Disclosure Statement for "Climate Risk and Insurer Adaptation: Evidence from the 2017–2018 California Wildfires"

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We declare that we have no relevant or material financial interests that relate to the research described in this paper.

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Climate Risk and Insurer Adaptation: Evidence from the 2017–2018 California Wildfires

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Abstract

Climate change poses growing challenges to the stability of insurance markets. This paper examines whether property insurers are adapting to climate risk by changing their underwriting behavior in response to large, unexpected losses, and the broader implications of insurer climate risk management on the functioning of insurance markets. Using firm-specific catastrophic losses from the 2017–2018 California wildfire seasons as a one-time shock, we find that insurers who suffered greater wildfire losses reduced their underwriting in high fire hazard areas within California, with stronger retreat among those with higher self-disclosed quality in climate risk management. These insurers also curtailed underwriting in other high fire hazard states and in hurricane-prone areas in Florida, suggesting both geographic and cross-peril spillovers. The selective retreat of climate-conscious insurers from high-risk areas raises concerns about the concentration of solvency risk and coverage reliability in these regions. Meanwhile, these firms tend to offer larger premium discounts and provide stronger incentives for hazard mitigation, highlighting policy opportunities to enhance both insurance supply and climate adaptation.

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1 Introduction

Over the past decade, we have seen a sustained rise in global losses from climate-related disasters such as wildfires, hurricanes, and floods. This trend has been particularly acute in the United States: In 2025, the U.S. accounted for approximately 78% of global insured losses, with the January Los Angeles wildfires alone setting a new record as the costliest wildfire to date (Banerjee et al., 2025).

Historically, property insurance has played a central role in helping households, firms, and communities manage exposure to catastrophic risks. In a changing climate, insurance markets are increasingly viewed as a critical component of society's adaptation infrastructure, given their ability to price risk and potentially incentivize investments in risk reduction (Kousky, 2019). However, the extent to which insurance can serve these functions depends on how insurers respond to the evolving nature of catastrophic risks. Such responses influence both the level of exposure and the allocation of climate risk across households, firms, and governments. In recent years, we have observed increasing stress in the property insurance market, characterized by sharp premium increases, rising nonrenewals, and insurer withdrawals across multiple states.[1] As such, there are growing concerns about the availability and reliability of coverage in high-risk areas and their implications for household financial health, mortgage market functioning, and disaster recovery.[2] These issues are often at the center of policy discussions.

As insurers confront rising climate risk, an important question emerges: Do insurers exhibit differential responses to the challenge, and if so, how do these varying responses influence market availability as well as their broader role in catastrophe risk management and climate adaptation at a societal level? Answering these questions involves first understanding how individual insurers incorporate climate change into their risk management strategies.

From an operational perspective, insurers can adjust to the changing risk of climate in several ways. They may change rates by repricing existing portfolios in response to realized losses and updated risk expectations, though the extent of such pricing adjustments may be limited by regulatory constraints. Boomhower et al. (2024) also show substantial heterogeneity across insurers in how they adopt more sophisticated methods to model and price

[1] See, for example, https://www.nytimes.com/2023/05/31/climate/climate-change-insurance-wildfires-california.html.

[2] Sastry et al. (2025) and Cookson et al. (2025) document widespread underinsurance driven by rising premiums, household financial constraints, and behavioral bias. Higher insurance costs have also been shown to affect mortgage performance (Ge, 2022). Related evidence from flood insurance markets shows that coverage gaps can slow disaster recovery (Billings et al., 2022) and contribute to credit rationing following disasters (Sastry, 2022).

wildfire risk. Reinsurance purchases are a means for insurers to manage capacity for their existing portfolios, balancing the efficient use of capital with their obligation to pay claims. Yet, fluctuations in the reinsurance market may restrict an insurer's options even when its underlying risk remains unchanged. In contrast, insurers typically have greater flexibility in underwriting decisions, determining where they are willing to deploy capital based on expectations of future losses, uncertainty, and regulatory feasibility. Thus, the underwriting responses of insurers are particularly relevant to the evolving nature of climate risks, as these decisions reflect their forward-looking commitment and influence their exposure to catastrophe risks.

Still, it remains unclear whether and how insurers are accounting for climate risks in their underwriting strategies. Underwriting decisions are typically made on an annual basis, whereas climate change unfolds over much longer horizons, complicating the incorporation of long-run risk into short-run decision-making. Berry-Stölzle et al. (2024) document that insurers' stated climate risk management intentions respond to past loss experiences, but whether these intentions translate into observable underwriting decisions remains an open question. Also, an insurer's underwriting choices may be interdependent with other approaches. Constraints in pricing adjustments, for example, may heighten the need for changes in underwriting. Addressing this gap is central to understanding how insurance markets respond to climate risk and to evaluating the role of insurers in shaping the allocation of climate-related losses.

In this paper, we examine whether insurers are adapting to climate risk by adjusting their underwriting behavior in response to large loss events, how these adjustments relate to insurers' climate risk management (CRM) approaches, and the broader implications of such adaptation for the functioning of insurance markets. We focus on the 2017–2018 wildfire seasons in California, which generated unprecedented and spatially concentrated insured losses. We exploit variation in insurers' exposure to these wildfire losses, driven by idiosyncratic wildfire extents and insurers' predetermined market shares across affected locations, as a plausibly exogenous shock to firms' realized losses and risk perceptions. This setting allows us to isolate insurers' underwriting responses to extreme wildfire losses while holding broader market conditions fixed.

A key contribution of the paper is to examine how insurers' underwriting responses to extreme losses vary with their CRM practices. We measure CRM using information from the Climate Risk Disclosure Survey, which captures insurers' stated approaches to identifying, managing, and governing climate-related physical risks. This measure allows us to distinguish

insurers with stronger versus weaker internal CRM frameworks and to assess whether large loss events trigger differential underwriting responses across these groups.

We find that insurers with stronger CRM practices respond to their 2017–18 California wildfire losses by contracting underwriting more aggressively in high-hazard areas. Importantly, these responses are not confined to the locations or perils directly affected by the losses. Instead, we document spillovers to other states and to other climate-sensitive hazards (i.e. hurricanes in this case), suggesting that high-CRM insurers interpret large wildfire losses as signals that prompt broader reassessments of risk exposure. This pattern contrasts sharply with the behavior of insurers with weaker CRM practices, whose underwriting activity appears comparatively unresponsive, particularly outside California. These differences are not driven by systematic variation in key insurer characteristics: high- and low-CRM insurers are similar in ex ante financial conditions and portfolio diversification, and our regressions explicitly control for a range of time-varying factors. Taken together, these findings indicate that CRM shapes firm-wide portfolio adjustments rather than isolated, location-specific reactions to loss events.

In addition, we also find that the observed geographic spillover effects are concentrated in states with regulatory environments that limit insurers' ability to adjust pricing in response to changing risk. This suggests that insurer withdrawal from high-risk areas is partly a rational response. When faced with regulatory constraints on flexibility to reprice escalating risks at adequate rates, insurers–particularly those with stronger CRM practices–evaluate alternative uses of capital across regions. They adjust their underwriting strategies accordingly and shift their portfolios away from regions where regulatory friction is too high to effectively manage climate risks.

Lastly, we show that insurers with varying CRM practices differ in how they incentivize risk mitigation among their policyholders. Insurers with stronger CRM practices tend to offer larger premium discounts for the same risk reduction activities when they occur, representing a differentiation in how insurers integrate the valuation of mitigation efforts into their pricing mechanisms.

Our findings have several policy implications for insurance markets under intensifying climate risk. First, they suggest that heterogeneity in insurers' CRM practices can reshape the spatial distribution of insurance availability, as insurers with stronger CRM frameworks disproportionately retreat from high-hazard areas. This dynamic may concentrate coverage in the hands of insurers with weaker CRM capacity, raising concerns about the reliability of insurance supply and the potential for heightened solvency risk following future catastrophic

events. These concerns are particularly relevant in light of ongoing debates about whether existing risk-based capital frameworks adequately reflect climate-related physical risks.[3] Second, while insurers with stronger CRM practices appear to provide stronger incentives for risk mitigation in the form of premium discounts, these benefits may be attenuated if such insurers reduce their market presence in precisely the areas where risk reduction is most needed. Taken together, the results point to a potential misalignment between insurer private risk management responses and public adaptation objectives, underscoring the importance of regulatory approaches that simultaneously address insurer solvency, insurance availability, and incentives for risk mitigation as climate risks continue to intensify. More importantly, our findings also highlight the need to recognize insurer-specific constraints that affect their risk management adjustments. Understanding how these constraints are translated into market outcomes helps inform the design of public policies that better align with how insurance markets actually function.

This paper contributes to several strands of the literature on insurance and climate risk. First, an emerging literature examines how insurers perceive, disclose, and manage climate-related risks, with a particular focus on climate risk disclosures. Analyzing disclosures from 183 insurance companies, Thistlethwaite and Wood (2018) document that, as of the early 2010s, most insurers had not yet integrated climate risk into core risk management processes. Using disclosures from more recent periods, Berry-Stölzle et al. (2024) show that insurers' climate risk management quality responds to disaster experience. Other studies document how disclosure requirements affect insurer behavior along additional margins: Ivantsova et al. (2021) find that mandatory climate risk disclosure leads insurance companies to reduce investments in carbon-intensive bonds, while Lin et al. (2023) provide descriptive evidence on the content and evolution of insurers' climate disclosures. Overall, this literature establishes that CRM practices among insurers are relatively recent and that insurers differ substantially in their approaches. We extend this literature by providing the first evidence linking insurers' CRM quality to underwriting behavior, showing how differences in internal CRM frameworks translate into differential market responses to climate-related losses. In doing so, we extend this literature to include new insights into the functioning of insurance markets under climate change.

Another recent literature examines how climate impacts interact with institutional constraints in insurance markets, including rate and capital regulation, reinsurance supply, and

[3]The National Association of Insurance Commissioners (NAIC) has recently launched a task force for improving governance regarding the risk-based capital framework. See https://content.naic.org/article/naic-executive-committee-launches-risk-based-capital-task-force-improve-governance.

information frictions. Born and Klimaszewski-Blettner (2013) and Sastry et al. (2023) show that regulatory policies can distort pricing and increase insurer exits following disasters, while Taylor et al. (2025) find that regulatory rules like moratoria for insurance nonrenewals do not sustain insurance availability in high-risk areas over the long run. Other work highlights financial constraints: Eastman and Kim (2023) find that incorporating catastrophe risk into regulatory capital requirements leads to modest premium increases, and Keys and Mulder (2024) show that reinsurance price shocks also pass through to premiums. In addition, Boomhower et al. (2024) emphasize the role of information asymmetries across insurers, documenting winner's curse dynamics that contribute to insurance availability challenges. We complement these studies by showing that insurers' internal climate risk management practices also shape underwriting responses to climate-related losses.

Our findings of spillovers across geographic markets are consistent with a growing body of work documenting cross-market and cross-division responses to shocks in insurance and reinsurance markets. Early work by Froot and O'Connell (1999) demonstrates that catastrophe events drive pricing dynamics in reinsurance markets, indicating that shocks can propagate well beyond directly affected areas. Oh et al. (2021) show that P&C insurers engage in cross-subsidization across states with different regulatory stringency. More recent work further explores the underlying mechanisms: Kalda et al. (2025) find that insurers pass on climate risk costs through higher premiums in both disaster-affected and unaffected areas, with spillover patterns shaped by consumer price sensitivity and insurer financial constraints. In addition, Ge (2022) document that shocks to P&C divisions are transmitted to life insurance divisions, particularly among financially constrained insurers. Relative to this literature's focus on pricing, our paper examines underwriting behavior more broadly and shows that insurers' climate risk management frameworks are an additional driver of spillover effects across markets.

2 Background

2.1 2017-18 California Wildfire Seasons

The 2017–18 wildfire seasons in California marked a watershed moment in the state's catastrophe risk landscape, causing losses at unprecedented levels. In 2017 alone, more than 9,000 fires scorched over 1.5 million acres, destroying or damaging more than 10,000 structures and producing insured losses on the order of $13.2 billion (in 2018 USD) (CAL FIRE, 2017). While 2017 was the most destructive wildfire season on record in California at the

time, the following year superseded it: the Camp Fire alone devastated parts of Butte County, consumed over 150,000 acres, destroyed nearly 19,000 structures, and generated damage estimates exceeding $16 billion.

According to analysis by Milliman, an insurance consultancy company, the 2017 wildfire losses wiped out just over ten years' worth of underwriting profits for California homeowners insurers. When combined with 2018, these seasons erased roughly twice the cumulative underwriting gains of the prior 26 years—leaving the industry with an aggregate underwriting loss exceeding $10 billion (Xu et al., 2019). Given the severity of the 2017–18 wildfire episodes, they triggered a structural shock to insurers' risk calculus, underwriting strategy, and pricing regimes.

Following the 2017–18 wildfire seasons, insurance availability declined sharply in the private market. We observe marked growth in insurance non-renewals, stricter restrictions in new business underwriting, and accelerated enrollments in the insurer of last resort – the California FAIR Plan. Statewide, FAIR Plan market share more than doubled, rising from 1.66% in 2015 to 3.75% in 2023. The effects were particularly concentrated in high-fire-risk regions. Among the top 10 counties with the highest wildfire risk, the FAIR Plan's market share, measured by policy count, increased from 0.61% to 32.62% over the same period, indicating a substantial withdrawal of private insurers from these markets (CDI, 2025).

2.2 Homeowners Insurance Markets in California and Other States

California's homeowners insurance market is primarily dominated by large national carriers. As of 2016, California's insurers also operate in an average of 24 other states, with 57% of total homeowners insurance premiums written in states outside of California. This geographic diversification allows insurers to spread losses across different regions and perils. However, it also creates interconnectedness, where significant underwriting losses from one jurisdiction could potentially have spillover effects on risk management decisions, such as underwriting, pricing, and capital allocation, in other states or across lines of business (see, e.g., Ge, 2022; Oh et al., 2021).

The primary outcome of interest in this paper is insurers' underwriting responses to climate risk. As insurers write businesses across states with varying climate exposure and regulatory frameworks, any underwriting decisions about whether to expand, maintain, or reduce their presence in a specific area must explicitly account for both geographic risk exposure and regulatory constraints.

In the homeowners insurance markets, rate regulations vary widely across states. When-

ever an insurer plans to update rates in the state they operate in, they must submit rate change requests to the state's Department of Insurance. Some states allow relatively rapid price adjustments, while others impose more stringent prior-approval requirements or limits on risk-based pricing, which can delay or suppress rate changes needed for long-term rate adequacy. For example, California is known to be one of the states with stringent rate regulations, which for many decades did not allow insurers to use catastrophe models or incorporate reinsurance costs when setting rates, a practice that has changed only recently. These regulatory constraints on price adjustments may influence how insurers respond to climate risk through non-price measures, such as increasing non-renewals, tightening underwriting standards, restricting new business, or reallocating capital toward areas with more predictable risks and regulatory conditions.

3 Data

To account for the various factors that may influence an insurer's underwriting adjustments, we combine data, as detailed below, on insurer-level underwriting behavior in both California and other states, along with their financial characteristics, climate risk management quality, geographic natural hazards, and the stringency of rate regulation in the states where they operate.

3.1 Insurer Underwriting Operations and Financial Characteristics

To capture insurers' underwriting decisions within California, we obtain insurer-specific earned exposure units data (i.e., number of policies earned within a calendar year) at the ZIP code level for residential homeowners policies from the California Department of Insurance's (CDI) Community Service Statement (CSS) dataset. We only include insurance companies that are licensed to operate in California's admitted market and have at least 0.1% market share in 2016, as measured by direct premiums written, representing over 99% of the voluntary market. In total, our main sample consists of 42 insurers and their ZIP-level earned exposure units collected annually from 2013 to 2022.

To examine these California insurers' underwriting in other states, we collect state-level information on total homeowners' premiums written and incurred losses through their annual financial statements submitted to the National Association of Insurance Commissioners (NAIC), accessed via S&P's Market Intelligence database. The financial statement data,

available at the insurer-year level, also include details on assets, liabilities, surplus, reinsurance usage, group affiliation, and other variables, which we use as control variables. We obtain these data for the subset of 37 P&C insurers that sell homeowners insurance in both California and other states from 2013 to 2024.

Additionally, we acquire more geographically granular underwriting variables for Florida insurers at the county level from the Florida Office of Insurance Regulation (FOIR). This data includes the number of non-renewals issued and the number of new policies written by each insurer in a given year-quarter. Again, we exclusively focus on P&C insurers that wrote homeowners insurance business in both California and Florida during the period from 2014-Q1 to 2022-Q3, totaling 11 firms. These datasets are merged together by an insurer's unique NAIC company code.

3.1.1 Insurer Climate Risk Management Quality

To measure insurers' awareness and management of climate risk, we use an index developed by Berry-Stölzle et al. (2024), which is based on textual analysis of the Climate Risk Disclosure Survey. This survey, adopted by the NAIC, collects self-disclosed information from insurers on how they incorporate climate risks into their risk mitigation, risk management, and investment activities. Data from the survey is reported at the insurance group level. The index, standardized to have a mean of zero and variance of one, captures the extent to which insurers identify, manage, and adjust their business model to climate change risk, with higher values indicating better management quality.

For our analysis, we use the 2016 index as an indicator of "climate risk management (CRM) quality" for P&C insurers in our sample prior to the wildfire loss shocks experienced in 2017-18. Among the 42 California insurers included in our main sample, two did not respond to the survey. For the remaining 40 insurers, we categorize them into low and high CRM quality firms based on the median value of the 2016 indices.

In Table 1, we compare the underwriting distribution, as well as key financial characteristics (e.g., firm size, leverage, reinsurance usage, and geographic diversification) across the two groups. The last column reports t-statistics for differences in means. As of 2016, prior to the substantial loss shocks from the 2017–18 California wildfire seasons, insurers with low CRM quality appear to write more policies on average, although the difference is not statistically significant. High-CRM-quality insurers also experienced slightly larger relative wildfire-related losses, though this difference is likewise statistically insignificant. Throughout our analysis, we measure insurers' loss shock using the combined ratio, defined as the

sum of incurred losses and operating expenses divided by earned premiums; values below one indicate underwriting profitability, while values above one reflect underwriting losses. We construct this measure using each insurer's California-specific wildfire-related losses and expenses in 2017–18 divided by its national premiums over the same period, capturing variation in the severity of wildfire shocks relative to insurer scale. Overall, the two groups are similar across most financial characteristics. The only marginally significant differences are that low-CRM-quality insurers rely less on reinsurance in California and maintain lower leverage in their operations outside the state.

3.1.2 Hazard and Regulatory Characteristics

Wildfire and Other Natural Hazard Risk. Our primary measure of California's wildfire risk comes from CDI's wildfire risk score reported for each ZIP code, measured as of the 2018 estimates. Collected from admitted homeowners insurers by the CDI, the wildfire risk score represents a policy-weighted average risk score for residential properties within the ZIP code, reflecting the actual distribution of policies in the voluntary market. Insurers reported the distribution of property-level risk scores based on outputs from commercial models that they used to assess the wildfire risk of individual properties among the policies they issued. The risk score ranges from 0 to 4, where a score of 4 indicates the highest level of wildfire risk for a given ZIP code. Based on these scores, we categorize ZIP codes into three risk levels–high, moderate, and low–by dividing them into terciles.

To measure natural hazard risk in other states, we also use the National Risk Index (NRI) from FEMA. In particular, we use the expected annual loss (EAL) rates per dollar of building value for wildfires, as well as other climate-related perils, such as hurricanes, which Florida is particularly exposed to, for our cross-peril spillover analysis.

Exposure to 2017-18 Wildfires. We measure wildfire exposure at the ZIP-code level as the share of the local population exposed to wildfire during the 2017–18 seasons. Wildfire extent is obtained from the Monitoring Trends in Burn Severity (MTBS) program, an interagency effort that provides consistent, spatially explicit information on the location and severity of large wildfires across the United States. MTBS maps fire perimeters and burn severity using Landsat satellite imagery and standardized classification methods, covering all fires larger than 1,000 acres in the western United States and 500 acres in the eastern United States since 1984.[4]

[4]For more information, see https://www.mtbs.gov/.

Table 1: Summary Statistics, 2016

	All Insurers			By CRM Quality		
	Mean (1)	Median (2)	SD (3)	Low (4)	High (5)	t-stat (6)
California Sample						
Loss Shock$^{2017-18}$	0.80	0.55	0.75	0.73	0.86	−0.53
Number of Earned Exposure Units (in Thousands):						
in Low-Fire-Risk ZIP Codes	55.35	18.61	104.93	82.53	32.47	1.50
in Moderate-Fire-Risk ZIP Codes	67.15	23.71	123.24	99.76	39.81	1.53
in High-Fire-Risk ZIP Codes	89.40	30.31	161.22	134.36	51.71	1.62
(log) Assets	14.58	14.46	2.28	15.17	14.26	1.29
Surplus-to-Liability Ratio	1.52	0.70	4.43	0.92	2.16	−0.86
Group Indicator	0.98	1.00	0.15	0.95	1.00	−1.00
Reinsurance Usage (Homeowners Line)	0.46	0.46	0.35	0.34	0.55	−1.92*
Geographic Diversification (Homeowners Line)	0.34	0.16	0.34	0.35	0.31	0.43
Line Diversification - California	0.31	0.28	0.18	0.30	0.29	0.10
Share of Homeowners Business in California	0.43	0.30	0.34	0.42	0.41	0.09
Number of Operating States (Homeowners Line)	25.69	22.50	20.45	28.15	25.45	0.42
Number of Insurers	42			20	20	
Other States Sample						
Loss Shock$^{2017-18}$	0.70	0.52	0.69	0.62	0.76	−0.59
Direct Premiums Written ($M):						
in Low-Fire-Risk, Low-Friction States	321.72	48.41	758.34	476.65	210.92	0.99
in Low-Fire-Risk, High-Friction States	209.80	34.75	616.58	332.15	117.56	0.98
in High-Fire-Risk, Low-Friction States	199.50	29.91	600.16	333.24	95.31	1.12
in High-Fire-Risk, High-Friction States	150.64	49.31	319.28	249.38	73.37	1.59
(log) Assets	14.83	14.66	2.14	15.30	14.73	0.82
Surplus-to-Liability Ratio	0.82	0.69	0.55	0.95	0.64	1.78*
Reinsurance Usage (Homeowners Line)	0.46	0.51	0.33	0.39	0.50	−0.93
Geographic Diversification (Homeowners Line)	0.25	0.15	0.25	0.24	0.23	0.11
Number of Insurers	37			18	17	
Florida Sample						
Loss Shock$^{2017-18}$	0.32	0.14	0.36	0.18	0.50	−1.43
Number of Nonrenewed Policies:						
in Low-Hurricane-Risk Counties	87.18	11.00	250.01	154.50	6.40	1.08
in High-Hurricane-Risk Counties	313.91	180.00	415.70	451.33	149.00	1.35
Number of Nonrenewed Policies Due To Hurricane Risk:						
in Low-Hurricane-Risk Counties	0.09	0.00	0.30	0.17	0.00	1.00
in High-Hurricane-Risk Counties	8.64	0.00	19.03	5.50	12.40	−0.53
Number of New Policies (in Thousands):						
in Low-Hurricane-Risk Counties	1.04	0.20	1.51	1.06	1.03	0.03
in High-Hurricane-Risk Counties	17.88	3.57	37.95	9.35	28.11	−0.73
(log) Assets	16.50	17.13	1.26	16.51	16.50	0.02
Surplus-to-Liability Ratio	0.85	0.72	0.74	1.09	0.56	1.31
Reinsurance Usage (Homeowners Line)	0.44	0.51	0.30	0.45	0.43	0.14
Geographic Diversification (Homeowners Line)	0.07	0.05	0.05	0.05	0.09	−1.40
Number of Insurers	11			5	6	

Notes: Table presents insurer-level summary statistics as of 2016, except for the loss shock variable, $LossShock^{2017-18}$, which reflects an insurer's actual losses and expenses from the 2017-18 California wildfire seasons. *p<0.1; **p<0.05; ***p<0.01.

To construct population-weighted exposure, we overlay MTBS wildfire perimeters with gridded population data from the Gridded Population of the World (GPW).[5] This procedure yields the fraction of ZIP-code residents located within wildfire-affected areas. Compared with an area-based measure, a population-weighted measure is particularly relevant for insurance markets, as insurers' underwriting exposure and potential losses are driven by the concentration of people, housing units, and insured properties at risk rather than by burned area alone.

State-Level Regulatory Friction. As mentioned earlier, one important dimension to consider when it comes to insurers' underwriting responses to climate risk is the pricing flexibility under a state's rate regulatory framework. To do so, we use the regulatory friction measure developed by Oh et al. (2021), which assesses the extent to which approved rate changes align with the insurers' targeted rate changes in a state. Based on the median value of this measure, we categorize states into two groups: those with high regulatory friction and those with low regulatory friction.

4 Econometric Framework

Our analysis investigates how insurers adjust underwriting behavior in response to losses incurred during the 2017–18 wildfire seasons. The empirical framework is designed to capture separate responses across locations with different levels of climate risk exposure and regulatory challenges. We first develop a baseline econometric framework to estimate underwriting responses within California, focusing specifically on wildfire hazards. We then extend this framework in two directions: first, to examine whether underwriting responses vary systematically with insurers' CRM quality; and second, to assess spillover effects outside California, including changes in other states and adjustments concerning other climate-related hazards beyond wildfires.

[5] Data retrieved from https://www.earthdata.nasa.gov/data/projects/gpw.

4.1 Baseline Estimation

To examine how insurers adjust underwriting in California locations with varying wildfire hazard levels following the 2017–18 wildfire losses, we estimate the following specification:

$$Y_{izt} = \sum_{h=H,M,L} \beta_h \text{LossShock}_i^{2017-18} \times \text{Post}_t \times \mathbb{1}(\text{Hazard}_z = h) + \gamma' X_{it} + \delta_{iz} + \eta_{zt} + \varepsilon_{izt}. \quad (1)$$

The outcome variable, Y_{izt}, measures underwriting activity by insurer i in ZIP code z and year t, proxied by the number of active policies. The coefficient of interest β_h is identified from a three-way interaction that links insurer-specific wildfire losses to post-event underwriting outcomes across locations with varying hazard exposure.

The first component of the interaction, $\text{LossShock}_i^{17-18}$, captures insurer i's exposure to the 2017–18 wildfire seasons. As previously described, we measure loss shock using each insurer's California-specific wildfire-related losses and expenses in 2017–18 divided by its national premiums over the same period. The second component, Post_t, is an indicator for the post-2018 period, isolating adjustments following the wildfire loss events. The third component includes a set of indicators for wildfire hazard exposure at the ZIP-code level. Based on the CDI wildfire risk score, all California ZIP codes are classified into high, moderate, or low hazard categories, with each category containing one-third of the ZIP codes. This structure allows underwriting responses to differ flexibly across hazard levels.

The specification includes a rich set of time-varying insurer controls, X_{it}, including lagged combined ratios, capitalization, geographic and line-of-business diversification, and reinsurance utilization for homeowners insurance and other lines. We further include insurer-by-ZIP fixed effects, δ_{iz}, which absorb time-invariant differences in market share composition across ZIP codes, and ZIP-by-year fixed effects, η_{zt}, which control for local demand conditions and wildfire-related shocks common to all insurers within a ZIP code. Identification of any differential post-wildfire adjustments in outcomes, therefore, only comes from insurers' loss exposure during 2017-18.

However, an insurer's losses from the 2017–18 wildfire seasons may be endogenous to its business model, underwriting strategy, or time-varying financial and regulatory conditions, all of which may also influence underwriting behavior over time. To address this concern, we employ an instrumental variables (IV) strategy in which insurer-level wildfire losses are instrumented using a measure of predicted exposure, constructed as:

$$\text{PredictedExposure}_i^{2017-18} = \sum_z \text{MarketShare}_{iz}^{2017-18} \times \text{PopExposure}_z^{2017-18} \quad (2)$$

This measure combines the insurer's 2017-18 market share across ZIP codes[6] with idiosyncratic population-weighted wildfire exposure at a particular ZIP code. Population exposure is measured by the share of the ZIP-code population exposed to wildfire during the 2017–18 seasons. In the IV estimation, all interaction terms involving the insurer loss shock are instrumented by the corresponding interactions with predicted exposure.

By leveraging cross-sectional variation in wildfire intensity across locations and differences in insurers' geographic portfolios, this approach isolates variation in losses driven by mechanical geographic exposure rather than insurer-specific risk-taking or post-event strategic adjustments. For this reason, we treat the IV estimates as our primary specification.

4.2 Extensions

Dynamic Effects

While the baseline specification estimates average post-2017 adjustments in underwriting behavior, it abstracts from the timing and persistence of insurers' responses following the wildfire losses. To examine the dynamic evolution of underwriting decisions, we extend the analysis to an annual event-study framework that traces insurer responses before and after the 2017–18 wildfire seasons. This approach allows us to assess whether underwriting adjustments occur immediately or with delay, whether they intensify or attenuate over time, and whether responses differ systematically across locations with low, moderate, and high wildfire hazard. Importantly, the event-study specification also provides a transparent assessment of pre-trends, helping to distinguish discrete post-event adjustments from gradual changes in underwriting behavior that may have been underway prior to the wildfire seasons.

Heterogeneity by Climate Risk Management Quality

While the 2017–18 wildfire seasons represent an unprecedented and largely unanticipated shock to insurers, firms differ in their capacity to absorb and manage climate-related risks and may therefore respond differently to such shocks. To explore the potential of such differential responses, we split the sample based on whether an insurer's CRM quality is above or below the sample median and estimate the model separately for each group. This approach allows us to assess whether insurers with more developed CRM frameworks adjust underwriting with different intensity following wildfire losses, while holding constant the

[6]As shown below in the event study estimates, insurers' underwriting behaviors only start to adjust drastically starting in 2019, while their 2017-18 behaviors are quite stable. Our results are also robust to using pre-determined market share from 2016. These results are available upon request.

underlying hazard exposure faced by insured locations. We use the CRM measure from 2016 so that it captures insurers' *ex ante* approach to managing climate-related underwriting risk.

4.3 Underwriting Responses Beyond California

We also examine cross-state spillover effects in insurers' underwriting responses to wildfire losses in California. Such spillovers may arise because underwriting decisions are shaped by insurers' broader CRM strategies, which may not be confined to individual states. In addition, capital and reinsurance constraints are managed at the firm or insurance-group level, providing a further channel through which losses in one state can influence underwriting decisions elsewhere (Ge, 2022). To estimate these potential spillover effects, we adopt a specification analogous to our baseline model and estimate insurer underwriting outcomes at the state level for states outside California:

$$Y_{ist} = \sum_{g \in \{H,L\}} \beta_g \, \text{LossShock}_i^{2017\text{–}18} \times \text{Post}_t \times \mathbb{1}(G_s = g) + \gamma' X_{it} + \delta_{is} + \eta_{st} + \varepsilon_{ist}. \quad (3)$$

The outcome of interest is the log of total premiums written by insurer i in state s. States are classified as high- or low-wildfire-hazard, allowing underwriting responses to vary across hazard levels.

In further variants, we incorporate regulatory friction as an additional dimension, categorizing states into four mutually exclusive groups defined by high or low wildfire hazard and high or low regulatory friction. We consider regulatory frictions because pricing constraints such as rate-setting requirements influence how insurers can respond to losses. When such constraints are binding, insurers may reallocate underwriting or pricing adjustments toward less regulated markets as part of broader portfolio management. Consistent with this mechanism, recent evidence shows that insurers engage in cross-state cross-subsidization in pricing (Oh et al., 2021). Regulatory frictions therefore play a central role in determining the magnitude and direction of interstate spillovers in underwriting responses following large climate-related shocks. Additionally, we argue that repricing flexibility is important for insurers in managing risks that are constantly changing, and any limitations on this flexibility may impact insurers' decisions regarding where to provide coverage in the longer term through underwriting.

For Florida, we observe underwriting outcomes at the county level, which allows us to examine locations that differ not only in wildfire risk but also in hurricane risk, the primary climate-related hazard in the state. The estimation specification parallels the cross-state

Table 2: California Underwriting Responses

	log(1+Earned Exposure Units)				
	Baseline		IV		
	(1)	(2)	(3)	(4)	(5)
Loss Shock$^{CA}_{2017-18}$ × Post	−0.044***				
	(0.002)				
Loss Shock$^{CA}_{2017-18}$ × Post					
× Low Wildfire Hazard		−0.033***	−0.026***	−0.077***	0.010**
		(0.003)	(0.004)	(0.007)	(0.005)
× Moderate Wildfire Hazard		−0.041***	−0.043***	−0.077***	−0.018***
		(0.004)	(0.004)	(0.009)	(0.005)
× High Wildfire Hazard		−0.090***	−0.106***	−0.163***	−0.070***
		(0.004)	(0.005)	(0.009)	(0.006)
Ex-Ante CRM Quality	All	All	All	High	Low
Controls	Yes	Yes	Yes	Yes	Yes
Insurer × ZIP FEs	Yes	Yes	Yes	Yes	Yes
ZIP × Year FEs	Yes	Yes	Yes	Yes	Yes
Observations	981,540	789,600	789,600	376,000	376,000
Adjusted R^2	0.961	0.956	0.956	0.943	0.967
First Stage: Loss Shock$^{CA}_{2017-2018}$					
Share of Premiums in Burned Areas (%)			1.828***	1.550***	2.048***
			(0.186)	(0.279)	(0.267)
F-statistic			96.214	30.854	58.720

Note: The table reports results of underwriting responses across California ZIP codes following Equation (1). Standard errors are clustered at the insurance-group-by-ZIP-code level. *p<0.1; **p<0.05; ***p<0.01

models above but replaces wildfire hazard measures with hurricane hazard measures.

Finally, for all cross-state analyses, we incorporate the econometric extensions described in Section 4.2 to examine dynamic effects and assess the role of insurers' climate risk management quality.

5 Results

5.1 Underwriting Responses in California

We begin by estimating insurers' underwriting responses in California to losses incurred during the 2017–18 wildfire seasons, following Equation (1). Table 2 reports these results, with the outcome measured as the log of earned exposure units (insured property counts).

Column (1) presents the OLS estimate of the average response across all California ZIP codes. The estimate is statistically significant at the 1 percent level and indicates that insurers reduce underwriting by approximately 3.3 percent, on average, for a one-standard-deviation increase in the combined ratio during the 2017–18 wildfire seasons.

Column (2) allows underwriting responses to vary across ZIP codes with low, moderate, and high wildfire hazard. The estimates show a decline in insured property counts across all hazard categories, with the largest effects concentrated in high wildfire hazard ZIP codes. In these areas, a one-standard-deviation increase in the 2017–18 combined ratio is associated with a 6.8 percent reduction in insured properties. Column (3) reports estimates from the instrumental variables specification, which we treat as our preferred framework. While the qualitative patterns remain similar, the IV estimates reveal sharper contrasts between high- and low-hazard ZIP codes, consistent with stronger responses to exogenous wildfire-driven loss exposure.

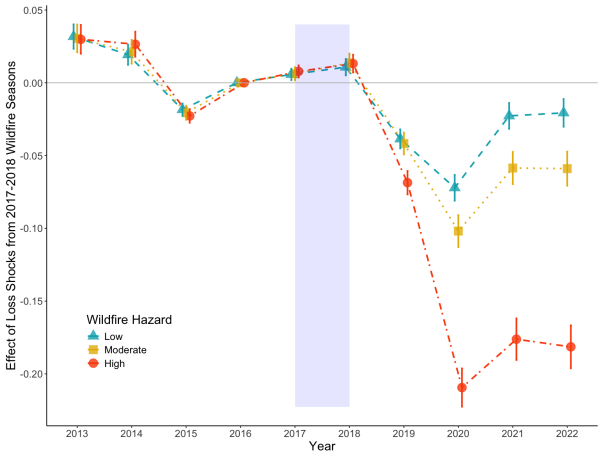
Using this preferred specification, we next examine heterogeneity by insurers' CRM quality. Columns (4) and (5) report estimates for insurers with above- and below-median CRM quality, respectively. Although both groups exhibit greater underwriting decline in higher-risk ZIP codes, the magnitude of the response is substantially larger for insurers with higher CRM quality. Notably, even in low wildfire hazard ZIP codes, high-CRM insurers reduce underwriting more aggressively than low-CRM insurers do in the highest-risk areas, suggesting that firms with more developed CRM frameworks adjust underwriting more broadly and proactively following wildfire losses.

Figure A.3 illustrates the dynamic underwriting responses by plotting event-study coefficient estimates for each year from 2013 to 2022, with 2016 serving as the baseline year. Panel A presents estimates pooling all insurers, while Panels B and C report results separately for insurers with above- and below-median CRM quality, respectively. Focusing on Panel A, underwriting trends across ZIP codes with different hazard levels track each other closely through 2018, providing no evidence of differential pre-trends. Beginning in 2019, underwriting declines sharply across all hazard categories, with the most pronounced effect in high-hazard ZIP codes. In 2020, differential declines in underwriting further widen the gaps between high- and moderate-hazard ZIP codes and between moderate- and low-hazard ZIP codes. Beginning in 2021, underwriting stabilizes across all three categories, while maintaining substantial divergence between them.

Panels B and C reveal substantial heterogeneity by insurers' CRM quality. The dynamic responses for high-CRM insurers in Panel B closely mirror the aggregate patterns observed

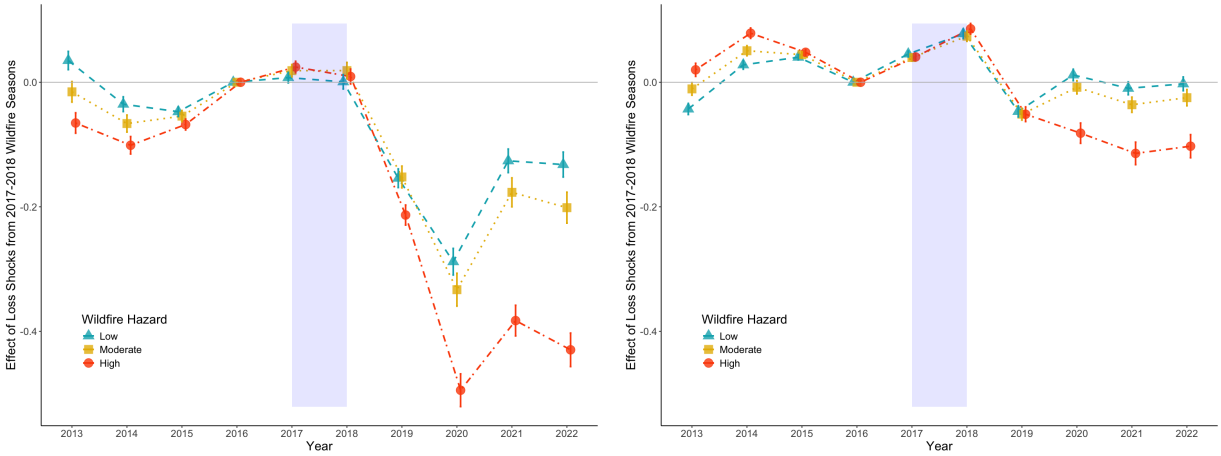
Figure 1: Effects of 2017-18 Wildfire Losses on California Underwriting Responses

A. All Insurers



B. High CRM Quality Insurers

C. Low CRM Quality Insurers



Note: Panel A shows event-study estimates and their 95% confidence intervals of underwriting responses across California ZIP codes, while Panels B and C show the corresponding estimates for above- and below-median CRM insurers.

in Panel A, including the sharp post-2018 contraction and the pronounced differentiation across hazard levels. In contrast, Panel C shows that low-CRM insurers exhibit considerably smaller underwriting reductions across all locations and a weaker differentiation by hazard. By 2022, underwriting by low-CRM insurers in low- and moderate-hazard ZIP codes has largely returned to baseline levels, while underwriting in high-hazard ZIP codes remains below baseline, though with a much smaller gap relative to lower-risk areas.

Taken together, these results indicate that underwriting responses to the unprecedented 2017–18 wildfire losses emerged with a lag, beginning in 2019, and were concentrated in higher-hazard areas. Moreover, these dynamic adjustments appear to be driven primarily by

Table 3: Underwriting Responses in Other States, IV Estimates

	log(1+Direct Premiums Written)				
	(1)	(2)	(3)	(4)	(5)
Loss Shock$^{CA}_{2017-2018}$ × Post	−0.320**				
	(0.134)				
Loss Shock$^{CA}_{2017-2018}$ × Post					
× Low Wildfire Hazard		−0.039			
		(0.131)			
× High Wildfire Hazard		−0.583***			
		(0.218)			
Loss Shock$^{CA}_{2017-2018}$ × Post					
× Low Wildfire Hazard, Low Reg. Friction			−0.078	0.150	0.177
			(0.165)	(0.237)	(0.177)
× Low Wildfire Hazard, High Reg. Friction			0.082	0.349	0.331
			(0.185)	(0.244)	(0.219)
× High Wildfire Hazard, Low Reg. Friction			−0.216	−0.071	0.036
			(0.205)	(0.251)	(0.295)
× High Wildfire Hazard, High Reg. Friction			−0.785**	−0.556**	−0.814
			(0.326)	(0.260)	(0.638)
Ex-Ante CRM Quality	All	All	All	High	Low
Controls	Yes	Yes	Yes	Yes	Yes
Insurer × State FEs	Yes	Yes	Yes	Yes	Yes
State × Year FEs	Yes	Yes	Yes	Yes	Yes
Observations	12,432	12,432	12,432	5,856	6,516
Adjusted R^2	0.824	0.824	0.824	0.766	0.887

Note: This table reports results of underwriting responses in other states following Equation (3). Standard errors are clustered at the insurance-group-by-state level. *p<0.1; **p<0.05; ***p<0.01

insurers with stronger CRM frameworks, consistent with more proactive and differentiated underwriting responses following large climate-related shocks.

5.2 Underwriting Responses in Other States

Large wildfire losses in California may lead insurers to reassess wildfire risk and adjust underwriting across their broader portfolios. To the extent that underwriting decisions reflect firm-wide risk management considerations rather than purely local conditions, insurers' responses to California losses may extend to other states with similar hazard profiles. This section examines whether insurers facing larger wildfire losses in California subsequently reduce their exposure to wildfire risk outside the state.

We estimate insurers' underwriting responses in states other than California following

Equation (3) under the IV framework. The outcome variable is the log of total written premiums by insurer, state, and year. Table 3 reports these results. Column (1) estimates the average effect across all non-California states and shows that insurers experiencing larger losses during the 2017–18 wildfire seasons significantly reduce their average underwriting across states. Column (2) allows responses to differ by wildfire hazard exposure and reveals that this effect is entirely driven by states with high wildfire hazard. The magnitude implies that insurers reduce written premiums in high-hazard states by approximately 33 percent for each one-standard-deviation increase in the combined ratio during the 2017–18 California wildfire seasons.[7]

Column (3) further incorporates regulatory friction as an additional dimension, categorizing states into four groups defined by high or low wildfire hazard and high or low regulatory friction, as displayed in Figure A.1. We examine regulatory frictions because constraints on rate setting can shape where insurers are able to rebalance risk following large losses. The estimates indicate that spillover effects are concentrated in states characterized by both high wildfire hazard and high regulatory friction. States with high wildfire hazard but low regulatory friction also exhibit a negative point estimate, but its magnitude is about a quarter as large and statistically insignificant.

Columns (4) and (5) further split the sample by insurers' CRM quality. Both groups reduce underwriting in states with high wildfire hazard and high regulatory friction. However, the effect is statistically significant only for insurers with higher CRM quality. In contrast, estimates for insurers with lower CRM quality are imprecisely estimated, suggesting substantial heterogeneity in how these firms adjust underwriting across states following the 2017-18 wildfire losses.

Overall, these results suggest that insurers' responses to the 2017–18 wildfire losses extend beyond California and are shaped by both wildfire risk and regulatory frictions across states, with stronger and more systematic adjustments among insurers with higher climate risk management quality.

5.3 Underwriting Responses in Florida

Large wildfire losses may also spill over to insurers' underwriting decisions for other climate-related perils. Losses from one climate peril can induce broader reassessments of exposure to correlated risks, particularly in regions where climate hazards are salient. In

[7] As shown in Table 1, the standard deviation of combined ratio is 0.69 in this sample. The change in underwriting is calculated as $e^{-0.583\times0.69} - 1 \approx -0.33$.

Table 4: Underwriting Responses in Florida, IV Estimates

	Count Number of					
	Nonrenewed Policies		Nonrenewed Policies Due to Hurricane Risk		New Policies Written	
	(1)	(2)	(3)	(4)	(5)	(6)
Loss Shock$^{CA}_{2017-2018}$ × Post	1.043***		0.538*		−49.172***	
	(0.377)		(0.313)		(12.035)	
Loss Shock$^{CA}_{2017-2018}$ × Post						
× Low Wildfire Hazard		−0.288				
		(0.313)				
× High Wildfire Hazard		2.414***				
		(0.767)				
Loss Shock$^{CA}_{2017-2018}$ × Post						
× Low Hurricane Hazard				−0.613***		−20.322***
				(0.210)		(7.709)
× High Hurricane Hazard				1.723***		−78.897***
				(0.629)		(18.853)
Ex-Ante CRM Quality	All	All	All	All	All	All
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Insurer × County FEs	Yes	Yes	Yes	Yes	Yes	Yes
County × Year-Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,058	25,058	25,058	25,058	25,058	25,058
Adjusted R^2	0.661	0.661	0.160	0.163	0.935	0.936

Note: This table reports results of underwriting responses across Florida counties. Standard errors are clustered at the insurance-group-by-county level. *p<0.1; **p<0.05; ***p<0.01

this section, we test these potential spillovers using county-level underwriting data from Florida, where hurricanes constitute the primary climate-related risk. We estimate a model analogous to Equation (3), classifying Florida counties based on their wildfire or hurricane risk, and estimate the model under the IV framework.

Table 4 reports three sets of results based on different underwriting outcomes. Columns (1) and (2) focus on the total number of nonrenewed policies and show that insurers with larger California wildfire losses during 2017–18 nonrenew more policies overall, with the effect largely driven by counties with high wildfire hazard. The magnitude is modest: a one-standard-deviation increase in the combined ratio is associated with an average increase of 0.87 nonrenewed policies per county in high-hazard counties.[8]

Columns (3) and (4) turn to nonrenewals explicitly attributed to hurricane risk, as disclosed by insurers. Column (3) shows that insurers with greater 2017–18 wildfire losses also

[8]The standard deviation of the combined ratio in this sample is 0.36.

Table 5: Underwriting Responses in Florida by CRM Quality, IV Estimates

	Number of Nonrenewed Policies Due to Hurricane Risk		Number of New Policies Written	
	(1)	(2)	(3)	(4)
Loss Shock$^{CA}_{2017-2018}$ × Post				
× Low Hurricane Hazard	−0.520	0.092	−64.802***	53.198***
	(0.385)	(0.078)	(16.349)	(16.047)
× High Hurricane Hazard	2.738***	0.477***	−198.516***	−8.380
	(0.806)	(0.173)	(35.861)	(31.016)
Ex-Ante CRM Quality	High	Low	High	Low
Controls	Yes	Yes	Yes	Yes
Insurer × County FEs	Yes	Yes	Yes	Yes
County × Year-Quarter FEs	Yes	Yes	Yes	Yes
Observations	11,390	13,668	11,390	13,668
Adjusted R^2	0.162	0.211	0.937	0.912

Note: The table reports heterogeneous underwriting responses across Florida counties for insurers with high and low CRM quality, shown in columns (1) and (3) for high-CRM-quality insurers and columns (2) and (4) for low-CRM-quality insurers. Standard errors are clustered at the insurance-group-by-county level. *p<0.1; **p<0.05; ***p<0.01

adjust nonrenewals due to hurricane risk. Column (4) further allows these responses to differ by county hurricane hazard exposure (see Figure A.2) and reveals a clear divergence: affected insurers increase nonrenewals in high hurricane hazard counties while reducing nonrenewals in low hazard counties. This pattern is consistent with insurers rebalancing their portfolio exposure to hurricane risk in response to wildfire losses.

Adjustments along the hurricane risk margin are also evident in Columns (5) and (6), where the outcome is the number of new policies written. Insurers experiencing a one-standard-deviation increase in 2017-18 combined ratio reduce new policy issuance by approximately 18 policies per county on average. This effect is the average of a larger reduction of about 28 policies in high hurricane hazard counties, and a smaller reduction of roughly 7 policies in low hurricane hazard counties.

Figure A.3 plots the corresponding dynamic effects for nonrenewals due to hurricane risk and new policy issuance. For nonrenewals, insurers with larger 2017–18 wildfire losses exhibit an overall upward trend in nonrenewals attributed to hurricane risk, with a notably larger increase in high hurricane hazard counties in 2019 and 2020. For new policies, insurers hit by larger wildfire losses issue systematically fewer new policies in high hurricane hazard counties beginning in 2018, and this differential persists over time.

Table 5 examines heterogeneity in underwriting responses by CRM quality. Columns (1)

and (2) report responses for insurers with high and low CRM quality, respectively, focusing on nonrenewals due to hurricane risk. The estimates indicate that while both groups increase nonrenewals in response to losses incurred during the 2017–18 wildfire seasons, high-CRM insurers exhibit substantially larger adjustments. Columns (3) and (4) turn to new policy issuance. For high-CRM insurers, we find reductions in new policies written in both low- and high-hurricane-hazard counties, with the decrease in high-hazard counties being approximately three times as large. In contrast, low-CRM insurers increase new policy issuance in low-hazard counties and exhibit no statistically significant change in high-hazard counties. Taken together, these patterns suggest that insurers with stronger CRM frameworks respond to wildfire losses by more actively curtailing exposure in hurricane-prone areas, whereas insurers with weaker CRM practices exhibit more limited or less differentiated adjustments.

Figure 2 examines the dynamics of these responses by insurer CRM quality. Panels A and B show that, for hurricane-related nonrenewals, high-CRM insurers respond to larger 2017–18 wildfire losses by increasing nonrenewals in both low- and high-hurricane-hazard counties, with a particularly pronounced increase in high-hazard counties in 2019 and 2020. By contrast, low-CRM insurers exhibit little systematic change in nonrenewal behavior. Consistent with this heterogeneity, the aggregate pattern in Figure A.3 is primarily driven by the high-CRM group. Panels C and D reveal even sharper differences for new policy issuance. High-CRM insurers reduce new policies across Florida beginning in 2017, with larger declines in high-hurricane-hazard counties. In contrast, low-CRM insurers increase new policy issuance in both high- and low-hazard counties by similar magnitudes. Taken together, these patterns are consistent with a shift of market composition in which a growing share of policies in high-hurricane-hazard areas is held by insurers with weaker climate risk management practices.

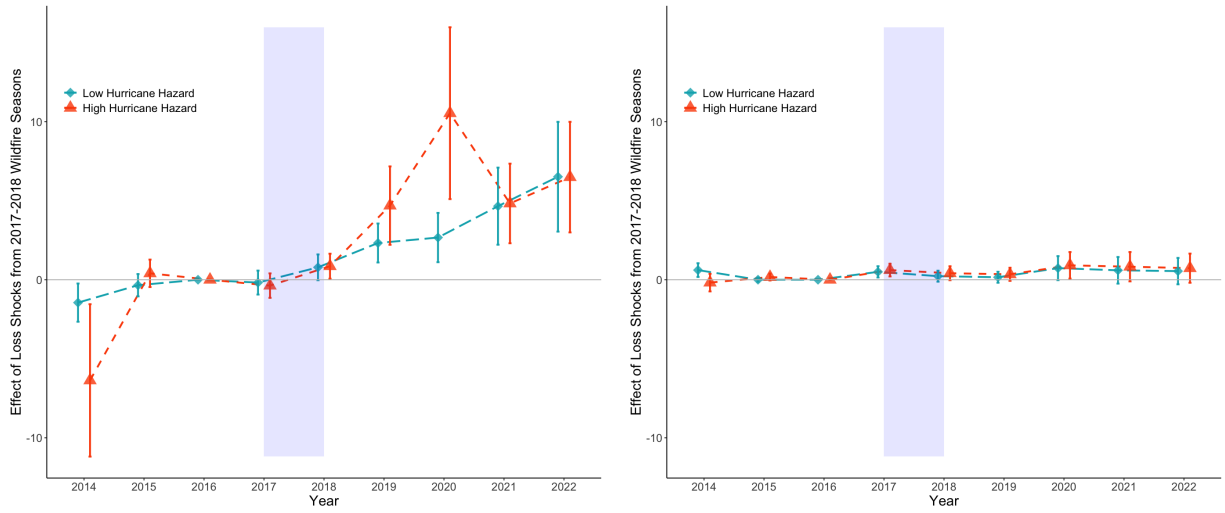
In the above results, our primary outcomes are the counts of nonrenewals and new policies. We prefer specifications in levels rather than logs because these variables contain a large number of zeros. Nonetheless, we also estimate the same specifications using log-transformed outcomes and report the results in Tables A.1 and A.2 in the Appendix. The qualitative conclusions remain unchanged.

Overall, the Florida results provide evidence that wildfire losses in California spill over to insurers' underwriting decisions for other climate-related perils such as hurricanes. Insurers experiencing larger wildfire losses increase nonrenewals and reduce new policy issuance in Florida, with these adjustments concentrated in counties facing higher hurricane risk. Importantly, these spillovers are driven primarily by insurers with stronger CRM practices,

Figure 2: Effects of 2017-18 Wildfire Losses on Underwriting Responses in Florida by Insurer CRM Quality

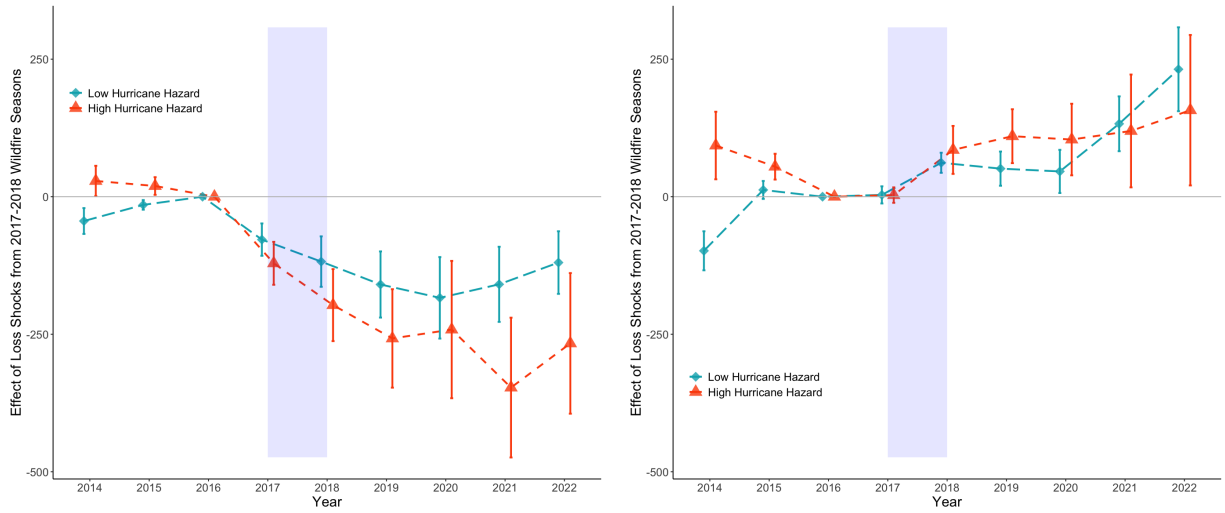
A. Number of Nonrenewed Policies Due to Hurricane Risk, High CRM Quality Insurers

B. Number of Nonrenewed Policies Due to Hurricane Risk, Low CRM Quality Insurers



C. Number of New Policies Written, High CRM Quality Insurers

D. Number of New Policies Written, Low CRM Quality Insurers



Note: Panels A and B plot event-study coefficient estimates and their 95% confidence intervals for the number of nonrenewed policies due to hurricane risk for insurers with high and low CRM quality, respectively. Panels C and D plot the corresponding estimates for the number of new policies written. In each panel, effects for high- and low-hurricane-hazard counties are shown in red and green, respectively.

which respond by curtailing exposure in high-hurricane-hazard areas, while insurers with weaker CRM practices exhibit limited or even opposite adjustments. Taken together, these findings suggest that cross-peril underwriting responses are shaped by firm-wide climate risk management strategies and may contribute to a reallocation of climate risk exposure across insurers, with a growing share of high-hazard policies held by less climate-aware firms.

6 Discussion: Implications for Insurance Markets

In the previous section, we document systematic differences in insurers' underwriting responses to major wildfire losses, showing that insurers with stronger climate risk management practices disproportionately withdraw from high-hazard areas in response to their 2017–18 California wildfire losses. These adjustments are not confined to the locations or perils directly affected by the losses. Instead, we find that underwriting contractions extend to other states and to other hazards exacerbated by climate change, indicating that these insurers respond to wildfire losses by reassessing and rebalancing risk across their entire underwriting portfolio rather than treating events as isolated shocks. This pattern is consistent with a centralized, firm-wide approach to managing climate-related physical risk. Importantly, this behavior contrasts with that of insurers with weaker CRM practices, whose underwriting activity appears comparatively unresponsive to large loss events, especially outside California. The divergence reflects heterogeneous internal risk management capabilities and strategic responses to climate information.

Taken together, our findings suggest that CRM shapes the spatial distribution of insurance availability as climate risks intensify. In particular, as high CRM insurers disproportionately retreat from high-hazard areas, a larger share of policies in these areas will be held by low CRM insurers. This raises concerns about the reliability of insurance supply, as low CRM insurers might have higher solvency risk in the wake of future catastrophic events.

These solvency concerns come amid ongoing debates and potential reforms in regulatory capital frameworks. U.S. regulators and industry stakeholders have recently signaled a renewed focus on updating risk-based capital (RBC) standards to better reflect emerging climate-related risks. For example, the NAIC has launched a dedicated task force to evaluate the existing RBC system and consider how to incorporate climate-related perils such as wildfire and hurricanes more explicitly into capital requirements rather than just for informational reporting. Such changes would aim to ensure that insurers holding concentrated exposures to climate-sensitive perils maintain capital cushions commensurate with their risk

profiles, potentially reducing the probability that weaker risk managers become overexposed in high hazard regions.

However, the current RBC regime does not yet mandate capital increases based on climate scenario outputs, and formal integration of wildfire and other physical risks into solvency requirements remains under discussion rather than adoption in most states. In this context, our results underscore the importance of regulatory attention to capital adequacy: as private underwriting shifts geographically in response to climate losses, regulators may need to recalibrate solvency frameworks to mitigate the systemic risk of a market increasingly populated by carriers with lower CRM capacity.

Another implication of our findings concerns incentives for hazard mitigation embedded in the insurance system. Investments in hazard mitigation are a fundamental response to rising climate risks, and insurance markets are often viewed as a powerful mechanism for promoting such adaptation at scale through pricing (Kousky, 2019). However, little is known about insurers' motivation to incorporate mitigation explicitly into their rating and underwriting practices. In particular, insurers with stronger CRM practices may play a more active role in encouraging mitigation by policyholders and communities because they are more likely to systematically assess the loss-reducing benefits of mitigation and internalize these benefits in pricing.

To examine whether this is the case, we study California's Safer from Wildfires framework, introduced in 2022, which requires insurers to offer premium discounts to homeowners and communities that complete twelve approved wildfire mitigation measures. These measures include structure-level hardening (such as fire-resistant roofs, vents, and windows), parcel-level defensible space through vegetation management, and community-level certification programs such as Firewise USA. While the regulation mandates the provision of discounts, it does not prescribe their magnitude or structure, leaving substantial discretion to insurers. We construct a novel dataset of insurer-specific mitigation discounts for each measure using information from insurers' rule filings, and test whether insurers with higher CRM index values set systematically different discount levels for the same mitigation actions.

Table 6 presents results from this test. Column (1) regresses mitigation discounts on the CRM index, controlling for mitigation-measure fixed effects. The estimated coefficient is positive and statistically significant at the 1% level, indicating that insurers with higher CRM quality offer systematically larger premium discounts for the same mitigation actions. The magnitude of the effect is also economically meaningful: a one-standard-deviation increase in the CRM quality index increases the discount rate by nearly the same magnitude

Table 6: California Mitigation Discounts and Insurers' CRM Quality

	California Mitigation Discount	
	(1)	(2)
Climate Risk Management Quality	0.011***	0.008**
	(0.002)	(0.004)
I(Discounts Applied to All-Peril Premiums)		−0.004
		(0.003)
Fire/Wildfire Premium Share		−0.009
		(0.007)
Average Discount	0.011	0.011
Mitigation Measure FEs	Yes	Yes
Adjusted R^2	0.111	0.107
N	237	237

Note: The table reports regressions testing whether high CRM insurers offer systematically different discounts from low CRM insurers, conditional on the measure. *p<0.1; **p<0.05; ***p<0.01

as the sample mean. Column (2) further controls for the discount regime.[9] The estimated effect is only slightly smaller and remains statistically significant, suggesting that the results are not driven by systematic differences in how insurers define discount bases. These results indicate that insurers with stronger CRM practices price mitigation more aggressively into their premiums. However, it is important to recognize that these enhanced incentives for risk reduction in high-hazard areas may be undermined by the same insurers' disproportionate withdrawals from those markets, thereby constraining the effectiveness of the insurance market as a mechanism for delivering mitigation incentives.

Overall, our findings highlight the importance of accounting for heterogeneity in insurers' risk management practices when interpreting changes in P&C insurance markets following the unprecedented losses of recent years, and when charting a path forward as extreme events continue to intensify. The results point to a potential misalignment between private risk management responses and public adaptation objectives that policymakers will need to confront in designing effective policy and regulatory approaches.

[9]There are two main discount regimes, defined by the portion of the premium to which the discount applies. Some insurers apply the discount to the entire premium, while others apply it only to the wildfire-risk component of the premium. Discounts in the latter regime tend to be larger in percentage terms.

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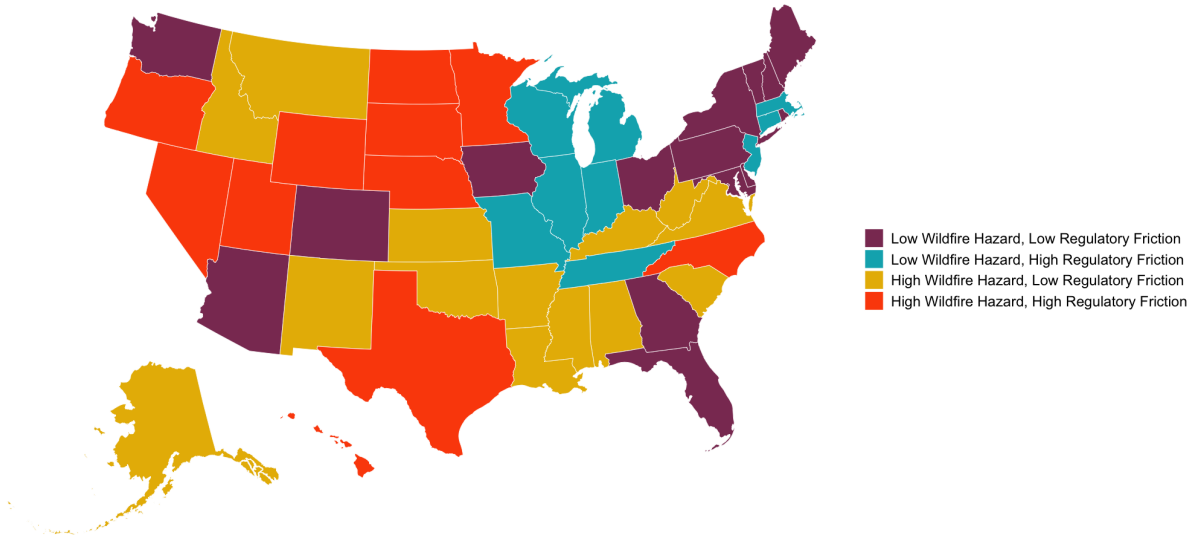
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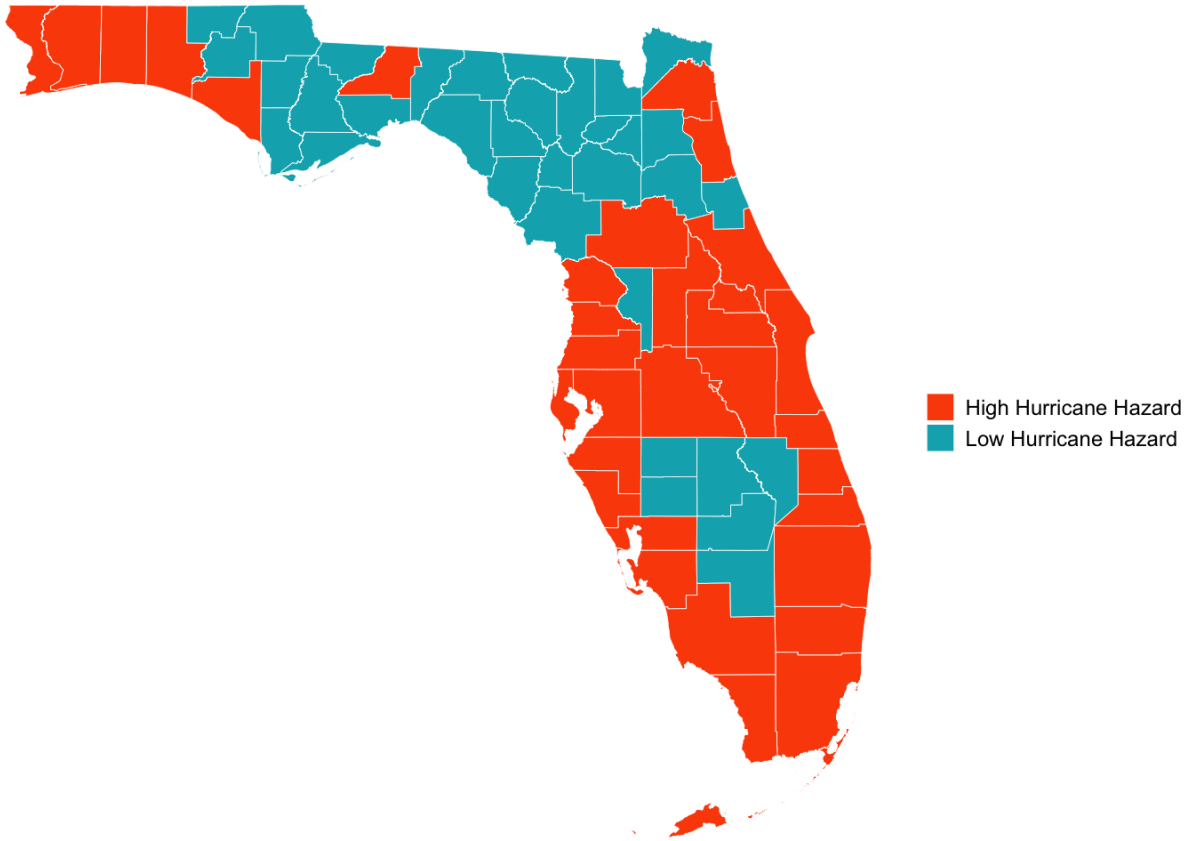
Appendix A Other Tables and Figures

Figure A.1: State Map by Wildfire Hazard and Regulatory Friction



Note: The figure presents the classification of states into four mutually exclusive groups defined by wildfire hazard, measured using FEMA's National Risk Index, and regulatory friction, as developed in Oh et al. (2021).

Figure A.2: Florida Map by Hurricane Hazard

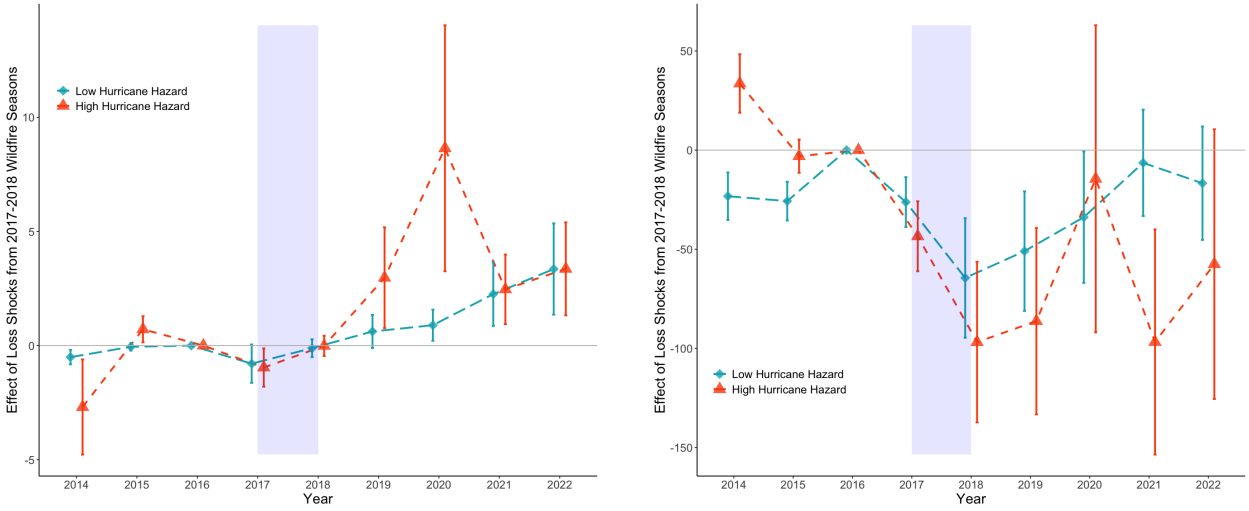


Note: The figure illustrates counties with above-median hurricane hazard in red and below-median hurricane hazard in green.

Figure A.3: Effects of 2017-18 Wildfire Losses on Underwriting Responses in Florida

Panel A: Number of Nonrenewed Policies Due to Hurricane Risk, All Insurers

Panel B: Number of New Policies Written, All Insurers



Note: Panel A plots event-study coefficient estimates and their 95% for the number of nonrenewed policies due to hurricane risk in counties with low (green) and high (red) hurricane hazard. Panel B plots the corresponding estimates for the number of new policies written. The sample includes all insurers.

Table A.1: Underwriting Responses in Florida, IV Estimates

	log(1 + Count Number)					
	Nonrenewed Policies		Nonrenewed Policies Due to Hurricane Risk		New Policies Written	
	(1)	(2)	(3)	(4)	(5)	(6)
Loss Shock$^{CA}_{2017-2018}$ × Post	0.074***		0.037**		0.068	
	(0.025)		(0.018)		(0.045)	
Loss Shock$^{CA}_{2017-2018}$ × Post						
× Low Wildfire Hazard		0.046*				
		(0.027)				
× High Wildfire Hazard		0.103***				
		(0.036)				
Loss Shock$^{CA}_{2017-2018}$ × Post						
× Low Hurricane Hazard				−0.076***		0.198***
				(0.016)		(0.048)
× High Hurricane Hazard				0.154***		−0.067
				(0.031)		(0.060)
Ex-Ante CRM Quality	All	All	All	All	All	All
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Insurer × County FEs	Yes	Yes	Yes	Yes	Yes	Yes
County × Year-Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,058	25,058	25,058	25,058	25,058	25,058
Adjusted R^2	0.755	0.755	0.378	0.384	0.950	0.950

Note: This table reports results of underwriting responses across Florida counties. Standard errors are clustered at the insurance-group-by-county level. *p<0.1; **p<0.05; ***p<0.01

Table A.2: Underwriting Responses in Florida by CRM Quality, IV Estimates

	log(1 + Count Number)			
	Nonrenewed Policies Due to Hurricane Risk		New Policies Written	
	(1)	(2)	(3)	(4)
Loss $\text{Shock}^{CA}_{2017-2018}$ × Post				
× Low Hurricane Hazard	−0.057**	0.028	−0.082	1.047***
	(0.025)	(0.030)	(0.057)	(0.254)
× High Hurricane Hazard	0.215***	0.194***	−0.481***	0.027
	(0.040)	(0.062)	(0.048)	(0.250)
Ex-Ante CRM Quality	High	Low	High	Low
Controls	Yes	Yes	Yes	Yes
Insurer × County FEs	Yes	Yes	Yes	Yes
County × Year-Quarter FEs	Yes	Yes	Yes	Yes
Observations	11,390	13,668	11,390	13,668
Adjusted R^2	0.408	0.248	0.960	0.948

Note: The table reports heterogeneous underwriting responses across Florida counties for insurers with high and low CRM quality, shown in columns (1) and (3) for high-CRM-quality insurers and columns (2) and (4) for low-CRM-quality insurers. Standard errors are clustered at the insurance-group-by-county level. *p<0.1; **p<0.05; ***p<0.01