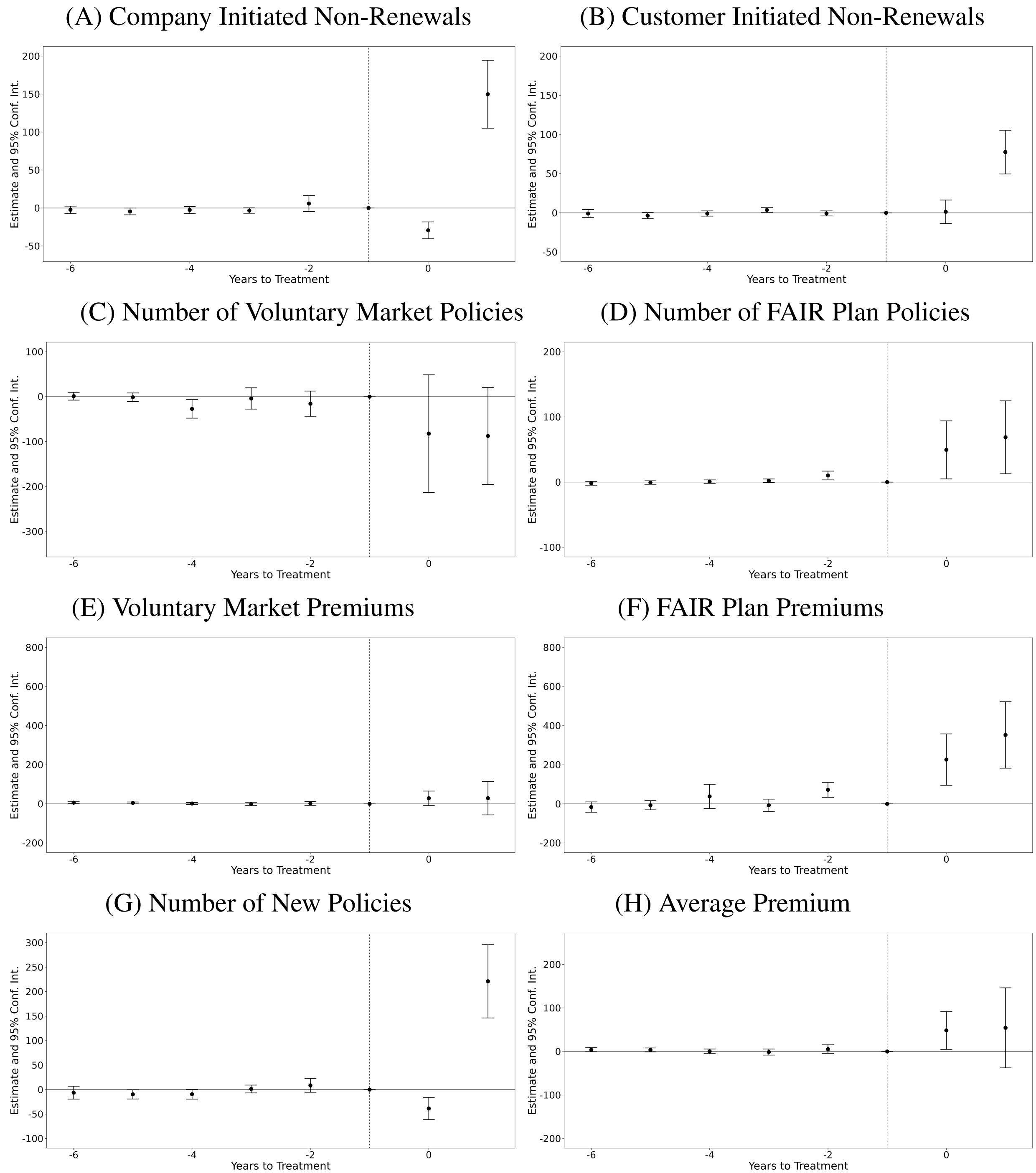
(c) 3rd



(d) 4th

Notes: Event study results for the effect of the nonrenewal moratorium on company-initiated nonrenewals broken out by 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.

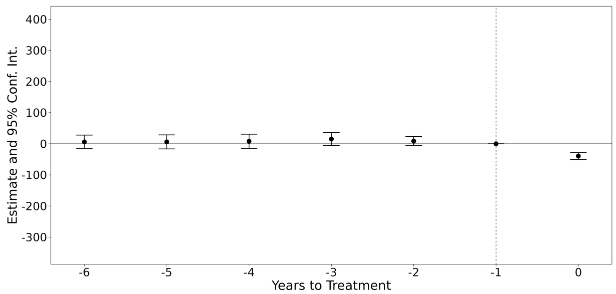
Appendix Figure A5: Direct Effect of the Nonrenewal Moratorium on Insurance Market Outcomes: All Control Zip Codes



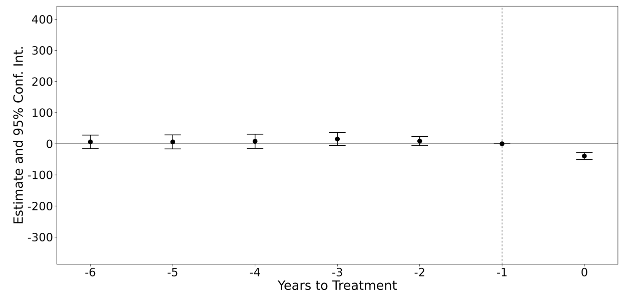
Notes: Event study results for the effect of the nonrenewal moratorium using the two-stage DID estimator from Gardner et al. (2024) are shown for various insurance market outcome variables. Treatment zip codes are non-fire areas covered by a nonrenewal moratorium. Control zip codes are all adjacent zip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

Appendix Figure A6: Spillover Effect of the Nonrenewal Moratoriums on Insurance Market Outcomes: Matching Estimator

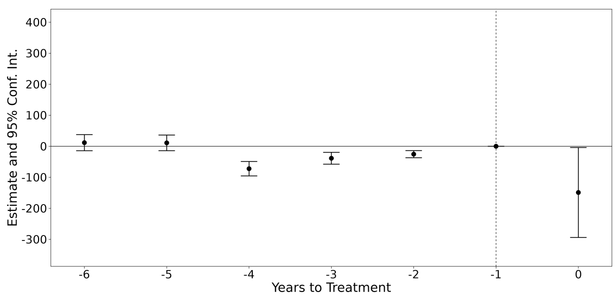
(A) Company-Initiated Nonrenewals



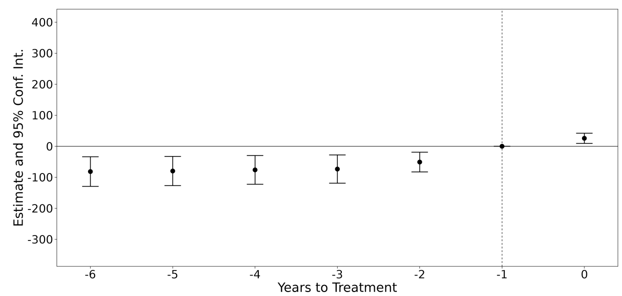
(B) Customer-Initiated Nonrenewals



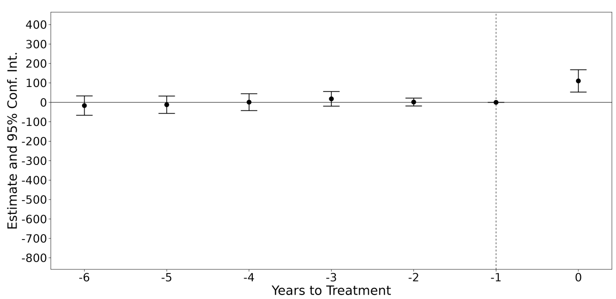
(C) Number of Voluntary Market Policies



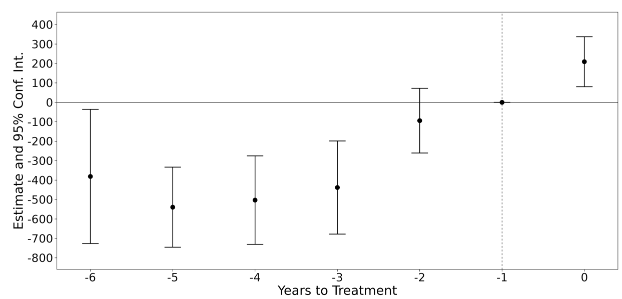
(D) Number of FAIR Plan Policies



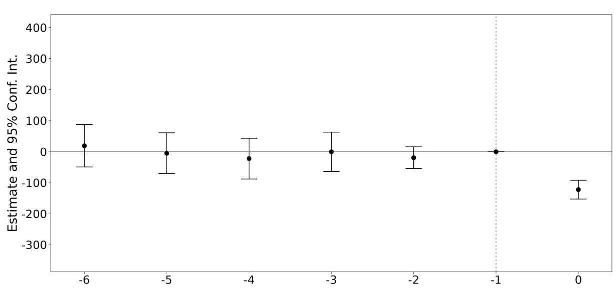
(E) Voluntary Market Premiums



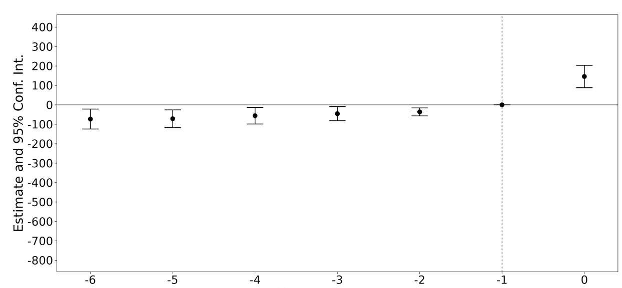
(F) FAIR Plan Premiums



(G) Number of New Policies



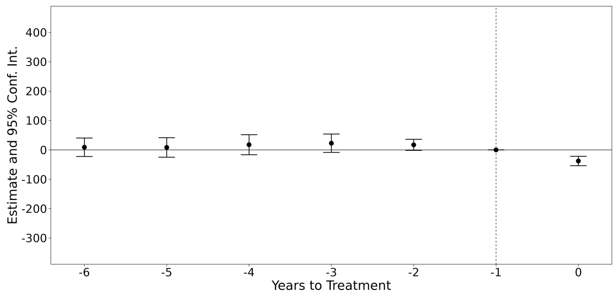
(H) Average Premium



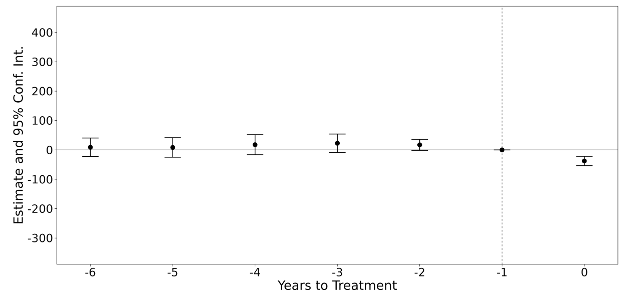
Notes: Event study results for the spillover effect of the 2021 nonrenewal moratorium are shown for various insurance market outcome variables. The sample consists of zip codes never covered by a moratorium. Treatment zip codes are those designated as highly impacted by the moratorium. Control zip codes are selected from the pool of low impacted zip codes using a nearest neighbor matching process. Error bars represent 95% confidence intervals with standard errors clustered at the zip code level.

Appendix Figure A7: Direct Effect of the Nonrenewal Moratoriums on Insurance Market Outcomes: Neighboring Zip Codes

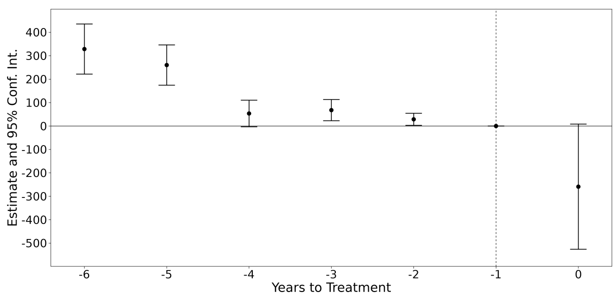
(A) Company-Initiated Nonrenewals



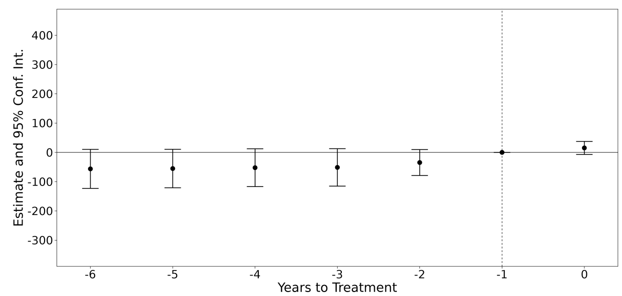
(B) Customer-Initiated Nonrenewals



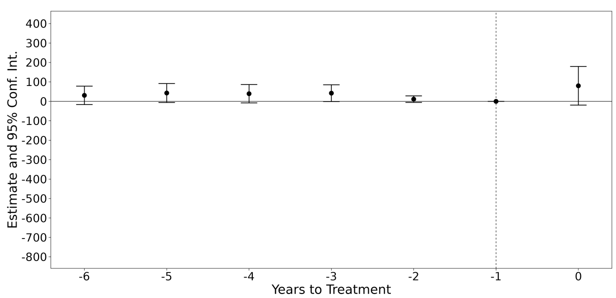
(C) Number of Voluntary Market Policies



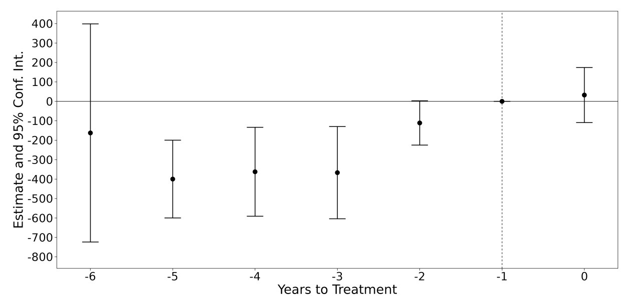
(D) Number of FAIR Plan Policies



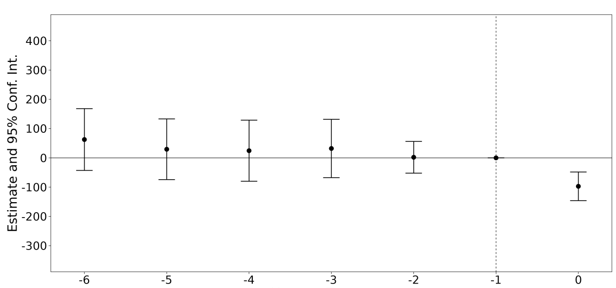
(E) Voluntary Market Premiums



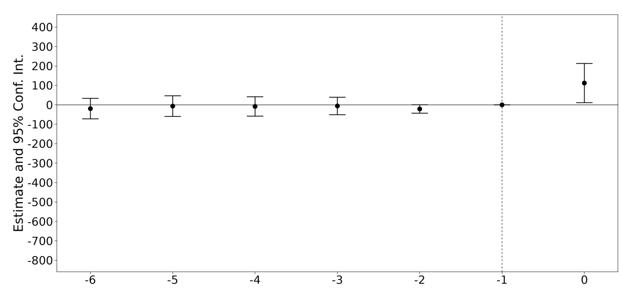
(F) FAIR Plan Premiums



(G) Number of New Policies



(H) Average Premium



Notes: Event study results for the spillover effect of the 2021 nonrenewal moratorium are shown for various insurance market outcome variables. The sample consists of zip codes never covered by a moratorium. Treatment zip codes are those designated as highly impacted by the moratorium. Control zip codes are restricted to only those low impacted zip codes which directly border the treated zip codes. Error bars represent 95% confidence intervals with standard errors clustered at the zip code level.

B 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	148.61	484.93	141.61	302.11	111.81	230.88	86.83	291.29
Voluntary Policies	4429.49	4126.21	6698.71	4648.94	5964.33	4960.95	4191.46	4394.83
Average Premium	1134.56	540.87	1215.85	763.59	1174.09	908.00	1034.22	635.62
Average Fair Plan Premium	1050.10	897.18	1072.17	947.90	890.84	901.69	966.32	908.10
Average Voluntary Premium	1143.20	534.11	1230.14	849.79	1187.24	970.91	1029.08	624.89
New Policies	618.95	601.58	952.10	727.77	856.08	783.68	560.13	630.34
Renew Policies	4369.29	3949.51	6424.80	4368.08	5731.33	4724.45	4068.75	4233.95
Company-Initiated Nonrenewals	140.64	175.70	215.97	203.11	175.01	182.08	109.97	132.19
Customer-Initiated Nonrenewals	447.43	415.05	679.01	509.36	629.60	567.20	415.47	467.36
RPS	0.54	0.56	0.49	0.55	0.39	0.53	0.24	0.44
Median Income	77412.27	26647.19	83396.07	35170.92	77311.95	31113.80	71693.18	34219.46

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

Appendix Table A2: Summary Statistics by Zip Code Classification (2021 Moratorium)

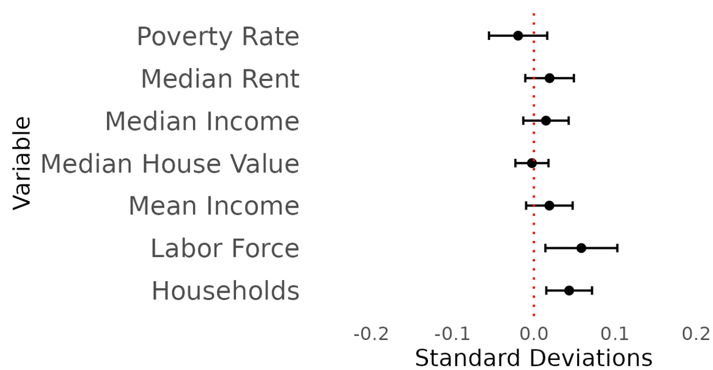
Zip code Classification	Fire		Treatment		Adjacent		Rest of State	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Fair Plan Policies	38.13	142.79	79.35	262.15	58.55	180.02	133.39	372.55
Voluntary Policies	2510.14	4011.13	4248.62	4441.37	4630.31	4593.09	5124.84	4434.92
Average Premium	1118.95	600.05	1057.00	425.38	1032.32	474.47	1045.00	815.71
Average Fair Plan Premium	1361.48	1053.48	1220.16	1005.21	1014.97	944.97	732.51	718.03
Average Voluntary Premium	1097.82	583.20	1039.94	385.90	1025.68	453.98	1055.87	838.58
New Policies	347.96	578.23	587.54	675.05	653.79	706.72	674.67	629.15
Renew Policies	2445.05	3918.52	4109.70	4291.24	4454.46	4368.68	4987.70	4247.20
Company-Initiated Nonrenewals	69.27	112.36	127.17	164.22	132.46	167.05	131.51	131.69
Customer-Initiated Nonrenewals	256.76	435.34	424.19	483.27	478.98	507.79	503.19	468.76
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	73014.26	36040.88	76246.14	35221.66

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

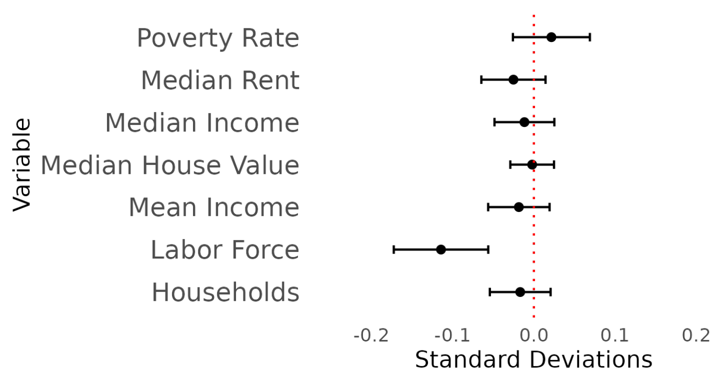
C Baseline Demographics

Figure A8 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 A8: Effect of Station Entry and Exit on Incumbent Pricing, by Initial Market Size



(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 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 on to 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.

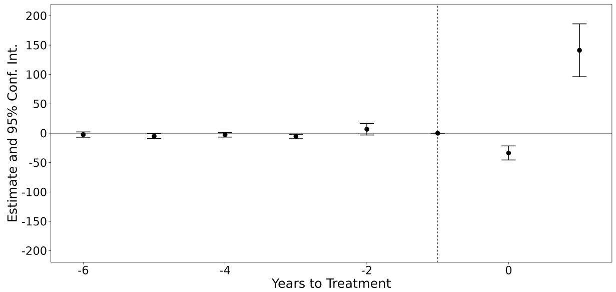
In a robustness check of our main results, we can make use of the fact that conditional on wildfire risk, the exact location of a wildfire in a given year is essentially random. We use a nearest-neighbor matching process to identify "control" zip codes from the rest of state group that were never impacted by a fire, never treated, nor 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.

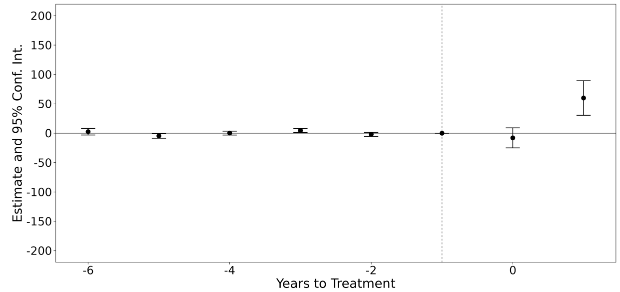
The results limiting to the matched control sample closely match our main results using the adjacent and low impacted zip codes as controls. This provides evidence that using the nearby zip codes represent strong counterfactuals for the treatment zip codes. It also supports the claim that there are no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

Appendix Figure A9: Direct Effect of Moratorium using Nearest-Neighbor Matching Process

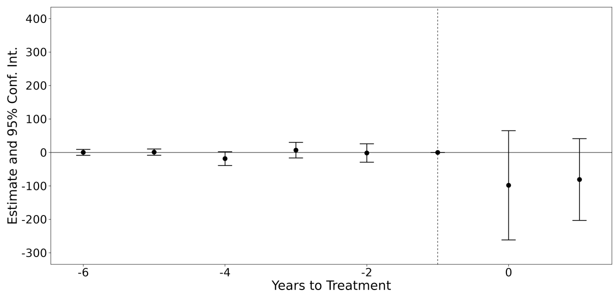
(A) Company-Initiated Nonrenewals



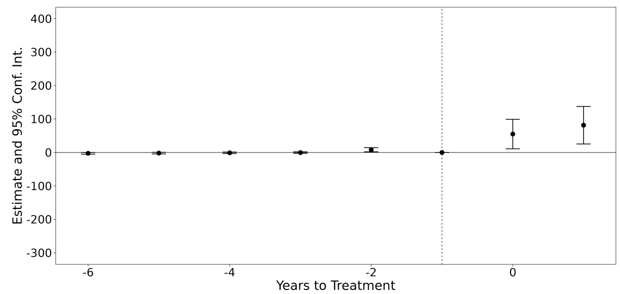
(B) Customer-Initiated Nonrenewals



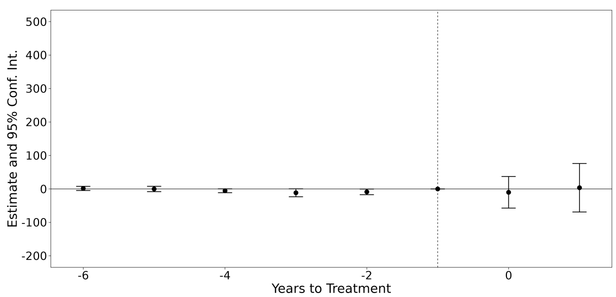
(C) Number of Voluntary Market Policies



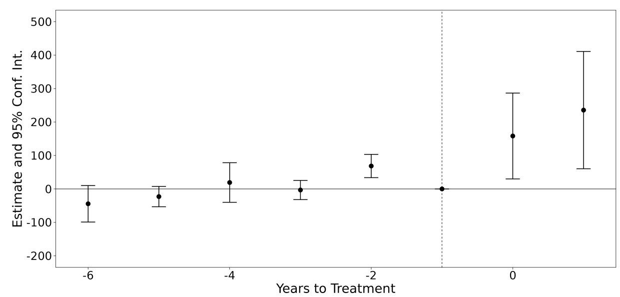
(D) Number of FAIR Plan Policies



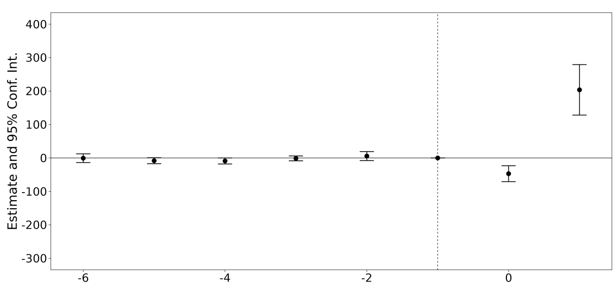
(E) Voluntary Market Premiums



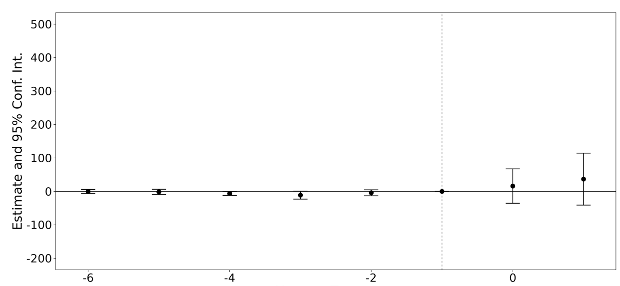
(F) FAIR Plan Premiums



(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 adjacent zip codes not covered by a moratorium that are matched using a nearest neighbor process. Error bars represent 95% confidence intervals with standard errors clustered at the zip code level.

E 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 changes to the number of policies and customer-initiated non-renewals is that the moratorium had a direct effect on homeowner's location decision and that our results are driven by migration decisions instead of insuring decisions (McConnell et al., 2024). Our identification strategy assumes that there are no other contemporaneous factors to the moratorium that could impact our outcomes of interest. The time period of our study coincides with the COVID-19 pandemic which led 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 or 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 zipcode-quarter level for zip codes in California. Lastly, we calculate net outflows which subtracts in-migration from out-migration. We present summary statistics for the four variables in Table A3.

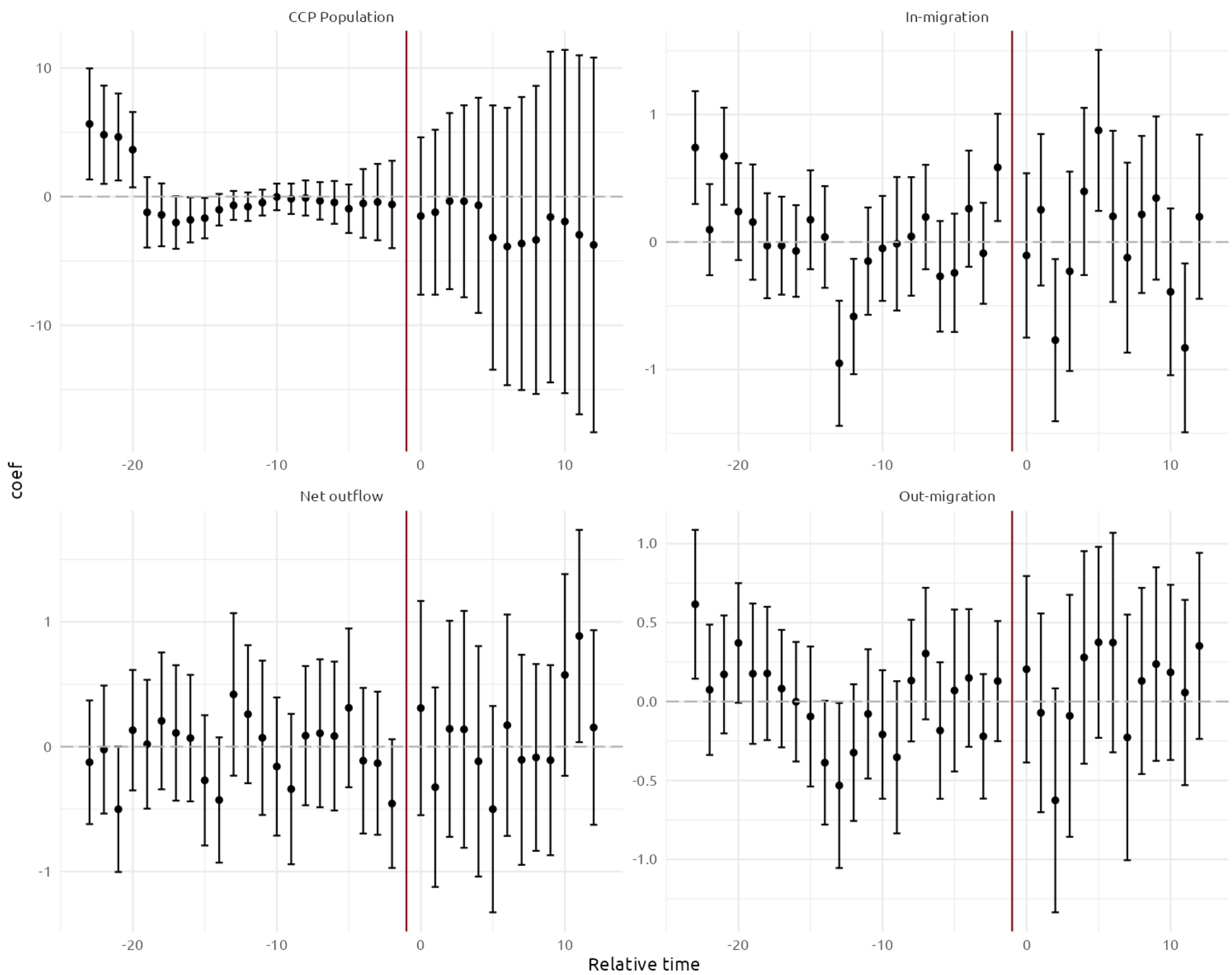
Appendix Table A3: CCP Summary Statistics for Treated and Adjacent Zip Codes

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 A10 presents the overall effects, while Figure A11 presents heterogeneity effects by wildfire risk quartiles.

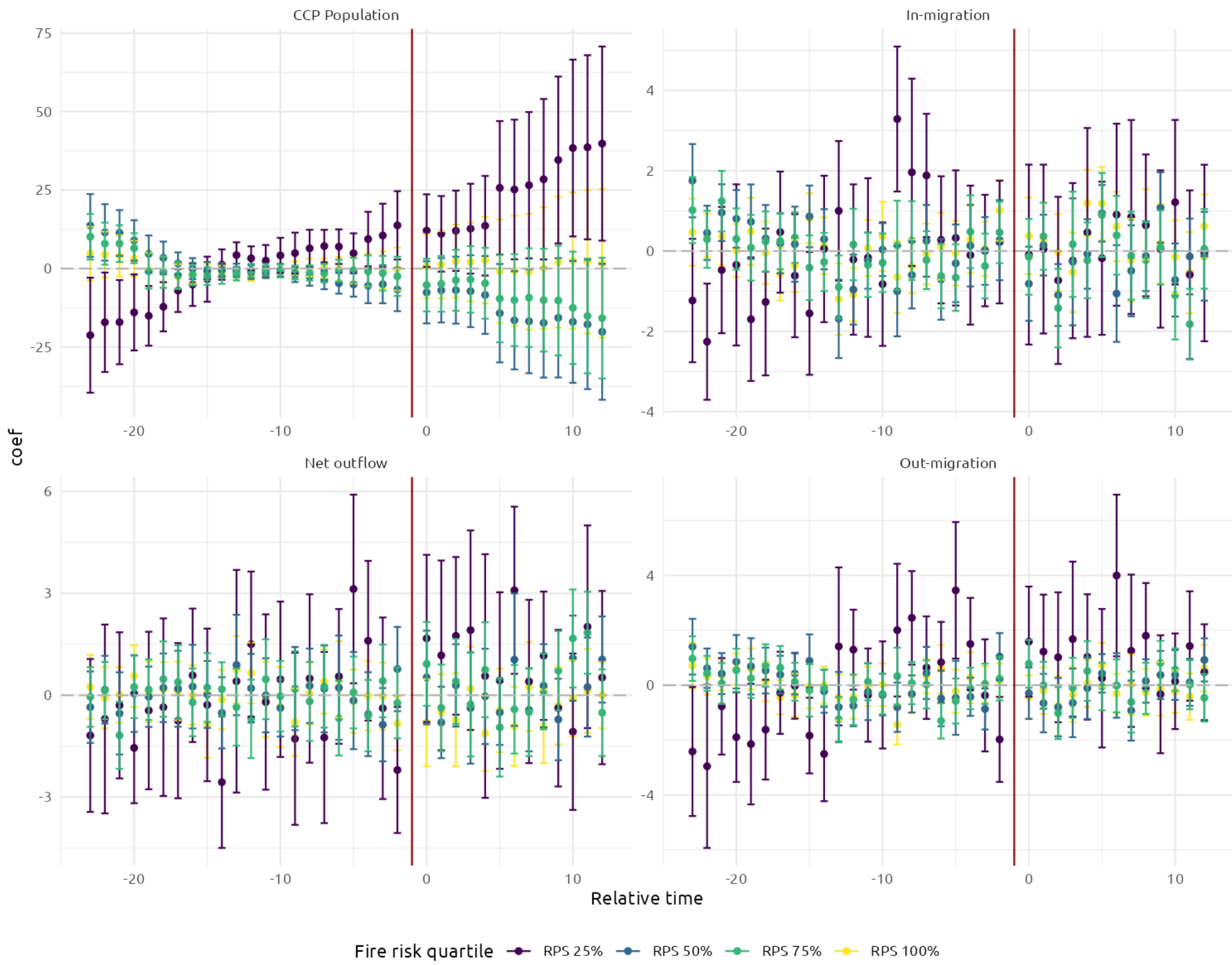
Across all outcomes, we do not detect any significant effect of the moratorium on migration patterns. The estimates by fire risk quartiles (Figure A11) suggests some significant effect in the top left panel for the CCP population outcome, but these estimates display some pre-trends and are not detected with any of the subsequent three outcomes. Overall, these estimates do not reject our assumption that the moratoriums had no differential impact on the migrations decisions of populations living in treated vs. control zip codes.

Appendix Figure A10: 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 A11: 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.