Climate Change and the Regulation of a Crashing Insurance Market

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Abstract

Climate change threatens the functioning of private insurance markets as natural disasters become more frequent and severe. As firms seek to limit exposure to catastrophic losses, customers are increasingly unable to find insurance in the private market, forced to turn towards state-sponsored residual risk pools known as ”insurers of last resort”. In this paper, we examine how price regulation and market structure can lead to market unraveling when firms face rapidly increasing risk due to climate change. We develop a model of an adversely selected natural disaster insurance market with an empirical application to California, the largest homeowner insurance market in the country. We then empirically study the California non-renewal moratoriums, a first-of-its-kind regulation aimed at stymieing the retreat of insurance companies from high wildfire risk areas by forcing insurers to supply insurance to current customers following disasters in 2019 and 2020. Using quasi-random geographic variation in regulatory borders and the location of wildfires, and a difference-in-differences identification strategy, we show that while the moratorium was binding in the short term, reducing company-initiated non-renewals, the effect only lasted for the one-year length of the moratorium. Additionally, the moratorium had no discernible effect on participation in the State's insurer of last resort .

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1 Introduction

Climate change is amplifying the frequency and severity of natural disasters. These extreme events pose substantial financial risks to households, firms, and communities, highlighting the urgent need for well-functioning insurance markets. However, uncertainty surrounding escalating costs associated with disasters, compounded by the growing potential for spatially correlated and catastrophic losses, presents new challenges for firms selling insurance against natural disaster events. In 1927, the Great Mississippi River Flood crippled insurance firms, leading private insurers to exit the market (Knowles and Kunreuther, 2014). Nearly a century later, wildfires in the American West threaten to do the same.

Wildfires are the fastest growing economic climate risk, with more than USD $150 billion in damages predicted in the United States for 2020-2029 – almost triple the amount from 2010-2019 (NOAA, 2020; FSF, 2021; Kearns et al., 2022). Following consecutive record-setting wildfire seasons, in 2019 insurers in California refused to renew more than 200,000 homeowner policies, a 61% increase from 2018 (California Department of Insurance, 2021). Non-renewals were heavily concentrated in areas of moderate to high wildfire risk (Bikales, 2020). At the same time, take-up of policies offered through the state's "insurer of last resort", the California FAIR plan, spiked in high wildfire risk areas, signaling that many customers were subsequently unable to find new policies in the private insurance market with firms reducing their exposure.[1]

In this paper, we examine how price regulation and market structure can result in the unraveling of the private insurance market when firms face rapidly increasing risk due to climate change. Prices in most homeowner's insurance markets are constrained by state regulators with the explicit goal of preventing excessive, inadequate, and unfairly discriminatory rates (McCarran-Ferguson Act, 1945). We begin by establishing a conceptual model of a natural disaster insurance market capturing three main features found in practice. 1) The market exhibits adverse selection which results from regulatory restrictions on the set of information firms can use to set prices, resulting

[1]A feature of the California FAIR plan is that a homeowner must first be denied coverage in the private market before they are eligible to purchase FAIR Plan insurance.

in the costliest customers having the highest willingness to pay for insurance. 2) Firms have information on the expected costs of customers and thus can choose which customers to insure. 3) Customers not offered insurance through the competitive portion of the market are insured through a residual public insurer which has a no-profit condition. We show that common price regulation practices used by state departments of insurance that suppress premiums below expected costs for some customers can result in firms reducing supply to the costliest customers, "cream-skimming", and eventually lead to complete unraveling of the competitive portion of the market as firms leave the market. In the short run, regulation increases reliance on the public insurer with the marginal customers pushed out of the competitive market bearing the loss in surplus due to higher premiums in the residual market.

We next present an empirical analysis of a first-of-its-kind non-renewal moratorium regulation aimed at stymieing the retreat of insurance companies from high wildfire risk areas, and thus slow the movement of policies out of the voluntary market, by forcing insurers to supply insurance to *current* customers following disasters. Before the moratorium, firms were able to non-renew a customer's policy at the end of the contract term, citing increased risk. The regulation restricts the ability of insurers to non-renew currently insured customers located near large wildfires that resulted in a state of emergency for one year following the fire, starting with the 2019 fire season. We use the conceptual model as a framework to derive the implications of the moratorium restrictions on insurers, FAIR plan and private market take-up, as well as consumer welfare.

We exploit the quasi-random variation generated by the regulatory boundaries of the moratorium and wildfire locations as well as the staggered timing of moratorium cohorts to test the causal impact of the policy on insurance market outcomes using a difference-in-differences framework. We make use of a feature of the moratorium that zip codes located adjacent to, but not directly impacted by the fire, are also included in the regulation. These "covered", but non-fire zip codes, form the basis of our treatment group to avoid confounding treatment effects with the direct effects of the fire which are likely correlated with our outcomes of interest. Our control group is constructed in two ways. First we make use of the sharp discontinuity at the border of treatment zip codes to designate adjacent zip codes, not covered in the moratorium, as control units. These areas represent a plausible counterfactual and were by chance not included in the moratorium. Second, we match treatment zip codes to observably similar areas in the rest of the state that have never been covered by a moratorium using a nearest neighbor matching approach, matching on zip code characteristics and pre-period trends in outcome variables. The estimation using matched controls provides two advantages. First, it is possible that the most similar zip codes to those covered by the moratorium are not located in close geographic proximity, but yeat located elsewhere in the state, in similar wildfire risk zones. Second, the estimation avoids the potential for spatial spillover effects to confound the estimates by excluding zip codes that are just outside the moratorium boundary from the pool of potential matches. We find that results between the two control groups are quantitatively similar, providing evidence that differential spatial spillovers are likely not a concern in our setting.

We find that the moratoriums successfully increase insurance supply by decreasing company-initiated non-renewals while they are active, with no evidence that firms are able to avoid the regulation by forcing out customers using other methods. However, we find that this effect is short-lived: that firms increase non-renewals by 72% to 96% as soon as the year-long moratoriums have ended. Additionally, we estimate that the moratorium had no discernible impact on slowing the transition of policies from the voluntary market into the FAIR plan. While the regulation restricted non-renewals of currently insured customers, it had no effect on firms refusing to insure new customers, with firms simply continuing to cede policies to the FAIR plan at similar rates in both treatment and control zip codes. These results are in line with the model predictions.

This paper contributes to the large literature on the economics of climate adaptation (Barreca et al., 2016; Diaz and Moore, 2017; Kousky, 2019; Botzen et al., 2019; Kahn, 2021; Sastry, 2021), and in particular, to the literature focused on the insurance of natural disaster risks (Kunreuther, 1996, 2001; Kousky, 2011; Knowles and Kunreuther, 2014; Kousky, 2022; Wagner, 2022; Oh et al., 2023). While climate change is expected to increase demand for disaster insurance, we find that wildfires lead firms to reduce their operations in locations exposed to more wildfire risk. We clarify how regulatory frictions can limit private insurer participation in insurance markets and provide the first analysis of a “forced-supply” regulation in the insurance sector, finding that such regulation only achieves its stated goal in the short-term. We also add to the limited but growing number of studies that focus on the adaptation of firms (Sastry, 2021; Prankatz and Schiller, 2021; Gu and Hale, 2022; Castro-Vincenzi, 2022).

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 econometric framework and section 6 presents the results. Section 7 concludes.

2 Institutional Background

This section provides background on three topics important to our study. First, we discuss markets for homeowner’s insurance with a focus on the California market. We provide further discussion of the regulations in California which are later incorporated into our conceptual model. Next, we provide background on the California non-renewal moratoriums, which we analyze in the empirical portion of our paper. Lastly, we discuss the role of the FAIR plan in providing insurance for consumers unable to purchase insurance from a private insurer in the voluntary market.

2.1 Insurance Markets

The price of an insurance policy is set before any potential losses are incurred.[2] This implies that the profitability of insurers relies on both having accurate projections of expected losses, and using these projections to calculate insurance premiums. Theoretically, if firms were unconstrained in their ability to calculate and set policy premiums, they would be able to offer a price for all risks. However, regulations have emerged with the dual goals of protecting customers from rates that are unfairly discriminatory and unreasonable, and ensuring premiums are sufficient to guarantee sol-

[2]Most property and casualty lines of insurance follow experience rating whereby premiums can be adjusted for losses incurred in previous contract periods. However, some policies use retrospective rating, which settles the final premium amount due at the end of the period and takes into account losses from that same period. Retrospective rating is generally reserved for worker’s compensation and commercial policies.

vency. The fear being firms would be able to perfectly price discriminate if unregulated, leading to a loss of consumer welfare. In some cases, regulation can lead premiums to diverge from expected costs through both suppressing premium growth and limiting the firm's ability to accurately incorporate cost forecasts. We focus our discussion on the main distortions rate regulation introduces to pricing of natural disaster risk in the California homeowner's insurance market, which generalize, to a varying degree, to other state markets.

In California, firms must have prior approval of rates by the California Department of Insurance before they can be implemented, and face three specific regulations which suppress premium growth in practice. First, overall rate increases 7% or higher are subject to in-depth public scrutiny at the unrecoverable cost of the insurer (California Ballot Propositions and Initiatives, 1988). This regulation has resulted in an effective rate increase cap as most rate increase filings below are below this threshold, with a significant bunching effect at +6.9% (Boomhower et al., 2023). Secondly, California regulation requires the overall rate for natural disasters to be justified by historical averages of losses over at least the past 20 years. Firms are not able to incorporate catastrophe models or other means of forecasting future expected losses as justification, exacerbating premium inadequacy in face of accelerating risk. Finally, California restricts firms from passing reinsurance costs through to consumer premiums. Recent industry literature has highlighted greatly increasing reinsurance premiums as climate risks increase, with reinsurance companies not subject to the same regulatory oversight as consumer facing insurance companies. This further drives the difference between the costs firms incur and the premium they are able to charge the customer.

Regulation in each state also specifies which observable home and homeowner characteristics are permissible in the underwriting and rating processes. 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 permissible characteristics used for pricing that can inform risk level. Thus, after conditioning on permissible observables, consumers that must be charged the same premium can still vary in their expected costs and willingness to pay. Regulation in California in late 2022 made two changes to the underwriting process: firms were forced to incorporate defensible space characteristics into their rating plan, and any use of catastrophe or risk scoring to underwrite or create rate differentials had to be filed with the state. The latter presents a hurdle to firms as they were given the option of publicly filing proprietary and confidential models (some contracted through 3rd party companies) or to cease their use.

2.2 California Moratoriums

In response to large losses from record breaking wildfires in 2017 and 2018, insurance companies began to withdraw from high wildfire-risk areas. An insurance policy can typically only be cancelled mid-term by the insurer due to lack of payment or material fraud on behalf of the insured. However, an insurer is able to non-renew (not offer a subsequent contract) for a wider range of reasons, including changing beliefs about the probability of a claim. In an attempt to stymie the retreat of insurance companies from high-risk locations, the California legislature passed Senate Bill 824 in 2018. This bill prohibits insurance companies from non-renewing a policy because of wildfire risk in any zip code either directly impacted by, or adjacent to, a wildfire that was declared a state of emergency by the state government. The commissioner of the department of insurance cited the bill as giving, "millions of Californians breathing room and hits the pause button on insurance non-renewals while people recover."[3] The regulation impacts firms by limiting their ability to geographically diversify and to drop policies which are likely otherwise unprofitable given the firm's rating plan.

Each moratorium lasts one year from the date of disaster declaration. For the years examined in our study, the earliest start date for a moratorium occur on August 18 and the latest start date is November 18. We refer to the moratoriums by yearly cohorts. The collection of non-renewal moratoriums initiated following the 2019 fire season is the "2020 Moratorium", while those initiated after the 2020 fires is referred to as the "2021 Moratorium".

Due to the stochastic nature of wildfires, and specifically wildfire perimeters, zip codes located near each other can be differentially impacted by the moratorium despite being observably similar.

[3] See https://www.insurance.ca.gov/01-consumers/140-catastrophes/MandatoryOneYearMoratoriumNonRenewals.cfm

Additionally, high risk areas in other parts of the state that have not yet experienced a fire post-legislation are not covered by the moratoriums, despite being similar. The quasi-random nature of the initial coverage of the moratorium, coupled with the lack of lead time and anticipation for firms, forms the basis of our identification strategy to identify the causal impacts of the moratoriums on various insurance and consumer outcomes.

2.3 California FAIR Plan

A crucial feature of the moratorium is the voluntary markets interaction with the FAIR Plan. Fair Access to Insurance Requirements (FAIR) plans were implemented as the insurer of last resort in twenty-six states, the District of Columbia, and Puerto Rico in 1968 following the riots and bushfires of the 1960s. Since the creation of the first FAIR plan, similar plans have been established in other states, providing access to insurance for high-risk properties and individuals. The FAIR Plan serves as an important backstop for the public by making insurance available in all high-risk areas. FAIR plans are important in homeowner's and auto insurance markets as insurance is often a requirement for mortgages and access to driving. Kousky (2011) offers a review of state-sponsored disaster insurance programs.

In California, the FAIR Plan issues policies on behalf of all companies licensed to write property & casualty insurance in California. Each member company participates in the profits, losses, and expenses in direct proportion to its market share of business written in the state thereby creating an incentive for firms to not write unprofitable to avoid the entirety of the risk. Its purpose is to provide temporary, basic fire insurance when traditional insurance is not available. It is designed to act as an emergency safety net while homeowners search for insurance in the traditional (or voluntary) market. As we explore in the modeling section of our paper, FAIR Plan policies are usually more expensive than the voluntary market, have a maximum policy coverage amount of $3 million, and require customers to obtain an additional Difference in Coverage (DIC) policy in order to package together all the coverages typically offered in a standard homeowner's insurance policy.

3 Conceptual Model

In this section, we model a natural disaster insurance market as a market with adverse selection to show how strict price regulation acts to segment an insurance market. We begin by characterizing supply and demand in this market, then use a graphical approach to illustrate equilibrium in the presence of increasing wildfire risk perceptions. Finally, we use this model to analyze welfare implications from a non-cancellation moratorium.

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 FAIR plan.

The property insurance industry in the US is subject to significant regulation, and our model captures a key regulatory aspect: a strict pricing constraint. Specifically, conditional on a set of property characteristics $\{c_i\}$, the regulator sets a fixed price, denoted as P^R, for the voluntary market. This pricing constraint reflects two important characteristics of property insurance rate-making in California. First, the Department of Insurance limits the characteristics $\{c_i\}$ that insurers can use to determine premiums. For instance, property-level estimates of risk from catastrophe models cannot be used to set insurance premium levels (California Code of Regulations, 2023).[4] Insurers determine rates through a complex rate-filing process, in which requested premium increases above 7% require a costly public hearing. As a result, most rate filings tend to bunch exactly below the 7% threshold (Boomhower et al., 2023). Second, in the FAIR Plan, prices can adjust freely but the regulator imposes a zero-profit condition.

Most property-level characteristics that impact expected losses (such as location, building materials, number of floors, etc) are readily observable to insurers. This stands in contrast to health or auto insurance markets, where consumers typically have private information about their expected losses. However, regulations that restrict the observable characteristics c_i permitted for

[4]Relaxing premium regulation to allow for catastrophe modeling is an active debate (Watkins and Lee, 2022; State of California Department of Insurance, 2023).

rate-making prevent insurers from achieving perfectly segmenting business, resulting in what is known as "asymmetrically used" information (Finkelstein and Poterba, 2014). This manifests as all consumers with the same allowable characteristics being charged the same price, despite otherwise observable differences in their expected costs. We assume that the information asymmetry results in adverse selection, characterized by consumers with the highest expected costs also having the highest willingness to pay resulting in downward sloping marginal and average cost curves Einav et al. (2010). For simplicity, we assume that demand is higher than average cost at every point, implying that at actuarially fair prices, every consumer prefers insurance to no insurance.[5]

Although firms do not have the freedom to set prices, they control which customers to serve at the regulated price, and thus quantities: insurers can observe the marginal cost curve and decide not to offer insurance contracts to certain properties. However, the California moratoriums implemented in 2020 and 2021 directly eliminate this decision-making variable for insurers.

3.1 Market Segmentation

In the graphical analysis that follows we depict one tranche of the market where all consumers have the same set of permissible characteristics and are charged the same premium, but vary in their expected losses. In Figure 1 panel (a), we consider the case where the regulator imposes an exogenous price P^r below the average cost curve 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 producers.

In panel (b), firms use their knowledge about the marginal cost curve to select which consumers they offer coverage. They choose to offer coverage only to consumers that are profitable, such that $P^r \geq MC$. This results in only a portion of the market receiving insurance coverage from the traditional market, consumers from Q^F to Q^{max}. The remainder of the market (Q^0 to Q^F) is forced to purchase from the FAIR Plan, at a price that results in zero-profits $P^{FAIR} = AC^{FAIR}$. In this setting, all consumers continue to purchase insurance as their willingness to pay is greater

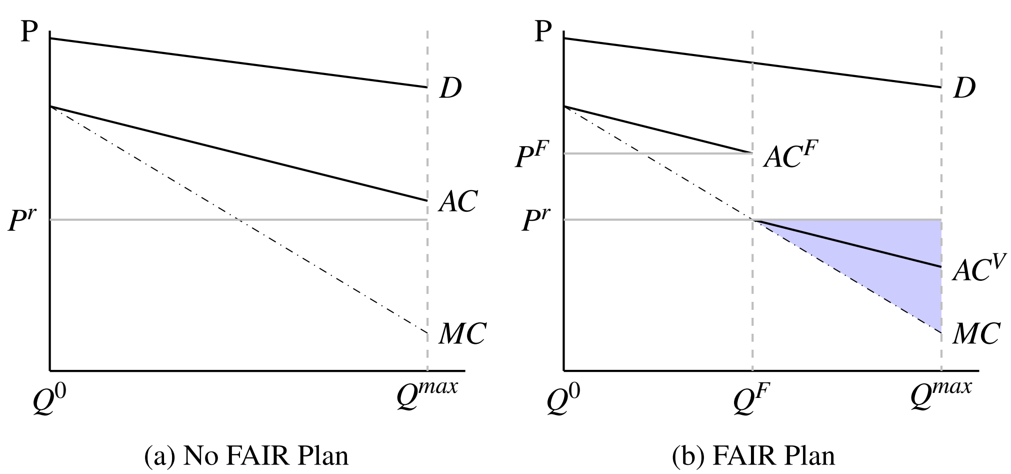
[5] According to the National Association of Insurance Commissioners, about 90% of homeowners have insurance, largely due to the requirement to buy insurance to obtain a mortgage.

than the price. Profits are positive in the voluntary market, shown in blue. Positive profits are possible in the short-run as prices are fixed at the regulated level and market entry is non-trivial. Characterization of the long-run, dynamic nature of rate requests and the role profits play in future negotiation with the regulators is beyond the scope of this paper.

This basic stylized case highlights the crucial role of the FAIR plan: it does not solve an asymmetric information failure, but rather eliminates the welfare costs of a regulatory constraint. To see this, note than in the absence of the FAIR Plan, consumers with marginal costs above the regulated price cannot buy insurance *regardless of how much they are willing to pay*. In contrast, in the absence of regulation, competitive firms would perfectly discriminate and charge each household a price equal to their marginal cost.

Although the FAIR Plan does not increase efficiency in our example (due to the high demand curve), it has clear distributional consequences. First, all households in the voluntary market are charged more than their marginal costs with the lowest risk customers paying the highest markups. Households buying in the FAIR Plan are charged an average cost necessarily greater than the regulated price of the voluntary market as the risk pooling is concentrated on only the highest risk customers. Within the FAIR Plan, the riskiest consumers are the ones benefiting the most, while the least risky consumers are charged more than their marginal cost.

Figure 1: Baseline Market



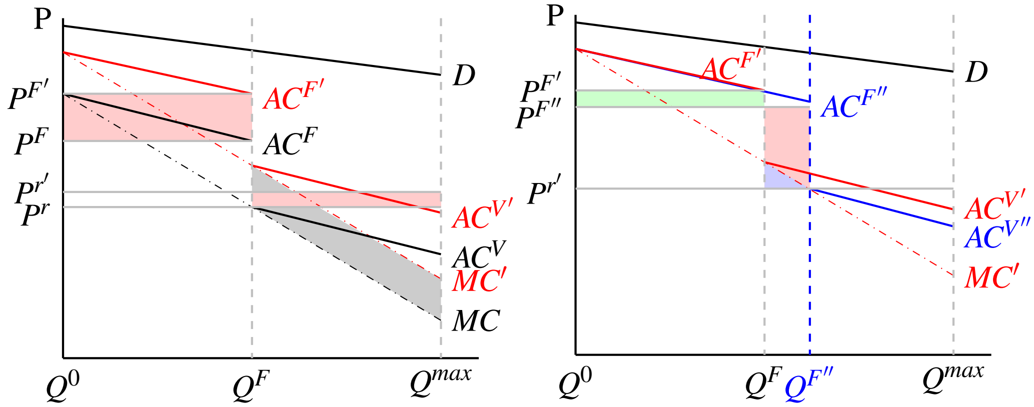
3.2 Increasing perceptions of wildfire risk

Consider what happens when the industry experiences an extreme wildfire season that causes insurers and consumers to update their perceptions of wildfire risk. We distinguish between actual wildfire risks (which we assume remain constant) and perceptions of wildfire risk (which are impacted by recent wildfire activity). We assume that when perceptions change, they shift closer to the actual experienced wildfire risk levels. In Figure 2 the new curves MC' and AC' represent the increase in wildfire risk perceptions following a particularly bad wildfire season and are shown in red. For simplicity we assume these curves are a parallel shift in expected costs for each consumer.

Regulation stipulating that insurers must use at least twenty years of loss history results in the regulated price increasing from P^r to $P^{r'}$ with $P^{r'} - P^r < AC' - AC$: the regulated price responds slower than increases in perceived average costs. The price in the FAIR Plan market is not constrained by this same regulation and adjusts to $P^{FAIR'} = AC^{FAIR'}$, keeping profits equal to zero in the FAIR Plan.

Panel (a) of Figure 2 depicts the market under the California non-renewal moratoriums, i.e., when firms are not allowed to adjust which consumers they serve in the voluntary market (Q^F is held constant). As premiums increase, consumers suffer a reduction in wealth represented by the red rectangles in the FAIR Plan and voluntary market. Firms in the voluntary market expect higher costs, shown by the grey areas, which is only partially offset by the increase in the regulated price. In this situation firms lose money on customers with a marginal cost greater than the new regulated price, and would not insure these risks absent the moratorium. If the increase in costs is high enough that the AC over the remaining customers is above the regulated price, firms will exit the voluntary market in the long run and the market will collapse.

Figure 2: Market With Expected Cost Increase



(a) No FAIR Plan Adjustment

(b) Fair Plan Adjustment

Panel (b) depicts the market when there is no moratorium in place, meaning that Q^F is allowed to adjust. Although firms are not allowed to price all observable characteristics that impact wildfire risk, they can stop insuring higher-risk, unprofitable consumers in the voluntary market. Following the increase in wildfire risk perceptions, these consumers are between Q^F and $Q^{F''}$, where $Q^{F''}$ is determined by the intersection of the updated marginal cost curve and the updated regulated price. Because we consider a demand curve above the FAIR Plan's average cost curve, the consumers dropped from the voluntary market will purchase insurance in the FAIR Plan. Given the FAIR Plan operates as a non-profit, and that the customers dropped from the voluntary market have lower marginal costs than those already participating in the FAIR Plan, the FAIR Plan price drops to $P^{F''}$.

The costs of allowing adjustment from Q^F to $Q^{F''}$ are entirely born 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 2 (b) due to the higher price $P^{F''}$. The reduction in price in the FAIR Plan results in a benefit for existing customers, shown by the green rectangle. The firms capture the blue portion of the welfare loss due to the reduction in expected losses.

In sum, this model generates four simple predictions following the wildfires: (i) premiums increase in both the FAIR Plan and voluntary market, (ii) consumers in the voluntary market are not dropped to the FAIR Plan when the moratorium is active, (iii) the FAIR Plan market share increases when the moratoriums become inactive, and (iv) the FAIR Plan price decreases when the moratoriums become inactive. We test these predictions in the follow section (where the data permit) and assess how the characteristics of consumers in the FAIR Plan and voluntary market changed following the moratoriums.

4 Data

4.1 Insurance Data

We obtain homeowner's insurance data from the California Department of Insurance (DOI). These data are a combination of three separate products: the Community Service Statement (CSS), the Personal Property Exposure (PPE), and the Residential Property Experience (RPE). The CSS contains information on earned exposures, earned premiums, number of policies, and average premium at the company-zip code-year level for all insurance companies licensed to operate in California from 2009 to 2020. The PPE survey reports the amount of coverage, units insured, and deductible amounts at the company-zip code-year level from 2009 to 2021. All companies writing more than $5 million in insurance in California are required to report. Lastly, the RPE data set reports the number of new, renewed, and non-renewed policies at the zip code-year level. Importantly, we observe whether the decision to non-renew the policy was initiated by the insurer or by the customer. The RPE is reported yearly from 2009 to 2021.

4.2 Wildfire Risk

We use the Risk to Potential Structure (RPS) data from the US Forest Service to construct zip code level measures of wildfire risk.[6] The RPS relates both the probability of a fire as well as the likely intensity of a potential fire, asking the question, "What would be the relative risk to

[6]Formally, zip codes are not geographic in nature, but yet relate a collection of mail routes. The census thus created Zip Code Tabulation Areas (ZCTA) which are geographic representations of zip codes. We use ZCTAs to construct all geographic level data to match the level of observation of our insurance data, but use the more common term "zip code" in the rest of the text.

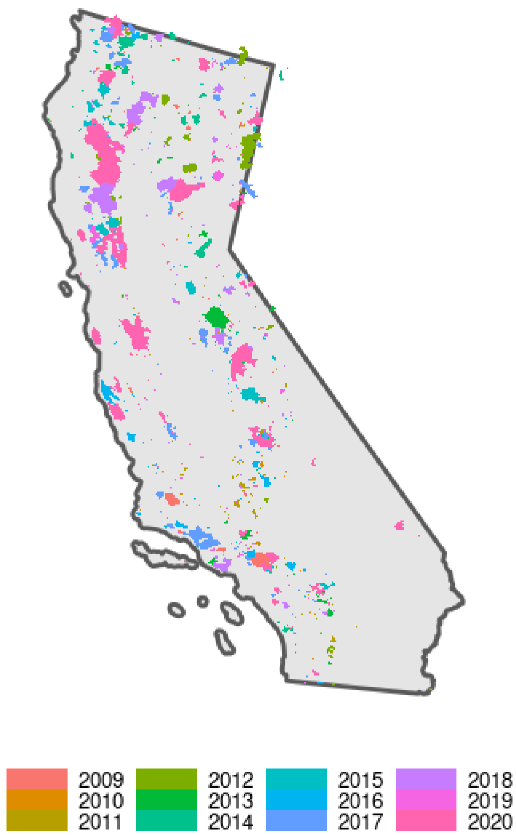
a house being located on this pixel?" Thus, the measure does not rely on the current presence of a building in order to assess the risk. This allows for an insurance relevant wildfire risk measure to be calculated even in sparsely populated portions of the state. We calculate the zip code level average RPS by calculating the mean of the RPS value for each 30 meter pixel located within the boundary of the zip code. We also calculate the standard deviation of the RPS values within a zip code to capture the variability of fire risk within the boundary. The RPS is time invariant and represents a snapshot of wildfire conditions modeled in 2014. In reality, wildfire risk can change over time following drought conditions and recent wildfire activity. Additionally, the RPS data does not account for changes or variation in home construction types, which is an important way homeowners can manage wildfire risk.

4.3 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.[7] Figure 3 shows the location of wildfires for the years 2009-2020. The fire perimeters are developed by CalFire jointly with the US Forest Service, the Bureau of Land Management, and the National Park Service for both public and private lands in California. Data on the location, area covered, cause of the fire, and the responding agency are available. Wildfires occur in both Northern and Southern California, largely concentrated in the foothill and mountainous areas along both the coastal and Sierra Nevada ranges.

[7] We do not include prescribed burns in any of our analysis.

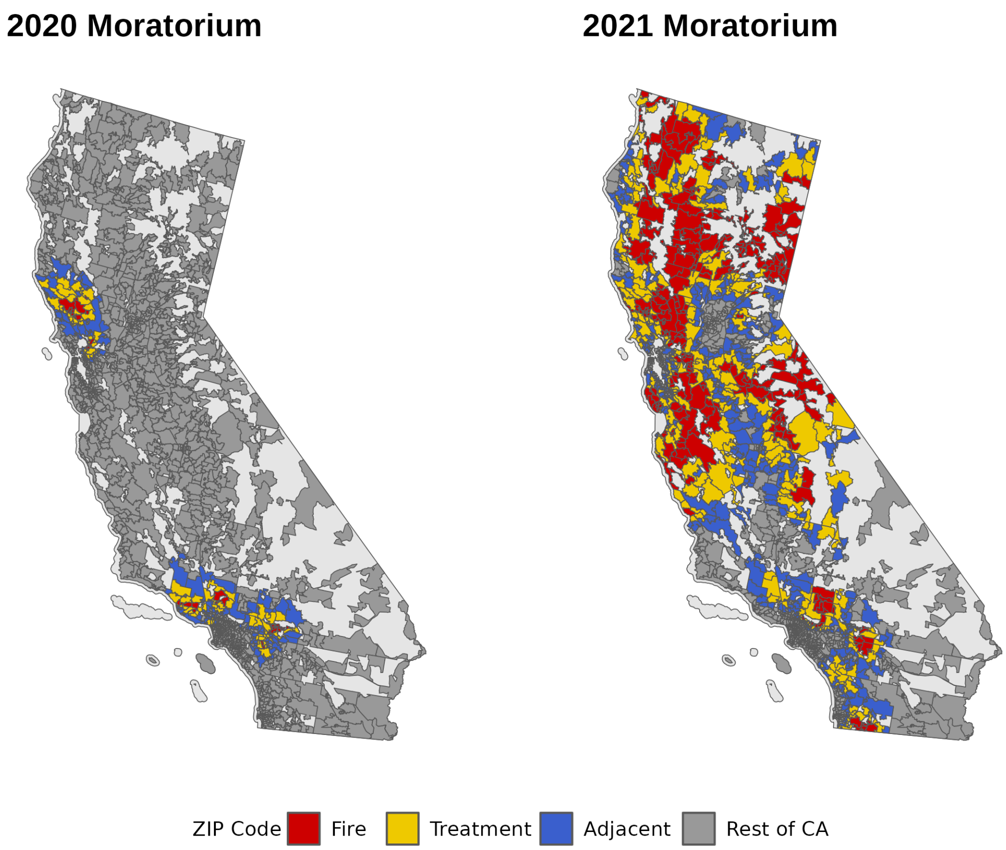
Figure 3: Wildfires from 2009 to 2020



4.4 Non-Renewal Moratorium Status

We identify zip codes subject to a non-renewal moratorium in 2020 or 2021 using data from the office of the California Insurance Commissioner. We classify zip codes into 4 categories. 'Fire' zip codes are those that were included in the Moratorium because they directly experienced a fire that was declared a disaster. 'Treatment' zip codes are included in the moratorium by regulation due to being adjacent to zip codes which burned, but did not directly experience the fire causing the disaster declaration. These zip codes are labeled as treatment since they form the basis of our identification strategy discussed in the following sections. 'Control' zip codes are zip codes that are not included in the Moratorium but border zip codes covered by a moratorium. 'Rest of State' encompasses all other unimpacted zip codes. Figure 4 shows the Moratorium classifications for the state of California in 2020 and 2021.

Figure 4: Zip Code Classifications



4.5 Descriptive Statistics

Table 1 presents summary statistics by zip code for the initial 2020 moratorium classification. Zip codes impacted by fire were also the riskiest, *ex ante*, as measured by RPS, but indistinguishable from nearby zip codes. Zip codes in the 'Rest of State' have the lowest wildfire risk level, as expected. While areas impacted by fires and the moratorium have higher FAIR Plan market shares, only 3% of the market is served by the FAIR plan on average in wildfire impacted zip codes. Over the entire sampling period, there does not appear to be any trends associated with the number of new policies, renewals, or customer or company initiated non-renewals.

Table 1: Summary Statistics by Zip Code Classification (2020 Moratorium)

Zip code Classification	Fire		Treatment		Control		Rest of State	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Premium (dollars)	1049.5	388.4	1099.2	579.8	1085.1	677.0	966.3	495.2
New Policies (count)	517.9	513.5	848.6	653.5	790.6	710.8	511.8	577.5
Renewals (count)	4262.1	3924.9	6309.0	4303.0	5672.2	4639.0	3995.7	4171.0
Customer Nonrenewals (count)	404.7	385.7	622.9	481.1	594.5	540.4	382.0	433.4
Company Nonrenewals (count)	101.2	100.3	168.0	128.3	143.5	123.1	95.3	102.9
FAIR Plan Market Share	0.03	0.05	0.02	0.04	0.02	0.05	0.02	0.04
RPS	0.5	0.6	0.5	0.6	0.4	0.5	0.2	0.4

Figures 5 and 6 show the evolution of the number of company initiated non-renewals, customer initiated non-renewals, new policies, and renewals by zip code classification status for each moratorium. Statistics are shown relative to their level in 2015.

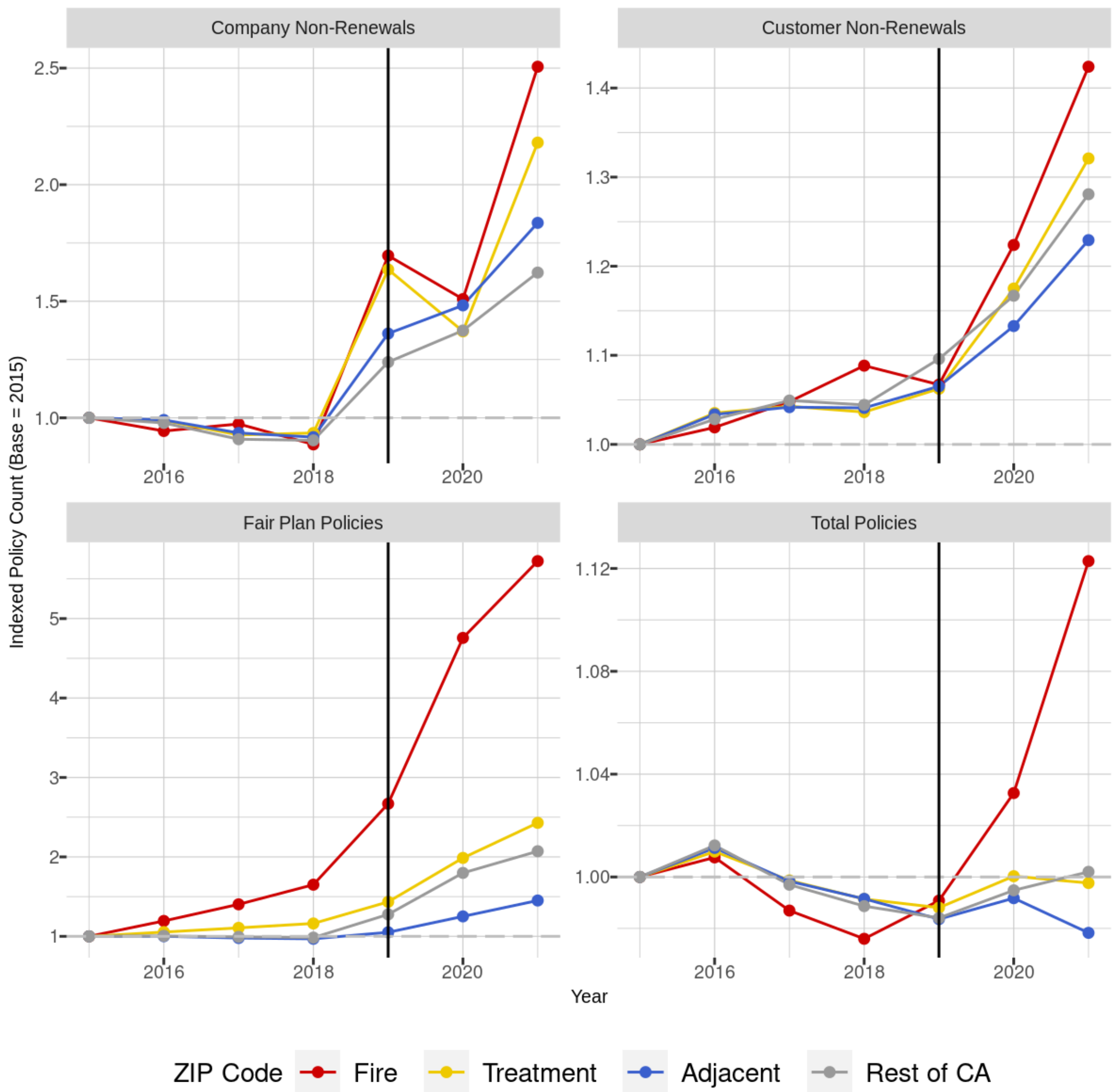
For the 2020 moratorium, Fire and Treatment zip codes both saw a decrease in the number of company initiated non-renewals in the year they were covered by the moratorium. We also see a large reversal the year the moratorium was lifted for these zip codes. While only preliminary, this suggests that the moratorium was successful in constraining insurers in the short term. A potential concern in our setting is that firms are able to circumvent the moratorium by forcing-out customers through making their product less attractive to consumers in an effort to have them cancel, thereby disguising a company initiated non-renewal as a customer initiated non-renewal. This would result in the Moratorium seeming more effective than it actually is. While we note here that customer initiated non-renewals increased the most in fire zip codes, we return to this question later in our results using a causal framework, showing that this is likely not a concern.

In both figures 5 and 6 there is an increase in the number of new polices, most prominent in fire zip codes.[8] This can be a result of people moving houses and purchasing a new insurance policy, or by households changing their insurance provider. An increase in the number of new policies is consistent with the evidence of higher premiums and non-renewals, as well as increased expansion of households into the wildlife urban interface.

Taken together, this descriptive evidence suggests that the moratorium may have had signif-

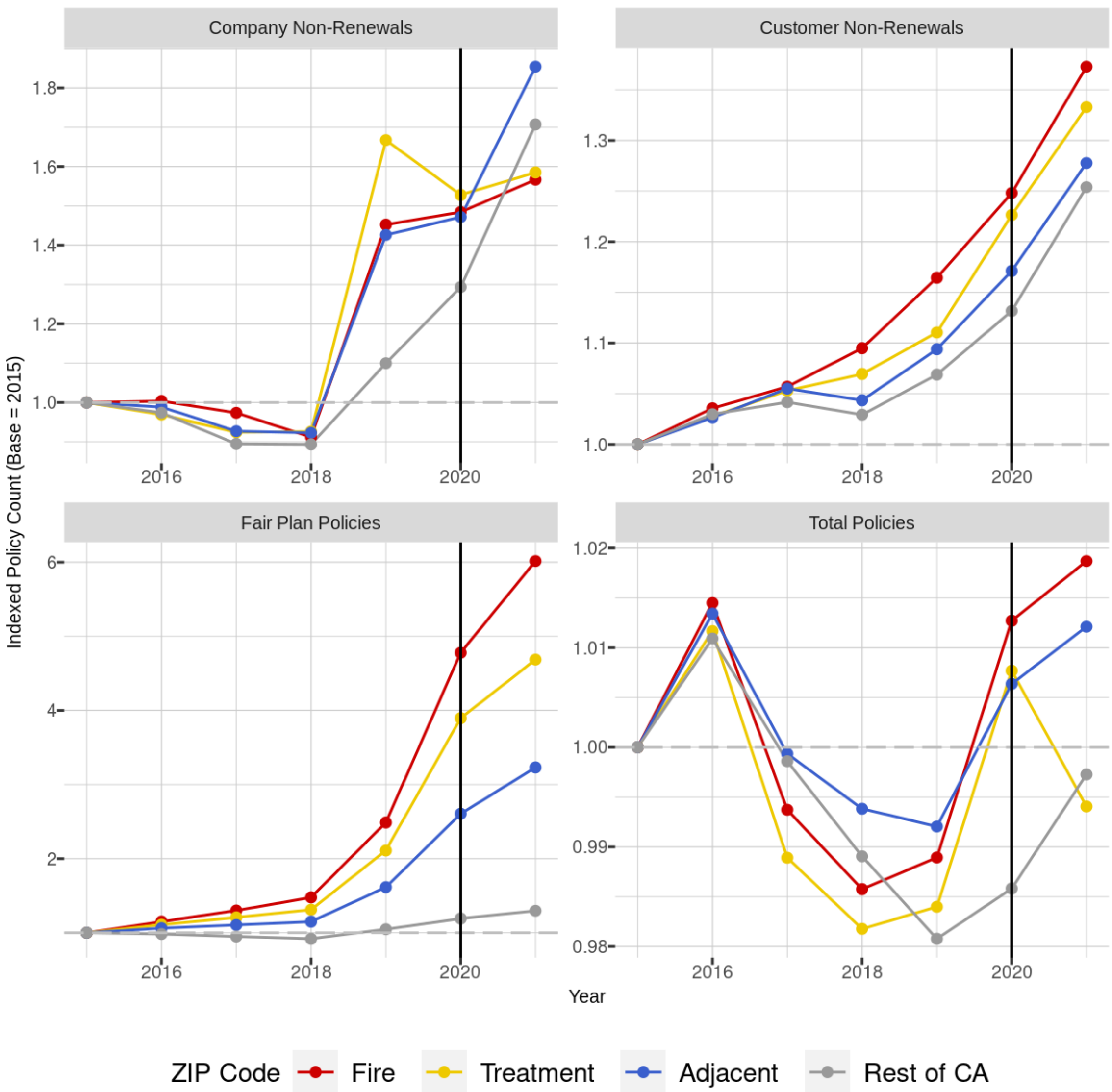
[8] A new policy is one that is initiated in the relevant year.

Figure 5: Statistics by 2020 Moratorium Classification



Notes: Zip codes are broken out by moratorium classifications. Fire zip codes were directly impacted by a wildfire in 2019 and covered by the non-renewal moratorium in 2020. Treatment zip codes were covered by the non-renewal moratorium in 2020 but did not experience a wildfire in 2019. Control zip codes share a border with zip codes covered by the non-renewal moratorium in 2020. Rest of State zip codes are the remaining unimpacted zip codes not covered by the moratorium.

Figure 6: 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. Control zip codes share a border with zip codes covered by the non-renewal moratorium in 2020. Rest of State zip codes are the remaining of the unimpacted zip codes not covered by the moratorium.

icant impacts on the market by reducing non-renewals in the short-term, but that these reductions were concentrated to just the year of the moratorium coverage. In our next section we formalize the assumptions needed to identify the causal impacts of the moratoriums.

5 Methods

The stochastic nature of wildfires and the unique geographic coverage of the California non-renewal moratorium allow for a difference-in-differences specification to recover causal estimates of the policy's impacts. We make use of the sharp geographic border discontinuity between neighboring zip codes comparing zip codes located just outside the borders of the moratorium as control units for zip codes covered by the regulation, before and after the policy change.

By regulation, the non-renewal moratorium covers policies in zip codes that experienced a state declared disaster fire and their immediate neighboring zip codes. Identification in our model requires no other changes, contemporaneous with the policy, that could explain changes in the outcome variables. As such, we omit zip codes that are directly impacted by a disaster fire from treatment as they suffer housing supply shocks, receive disaster relief funding, and are impacted by other unobserved factors correlated with the timing of the Moratorium.

Our main estimating equation is the following two-way fixed-effect (TWFE) model,

$$y_{zt} = \alpha + \sum_{j=0}^{1} \beta_j T_z D_j + \sigma_z + \delta_t + \varepsilon_{zt}, \tag{1}$$

where y_{zt} is the insurance outcome of interest in zip code z in year t, T_z is the treatment incicator variable which takes a value of 1 if zip code z is impacted by a moratorium during the sample period, D_t are post-period event time indicators taking a value of $D_t = 1$ for the year of the moratorium ($j = 0$) and the first year post treatment ($j = 1$). We include zip code fixed effects, σ_z, to control for time-invariant geographic heterogeneity correlated with wildfire risk and the insurance outcome variables, such as climate, elevation, slope, vegetation types, population density, and access to emergency services. We also include a panel of year fixed effects, δ_t, to account for common annual shocks across all units. This controls for unusually dry or hot seasons or macro-financial trends which impact the risk appetite of firms. We cluster model standard errors at the zip code level.

Identification of causal estimates from our main difference-in-differences model in equation (1) relies on three main assumptions. First, the common trends assumption requires that outcome variables in both treatment and control areas should evolve along the same trend over time, and would have continued along a similar path absent the moratorium. We can test the pre-intervention portion of this assumption directly through estimation of the following event study analog of equation (1):

$$y_{zt} = \alpha + \sum_{j=-6}^{1} \beta_j D_{j(gj)} + \sigma_z + \delta_t + \varepsilon_{zt}, \tag{2}$$

where y_{zt} is our outcome of interest, $D_{j(gt)}$ is matrix of indicator variables which take a value of one if the first year of the moratorium is j years away for zip codes in moratorium group g in year t.

Secondly, recent methodological advances show that the TWFE model only yields consistent causal estimates of the average treatment effect on the treated when the treatment effects are homogeneous across groups (Goodman-Bacon, 2021; Sun and Abraham, 2021; Callaway and Sant'Anna, 2021; de Chaisemartin and D'Haultfoeuille, 2020). The main concern is due to the staggered timing of the policy across zip codes, that the two-way fixed-effects model uses all possible combinations of treatment and control comparisons, including using earlier treated groups as controls for later treated groups, resulting in inconsistent estimates for the average treatment effect on the treated if effects are heterogeneous across cohorts.

There are two reasons why we would expect heterogeneous treatment effects in our setting. First, a non-renewal moratorium is novel to the California insurance market, meaning insurers may adapt over time in how they respond to the policy and the Department of Insurance may also adapt in their enforcement role. Second, due to the record-breaking 2020 wildfire season, the 2021 moratorium covered more territory than in 2020, leading to a potentially different response from the insurers as a larger share of their business was under compulsory supply.

We take several steps to address these concerns. We first estimate the dynamic event study model using the estimator from Sun and Abraham (2021) which delivers consistent estimates in the presence of heterogeneous effects and differential timing of treatment. Secondly, we estimate equation (1) separately for the 2020 and 2021 treatment cohorts selecting only never-treated control units from each cohort's neighboring zip codes, limiting the "forbidden comparisons".

Lastly, as we use geographic borders to designate treatment, identification requires that the populations on either side of the border are homogeneous and that there is no selection into treatment or other feature of zip codes correlated with treatment. In order to limit the inherent differences between treatment and control groups, and to account for unobserved heterogeneity, we restrict the control group to zip codes that directly border the treatment group but do not experience the Moratorium. We believe these zip codes represent a plausible counterfactual due to geographic proximity, a fact supported by observable similarities shown in the summary statistics. After controlling for observable factors, it is by random chance that these zip codes were not included in the Moratorium boundaries because the location and size of disaster fires is as good as random each year. Importantly, as zip codes are not administrative boundaries, such as city our county borders, we would expect the unobserved heterogeneity to be smooth across the border. We also unaware of any increased funding or interventions implemented by jurisdictions in response to the fires that follows the zip code designations.

To the extent that there is some positive selection into being impacted by a wildfire or just general differences between wildfire communities and their immediate surrounding areas, it is plausible that the most geographically proximate zip codes follow different trends and that the most similar zip codes are actually located elsewhere in the state. for example, zip codes along the foothills of the central valley have very high fire risk, but border flat farm land which has near zro wildfire risk as measured in our data.

In response, we in addition to our main difference-in-difference specification, we refine the control group by using a nearest-neighbor matching approach, pairing treated zip codes covered under the moratorium with zip codes from the unaffected part of the state that does not border the treatment area, and is never treated during our sample period. Following the synthetic control literature, we match based on pre-treatment period trends in outcome variables as well as our time invariant measures of average and variance of wildfire risk (RPS) at the zip code level.

An additional benefit of our matching approach is that by choosing zip codes that do not directly neighbor the moratorium zip codes, we are able to test whether there are differential spill over effects across neighboring zip codes. The imposition of the moratorium disrupts firms' ability to balance the geographic concentration of their portfolio by forcing supply in the moratorium zip codes. This may lead to increased departure from the closest zip codes to avoid being too highly concentrated, biasing the estimates from our base DiD approach. Similar results between the base sample and our nearest neighbor-matched sample provides supporting evidence that there is no differential spillover onto nearby zip codes.

6 Results

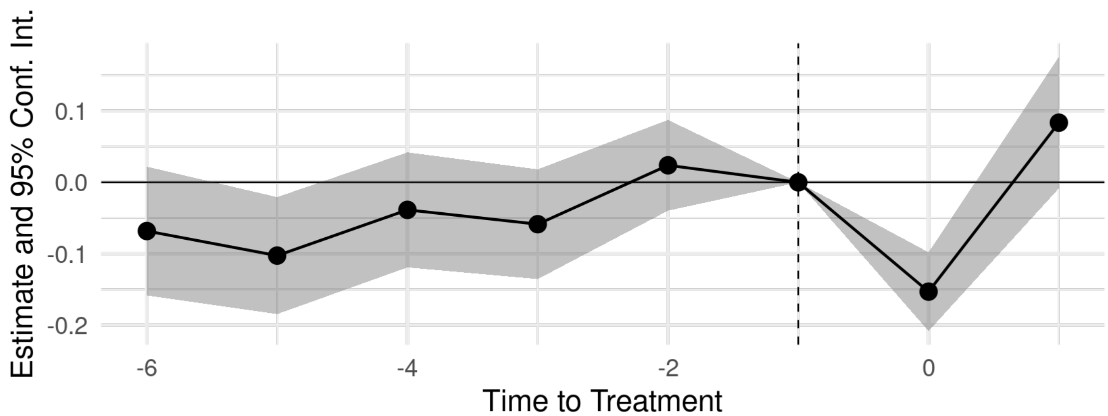
We begin our discussion of the impact of the non-renewal moratorium by estimating whether the regulation was in fact binding for firms. We present event study results using the Sun and Abraham (2021) estimator for the effect of the non-renewal moratorium on company-initiated non-renewals in Figure 7. Event time 0 represents the year the moratorium was in effect, while event time 1 represents the year after the moratorium has lifted and the regulation is no longer in effect. Point estimates are graphed along with the 95% confidence intervals.

Results from the specification using the adjacent neighboring zip codes as the control group are shown in panel (a). We find a large and statistically significant decrease in company non-renewals the year of treatment. During the period of the moratorium, 40 fewer policies were non-renewed than otherwise would have been in the treated zip codes. Firms are able to non-renew policies for a variety of reasons, and only non-renewals for increased wildfire risk were restricted by the moratorium. The sharp decrease provides evidence that the regulation was binding and firms were not able to, at least not fully, avoid the regulation. However, the effect of the moratorium is short-lived as the decrease is quickly reversed the year after the moratorium is lifted. We estimate an equal and opposite increase in non-renewals at event time 1. This is consistent with firms simply delaying the non-renewal action to the following contract period.

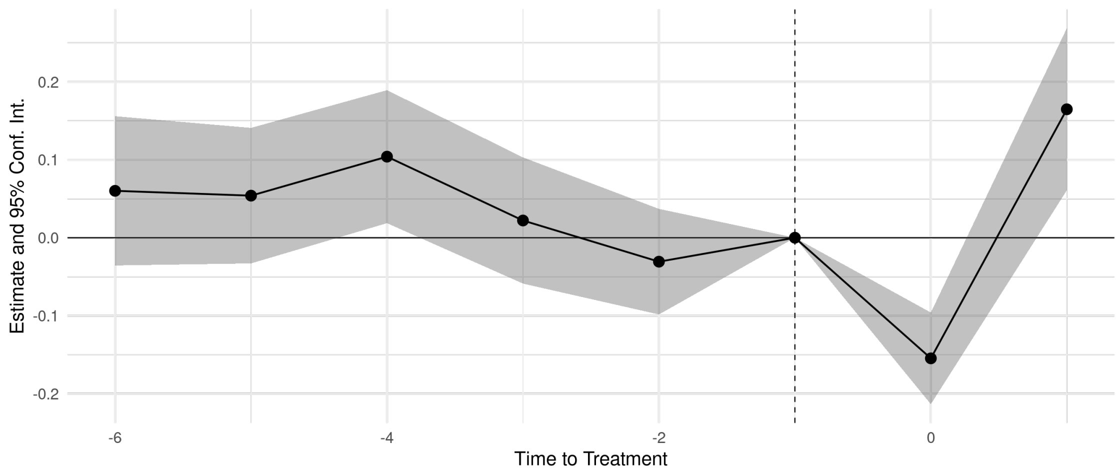
The coefficients on the pre-treatment years exhibit some evidence of differential trends between the treatment and control groups, as shown by the negative and statistically significant coefficients for event years -5, -4, and -3. While the control zip codes are located adjacent to treatment zip codes covered by the moratorium, it is possible that these zip codes differ, not just in their levels, but also trends in insurance outcomes over time. Zip codes that burn may be systematically different than zip codes geographically close by, and the best counterfactual setting may be located in other parts of the state. To address this, we also report estimates from a matched difference-in-differences model, where control zip codes are chosen through nearest-neighbor matching on average pre-treatment outcomes and zip code wildfire risk (RPS), in panel (b) of Figure 7. We estimate a slightly larger magnitude effect, with 50 policies being retained, but still see the equal sized rebound effect the year the moratorium expires. Precision of the estimates increased and the estimates no longer exhibits differential pre-trends.

Additionally, a concern with using adjacent zip codes as the counterfactual control group is that there may be spatial spillovers correlated with the timing of the treatment. Forcing firms to retain additional policies in treated areas that they would have counterfactually non-renewed, could lead firms to adjust their portfolio in adjacent zip codes in order to avoid being geographically concentrated in high risk areas. The similarity between the results using adjacent control zip codes and the matched control group using non-adjacent zip codes suggests that differential geographic spillovers are not a concern in our setting.

Figure 7: Effect on Company-Initiated Non-Renewals



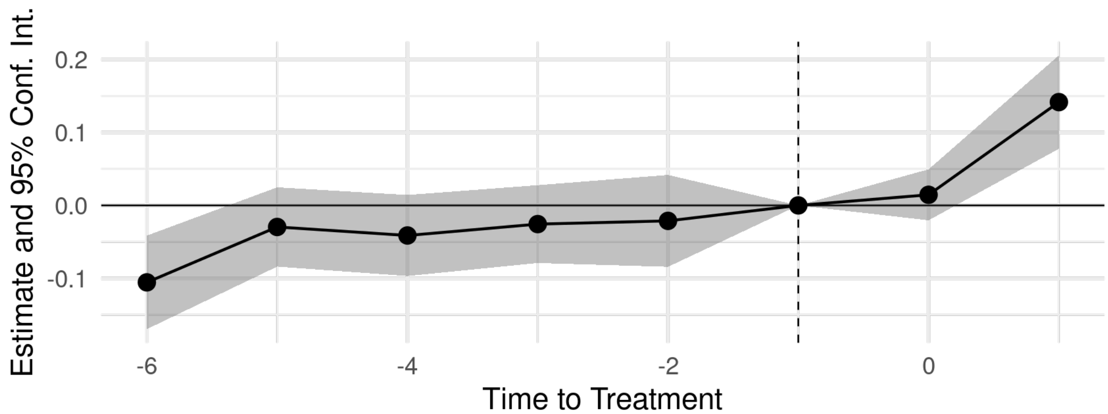
(a) Control group: Adjacent zip codes



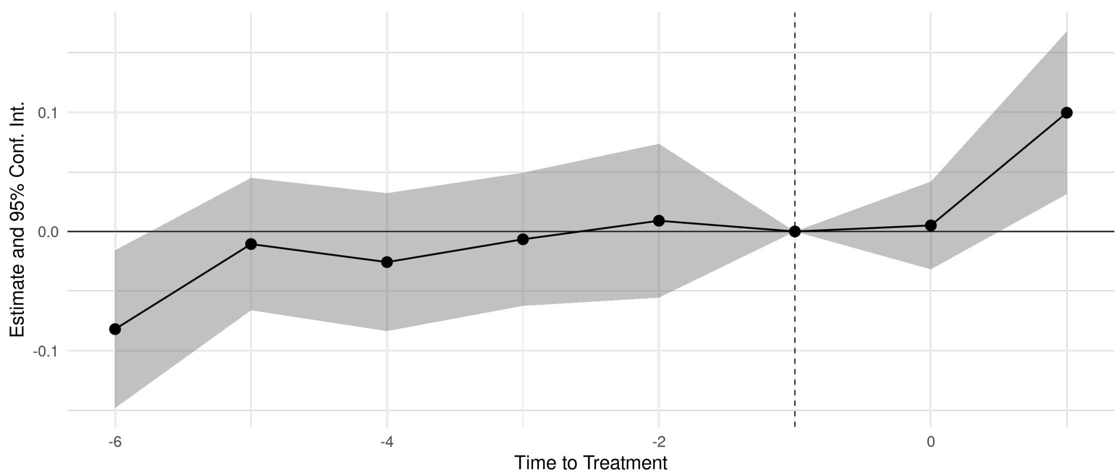
(b) Control group: NN-matched zip codes

Figure 9 shows the effect of the moratorium on customer-initiated non-renewals using the Sun and Abraham (2021) estimator and adjacent zip codes as controls. Customer-initiated non-renewals were unaffected during the moratorium, but increased dramatically the year it was lifted. Coefficients on the pre-treatment years are precisely estimated and indistinguishable from zero, providing support that the parallel trends assumption holds n this setting. The lack of an effect the year of the moratorium provides further supporting evidence that the moratorium was binding for firms and that companies were not able to force customers to cancel through other means or through manipulating reporting. If they had been able to do so, we would expect to see a positive coefficient, similar in magnitude, to the coefficient from the regression on company-initiated non-renewals in Figure 7 at event time 0.

Figure 8: Effect on Customer-Initiated Non-Renewals



(a) Control group: Adjacent zip codes



(b) Control group: NN-matched zip codes

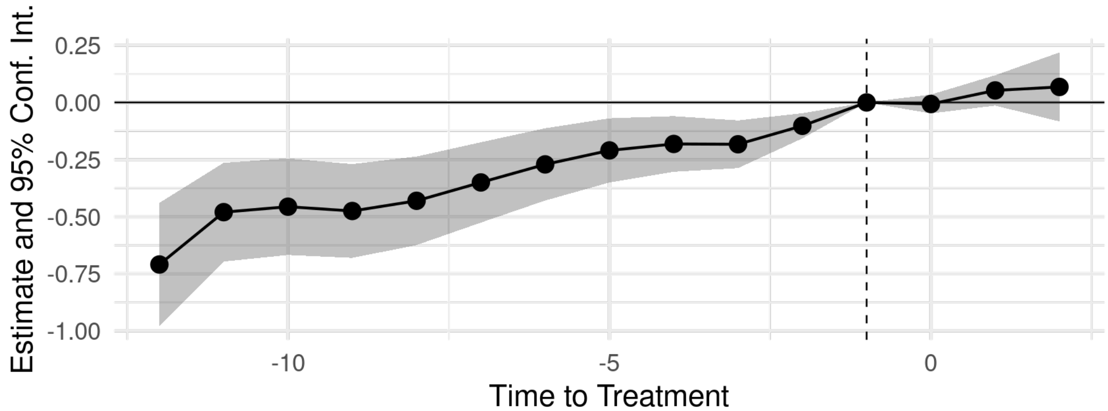
We provide the following explanation for the large post-moratorium coefficient. Once firms were able to non-renew policies again, this created a salient shopping trigger for customers. Non-renews have to be delivered in writing to the policyholder and atleast 75 days in advance of the expiration date of the policy (California Code, Insurance Code – INS § 678.1). Thus, the process of the insurers initiating non-renewal actions likely drove increased customer-initiated non-renewals as customers shopped for new policies ahead of their contract expiry. Thus, the true effect of the moratorium being lifted represents a combination of the customer and company-initiated non-renewals in event time 1.

Table A1 reports the results from the regressions that use neighboring zip codes as the control group for our four main dependent variables, breaking out estimates for the 2020 Moratorium and the 2021 Moratorium separately. By estimating separate models for the different cohorts of treated moratorium zip codes, we can determine if the effect of the regulation changes over time with subsequent treatment cohorts. We are able to estimate the model on two additional outcomes (FAIR Plan market share and average premium) only in 2020 because of data limitations.

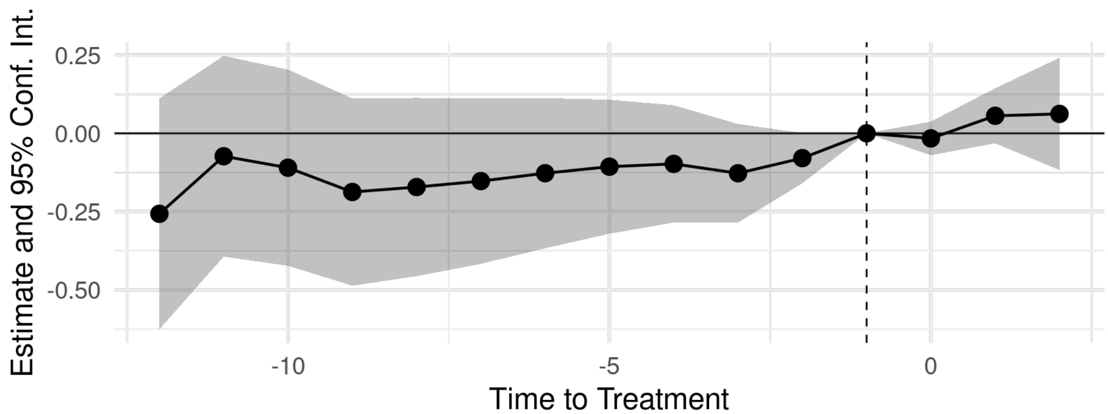
We find that the 2020 moratorium had a smaller impact on reducing company non-renewals during the moratorium than the the 2021 moratorium. This effect is even more pronounced when we use the matched difference-in-differences model (table A2).

We next turn to the efficacy of the moratorium in slowing the transition of policies from being insured by the voluntary market to being covered by the FAIR plan. From the descriptive evidence shown above, we know that the number of policies in the FAIR plan in both treated and control area is increasing the the period leading up to the moratorium as firm had already begun to limit their exposure in high risk areas. However, when using our econometric approach, with FAIR plan policies as the outcome variable in the regression, we are unable to detect any discernible impact of the moratorium.

Figure 9: Effect on FAIR Plan Policies



(a) Control group: Adjacent zip codes



(b) Control group: NN-matched zip codes

Results using the adjacent control zip codes exhibit significant pre-trends, which violate the assumption needed for causal interpretation of the regression coefficients. The results are consistent with the story that fair plan participation was increasing in the treated zip codes faster than in control zip codes prior to the moratorium. However, when using the matched control units, we continue to estimate precise null effects as well as fail to reject the parallel pre-trends assumption.

The moratorium eliminated one channel through which firms could reduce their exposure, by non-renewing an existing policy holder. However, customers were moved out of the voluntary market in a similar manner to the areas not covered by the moratorium. This can be accounted for by firms refusing to write new policies for current residents who had their policy cancelled by another firm for non-protected reasons, or homeowners new to the zip code, also not protected by the moratorium.

7 Conclusion

As climate change increases the risk of large scale natural disasters, well-functioning insurance markets will be necessary for consumers who rely on them often as the sole method of risk transfer. Our paper highlights how regulation and market structures that has traditionally been designed to benefit consumers by suppressing price levels can have large distortionary effects and lead to the unraveling of the market as prices and risk diverge. The California non-renewal moratorium is a unique policy tool the government implemented in an attempt to maintain a stable supply of homeowners insurance in the face of rapidly increasing wildfire risk. The moratoriums were effective in achieving this goal, but only in the short-term, and the strong rebound effect suggests that this policy is not an effective long term solution to correct market failures.

There is still a need for a permanent solution to this problem, which should include measures to reduce wildfire risk faced by households, both by adapting to wildfire risk and discouraging migration to high risk areas exacerbated by artificially low homeowner's rates. Regulating the industry in a way that allows firms to react to increased risk and earn reasonable profits can reduces the incentive for firms to retreat from the market and results in a functioning private market, a stated goal of the Department of Insurance.

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A Tables

Appendix Table A1: Treatment vs. Control Zip Codes: TWFE by Cohort

Dependent Variable:	Average Premium (1)	Fair Plan Market Share (2)	Company Nonrenewals (3)	Customer Nonrenewals (4)
Panel A: 2020 Moratorium				
Treatment (during moratorium)	18.40	0.0048	-13.33	24.65
	(33.56)	(0.0053)	(12.80)	(16.97)
Post Treatment (after moratorium)			91.97***	74.43***
			(25.99)	(21.09)
N	1,047	1,047	1,244	1,244
R^2	0.98324	0.94368	0.83012	0.98821
Within R^2	0.00091	0.00372	0.04047	0.04357
Panel B: 2021 Moratorium				
Treatment (during moratorium)			-27.77***	6.615
			(7.054)	(9.830)
N			4,527	4,527
R^2			0.79392	0.98311
Within R^2			0.00424	0.00032
Fixed Effects				
Year FE	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes

Standard-errors clustered by zip code in parentheses.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Appendix Table A2: Matched Difference-in-Differences by Cohort

Dependent Variable:	Average Premium (1)	Fair Plan Market Share (2)	Company Nonrenewals (3)	Customer Nonrenewals (4)
Panel A: 2019 Moratorium				
Treatment (during moratorium)	38.07	-0.0047	1.475	-8.212
	(32.33)	(0.0076)	(15.28)	(24.72)
Post Treatment (after moratorium)			121.3***	43.06*
			(26.46)	(25.59)
N	804	804	938	938
R^2	0.98562	0.90721	0.82367	0.97895
Within R^2	0.00661	0.00213	0.06740	0.01165
Panel B: 2020 Moratorium				
Treatment (during moratorium)			-58.41***	-12.88
			(8.614)	(11.27)
N			3,379	3,379
R^2			0.81327	0.98402
Within R^2			0.02203	0.00120
Fixed Effects				
Year FE	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes

Control units are chosen using propensity score matching on wildfire risk.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Appendix Table A3: Treatment vs. Rest of State Zip Codes: TWFE by Cohort

Dependent Variable:	Average Premium	Fair Plan Market Share	Company Nonrenewals	Customer Nonrenewals
	(1)	(2)	(3)	(4)
Panel A: 2019 Moratorium				
Treatment	61.80**	-0.0083*	15.83**	36.30**
	(25.45)	(0.0047)	(7.797)	(15.50)
Post Treatment			145.8***	92.19***
			(21.40)	(18.71)
N	8,103	8,103	9,597	9,597
R^2	0.88799	0.78050	0.85685	0.98466
Within R^2	0.00062	0.00076	0.04322	0.01412
Panel B: 2020 Moratorium				
Treatment			-28.74***	6.056
			(5.166)	(8.743)
N			7,400	7,400
R^2			0.84189	0.98526
Within R^2			0.00632	0.00026
Fixed Effects				
Year FE	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes

Standard-errors clustered by zip code in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*