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

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Abstract

With homeowners' insurance markets under growing climate strain, jurisdictions are expanding the role of government-backed insurers of last resort. Using policy-level data and natural disasters, we examine how these insurers pass climate costs to policyholders. Following disasters, we find premiums increase in both affected and unaffected areas, while claim rejections rise only in unaffected areas. These spillovers vary by consumer price sensitivity: less price-sensitive consumers in unaffected areas face higher premiums, while price-sensitive consumers experience increased claim rejections. These effects are further shaped by insurers' financial constraints. During financially constrained periods, insurers raise premiums broadly; during unconstrained periods, they primarily increase rejections in unaffected areas. Our welfare analysis reveals that rejection rates serve as a hidden but powerful mechanism for redistributing climate costs and ignoring them, while focusing only on premiums, substantially mischaracterizes distributional impacts. Overall, we find that even government-backed insurers are forced to act as profit maximizers when facing extreme losses, redistributing climate costs across geographic and demographic boundaries.

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

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1 Introduction

The U.S. homeowners' insurance market is under growing strain as climate risks and weather-related disasters—such as hurricanes, wildfires, and floods—have increased markedly in frequency and severity over the past two decades.[1] This increasing stress has triggered fallout across multiple dimensions including widening gaps in insurance ownership (Keys and Mulder, 2024; Sastry et al., 2024a), rising mortgage delinquencies (Ge et al., 2025; Sastry et al., 2024a), and insurer exits from high-risk states (Sastry et al., 2024b). 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.[2]

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 carriers. 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 households? 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 guide our empirical analysis, we develop a model of an insurer of last resort (hereafter, insurer). 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 future demand and litigation activity. The core trade-off the insurer faces reflects its dual mandate: expanding access to insurance while

[1] For example, in 2023, the industry reported a combined loss ratio of 110%, signaling unsustainable losses for private insurers (S&P Global Market Intelligence)

[2] 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.).

maintaining solvency. When facing a disaster that reduces their capital (e.g. when losses are high due to a hurricane), we show that 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., Forthcoming). 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 also responds to a disaster through the rejection of claims. There are 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 the treatment status of a location. 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.

Empirically evaluating the impact of natural disasters on insurance contracts is challenging because it requires detailed policy-level data to track how contracts evolve over time. 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 Property Insurance Corporation (Citizens), a non-profit organization that serves as Florida's insurer of last resort. This dataset 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 $1,847.97, 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.

With the theoretical predictions in hand, we then turn to our empirical setting. 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. The stacked DiD framework addresses issues associated with staggered treatment timing (Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021), providing consistent and unbiased estimates of the effects of disasters on insurance contracts.

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, in the hurricane year, the affected group experiences a sharp spike in claims, with approved claims rising 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.

Premiums and the premium-to-coverage ratio evolve similarly for both affected and unaffected groups in the years leading up to hurricanes, consistent with the parallel trends assumption. However, during the hurricane year, the affected group experiences a discrete jump in these variables, which persists for an additional two years. In contrast, the unaf-

fected group exhibits a slightly delayed reaction, with a discrete jump occurring only in the year after the hurricane. This increase is about half the magnitude of the affected group's and lasts for two years, indicating that premiums for the unaffected group rise for two years post-hurricane. Meanwhile, the increase in mandatory charges-to-coverage occurs simultaneously in the year following the hurricane and is similar in magnitude across both affected and unaffected groups.[3] Interestingly, we find that insurers also pass through costs ex-post via rejection rates, which inherently allows for price shrouding. While there is no change in rejection rates for the affected group, the unaffected group shows an increase in rejection rates in the year immediately following the disaster.

Our model predicts that spillover effects depend on consumer price elasticities. We test this hypothesis using neighborhood (zip code) income as a proxy for price elasticities. We find that premiums increase in unaffected areas only in high-income neighborhoods, where households are likely to be less price-sensitive. In contrast, rejection rates remain unchanged in these areas. Meanwhile, in low-income neighborhoods, policies experience an increase in rejection rates but no change in premiums, indicating that price shrouding is concentrated among more price-sensitive consumers. These findings suggest that insurers strategically redistribute costs, with households in both low- and high-income low-risk areas subsidizing those in high-risk areas—through higher rejection rates and premiums, respectively.

Pass-through in our model depends on both price targets and insurers' capital (i.e., their surplus-to-assets ratio). When surplus is decreasing, it is likely decreasing for competitors in the region as well, leading most insurers in the market to raise prices.[4] This allows Citizens to follow suit without losing competitiveness. However, when surplus is increasing, competitors are less likely to raise prices, limiting Citizens' ability to increase premiums. In such cases, insurers may instead pass on costs through higher rejection rates, as price targets remain anchored by competitors' pricing. Splitting hurricane events into periods of declining

[3]Citizens has the ability to levy mandatory charges on all active policies as a means of risk sharing. We discuss mandatory charges in depth in Section section 3.

[4]We verify that a measure of competitor surplus is positively correlated with Citizens' surplus in section 3.

and increasing surplus, we find results consistent with this hypothesis. Premium spillovers occur exclusively during declining surplus periods, whereas increases in rejection rates for unaffected areas are concentrated in periods of increasing surplus.

A natural question that follows is how households respond to these additional costs. We find that, on average, households in both affected and unaffected areas increase both coverage and deductibles, suggesting that they take on greater liquidity risk while seeking to increase insurance against disaster risk. However, examining heterogeneity by zip code income reveals distinct patterns in unaffected areas. In high-income neighborhoods, where premium increases are more pronounced, households respond by increasing coverage and deductibles. In contrast, households in low-income unaffected areas do not make similar adjustments but are more likely to initiate litigation and appraisal in response to the higher rejection rates they experience. 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 then assess which set of households lose the most from Citizens' response. We propose a simple logit demand model in which household utility depends on prices, rejection rates, and a firm-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. 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 that untreated, low-income households face neither gains nor losses from Citizens' behavior, high-income treated and untreated locations are worse off by approximately 0.8%, and low-income treated locations are worse off by 1.3%. However, if we had only considered the pricing response, low-income untreated locations would actually be better off by 0.5%, while high-income treated locations would be worse off by 1.6%. Therefore, the ability for Citizens to reject claims significantly impacts our welfare estimates, highlighting the importance of this ex-post risk sharing channel.

Using Citizens as our setting offers unique advantages and certain limitations for our analysis. As Florida's insurer of last resort, Citizens is designed to provide insurance to all residents and improve accessibility, particularly for those unable to obtain coverage from private insurers. The fact that climate risk significantly affects insurance policies even for an insurer of last resort raises serious concerns about the accessibility and reliability of insurance for consumers, especially in high-risk areas. However, this setting differs from private insurers, and our results may not fully generalize to broader insurance markets. Nevertheless, to the extent that similar mechanisms—such as strategic pricing and financial constraints—are at play, our qualitative findings are likely to hold.

Our paper contributes to the growing literature on the intersection of climate risk and real estate markets, including mortgages and homeowners' insurance.[5] In the context of mortgage markets, Sastry (2021) finds that lenders require higher down payments from borrowers who underinsure, likely due to concerns about post-disaster default. An et al. (2024) examine the impact of wildfires on housing and mortgage outcomes, emphasizing the role of insurance constraints. Ge et al. (2025) demonstrate that rising homeowners' insurance premiums—independent of direct disaster exposure—can increase mortgage default risk, while Ge et al. (2024) find that exogenous flood insurance premium increases reduce mortgage take-up rates. Sastry et al. (2023) show that mortgage defaults rise in areas with high insurer insolvency following disasters, highlighting the financial fragility caused by insurance market disruptions. Issler et al. (2024) and Eastman and Kim (2023) further investigate how state insurance regulations shape market responses to disaster risk, particularly their role in premium adjustments and coverage availability.

Within the insurance sector, studies have examined both how insurance affects post-disaster recovery and how disaster risks influence insurance markets. Cookson et al. (2024) and Sastry et al. (2024b), for example, highlight the prevalence of underinsurance in high-

[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.

risk areas, underscoring the systemic issues that leave many properties inadequately covered against potential losses. Born and Viscusi (2006) use insurer-by-state level data and document how natural disasters reduce total premiums earned by insurers in affected states, decrease the number of firms offering coverage, and lead to insurer exits from the market. Sastry et al. (2023) shows that the composition of insurers changes due to climate-related losses as traditional insurers withdraw from high-risk areas and less stable insurers enter to fill this gap, thereby increasing vulnerabilities in mortgage markets. Boomhower et al. (2023) and Boomhower et al. (2024) analyze how property insurance markets adapt to climate risk, focusing on regulatory constraints and risk selection. Keys and Mulder (2024) demonstrate that rising reinsurance costs, driven by increasing disaster risks, are passed on to homeowners through higher insurance premiums, disproportionately affecting disaster-prone areas.

We extend this literature by providing the first evidence of how insurers pass on climate risk to insurance contracts through multiple channels and across different populations, including areas unaffected by disasters. We do so in the context of an insurer of last resort and highlight how consumer price elasticity and financial constraints shape this pass-through. Unlike previous studies, we document not only regional spillovers from cost shocks but also how these dynamics unfold through both price and non-price mechanisms. By showing that insurers redistribute costs across households in distinct ways, our findings raise important questions about equity and affordability in insurance markets.

2 A Model of Insurance Pricing and Claims Management

We first present a simple model to organize our empirical findings. 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, Citizens) that operates across several locations, $\ell \in \mathscr{L}$. We assume Citizens 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, Citizens has the ability to review insurance 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 Citizens' capital, claims also factor into expected losses. We assume that Citizens 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 $C_{\ell t}$.

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. 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 increasing in total damages $C_{\ell t}$. The interpretation is that that claims are easier to justify in the wake of a disaster. In normal times, 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 Citizens is

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

We assume that Citizens faces two core objectives. First, they act as profit maximizers, consistent with Citizens' desire to not set prices that are too competitive (Hudson, 2024). However, Florida statute also requires Citizens to price according to sound actuarial principles (Citizens Property Insurance Corporation, 2024). To capture this requirement, we assume that the state acts as a backstop to a fraction ς_ℓ of Citizens' losses for each location ℓ. This assumption is rooted in the legal structure of insurers of last resort. For example, Citizens 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 Citizens. Profits in each location are then $\pi_{\ell t} = (p_{\ell t} - (1 - \varsigma_\ell)l_{\ell t})Q_{\ell t}(p_{\ell t}, x_{\ell t})$.

Citizens' second objective 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). Given this setup, Citizens solves the following optimization

problem:

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

2.2 Optimal Pricing Behavior

We begin by analyzing the Citizens' 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 Citizens. 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 Citizens' 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 A.1.

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 Citizens' 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 Citizens' capital declines, they put more weight on their regulatory capital relative to their economic profits. They therefore shift to the price that optimizes their regulatory capital.

The third component is specific to our setting. The insurer of last resort discount comes from the state backstop, $\varsigma_\ell > 0$, which allows Citizens to price below their private market counterparts. When the state sets a particular value for this backstop — $\varsigma_\ell = \varepsilon_\ell^{-1}$ — Citizens' optimal price without financial frictions ($\lambda_t = 0$) is precisely equal to $l_{\ell t}$. Therefore, in a setting without financial distress, Citizens prices at fair value while also behaving competitively, which is line with Florida statute.[6]

The insurer of last resort discount, notably, is also decreasing in Citizens' financial distress λ_t. This implies, conditional on financial distress, that the gap between Citizens' prices and the prices of private market participants declines as financial distress becomes large. In other words, in the wake of a disaster, we should expect Citizens to behave more like a private insurer rather than an insurer of last resort.

We now analyze the consequences of Citizens' pricing rules. Suppose Citizens faces major losses due to a disaster, and therefore faces a drop in their capital K_t. Since the cost of capital $F(\cdot)$ is steeper at low levels of capital, this leads to an increase in the shadow cost of holding 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 Citizens from excessive capital losses. This result is

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

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 A.2.

2.3 Optimal Claims Management

Given Citizens' pricing decisions, how should they manage their claims? On one hand, rejecting claims may reduce losses to their operations; however, doing so may reduce future 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 Citizens' 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 Citizens 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 A.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, Citizens will increase prices to reduce the burden on their capital. How does that translate into their claims management behavior? We show in Appendix A.4 that Citizens rejects more claims. When Citizens' 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 A.4.

However, periods of distress are also accompanied by increases in claims shocks in each location. As such, Citizens 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, Citizens 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 A.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 Citizens 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 A.6.

Having characterized how Citizens 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 and its sources, details the construction of the sample, examines the determinants of insurance premiums, and describes our main empirical methodology.

3.1 Data

Our analysis relies on the intersection of five 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 competitive premiums, making it a valuable benchmark for comparison with private insurers. For instance, Table B.1 shows that Citizens' average premium is comparable to that of private insurers for a Florida masonry home built in 2005 with a $300,000 replacement value, a 2% hurricane deductible, a $500 non-hurricane deductible, and no claims in the past three years.

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 full 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.

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.

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 prop-

erties 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 collect financial data from Citizens' quarterly and annual financial statements, which are publicly available on the company's website. 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 Citizens' financial standing and its ability to absorb climate-related risks.

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, Citizens 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. The average mandatory charges-to-coverage ratio of 0.09 shows that these charges represent a small fraction of the

coverage amount.

Figure 1 plots the average premium and premium-to-coverage ratio for policies issued by Citizens 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. High-risk (low-risk) areas are defined as properties located within (outside) the 100-year or 500-year floodplain. Panel A displays the premium, while Panel B shows the premium-to-coverage ratio.

Consistent with other data sources, we find that both premiums and the premium-to-coverage ratio for policies issued by Citizens have increased over the last two decades.[7] 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 per policy-year is $747, with a high standard deviation of $8,256, reflecting the significant variability in claims. 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, Citizens paid 46 cents in claims for every dollar collected in premiums.

3.3 Determinants of insurance premium

To better understand Citizens' 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. Panel (a) of Figure 2 presents this plot, revealing a strong linear relationship between premium and coverage. Similarly, panel (b) plots mandatory charges against coverage and

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

also finds a linear relationship.

Given this visual evidence, we formally evaluate the relationship using a simple ordinary least squares (OLS) model. Table 2 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 by 34%, suggesting that property-level time-invariant characteristics account for a significant portion of the variation in premiums. Overall, property-level characteristics combined with coverage explain 89% of the total variation. 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 Citizens' pricing function, as it does for any insurer.

3.4 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

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.[8]

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 B.2 lists these sixteen hurricanes, along with their names and the number of affected counties (i.e., those with reported damages exceeding $2 million).

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.[9] Finally, we restrict the analysis to three years before and after each event, resulting in a final sample of over 800,000 policies.

3.5 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 estimation bias from staggered difference-in-differences specifications with two-way fixed effects

[8] See Florida Climate Center for a list of major hurricanes in Florida.
[9] Our results remain robust even when including these counties as shown in Table B.3.

(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. This restriction ensures that we compare counties with relatively similar risk profiles, mitigating concerns about systematic differences between treated and control groups. 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:

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

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.[10]

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 that our specification is correctly specified, whereas deviations may indicate endogeneity issues or

[10]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.

misspecification.

Panel (a) of Figure 3 plots the dynamic coefficients estimated using equation 11, with the likelihood of a claim as the outcome variable. Panel (b) presents estimates for claim amount three years before and after a hurricane. The figure shows coefficient estimates and 95% confidence interval error bands on event-time dummies, separately for affected and unaffected policies, relative to the 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 claims 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 3 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.[11]

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

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

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

Figure 4 plots the evolution of premium three years before and after a hurricane. Panel (a) plots the coefficient and error bands at a ninety-five percent confidence level for $\Delta log(Premium)$ on event-time dummies for the treated and control policies separately relative to three years before the occurrence of the hurricane. The specification includes policy $\times$ cohort fixed effect. Panel (b) plots similar estimates for $\Delta Premium\ to\ coverage\ ratio$.

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., treated group) 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.

Figure 5 plots similar results using mandatory charges as the outcome variable. While the estimates exhibit greater noise, they follow a similar pattern. As before, panel (a) plots estimates for changes in mandatory charges, while panel (b) examines the ratio of mandatory charges to coverage. Panel (a) shows that both groups trend similarly before hurricanes, except for a slight divergence in the year immediately preceding the event. However, both groups experience a discrete jump in mandatory charges in the two years following hurricanes, suggesting that insurers increased these charges for both affected and unaffected areas. A similar pattern emerges when using mandatory charges standardized by coverage as the

outcome, except for an outlier jump in the unaffected group for two years before hurricanes.

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: as the proportion of claims rejected for a policy-year and as a dummy variable that takes a value of 1 if at least one claim is rejected during the policy-year. Figure 6 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 substantially for the control group.

We re-estimate the changes in these outcomes using a static DiD model, as specified in equation 10. Table 4 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.

How is Citizens able to adjust their rejection rates over time? To answer this question, we obtain data on claims rejection reasons from the Catastrophe Claims Database from the Office of Insurance Regulation in the state of the Florida.[12] 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

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

claim may fall under a risk category that is not insured by the insured's policy; or example, if a hurricane resulted in flooding for nearby but unaffected locations and a household did not carry flood insurance, any claimed damages due to the flooding could be rejected on this basis. Third, insurers may report a problem with their claims management system not picking up a precise 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 7. We consider Citizens' 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. However, Citizens is especially prone to not recording precise reasons for their claims.

We conjecture that the first and third reasons give Citizens and other insurers flexibility in rejecting claims. For example, if Citizens 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 Citizens' rejection reasons are not recorded clearly, they may face some flexibility in the case that the policyholder follows up with any litigious activity. We test several 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 elasticity locations will experience lower pricing spillovers than low elasticity locations, but will pay more ex-post through higher rejection rates. While we do

not estimate property-level elasticities explicitly, 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 5 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, Citizens strategically raises premiums in locations where they can exert their pricing power and raise capital the most. 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 approximately 4 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 Citizens 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 Citizens has in a less competitive market. We therefore consider another 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.[13]

We estimate our framework for the increasing and decreasing surplus periods in Table 6. We find that the premium growth rates increase for both treated and control counties when surplus the private market is more distressed (e.g., 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., Forthcoming), which increases Citizens' 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 Citizens is not able to recover their losses 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 Citizens' 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 Citizens' own responses.

We explore four margins of adjustment. First, we consider the log change in total cov-

[13]Note that this particular sample split is almost identical to splitting on the median in-sample surplus change.

erage associated with each property. Households may increase or decrease their coverage in response to a hurricane. If Citizens 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., 2024b), 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 feel that their claims were wrongly rejected, they may respond by filing a lawsuit against Citizens. Our dependent variable for this test is an indicator for whether or not the household files any litigation against Citizens 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, Citizens 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 Citizens' may also be responding on the intensive margin when cutting back on claims.

We first report results for our full sample in Table 7. 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 8. 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.

5 Normative Analysis

We have now established both theoretically and empirically how Citizens 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 Citizens, being backed by state funds, has 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 specifications 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 Citizens' behavior on policyholder utility, we include a Citizens indicator 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 of 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, certain commercial homeowners association properties, mobile homes, and broadly defined dwellings. Since we do not observe prices explicitly, we construct a proxy for each insurer-location-year as $\text{price}_{j\ell t} = \text{premiums}_{j\ell t}/\text{coverage}_{j\ell t}$.[14] 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

[14] In Appendix Figure B.2, 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.

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 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).[15] For each insurer j, we set

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

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, which was also provided to us by the Office of Insurance Regulation. The data include detailed information on all hurricane-related claims filed and handled by each insurance company since 2018.[16]. 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

[15] 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.

[16] 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

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 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 9. 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 $\varepsilon_{\text{low-income}} > 0$ and $\beta > 0$, which implies that both prices and rejection rates enter negatively in policyholder utility. We further find that $\varepsilon_{\text{high-income}} > \varepsilon_{\text{low-income}}$, 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. 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. 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 rely 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 Citizens' Response on Policyholder Utility

We now use our demand system estimates to estimate utility effects of Citizens' 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[17]

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

In response to a climate shock that changes insurers' prices and rejection behavior, the average utility response is therefore[18]

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

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 Citizens using our es-

[17] 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.

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

timates in Section 3. We use results from Table 5 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.[19]

We display our estimates in Figure 8. Each panel represents one of the four policyholder groups. Within each panel, 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

[19] Our estimates in Table 5 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: $\Delta \text{price}_{j\ell t} \approx \Delta \log(\text{price}_{j\ell t}) \times \overline{\text{price}}_{j\ell t}$.

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 investigates how natural disasters influence homeowners' insurance contracts. Using detailed policy-level data from Citizens, we demonstrate that climate risks significantly impact insurance pricing, both in disaster-affected areas and through spillover effects to unaffected areas. In disaster-affected areas, premiums increase immediately and continue to rise for three years following a hurricane. In unaffected areas, premiums exhibit a delayed and smaller increase, with growth persisting for two years post-disaster. Beyond premiums, we show that insurers also pass on costs through rejection rates. While rejection rates remain unchanged in disaster-affected areas, they increase in unaffected areas, highlighting a novel dimension of climate risk spillovers. These findings indicate that even households in low-risk areas bear part of the financial burden associated with climate risk—either through higher premiums or reduced access to coverage.

Spillover effects are heterogeneous based on price sensitivity. In high-income areas, where households are less price-sensitive, insurers pass on costs through higher premiums, whereas in low-income areas, where households are more price-sensitive, insurers increase rejection rates instead. This suggests a strategic redistribution of costs, with both low- and high-income households in low-risk areas subsidizing those in high-risk areas through different mechanisms. Additionally, insurers' financial constraints shape how these costs are passed through. During periods of decreasing surplus, premium increases are broader, affecting both affected and unaffected areas. In contrast, during periods of increasing surplus, insurers primarily adjust rejection rates rather than premiums, particularly in unaffected areas.

Our findings highlight the dual role of price and non-price mechanisms in insurers' responses to climate risk and underscore how consumer price sensitivity and insurers' financial condition shape the distribution of costs across households. As climate risks intensify, these results raise important questions about equity and affordability in insurance markets, particularly as insurers adjust their pricing and underwriting strategies to manage growing risk exposure.

References

Acharya, Viral V, Richard Berner, Robert Engle, Hyeyoon Jung, Johannes Stroebel, Xuran Zeng, and Yihao Zhao, 2023, Climate stress testing, *Annual Review of Financial Economics* 15, 291–326.

An, Xudong, Stuart A Gabriel, and Nitzan Tzur-Ilan, 2024, Extreme wildfires, distant air pollution, and household financial health .

Angrist, Joshua D, Guido W Imbens, and Alan B Krueger, 1999, Jackknife instrumental variables estimation, *Journal of Applied Econometrics* 14, 57–67.

Bakkensen, Laura A, and Lint Barrage, 2021, Going underwater? flood risk belief heterogeneity and coastal home price dynamics, *The Review of Financial Studies* .

Baldauf, Markus, Lorenzo Garlappi, and Constantine Yannelis, 2020, Does climate change affect real estate prices? only if you believe in it, *The Review of Financial Studies* 33, 1256–1295.

Bartik, Timothy J, 1991, Who benefits from state and local economic development policies? .

Bernstein, Asaf, Matthew T Gustafson, and Ryan Lewis, 2019, Disaster on the horizon: The price effect of sea level rise, *Journal of Financial Economics* 134, 253–272.

Boomhower, Judson, Meredith Fowlie, Jacob Gellman, and Andrew Plantinga, 2024, How are insurance markets adapting to climate change? risk selection and regulation in the market for homeowners insurance, Technical report, National Bureau of Economic Research.

Boomhower, Judson, Meredith Fowlie, and Andrew Plantinga, 2023, How are insurance markets adapting to climate change? evidence from homeowners insurance, Technical report, National Bureau of Economic Research.

Born, Patricia H, and W Kip Viscusi, 2006, The catastrophic effects of natural disasters on insurance markets, *Journal of Risk and Uncertainty* 33, 55–72.

Callaway, Brantly, and Pedro HC Sant'Anna, 2021, Difference-in-differences with multiple time periods, *Journal of econometrics* 225, 200–230.

Cengiz, Doruk, Arindrajit Dube, Attila Lindner, and Ben Zipperer, 2019, The effect of minimum wages on low-wage jobs, *The Quarterly Journal of Economics* 134, 1405–1454.

Citizens Property Insurance Corporation, 2024, Citizens statute 2024, Accessed: 2025-02-04.

Cookson, J Anthony, Emily Gallagher, and Philip Mulder, 2024, Coverage neglect in homeowners insurance, *Available at SSRN 5057551* .

Dubé, Jean-Pierre, Joonhwi Joo, and Kyeongbae Kim, 2025, Discrete/continuous choice models and representative consumer theory, *Journal of Economic Theory* 106012.

Eastman, Evan, and Kyeonghee Kim, 2023, Regulatory capital and catastrophe risk, *Available at SSRN* .

Federal Emergency Management Agency, FEMA, n.d., Climate change and disaster risk, https://www.fema.gov, Accessed: 2025-01-14.

Froot, Kenneth A, 2001, The market for catastrophe risk: a clinical examination, *Journal of Financial Economics* 60, 529–571.

Ge, Shan, Stephanie Johnson, and Nitzan Tzur-Ilan, 2025, Climate risk, insurance premiums and the effects on mortgage and credit outcomes, *Federal Reserve Bank of Dallas Working Paper* Working Paper 2505.

Ge, Shan, Ammon Lam, and Ryan Lewis, 2024, The effect of insurance premiums on the housing market and climate risk pricing, *Available at SSRN 4192699* .

Giglio, Stefano, Bryan T Kelly, and Johannes Stroebel, 2020, Climate finance, *Annual Review of Financial Economics* 12, 399–424.

Giglio, Stefano, Matteo Maggiori, Krishna Rao, Johannes Stroebel, and Andreas Weber, 2021, Climate change and long-run discount rates: Evidence from real estate, *The Review of Financial Studies* 34, 3527–3571.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift, 2020, Bartik instruments: What, when, why, and how, *American Economic Review* 110, 2586–2624.

Goodman-Bacon, Andrew, 2021, Difference-in-differences with variation in treatment timing, *Journal of econometrics* 225, 254–277.

Gormley, Todd A, and David A Matsa, 2011, Growing out of trouble? corporate responses to liability risk, *The Review of Financial Studies* 24, 2781–2821.

Handbury, Jessie, 2021, Are poor cities cheap for everyone? non-homotheticity and the cost of living across us cities, *Econometrica* 89, 2679–2715.

Hudson, Tom, 2024, Citizens to hike homeowners insurance rates by 14 percent, double them for competitive markets, *WUSF News* Accessed: 2025-02-04.

Issler, Paulo, Richard Stanton, Carles Vergara-Alert, and Nancy Wallace, 2024, Mortgage markets with climate-change risk: Evidence from wildfires in california, Technical report.

Keys, Benjamin J, and Philip Mulder, 2020, Neglected no more: Housing markets, mortgage lending, and sea level rise, Technical report, National Bureau of Economic Research.

Keys, Benjamin J, and Philip Mulder, 2024, Property insurance and disaster risk: New evidence from mortgage escrow data, Technical report, National Bureau of Economic Research.

Koijen, Ralph SJ, and Motohiro Yogo, 2015, The cost of financial frictions for life insurers, *American Economic Review* 105, 445–475.

Koijen, Ralph SJ, and Motohiro Yogo, 2016, Shadow insurance, *Econometrica* 84, 1265–1287.

Murfin, Justin, and Matthew Spiegel, 2020, Is the risk of sea level rise capitalized in residential real estate?, *The Review of Financial Studies* 33, 1217–1255.

National Oceanic and Atmospheric Administration (NOAA), 2025, Billion-dollar weather and climate disasters, https://www.ncdc.noaa.gov/billions, Accessed: 2025-01-14.

Oh, Sangmin, Ishita Sen, and Ana-Maria Tenekedjieva, Forthcoming, Pricing of climate risk insurance: Regulation and cross-subsidies, *Journal of Finance* .

Sastry, Parinitha, 2021, Who bears flood risk? evidence from mortgage markets in florida, Technical report.

Sastry, Parinitha, Ishita Sen, and Ana-Maria Tenekedjieva, 2023, When insurers exit: Climate losses, fragile insurers, and mortgage markets, *Working paper* .

Sastry, Parinitha, Ishita Sen, Ana-Maria Tenekedjieva, and Therese C Scharlemann, 2024a, Climate risk and the us insurance gap: Measurement, drivers and implications, *Working paper* .

Sastry, Parinitha, Ishita Sen, Ana-Maria Tenekedjieva, and Therese C Scharlemann, 2024b, Climate risk and the us insurance gap: Measurement, drivers and implications, *Available at SSRN 4909444* .

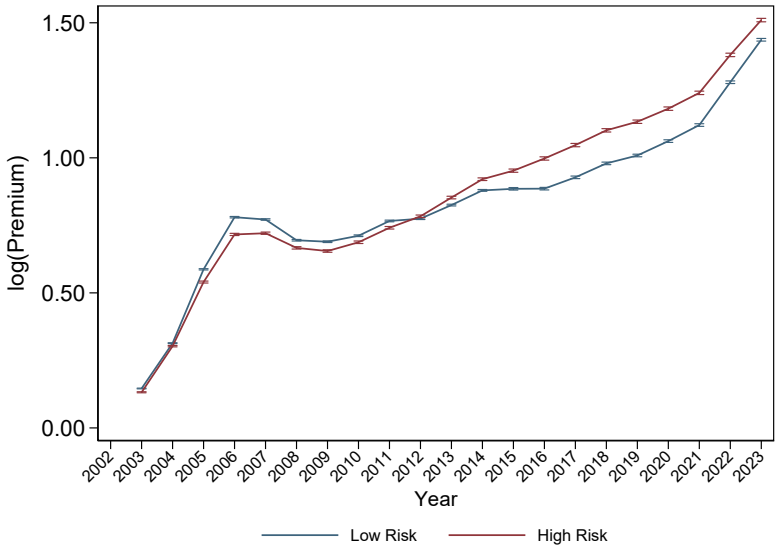
Sun, Liyang, and Sarah Abraham, 2021, Estimating dynamic treatment effects in event studies with heterogeneous treatment effects, *Journal of econometrics* 225, 175–199.

United Nations Office for Disaster Risk Reduction, UNDRR, n.d., Global assessment report on disaster risk reduction, https://www.undrr.org, Accessed: 2025-01-14.

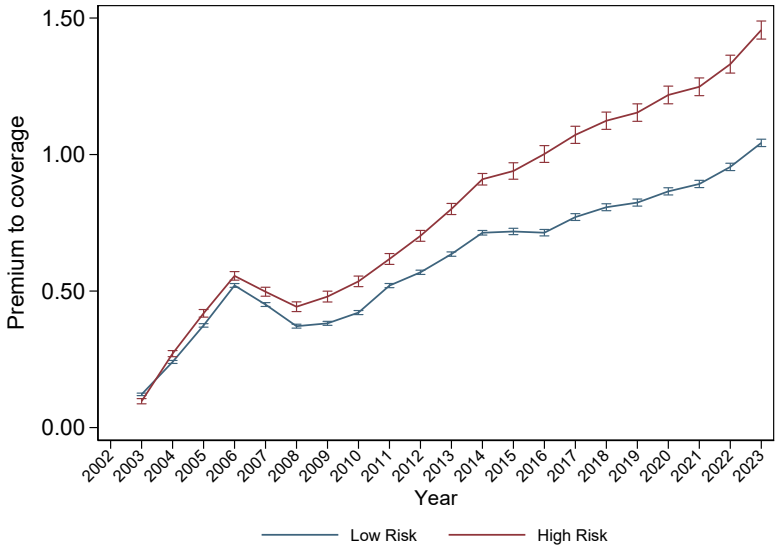
I Figures

Figure 1: Evolution of home insurance premiums

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



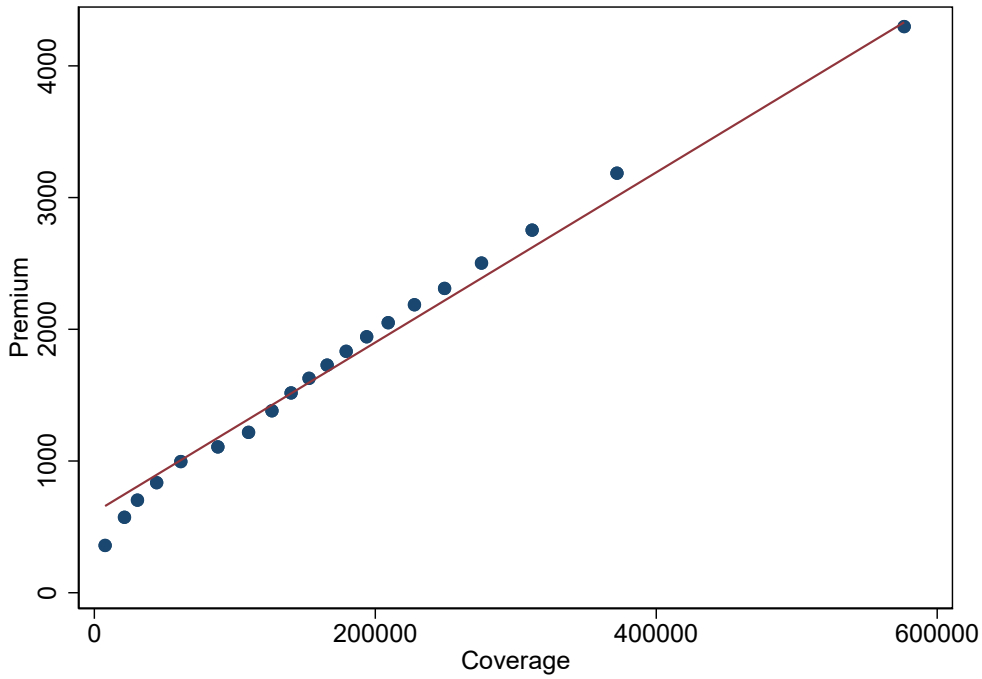
(a) Premium



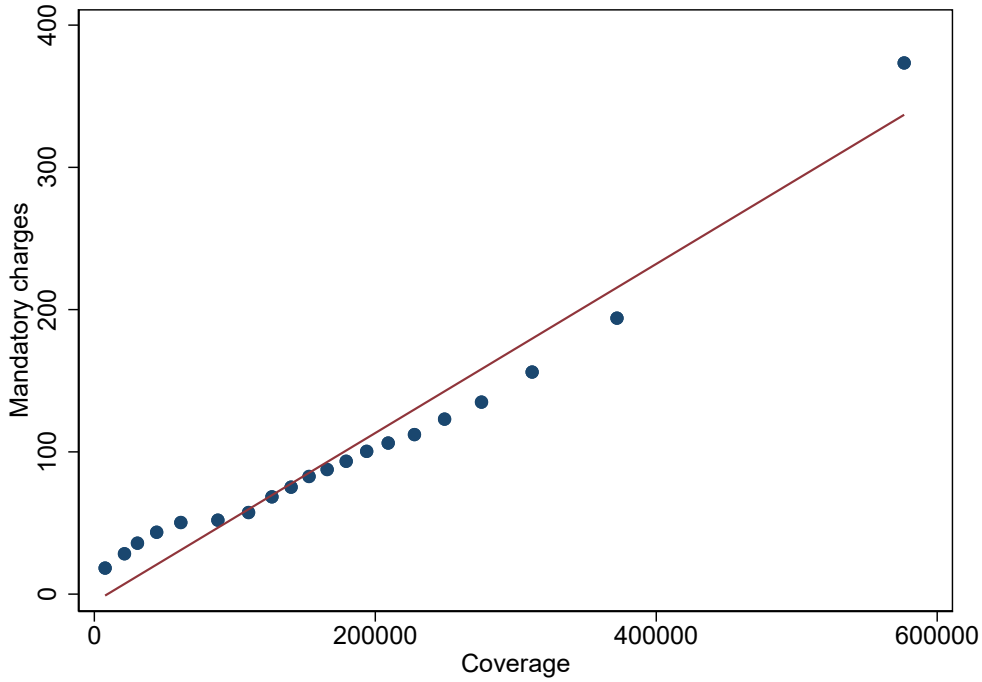
(b) Premium to coverage ratio

Figure 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



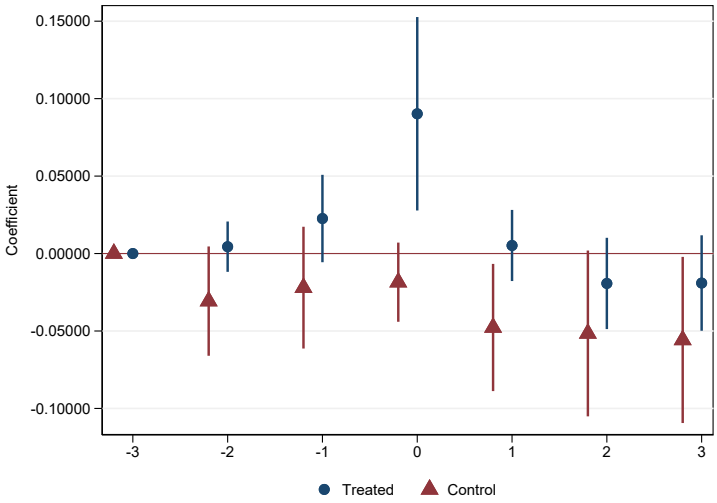
(b) Mandatory charges and coverage

Figure 3: Claims and hurricane

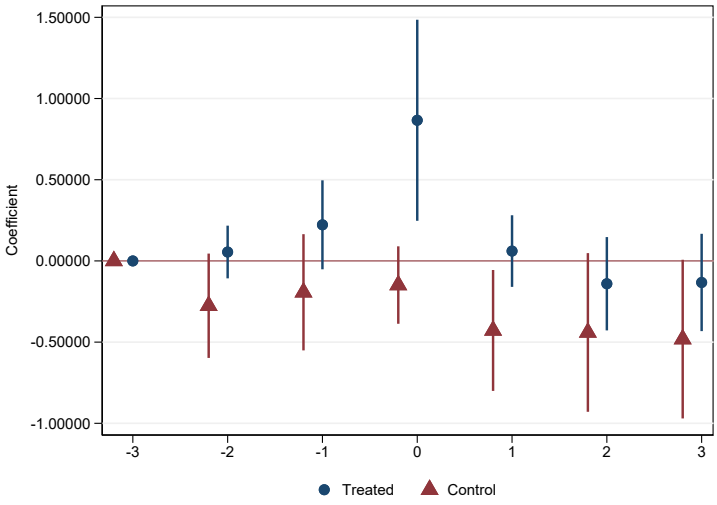
The figure shows the evolution of claims/losses three years before and after a hurricane. We estimate the following model:

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

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. $\alpha_{p,j}$ 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 dummy



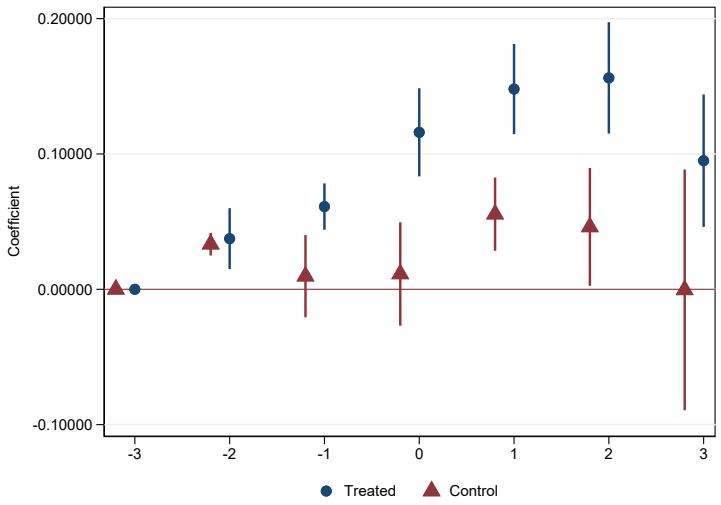
(b) Claim amount

Figure 4: Premium and hurricane

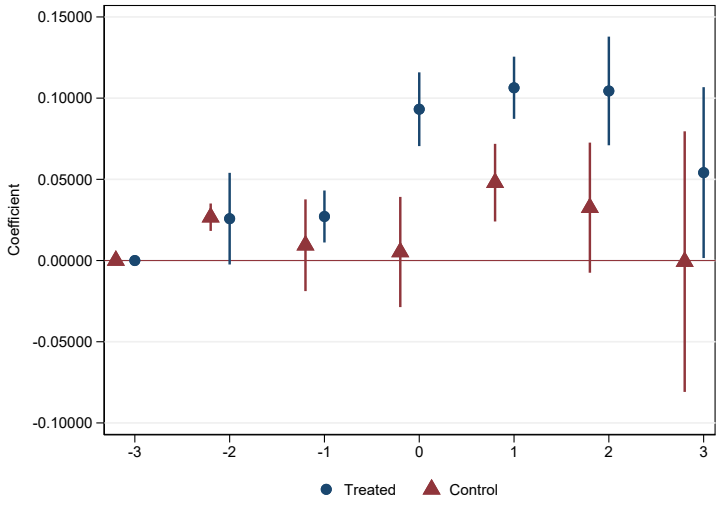
The figure shows the evolution of home insurance premium and premium to coverage three years before and after a hurricane. We estimate the following model:

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

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. $\alpha_{p,j}$ 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



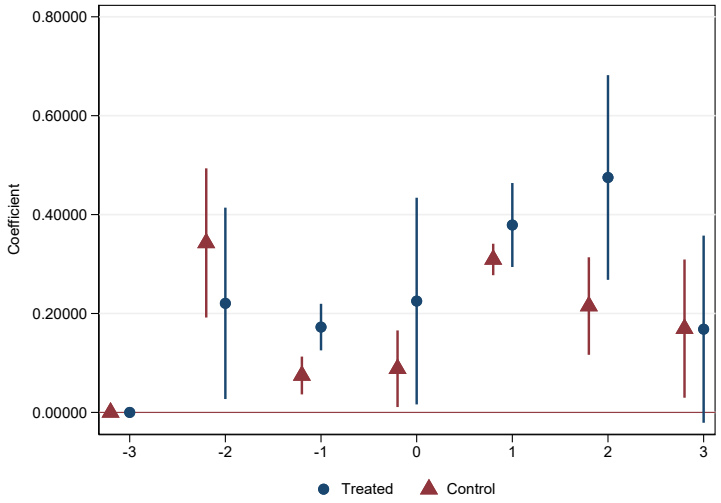
(b) Changes in premium to coverage

Figure 5: Mandatory charges and hurricane

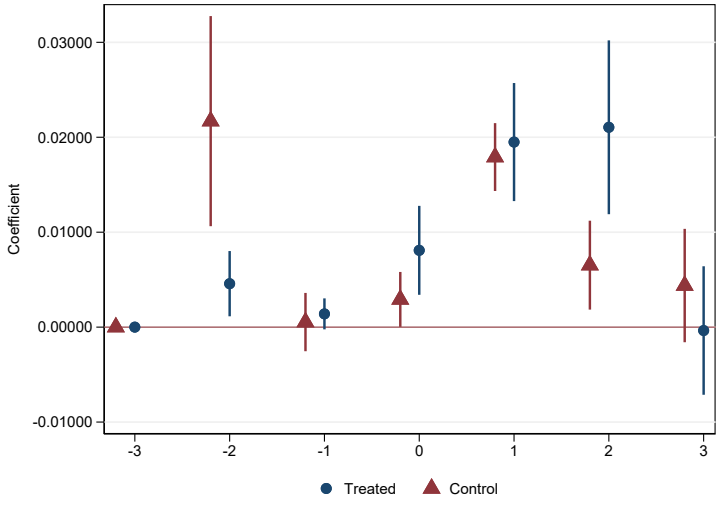
The figure shows the evolution of mandatory charges and mandatory charges to coverage three years before and after a hurricane. We estimate the following model:

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

where the outcome variables include $\Delta log((Mandatorycharges)_{p,c,t}$, which represents the growth rate in mandatory charges for policy p in treatment cohort c at event-time t, and $\Delta log(\frac{Mandatorycharges}{coverage})_{p,c,t}$, which denotes the corresponding growth rate of the mandatory charges-to-coverage ratio. $\alpha_{p,j}$ represents policy $\times$ cohort fixed effects. $\mathbb{1}_t$ denotes an indicator variable that equals 1 for a given event time and 0 otherwise. 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 mandatory charges



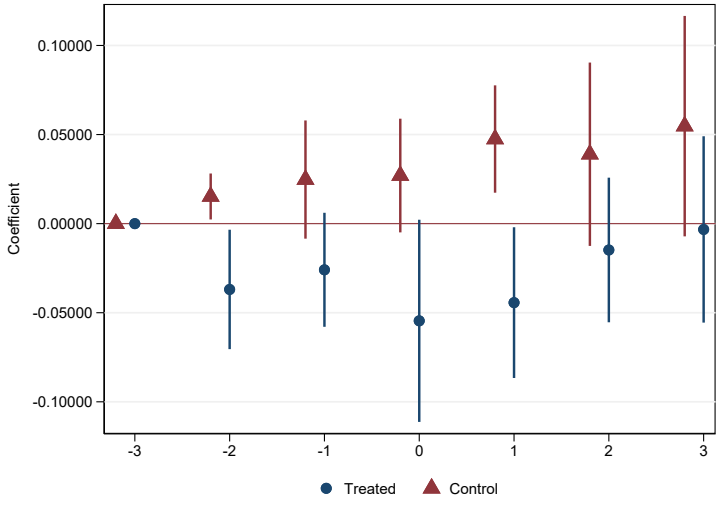
(b) Changes in mandatory charges to coverage

Figure 6: Claim rejection and hurricane

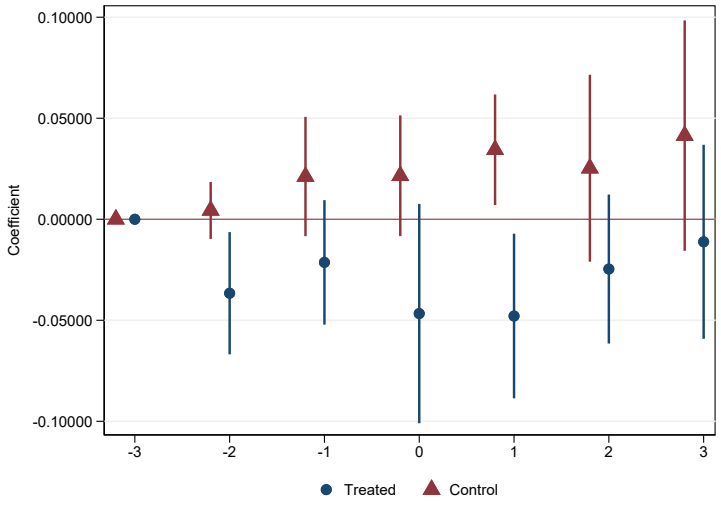
The figure shows the evolution of rejected claims three years before and after a hurricane. We estimate the following model:

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

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. $\alpha_{p,j}$ 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 7: 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).

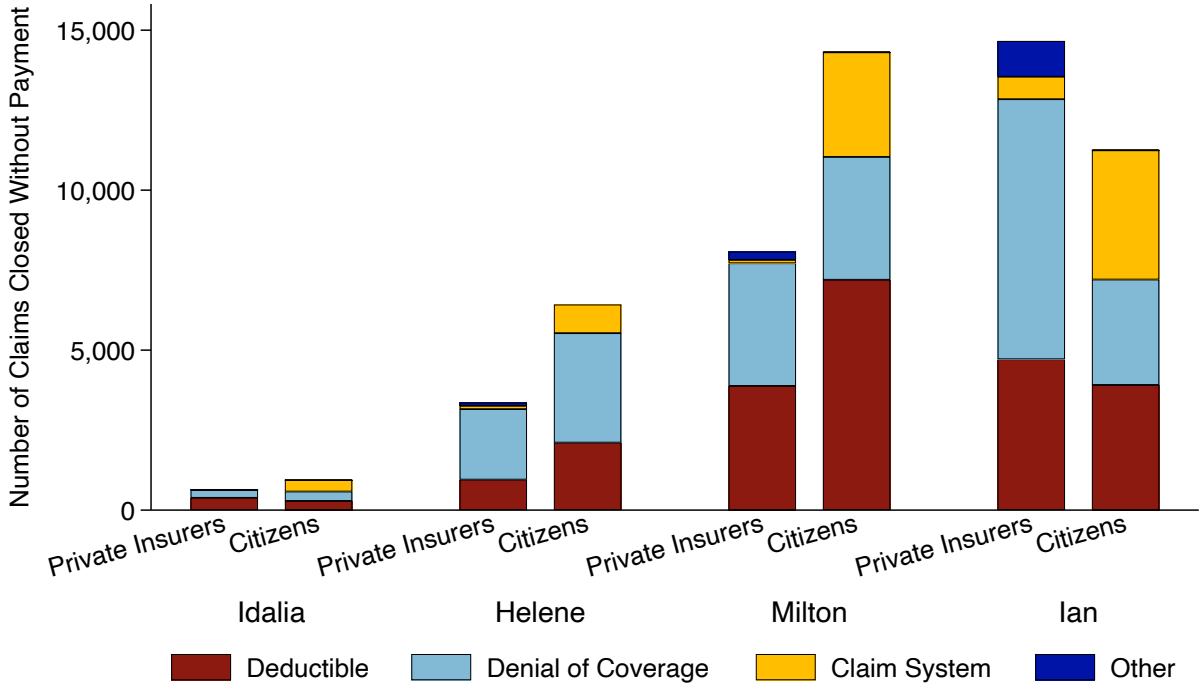
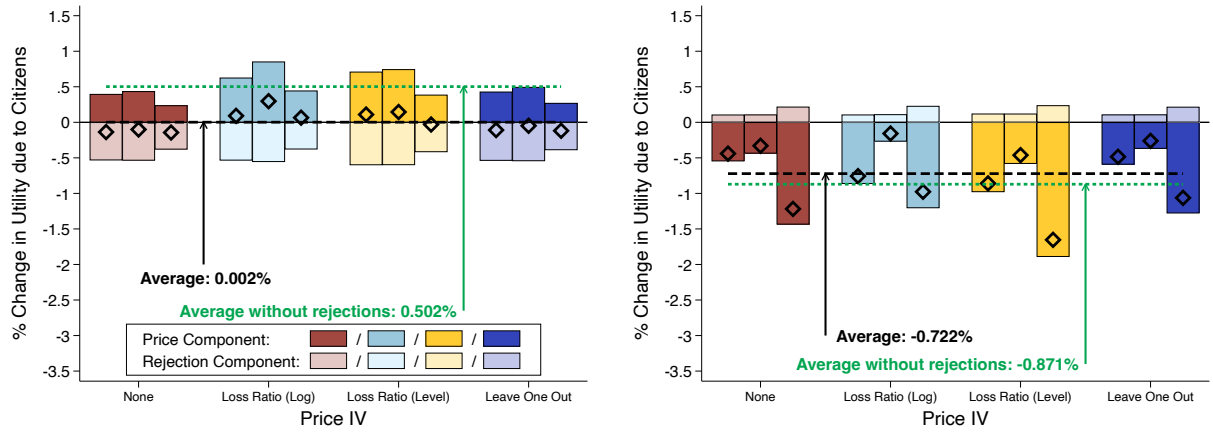


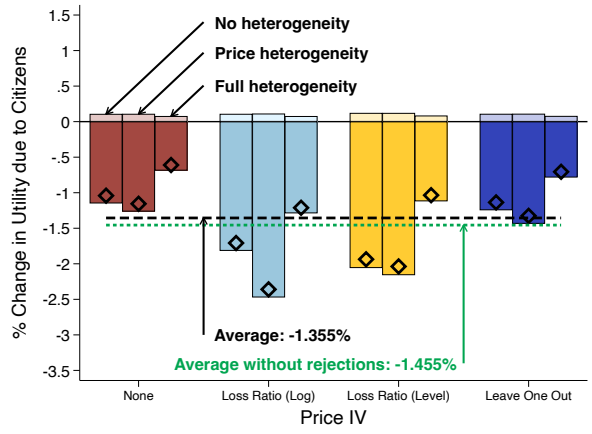
Figure 8: The Effect of Citizens' Post-Hurricane Response on Policyholder Utility

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.

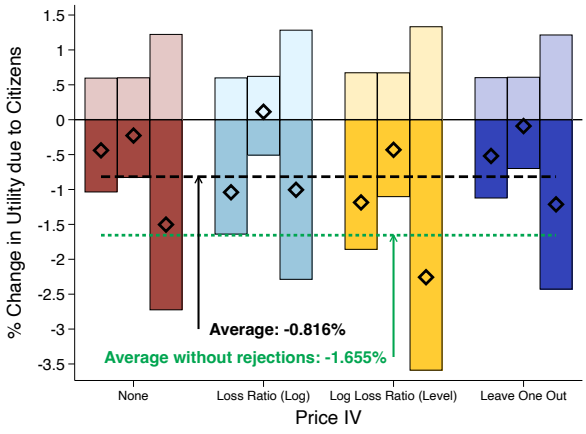


(a) Low Income, Untreated

(b) High Income, Untreated



(c) Low Income, Treated



(d) High Income, Treated

II Tables

Table 1: Summary statistics

The table shows 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: 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 3: 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)
Observations	13793212	13793171
R-squared	.29	.29

Table 4: 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.

	$\Delta\ln(\text{Premium})$	$\Delta\ln(\text{Mandatory charges})$	$\Delta(\frac{\text{Premium}}{\text{Coverage}})$	$\Delta(\frac{\text{Mandatory charges}}{\text{Coverage}})$	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)
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 5: 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)
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 6: 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)
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 7: 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(Deductible)	Litigation Rate	Appraisal Rate
	I	II	III	IV
$Post_t$	0.011**	0.010**	0.011	0.025
	(0.004)	(0.004)	(0.013)	(0.021)
$Post_t \times Treated_p$	0.021***	0.018***	-0.002	0.030**
	(0.006)	(0.005)	(0.004)	(0.013)
Observations	10,040,590	8,898,157	275,982	275,982
R-squared	0.30	0.31	0.58	0.52

Table 8: 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			
	Δln(Coverage)	Δln(Deductible)	Litigation Rate	Appraisal Rate	Δln(Coverage)	Δln(Deductible)	Litigation Rate	Appraisal Rate
	I	II	III	IV	V	VI	VII	VIII
$Post_t$	0.001	-0.000	0.025**	0.042*	0.018***	0.016***	-0.011	0.002
	(0.004)	(0.004)	(0.012)	(0.023)	(0.003)	(0.003)	(0.007)	(0.012)
$Post_t \times Treated_p$	0.038***	0.035***	-0.004	0.015	0.011*	0.009***	-0.007	0.053***
	(0.006)	(0.007)	(0.004)	(0.013)	(0.007)	(0.004)	(0.007)	(0.011)
Observations	4,310,733	3,711,406	165,993	165,993	5,545,681	5,029,292	98,961	98,961
R-squared	0.29	0.30	0.57	0.52	0.31	0.33	0.60	0.52

Table 9: 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$_{j\ell t} \times \mathbf{1}\{\text{high-income}\}_{\ell}$	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 10: 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 11: 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$_{j\ell t} \times \mathbf{1}\{\text{high-income}\}_\ell$	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$_{j\ell t} \times \mathbf{1}\{\text{high-income}\}_\ell$	0.246	0.226	0.252	0.254
	(0.389)	(0.404)	(0.407)	(0.390)
$\mathbf{1}\{\text{Citizens}\}_j$	2.229***	2.162***	2.239***	2.237***
	(0.186)	(0.191)	(0.202)	(0.186)
$\mathbf{1}\{\text{Citizens}\}_j \times \mathbf{1}\{\text{high-income}\}_\ell$	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 Model Proofs

A.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. □

A.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 A.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. □

A.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. □

A.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

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

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 $\Delta C_{\ell t} = 0$. □

A.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 $[1-\kappa\alpha(C_{\ell t})]C_{\ell t}$. □

A.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 A.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. □

A.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

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

where $\overline{\mathbf{C}}_t = \beta \mathbf{C}^1_t + (1 - \beta)\mathbf{C}^2_t$ 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 $K^2_t \geq K^1_t$. Then $\lambda^2_t \leq \lambda^1_t$ and, therefore, $\mathcal{M}_{\ell t}(\lambda^2_t) < \mathcal{M}_{\ell t}(\lambda^1_t)$ for all t. This implies that $\pi^E_{\ell t}(\lambda^2_t) > \pi^E_{\ell t}(\lambda^1_t)$, 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

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

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

B Additional Figures and Tables

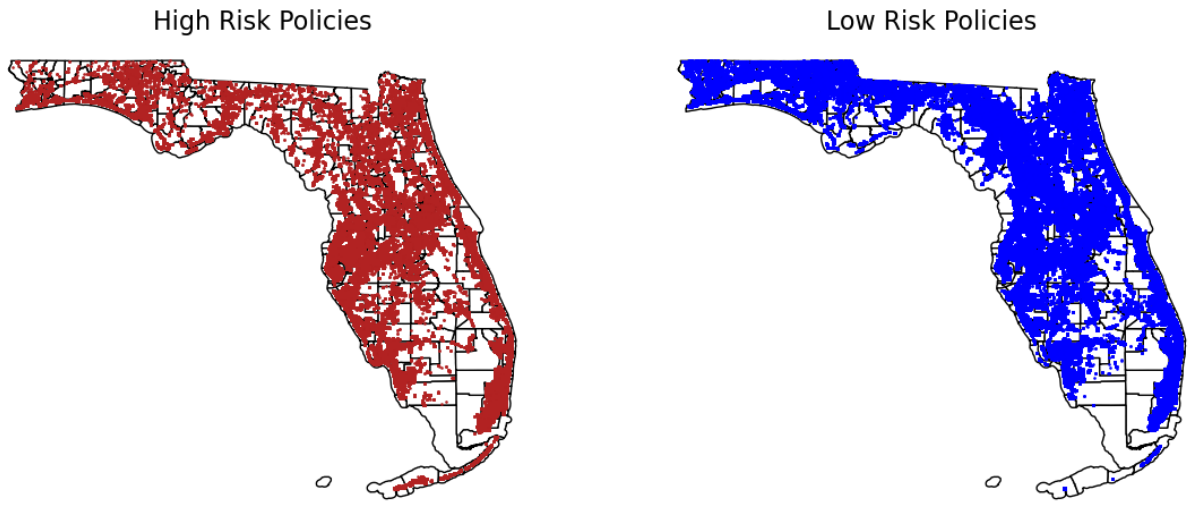
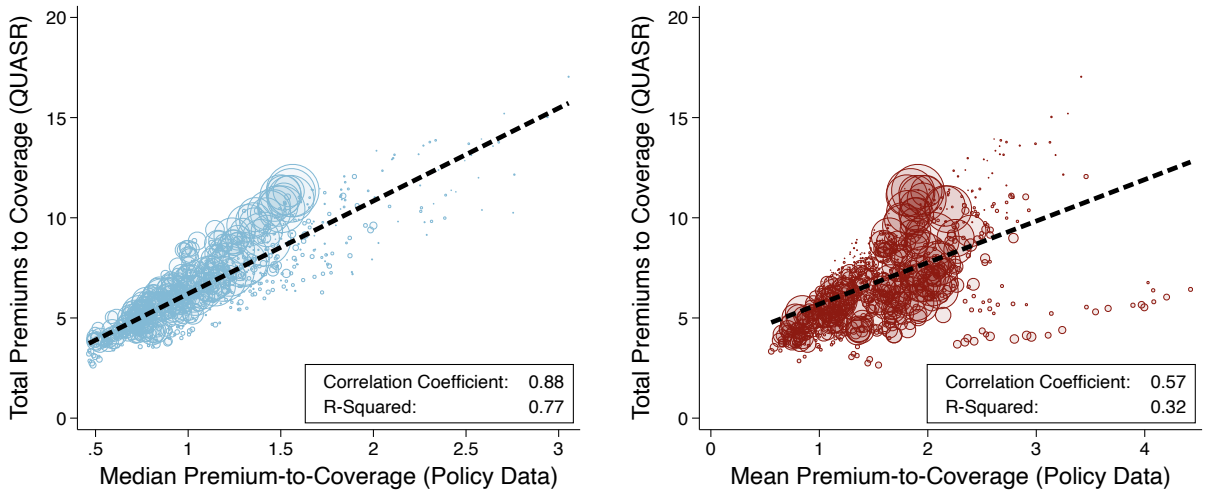


Figure B.1: Policies by FEMA risk

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



(a) Median

(b) Mean

Figure B.2: 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 B.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 a current replacement value of $300,000, a 2% hurricane deductible, a $500 non-hurricane deductible, no claims in the past three years, 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 B.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
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 B.3: 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. *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)
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