Beyond the Storm: Climate Risk and Insurers of Last Resort*

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Abstract

Insurers of last resort are becoming critical due to climate-related stress on private markets. Using policy-level data, we show such insurers pass costs of climate disasters through both premiums and claim rejections. Following disasters, premiums rise in affected and unaffected areas, while rejections increase in unaffected areas. Spillovers depend on price sensitivity: less sensitive pay higher premiums, more sensitive face higher rejections. Premiums (rejections) increase during financially constrained (unconstrained) periods. Households respond by increasing insurance against disasters while accepting smaller risks. Welfare analysis shows rejections are critical in redistributing costs. Disasters force even government-backed insurers to act like profit maximizers.

Keywords: Climate risk; Home insurance; Premiums; Spillovers; Cost Pass-through; Risk sharing

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1 Introduction

In 2023, the U.S. homeowners insurance industry reported a combined loss ratio of 110%, meaning insurers paid $1.10 in claims and expenses for every dollar collected in premiums, signaling unsustainable losses for private insurers (S&P Global Market Intelligence, 2024). This increasing stress and growing losses due to climate disasters have triggered fallout across multiple dimensions including insurance pricing (Keys and Mulder, 2024; Oh et al., 2025), rising mortgage delinquencies (Ge et al., 2025), and insurer exits from high-risk states (Sastry et al., 2023). In response, policymakers across several jurisdictions have instated and expanded the role of insurers of last resort—non-profit, taxpayer-backed entities that provide coverage when private markets fail—to preserve access to insurance.[1]

While these state-run insurers play a critical safety-net role, their ability to absorb repeated climate shocks is limited—particularly given the geographic concentration of the high-risk properties they cover. Like private insurers, they face mounting climate-related costs, but often without the pricing flexibility or underwriting discretion available to commercial providers. This raises a central question that we address in this paper: How do insurers of last resort pass on the costs of climate risk to policyholders? Answering this question has broad implications—not only for the financial resilience of these institutions, but also for who ultimately bears the cost of climate change.

To understand the pass-through, we develop a theoretical model of an insurer of last resort (hereafter, insurer) facing the dual mandate of enhancing coverage access while maintaining solvency. Testing the model's predictions poses significant challenges since it requires observing both policy pricing and claim rejections. We overcome this issue by using policy-level data from Citizens Property Insurance Corporation (Citizens), Florida's insurer of last resort. This data includes granular detail on premiums, claims, and rejection decisions al-

[1] In the United States, more than 30 states have established programs, often known as FAIR (Fair Access to Insurance Requirements) plans, to provide insurance coverage to individuals and businesses unable to obtain it in the regular market (e.g., see NAIC FAIR Plans). Internationally, countries such as Turkey, Mexico, and New Zealand have implemented public entities or compulsory catastrophe pools to serve as insurers of last resort, ensuring coverage in high-risk areas (e.g., see here for more details.).

lowing us to be the first to document how insurers of last resort redistribute climate-related costs. Our findings suggest that even government-backed insurers act like profit maximizers when facing extreme losses and pass costs of disasters through both premiums and claim rejections. Welfare analysis shows that ignoring rejections and focusing solely on premiums to evaluate pass-through misclassifies distributional consequences. We document that rejection rates serve as a hidden mechanism to redistribute costs that disproportionately burdens low-income households.

We model the insurer as a competitive entity whose losses are subsidized by the state. The insurer incurs financial costs of holding too little regulatory capital, can set prices, and can reject claims, albeit at a cost to contemporaneous demand and litigation activity. The core trade-off the insurer faces reflects its dual mandate: expanding access to insurance while maintaining solvency. We show that when facing a disaster that reduces their capital (e.g. when losses are high due to a hurricane), the insurer optimally raises prices in both affected and unaffected locations to try and dampen their capital losses (Froot, 2001; Koijen and Yogo, 2015; Oh et al., 2025). As financial frictions become more binding, pricing behavior increasingly mirrors that of private insurers, thereby eliminating their incentives to act as an insurer of last resort that sets fair prices. Moreover, the extent of price increases across locations depends on local demand characteristics: areas with more price-elastic policyholders experience smaller premium hikes than areas with less elastic demand.

The insurer simultaneously adjusts claim rejection rates in response to a disaster with two competing effects. First, heavy losses result in higher prices, which reduces the insurer's profitability in local markets. They therefore increase rejection rates in locations that do not experience high losses. Second, when litigious activity is increasing in the scale of losses, the insurer may optimally reject *fewer* claims in heavily affected locations to offset potential additional legal fees. Therefore, the effect on rejection rates depends on whether a location is directly affected by a disaster. We also derive a local demand counterpart to our pricing results: in high elasticity locations, the profitability response is stronger, which implies higher rejection rates in these locations relative to low elasticity locations.

To test these theoretical predictions, we empirically evaluate the impact of natural disasters on insurance contracts. This is challenging because it requires detailed policy-level data to track how contracts evolve over time—data rarely available for insurance markets. Aggregated data can obscure critical heterogeneity and make it difficult to disentangle competing theoretical predictions. We address this challenge by leveraging a unique dataset from Citizens that provides granular policy-level information, including premiums, coverage types, and various deductibles for each issued policy. Additionally, it contains claims-level details such as filing dates, claim approval status, and disbursement amounts, all of which are crucial for our analysis.

Our data covers over 4 million properties underwritten between 2002 and 2023. These policies represent a significant portion of homeowners' insurance in Florida, with Citizens accounting for approximately 23% of the state's residential property insurance market at its peak. The average premium across these policies is $1,748.64, with considerable variation. The premiums are primarily driven by coverage amounts. Coverage alone explains 55% of the variation in premiums, while property-level characteristics combined with coverage account for 89% of the total variation. The time-series explains only 2% of the variation.

To estimate the impact of natural disasters on insurance contracts, we employ a stacked difference-in-differences (DiD) approach using hurricanes as the treatment events. We restrict the sample to counties that experienced losses exceeding two million USD (the median) from hurricanes at some point during the sample period. Our estimation exploits variation in hurricane timing by comparing counties exposed to hurricanes earlier versus later. This approach ensures that we compare counties with similar risk profiles and exposure histories.[2] The stacked DiD framework addresses issues associated with staggered treatment timing (Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021) and provides consistent and unbiased estimates of the effects of disasters on insurance contracts.

[2]In robustness tests, we ensure that our results are not sensitive to this choice and remain similar when including never-treated counties in the sample.

We begin by validating our empirical setting by examining how claims evolve around hurricane events. Both the affected and unaffected groups exhibit similar trends before and after hurricanes, supporting the parallel trends assumption. However, during the hurricane year, the affected group experiences a sharp spike in claims by 90% relative to the unaffected group. The unaffected group remains stable throughout the seven-year estimation period, which spans three years before and three years after the hurricane year.

Following hurricanes, premiums in affected areas jump immediately and remain elevated for three years. Unaffected areas experience a delayed but significant spillover: premiums increase starting one year post-hurricane at roughly half the magnitude of affected areas, persisting for two years. Consistent with our model, rejection rates decline slightly in hurricane-affected areas but increase significantly in unaffected areas the year immediately following disasters. This asymmetric pattern suggests insurers use rejections as an additional mechanism to redistribute climate costs. Across all outcomes we find similar pre-hurricane trends between affected and unaffected groups, validating our identification strategy.

Our model predicts that spillover effects depend on neighborhood demand characteristics. We test this hypothesis using zip code-level income as a proxy for fraction of price sensitive consumers, as lower-income households typically face tighter budget constraints. Consistent with our model, we find stark differences in how insurers pass through costs. In unaffected high-income neighborhoods, where households are less price-sensitive, premiums increase while rejection rates remain unchanged. In unaffected low-income neighborhoods, where households are more price-sensitive, rejection rates rise but premiums remain stable. Both groups in unaffected areas ultimately subsidize those in hurricane-affected areas, but through distinct channels. This pattern shows how insurers strategically use different mechanisms to redistribute climate costs: extracting higher premiums from price-insensitive households while increasing claim rejections for price-sensitive ones.

Pass-through in our model also depends on market-wide financial constraints, measured by surplus-to-assets ratio. When surplus is declining, competitors face similar pressures and raise prices market-wide, allowing insurer of last resort to increase premiums without losing competitiveness. However, when surplus is increasing, competitors are less likely to raise prices, constraining insurer of last resort's pricing power. In such cases, insurer instead passes costs through higher rejection rates. Consistent with this mechanism, we find that premium spillovers to unaffected areas occur exclusively during periods of declining surplus, while rejection rate increases in unaffected areas concentrate in periods of increasing surplus.

A natural question is how households respond to these cost shifts. On average, households in both affected and unaffected areas increase coverage and deductibles—suggesting that they take on greater liquidity risk while seeking to increase insurance against disaster risk. However, responses vary significantly by income and exposure. In unaffected high-income areas facing premium increases, households adjust by increasing both coverage and deductibles. In unaffected low-income areas facing higher rejection rates, households instead pursue litigation and appraisals without adjusting coverage. In affected areas, coverage and deductible increases are more pronounced in low-income neighborhoods, where price sensitivity is higher, while litigation and appraisal rates remain unchanged.

We next quantify the welfare implications of the insurer's response using a logit demand model where household utility depends on prices, rejection rates, and a insurer-specific component. We estimate the model using data on Citizens' and private market participants' total premiums, coverage, and claims rejections at the county-year level following four major hurricane events.[3] We conduct our analysis using multiple instruments and specifications that vary the degree of heterogeneity across the demand parameters. Averaging across specifications and instruments, we find low-income households in unaffected areas face no net welfare change—the decline in utility from higher rejection rates offsets their exemption from premium increases. High-income households in both affected and unaffected areas experience similar welfare losses (approximately 0.8%), while low-income households in affected areas bear the largest costs (1.3%). Crucially, ignoring rejection rates fundamentally

[3]These data come from the Florida office of insurance regulation and are described in section 5.2.

mischaracterizes these distributional effects: an analysis focused solely on premiums would incorrectly suggest low-income unaffected households benefit (+0.5%) and would overstate losses for high-income affected households (1.6%). Therefore, the ability for the insurer to reject claims significantly impacts our welfare estimates, highlighting the importance of this ex-post risk sharing channel.

A potential concern is that the increase in rejection rates in unaffected areas may be driven by an increase in fraudulent claims rather than insurer behavior. For instance, households residing close to affected counties but in unaffected areas might opportunistically file false claims following a disaster, leading to higher rejection rates. However, several pieces of evidence suggest this is less likely to be the primary driver of our results. First, filing fraudulent claims is costly for policyholders: it can lead to premium increases, heightened scrutiny of future claims, and in some cases, policy cancellations.[4] Second, we do not observe any increase in the likelihood of claim filing in unaffected areas following disasters, thereby making fraud less likely to be a driver. Third, household responses to rejection are inconsistent with fraudulent behavior: policyholders are more likely to litigate in areas where rejection rates are higher, suggesting they believe their claims are legitimate and worth the additional cost of legal action.

While our analysis focuses on Citizens that operates under Florida's specific regulatory framework, the pass-through mechanisms we document likely apply more broadly to insurers of last resort facing similar constraints—whether regulatory or financial—and climate-related losses. The fundamental trade-offs between maintaining solvency and enhancing coverage access are inherent to all such institutions. For example, other state FAIR plans—such as the California FAIR Plan (now covering over 300,000 properties), Louisiana Citizens (insuring roughly 10% of the state's homes), and the Texas Windstorm Insurance Association—face similar pressures from concentrated geographic exposure and limited pricing flexibility when absorbing catastrophic losses. However, the relative importance of premium adjustments

[4] These points are supported by this article by CBS news and this article by Bankrate.

versus claim rejections may vary based on local regulatory environments, the competitive landscape, and the specific mandate of each institution.

Our paper contributes to the growing literature on the intersection of climate risk and real estate markets, including mortgages and homeowners' insurance.[5] Within the insurance sector, Born and Viscusi (2006) use insurer-by-state level data to document how natural disasters reduce total premiums earned by insurers in affected states and lead to market exits. More recently, Keys and Mulder (2024) demonstrate that rising reinsurance costs, driven by increasing disaster risks, are passed on to homeowners through higher insurance premiums. Building on these pricing mechanisms, Jotikasthira et al. (2025) use balance sheet information to document that insurers also strategically slow claim payment speeds after adverse shocks, providing them with liquidity through increased float. Beyond climate related costs, Oh et al. (2025) show the effect of regulation on insurance premiums and cross-subsidization across jurisdictions. Damast et al. (2025) document the pass through of monetary policy shocks to insurance premiums. These studies establish how private insurers respond to climate-related and other cost shocks, primarily examining direct effects in affected areas with the exception of Oh et al. (2025).

The composition of insurers is also changing: Sastry et al. (2023) show that traditional insurers are withdrawing from high-risk areas while less stable insurers enter to fill this gap, thereby increasing vulnerabilities. State regulations shape these market responses—Issler et al. (2024) and Eastman and Kim (2023) investigate how regulatory frameworks influence insurer behavior, while Boomhower et al. (2023) and Boomhower et al. (2024) analyze how property insurance markets adapt to climate risk under regulatory constraints and through risk selection. These market disruptions have cascading effects on mortgage markets, particularly given widespread underinsurance documented by Cookson et al. (2024) and Sastry et al. (2024). While An et al. (2024) examine how wildfires affect housing and

[5] Several papers explore the extent to which future climate risks are capitalized into real estate prices. See, for example, Bernstein et al. (2019); Keys and Mulder (2020); Bakkensen and Barrage (2021); Baldauf et al. (2020); Giglio et al. (2021); and Murfin and Spiegel (2020). Refer to Acharya et al. (2023) and Giglio et al. (2020) for a discussion on the broader literature in the intersection of climate risk and finance.

mortgage outcomes through insurance constraints, Ge et al. (2025) demonstrate that rising homeowners' insurance premiums can increase mortgage default risk even without direct disaster exposure, and Sastry (2021) finds that lenders require higher down payments from borrowers who underinsure. Meanwhile, Ge et al. (2024) show that exogenous flood insurance premium increases reduce mortgage take-up rates.

We extend this literature along three critical dimensions. First, to the best of our knowledge, we provide the first analysis of insurers of last resort—institutions that policymakers worldwide are increasingly relying upon as private insurers retreat from high-risk markets. We do so by evaluating how they pass through climate costs and affect who bears the cost of disasters. Second, we are the first to use granular contract and claims-level data that allows us to document the pass through along both premiums and rejection rates simultaneously. Third, we show that insurers redistribute costs across households in distinct ways—high-income unaffected areas face premium increases while low-income unaffected areas experience higher rejection rates—with distributional consequences of climate risk depending on both consumer characteristics and insurer responses along price and non-price mechanisms.

2 A Model of Insurance Pricing and Claims Management

We first present a simple model to organize our empirical analysis. We begin by exploring how an insurer of last resort should set premiums and manage claims across geographic regions when they experience losses to their capital (e.g. due to a hurricane or a major storm). We then explore how their decisions change depending on the severity of their losses and the characteristics of household demand across regions.

2.1 Model Setup

We consider the problem of an insurer of last resort (henceforth, "insurer") that operates across several locations, $\ell \in \mathscr{L}$. We assume the insurer makes two sets of decisions. First, in each location and time period, they set prices for their insurance policies, $p_{\ell t}$. The price they charge is influenced by their expected loss rate in a given location, $l_{\ell t}$. We refer to $l_{\ell t}$ as the fair value of a policy. We express prices and loss rates as relative to total coverage, $Q_{\ell t}$, so that total premiums collected are $p_{\ell t}Q_{\ell t}$ and total expected losses are $l_{\ell t}Q_{\ell t}$. We assume total written coverage is decreasing in the level of prices, $\partial Q_{\ell t}/\partial p_{\ell t} < 0$.

Second, the insurer has the ability to review claims. Whether or not a household decides to file a claim is exogenous to the insurer. We denote the claim rate relative to total value of coverage insured in a location as $c_{\ell t}$. Since claims are filed with a lag relative to when the policies are written, total claims filed in period t are $C_{\ell t} = c_{\ell t}Q_{\ell t-1}$. We assume that beyond affecting the insurer's capital, claims also factor into expected losses. We assume that the insurer employs historical cost accounting when estimating losses, so that $\ell_{\ell t} = \mathcal{L}(l_{\ell t-1}, C_{\ell t})$ is strictly increasing in $C_{\ell t}$.[6]

The insurer can choose to reject a share $x_{\ell t} \in [0, 1]$ of claims. There are two forces that disincentivize claim rejection. First, we assume that contemporaneous demand is downward sloping in the rejection rate, $\partial Q_{\ell t}/\partial x_{\ell t} < 0$. Second, we assume that policyholders whose claims are rejected will choose to litigate.[7] If the household wins their lawsuit, the insurer has to pay out the claim at a rate $\kappa > 1$, which reflects the addition of legal costs. The household wins the case with probability $\alpha(C_{\ell t})$, which we assume is continuous and increasing in total damages $C_{\ell t}$. The interpretation is that claims are easier to justify in court when damages are severe. In contrast, when damages are small, there is some ambiguity to the damage, making it difficult to discern whether the claim is valid or not. This ambiguity gives the insurer more legal power, resulting in a lower probability that the lawsuit favors the policyholder. Given our assumptions, the ex-post amount of claims to be paid out by the insurer is

$$\mathcal{C}(C_{\ell t}, x_{\ell t}) = \underbrace{(1 - x_{\ell t})C_{\ell t}}_{\text{accepted claims}} + \underbrace{x_{\ell t}\kappa\alpha(C_{\ell t})C_{\ell t}}_{\text{rejected but litigated claims}} = C_{\ell t} - (1 - \kappa\alpha(C_{\ell t}))C_{\ell t}x_{\ell t}.$$

[6]For a discussion of insurers of last resort incorporating past performance into their loss projections, see Citizens' statutory filings in 2024, page 12.

[7]It is without loss of generality to assume households always litigate. If they litigated with some exogenous probability, the rest of the modeling choices could be rescaled to achieve the same results.

We assume that the insurer faces two core objectives. First, they act as profit maximizers, consistent with their desire to not set prices that are too competitive (Hudson, 2024). However, as an insurer of last resort, the first part of their dual mandate requires the insurer to price according to sound actuarial principles in order to promote access to insurance markets (Citizens Property Insurance Corporation, 2024). To capture this requirement, we assume that the state acts as a backstop to a fraction ς_ℓ of the insurer's realized losses for each location ℓ. This assumption is rooted in the legal structure of insurers of last resort. For example, the insurer is backed by state taxpayers, and is permitted to levy surcharges on policyholders and private insurers to help fund their operations. We treat ς_ℓ as exogenously set by the state government so that it is taken as given by the insurer. Expected profits in each location are then $\pi_{\ell t} = (p_{\ell t} - (1 - \varsigma_\ell) l_{\ell t}) Q_{\ell t}(p_{\ell t}, x_{\ell t})$.

Their second objective, which reflects the insurer's second dual mandate to maintain solvency, is to minimize the regulatory cost of holding too little statutory capital, K_t. We express this cost as a decreasing and convex function $F(K_t)$. Statutory capital takes the form

$$K_t = \underbrace{R_t \left[A_{t-1} + \sum_{\ell \in \mathscr{L}} p_{\ell t-1} Q_{\ell t-1} \right]}_{\substack{\text{financial return on last period's} \\ \text{assets and premiums}}} - \underbrace{\sum_{\ell \in \mathscr{L}} \mathcal{C}(C_{\ell t}, x_{\ell t})}_{\substack{\text{resolution of} \\ \text{unlitigated claims}}} + \underbrace{\sum_{\ell \in \mathscr{L}} (p_{\ell t} - \phi l_{\ell t}) Q_{\ell t}(p_{\ell t}, x_{\ell t})}_{\substack{\text{additional capital from} \\ \text{the sale of new policies}}} \tag{1}$$

We assume that statutory reserves generated through the sale of new policies have to be recorded conservatively relative to expected losses, which we capture through the parameter $\phi > 1$ (Koijen and Yogo, 2016). Since the insurer adheres to the same statutory accounting principles as the private market, we assume that they do not internalize the state backstop when setting reserves.[8,9] Given this setup, the insurer solves the following optimization

[8]For example, in an independent auditor's note for Citizens' statutory filings in 2024 (see here), it is stated that loss reserves and loss adjustment expense reserves should be adequate to cover anticipated losses given past performance, expected inflation, and projected changes in environmental variables. Since Citizens' surcharges are ultimately recorded as investment income (since they act as collateral on disaster bonds; see Note 8 on page 23 of their most recent statutory filings for a discussion), their reserves do not reflect these sources of income.

[9]As we discuss in the ensuing section, this assumption is not strictly necessary. The results continue to

problem:

$$\max_{\{p_{\ell t}, x_{\ell t}\}_{\ell \in \mathscr{L}}} \quad \sum_{\ell \in \mathscr{L}} (p_{\ell t} - (1-\varsigma_\ell) l_{\ell t}) Q_{\ell t}(p_{\ell t}, x_{\ell t}) - F(K_t) \tag{2}$$
$$\text{subject to} \quad (1) \text{ and } x_{\ell t} \in [0,1] \text{ for all } \ell \in \mathscr{L}$$

2.2 Optimal Pricing Behavior

We begin by analyzing the insurer's price setting behavior. Before doing so, it will simplify the analysis to assume that insurance coverage demand takes an explicit form:

$$Q_{\ell t}(p_{\ell t}, x_{\ell t}) = \frac{A_\ell \tau(x_{\ell t})}{l_{\ell t}} \left(\frac{p_{\ell t}}{l_{\ell t}}\right)^{-\varepsilon_\ell} \tag{3}$$

Insurance demand has three components. The A_ℓ component is an exogenous demand shifter that could include competitive forces, the size of the market, household expenditures, etc. We treat it as exogenous to the insurer. The second component, $\tau(x_{\ell t})$, is the claims rejection component. As such, we assume $\tau'(\cdot) < 0$. The final component, $l_{\ell t}^{-1}(p_{\ell t}/l_{\ell t})^{-\varepsilon_\ell}$, assumes that demand is downward sloping in the markup over fair value. The price elasticity of demand in location ℓ is $-\varepsilon_\ell$. Given this functional form, we can directly solve for the insurer's optimal price of insurance in location ℓ at a point in time.

Lemma 1: Optimal Pricing

The insurer's optimal markup over fair value in location ℓ at time t satisfies

$$\frac{p_{\ell t}}{l_{\ell t}} = \underbrace{\left(\frac{\varepsilon_\ell}{\varepsilon_\ell - 1}\right)}_{\substack{\text{demand-specific} \\ \text{markup}}} \times \underbrace{\left(\frac{1+\phi\lambda_t}{1+\lambda_t}\right)}_{\substack{\text{financial frictions} \\ \text{markup}}} - \underbrace{\left(\frac{\varepsilon_\ell \varsigma_\ell}{(\varepsilon_\ell - 1)(1+\lambda_t)}\right)}_{\text{insurer of last resort discount}} \equiv \mathcal{M}_\ell(\lambda_t) \tag{4}$$

where $\lambda_t \equiv -F'(K_t) > 0$. Further, if $\varsigma_\ell = \varepsilon_\ell^{-1}$, then $\mathcal{M}(0) = 1$.

Proof: See Appendix B.1.

go through as long as remittances $\sum_\ell \varsigma_\ell l_{\ell t} Q_{\ell t}$ themselves are not recorded conservatively, which, since they are not reserves, should not be the case.

The Lemma states that markups over fair value in a given location ℓ at a point in time t have three components. First, there is a component that is determined through the price elasticity of demand in location ℓ. This is standard in models of differentiated demand. Second, there is a financial frictions component that is increasing in the insurer's financial distress, which we measure through the marginal cost of capital, $\lambda_t \equiv -F'(K_t)$ (Koijen and Yogo, 2016). This component is equal to 1 when $\lambda_t = 0$, and is equal to $\phi > 1$ when $\lambda_t \to \infty$. The interpretation is that as the insurer's capital declines, they put more weight on their regulatory capital relative to their economic profits, thereby shifting toward the price that optimizes their regulatory capital.

The third component — the insurer of last resort discount — comes from the state backstop, $\varsigma_\ell > 0$, which incentivizes the insurer to price below their private market counterparts. When the state sets a particular value for this backstop ($\varsigma_\ell = \varepsilon_\ell^{-1}$), the insurer's optimal price without financial frictions ($\lambda_t = 0$) is precisely equal to $l_{\ell t}$. Therefore, in a setting without financial distress, the insurer prices at fair value while also behaving competitively. In the case of Citizens, this is in line with Florida statute.[10]

The insurer of last resort discount, notably, is also decreasing in the insurer's financial distress λ_t. This implies, conditional on financial distress, that the gap between the insurer's prices and the prices of private market participants declines as financial distress becomes large; thus, in the wake of a disaster, we should expect the insurer to behave more like a private insurer rather than an insurer of last resort. This result follows from the tension between their dual mandates: since statutory accounting principles do not account for the state backstop, prices reflect the access mandate more when the insurer faces lower risk of running a surplus deficit.[11]

We now analyze the consequences of the insurer's pricing rules. Suppose they face major losses due to a disaster, and therefore face a drop in their capital K_t. Since the cost of

[10]See Citizens Property Insurance Corporation (2024).

[11]If the insurer does internalize the state backstop by accounting for remittances $\sum_\ell \varsigma_\ell l_{\ell t} Q_{\ell t}$ in their regulatory capital, then the discount itself would not decline with λ_t; however, the difference in prices between the insurer and a similarly distressed private insurer would still decline as λ_t increased.

capital $F(\cdot)$ is steeper at low levels of capital, this leads to an increase in the shadow cost of capital, λ_t, and therefore a higher financial frictions markup and lower insurer of last resort discount. Therefore, even in locations in which risk assessments stay the same ($dl_{\ell t} = 0$), prices may rise, which helps protect the insurer from excessive capital losses. This result is captured formally in the following expression:

$$dp_{\ell t} = \underbrace{\mathcal{M}'_{\ell}(\lambda_t) d\lambda_t \times l_{\ell t}}_{\substack{\text{change due to} \\ \text{financial frictions}}} + \underbrace{\mathcal{M}_{\ell}(\lambda_t) \times dl_{\ell t}}_{\substack{\text{change due to} \\ \text{risk assessments}}}. \tag{5}$$

Lemma 1 also suggests a cross-sectional relationship: among locations with identical risk assessment levels and changes, the pricing response is higher when demand-specific markups are higher. If low-income households tend to be more sensitive to prices than high income households (Handbury, 2021), then we should expect demand-specific markups to be smaller in low-income locations. As such, pricing responses to natural disasters should be muted for low-income regions. We collect this discussion into the following proposition, which serves as our first set of testable predictions.

Proposition 1: Price Responses Following a Disaster

Consider two sets of shocks, $\mathbf{C}_t^1 = \{C_{\ell t}^1\}_{\ell \in \mathscr{L}}$ and $\mathbf{C}_t^2 = \{C_{\ell t}^2\}_{\ell \in \mathscr{L}}$, such that $C_{\ell t}^1 \leq C_{\ell t}^2$ for all ℓ and a strict inequality for at least one ℓ. Let $\Delta y_t \equiv y_t^2 - y_t^1$ denote the difference between variable y_t across the two sets of shocks. Then, if financial returns in the two scenarios are equivalent, the following statements hold:

1. $\Delta p_{\ell t} > 0$ *for all* $\ell \in \mathscr{L}$
   (Prices rise in all locations, regardless of where the losses occur)
2. $\Delta p_{\ell_2 t} > \Delta p_{\ell_1 t}$ *if* $l_{\ell_1 t}^1 = l_{\ell_2 t}^1$ *and* $\varepsilon_{\ell_1} = \varepsilon_{\ell_2}$ *but* $\Delta C_{\ell_2 t} > \Delta C_{\ell_1 t}$
   (Conditional on location type, higher losses lead to higher prices)
3. $\Delta p_{\ell_2 t} > \Delta p_{\ell_1 t}$ *if* $l_{\ell_1 t}^1 = l_{\ell_2 t}^1$ *and* $\Delta C_{\ell_1 t} = \Delta C_{\ell_2 t}$ *but* $\varepsilon_{\ell_1} > \varepsilon_{\ell_2}$
   (Conditional on losses, low elasticity locations experience larger price increases)

Proof: See Appendix B.2.

2.3 Optimal Claims Management

Given the insurer's pricing decisions, how should they manage their claims? On one hand, rejecting claims originating from policies in the previous period may reduce losses to their statutory capital; however, doing so may reduce contemporaneous demand for their policies and lead to litigation. The cost of the demand reductions will in part depend on how profitable a given location is. We can construct measures of economic profitability, $\pi^E_{\ell t}$, and regulatory capital profitability, $\pi^R_{\ell t}$, that explicitly depend on the insurer's financial state, λ_t:

$$\pi^E_{\ell t}(\lambda_t) = A_\ell\Big(\mathcal{M}_\ell(\lambda_t) - 1 + \varsigma_\ell\Big)\mathcal{M}_\ell(\lambda_t)^{-\varepsilon_\ell}, \qquad \pi^R_{\ell t}(\lambda_t) = A_\ell\Big(\mathcal{M}_\ell(\lambda_t) - \phi\Big)\mathcal{M}_\ell(\lambda_t)^{-\varepsilon_\ell}. \tag{6}$$

The additional value to the insurer from a marginal increase in rejection rates can therefore be expressed as

$$\underbrace{\pi^E_{\ell t}(\lambda_t)\tau'(x_{\ell t})}_{\text{loss of economic profits}} + \underbrace{\lambda_t\pi^R_{\ell t}(\lambda_t)\tau'(x_{\ell t})}_{\text{loss of regulatory capital}} + \underbrace{\lambda_t[1-\kappa\alpha(C_{\ell t})]C_{\ell t}}_{\text{reduction in unlitigated claims}}, \tag{7}$$

which follows directly from the first-order condition with respect to $x_{\ell t}$ in the insurer's optimization problem. Using (7), we can solve directly for the insurer's optimal rejection rate.

Lemma 2: Optimal Claims Management

The insurer's optimal rejection rate in location ℓ at time t satisfies

$$x_{\ell t} = \chi\left(\frac{\lambda_t[1-\kappa\alpha(C_{\ell t})]C_{\ell t}}{\pi^E_{\ell t}(\lambda_t) + \lambda_t\pi^R_{\ell t}(\lambda_t)}\right). \tag{8}$$

Further, $\chi(\cdot)$ has the following properties:

1. $\chi'(y) > 0$ *for all* $y \geq 0$ *if* $\tau(y)$ *is strictly concave* ($\tau''(y) < 0$ *for all* y)

2. $\chi''(y) > 0$ *for all* $y \geq 0$ *if* $\tau(y)$ *has decreasing concavity* ($\tau'''(y) > 0$ *for all* y)

Proof: See Appendix B.3.

The proposition implies that the optimal rejection rate is increasing in expected savings and decreasing in expected economic losses. This is sensible: if the insurer expects to lose many customers in a particular location when they reject claims, they may optimally choose a low rejection rate, especially if this location contributes significantly to their total profits or capital.

But we also know that, after a disaster, the insurer will increase prices to reduce the burden on their capital. How does that translate into their claims management behavior? We show in Appendix B.4 that the insurer rejects more claims. When the insurer's capital declines and their financial frictions become more binding, their combined economic and regulatory profit declines. This reduces their incentive to honor claims in a given region, resulting in higher rejection rates. Therefore, all else equal, we should expect periods of distress to coincide with more aggressive claims management. This result is collected in the following lemma.

Lemma 3: Rejection Rate Response to Financial Distress
Consider two sets of shocks, $\mathbf{C}_t^1 = \{C_{\ell t}^1\}_{\ell \in \mathscr{L}}$ *and* $\mathbf{C}_t^2 = \{C_{\ell t}^2\}_{\ell \in \mathscr{L}}$*, such that* $C_{\ell t}^1 \leq C_{\ell t}^2$ *for all* ℓ *and a strict inequality for at least one* ℓ*. If financial returns in the two scenarios are equivalent, then for all* ℓ *such that* $dC_{\ell t} = 0$*, rejection rates increase:* $dx_{\ell t} > 0$*.*

Proof: See Appendix B.4.

However, periods of distress are also accompanied by increases in claims shocks in each location. As such, the insurer not only takes into account how profitable each location is, but also changes in the amount and/or size of claims. If damages are large enough, the insurer may optimally choose to *reduce* rejection rates to offset potential litigation costs that follow from rejecting claims during disaster episodes. This suggests that the response of rejection rates to an increase in filed claims will follow that of their expected post-litigation losses. The following lemma captures this formally given some structure on the probability of litigation success, $\alpha(C)$.

Lemma 4: Rejection Rate Response to Higher Claims

Suppose that $\alpha(0) = 0$, $\lim_{C\to\infty} \alpha(C) = 1$, and $C\alpha''(C)/\alpha'(C) > -2$. Then there exists two thresholds $C^*, \overline{C} > 0$ with $\overline{C} > C^*$ such that $x_{\ell t}$ is maximized at C^*, is increasing on the interval $[0, C^*)$, and is decreasing on the interval $[C^*, \overline{C}]$. Further, $x_{\ell t} = 0$ if $C_{\ell t} > \overline{C}$.

Proof: See Appendix B.5.

The lemma states that, as long as the amount of claims filed is high enough ($C_{\ell t} \geq C^*$), the expected losses from litigation begin to outweigh the potential benefit of rejecting claims. As such, any increase in claims above C^* within a location is associated with a *decline* in rejection rates, all else equal. Disasters therefore create two offsetting forces that push rejection rates in different directions:

$$dx_{\ell t} = \underbrace{\frac{\partial x_{\ell t}}{\partial \Lambda_t} d\Lambda_t}_{\substack{\text{positive change due to} \\ \text{reduction in profitability}}} + \underbrace{\frac{\partial x_{\ell t}}{\partial C_{\ell t}} dC_{\ell t}}_{\substack{\text{negative change due to} \\ \text{higher litigation costs}}} \tag{9}$$

In response to a disaster, we should therefore expect locations that did not see an increase in claims to experience higher rejection rates, while those that were hit the hardest may actually see lower rejection rates, depending on the size of the disaster and the extent of the insurer's financial distress.

Finally, we also consider what happens to rejection rates in the cross section of locations. As with pricing, we focus on differences in demand conditions, ε_ℓ. Consider two locations with identical claims shocks, $C_{\ell_1 t} = C_{\ell_2 t}$, and demand shifters, $A_{\ell_1} = A_{\ell_2}$, and suppose that $\varepsilon_{\ell_1} > \varepsilon_{\ell_2}$ as in Proposition 1. In this case, location 1 has less profitable demand, so $\pi^E_{\ell_1 t}(\Lambda_t) < \pi^E_{\ell_2 t}(\Lambda_t)$ and $\pi^R_{\ell_1 t}(\Lambda_t) < \pi^R_{\ell_2 t}(\Lambda_t)$. Therefore, we should expect the high elasticity location to experience more rejection: $x_{\ell_1 t} > x_{\ell_2 t}$.

But what happens when the insurer becomes increasingly distressed, $d\lambda_t > 0$? Since low elasticity locations are going to be less responsive to the increase in prices, we should expect their profitability to decline less. Therefore, the rejection rate response should itself be muted relative to high elasticity location responses. This gives us our final testable prediction. We formalize all of our claim rejection predictions in the following proposition.

PROPOSITION 2: CLAIMS MANAGEMENT FOLLOWING A DISASTER
Consider two sets of shocks, $\mathbf{C}_t^1 = \{C_{\ell t}^1\}_{\ell \in \mathscr{L}}$ *and* $\mathbf{C}_t^2 = \{C_{\ell t}^2\}_{\ell \in \mathscr{L}}$*, such that* $C^* \leq C_{\ell t}^1 \leq C_{\ell t}^2$ *for all* ℓ *and a strict inequality for at least one* ℓ*. Then, if financial returns in the two scenarios are equivalent, the following statements hold:*

1. $\Delta x_{\ell t} > 0$ *for all* ℓ *such that* $dC_{\ell t} = 0$
   (In locations with unchanged losses, rejection rates increase)

2. $\Delta x_{\ell t} < 0$ *for all* ℓ *such that* $dC_{\ell t} > 0$ *is sufficiently large*
   (In locations with large losses, rejection rates decline)

3. *Suppose* $\Delta \mathbf{C}_t = d\mathbf{C}_t$ *is small, and let* $C_{\ell_1 t} = C_{\ell_2 t} = C_t$ *and* $dC_{\ell_1 t} = dC_{\ell_2 t} = dC_t$ *for two locations* $\ell_1, \ell_2 \in \mathscr{L}$ *such that* $\varepsilon_{\ell_2 t} > \varepsilon_{\ell_1 t}$*. Then:*

   - *If* $dC_t = 0$*, then* $dx_{\ell_2 t} > dx_{\ell_1 t}$*.*
   - *If* $dC_t > 0$*, there exists a threshold* $\lambda^*(C_t)$ *such that* $dx_{\ell_2 t} > dx_{\ell_1 t}$ *if* $\lambda_t \leq \lambda^*(C_t)$*. If* $\lambda_t > \lambda^*(C_t)$*, then there exists an additional threshold* $\varepsilon^*(\lambda_t, C_t)$ *such that* $dx_{\ell_2 t} > dx_{\ell_1 t}$ *if* $\varepsilon_{\ell_2 t} > \varepsilon^*(\lambda_t, C_t)$*.*

   (Rejection respond more to a claims shock in high elasticity locations)

Proof: See Appendix B.6.

Having characterized how the insurer changes prices and claims management behavior, we now turn to our empirical setting.

3 Data & Empirical Methodology

This section outlines the data used in our analysis, details the construction of the sample, evaluates the determinants of insurance premiums, and describes our main empirical methodology.

3.1 Data

3.1.1 Insurance and Claims

Our analysis relies on the intersection of a number of different datasets obtained from various sources. The primary dataset consists of individual policy-level home insurance contracts and claims from Citizens Property Insurance Corporation, a non-profit organization that serves as Florida's insurer of last resort. The dataset is comprehensive, covering all contracts and claims issued by Citizens from 2002 to September 2023. As Florida's largest provider of multi-peril home insurance policies, Citizens accounted for 23% of the state's insurance market at its peak and 15% of the market in 2023. As an insurer of last resort, Citizens provides coverage to all homeowners, including those unable to obtain insurance from private insurers. Despite this role, it offers coverage at a rate comparable to the private market, consistent with its mandate of staying afloat. For instance, Table C.1 shows that Citizens' average premium is comparable to that of private insurers for a Florida masonry home built in 2005 with $300,000 replacement value and 2% hurricane deductible.

The contract-level dataset provides detailed information on both policy and property attributes. Policy details include policy and term numbers, effective, renewal and cancellation dates, policy premiums, and any mandatory charges levied. The dataset also contains information on various deductibles and coverage types, including Coverages A through D. Coverage A insures the dwelling, protecting the structure of the home, including floors, windows, and doors. Coverage B covers other structures not attached to the home, such as fences, sheds, and driveways. Coverage C insures personal property, while Coverage D provides loss-of-use coverage, helping pay for additional living expenses while the home is being repaired. Deductibles are categorized by event type, including hurricane, windstorm, sinkhole, and other perils.

Property-level details include the street address, year of construction, total dwelling area, number of units in the building, and number of stories, among other characteristics. The claims dataset contains detailed attributes about claims and the claims process, such as claim and loss dates, resolution dates, cause of loss, claim status (e.g., approved, denied), and net losses incurred (which reflects the total reimbursement provided). We merge these datasets using policy and term numbers as unique identifiers, allowing us to link policy characteristics with claims data for a comprehensive analysis.

3.1.2 Natural Disasters

To analyze the impact of hurricanes and tropical storms on insurance policies, we obtain climate event data from the Spatial Hazard Events and Losses Database for the United States (SHELDUS). This database provides detailed information on the timing of events, disaster type, affected counties, and property loss amounts at the county level. SHELDUS compiles data from multiple federal and state agencies, ensuring comprehensive coverage of disaster-related losses. The dataset includes both insured and uninsured losses, allowing us to capture broader economic damages beyond claims paid by insurers. We leverage this dataset to examine the spillover effects of hurricanes and tropical storms in the home insurance market, focusing on how insurers adjust pricing and claim evaluation in both directly affected and unaffected areas.

3.1.3 Other Data

We augment this data with zip-code-level income data from the Internal Revenue Service (IRS) and flood risk data from the Federal Emergency Management Agency (FEMA). The IRS income data allows us to assess whether insurers pass on costs differently based on the economic characteristics of policyholders and whether lower-income households face greater financial barriers in obtaining or maintaining coverage. We merge this data with other datasets using zip codes.

FEMA flood risk zone information comes from flood zone Shapefiles, which classify properties based on different levels of flood risk. Properties are categorized as either no-risk or at flood risk if they are located within the 100-year or 500-year floodplain. The 100-year floodplain represents areas with a 1% annual chance of flooding, while the 500-year floodplain includes areas with a 0.2% annual chance. We spatially merge the flood zone Shapefiles with property locations using geocodes.

Finally, we use balance sheet and income statement information on insurers (including both Citizens' and private insurers) from S&P Capital IQ. This dataset includes key financial metrics such as net losses, loss adjustment expenses, net premium revenues, surplus, assets, and liabilities, allowing for a detailed examination of the financial standing of homeowners' insurance markets.

3.2 Summary Statistics

Table 1 presents key statistics for the policies in our sample, which consists of 18,677,633 policy-year observations covering 4,119,075 properties underwritten between 2002 and 2023. The average premium is $1,748, with a right-skewed distribution, as indicated by the median premium of $1,400 being lower than the mean. The variation in policy costs is reflected in the 10th and 90th percentiles of premiums, which are $423 and $3,469, respectively.

In addition to premiums, the insurer levies mandatory charges to help cover potential losses and maintain solvency, particularly in response to catastrophic weather events. The average mandatory charge is $99, with a median of $60. The non-zero 10th percentile suggests that most policies incur additional charges, which account for approximately 5.4% of the total premium on average. The distribution of total charges (i.e., the sum of premiums and mandatory charges) closely mirrors that of premiums, with an average of $1,847.97 and a median of $1,478. The premium-to-coverage ratio, which captures policies' relative cost in percentage of coverage, has a mean and median of 1.64 and 1.06, respectively.

Figure C.1 plots the average premium and premium-to-coverage ratio for policies issued by the insurer over the sample period. We present separate trends for homes in high- and low-risk areas based on FEMA's classification to examine how insurance costs evolve across different risk levels in panels A and B respectively. High-risk (low-risk) areas are defined as properties located within (outside) the 100-year or 500-year floodplain. Consistent with other data sources, we find that both premiums and the premium-to-coverage ratio in our sample have increased over the last two decades.[12] Moreover, we observe that both the premium and the premium-to-coverage ratio have risen at a faster rate in high-risk areas compared to low-risk areas, indicating a growing cost differential based on risk exposure.

As reported in Table 1, the average approved claim amount per policy-year is $747, with a high standard deviation of $8,256. Notably, the median claim amount is $0, and even the 90th percentile shows no claims, indicating that the majority of policy-years do not have any claims payments. The average claim-to-premium ratio is 0.46, suggesting that, on average, the insurer paid 46 cents in claims for every dollar collected in premiums.

We analyze a hedonic model for premiums in section A to shed light on the insurer's pricing function. We find that coverage amounts are the primary determinant of premiums, explaining 55% of the variation, with property fixed effects accounting for an additional 34%, with time-series factors not contributing in a significant manner.

3.3 Stacked Sample Construction

We begin with the SHELDUS dataset, which contains information on various weather-related events, including wildfires, droughts, coastal storms, floods, earthquakes, tornadoes, and hurricanes. We restrict the sample to major loss events classified as hurricanes or tropical storms (henceforth, hurricanes) with reported damages exceeding $2 million (the median) for any county in Florida. Using hurricane-related losses from SHELDUS, rather than relying solely on a predefined list of major hurricanes in Florida, allows us to capture events that caused significant damage without making direct landfall in the state. For example, the

[12] For example, National Oceanic and Atmospheric Administration (NOAA) (2025); Federal Emergency Management Agency (n.d.); United Nations Office for Disaster Risk Reduction (n.d.).

Florida Climate Center does not classify Hurricane Katrina as a major hurricane impacting Florida, even though it caused substantial damage to counties in southern Florida.[13]

This yields a set of sixteen hurricane events for our analysis. These hurricanes caused damages across 54 unique counties, corresponding to 125 county-year-month observations as the affected (treated) groups. Table C.2 lists these sixteen hurricanes, along with their names and the number of affected counties (i.e., those with reported damages exceeding $2 million). There were no events for at least three years prior to our first event, alleviating concerns that we mischaracterize those time periods by treating them as pre-event.

Next, we identify all policies that were in effect during these hurricane events. For each county-event combination, we select policies that were already active in both affected and unaffected counties. Policies in affected counties serve as the treated group, while those in unaffected counties act as the control group for the respective event. We then stack these samples across different events, allowing the same counties to serve as treated for some events and control for others.

With the stacked sample of policies in place, we merge time-series data for all policies, allowing us to track outcomes over time. To ensure comparability across similar geographies and risk levels, we exclude policies in counties that were never affected by any hurricane event throughout the sample period. Specifically, we remove policies in counties that never experienced a loss exceeding $2 million.[14] Finally, we restrict the analysis to three years before and after each event, resulting in a final sample of over 800,000 policies.

3.4 Empirical Methodology

Our empirical setting uses hurricanes and storms to evaluate the association between natural disasters and insurance contracts. Since these disasters occur at different times across locations, we employ a stacked DiD approach using hurricanes/storms as the treatment events. The stacked DiD framework helps address concerns raised in the literature regarding esti-

[13] See Florida Climate Center for a list of major hurricanes in Florida.

[14] Our results remain robust even when including these counties as shown in Table C.4.

mation bias from staggered difference-in-differences specifications with two-way fixed effects (Callaway and Sant'Anna, 2021; Cengiz et al., 2019; Goodman-Bacon, 2021; Gormley and Matsa, 2011; Sun and Abraham, 2021), thereby providing consistent and unbiased estimates of the effects of disasters on insurance contracts.

We first identify hurricane-affected counties using SHELDUS data. We then restrict our sample to home insurance policies on properties located in counties that experienced hurricane-related losses exceeding two million USD (the median) at some point during the sample period. Our identification strategy leverages variation in hurricane timing, comparing counties exposed to hurricanes earlier versus later.

Formally, we estimate the following model:

$$Outcome_{p,c,t} = \beta \times Post_{c,t} \times Treated_{p,c} + \gamma \times Post_{c,t} + \alpha_{p,c} + \epsilon_{p,c,t} \tag{10}$$

where $Outcome$ denotes various insurance contract-related variables for policy p in treatment cohort c during year t. The variable $Post$ is a dummy that takes a value of one for all time periods following a natural disaster within cohort c, while $Treated$ is a dummy that equals one for policies on properties located in counties affected by hurricanes during treatment cohort c. $\alpha_{p,c}$ represents policy $\times$ cohort fixed effects, which control for any time-invariant observable or unobservable differences across policies within the same cohort. Since hurricane shocks are measured at the county level, we cluster standard errors at the county level to account for spatial correlation.

Our theoretical model predicts that insurers adjust premiums and rejection rates not only for disaster-affected areas but also for unaffected areas. As a result, we focus on both β and γ coefficients. The coefficient β captures the differential effect of disasters on outcome variables for affected areas relative to unaffected areas, while γ captures changes in outcomes for unaffected areas. This differentiates our setting from traditional stacked DiD models where the coefficient of interest is mainly the interaction variable. Because we aim to estimate

γ, we do not include time fixed effects, as they would be collinear with the *Post* variable. Instead, we rely on single differences in outcome variables to account for time trends.

To assess the possibility of differential trends between policies in affected and unaffected areas and to analyze the effects over time, we estimate the dynamic version of equation 10 separately for each group. Specifically, we estimate the following model:

$$Outcome_{p,c,t} = \sum_{\substack{t=-3 \\ t\neq -3}}^{+3} \beta_t \mathbb{1}_{c,t} + \alpha_{p,c} + \epsilon_{p,c,t} \tag{11}$$

where the outcome variables and fixed effects remain the same as previously defined. $\mathbb{1}_t$ is an indicator variable that takes a value of 1 for a given event time and 0 otherwise. We exclude the year three time periods prior to the event as the benchmark. Thus, β_t captures the change in the outcome variable at each event time relative to the benchmark year prior to disasters.

In addition, we estimate the stacked difference-in-differences regressions separately across different time periods and sub-samples to examine heterogeneity in our findings based on the income of the insured and changes in private insurers' surplus.[15]

4 Climate Risk and Insurance Contracts

4.1 Climate Risk and Claims

We begin by validating our empirical setting by examining how claims evolve around hurricane events in affected areas (those hit by hurricanes) and unaffected areas (those not yet hit by hurricanes). Claims should mechanically increase in affected areas while remaining relatively unchanged in unaffected areas. Observing this pattern would confirm our specification is correct, whereas deviations may indicate endogeneity issues or misspecification.

Panels (a) and (b) of Figure 1 plot the dynamic coefficients estimated using equation (11),

[15] Data on private insurers' surplus, assets, and Florida homeowners insurance market shares come from their statutory filings. We access the filings through S&P Capital IQ.

with the likelihood of a claim and claim amount as outcome variables respectively. The figure shows coefficient estimates and 95% confidence interval error bands on event-time dummies, separately for affected and unaffected policies, relative to the third year before the hurricane. Across both outcomes, we find that the treated and control groups exhibit similar trends before and after hurricanes, supporting the parallel trends assumption. However, we observe a significant spike in claims for the treated group during the hurricane year, with approved claims increasing by approximately 100% relative to the control group. In contrast, claims in the control group remain stable throughout the seven-year estimation period, spanning three years before and three years after the hurricane.

In addition, we find evidence of a decline in approved claim amounts for policies in unaffected areas during the post-hurricane period. The decline is approximately 50%, with the effect being statistically significant at the 95% confidence level in the year immediately following the hurricane.

Table 2 reports coefficients for similar analysis estimated using equation (10). While for the unaffected policies the likelihood of filing a claim declines by 1.6 percentage points (pp) following hurricanes, the treated group experiences an increase in this likelihood of 2.5pp.[16]

Overall, the results in this section support the validity of our empirical specification in capturing the effects of disasters.

4.2 Climate Risk Pass-through

To test the predictions of our model, we examine how insurers pass through climate-related costs to home insurance policies via both ex-ante charges and ex-post claim outcomes. Ex-ante charges include premiums and mandatory charges imposed by insurers to offset negative shocks such as climate-related costs. Ex-post claim outcomes represent approval/rejection rates. Because we estimate changes for both affected and unaffected groups around disaster events, we do not include time fixed effects, as they would be collinear with the time

[16] Since 0.041 reflects the relative estimate, the total effect for the treated group is given by 0.041-0.016=0.025.

dimension (i.e., the *Post* variable in static setting). Instead, we rely on single differences in outcome variables to account for time trends.

Figure 2 plots the evolution of premiums three years before and after a hurricane. Panel (a) plots the coefficient and error bands at a ninety-five percent confidence level for Δ*log(Premium)* on event-time dummies for the treated and control policies separately relative to three years before the occurrence of the hurricane, as in specification (11). Panel (b) plots similar estimates for Δ*Premium to coverage ratio*.

We find that premiums evolve similarly for treated and control groups in the years prior to hurricanes, consistent with parallel trends. However, during the hurricane year, the affected areas (i.e., the treated groups) experience a discrete jump in premiums, which persists for two additional years. This pattern suggests that premiums for the treated group continue to rise for three years following a hurricane. In contrast, the control group shows a slightly delayed reaction, with a discrete jump in the growth rate occurring only in the year after the hurricane. This increase is about half the size of the treated group's and lasts for two years, indicating that premiums for the control group rise for two years post-hurricane. Results for premium-to-coverage exhibit similar patterns.

We next examine how claim rejection rates evolve around hurricanes. Since the same policy may have multiple claims in a given year, we measure rejection rates in two ways: (i) as the proportion of claims rejected for a policy-year and (ii) as a dummy variable that takes the value of 1 if at least one claim is rejected during the policy-year. Figure 3 plots results for these analyses. While the coefficients for treated and control groups are largely indistinguishable within the 95% confidence interval in the years prior to hurricanes, they diverge in the year immediately after the hurricane, with rejection rates increasing significantly for the control group.

We re-estimate the changes in these outcomes using a static DiD model, as specified in equation (10). Table 3 reports these estimates. Columns I and III report results for premiums and premium-to-coverage, while columns II and IV examine mandatory charges and mandatory charges-to-coverage. Across all outcomes, we estimate a positive coefficient but do not find a statistically significant association between hurricane events and the outcome variables for the unaffected groups. This is likely because the effects are not persistent throughout the post-event period but are instead concentrated in years one and two following hurricanes. However, the changes are statistically significant for the treated group, likely due to the more consistent impact over time. The final two columns present results for claim rejection rates, measured both as the proportion of claims rejected and as a dummy variable for any rejection. Here, we again find a positive coefficient for the unaffected group, though it is statistically weak, with a negative and significant estimate for the affected group.

A natural question at this point is how the insurer is able to adjust their rejection rates over time. To help shed light on this, we obtain data on claims rejection reasons from the Catastrophe Claims Database from the Office of Insurance Regulation in the state of Florida.[17] There are three predominant reasons that Citizens (as well as private insurers) reject claims. First, they may reject a claim simply because the assessed damage was below the policyholder's deductible. Second, the claim may fall under a risk category not covered by the policyholder's policy (e.g., flooding). Third, the insurer's claims management system may fail to record a specific reason for rejection. All other reasons we combine into a fourth category, which we title "other."

We plot the total number of claims for four separate hurricanes broken down by the four rejection categories in Figure 4. We consider the insurer of last resort's rejections and private insurers' rejections separately. The majority of claims are rejected due to damages not meeting deductibles, followed by lack of coverage for flood and other specific damages, and then followed by claim system ambiguity. We conjecture that the first and third reasons give the insurers flexibility in rejecting claims. For example, if the insurer mechanically raises deductibles over time for repeat policyholders due to unperceived increases in coverage, this could lead to a higher likelihood of rejection. Alternatively, if the insurer's rejection reasons

[17] We discuss this data set in more detail in Section 5.2.

are not recorded clearly, they may face some flexibility in the case that the policyholder follows up with any litigious activity. We test some of these conjectures in Section 4.5.

Overall, our results show that climate risk pass-through occurs both through ex-ante costs and ex-post claim outcomes. Both affected and unaffected groups bear the costs with average spillovers being smaller in magnitudes than the effects on the treated group.

4.3 Climate Risk Pass-through: The Role of Local Income

While our pooled analysis suggests that unaffected groups experience smaller spillovers, this could be masking important heterogeneity in the cross section of locations. For example, our theory predicts that high price elasticity locations will experience lower pricing spillovers than low elasticity locations, but will pay more ex-post through higher rejection rates. We test these hypotheses by conditioning our sample on zip code income. If low-income households are more sensitive to changes in premiums (e.g., due to budget constraints), we should expect pricing spillovers to be weaker in poorer locations, but should also expect these locations to face higher rejection rates following a diaster.

We test this formally by re-estimating our regressions separately for zip codes that are below and above median zip code income. Table 4 presents the results. Consistent with the theory, we find that prices do not increase in low income control locations, but increase by 4% in high income control locations. This suggests that in response to hurricane losses, the insurer strategically raises premiums in locations where they can most exert their pricing power. In a distributional sense, this implies that high-income households in low risk locations are subsidizing households in risky locations, while low-income households outside of risky locations are spared. This partially explains the small spillover results in the previous section: the average spillover effect masks the heterogeneity across regional income groups.

However, our results also suggest that unexposed low-income households pay in the form of higher rejection rates on their claims. Households in poor but unexposed locations face 3.9 percentage point higher rejection rates after a hurricane, while rich and unexposed locations do not experience any change. For both high- and low-income locations that are exposed to the hurricane, rejection rates decline, consistent with the insurer having to pay out more claims after the disaster.

4.4 Climate Risk Pass-through: The Role of Capital

Our theory also predicts that in periods of private market distress, spillovers will be higher due to the elevated pricing power that the insurer has in a less competitive market.[18] We therefore consider a split on a measure of private market distress. First, we calculate the surplus-to-asset ratio of each insurance company that sells homeowners insurance in the state of Florida for each year. We then compute a weighted average of surplus-to-assets across private insurers, where we use homeowners insurance premiums in the state of Florida as the weights. We then compute year-over-year changes in this measure and match the changes to each event. We define "increasing surplus" events as those that occurred when the market surplus-to-asset ratio was increasing in the prior quarter, and "decreasing surplus" events as the opposite.[19]

We estimate our framework for the increasing and decreasing surplus periods and report results in Table 5. We find that the premium growth rates increase for both treated and control counties when the private market is more distressed (i.e., decreasing surplus). In particular, the growth in premiums is 5.8% higher for control counties, and 8.1% higher for treated counties. But in increasing surplus periods, the premium growth rate increases only for treated properties (10.1%), but not for control properties. This is consistent with our theory: when the private market is distressed, private insurers raise prices in all locations (Oh et al., 2025), which increases the insurer's pricing power and relaxes their pricing constraints.

At the same time, rejection rates are unaffected in decreasing surplus periods, but increase by 3.9 percentage points only for control counties in increasing surplus periods. This result is also consistent with our theory: since the insurer is not able to recover their losses

[18] In the theory, this would appear as a uniform decline in price elasticities (ε_ℓ) in times of general distress.
[19] Note that this particular sample split is almost identical to splitting on the median in-sample surplus change.

through subsequent price increases when the private market is stable, they resort to increasing rejection rates. This is not the case when the private market is distressed and they have pricing power.

4.5 How do households respond?

We have primarily focused our analysis so far on the insurer's behavior. We now shift our focus to the household sector. Households, who have some control over the characteristics of their policies, may respond both to heightened climate risk and to the insurer's own responses.

We explore four margins of adjustment. First, we consider the log change in total coverage associated with each property. Households may increase or decrease their coverage in response to a hurricane. If the insurer raises prices, households may opt for a lower coverage level to reduce their premiums. But at the same time, it is known that households are generally underinsured (Sastry et al., 2024), largely due to informational frictions (Cookson et al., 2024). In response to a hurricane, households may opt for higher coverage, recognizing that they were underinsured in the first place.

Second, we consider how households change their deductibles. It is not ex-ante obvious which direction deductibles should change: if households only internalize changes in prices, we would expect deductibles to move in the same direction, as higher deductible policies are typically cheaper. But if households also factor in heightened climate risk, they may opt for lower deductibles, especially in treated areas.

Third, we address households' responses to heightened rejection rates through subsequent litigious activity. If households determine that their claims were wrongly rejected, they may respond by filing a lawsuit against the insurer. Our dependent variable for this test is an indicator for whether or not the household files any litigation against the insurer in a given year. We can therefore interpret our estimates as litigation rates.

Last, we explore whether households dispute their claim outcome through external appraisers. If a household incurs damages, the insurer will provide an off-the-shelf quote for the household that may be undervalued. Households have the option to acquire an external quote which may increase the value of their insurance claim. We may expect to see an increase in the appraisal rate in locations with higher rejections, as the insurer may also be responding on the intensive margin when cutting back on claims. Additionally, we know from Figure 4 that many claims are rejected due to not reaching the deductible. External appraisals may therefore give households a higher likelihood of reaching their deductible and allow them to try and reverse the rejection.

We first report results for our full sample in Table 6. We find that households respond to a hurricane by increasing both their coverage and their deductibles. This is consistent with households increasing disaster insurance, but reducing insurance for smaller events that are now less likely to meet their deductible. The responses are positive for all households, but more so for treated households. This suggests both heightened salience and cost-cutting behavior. We do not find any response of litigious behavior to a hurricane event for either treated or control counties, though treated counties do increase their appraisal rate by 5.5 percentage points.

We then split our results by household income in Table 7. The results are consistent with the heterogeneous effects of cost pass-through across income groups. Low-income households only alter their coverage and deductibles in treated locations, while high-income households alter these characteristics in both sets of locations. However, low-income households in control locations increase both litigation and appraisal rates, which is likely in response to the increase in rejections. Low-income treated locations do not experience a statistically significant difference in litigation rates relative to the control group, though the estimate is negative, suggesting that the effects are concentrated in control locations. High-income locations do not experience an increase in litigation rates.

4.6 Alternative Explanation: Fraudulent Claims

An alternative explanation for the increase in rejection rates in unaffected areas is that these areas experience a surge in fraudulent claims following nearby disasters. Under this interpretation, opportunistic policyholders in neighboring unaffected counties might attempt to attribute pre-existing damage or unrelated losses to the recent catastrophe, prompting the insurer to reject these illegitimate claims. While this represents a plausible concern, we present several pieces of evidence that suggest fraudulent behavior is unlikely to account for the patterns we document.

First, we examine whether the likelihood of filing a claim increases in unaffected areas following disasters in nearby counties. If fraud were widespread, we would expect to see a notable uptick in claim frequency in these areas as opportunistic policyholders submit false claims. In contrast, as discussed earlier, we find that claims in the control group remain stable throughout the seven-year estimation period, spanning three years before and three years after the hurricane (Figure 1).

Second, the costs and risks associated with filing fraudulent insurance claims create strong disincentives for such behavior. Insurance fraud is a felony in Florida, punishable by imprisonment and fines.[20] Beyond legal consequences, policyholders who file suspicious claims face material economic costs: insurers may increase their premiums, subject future claims to heightened scrutiny, or cancel their policies entirely. Given that homeowners' insurance is mandatory for mortgaged properties, policy cancellation would force households into the much more expensive private market or jeopardize their mortgage agreements. These substantial costs make opportunistic fraud a high-risk strategy, particularly for a one-time potential gain.

Third, we examine household responses to claim rejections. If rejected claims were fraudulent, we would expect policyholders to accept these rejections rather than incur additional

[20] Florida Statutes § 817.234 defines insurance fraud as a third-degree felony, punishable by up to five years in prison and a $5,000 fine.

costs to challenge them. However, we find the opposite pattern: in areas with higher rejection rates, policyholders are significantly more likely to engage in costly litigation against the insurer. This willingness to invest in legal action—which incurs both pecuniary and non-pecuniary costs—suggests that policyholders believe their claims are legitimate and worth defending. Fraudulent claimants would have little incentive to pursue costly legal challenges that would subject their claims to additional scrutiny and potential criminal investigation.

Taken together, these findings suggest that opportunistic claims are unlikely to be the primary driver of the systematic increase in rejection rates we observe in unaffected areas.

5 Normative Analysis

We have now established both theoretically and empirically how the insurer responds to large natural disasters. But what does this imply for the well-being of their policyholders? Do the decisions they make ultimately make policyholders better or worse off? How does this depend on the characteristics of policyholders within a location, or on whether or not the policyholder experienced a climate event?

This section provides one answer to these questions through the lens of a logit demand model in which policyholders derive utility from consuming insurance. We begin by laying out our framework for the analysis, which borrows heavily from the discrete choice industrial organization literature. We then discuss our data sources for the analysis. We end with a discussion of our results.

5.1 A Discrete Choice Framework for Estimating Insurance Demand

We specify a model of homeowners insurance demand following the industrial organization literature. Consider a policyholder h in location ℓ at time t. The policyholder chooses an insurance policy from a pre-specified set of available insurance companies, $\mathscr{J}_{\ell t}$. We will assume all policyholders in this location are identical aside from an idiosyncratic preference shock across insurers, $\nu^h_{j\ell t}$, which is distributed according to an extreme value type I distribution with zero mean and unit variance. Their indirect utility from consuming a policy by insurer $j \in \mathscr{J}_{\ell t}$ is

$$u^h_{j\ell t} = \alpha_j - \varepsilon_\ell \text{price}_{j\ell t} - \beta \text{rejection rate}_{j\ell t} + \nu^h_{j\ell t}. \tag{12}$$

Here, α_j is an insurer-specific demand component that may be thought of as the insurer's quality. For example, small and risky insurers may have a low α_j while insurers of last resort, being backed by state funds, have a high α_j. Policyholders have a distaste for prices, and their sensitivity to price changes is measured through $\varepsilon_\ell > 0$. We will ultimately allow ε_ℓ to depend on policyholder income: $\varepsilon_\ell = \varepsilon_{\text{low-income}} + \mathbf{1}\{\ell = \text{high-income}\}(\varepsilon_{\text{high-income}} - \varepsilon_{\text{low-income}})$. Policyholders also dislike when there is a high chance that their policy will be rejected, which we capture through β. Our baseline results assume β is constant across policyholder types, but we also estimate a specification in which β depends on policyholder income for robustness.

We also allow for the presence of an outside option, which we index by $j = 0$. The outside option can be interpreted as having no insurance. We normalize the price and rejection rate of the outside option to 0, so that their utility of being uninsured is simply $u^h_{0\ell t} = \nu^h_{0\ell t}$.

We can then aggregate preferences at the location level. The market share of insurance expenditures (premiums) of insurer j in location ℓ at time t is

$$\text{market share}_{j\ell t} = \frac{\exp\left\{\alpha_j - \varepsilon_\ell \text{price}_{j\ell t} - \beta \text{rejection rate}_{j\ell t}\right\}}{1 + \sum_{i \in \mathscr{J}_{\ell t}} \exp\left\{\alpha_i - \varepsilon_\ell \text{price}_{i\ell t} - \beta \text{rejection rate}_{i\ell t}\right\}} \tag{13}$$

Taking logs, we come to our primary estimating equation:

$$\log(\text{market share}_{j\ell t}) = \alpha_j - \varepsilon_\ell \text{price}_{j\ell t} - \beta \text{rejection rate}_{j\ell t} + \gamma_{\ell t} + \xi_{j\ell t} \tag{14}$$

where $\gamma_{\ell t}$ is a location-time fixed effect that absorbs the denominator term in (13) and $\xi_{j\ell t}$ reflects unobservable variation that we treat as a residual. Since we are primarily interested in the effect of the insurer's behavior on policyholder utility, we include an indicator for the insurer (i.e., Citizens) in place of α_j. We therefore treat private insurers as all sharing the same α_i, $i \neq j$.

5.2 Data Sources and Variable Construction

5.2.1 Prices

While we do not have policy-level data for the entire set of insurers in Florida, we obtain quarterly information on county-level insurance coverage and premiums for a variety of insurance categories from the Quarterly and Supplemental Reporting System (QUASR), which was provided to us by the Office of Insurance Regulation in the state of Florida. The data cover all quarters from 2009Q1 to 2024Q3, and we focus broadly on homeowners insurance, including residential properties, mobile homes, and broadly defined dwellings. Since we do not observe prices explicitly, we construct a proxy for each insurer-location-year as $\text{price}_{j\ell t} = \text{premiums}_{j\ell t}/\text{coverage}_{j\ell t}$.[21] We remove outliers at the 1% and 99% level.

A key challenge with the estimation of demand systems is that prices are endogenous to both supply and demand. As such, we need an exogenous supply shifter to identify demand elasticities. We consider two instruments. First, we utilize a Bartik-style instrument (Bartik, 1991; Goldsmith-Pinkham et al., 2020) centered around insurers' loss ratios using variation in county-level losses. Specifically, we calculate

$$\widehat{\text{loss ratio}}_{j\ell t} = \frac{(\text{coverage share}_{j\ell t-k}) \times \text{losses}_{\ell t}}{\text{premiums}_{j\ell t-k}} \tag{15}$$

We consider both the raw and log values of $\widehat{\text{loss ratio}}_{j\ell t}$, and set the lag length $k = 3$. We use lagged premiums in the denominator to avoid co-linearity issues since the left-hand

[21] In Appendix Figure C.4, we validate our measure as a true measure of price by comparing Citizens' price with the median (average) premium-to-coverage from our policy-level data within each county-year pair. The two measures have a correlation coefficient of 88% (57%) and an R^2 of 0.77 (0.32), suggesting that our price measure at the county level acts as a sufficient proxy to the price of risk across policies within a county.

side variable in our estimating equation also includes log premiums. The lags are meant to address the exclusion restriction for a valid instrumental variable. By considering a long enough lag length, we reduce concerns that coverage market shares are also correlated with other factors that influence demand in a given market.

Our second instrument is a leave-one-out instrument (Angrist et al., 1999).[22] For each insurer j, we set

$$\text{price}_{j\ell t}^{\text{loo}} = \frac{1}{|\mathscr{J}_{\ell t}| - 1} \sum_{\substack{i \in \mathscr{J}_{\ell t} \\ i \neq j}} \text{price}_{i\ell t}. \tag{16}$$

We will therefore report four separate results: one with no instrument, two with the log and level of the loss ratio instrument, and one with the leave-one-out instrument.

5.2.2 Claims and Rejection Rates

We further obtain information on insurers' claims and rejections at the county-level following major hurricane events from the Catastrophe Claims Data. These data include detailed information on all hurricane-related claims filed and handled by each insurance company since 2018.[23] We aggregate events to the year level. When merging the data set with our price data, we include one year of lag to account for the fact that the previous year's rejection rates should be relevant for the purchase (or renewal) of insurance policies; for example, when we match 2018 claims to 2019 price and market share data, we are assuming that an insurer's rejections in 2018 matter for their market share in 2019. We define rejection rate$_{j\ell t}$ as the ratio of insurer j's total number of claims that were closed without payment in location ℓ at time t over the total claims filed to insurer j in that location in the same year.

Since our data on claims rejections are sparse, we do not include a specific instrument for the rejection rate. However, in an attempt to reduce potential endogeneity concerns, we

[22]While leave-one-out, or "jackknife", instruments have received scrutiny due to their strong assumptions about exclusion restrictions, we treat this specification primarily as a robustness check.

[23]The data technically include information on hurricane events in 2017. However, due to data sparsity issues among these events, we focus on claims information from 2018 onward

use each insurer's rejection rates across all insurance categories in a location in a given year. This includes automobile insurance, commercial insurance, and a variety of other sources in addition to the homeowners insurance policies we take from the QUASR data set. This further helps to reduce outliers from insurer-county pairs that have very few claims filed within a year.

5.3 Demand Estimation Results

We report our estimation results of equation (14) in Table 8. Column (1) reports the results with no instrument, column (2) reports the results with the log loss ratio instrument, column (3) reports the results with the level loss ratio instrument, and column (4) reports results with the leave-one-out instrument. In all specifications, we find that the price elasticity $-\varepsilon_{\text{low-income}} < 0$ and the rejection rate elasticity $-\beta < 0$, which implies that both prices and rejection rates enter negatively in policyholder utility. We further find that $-\varepsilon_{\text{low-income}} < -\varepsilon_{\text{high-income}} < 0$, suggesting that low-income households are more sensitive to prices than high-income households, though the difference is only statistically significant for one of the four specifications. Last, we find $\alpha_{\text{Citizens}} > 0$, which reflects Citizens' role as an insurer of last resort and its ubiquity in the Florida homeowners insurance market.

We also consider two other specifications for robustness. First, we re-conduct our analysis with the assumption that there is no heterogeneity in preference parameters across policyholders (Table 9). This specification is primarily used for robustness in the utility calculations in the upcoming section. Second, we conduct our analysis with the assumption that all inputs' parameters (prices, rejection rates, and the Citizens indicator) are heterogeneous in policyholder income (Table 10). This specification addresses concerns that policyholders with different income levels may differentially respond to rejection rates. It could also be that one type of policyholder is more likely to be rejected by other insurance companies, and therefore relies more heavily on Citizens. We find that the latter case is true: policyholders in high-income locations put a higher preference weight on Citizens relative to low-income locations. On the other hand, rejection rate preference heterogeneity is not statistically different from zero.

5.4 Estimating the Effect of the Insurer's Response on Policyholder Utility

We now use our demand system estimates to estimate utility effects of the insurer's hurricane response that we estimate in Section 3. Given our setup in Section 5.1, we can write the average utility for ℓ policyholders at time t as[24]

$$U_{\ell t} \equiv \mathbb{E}\left[\max_{i \in \mathcal{J}_{\ell t}} u^h_{i\ell t}\right] \;\propto\; 1 + \sum_{i \in \mathscr{J}_{\ell t}} \exp\left\{\alpha_i - \varepsilon_\ell \text{price}_{i\ell t} - \beta \text{rejection rate}_{i\ell t}\right\} \tag{17}$$

In response to a climate shock that changes insurers' prices and rejection behavior, the average utility response is therefore[25]

$$\begin{aligned}\Delta \log U_{\ell t} &= \Delta \log\left(1 + \sum_{i \in \mathscr{J}_{\ell t}} \exp\left\{\alpha_i - \varepsilon_\ell \text{price}_{i\ell t} - \beta \text{rejection rate}_{i\ell t}\right\}\right) \\ &\approx - \sum_{i \in \mathscr{J}_{\ell t}} \exp(\alpha_i)\left\{\varepsilon_\ell \Delta \text{price}_{i\ell t} + \beta \Delta \text{rejection rate}_{i\ell t}\right\} \end{aligned} \tag{18}$$

The approximation in (18) is useful because it allows us to separate the effect of each insurer's response on policyholder utility. Since we do not observe how most insurance companies respond to a climate event, we cannot estimate the full effect of a climate shock on policyholder utility. However, using the approximation, we can assign an effect to the insurer using our estimates in Section 3. We use results from Table 4 and compare utility outcomes for four policyholder groups: untreated low income counties, treated low income counties, untreated high income counties, and treated high income counties.[26]

[24]The average utility is aggregate across idiosyncratic preference shocks, $\nu^h_{j\ell t}$. See Dubé et al. (2025) for a derivation of the average utility expression.

[25]The derivation follows from first using the Taylor approximation $\log(1 + x) \approx x$ and then using the Taylor approximation $\exp(x) \approx 1 + x$.

[26]Our estimates in Table 4 measure the effect on log prices rather than levels, which we use in our analysis in Section 5.1. We therefore use the average estimated change in log prices times the average price as a proxy for price changes: $\Delta \text{price}_{j\ell t} \approx \Delta \log(\text{price}_{j\ell t}) \times \overline{\text{price}}_{j\ell t}$.

We display our estimates in Figure 5. Each panel represents one of the four policyholder groups. Within each panel, we separate the utility effects into four additional groups corresponding to the estimation strategy: (1) no price instrument, (2) log loss ratio instrument, (3) level loss ratio instrument, and (4) leave-one-out instrument. Within each estimation strategy we further disaggregate the estimates by our choice of parameter heterogeneity: (i) no income heterogeneity, (ii) only price elasticity heterogeneity, (iii) heterogeneity allowed for all parameters. Finally, we separately plot the effects of price changes on utility (dark bars) and the effects of rejection rate changes on utility (light bars). Total effects are captured by black diamonds. Overall, we therefore provide 12 estimates for each policyholder group. Average total effects across specifications are indicated by a black dashed line, and average price effects are indicated by a green dashed line.

We find that policyholders in treated locations are worse off, but that the gap between treated and untreated is much larger for low-income locations (−1.355% vs. 0.002%) than high-income locations (−0.816% vs. −0.722%). This is in part due to differences in price setting behavior across policyholder groups: low-income policyholders in untreated locations experience a modest *decline* in prices, while high-income untreated policyholders experience an increase in prices. There is therefore a large gap in the price-specific utility effects between treatment groups for low-income locations that is not as strong among high-income locations.

However, another key finding is that the gaps across treatment groups would be exacerbated without accounting for changes in rejection rates. Rejection rates increase in low-income untreated locations, which ultimately lowers policyholder utility by about 0.5%. Likewise, rejection rates strongly decline in high-income treated locations, increasing their utility by about 0.84%. If we only accounted for changes in prices, we would see utility effect differences of 1.957% (rather than 1.357%) for low-income locations, and 0.784% (rather than 0.094%) for high-income locations. The estimates therefore highlight the importance of accounting for the entire scope of insurers' choices when evaluating their effects on the well-being of policyholders.

6 Conclusion

This paper provides the first comprehensive analysis of how insurers of last resort respond to climate disasters and pass these costs through to policy holders. These insurers face a fundamental trade-off in their dual mandate to expand coverage access while maintaining solvency. Our granular policy-level data from Citizens Property Insurance Corporation enables us to document previously unobservable mechanisms through which these institutions redistribute climate costs across households.

Three key insights emerge from our analysis. First, the traditional view that government-backed insurers serve as stable alternatives to volatile private markets seems incomplete. When faced with catastrophic losses, these institutions adopt profit-maximizing behaviors strikingly similar to their private counterparts. Second, insurers pass-through disaster costs on policy holders via both premiums and rejection rates, that can potentially obscure the true incidence of climate costs. While premium changes are transparent and observable, rejection rate adjustments operate as a hidden tax that systematically disadvantages price-sensitive households. Third, market-wide financial conditions fundamentally shape pass-through strategies: capital constraints drive premium adjustments, while periods of financial stability shift costs through claim denials.

Our welfare analysis shows that focusing solely on premium changes to analyze distributional effects mischaracterizes who bears climate costs. Low-income households in unaffected areas, who appear protected from premium increases, face equivalent welfare losses through elevated rejection rates. This finding has immediate policy relevance: as states increasingly adopt insurers of last resort to address private market failures, policymakers must recognize that these institutions redistribute rather than absorb climate risks, with distinct impacts across income groups.

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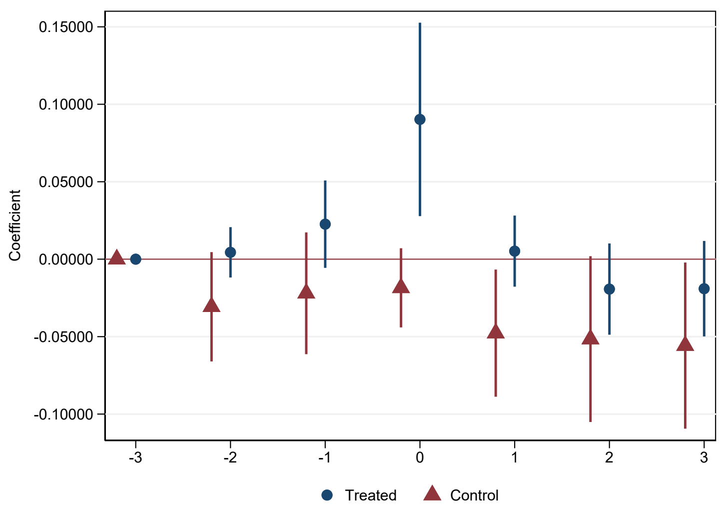
I Figures

Figure 1: Claims and hurricane

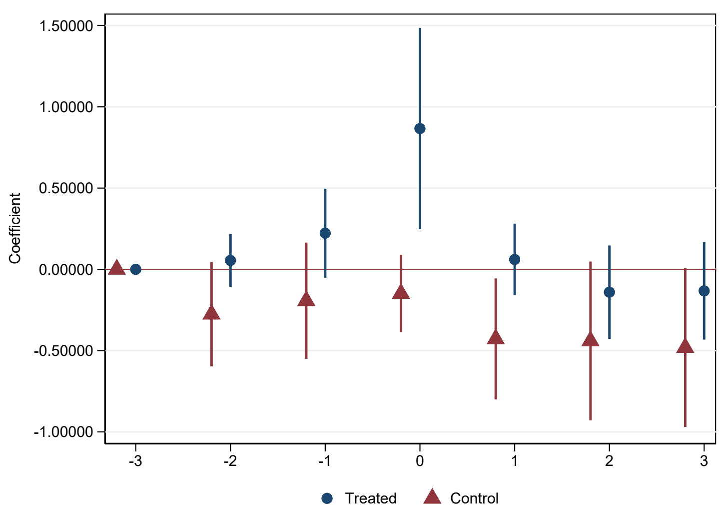
The figure shows the evolution of claims/losses three years before and after a hurricane. We estimate the following model:

$$Outcome_{p,c,t} = \sum_{t=-3}^{+3} \beta_t \mathbb{1}_t + \alpha_{p,c} + \epsilon_{p,c,t},$$

where the outcome variables include $\mathbb{1}_{p,c,t}$, an indicator variable that equals 1 if a claim is filed against policy p in treatment cohort c at event-time t, and $\log(1+claim)_{p,c,t}$, which represents the approved claim amount for policy p at event-time t. $\mathbb{1}_t$ denotes an indicator variable that equals 1 for a given event time and 0 otherwise. $\alpha_{p,c}$ represents policy × cohort fixed effects. The figure plots the estimated coefficients along with 95% confidence intervals, measured relative to three years before the hurricane event. Standard errors are clustered at the county level.



(a) Claim dummy



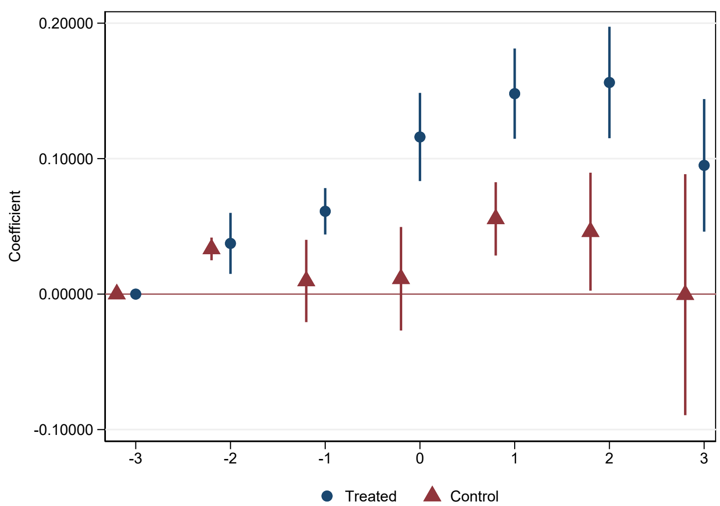
(b) Claim amount

Figure 2: Premium and hurricane

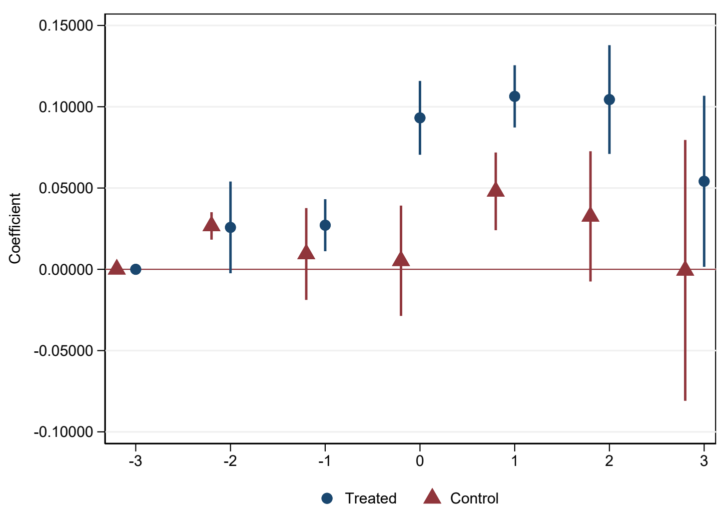
The figure shows the evolution of home insurance premium and premium to coverage three years before and after a hurricane. We estimate the following model:

$$Outcome_{p,c,t} = \sum_{t=-3}^{+3} \beta_t \mathbb{1}_t + \alpha_{p,c} + \epsilon_{p,c,t},$$

where the outcome variables include $\Delta log(Premium)_{p,c,t}$, which represents the growth rate in premium for policy p in treatment cohort c at event-time t, and $\Delta log(\frac{Premium}{coverage})_{p,c,t}$, which denotes the corresponding growth rate of the premium-to-coverage ratio. $\mathbb{1}_t$ denotes an indicator variable that equals 1 for a given event time and 0 otherwise. $\alpha_{p,c}$ represents policy $\times$ cohort fixed effects. The figure plots the estimated coefficients along with 95% confidence intervals, measured relative to three years before the hurricane event. Standard errors are clustered at the county level.



(a) Changes in premium



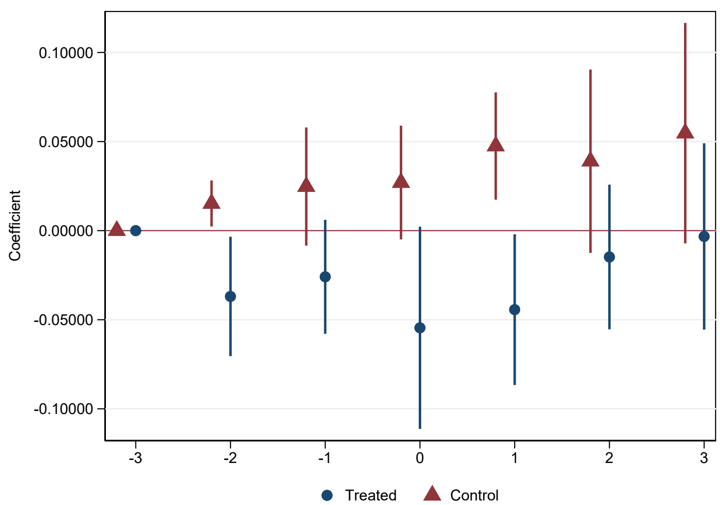
(b) Changes in premium to coverage

Figure 3: Claim rejection and hurricane

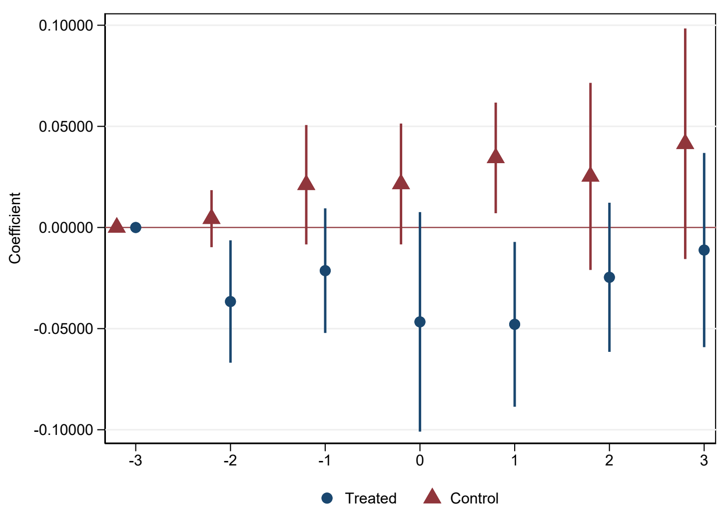
The figure shows the evolution of rejected claims three years before and after a hurricane. We estimate the following model:

$$Outcome_{p,c,t} = \sum_{t=-3}^{+3} \beta_t \mathbb{1}_t + \alpha_{p,c} + \epsilon_{p,c,t},$$

where the outcome variables include Rejection rates, which represents the proportion of claims filed against policy p in treatment cohort c at event-time t that were rejected, and $\mathbb{1}_{p,c,t}$, an indicator variable that equals 1 if a claim is filed against policy p at event-time t. $\mathbb{1}_t$ denotes an indicator variable that equals 1 for a given event time and 0 otherwise. $\alpha_{p,c}$ represents policy $\times$ cohort fixed effects. The figure plots the estimated coefficients along with 95% confidence intervals, measured relative to three years before the hurricane event. Standard errors are clustered at the county level.



(a) Claim rejection proportion



(b) Claim rejection dummy

Figure 4: Reasons for Claim Rejection

This figure plots total rejected claims across four hurricane events. We plot Citizens and other private insurers rejected claims separately for each hurricane. Claim rejection reasons are: (1) assessed damages were too low relative to deductible (red); (2) damage category was not covered by the insured's policy (blue); (3) the insurer's claims management system does not report a rejection reason (yellow); and (4) other reasons (dark blue).

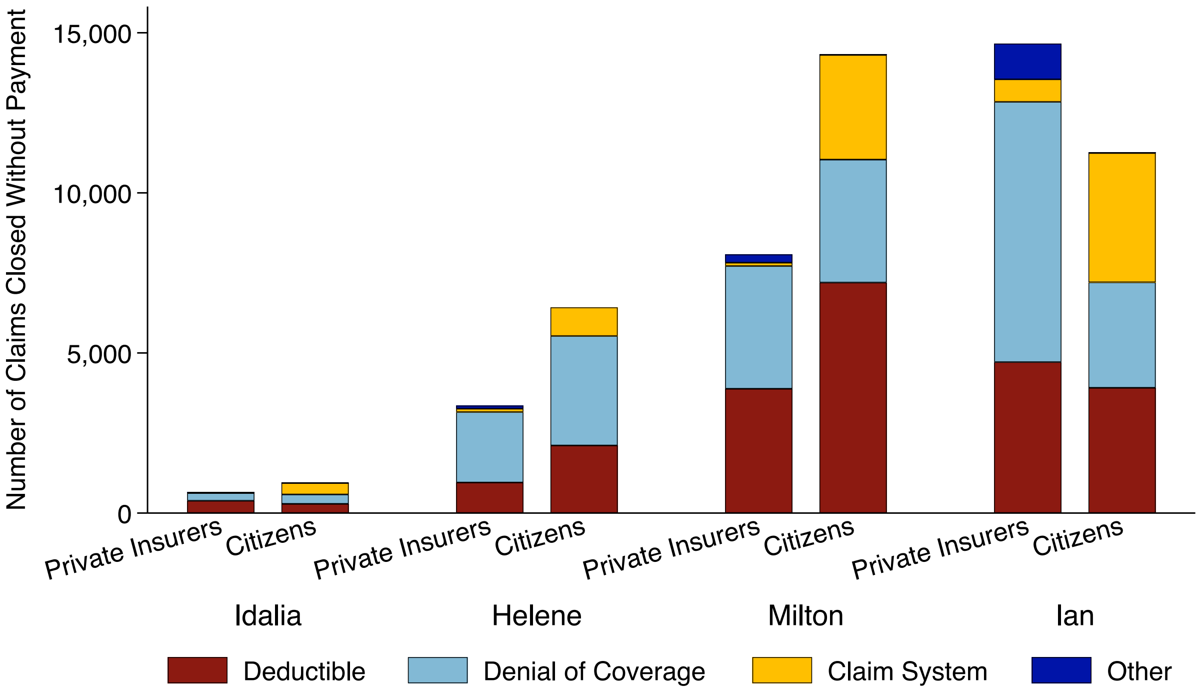
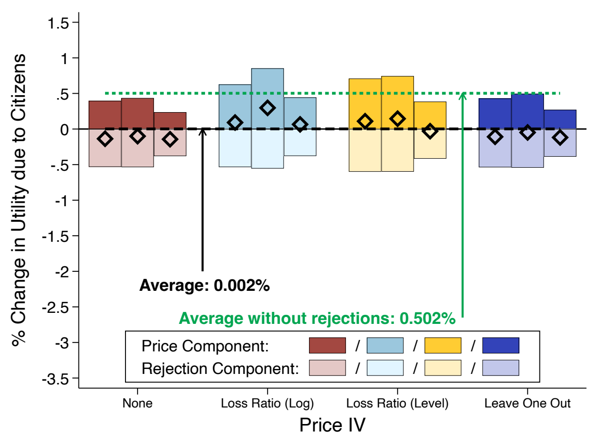
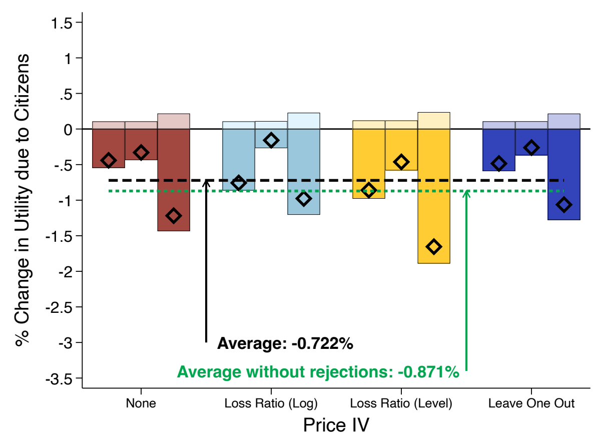


Figure 5: The Effect of Citizens' Post-Hurricane Response on Policyholder Utility

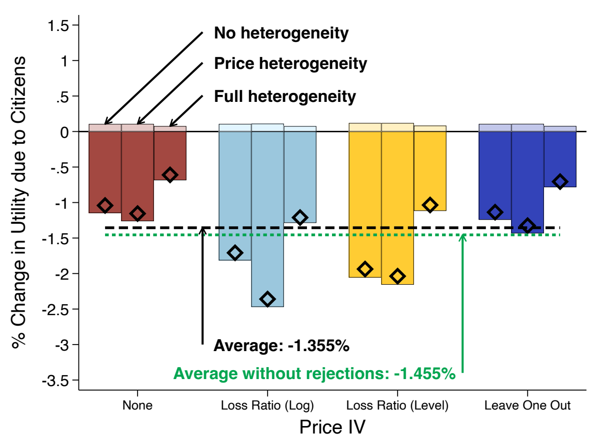
This figure reports the results of the policyholder utility analysis. We report estimates for four categories: (a) low income untreated counties, (b) high income untreated counties, (c) low income treated counties, and (d) high income treated counties. Within a category, we plot both the total effect of Citizens' post-hurricane response (black diamonds) as well as the pricing effect (dark bars) and rejection effect (light bars) separately. Red bars reflect estimates with no price IV, blue bars reflect the log loss ratio IV, yellow bars reflect the raw loss ratio IV, and the dark blue bars reflect the leave-one-out IV. The first bar in each cluster represents the case with no parameter heterogeneity, the second bar represents the case with price elasticity heterogeneity, and the third bar represents the case with price, rejection rate, and Citizens preference heterogeneity. Dashed black lines represent the average total effect across specifications, and the dashed green lines represent the average effect excluding the rejection rate component.



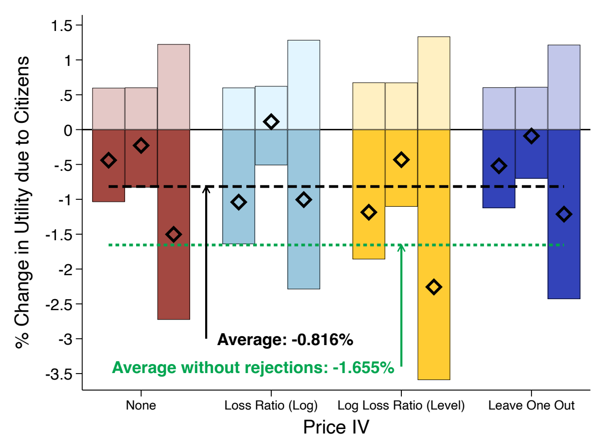
(a) Low Income, Untreated



(b) High Income, Untreated



(c) Low Income, Treated



(d) High Income, Treated

II Tables

Table 1: Summary statistics

This table reports the summary statistics of policies in our sample.

	Observations	Mean	StDev	P10	P25	Median	P75	P90
Premium	18677633	1748.64	1424.84	423.00	784.00	1400.00	2297.00	3469.00
Mandatory charges	18677633	99.33	147.89	15.00	29.00	60.00	111.00	205.00
Total (Premium + Mandatory charges)	18677633	1847.97	1514.11	449.00	829.00	1478.00	2426.00	3657.00
Premium to coverage	18568132	1.64	12.17	0.48	0.70	1.06	1.64	2.60
Mandatory charges to coverage	18568132	0.09	0.61	0.02	0.03	0.05	0.09	0.16
Claim Amount	18677633	747.38	8256.46	0.00	0.00	0.00	0.00	0.00
Claim to premium	18566864	0.46	5.19	0.00	0.00	0.00	0.00	0.00

Table 2: Claims

The table examines the impact of hurricanes on claim amount and probability of filing a claim. $log(1{+}Claim\ Amount)_{p,t}$ is the amount of claim for the policy p that files a claim at event-time t and $\mathbb{1}(Claim)$ is an indicator value that takes the value of 1 for a policy p that files a claim at event-time t and zero otherwise. *Post* is an indicator variable that takes on a value of one for periods following a hurricane and zero otherwise. *Treated* is an indicator variable that takes a value of one for policies in counties experiencing a hurricane and zero otherwise. Standard errors are clustered at the county-level, and are shown in parentheses. ***, **, and * represent result significant at 1%, 5%, and 10% level, respectively.

	ln(1+Claim Amount)	$\mathbb{1}(Claim)$
	I	II
$Post_t$	-0.136***	-0.016***
	(0.043)	(0.004)
$Post_t \times Treated_p$	0.378***	0.041***
	(0.098)	(0.010)
Policy × Cohort FE	✓	✓
Observations	13,793,212	13,793,171
R-squared	0.29	0.29

Table 3: Premium, Mandatory Charges, and Rejection Rate

The table examines the impact of hurricanes on premium, mandatory charges, and claim rejection rate. *Post* is an indicator variable that takes on a value of one for periods following a hurricane and zero otherwise. *Treated* is an indicator variable that takes a value of one for policies in counties experiencing a hurricane and zero otherwise. Standard errors are clustered at the county-level, and are shown in parentheses. ***, **, and * represent result significant at 1%, 5%, and 10% level, respectively.

	Δln(Premium)	Δln(Mandatory charges)	$\Delta(\frac{\text{Premium}}{\text{Coverage}})$	$\Delta(\frac{\text{Mandatory charges}}{\text{Coverage}})$	Rejection Rate	$\mathbb{1}(Rejection)$
	I	II	III	IV	V	VI
$Post_t$	0.013	0.038	0.008	0.001	0.020*	0.015
	(0.014)	(0.051)	(0.011)	(0.002)	(0.010)	(0.010)
$Post_t \times Treated_p$	0.067***	0.100	0.064***	0.010***	-0.040***	-0.035***
	(0.014)	(0.060)	(0.013)	(0.001)	(0.012)	(0.013)
Policy × Cohort FE	✓	✓	✓	✓	✓	✓
Observations	10,088,100	10,088,100	10,040,590	10,040,590	275,982	275,982
R-squared	0.29	0.18	0.27	0.17	0.50	0.50

Table 4: Heterogeneity by Income

The table examines the impact of hurricanes on premiums, mandatory charges, and claim rejection rates in low-income and high-income areas. *Post* is an indicator variable that takes on a value of one for periods following a hurricane and zero otherwise. *Treated* is an indicator variable that takes a value of one for policies in counties experiencing a hurricane and zero otherwise. Standard errors are clustered at the county-level, and are shown in parentheses. ***, **, and * represent result significant at 1%, 5%, and 10% level, respectively.

	Income Low			Income High		
	Δln(Premium)	Δln(Mandatory charges)	Rejection Rate	Δln(Premium)	Δln(Mandatory charges)	Rejection Rate
	I	II	III	IV	V	VI
$Post_t$	-0.029*	-0.090	0.039***	0.040***	0.125***	-0.008
	(0.014)	(0.062)	(0.005)	(0.009)	(0.028)	(0.018)
$Post_t \times Treated_p$	0.113***	0.008	-0.047***	0.036***	0.119***	-0.037*
	(0.016)	(0.118)	(0.012)	(0.013)	(0.043)	(0.020)
Policy × Cohort FE	✓	✓	✓	✓	✓	✓
Observations	4,300,618	4,300,618	165,993	5,602,322	5,602,322	98,961
R-squared	0.25	0.15	0.49	0.35	0.22	0.51

Table 5: Heterogeneity by Private Market Surplus

The table examines the impact of hurricanes on premiums, mandatory charges, and claim rejection rates in periods with increasing and decreasing surplus for private insurers in the region. *Post* is an indicator variable that takes on a value of one for periods following a hurricane and zero otherwise. *Treated* is an indicator variable that takes a value of one for policies in counties experiencing a hurricane and zero otherwise. Standard errors are clustered at the county-level, and are shown in parentheses. ***, **, and * represent result significant at 1%, 5%, and 10% level, respectively.

	Surplus Increasing			Surplus Decreasing		
	Δln(Premium)	Δln(Mandatory charges)	Rejection Rate	Δln(Premium)	Δln(Mandatory charges)	Rejection Rate
	I	II	III	IV	V	VI
$Post_t$	-0.027	-0.094	0.039***	0.058***	0.188***	-0.008
	(0.021)	(0.075)	(0.011)	(0.007)	(0.015)	(0.013)
$Post_t \times Treated_p$	0.101***	-0.348***	-0.038***	0.023**	0.104**	-0.040**
	(0.021)	(0.077)	(0.013)	(0.011)	(0.041)	(0.019)
Policy × Cohort FE	✓	✓	✓	✓	✓	✓
Observations	5,362,097	5,362,097	175,143	4,726,003	4,726,003	100,839
R-squared	0.27	0.15	0.50	0.31	0.25	0.51

Table 6: Coverage, hurricane deductible, litigation, and appraisal rate

The table examines the impact of hurricanes on coverage, hurricane deductible, litigation, and appraisal rate. *Post* is an indicator variable that takes on a value of one for periods following a hurricane and zero otherwise. *Treated* is an indicator variable that takes a value of one for policies in counties experiencing a hurricane and zero otherwise. Standard errors are clustered at the county-level, and are shown in parentheses. ***, **, and * represent result significant at 1%, 5%, and 10% level, respectively.

	Δln(Coverage)	Δln(Deductable)	Δ(Deductable/Coverage)	Litigation Rate	Appraisal Rate
	I	II	III	IV	V
$Post_t$	0.011**	0.010**	0.003	0.011	0.025
	(0.004)	(0.004)	(0.002)	(0.013)	(0.021)
$Post_t \times Treated_p$	0.021***	0.018***	0.014*	-0.002	0.030**
	(0.006)	(0.005)	(0.007)	(0.004)	(0.013)
Policy × Cohort FE	✓	✓	✓	✓	✓
Observations	10,040,590	8,898,157	9,041,808	275,982	275,982
R-squared	0.30	0.31	0.07	0.58	0.52

Table 7: Coverage, hurricane deductible, litigation, and appraisal rate: Heterogeneity by Income

The table examines the impact of hurricanes on coverage, hurricane deductible, litigation, and appraisal rate in low-income and high-income areas. *Post* is an indicator variable that takes on a value of one for periods following a hurricane and zero otherwise. *Treated* is an indicator variable that takes a value of one for policies in counties experiencing a hurricane and zero otherwise. Standard errors are clustered at the county-level, and are shown in parentheses. ***, **, and * represent result significant at 1%, 5%, and 10% level, respectively.

	Income Low					Income High				
	$\Delta\ln$(Coverage)	$\Delta\ln$(Deductable)	Δ(Deductable/Coverage)	Litigation Rate	Appraisal Rate	$\Delta\ln$(Coverage)	$\Delta\ln$(Deductable)	Δ(Deductable/Coverage)	Litigation Rate	Appraisal Rate
	I	II	III	IV	V	VI	VII	VIII	IX	X
$Post_t$	0.001	-0.000	-0.000	0.025**	0.042*	0.018***	0.016***	0.005	-0.011	0.002
	(0.004)	(0.004)	(0.003)	(0.012)	(0.023)	(0.003)	(0.003)	(0.003)	(0.007)	(0.012)
$Post_t \times Treated_p$	0.038***	0.035***	0.008*	-0.004	0.015	0.011*	0.009***	0.016	-0.007	0.053***
	(0.006)	(0.007)	(0.004)	(0.004)	(0.013)	(0.007)	(0.004)	(0.011)	(0.007)	(0.011)
Policy × Cohort FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	4,310,733	3,711,406	3,763,455	165,993	165,993	5,545,681	5,029,292	5,118,281	98,961	98,961
R-squared	0.29	0.30	0.28	0.57	0.52	0.31	0.33	0.06	0.60	0.52

Table 8: Demand Estimation Results: Price Elasticity Heterogeneity

This table reports estimation results for the demand model with heterogeneous price elasticities. The first column reports results without using an instrumental variable for prices, the second column uses the log loss ratio instrument, the third column uses the level of the loss ratio instrument, and the fourth column uses the leave-one-out price. Heteroscedasticity-robust standard errors are reported in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

	Dependent Variable: log market share$_{j\ell t}$			
	No IV	Loss Ratio (Log)	Loss Ratio (Level)	Leave-One-Out
price$_{j\ell t}$	−0.081***	−0.170***	−0.138**	−0.092***
	(0.021)	(0.026)	(0.055)	(0.024)
price$_{j\ell t}$ × $\mathbf{1}\{\text{high-income}\}_\ell$	0.022	0.131**	0.060	0.042
	(0.044)	(0.056)	(0.088)	(0.046)
rejection rate$_{j\ell t}$	−0.526***	−0.584***	−0.585***	−0.532***
	(0.193)	(0.201)	(0.203)	(0.194)
$\mathbf{1}\{\text{Citizens}\}_j$	2.808***	2.737***	2.812***	2.810***
	(0.165)	(0.168)	(0.177)	(0.164)
County-Year FE	✓	✓	✓	✓
Observations	1149	1029	1023	1149
1st stage F		705.76	7.88	260.08
R-squared	0.38	0.21	0.22	0.20

Table 9: Demand Estimation Results: No Heterogeneity

This table reports estimation results for the demand model with no heterogeneity. The first column reports results without using an instrumental variable for prices, the second column uses the log loss ratio instrument, the third column uses the level of the loss ratio instrument, and the fourth column uses the leave-one-out price. Heteroscedasticity-robust standard errors are reported in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

	Dependent Variable: $\log$ market share$_{j\ell t}$			
	No IV	Loss Ratio (Log)	Loss Ratio (Level)	Leave-One-Out
price$_{j\ell t}$	−0.073***	−0.123***	−0.129***	−0.079***
	(0.019)	(0.023)	(0.048)	(0.020)
rejection rate$_{j\ell t}$	−0.521***	−0.555***	−0.577***	−0.524***
	(0.193)	(0.200)	(0.203)	(0.194)
$\mathbf{1}\{\text{Citizens}\}_j$	2.810***	2.752***	2.828***	2.816***
	(0.165)	(0.170)	(0.178)	(0.165)
County-Year FE	✓	✓	✓	✓
Observations	1149	1029	1023	1149
1st stage F		1754.60	159.69	805.49
R-squared	0.38	0.22	0.22	0.20

Table 10: Demand Estimation Results: Full Heterogeneity

This table reports estimation results for the demand model with heterogeneous price elasticities, heterogeneous rejection rate elasticities, and heterogeneous preferences for Citizens. The first column reports results without using an instrumental variable for prices, the second column uses the log loss ratio instrument, the third column uses the level of the loss ratio instrument, and the fourth column uses the leave-one-out price. Heteroscedasticity-robust standard errors are reported in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

	Dependent Variable: log market share$_{j\ell t}$			
	No IV	Loss Ratio (Log)	Loss Ratio (Level)	Leave-One-Out
price$_{j\ell t}$	−0.077***	−0.154***	−0.124**	−0.087***
	(0.022)	(0.025)	(0.054)	(0.025)
price$_{j\ell t}$ × $\mathbf{1}$\{high-income\}$_\ell$	0.003	0.086	0.024	0.021
	(0.042)	(0.053)	(0.084)	(0.043)
rejection rate$_{j\ell t}$	−0.651***	−0.693***	−0.706***	−0.660***
	(0.250)	(0.263)	(0.269)	(0.251)
rejection rate$_{j\ell t}$ × $\mathbf{1}$\{high-income\}$_\ell$	0.246	0.226	0.252	0.254
	(0.389)	(0.404)	(0.407)	(0.390)
$\mathbf{1}$\{Citizens\}$_j$	2.229***	2.162***	2.239***	2.237***
	(0.186)	(0.191)	(0.202)	(0.186)
$\mathbf{1}$\{Citizens\}$_j$ × $\mathbf{1}$\{high-income\}$_\ell$	1.526***	1.499***	1.487***	1.509***
	(0.333)	(0.340)	(0.361)	(0.333)
County-Year FE	✓	✓	✓	✓
Observations	1149	1029	1023	1149
1st stage F		510.92	7.46	258.47
R-squared	0.39	0.23	0.24	0.22

Beyond the Storm: Climate Risk and Homeowners' Insurance

Appendix for Online Publication

A Determinants of insurance premium

To better understand the insurer's pricing function, we analyze a hedonic model for premiums. Risk-based pricing suggests that premiums should increase with coverage, as higher coverage raises the insurer's financial risk, expected losses, and capital requirements. Motivated by this, we begin by plotting premiums against coverage to examine the nature of their relationship and find a strong linear relationship as shown in panel (a) of Figure C.2. Panel (b) plots mandatory charges against coverage and exhibits a similar linear relationship.

Given this visual evidence, we formally evaluate the relationship using a simple ordinary least squares (OLS) model. Table C.3 presents the results. Column I shows that premiums are primarily driven by coverage amounts, with coverage alone explaining 55% of the variation in premiums, highlighting its dominant role in pricing. Adding property fixed effects increases the R-squared to 89%, suggesting that property-level time-invariant characteristics account for a significant portion of the variation in premiums. Surprisingly, time trends contribute only 2% to the explained variation.

On the other hand, property-level characteristics and coverage together explain only 76% of the variation in mandatory charges, with property-level characteristics having greater explanatory power, as shown in columns IV through VI. Specifically, we find that coverage amounts account for 37% of the variation in mandatory charges, while property-specific characteristics—such as location and structural attributes—explain approximately 39%. Additionally, aggregate time-series factors contribute 14% to the variation in mandatory charges.

Overall, these findings underscore the dominant role of policy-level factors, such as coverage and property characteristics, in determining total policy costs and suggest that risk appropriately plays a significant role in the insurer's pricing function.

B Model Proofs

B.1 Proof of Lemma 1

Begin by substituting in the expression (3) into the profit function (2). Differentiating with respect to $p_{\ell t}$, the first order condition is

$$Q_{\ell t} - \varepsilon_\ell (p_{\ell t} - (1 - \varsigma_\ell) l_{\ell t}) \frac{Q_{\ell t}}{p_{\ell t}} - F'(K_t) \left[Q_{\ell t} - \varepsilon_\ell (p_{\ell t} - \phi l_{\ell t}) \frac{Q_{\ell t}}{p_{\ell t}} \right] = 0$$

Let $\lambda_t \equiv -F'(K_t) > 0$. Divide through by $Q_{\ell t}$, multiply through by $p_{\ell t}$, and collect terms around $p_{\ell t}$ and $l_{\ell t}$ to get

$$-(1 + \lambda)(\varepsilon_\ell - 1) p_{\ell t} + \varepsilon_\ell (1 - \varsigma + \phi \lambda) l_{\ell t} = 0$$

Rearranging, this gives the desired expression:

$$\frac{p_{\ell t}}{l_{\ell t}} = \left(\frac{\varepsilon_\ell}{\varepsilon_\ell - 1} \right) \left(\frac{1 + \phi \lambda_t}{1 + \lambda_t} \right) - \left(\frac{\varepsilon_\ell \varsigma_\ell}{(\varepsilon_\ell - 1)(1 + \lambda_t)} \right) \equiv \mathcal{M}_\ell(\lambda_t).$$

The last statement follows by setting $\lambda_t = 0$ and noting that

$$\mathcal{M}_\ell(0) = \frac{\varepsilon_\ell}{\varepsilon_\ell - 1}(1 - \varsigma_\ell) = \frac{1 - \varsigma_\ell}{1 - \varepsilon_\ell^{-1}}.$$

If $\varsigma_\ell = \varepsilon_\ell^{-1}$, this expression is equal to 1. □

B.2 Proof of Proposition 1

This set of results follows directly from the pricing equation (8). First, conditional on equivalent financial returns across periods, we rely on the following lemma which we prove at the end of this appendix in Section B.7.

Lemma 5: Claims Shocks and Statutory Capital

Consider two sets of shocks, $\mathbf{C}_t^1 = \{C_{\ell t}^1\}_{\ell \in \mathscr{L}}$ *and* $\mathbf{C}_t^2 = \{C_{\ell t}^2\}_{\ell \in \mathscr{L}}$*, such that* $C_{\ell t}^1 \leq C_{\ell t}^2$ *for all* ℓ *and a strict inequality for at least one* ℓ*. If financial returns are equivalent across the two scenarios, then* $K_t^2 < K_t^1$*.*

Lemma 5 therefore implies that $d\lambda_t \equiv \lambda_t^2 - \lambda_t^1 > 0$ since $-F'(K_t)$ is decreasing in K_t. Since $\mathcal{M}_\ell(\lambda_t)$ is increasing in λ_t for all $\ell \in \mathscr{L}$, it follows that $\mathcal{M}'(\lambda_t)d\lambda_t > 0$. Further, since $dl_{\ell t} \geq 0$ (since $C_{\ell t}^2 \geq C_{\ell t}^1$ for all t and $l_{\ell t}$ is increasing in $C_{\ell t}$), it follows that $dp_{\ell t} = \mathcal{M}_\ell'(\lambda_t)d\lambda_t l_{\ell t} + \mathcal{M}_\ell(\lambda_t)dl_{\ell t} > 0$ for all ℓ. This proves claim 1.

The second claim follows in a straightforward way. If $\varepsilon_{\ell_1} = \varepsilon_{\ell_2}$ for two locations $\ell_1, \ell_2 \in \mathscr{L}$, then $\mathcal{M}_{\ell_1}(\lambda_t) = \mathcal{M}_{\ell_2}(\lambda_t)$ for all λ_t. Therefore, if $l_{\ell_1 t}^1 = l_{\ell_2 t}^2$, then

$$\begin{aligned}
\Delta p_{\ell_2 t} &= (\mathcal{M}_{\ell_2}(\lambda_t^2) - \mathcal{M}_{\ell_2}(\lambda_t^1))l_{\ell_2 t}^1 + \mathcal{M}_{\ell_2}(\lambda_t^2)(l_{\ell_2 t}^2 - l_{\ell_2 t}^1) \\
&\underset{(1)}{=} (\mathcal{M}_{\ell_1}(\lambda_t^2) - \mathcal{M}_{\ell_1}(\lambda_t^1))l_{\ell_1 t}^1 + \mathcal{M}_{\ell_1}(\lambda_t^2)(l_{\ell_2 t}^2 - l_{\ell_2 t}^1) \\
&\underset{(2)}{>} (\mathcal{M}_{\ell_1}(\lambda_t^2) - \mathcal{M}_{\ell_1}(\lambda_t^1))l_{\ell_1 t}^1 + \mathcal{M}_{\ell_1}(\lambda_t^2)(l_{\ell_1 t}^2 - l_{\ell_1 t}^1) \\
&= \Delta p_{\ell_1 t}.
\end{aligned}$$

The first line (1) follows from equivalence of markups across the two locations, and the second line (2) follows from the assumption that $\Delta l_{\ell_2 t} > \Delta l_{\ell_1 t}$.

The third claim is shown in a similar way to the second claim. Assume now that $\Delta l_{\ell_2 t} = \Delta l_{\ell_1 t}$ but $\varepsilon_{\ell_1} > \varepsilon_{\ell_2}$. Note that

$$\frac{\partial^2 \mathcal{M}}{\partial \lambda \partial \varepsilon} = \frac{\partial}{\partial \varepsilon}\left[\left(\frac{\varepsilon}{\varepsilon - 1}\right)\left(\frac{\phi + \varsigma - 1}{(1+\lambda)^2}\right)\right] = -\left(\frac{1}{\varepsilon - 1}\right)^2\left(\frac{\phi + \varsigma - 1}{(1+\lambda)^2}\right) + \left(\frac{\varepsilon}{\varepsilon - 1}\right)(1+\lambda)^{-2}\frac{\partial \varsigma}{\partial \varepsilon} < 0.$$

since $\partial\varsigma/\partial\varepsilon = -\varepsilon^{-2} < 0$. This implies that the markup response to an increase in financial frictions λ is weaker for high elasticity locations. Therefore, we have that

$$\begin{aligned}\Delta p_{\ell_2 t} &= (\mathcal{M}_{\ell_2}(\lambda_t^2) - \mathcal{M}_{\ell_2}(\lambda_t^1)) l_{\ell_2 t}^1 + \mathcal{M}_{\ell_2}(\lambda_t^2)(l_{\ell_2 t}^2 - l_{\ell_2 t}^1) \\ &\underset{(1)}{=} (\mathcal{M}_{\ell_2}(\lambda_t^2) - \mathcal{M}_{\ell_2}(\lambda_t^1)) l_{\ell_1 t}^1 + \mathcal{M}_{\ell_2}(\lambda_t^2)(l_{\ell_1 t}^2 - l_{\ell_1 t}^1) \\ &\underset{(2)}{>} (\mathcal{M}_{\ell_1}(\lambda_t^2) - \mathcal{M}_{\ell_1}(\lambda_t^1)) l_{\ell_1 t}^1 + \mathcal{M}_{\ell_1}(\lambda_t^2)(l_{\ell_1 t}^2 - l_{\ell_1 t}^1) \\ &= \Delta p_{\ell_1 t}.\end{aligned}$$

where now, line (1) follows from the fact that $l_{\ell_1 t}^1 = l_{\ell_2 t}^1$ and $dl_{\ell_1 t} = dl_{\ell_2 t}$ and line (2) follows from the fact that $\mathcal{M}_{\ell_2}(\lambda_t) > \mathcal{M}_{\ell_1}(\lambda_t)$ for all λ_t and from the second derivative computed above. This completes the proof. □

B.3 Proof of Lemma 2

The first part of the proof follows directly from (7). Solving for $x_{\ell t}$, we have

$$x_{\ell t} = (\tau')^{-1}\left(-\frac{\lambda_t [1 - \kappa \alpha(C_{\ell t})] C_{\ell t}}{\pi_{\ell t}^E(\lambda_t) + \lambda_t \pi_{\ell t}^R(\lambda_t)} \right).$$

Therefore, $\chi(y) = (\tau')^{-1}(-y)$. To prove the remaining claims, note that we can write $\tau'(\chi(y)) = -y$. Differentiating with respect to y, we have

$$\tau''(\chi(y))\chi'(y) = -1 \qquad \iff \qquad \chi'(y) = -\frac{1}{\tau''(\chi(y))} > 0.$$

The final line of the expression holds true due to the strict concavity of $\tau(y)$. Differentiating again, we have that

$$\chi''(y) = \frac{\chi'(y)\tau'''(\chi(y))}{(\tau''(\chi(y))^2} > 0$$

since $\tau'''(y) > 0$. This completes the proof. □

B.4 Proof of Lemma 3

Given the assumption that $\Delta C_{\ell t} = 0$, it will be sufficient to show that $x_{\ell t}$ is increasing in λ_t. Differentiating, we have

$$\frac{\partial x_{\ell t}}{\partial \lambda_t} = \chi'(\cdot) \times [1 - \kappa\alpha(C_{\ell t})]C_{\ell t} \times \frac{\partial}{\partial \lambda_t}\left[\frac{\lambda_t}{\pi^E_{\ell t}(\lambda_t) + \lambda_t \pi^R_{\ell t}(\lambda_t)}\right].$$

Since the first two terms are positive, the sign of $\partial x_{\ell t}/\partial \lambda_t$ will depend on the final term. It will be useful to make note of a few simplifications before differentiating. First, note that we can substitute the expressions (6) into the third term to get

$$\frac{\lambda_t}{(\mathcal{M}_\ell(\lambda_t) - 1 + \varsigma_\ell)A_\ell \mathcal{M}_\ell(\lambda_t)^{-\varepsilon_\ell} + \lambda_t(\mathcal{M}_\ell(\lambda_t) - \phi)A_\ell \mathcal{M}_\ell(\lambda_t)^{-\varepsilon_\ell}} = \frac{A_\ell^{-1}\lambda_t \mathcal{M}(\lambda_t)^{\varepsilon_\ell}}{(1+\lambda)\mathcal{M}_\ell(\lambda_t) - \lambda\phi - 1 + \varsigma_\ell}$$

Next, take logs and differentiate with respect to λ_t. This gives

$$\text{(C.1)} \qquad \frac{1}{\lambda_t} + \varepsilon_\ell \frac{\mathcal{M}'_\ell(\lambda_t)}{\mathcal{M}_\ell(\lambda_t)} - \left(\frac{(1+\lambda)\mathcal{M}'_\ell(\lambda_t) + \mathcal{M}_\ell(\lambda_t) - \phi}{(1+\lambda)\mathcal{M}_\ell(\lambda_t) - \lambda\phi - 1 + \varsigma_\ell}\right).$$

We now need to simplify the third term. Recall the relevant expressions

$$\mathcal{M}_\ell(\lambda_t) = \frac{\varepsilon_\ell(1 - \varsigma_\ell + \phi\lambda)}{(\varepsilon_\ell - 1)(1+\lambda)}, \qquad \mathcal{M}'_\ell(\lambda_t) = \frac{\varepsilon_\ell(\phi + \varsigma_\ell - 1)}{(\varepsilon_\ell - 1)(1+\lambda)^2}.$$

Then the numerator in the third term can be written

$$\begin{aligned}
&(1+\lambda)\mathcal{M}'_\ell(\lambda_t) + \mathcal{M}_\ell(\lambda_t) - \phi \\
&= (\varepsilon_\ell - 1)^{-1}(1+\lambda)^{-1}\Big[\varepsilon_\ell(\phi + \varsigma_\ell - 1) + \varepsilon_\ell(1 - \varsigma_\ell + \phi\lambda) - \phi(\varepsilon_\ell - 1)(1+\lambda)\Big] \\
&= (\varepsilon_\ell - 1)^{-1}(1+\lambda)^{-1}\Big[(1+\lambda)\varepsilon_\ell\phi - (1+\lambda)\varepsilon_\ell\phi + (1+\lambda)\phi\Big] \\
&= \frac{\phi}{\varepsilon_\ell - 1}.
\end{aligned}$$

Turning to the denominator, we have

$$\begin{aligned}
&(1+\lambda)\mathcal{M}_\ell(\lambda_t) - \lambda\phi - 1 + \varsigma_\ell \\
&= (\varepsilon_\ell - 1)^{-1}\Big[\varepsilon_\ell(\phi\lambda + 1 - \varsigma_\ell) - (\varepsilon_\ell - 1)(\phi\lambda + 1 - \varsigma_\ell)\Big] \\
&= \frac{\phi\lambda + 1 - \varsigma_\ell}{\varepsilon_\ell - 1}.
\end{aligned}$$

Putting the two together, we end up with

$$\frac{(1+\lambda)\mathcal{M}'_\ell(\lambda_t) + \mathcal{M}_\ell(\lambda_t) - \phi}{(1+\lambda)\mathcal{M}_\ell(\lambda_t) - \lambda\phi - 1 + \varsigma_\ell} = \frac{\phi}{\phi\lambda + 1 - \varsigma_\ell} = \frac{1}{\lambda + (1-\varsigma_\ell)/\phi} < \frac{1}{\lambda}.$$

Therefore, we can now express (C.1) as

$$\frac{1}{\lambda} - \frac{1}{\lambda + (1-\varsigma_\ell)/\phi} + \varepsilon_\ell \frac{\phi - (1-\varsigma_\ell)}{(1+\lambda)(\phi\lambda + 1 - \varsigma_\ell)} > 0.$$

Finally, note that since for a given function $f(x)$, it's true that $d\log f(x) = df(x)/f(x)$, we have that

$$\frac{\partial}{\partial\lambda_t}\left[\frac{\lambda_t}{\pi^E_{\ell t}(\lambda_t) + \lambda_t\pi^R_{\ell t}(\lambda_t)}\right] = \frac{\partial}{\partial\lambda_t}\left[\log\left(\frac{\lambda_t}{\pi^E_{\ell t}(\lambda_t) + \lambda_t\pi^R_{\ell t}(\lambda_t)}\right)\right] \times \frac{\lambda_t}{\pi^E_{\ell t}(\lambda_t) + \lambda_t\pi^R_{\ell t}(\lambda_t)} > 0.$$

Therefore, $x_{\ell t}$ is strictly increasing in λ_t, so $x^2_{\ell t} > x^1_{\ell t}$ for all ℓ such that $\Delta C_{\ell t} = 0$. □

B.5 Proof of Lemma 4

We begin by noting that $1 - \kappa\alpha(C) \to 1 - \kappa < 0$ as $C \to \infty$. Therefore, when C is large enough, it is impossible for Citizens to recoup any money through rejections since they will always expect to pay more in litigation than they would expect to save. By continuity, there must exit some threshold $\overline{C} > 0$ such that $1 - \kappa\alpha(\overline{C}) = 0$. If $[1 - \kappa\alpha(C)]C$ is declining at $\overline{C}$, then it must be that for $C_{\ell t} \geq \overline{C}$, $x_{\ell t} = 0$. To check this, we can take a derivative with respect to $C_{\ell t}$:

$$\frac{\partial[(1-\kappa\alpha(C_{\ell t}))C_{\ell t}]}{\partial C_{\ell t}} = 1-\kappa\alpha(C_{\ell t})-\kappa\alpha'(C_{\ell t})C_{\ell t}. \tag{C.2}$$

Since $1-\kappa\alpha(\overline{C})=0$, it follows that evaluating (C.2) at $C_{\ell t}=\overline{C}$ returns $-\kappa\alpha'(\overline{C})\overline{C}<0$. Therefore, the claim above holds.

Next, note that at $C_{\ell t}=0$, (C.2) evaluates to 1 as long as $\lim_{C\to 0}\alpha'(C)C=0$, which will be the case if $\alpha(\cdot)$ does not have an Inada condition. Therefore, by the continuity of (C.2), there must be some $C^*\in(0,\overline{C})$ such that (C.2) is equal to 0. To verify that this is a unique maximum, we need to check that $[1-\kappa\alpha(C)]C$ is strictly concave on the interval $(0,\overline{C})$. Since

$$\frac{\partial^2[(1-\kappa\alpha(C_{\ell t}))C_{\ell t}]}{\partial C_{\ell t}^2} = -2\kappa\alpha'(C_{\ell t})-\kappa\alpha''(C_{\ell t})C_{\ell t}<0$$

by our restriction on $\alpha(\cdot)$, we have that C^* must be a unique maximum and that $[1-\kappa\alpha(C)]C$ is increasing on the interval $(0,C^*)$ and decreasing on the interval $(C^*,\overline{C})$. To complete the proof, note that

$$\frac{\partial x_{\ell t}}{\partial C_{\ell t}} = \frac{\lambda_t\chi'(\cdot)}{\pi^E_{\ell t}(\lambda_t)+\lambda_t\pi^R_{\ell t}(\lambda_t)} \times \frac{\partial[(1-\kappa\alpha(C_{\ell t}))C_{\ell t}]}{\partial C_{\ell t}}$$

It therefore follows that the behavior of $x_{\ell t}$ is governed by the behavior of $[1-\kappa\alpha(C_{\ell t})]C_{\ell t}$.

□

B.6 Proof of Proposition 2

It will be useful to start with a general expression for $\Delta x_{\ell t}$. It will also be useful for the purpose of this proof to introduce some notation. Let

$$\Lambda_{\ell t} = \frac{\lambda_t}{\pi^E_{\ell t}(\lambda_t)+\lambda_t\pi^R_{\ell t}(\lambda_t)}, \qquad \gamma_{\ell t} = C_{\ell t}[1-\kappa\alpha(C_{\ell t})].$$

By the mean value theorem, there exists some value $z_{\ell t} \in (\Lambda^1_{\ell t}\gamma^1_{\ell t}, \Lambda^2_{\ell t}\gamma^2_{\ell t})$ such that

$$\begin{aligned}\Delta x_{\ell t} &= \chi'(z_{\ell t})\Big(\Lambda^2_{\ell t}\gamma^2_{\ell t} - \Lambda^1_{\ell t}\gamma^1_{\ell t}\Big) \\ &= \chi'(z_{\ell t})\Big(\Delta\Lambda_{\ell t}\gamma^2_{\ell t} - \Lambda^1_{\ell t}\Delta\gamma_{\ell t}\Big) \\ &= \chi'(z_{\ell t})\Big(\Delta\Lambda_{\ell t}\gamma^1_{\ell t} - \Lambda^2_{\ell t}\Delta\gamma_{\ell t}\Big).\end{aligned}$$

We now turn to the primary parts of the proof.

Proof of Statement 1

When $\Delta C_{\ell t} = 0$, it is also true that $\Delta\gamma_{\ell t} = 0$. Therefore, we have

$$\Delta x_{\ell t} = \chi'(z_{\ell t})\Delta\Lambda_{\ell t}\gamma^1_{\ell t} > 0,$$

which holds since, by Lemma 3, $\Delta\Lambda_{\ell t} > 0$.

Proof of Statement 2

Note that when $\Delta C_{\ell t} > 0$, we can write

$$\Delta\gamma_{\ell t} = \gamma'(\overline{C}_{\ell t})\Delta C_{\ell t} < 0$$

As $\Delta C_{\ell t}$ increases, so does $\overline{C}_{\ell t}$ since $\gamma(\cdot)$ is concave. Therefore, $\Delta\gamma_{\ell t}$ is increasing in $\Delta C_{\ell t}$. If $\Delta C_{\ell t}$ is large enough such that

$$\Delta\gamma_{\ell t} > \frac{\Delta\Lambda_{\ell t}}{\Lambda^2_{\ell t}} \times \gamma^1_{\ell t}$$

then we have $\Delta x_{\ell t} < 0$.

Proof of Statement 3

Since we consider small claims shocks, we simply need to explore how the total differential of $x_{\ell t}$ changes with ε_ℓ. Note that we can adapt the expression (9) to read

$$dx_{\ell t} = \chi'(\Lambda_{\ell t}\gamma_{\ell t})\Lambda_{\ell t}\gamma_{\ell t}\left(\frac{\partial \log \Lambda_{\ell t}}{\partial \lambda_t} d\lambda_t + \frac{\partial \log \gamma_{\ell t}}{\partial C_{\ell t}} dC_{\ell t}\right).$$

We start with the case that $dC_{\ell t} = 0$. It is sufficient to prove that (i) $x_{\ell t}$ is increasing in $\varepsilon_{\ell t}$, since this would imply $\chi'(\cdot)$ is increasing; (ii) $\Lambda_{\ell t}$ is increasing in $\varepsilon_{\ell t}$, which we already argued in the main text; and (iii) $\partial_{\lambda\varepsilon} \log \Lambda_{\ell t} > 0$. We can use the expression derived in Section B.4 to shed light on (iii):

$$\begin{aligned}
&\frac{\partial}{\partial \varepsilon_\ell}\left[\frac{1}{\lambda} - \frac{\phi}{\phi\lambda + 1 - \varsigma_\ell} + \varepsilon_\ell \frac{\phi - (1-\varsigma_\ell)}{(1+\lambda)(\phi\lambda + 1 - \varsigma_\ell)}\right] \\
&= \frac{\phi}{(\phi\lambda + 1 - \varsigma_\ell)^2}\frac{1}{\varepsilon_\ell^2} + \frac{\phi - (1-\varsigma_\ell)}{(1+\lambda)(\phi\lambda + 1 - \varsigma_\ell)} - \frac{\phi}{\varepsilon_\ell(\phi\lambda + 1 - \varsigma_\ell)^2} \\
&= \frac{(1+\lambda)\phi + \varepsilon_\ell^2(\phi - 1 + \varsigma_\ell)(\phi\lambda + 1 - \varsigma_\ell) - \phi(1+\lambda)\varepsilon_\ell}{\varepsilon_\ell^2(1+\lambda)(\phi\lambda + 1 - \varsigma_\ell)^2} \\
&= \frac{[1 + \varepsilon_\ell^2(\phi - 1)]\phi\lambda + (\varepsilon_\ell - 1)^2(\phi - 1)}{\varepsilon_\ell^2(1+\lambda)(\phi\lambda + 1 - \varsigma_\ell)^2} \\
&> 0
\end{aligned}$$

Then since (ii) implies (i), we have that $dx_{\ell t} > 0$. This proves the $dC_{\ell t} = 0$ case.

Next, suppose instead that $dC_{\ell t} > 0$, and let $\Gamma(C_{\ell t}) \equiv -\partial_C \log \gamma_{\ell t}(C_{\ell t}) dC_{\ell t} > 0$. Since $\partial_\lambda \log \Lambda_{\ell t}$ is strictly increasing in ε_ℓ, it is bounded below by $\lim_{\varepsilon_\ell \to 1} \partial_\lambda \log \Lambda_{\ell t} = 1/\lambda_t(1+\lambda_t)$. Further, since $\varsigma_\ell \to 0$ as $\varepsilon_\ell \to \infty$, it follows that $\lim_{\varepsilon_\ell \to \infty} \partial_\lambda \log \Lambda_{\ell t} = \infty$.

First consider the case of $\varepsilon_\ell \to 1$. Since $\partial_\lambda \log \Lambda_{\ell t}$ diverges when $\lambda_t \to 0$ and converges to 0 as $\lambda_t \to \infty$, there exists a $\lambda^*(C_{\ell t})$ such that $1/\lambda^*(C_{\ell t})(1 + \lambda^*(C_{\ell t})) = \Gamma(C_{\ell t})/d\lambda_t$. Thus, for all $\lambda_t \leq \lambda^*(C_{\ell t})$, we have

$$dx_{\ell_2 t} > dx_{\ell_1 t} \geq 0.$$

Suppose now that $\lambda_t > \lambda^*(C_{\ell t})$. Then $dx_{\ell t} < 0$ for ℓ such that $\varepsilon_\ell \approx 1$. However, since $\partial_{\lambda\varepsilon} \log \Lambda_{\ell t} > 0$ and since $\lim_{\varepsilon_\ell \to \infty} \partial_\lambda \log \Lambda_{\ell t} = \infty$, there exists some $\varepsilon^*(C_{\ell t}, \lambda_t)$ such that $dx_{\ell t} = 0$ when $\varepsilon_\ell = \varepsilon^*(C_{\ell t}, \lambda_t)$ and $dx_{\ell_2 t} > 0$ when $\varepsilon_{\ell_2} > \varepsilon^*(C_{\ell t}, \lambda_t)$. Therefore, if $\varepsilon_{\ell_2} > \varepsilon^*(C_{\ell t}, \lambda_t)$ and $\varepsilon_{\ell_2} > \varepsilon_{\ell_1}$, we either have $dx_{\ell_2 t} > 0 > dx_{\ell_1 t}$ or $dx_{\ell_2 t} > dx_{\ell_1 t} > 0$. This completes the proof. □

B.7 Proof of Lemma 5

Let $v(\mathbf{C}_t)$ denote the value function associated with Citizens' objective function (2). Differentiating with respect to $C_{\ell t}$, we have

$$\frac{\partial v(\mathbf{C}_t)}{\partial C_{\ell t}} = \lambda_t \Big[-(1 - x^*_{\ell t}) - x^*_{\ell t} \kappa(\alpha'(C_{\ell t}) C_{\ell t} + \alpha(C_{\ell t})) \Big] < 0.$$

where $x^*_{\ell t}$ is the optimal rejection rate in location ℓ given a set of claims shocks, $\mathbf{C}_t$. Therefore, since $\Delta C_{\ell t} \geq 0$ for all ℓ and $\Delta C_{\ell t} > 0$ for a subset of $\mathscr{L}$, we must have

$$v(\mathbf{C}_t^2) - v(\mathbf{C}_t^1) = \sum_{\ell \in \mathscr{L}} \frac{\partial v(\overline{\mathbf{C}}_t)}{\partial C_{\ell t}} \Delta C_{\ell t} < 0,$$

where $\overline{\mathbf{C}}_t = \beta \mathbf{C}_t^1 + (1-\beta)\mathbf{C}_t^2$ for some value $\beta \in (0,1)$ that satisfies the multivariate mean value theorem.

Now suppose by way of contradiction that the claim is not true, so that $K_t^2 \geq K_t^1$. Then $\lambda_t^2 \leq \lambda_t^1$ and, therefore, $\mathcal{M}_{\ell t}(\lambda_t^2) < \mathcal{M}_{\ell t}(\lambda_t^1)$ for all t. This implies that $\pi^E_{\ell t}(\lambda_t^2) > \pi^E_{\ell t}(\lambda_t^1)$, since $\pi^E_{\ell t}$ is maximized at $\lambda_t = 0$. Next, note that since $\Delta \lambda_t \leq 0$, Lemma 3 and Lemma 4 imply that $\Delta x_{\ell t} \leq 0$ as well since $\Delta C_{\ell t} \geq 0$ for all ℓ. Therefore, $\tau(x^2_{\ell t}) > \tau(x^1_{\ell t})$ for all ℓ.

Writing out the value function explicitly, we have that

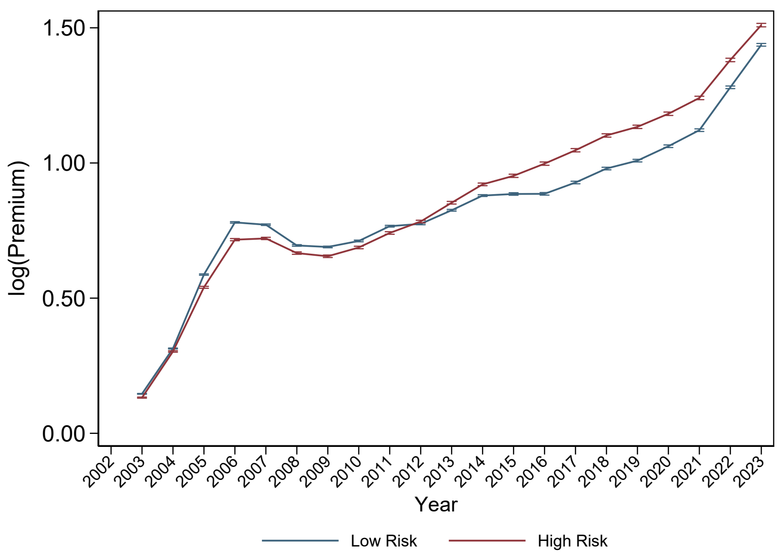
$$v(\mathbf{C}_t^1) = \sum_{\ell \in \mathscr{L}} \pi^E_{\ell t}(p^{1*}_{\ell t}) \tau(x^{1*}_{\ell t}) - F(K_t^1) < \sum_{\ell \in \mathscr{L}} \pi^E_{\ell t}(p^{2*}_{\ell t}) \tau(x^{2*}_{\ell t}) - F(K_t^2) = v(\mathbf{C}_t^2)$$

We have therefore reached a contradiction, and conclude that $K_t^2 < K_t^1$. □

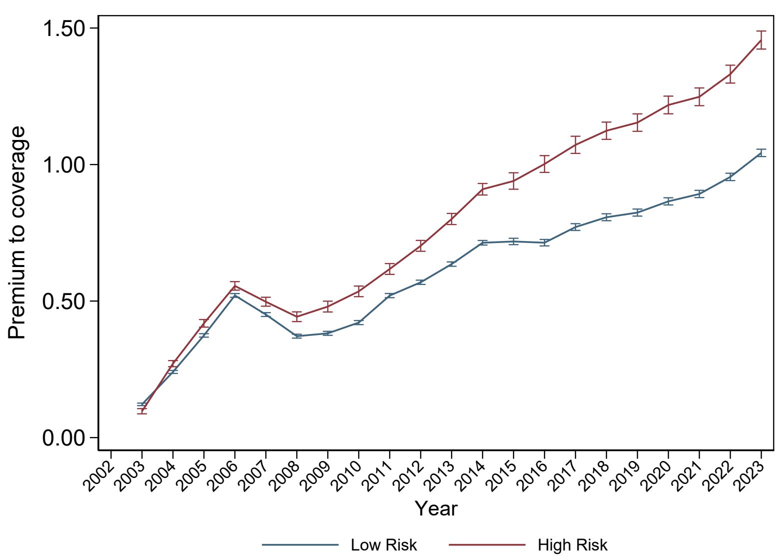
C Additional Figures and Tables

Figure C.1: Evolution of home insurance premiums

The figure shows the evolution of home insurance premiums over time by FEMA risk category.



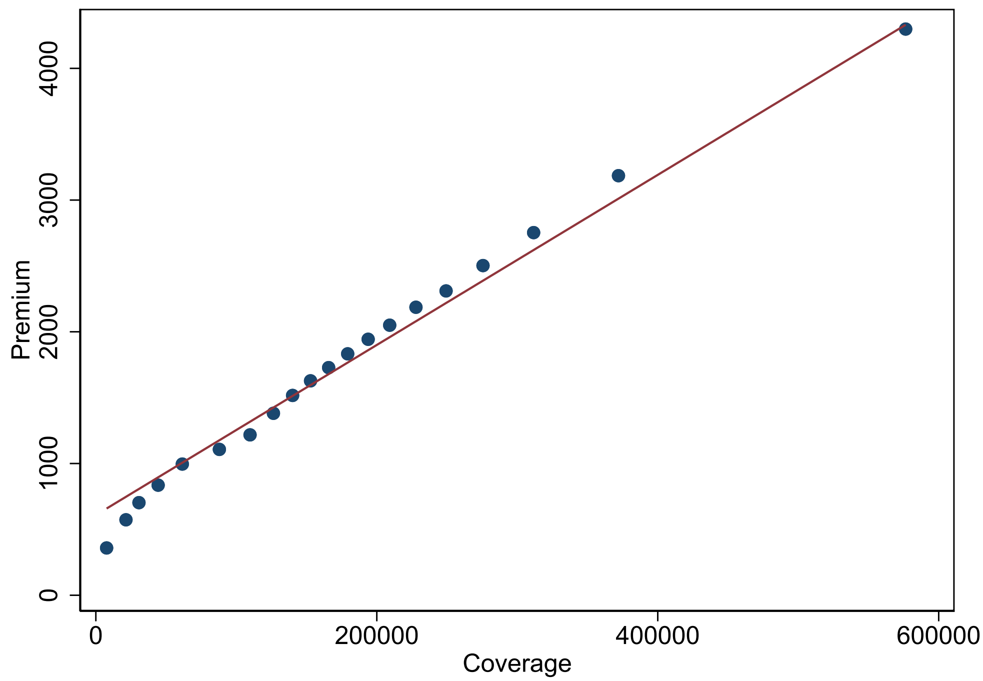
(a) Premium



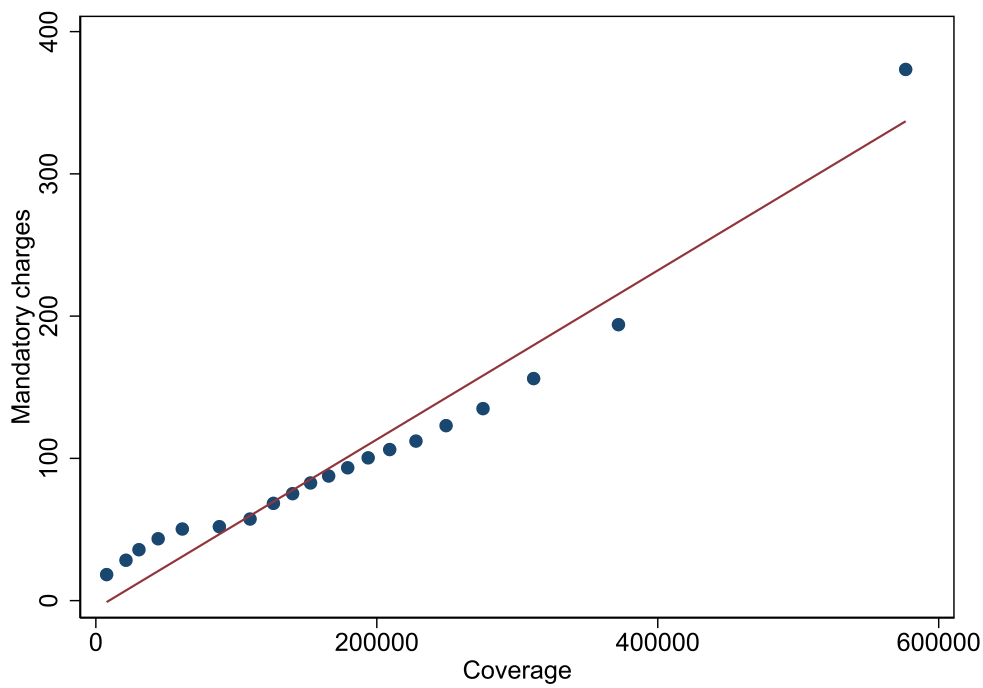
(b) Premium to coverage ratio

Figure C.2: Insurance premiums and coverage

The figure shows the relationship between home insurance premium and coverage in panel a and mandatory charges and coverage in panel b.



(a) Premium and coverage



(b) Mandatory charges and coverage

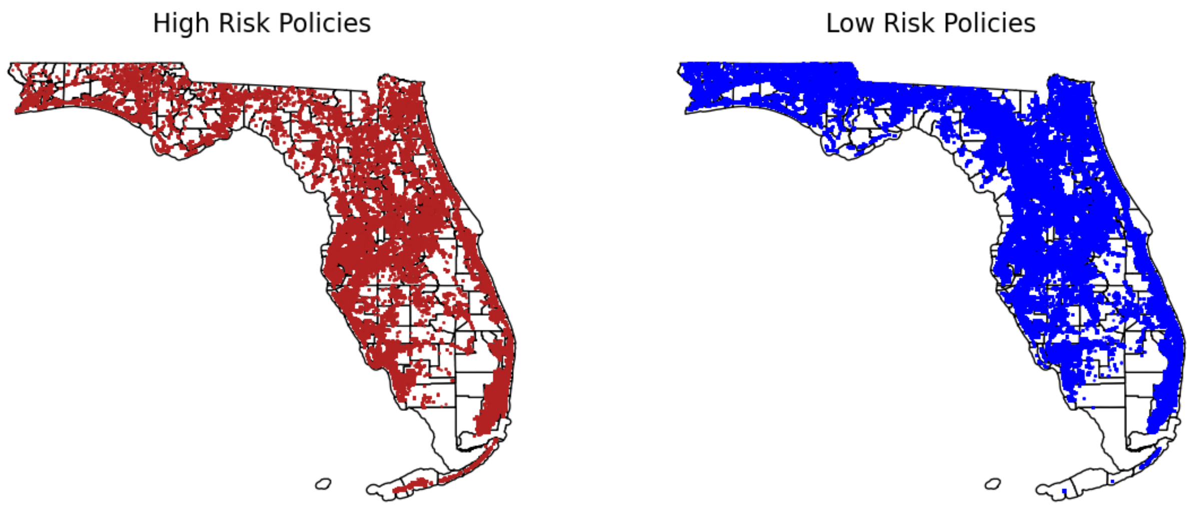
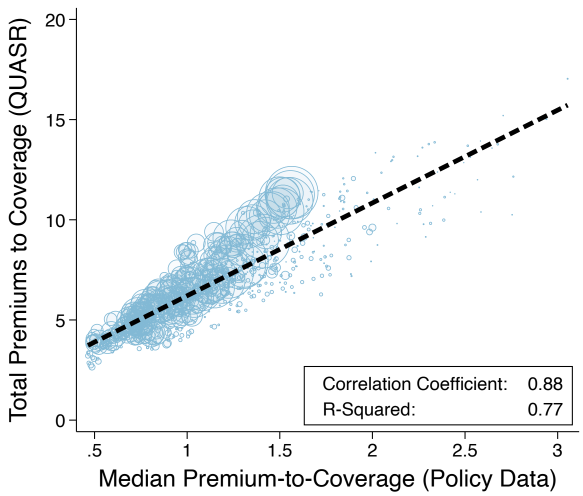
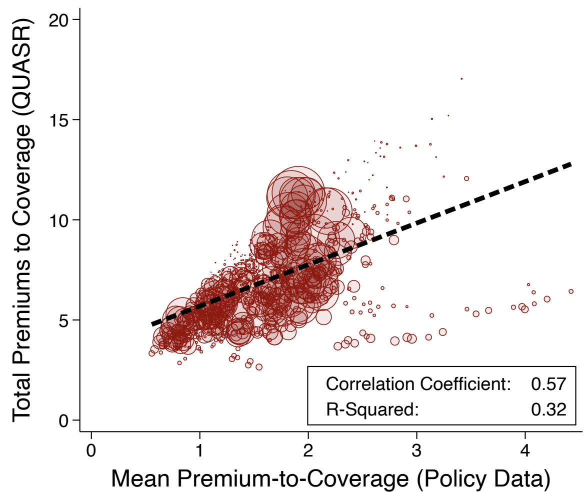


Figure C.3: Policies by FEMA risk

The figure shows the geographical distribution of policies by FEMA risk category



(a) Median



(b) Mean

Figure C.4: This figure plots Citizens' county-year total premium to total coverage ratio from QUASR against the county-year median [panel (a)] and mean [panel (b)] premium-to-coverage ratio taken from our policy-level data. The scatter plots are weighted by total insurance coverage in force at the county-year level.

Table C.1: Average premium by company in Florida

This table shows the average premium charged by companies for a Florida masonry home built in 2005, with current replacement value of $300,000, 2% hurricane deductible, and minimum premium discounts for limited wind mitigation features and no hip roof.

Company	**Average Premium ($)**
STILLWATER PROPERTY AND CASUALTY INSURANCE COMPANY	1601.87
TOWER HILL PRIME INSURANCE COMPANY	2169.94
TOWER HILL PREFERRED INSURANCE COMPANY	2302.63
CASTLE KEY INDEMNITY COMPANY	2618.18
FIRST PROTECTIVE INSURANCE COMPANY	2802.78
CITIZENS PROPERTY INSURANCE CORPORATION	3595.43
STATE FARM FLORIDA INSURANCE COMPANY	3783.90
FIRST COMMUNITY INSURANCE COMPANY	3800.00
ASI PREFERRED INSURANCE CORP	3861.19
UNIVERSAL PROPERTY & CASUALTY INSURANCE COMPANY	4034.72
LIBERTY MUTUAL FIRE INSURANCE COMPANY	4143.36
PEOPLE'S TRUST INSURANCE COMPANY	4505.46
FLORIDA FARM BUREAU CASUALTY INSURANCE COMPANY	4809.79
SOUTHERN OAK INSURANCE COMPANY	6162.97
SECURITY FIRST INSURANCE COMPANY	6210.99
AUTO CLUB INSURANCE COMPANY OF FLORIDA	8067.87

Source: Florida Office of Insurance Regulation

Table C.2: List of hurricane events

This table lists the hurricane events that took place during our sample period. The hurricane events are identified using Spatial Hazard Events and Losses Database for the United States (SHELDUS) dataset.

Year	Month	Hurricane/Tropical Storm	# Counties Impacted
2001	N/A	No event	N/A
2002	N/A	No event	N/A
2003	N/A	No event	N/A
2004	Aug	Charley	8
2004	Sep	Ivan, Frances, and Jeanne	30
2005	Jul	Dennis	10
2005	Aug	Katrina	4
2005	Oct	Wilma	5
2008	Aug	Fay	5
2008	Sep	Ike	1
2012	Aug	Isaac	1
2016	Sep	Hermine	2
2016	Oct	Matthew	7
2017	Sep	Irma	29
2018	Oct	Michael	10
2019	Sep	Dorian	1
2020	Sep	Sally	2
2022	Sep	Ian	8
2022	Nov	Nicole	2

Table C.3: Determinants of home insurance premium

The table examines the relation between home insurance premiums and house characteristics. Standard errors are clustered at the policy-level, and are shown in parentheses. ***, **, and * represent result significant at 1%, 5%, and 10% level, respectively.

	ln(Premium)			ln(Mandatory charges)		
	I	II	III	IV	V	VI
$ln(Coverage)_{p,t}$	0.537***	0.565***	0.403***	0.561***	0.632***	0.403***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Property Fixed Effects	No	Yes	Yes	No	Yes	Yes
Year Fixed Effects	No	No	Yes	No	No	Yes
Observations	18,457,390	17,423,880	17,423,880	18,457,390	17,423,880	17,423,880
R-squared	0.55	0.89	0.91	0.37	0.76	0.90

Table C.4: Premium, Mandatory Charges, and Rejection Rate: All counties as control

The table examines the impact of hurricanes on premium, mandatory charges, and claim rejection rate for a sample that includes all counties as controls. *Post* is an indicator variable that takes on a value of one for periods following a hurricane and zero otherwise. *Treated* is an indicator variable that takes a value of one for policies in counties experiencing a hurricane with property damage above the median value and zero otherwise. Standard errors are clustered at the county-level, and are shown in parentheses. ***, **, and * represent result significant at 1%, 5%, and 10% level, respectively.

	Δln(Premium)	Δln(Mandatory charges)	Δ(Premium/Coverage)	Δ(Mandatory charges/Coverage)	Rejection Rate	$\mathbb{1}(Rejection)$
	I	II	III	IV	V	VI
$Post_t$	0.017***	0.123***	0.026***	0.010***	0.029***	0.025***
	(0.006)	(0.010)	(0.008)	(0.001)	(0.005)	(0.005)
$Post_t \times Treated_p$	0.062***	0.015	0.046***	0.001	-0.049***	-0.045**
	(0.016)	(0.108)	(0.013)	(0.001)	(0.017)	(0.018)
Policy × Cohort FE	✓	✓	✓	✓	✓	✓
Observations	25,610,765	25,610,765	25,683,055	25,683,055	581,836	581,836
R-squared	0.30	0.20	0.28	0.25	0.52	0.51

Table C.5: Premium, Mandatory Charges, and Rejection Rate: After controlling for past losses

The table examines the impact of hurricanes on premiums, mandatory charges, and claim rejection rate, with the amount of claims filed for the policy in the last period as controls. *Post* is an indicator variable that takes on a value of one for periods following a hurricane and zero otherwise. *Treated* is an indicator variable that takes a value of one for policies in counties experiencing a hurricane with property damage above the median value and zero otherwise. Standard errors are clustered at the county-level, and are shown in parentheses. ***, **, and * represent result significant at 1%, 5%, and 10% level, respectively.

	Δln(Premium)	Δln(Mandatory charges)	Δ(Premium/Coverage)	Δ(Mandatory charges/Coverage)	Rejection Rate	$\mathbb{1}(Rejection)$
	I	II	III	IV	V	VI
$Post_t$	0.013	0.038	0.008	0.001	0.014	0.012
	(0.014)	(0.051)	(0.011)	(0.002)	(0.013)	(0.013)
$Post_t \times Treated_p$	0.066***	0.098	0.063***	0.010***	-0.068***	-0.063***
	(0.014)	(0.062)	(0.013)	(0.001)	(0.014)	(0.015)
Policy × Cohort FE	✓	✓	✓	✓	✓	✓
Controls	10,088,100	10,088,100	10,040,590	10,040,590	164,195	164,195
Observations	0.29	0.18	0.27	0.17	0.52	0.51

Table C.6: Premium, Mandatory Charges, and Rejection Rate: without hurricanes between 2011 and 2015

The table examines the impact of hurricanes on premiums, mandatory charges, and claim rejection rate for a sample that does not include hurricanes that came between 2011 and 2015. *Post* is an indicator variable that takes on a value of one for periods following a hurricane and zero otherwise. *Treated* is an indicator variable that takes a value of one for policies in counties experiencing a hurricane with property damage above the median value and zero otherwise. Standard errors are clustered at the county-level, and are shown in parentheses. ***, **, and * represent result significant at 1%, 5%, and 10% level, respectively.

	Δln(Premium)	Δln(Mandatory charges)	Δ(Premium/Coverage)	Δ(Mandatory charges/Coverage)	Rejection Rate	$\mathbb{1}(Rejection)$
	I	II	III	IV	V	VI
$Post_t$	0.013	0.036	0.006	0.001	0.019*	0.014
	(0.014)	(0.054)	(0.012)	(0.002)	(0.011)	(0.011)
$Post_t \times Treated_p$	0.073***	0.111*	0.068***	0.010***	-0.039***	-0.034**
	(0.013)	(0.064)	(0.013)	(0.001)	(0.012)	(0.013)
Policy × Cohort FE	✓	✓	✓	✓	✓	✓
Controls	9,810,744	9,810,744	9,756,184	9,756,184	273,050	273,050
Observations	0.29	0.17	0.23	0.14	0.50	0.50