Beyond the Storm: Climate Risk and Homeowners' Insurance

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Abstract

Using detailed policy-level data and natural disasters as our setting, we document that insurers pass on climate risk costs to policyholders through both premiums and claim rejection rates. Consistent with our theoretical model, premiums increase significantly in both disaster-affected and unaffected areas following disaster events, while rejection rates rise only in unaffected areas. Spillover effects are heterogeneous and depend on consumers' price sensitivity: in line with price shrouding, less price-sensitive consumers in unaffected areas face higher premiums, while more price-sensitive consumers bear the costs through increased rejection rates. These effects are further shaped by insurers' financial constraints. During constrained periods, insurers raise premiums in both affected and unaffected areas, whereas during unconstrained periods, they primarily increase rejection rates in unaffected areas. Our findings demonstrate that climate risk has contributed to rising premiums over the past two decades and reveal how insurers' responses redistribute costs and access, impacting homeowners in both high-risk and low-risk areas.

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

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1. Introduction

Climate risks and weather-related events—such as hurricanes, wildfires, and floods—have increased markedly in frequency and severity over the past two decades.[1] These trends pose significant challenges for insurers, raising serious concerns about their ability to absorb losses, particularly when these events are concentrated in time and geography. To manage the escalating costs of climate risks, insurers may transfer them, either partially or fully, to policyholders. How insurers allocate these costs not only determines their financial resilience but also dictates who ultimately bears the burden of climate change. For instance, insurers may deviate from strict risk-based pricing when passing on costs, leading to distributive effects with implications for equity and access in insurance markets.

In this paper, we examine how insurers pass through costs associated with climate risk to insurance contracts following natural disasters. Ex-ante, theoretical predictions remain ambiguous. Under frictionless risk-based pricing, disasters should have no effect on contracts, as climate risks would already be fully incorporated into premiums. However, under imperfect information, risk-based pricing suggests that insurers update premiums based on revised risk assessments, leading to higher premiums in affected areas where disasters amplify perceived risks. Alternatively, if disasters prompt a broader reassessment of climate risk across regions, premium increases may extend to nearby unaffected areas. Natural disasters may also mitigate adverse selection by enabling insurers to better differentiate between high- and low-risk policies or regions, potentially leading to increased premiums in affected areas while reducing premiums in unaffected areas.

Because insurers can transfer costs through both a more salient premium component and less salient rejection rates, they may engage in price shrouding to obscure the full cost of coverage (Gabaix and Laibson, 2006). The extent of this shrouding may depend on consumers' price sensitivity. For price-sensitive policyholders, insurers may rely more heavily

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

on rejection rates to manage risk exposure, whereas for less sensitive policyholders, costs are more likely to be passed on through higher premiums. Finally, insurers may respond by offloading riskier policies in affected areas while lowering prices in unaffected areas to attract new policies and rebalance their portfolios. We evaluate and distinguish these different hypotheses in our analysis.

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.

To guide our empirical analysis, we first build and analyze a simple model of an insurer of last resort (Citizens). We assume Citizens faces two sources of costs: deviations from an explicit price target in each location, as well as negative deviations in their capital. Citizens can manage their capital through prices and through claims rejections. When facing negative returns on capital, e.g. when losses are high due to a hurricane, Citizens optimally raises prices in both affected and unaffected locations to try and recoup their capital losses (Oh et al., 2022). The strength of the pricing spillovers depend on market demand: when the private market is distressed, Citizens faces less elastic demand curves, which allows them to offset their capital losses through prices. However, when the private market is stable, Citizens' pricing power falls. They therefore compensate by rejecting a larger share of claims.

We further show that the pass-through instrument depends on demand conditions in the cross-section of locations. Conditional on capital losses, Citizens primarily passes through costs using prices for low price-elasticity (e.g., high-income) locations, but passes through costs primarily using claims rejections for high price-elasticity (e.g., low-income) locations. This result speaks to the timing of risk sharing: high-income locations share risk ex-ante through prices, while low-income locations share risk ex-post through the probability of successfully filing a claim.

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 unaffected 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.[2] 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

[2] 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.

in the region as well, leading most insurers in the market to raise prices.[3] 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 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.

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.

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

Nevertheless, to the extent that similar mechanisms—such as strategic pricing and financial constraints—are at play, our qualitative findings are likely to hold. Furthermore, insurers of last resort are not unique to Florida; many states in the U.S. and regions around the world have adopted similar institutions.[4] Documenting and understanding these effects is therefore essential for informing policy and ensuring the resilience of these critical safety nets in the face of growing climate risks.

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. (2024), for example, highlight the prevalence of underinsurance in high-

[4]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.).

[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 Spillovers

We first present a simple model to organize our empirical findings. We begin by exploring how an insurer of last resort (henceforth, Citizens) 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 these their decisions depend on the stability of the private market and cross-sectional differences in demand across locations.

2.1. Model Setup

We assume that Citizens makes two sets of decisions. First, they set premium rates, $P_{\ell t}$, in each location, $\ell \in \mathcal{L}$, to hit a price target, $\widehat{P}_{\ell t}$. In standard models of insurance with differentiated demand (e.g., Koijen and Yogo 2015), one can think of this price target as the standard markup over marginal cost. We present a generalized structure to allow for motives beyond profit maximization, given that Citizens is an insurer of last resort.

Second, Citizens determines how many claims to reject in each location. In each time period and location, households will decide whether or not to file a claim. Given this decision, the claim rate will be $C_{\ell t}$, which Citizens takes as given. Citizens manages its claims through rejections. By rejecting a fraction $\chi_{\ell t}$ of claims in location ℓ, Citizens can reduce their effective claim rate to $(1 - \chi_{\ell t})C_{\ell t}$. The purpose of our model is to highlight how pricing and claims management interact in different states of the world.

Citizens has two objectives: hit their price targets and minimize capital losses. The latter objective is similar to the literature on financial frictions in insurance markets, such as Koijen and Yogo (2015) and Oh et al. (2022). Our departure is that Citizens cares about changes in their capital rather than the level. This assumption is reasonable if Citizens, being a state-owned entity, has to demonstrate to taxpayers and state legislators that it is managing its capital well. Pricing decisions matter for both objectives, while claims management only matters for minimizing capital losses.[6]

We begin by specifying the dynamics of Citizens' capital. We assume their only liabilities are reserves, which are dedicated to paying out insurance claims. Since damages and claims are uncertain, we assume that Citizens approximates future claims through historical cost accounting. We refer to $V_{\ell t}$ as the reserve rate, i.e. the dollar amount of reserves held per policy to accommodate future realized losses.

[6]It is reasonable to suspect that Citizens has other motives to manage their claims, such as minimizing fraudulent payments. It is straightforward to add claims management to normal periods by including an additional cost management term in Citizens' objective function, but doing so offers similar conclusions while complicating the analysis.

Citizens dedicates part of their premium revenues and their existing assets, A_t, to building up their reserves. Let $Q_{\ell t}$ be the coverage written in location ℓ at time t. Then Citizens' capital evolves according to

$$K_t = \underbrace{R_t^K K_{t-1} + \sum_{\ell \in \mathcal{L}} P_{\ell t} Q_{\ell t}}_{\text{Period } t \text{ Assets}} - \underbrace{\sum_{\ell \in \mathcal{L}} V_{\ell t} Q_{\ell t}}_{\text{Period } t \text{ Liabilities}} \tag{1}$$

where the return on existing capital satisfies

$$R_t^K K_{t-1} = \underbrace{R_t A_{t-1}}_{\substack{\text{return on} \\ \text{non-insurance assets}}} + \underbrace{\sum_{\ell \in \mathcal{L}} \Big[R_t P_{\ell t-1} - (1 - \chi_{\ell t}) C_{\ell t} \Big] Q_{\ell t-1}}_{\text{resolution of insurance claims}}, \tag{2}$$

The total coverage written in period t, $Q_{\ell t}$, depends on both current premium rates, $P_{\ell t}$, and current rejection rates, $\chi_{\ell t}$. The idea is that if Citizens rejects a large number of existing claims, households will update their beliefs about rejection rates. They will therefore be less likely to insure with Citizens since there will be a higher (subjective) likelihood that their future claims will be rejected. This implies that rejecting claims has a cost through the loss of future demand, which can reduce the ability for Citizens to raise capital in response to future losses.

We model Citizens' decisions through two cost functions. Citizens' first objective function is $H(P_{\ell t}, \widehat{P}_{\ell t})$, which captures the cost to Citizens of deviating from their price target in location ℓ. Second, let $F(K_t, K_{t-1})$ be their cost of capital losses. The two costs functions satisfy the following properties.

Assumption 1: Cost Function Properties

Price targeting costs satisfy $H(P, P) = 0$, $H_1(P, P) = 0$, $H_{11} > 0$, and $H(P, P') > 0$ if $P \neq P'$. Capital loss costs satisfy $F_1 < 0$, $F_2 > 0$, and $F(K, K') = 0$ if $K > K'$.

Assumption 1 implies that price targeting costs are minimized when $P_{\ell t} = \widehat{P}_{\ell t}$. The convexity of $H(\cdot,\cdot)$ reflects increasing costs of deviating from this target. The assumption on the costs of capital losses implies that Citizens' faces a higher cost when their capital declines more, but that the cost is negligible when their capital increases.

In each period, Citizens sets prices and rejection rates across locations to minimize the sum of their price targeting costs and cost of capital losses. The set of premium rates, $\{P_{\ell t}\}_{\ell\in\mathcal{L}}$, and rejection rates, $\{\chi_{\ell t}\}_{\ell\in\mathcal{L}}$, solves

$$\begin{aligned} \underset{\{P_{\ell t},\chi_{\ell t}\}_{\ell\in\mathcal{L}}}{\text{minimize}} \qquad & F(K_t, K_{t-1}) + \sum_{\ell\in\mathcal{L}} H(P_{\ell t}, P^*_{\ell t}) \\ \text{subject to} \qquad & K_t = R^K_t K_{t-1} + \sum_{\ell\in\mathcal{L}} (P_{\ell t} - V_{\ell t}) Q_{\ell t}. \end{aligned}$$

Given our framework, we now turn to an exploration of Citizens' optimal behavior in the presence of capital losses.

2.2. Spillovers Due to Capital Losses

Given Citizens' objective, how should they set prices and manage claims across locations? We begin with a study of pricing behavior. In what follows, we will care about the difference between Citizens' prices targets, $\widehat{P}_{\ell t}$, and what we refer to as the monopolistically competitive price,

$$P^M_{\ell t} \equiv \left(\frac{\varepsilon_{\ell t}}{\varepsilon_{\ell t}-1}\right) V_{\ell t}, \qquad \varepsilon_{\ell t} = -\frac{P_{\ell t}}{Q_{\ell t}}\frac{\partial Q_{\ell t}}{\partial P_{\ell t}}. \tag{3}$$

We will make the explicit assumption that $\widehat{P}_{\ell t} = V_{\ell t} < P^M_{\ell t}$ for all ℓ and t. This condition is consistent with Citizens' mandates. First, Citizens must set rates that are actuarially sound (Citizens Property Insurance Corporation, 2024). However, they also strive to be uncompetitive with the private market so as to function properly as an insurer of last resort. According to a recent report, Citizens' CEO stated that Citizens would need to raise premiums by 96% to be "uncompetitive" with current market conditions (Hudson, 2024). According to the article, Citizens allowed a 14% rate increase across many locations, roughly 40% higher than their permitted rate increase in 2022, citing skyrocketing market prices. In other words, when the private market is under distress and setting high rates, Citizens follows. As we will show, the strength of spillovers are sensitive to market conditions.

The optimal pricing decisions in period t are determined through the first order conditions with respect to each location's premium rate:

$$H_1(P_{\ell t}, V_{\ell t}) + F_1(K_t, K_{t-1})\left(Q_{\ell t} + (P_{\ell t} - V_{\ell t})\frac{\partial Q_{\ell t}}{\partial P_{\ell t}}\right) = 0. \tag{4}$$

When Citizens' previous capital position does not decline, $R_t^K \geq 1$, they face no costs associated with their capital unless they record more reserves per policy than they collect in premiums since $K_t \geq K_{t-1}$. Therefore, they will optimally neutralize the costs of deviating from their price targets: $H_1(P_{\ell t}, V_{\ell t}) = 0$ when $P_{\ell t} = V_{\ell t}$. When $R_t^K < 1$, however, setting $P_{\ell t} = V_{\ell t}$ for every location leaves Citizens with a capital loss and, therefore, a non-zero marginal benefit of raising capital, $F_1(K_t, K_{t-1}) \neq 0$. In this case, Citizens has to trade off capital losses and the cost of deviating from their price target. The following proposition formalizes our argument.

Proposition 1: Optimal Pricing and Spillovers

Citizens' optimal premium rate that they set in location ℓ at time t satisfies

$$\begin{aligned} P_{\ell t} &= V_{\ell t} && \textit{if } R_t^K \geq 1 \\ P_{\ell t} &\in (V_{\ell t}, P_{\ell t}^M) && \textit{if } R_t^K < 1 \end{aligned}$$

Further, if $R_t^K < 1$, $P_{\ell t}$ is increasing in $P_{\ell t}^M$.

Proof: See Appendix A.1.

The proposition implies that even absent an increase in reserve values, premiums in a location may increase due to a decline in capital, consistent with Koijen and Yogo (2015) and Oh et al. (2022). We refer to the resulting price change as a *spillover*. The size of the spillover is stronger if the private market itself is increasing rates quickly. This is case in the current environment, according to Citizens' CEO (Hudson, 2024). Since private insurers are distressed and setting high rates (Oh et al., 2022), demand elasticities are low from the perspective of Citizens, which increases the monopolistically competitive price.[7] This effectively relaxes Citizens' price target costs, allowing them to raise prices across the board to keep up with the private market.

A direct consequence of Proposition 1 is that conditional on capital losses, Citizens can raise their capital more in the current period when the private market is distressed. Therefore, they should not feel the need to supplement their capital through claim rejections. But when the private market is stable, Citzens can only recover a fraction of their capital, leaving them exposed to losses. It is then that they may choose to pull this additional lever. We can see this through their first order condition with respect to rejection rates:

$$F_1(K_t, K_{t-1})\left[C_{\ell t}Q_{\ell t-1} + (P_{\ell t} - V_{\ell t})\frac{\partial Q_{\ell t}}{\partial \chi_{\ell t}}\right] = 0. \tag{5}$$

It will be useful for interpretation to specify a functional form for $Q_{\ell t}$. In particular, we let $Q_{\ell t} \equiv N_{\ell t} q_{\ell t}(P_{\ell t}) f(\chi_{\ell t})$. One can interpret $N_{\ell t}$ as the size or population of location ℓ. The term $q_{\ell t}(P_{\ell t})$ is the price-component of demand. It is therefore decreasing in $P_{\ell t}$, and carries the associated elasticity $\varepsilon_{\ell t}$. The relevant component for claims management is $f(\chi_{\ell t})$, which we assume is decreasing and concave in $\chi_{\ell t}$ and satisfies $f(0) = 1$ and $f(1) = 0$. The interpretation is that when there are no rejections, demand is at its highest, but when Citizens rejects every claim, demand is non-existent. With this functional form, we come to our first result on claims management in the presence of capital losses.

[7] For example, in differentiated demand systems in which firms have price impact (e.g., Atkeson and Burstein 2008), optimal pricing implies an elasticity of $s_{\ell t} + (1 - s_{\ell t})\varepsilon_{\ell t}$, where $s_{\ell t}$ is Citizens' market share. As other insurers substantially raise prices, $s_{\ell t}$ increases, lowering the elasticity and increasing markups over fair value.

Proposition 2: Optimal Claims Management

Suppose $R_t^K < 1$. Citizens' optimal rejection rate satisfies

$$\chi_{\ell t} = g\left(\frac{C_{\ell t} Q_{\ell t-1}}{(P_{\ell t} - V_{\ell t}) q_{\ell t}(P_{\ell t}) N_{\ell t}}\right)$$

where $g(\cdot)$ is an increasing function. As such, conditional on losses $C_{\ell t} Q_{\ell t-1}$, $\chi_{\ell t}$ is decreasing in $P_{\ell t}^M$.

Proof: See Appendix A.2.

Proposition 2 highlights an important contrast between pricing and claims management: the two forces move in opposite directions. When the market is uncompetitive due to the distress of private insurers, Citizens has substantial pricing power, setting $P_{\ell t}$ well above actuarial values even in the absence of losses and generating large profits. But at the same time, increasing rejection rates for existing claims stifles their profits in the current period, since doing so would offset their pricing power. As a result, rejection rate spillovers are small when pricing spillovers are high.

Conversely, when pricing power is low, each market is no longer as profitable for Citizens. They therefore are more willing to stifle future demand by increasing rejection rates, which helps them limit their losses and increase their capital. Therefore, rejection rate spillovers are high when pricing spillovers are low.

2.3. Demand Heterogeneity and the Strength of Spillovers

The previous section highlighted how spillovers vary in the time series: when insurance markets are distressed, spillovers occur on the pricing margin; when they are not distressed, spillovers occur on the claims margin. But what about in the cross-section? Are spillovers stronger in poor or rich areas?

The effect will ultimately depend on the sensitivity of local demand. We do not take a stand on the direction of demand elasticities across households, but instead present a general result in Proposition 3.

Proposition 3: Demand Heterogeneity and Spillovers
Suppose $R_t^K < 1$*, and consider two locations,* 1 *and* 2*, such that* $V_{1t} = V_{2t} = V_t$ *and* $Q_{1t}(V_t) = Q_{2t}(V_t)$*. If* $\varepsilon_{1t}(P) > \varepsilon_{2t}(P)$ *for any price* P*, and if* $\partial\varepsilon_{\ell t}/\partial P \geq 0$ *for any* ℓ*, then* $P_{2t} > P_{1t} > V_t$*.*

Proof: See Appendix A.3.

The result is intuitive: the cost to raising premiums above fair value are identical in both locations, but since location 1 has a higher price elasticity, Citizens is less able to exploit their market power to recoup their capital losses. Households in location 2 have less elastic demand, so higher premiums do not scare off demand as much. Citizens can therefore raise premiums and attract more revenues. Therefore, conditional on the state of the private market, pricing spillovers are stronger in low-elasticity locations. In particular, if high-income households are less elastic, then we should expect pricing spillovers to occur in high-income locations rather than low-income locations.

The results of Section 2.2 hint that spillovers on the claims margin may go in the opposite direction. In fact, the mechanism is similar: from Citizens' perspective, the ideal claims to reject are precisely those that are associated with small premium revenues. If low-income households are more price elastic, then according to Proposition 3, markups — and therefore profitability — will be lower in poorer locations. We confirm this in the following proposition.

Proposition 4: Demand Heterogeneity and Claims Spillovers
Suppose $R_t^K < 1$*, and consider two locations,* 1 *and* 2*, such that* $V_{1t} = V_{2t} = V_t$ *and* $Q_{1t}(V_t) = Q_{2t}(V_t)$*. Suppose further that both locations face the same potential losses,* $C_{1t}Q_{1t-1} = C_{2t}Q_{2t-1}$*. If* $\varepsilon_{1t}(P) > \varepsilon_{2t}(P)$ *for any price* P*, and if* $\partial\varepsilon_{\ell t}/\partial P \geq 0$ *for any* ℓ*, then* $\chi_{1t} > \chi_{2t} > 0$*.*

Proof: See Appendix A.4.

Here, the claims spillovers occur purely due to profitability differences across locations, and do not incorporate household heterogeneity into the demand response to rejection rates. But in theory, low-income household demand may be less responsive than high-income household demand.[8] This may be the case if high-income households are more likely to self-insure if they feel that their future claims will be rejected with a high probability. In this case, conditional on the rejection rate, their demand would decline by more relative to low-income households, where self-insurance is unattractive or infeasible. This effect would therefore lead to amplified rejection spillovers.

2.4. Model Summary and Empirical Predictions

Our model admits a variety of empirical predictions. First, in response to a large shock to Citizens' capital, we expect spillovers to occur. However, the dimension of the spillovers should be sensitive to market-level factors in the time series and household heterogeneity in the cross-section. In particular, we arrive at the following testable predictions.

1. Pricing spillovers are more likely to occur and are more pronounced in periods of private market distress.

2. Claims spillovers are more likely to occur and are more pronounced in periods of private market stability.

3. Pricing spillovers are larger for less price sensitive (e.g., high-income) households and regions

4. Claims spillovers are larger for more price sensitive and less profitable (e.g., low-income) households and regions

Equipped with these predictions, we now turn to our empirical setting.

[8]We could incorporate this in the model by assuming the claims component of demand, f, depends on household income. This would be consistent with low-income households having a more concave f, so that only very large rejection rates noticeably reduce demand.

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

Finally, we 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.[9] 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

[9] 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.[10]

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.[11] 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

[10] See Florida Climate Center for a list of major hurricanes in Florida.
[11] 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:

$$Outcome_{p,c,t} = \beta \times Post_{c,t} \times Treated_{p,c} + \gamma \times Post_{c,t} + \alpha_{p,c} + \epsilon_{p,c,t} \tag{6}$$

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 6 separately for each group. Specifically, we estimate the following model:

$$Outcome_{p,c,t} = \sum_{t=-3}^{+3} \beta_t \mathbb{1}_{c,t} + \alpha_{p,c} + \epsilon_{p,c,t} \tag{7}$$

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.[12]

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

[12]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 7, 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 6. 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.[13]

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

[13] 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 Δ*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 Δ*Premium to coverage ratio*.

We find that premiums evolve similarly for treated and control groups in the years prior to hurricanes, consistent with parallel trends. However, during the hurricane year, the affected areas (i.e., 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 6. 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.

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.[14]

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., 2022), 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.

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

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 coverage 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., 2024), largely due to informational frictions (Cookson et al., 2024). In response to a hurricane, households may opt for higher coverage, recognizing that they were underinsured in the first place.

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

Third, we address households' responses to heightened rejection rates through subsequent litigious activity. If households 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. 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.

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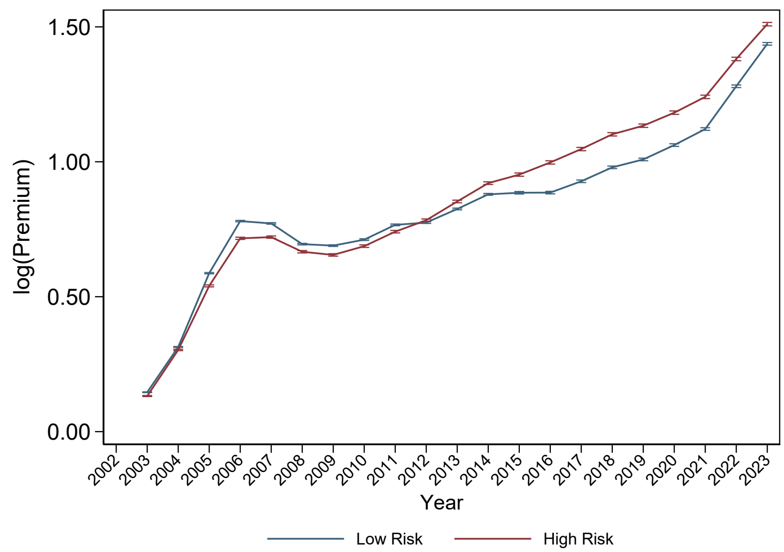
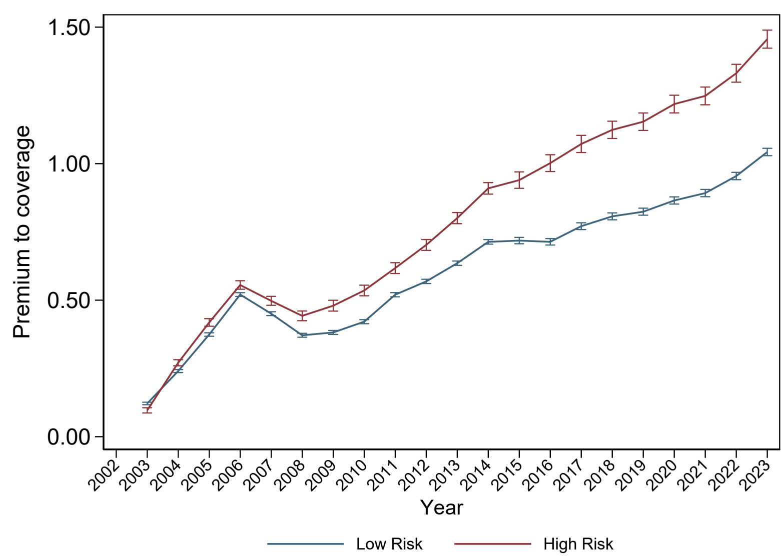
I. Figures

Figure 1: Evolution of home insurance premiums

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



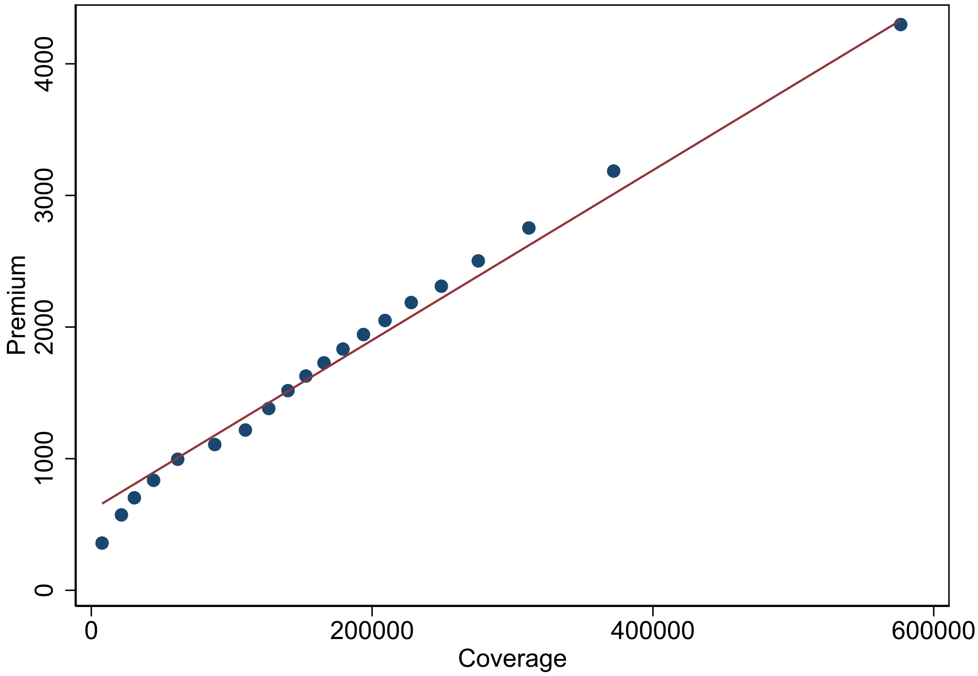
(a) Premium



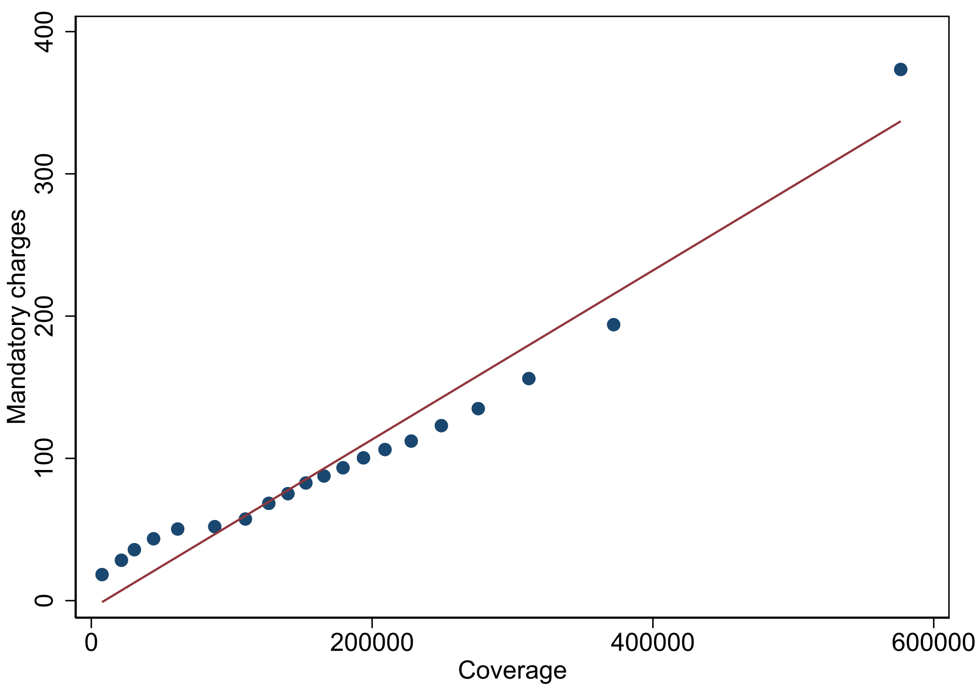
(b) Premium to coverage ratio

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



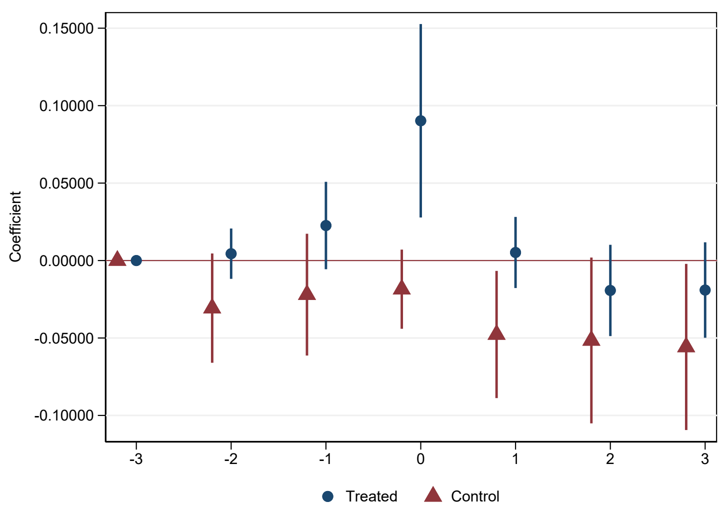
(b) Mandatory charges and coverage

Figure 3: Claims and hurricane

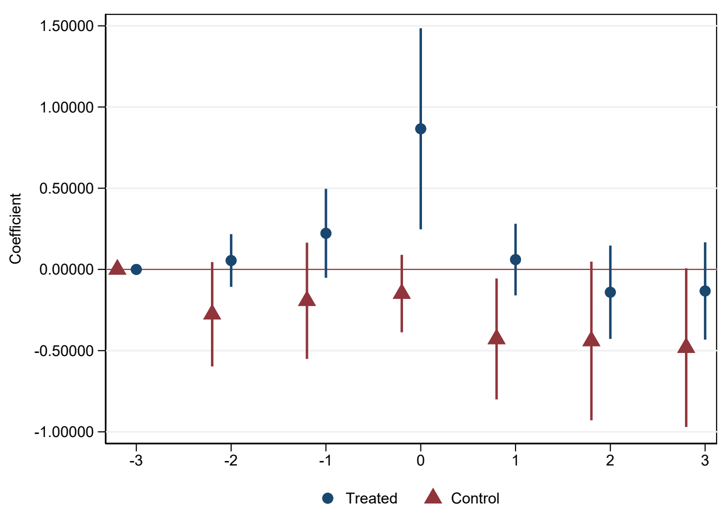
The figure shows the evolution of claims/losses three years before and after a hurricane. We estimate the following model:

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

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



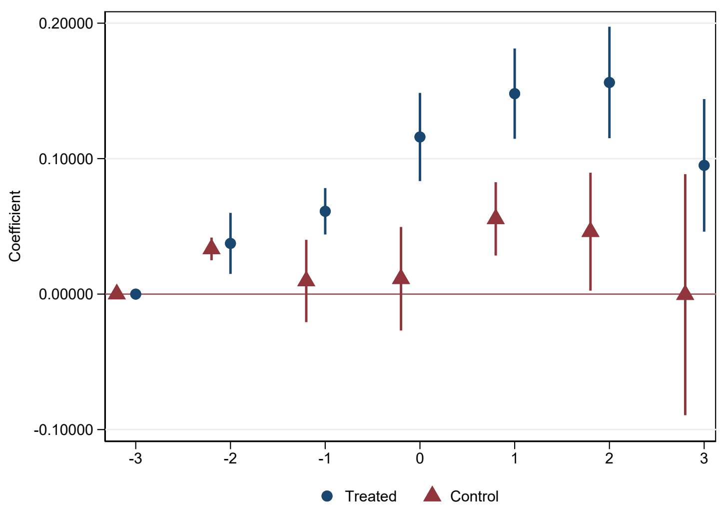
(b) Claim amount

Figure 4: Premium and hurricane

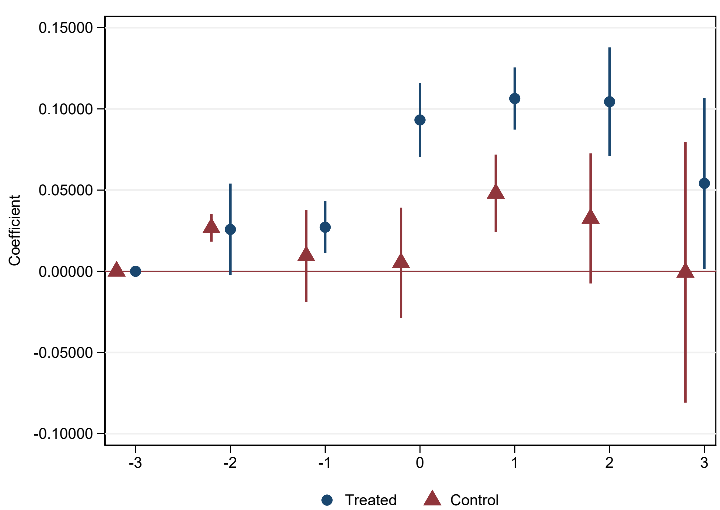
The figure shows the evolution of home insurance premium and premium to coverage three years before and after a hurricane. We estimate the following model:

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

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



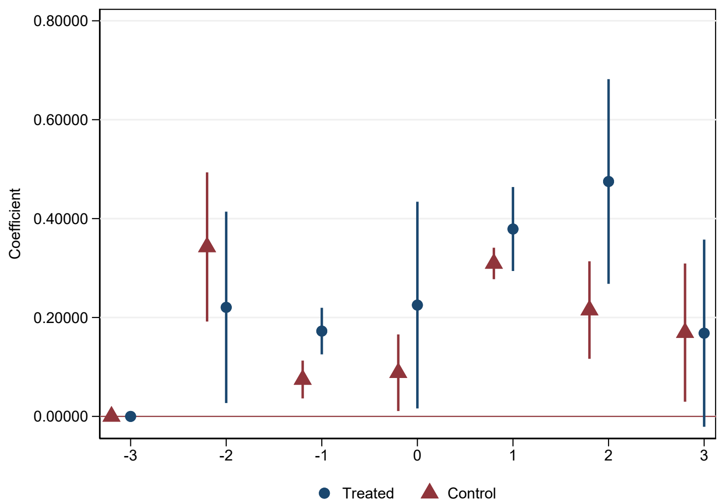
(b) Changes in premium to coverage

Figure 5: Mandatory charges and hurricane

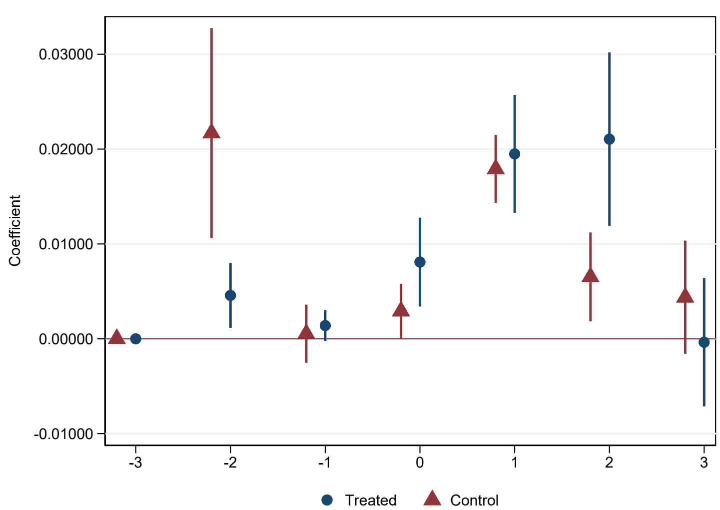
The figure shows the evolution of mandatory charges and mandatory charges to coverage three years before and after a hurricane. We estimate the following model:

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

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



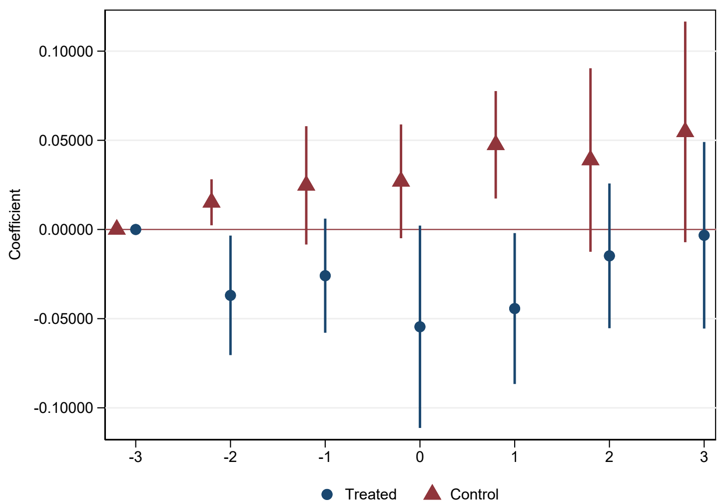
(b) Changes in mandatory charges to coverage

Figure 6: Claim rejection and hurricane

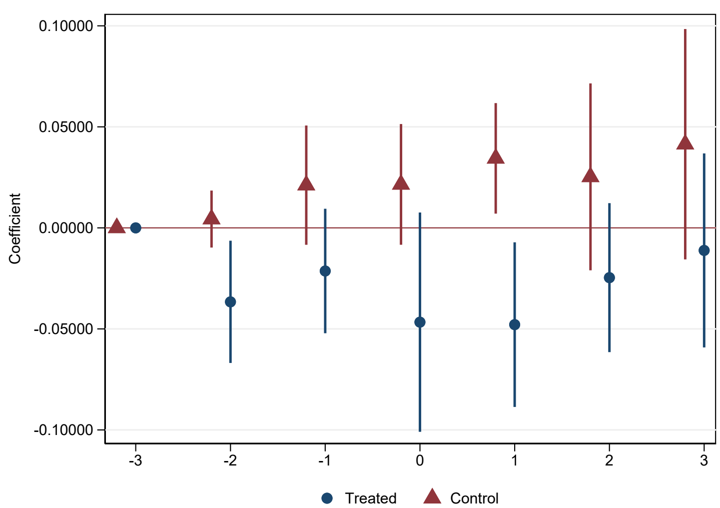
The figure shows the evolution of rejected claims three years before and after a hurricane. We estimate the following model:

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

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

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.

	$\Delta\ln$(Premium)	$\Delta\ln$(Mandatory charges)	$\Delta\ln(\frac{\text{Premium}}{\text{Coverage}})$	$\Delta\ln(\frac{\text{Mandatory charges}}{\text{Coverage}})$	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

Beyond the Storm: Climate Risk and Homeowners' Insurance

Appendix for Online Publication

A. Model Proofs

A.1. Proof of Proposition 1

Proof of Spillovers We'll start with the case of $R^K_{t-1} \geq 1$. Clearly, $F_1(K_t, K_{t-1}) = F(K_t, K_{t-1}) = 0$, so the first order condition simply becomes $H_1(P_{\ell t}, V_{\ell t}) = 0$. Therefore, $P_{\ell t} = V_{\ell t}$ is the solution for every $\ell \in \mathcal{L}$.

Next, consider the case where $R^K_{t-1} < 1$. First, we'll establish the bounds on $P_{\ell t}$. Then we'll show that $P_{\ell t}$ is in the interior of the two bounds for every ℓ. In this case, $F_1(R^K_{t-1}K_{t-1}, K_{t-1}) < 0$, so setting $P_{\ell t} = V_{\ell t}$ clearly is not an optimum for any ℓ. Since the first order condition is negative and both $H(\cdot, V_{\ell t})$ and $F(\cdot, K_{t-1})$ are convex in their first arguments, the optimal price must be larger than $V_{\ell t}$.

On the other hand, suppose $P_{\ell t} = P^M_{\ell t} = (1 - \varepsilon^{-1}_{\ell t})^{-1} V_{\ell t}$ for some ℓ. Note that

$$Q_{\ell t} + (P^M_{\ell t} - V_{\ell t}) \frac{\partial Q_{\ell t}}{\partial P_{\ell t}} = Q_{\ell t} - \frac{V_{\ell t}}{\varepsilon_{\ell t} - 1} \times \frac{\varepsilon_{\ell t}}{P_{\ell t}} Q_{\ell t} = 0,$$

and therefore, the first order condition is $H_1(P^M_{\ell t}, P_{\ell t}) > 0$. Therefore, again due to the convexity of H in its first argument, $P_{\ell t} < P^M_{\ell t}$ must hold.

It remains to be established that $P_{\ell t} \in (V_{\ell t}, P^M_{\ell t})$ for all ℓ. Suppose the contrary is true, e.g. that there exists some ℓ such that $P_{\ell t} = V_{\ell t}$. Then since this is an optimum, it must be that $F_1(K_t, K_{t-1}) = 0$ since $H_1(P_{\ell t}, V_{\ell t}) = 0$. But then for any other ℓ' such that $P_{\ell' t} > V_{\ell t}$, the first order condition is $H_1(P_{\ell' t}, V_{\ell t}) > 0$, which contradicts the optimality of $P_{\ell' t}$. It follows that $P_{\ell t} > V_{\ell t}$ for all $\ell \in \mathcal{L}$. $\square$

Proof that $\boldsymbol{\partial P_{\ell t} / \partial P^M_{\ell t} > 0}$ The comparative statics also follow from the arguments above. Consider two monopolistically competitive prices, $P^{M,2}_{\ell t} > P^{M,1}_{\ell t}$. Let $P^1_{\ell t}$ denote the optimal price given $P^{M,1}_{\ell t}$. We need to show that $P^2_{\ell t} > P^1_{\ell t}$. To do so, note that $(P_{\ell t} - V_{\ell t}) Q_{\ell t}(P_{\ell t})$ is increasing for $P_{\ell t} < P^M_{\ell t}$. Therefore, $Q_{\ell t} + (P_{\ell t} - V_{\ell t}) \partial Q_{\ell t} / \partial P_{\ell t}$ is positive for $P_{\ell t} < P_{\ell t}^M$. Further, since operating profits are concave, it must also be true that

$$Q_{\ell t}^1 + (P_{\ell t}^1 - V_{\ell t})\frac{\partial Q_{\ell t}^1}{\partial P_{\ell t}} < Q_{\ell t}^2 + (P_{\ell t}^1 - V_{\ell t})\frac{\partial Q_{\ell t}^2}{\partial P_{\ell t}}$$

since $|P_{\ell t}^1 - P_{\ell t}^{M,1}| < |P_{\ell t}^1 - P_{\ell t}^{M,2}|$. It therefore must be that

$$0 = H_1(P_{\ell t}^1, V_{\ell t}) + F_1\left[Q_{\ell t}^1 + (P_{\ell t}^1 - V_{\ell t})\frac{\partial Q_{\ell t}^1}{\partial P_{\ell t}}\right] > H_1(P_{\ell t}^1, V_{\ell t}) + F_1\left[Q_{\ell t}^2 + (P_{\ell t}^1 - V_{\ell t})\frac{\partial Q_{\ell t}^2}{\partial P_{\ell t}}\right].$$

Hence, since H_1 is increasing in $P_{\ell t}$ and $Q_{\ell t} + (P_{\ell t} - V_{\ell t})\partial Q_{\ell t}/\partial P_{\ell t}$ is decreasing in $P_{\ell t}$, it must be that $P_{\ell t}^2 > P_{\ell t}^1$. This proves the claim. □

A.2. Proof of Proposition 2

From the first order condition (5) and from the functional form for $Q_{\ell t}$, we can write

$$C_{\ell t}Q_{\ell t-1} + (P_{\ell t} - V_{\ell t})N_{\ell t}q_{\ell t}(P_{\ell t})f'(\chi_{\ell t}) = 0.$$

Solving for $\chi_{\ell t}$, we come to the expression

$$\chi_{\ell t} = (-f')^{-1}\left(\frac{C_{\ell t}Q_{\ell t-1}}{(P_{\ell t} - V_{\ell t})q_{\ell t}(P_{\ell t})N_{\ell t}}\right)$$

as claimed. For notational convenience, we let $g = (-f')^{-1}$. Since f is strictly concave, $-f$ is strictly convex, so $-f'$ is strictly increasing. It follows then that g is strictly increasing as well. From Proposition 1, we know that $P_{\ell t}$ is increasing in the monopolistically competitive price, so holding fixed $V_{\ell t}$ this implies that $(P_{\ell t} - V_{\ell t})q_{\ell t}(P_{\ell t})$ is increasing in $P_{\ell t}$. As such, for a given level of losses, $C_{\ell t}Q_{\ell t-1}$, $\chi_{\ell t}$ is decreasing in $P_{\ell t}^M$. □

A.3. Proof of Proposition 3

From Proposition 1, we know that $P_{\ell t} > V_{\ell t}$ for both locations. Further, since $R^K_{t-1} < 1$, we know that $F_1(K_t, K_{t-1}) < 0$. Suppose by way of contradiction that $P_{2t} \leq P_{1t}$. Note that we can write the first order condition for each location as

$$\frac{H_1(P_{1t}, V_t)}{Q_{1t}\left(1 - \dfrac{P_{\ell t} - V_{\ell t}}{P_{\ell t}}\varepsilon_{\ell t}\right)} = -F_1(K_t, K_{t-1})$$

Since the right-hand side is common across locations, equating them for locations 1 and 2 then implies

$$\frac{H_1(P_{1t}, V_t)}{H_1(P_{2t}, V_t)} = \frac{Q_{1t}\left(1 - \dfrac{P_{1t} - V_t}{P_{1t}}\varepsilon_{1t}\right)}{Q_{2t}\left(1 - \dfrac{P_{2t} - V_t}{P_{2t}}\varepsilon_{2t}\right)} \tag{C.1}$$

Since H_1 is convex in its first argument, it follows that the left-hand side of (C.1) is greater than or equal to 1 given our assumption that $P_{1t} \geq P_{2t}$. On the other hand, note that $Q_{1t} \leq Q_{2t}$ since

$$\log \frac{Q_{1t}(P_{1t})}{Q_{2t}(P_{2t})} \leq \log \frac{Q_{1t}(P_{2t})}{Q_{2t}(P_{2t})} < \log \frac{Q_{1t}(V_t)}{Q_{2t}(V_t)} = 0,$$

where the first inequality follows since demand curves are decreasing in the premium rate, and the second inequality follows from the fact that $\log(Q_{1t}(P)/Q_{2t}(P))$ is decreasing for all

P. It also true that $1 - V_t/P_{1t} > 1 - V_t/P_{2t}$, so therefore,

$$
\begin{aligned}
& -\left(1 - \frac{V_t}{P_{1t}}\right) \leq -\left(1 - \frac{V_t}{P_{2t}}\right) \\
\iff \quad & -\left(1 - \frac{V_t}{P_{1t}}\right)\varepsilon_{1t} < -\left(1 - \frac{V_t}{P_{2t}}\right)\varepsilon_{2t} \\
\iff \quad & 1 - \left(1 - \frac{V_t}{P_{1t}}\right)\varepsilon_{1t} < 1 - \left(1 - \frac{V_t}{P_{2t}}\right)\varepsilon_{2t}.
\end{aligned}
$$

Therefore, it follows that the right-hand side of (C.1) is strictly less than 1, which is a contradiction. We therefore conclude that $P_{1t} < P_{2t}$. □

A.4. Proof of Proposition 4

This proof follows the steps of Proposition 2, noting that the more elastic location has lower levels of profitability. All else equal, this implies that $\chi_{1t} > \chi_{2t}$. □

B. Additional Figures and Tables

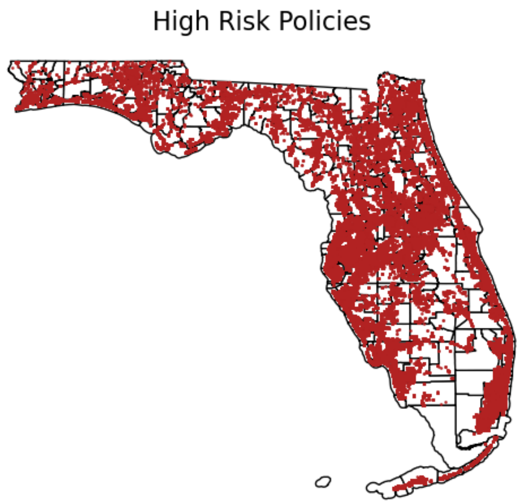


Figure B.1: Policies by FEMA risk

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

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