Regulatory Capital and Catastrophe Risk

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Abstract

In this study, we examine the effect of a capital regulation reform on U.S. insurers' pricing of homeowners insurance. The reform imposes greater regulatory capital costs for insurers exposed to catastrophe risks. We first document that the regulatory capital reform had a meaningful impact on insurers. Using a difference-in-differences design and homeowners insurance prices in the U.S., we find empirical evidence that the reform results in modest price increases per household. Our back-of-the-envelope calculation suggests the increase in insurance price is commensurate to 22-48% of the increase in regulatory capital costs due to catastrophes. We also find that the increase is driven by insurers with greater regulatory capital constraints. Overall, our study provides evidence that climate-related regulatory capital costs can be passed on to consumers at a modest level.

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JEL Codes: G20; G22; G28

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I. INTRODUCTION

The costs of catastrophes have increased steadily over time, especially due to climate change.[1] While the heightened cost of hurricanes, earthquakes, and, increasingly, wildfires are shared by many stakeholders, the property insurance industry bears outsized responsibility for financing these risks. Although insurers are typically in a better financial position to pay for catastrophic losses compared to insurance buyers (i.e., individuals and corporations), they still face considerable insolvency risk and financing costs when exposed to catastrophes. This creates difficulty for insurance regulators, who want to ensure that insurers are financially sound, while also providing affordable coverage to households located in catastrophe-prone areas.

In this study, we examine how property insurers respond to a change in regulatory capital regulation that requires insurers to hold additional capital when underwriting catastrophic risk. While insurers are regulated at the state-level, the regulatory capital framework is a uniform metric applied to all insurers in the U.S. By carefully reviewing National Association of Insurance Commissioner (NAIC) meeting minutes, which include discussions of the proposed regulation between regulators and the industry, we find that the reform, which we refer to as "RCat," was the result of years of negotiation between various stakeholders (summarized in Appendix Figure A1). Since Hurricane Katrina in 2005, there have been on-going discussions regarding the inclusion of catastrophe risk modeling in property insurers' regulatory capital framework. We first document that RCat has a material impact on insurers' regulatory capital ratios starting in the year it was introduced despite the time lag between the initial discussion date and the implementation date. We find that the industry-average regulatory capital ratio drops from 2016 to 2017 and that this

[1] According to Swiss Re (2021), insured losses from natural catastrophes have been increasing by 5% to 6% annually over the past few decades. Global insured losses in 2021 were $105 billion, which represents the fourth highest figure since 1970.

decline is driven by an increase in the denominator (i.e., regulatory required capital) rather than a drop in capital levels (numerator).

We next examine insurer capital management after the reform. Specifically, we study insurers' pricing behavior. Facing an increasing regulatory capital burden, insurers can improve their regulatory capital positions by increasing insurance prices although the increases are potentially constrained by regulatory price controls (i.e., rate regulation) and market competition. On the one hand, there are other reasons why we might not observe a price increase. For example, the delayed implementation gives sufficient time for insurers to prepare for the impact of RCat on their regulatory capital ratios or insurers may have already priced catastrophe risk into their insurance prices for reasons other than regulation (e.g., credit ratings or internal risk management). On the other hand, we may observe a price increase if the implementation of RCat puts more pressure on insurers than anticipated even if insurance price readily reflects catastrophe risk. In this case, we would observe a higher impact of RCat among insurers facing higher regulatory capital burden than those with low regulatory capital burden.

We first investigate the effect of RCat on national-level homeowners insurance prices. We use detailed US zip code-level data from 2014-2021 to examine the effect of RCat on homeowners insurance prices. We implement a difference-in-differences model where treatment is defined at the zip code based on catastrophe risk following the RCat guidelines.[2] Controlling for various state and zip code characteristics that can influence the supply and demand of homeowners insurance, in addition to a host of fixed effects, we find evidence that homeowners insurance prices increase in zip codes with more catastrophe risk following RCat's implementation in 2017. Our results are robust to various alternative specifications, such as limiting our sample to areas that did not

[2] As we discuss in greater detail later, we rely on a proxy from FEMA that measures expected annual losses due to hurricanes and earthquakes as we do not directly observe insurer's RCat risk charges.

experience catastrophic losses or focusing on metropolitan statistical areas (MSA). We also find that the observed increase in prices is robust to different treatment thresholds that we designate as "high catastrophe risk." In addition, we find evidence that the effect size is greater after 2018, suggesting that insurers responded more actively after observing the RBC effect in 2017.[3]

Our next set of analyses focuses on further disentangling the drivers of this relationship between RCat and price increases. We propose two potential drivers. First, we anticipate that firms with greater regulatory capital constraints prior to the implementation of RCat are more likely to increase prices to offset the greater costs imposed by RCat. Second, insurers that can access reinsurance markets for their property portfolio can defray the increased cost of writing insurance in catastrophe prone areas by shifting their catastrophe risks to reinsurers. We find evidence in support of both hypotheses—homeowners insurance prices increase following RCat implementation in risky areas more when states have more insurers with a greater regulatory capital burden and when fewer insurers have access to external reinsurance markets.

For the final step in our empirical analysis, we take advantage of detailed insurer-county-quarter level reporting for property insurers in Florida. Using the dataset, we can link insurers' financial information from their statutory statements to identify heterogeneity in insurance pricing across insurance company types. In addition, we are able to use publicly available data from a hurricane catastrophe model in Florida, which is the precise procedure used by insurers in calculating their RCat risk charge for hurricanes. We find consistent results when examining Florida—homeowners insurance prices increase following the implementation of the RCat for insurers that appear to be more exposed to RCat risk charges but not necessarily due to catastrophe losses. Consistent with our national estimates, we find evidence that this is primarily driven by

[3] Insurers are required to receive approval from state regulators on their insurance price increase, which may play a role in the delayed timing of any RCat effect on observed pricing (e.g., Born, Karl, and Klein 2023).

insurers facing high regulatory capital constraints and those transferring low-levels of property liabilities to reinsurers.[4]

We make several contributions to the literature. First, we contribute to the literature on regulatory frictions in insurance markets. Regulatory frictions arise when regulation, such as risk-based capital requirements, create potentially distorting incentives. A growing body of literature studies how RBC rules create distorting incentives in asset markets (e.g., Ellul et al. 2011; Becker and Ivashina 2015; Hanley and Nikolova 2021). Our study is the closest to Koijen and Yogo (2015) in that they document life insurers' pricing behavior associated with regulatory capital requirements. While Koijen and Yogo (2015) exploit the financial frictions arising from regulatory capital requirements and link them to life insurance pricing behavior, we exploit a regulatory reform to document how climate change risks influence insurers' pricing behavior in the homeowners insurance market.

Second, we contribute to the literature examining the effect of climate change risk on institutional investors. Most of the studies focus on disclosure requirements to financial institutions (e.g., Jouvenot and Krueger 2020; Mésonnier and Nguyen 2021; Lin et al. 2023; Ilhan et al. 2023) while we study a unique regulation that directly affects financial institutions' regulatory capital costs. We extend the literature by examining property insurers, who directly underwrite climate change related property risks in their operations. Our study is most related to Oh, Sen, and Tenekedjieva (2023), who find evidence that the state-based nature of insurance regulation is linked to pricing distortions in the homeowners insurance market. We contribute by providing

[4] We discuss additional details of the Florida property insurance market that may influence the generalizability of these findings in Section V. In particular, Florida has established a mandatory reinsurance program known as the Florida Hurricane Catastrophe Fund (FHCF) which may influence our reinsurance tests.

empirical evidence that a uniform regulatory framework, the risk-based capital ratios, can affect insurers' pricing behavior in homeowners insurance market.

Third, we contribute to the literature exploring how insurers and regulators respond to catastrophe risk. While we do not examine firms' operational changes to catastrophic risk (e.g., Born and Viscusi 2006; Born and Klimaszewski-Blettner 2013; Ragin and Xu 2019), the rising cost of catastrophes is part of the motivation for regulators to implement this risk charge. Prior studies find evidence that insurers react to catastrophic events by changing operations; it is also important to understand how they react to regulation that reflects catastrophic risk management, as financial regulators continue to implement and tweak climate-related regulatory tools.

II. INSTITUTIONAL DETAILS

A. Solvency Regulation in the Insurance Industry

The US insurance industry is predominantly regulated by individual state regulators. Despite this, there is considerable homogeneity in solvency regulation (when compared to other regulatory activities such as rate regulation or producer licensing) across states in large part due to historical efforts by the NAIC. Monitoring insurer solvency is an important regulatory activity, as there is a high degree information asymmetry between insurers and policyholders, as well as difficulty in monitoring insurer behavior over the term of an insurance contract (e.g., Klein 2012).

One tool regulators use for monitoring insurer solvency is the risk-based capital ratio (RBC ratio), which is uniform across states in the US. The RBC ratio is calculated as:

$$RBC\ Ratio = \frac{Total\ Adjusted\ Capital}{Total\ Risk - Based\ Capital} \tag{1}$$

where *Total Adjusted Capital* is an insurers' adjusted capital and surplus. The denominator, *Total Risk-Based Capital,* measures how much risk an insurer takes and can be considered the minimum amount of capital an insurer should be holding. Specifically, the denominator for property insurers can, prior to the implementation of the catastrophe exposure risk charge, be calculated as:[5]

$$Total\ Risk - Based\ Capital = R_0 + \sqrt{{R_1}^2 + {R_2}^2 + {R_3}^2 + {R_4}^2 + {R_5}^2} \qquad (2)$$

where:

R_0= affiliated insurance company assets RBC
R_1= fixed income assets RBC
R_2= equity assets RBC
R_3= credit-related assets RBC
R_4= underwriting reserves risk RBC
R_5= underwriting net written premiums risk RBC.

Each of these risk categories is calculated based on risk-weighted sums of financial statement information for each insurer. Higher risk weights are associated with riskier activities. Insurers are expected to hold more capital if they are taking more risks across the categories in equation (2).[6]

B. Regulatory Capital and Catastrophe Exposure—RCat Implementation

Before 2017, RBC calculations included the effect of catastrophic risk events based on the past 10 years of historical experience (Klein and Wang 2009) and were included as part of the underwriting premiums RBC (R5). Specifically, insurers with relatively higher loss ratios are subject to higher R5 risk charges. While this approach "only reflects catastrophe risk to a limited degree," attempts by the NAIC to more explicitly include exposure to catastrophe risk has historically "generated a number of concerns among insurers and industry actuaries" (Klein and Wang 2009, pp 618).

Discussions on a separate catastrophe risk charge in the RBC calculation began after the 2004-2005 hurricane seasons, where the initial proposal faced pushback from the industry. The

[5] This is RBC before operational risks. Operational risk is the risk of financial losses due to operational events, which is applied on an "add-on" approach to the resulting RBC in equation (2).
[6] Firms that report below minimum RBC ratio thresholds, 200%, may be subject to varying levels of regulatory intervention, ultimately with regulators taking over the insurer if their financial condition is sufficiently dire. When insurers report RBC ratios just above the threshold (i.e., 200-300%), they are on the watch list of the regulators and subject to trend tests over the next few years.

initial proposal in 2006 includes an RBC catastrophe risk charge net of reinsurance based on the result of an approved catastrophe model on the 1-in-250 years expected annual losses for hurricane and earthquake events. The industry quickly responded by requesting more detailed guidelines to limit potential double counting in the existing underwriting premium RBC charge (R5), that includes actual catastrophe loss exposure, as well as potential double counting of within group reinsurance transactions. The industry also disagreed with the use of 1-in-250 years modeled losses. Over the next five years, regulators and industry groups agreed in unofficial documentation to a catastrophe risk charge effective for the 2013 reporting period (NAIC CIPR Newsletter August 2017); since 2013, regulators and the industry have developed various insurer-level exemption rules for the catastrophe risk charge.

The final catastrophe risk charge, also known as the "RCat," is an additional capital requirement item added on top of the existing risk-based capital items and has been officially implemented starting in 2017, with RBC instructions for 2017 noting "[c]atastrophe risk, long identified as the most significant risk missing from the RBC formula, will finally become part of the formula for 2017 reporting after more than a decade of development."

After the introduction of the RCat, property insurers' RBC is calculated as follows (with changes in **bold**):

$$Total\ Risk - Based\ Capital = R_0 + \sqrt{{R_1}^2 + {R_2}^2 + {R_3}^2 + {R_4}^2 + \boldsymbol{{R_{5A}}^2} + \boldsymbol{RCat^2}} \tag{3}$$

where:

R_0= affiliated insurance company assets RBC
R_1= fixed income assets RBC
R_2= equity assets RBC
R_3= credit-related assets RBC
R_4= underwriting reserves risk RBC
$\boldsymbol{R_{5A}}$**= underwriting net written premiums risk RBC net of catastrophic risks**
$\boldsymbol{RCat}$**= Catastrophe risk.**

After the introduction of the RCat, historical hurricane and earthquake losses used in the underwriting premium risk charge (R5) have been removed to avoid double counting (now denoted as R5A). Each year, insurers exclude underwriting net written premium risk exposed to catastrophe losses using the list of approved catastrophe events provided by the NAIC (i.e., qualifying for a reduction in R5A).[7]

RCat is a sum of the earthquake risk charge and the hurricane risk charge. The earthquake risk charge and hurricane risk charge are calculated in the same manner and are conceptually 1-in-100 years estimated modeled losses. Specifically, RCat is calculated as:

$$RCat = \sqrt{Earthquake\ Catstrophe\ Risks^2 + Hurricane\ Catstrophe\ Risks^2} \tag{4}$$

Where catastrophe risks are defined as 1-in-100 years net modeled losses excluding loss adjustment expenses.[8] Each catastrophe risks charge is calculated by NAIC-approved commercially available catastrophe modelling vendors.[9] Reporting insurers can choose one of the models or any combination of the results of two or more vendors.

The RCat applies to certain lines of business written in certain geographic areas, defined by states. Insurers may be exempt from including the RCat risk charge under certain conditions even if they write in these lines of business in catastrophe exposed areas.[10] Fire, Allied Lines, Earthquake, Farmowners, Homeowners, and Commercial Multi-Peril are defined as catastrophe-exposed lines. Hurricane exposed geographies include Hawaii, Washington DC, and states bordering the Atlantic or the Gulf of Mexico. Earthquake-exposed states are Alaska, Hawaii,

[7] See, for example, Page 2304 of NAIC Proceedings Fall 2019.

[8] Net modeled losses refer to the amount of modeled losses except for modeled losses transferred to other insurers through reinsurance. Specifically, the net modeled losses equal to direct business modeled losses and transferred business modeled losses from other insurers minus transferred (ceded) amounts recoverable. If an insurer uses external reinsurance, a credit charge of 0.48 is added (i.e., contingent credit risk) to the catastrophe risk calculation.

[9] AIR, EQECAT, RMS for earthquake or hurricane and ARA HurLoss or the Florida Public model for hurricane only.

[10] For example, insurers with sufficient pooling within groups or insurers with low levels of insured property values are exempt.

Washington, Oregon, California, Idaho, Nevada, Utah, Arizona, Montana, Wyoming, Colorado, New Mexico, Puerto Rico, Missouri, Arkansas, Mississippi, Tennessee, Illinois, and Kentucky.

C. Insurance Rate Regulation

Insurance rates are typically subject to regulatory approval before insurers can change their prices, particularly in personal lines of insurance. These regulations are motivated by a regulatory and political desire to ensure that rates are sufficient to cover eventual claims payments, but not so excessive as to make insurance unaffordable to consumers. The process generally involves compiling historical claims information and submitting it to regulators as support for why an insurer wants to increase or decrease rates.

Historically, research has considered certain statutes governing rate regulation to be stringent or lenient based on the method of rate regulation. For example, studies consider prior approval laws, where insurers cannot change prices before regulators allow the change, to be strict (e.g., Harrington 1987). Other studies, however, provide evidence that the individual regulator characteristics (Grace and Phillips 2008) or political considerations (Liu and Liu 2023) may be more meaningful than the text of the statute governing rate regulation. Consistent with these findings, Oh et al. (2023) provide evidence of substantial heterogeneity between accepted and requested rates across states.

D. Descriptive Evidence of the RCat on Insurers' RBC Ratios

A detailed breakdown of the RBC formula for each insurer is not public information—only regulators have access to the information.[11] The NAIC, however, periodically reports aggregate industry values of each of the RBC component. During the 2013-2016 period, the NAIC published

[11] Insurers do disclose total RBC (the denominator) and total adjusted capital (the numerator) annually in their financial statements on the "Five-Year Historical Data") page.

aggregate values of underwriting premium RBC (R_5) and “hypothetical/informal” RCat components to facilitate regulators’ decision on the formal RCat rule.

Using these reports (along with reports of binding RCat charges from 2017 to 2021), we examine the trend of R5 and RCat in the property insurance industry in Figure 1, Panel A to assess the influence of RCat in the industry-level RBC ratio. Different colored lines represent each RBC component, from Asset RBC (R1, R2, and R3 in grey circles), Underwriting Reserves RBC (R4 in light blue squares), Underwriting Premiums RBC (R5 in dark blue triangles), and Catastrophe RBC (RCat in bright blue diamonds). In general, we find that RCat values have similar magnitudes to underwriting premium RBC in dark blue triangles during the unofficial period from 2013-2016 and is slightly lower than underwriting premium RBC since the official implementation in 2017. Based on discussions with the internal NAIC staff responsible for compiling these statistics, we acknowledge that the RCat value reported between 2013-2016 fluctuate due to potentially both changes in the definition of the RCat (e.g., exempt firm definitions and 1-in-100 vs. 1-in-150 modeled losses) and reporting error of the firms (e.g., some exempt firms reported before 2016). Since the official adoption, the RCat component’s industry-level values increase from $51 billion to $54 billion.

The industry-level RBC component statistics only speak to the effect of the RCat on the denominator of the RBC ratio. Next, we turn to insurers’ overall RBC ratio in the industry. In Figure 1, Panel B, we first examine trends during our sample period for the numerator and denominator of the RBC ratio separately, both reported in billions. We note that both the numerator (total adjusted capital) and the denominator (risk-based capital) of the RBC ratio appear to be increasing more after 2016. The horizontal line shows the level of RBC (denominator) in 2016, to easily see that the reported RBC increases steadily over the sample period.

To examine how these trends manifest in overall reported risk-based capital ratios, we calculate the average RBC ratio across homeowners insurers.[12] RBC ratio is a tool regulator use to examine each insurer's financial condition. While we do not observe the breakdown of RBC per insurer, each insurer annually discloses total RBC (the denominator of the RBC ratio) and total adjusted capital (the numerator of the RBC ratio). Using the reported value per insurer, we calculate the average RBC ratio across insurers in each year, weighted by insurer's reported assets. We report these results in Figure 2, Panel A. We note a striking drop in the average RBC ratio by more than 50 percentage points from 2016 to 2017. The drop suggests that many property insurers report lower RBC ratios due to RCat's introduction, despite the adoption date being known well in advance. We also find that the RBC ratio increases in 2018 but declines in 2021.

Finally, we examine differences in RBC ratios by insurers' RCat exposure. We estimate linear regression models where the dependent variable is the natural log of the RBC ratios. We then include year indicators interacted with a binary variable equal to one if an insurer provides coverage in an RCat state, along with controls for insurer size and insurer fixed effects.[13] We plot the coefficient estimates (along with 95% confidence intervals) from the interaction between year fixed effects and the RCat treatment variable in Figure 2, Panel B. We note that there is no pre-trend, while RBC Ratios are statistically significantly negative in RCat treated insurers following the enactment of RCat in 2017.

Overall, Figures 1 and 2 suggest, first, that RCat risk charges appear to be economically meaningful as a component of risk-based capital and, second, that rising capital levels in the property insurance industry offset this increase in capital requirements to some extent yet not fully, as the average RBC ratio is lower after this regulatory change.

[12] Homeowners insurers are those writing positive homeowners insurance premiums in a given year.
[13] We code insurers as writing in RCat states if they provide homeowners insurance in at least one RCat state.

III. RESEARCH DESIGN

A. Homeowners Insurance Prices

We next examine whether insurers increase prices to improve their capital positions following RCat implementation. There are three main reasons why we focus on insurance pricing. First, the capital shock model of insurance pricing theory predicts short-term insurance price increase in the event of capital shocks. We borrow Harrington, Niehaus, and Yu's (2013) framework on insurance pricing to discuss RCat's capital costs. In equilibrium, insurance companies would price insurance policies such that they are sufficient to fund expected claim costs and administrative costs, while also providing fair return on investment capital for the insurance company owners. A fair insurance price in a perfectly competitive insurance market, therefore, comprises expected claim costs, administrative costs, and fair profit loading. In practice, observed insurance prices in the market are not fully explained by the components of the fair insurance price (e.g., Gron 1994; Winter 1994). Capital shocks affect insurers' pricing behavior. For example, Koijen and Yogo (2015) document evidence that life insurers price products at a discount to increase capital levels in the short run during the 2007-2008 financial crisis. A vast literature in the property insurance industry documents unexplained variations of insurance prices, at least until early 1990s (e.g., Meier 2006; Boyer et al. 2012).

To illustrate, assume that insurers have an optimal capital level in the long-run equilibrium and that the supply of capital is sticky in the short-term (e.g., due to costly external financing (Myers and Majluf 1984; Winter 1994). A deviation from the optimal level due to negative capital shocks increases insurer insolvency risk, leading an insurer to increase price in the short-term until capital equates its long-run optimal. In the case of RCat, we conjecture that the adoption of the RCat is a type of capital shock that increases insolvency risk. In addition, RCat affects insurers' regulatory capital cost in terms of the probability of regulatory scrutiny given that it is a component of the RBC metric, a tool used by regulators to measure insolvency risk. Because RCat is only binding for areas exposed to catastrophic risks, we expect to observe increases in prices in areas with higher catastrophic risks if the price increase is attributable to RCat. An extreme pricing behavior for insurers writing in these catastrophic risk areas would be not to write any business in areas with high modeled losses (and, therefore, higher RCat charges); this is one option for insurers in catastrophic risk areas. Such insurer exits would lead to an even higher homeowners insurance price increase in catastrophic risk areas if the remaining insurers create an oligopoly market.

Second, one potential unintended consequence of regulatory reforms is passing on the cost of regulation to consumers. Ideally, regulatory reforms such as RCat are intended to make insurers salient of potential climate change risks and, therefore, proactively adopt measures ensuring financial strength. However, recent empirical evidence suggests that regulatory frictions often lead to decreased consumer welfare as firms pass costs to consumers (e.g., Sastry 2022). To better examine the effect of RCat on consumer welfare, we focus on homeowner's insurance. Many homeowners are required to purchase and maintain insurance coverage through their mortgage provider, suggesting that the observed insurance price is predominantly driven by supply side frictions rather than demand side frictions. In addition, homeowners insurance is one of the largest sources of capital for property insurers making up around 15% of total industry premiums written and $109 billion in 2021.

Third, there is an advantage in terms of the identification strategy that enables us to study insurer pricing behavior more clearly than other financing options, even if we do not assume costly external financing. Insurers can improve their capital position using methods other than external financing and insurance pricing: i) internal capital financing through capital contributions from affiliated companies if the insurer belongs to an insurance holding group (e.g., Niehaus 2018; Ge

2020), or ii) transfer all of the liabilities to another entity through reinsurance to decrease liability positions (e.g., Mayers and Smith 1990; Adiel 1996). Option i) is difficult to test empirically since these capital contributions are observed at insurer-level while the RCat is implemented at insurer-business line-state-level. Importantly, detailed RCat information for individual insurers is accessed only by state regulators, making it difficult for us to empirically create an insurer-level summary variable that measures to what extent an insurer is "treated" by RCat (i.e., a treatment intensity).[14] We view option ii) as unlikely to explain the average response, because we would observe a decrease in either or both of the underwriting RBCs (R4 and R5) and RCat, which is not the case in Figure 1; RCat is calculated on a net-of-reinsurance basis.[15] Additionally, option ii) also faces the same empirical challenge of identifying treated insurers. Our study, therefore, aims to empirically test insurers' pricing behavior, using the homeowners insurance price data.

B. Empirical Strategy

Our main empirical test examines whether insurers exhibit different pricing for markets that are subject to RCat. Using detailed zip code level panel data on homeowners insurance prices, we estimate differences in homeowners insurance prices between areas subject to the RCat and those not pre- and post-RCat. Our model is the conventional two-way fixed effects difference-in-differences design:[16]

[14] While annual statutory statements include detailed securities level information on insurer assets, there is no granular financial or geographical policy-level information which could have enabled us to create a measure that mimics RCat.
[15] External reinsurance has generally represented an expensive form of external financing. Froot (2001) finds evidence that catastrophe reinsurance is priced above expected losses. Anecdotally, property reinsurance prices are reported to be rising by as much as 50 percent in 2024 (Reuters 2024).
[16] The burgeoning literature documents potential bias in staggered difference-in-differences design when using the two-way fixed effects model, with the concern that treatment effects can be heterogeneous by treated status over time (e.g., Athey and Imbens, 2018; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2019; Sun and Abraham, 2020). Such a concern is likely not valid in our empirical setting, given that the treatment assignment is not staggered. One valid concern is that the price has been on an increasing trend even before the regulation went into effect; we document robustness test on this concern following Rambachan and Roth (2023) and discuss our findings in Section IV.

$$HOPrem_{jst} = \beta Treat_j \times Post_t + \boldsymbol{H}_{jst} + \boldsymbol{\zeta}_j + \boldsymbol{\tau}_t + \boldsymbol{S}_s + \epsilon_{jst} \quad (5)$$

where $HOPrem_{jst}$ is the natural log of average homeowners insurance prices in zip code j that belongs to state *s* in year t.[17] We are concerned with the outliers of average prices affecting our results and take the natural log value of the average prices. *Post* is a binary variable that equals one for 2017 and later years, and zero otherwise (i.e., the period following implementation of RCat). *Treat* is a binary variable that equals one for zip codes with expected annual loss scores (from FEMA's National Risk Index) great than 75, and zero otherwise.[18]

We define our treatment using the National Risk Index (NRI) from the FEMA website following the RCat guideline.[19] FEMA produces the National Risk Index (NRI) that incorporates expected annual loss estimates, social vulnerability, and community resilience (Zuzak et al. 2022). We specifically use the "Expected Annual Loss" component of the index, which provides a score that measures the dollar amount of economic losses within a certain zip code.[20] This involves consideration of each zip code's exposure to natural hazards as well as estimates based on historical values of frequency and severity. We use the expected annual loss scores to identify treated areas within states defined to be catastrophe-prone areas in the RCat guidelines.[21] While this is not perfectly comparable to the sophisticated catastrophe models that insurers use to calculate their RCat exposure, it provides a publicly available proxy. We plot values of the NRI's expected annual loss scores in Figure 3, where Panel A reports the states named in the RCat regulation (which we provide details of in Section II) and Panel B reports quartiles of expected

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[17] Our results are consistent to not taking the natural log of premiums (Appendix Table A4).
[18] We estimate this model with alternative definitions to ensure our results are robust to alternative cutoffs. The details are discussed in Section IV.
[19] Accessible at: https://hazards.fema.gov/nri/.
[20] The NRI scores are reported at either the census tract or the county level. We convert the census tract level estimates to zip code levels.
[21] All zip codes located in states exempt from the RCat requirement are not considered as treated areas.

annual loss scores. Within states, treatment intensity can vary substantially since the risk charge is based on modeled losses. Texas, for example, has significant hurricane exposure along the gulf coast, but very little in northern or western parts of the state. Accordingly, any actual impact of the RCat may differ substantially based on an insurer's portfolio of property coverage even within a single state, which will dictate potential modeled losses. In addition, property insurers typically price insurance differently across rating territories, which are usually defined at the zip code or county levels.[22] We, therefore, define treatment at the zip code level based on the NRI's expected annual loss scores. While there is considerable overlap between the expected annual loss scores and the RCat states, there is notable heterogeneity within certain states as shown in Figure 3, indicating that zip code is a more appropriate treatment unit than the state.

$\boldsymbol{H}_{jst-1}$ is a vector of zip code-level control variables. We control for socio-economic characteristics of the zip including population, median age, median household income, percent with bachelor's or higher education, and unemployment rate. Zip code housing characteristics are important factors explaining the elasticity of homeowners insurance demand (e.g., Grace, Klein and Kleindorfer 2004; Dumm et al. 2020). We, therefore, control for the total number of occupied homes, share of occupied homes rented, and the share of housing units with mortgages. We also control for supply side factors, including the prevalence of large insurers in the zip code following Ellis et al. (2022) and the Herfindahl index based on homeowners insurance premiums in each state.[23] In addition, prices in many insurance markets are monitored by regulators who will often have the legal authority to decline rate change requests. Prior studies find mixed evidence that

[22] Werner (1999) notes that a "CAS survey verified zip codes as the most prevalent geographic unit used in the industry." See also Klein and Grace (2001) and Kuacera (2004).

[23] Our data includes information on the number of homeowners policies written by certain insurers in each zip code. The companies are AAA/Auto Club, Allstate, American Family, Erie, Farm Bureau, Farmers/Zurich, GEICO, Hartford, Liberty Mutual, MetLife, Nationwide, Progressive, State Farm, Travelers, and USAA. GEICO and Progressive do not have data for 2014 and 2015, so we exclude them from our analysis.

more stringent forms of rate regulation, on their own, constrain rate increases, while also suggesting that regulator characteristics play a role (e.g., Grace and Phillips 2008; Oh et al. 2022).[24] Accordingly, we also control for characteristics of the time-varying regulatory environment, including whether there is a new insurance commissioner in the state, the natural log of the number of policies affected by rate change requests in a state, and the number of insurers that request a rate change in a state. These measures also control for the competitiveness of the homeowners insurers in the state.

We also include zip code fixed effects ($\boldsymbol{\zeta}_j$), year fixed effects (τ_t), and state fixed effects ($\boldsymbol{S}_s$). We cluster standard errors at the zip code level. To limit the influence of extreme outliers, however, we winsorize at the 1st and 99th percentile values of continuous variables (excluding natural log variables).

With zip code and year fixed effects, our estimates capture within zip code variations over time. If RCat results in increases in insurance prices for zip codes with larger expected modeled losses, we expect to observe a positive and statistically significant coefficient estimate on the interacted coefficient ($\beta > 0$). If, however, insurers either do not respond to the RCat requirement or respond to the requirement through other operational changes rather than financing through insurance prices, we would not observe a statistically significant coefficient estimate ($\beta = 0$). Alternatively, we would observe a negative and statistically significant coefficient if market frictions (e.g., competition or stringent rate regulation) drive down insurance prices in RCat states ($\beta < 0$).

[24] As we previously note, prior studies (e.g., Harrington 1987; 2002) consider some forms of rate regulation, such as prior approval, to be stringent, while other types, such as use-and-file, to be lenient. These differences could result in differences across states in insurer ability to change rates in reaction to the RCat. However, Grace and Leverty (2010) note that only two states changed their rate regulation laws during their sample period (1990-1997), suggesting that "states maintain their rate regulation laws for extended periods of time." We, therefore, additionally argue that some state-level differences in rate regulatory environments will be captured by our fixed effects.

In addition to our main model reported in equation (5), we perform three tests to rule out the possibility that price changes are associated with actual catastrophe losses. One concern with our specification and study period is that insurers that experience catastrophic losses may increase prices, regardless of the impact of the RCat. Such losses would increase the cost of capital, which will increase the price. To identify if the treatment effect is coming from the RCat rather than incurred losses, we include the natural log of property damage per capita in each county (in 2021 dollars) as a control variable. Our property damage per capital includes hurricanes and earthquakes, as well as other hazards to account for various property damages. In addition, we estimate equation (5) on a subsample of zip codes that did not experience any catastrophe losses across our sample period. This allows us to attribute any changes to homeowners insurance prices to the RCat risk-based capital charge and not responses to claims associated with catastrophes. Lastly, we estimate the main model on a subsample of zip codes that belong to MSAs. This test alleviates the concern that we are not comparing average homeowners insurance prices in rural control areas to RCat areas with dense population.

C. Data

Our data are from various sources. First, we use homeowners insurance market survey data gathered by Claritas and compiled by S&P Global from 2014 to 2021. Our sample begins in 2014 given that Claritas improved their reporting of homeowner insurance prices since 2014; before, they reported homeowner insurance prices including homeowners and renters insurance policies. Claritas' insurance market data are used by insurers for market segmentation and targeting purposes. Ellis et al. (2022) also use their auto insurance price data in an academic setting. Claritas performs online insurance survey during the first quarter of every odd year (Insurance Track Survey). While the sample size varies across survey years, approximately 35,000 households respond to the Insurance Track Survey, which are selected to represent seven US Census regions (Claritas, 2014-2021). Claritas uses statistical models to combine Insurance Track Survey responses and Pop-Facts© demographic data to estimate annual household-level insurance consumption at various geographic levels including zip codes.[25] In an odd year, Claritas' insurance market data are estimated based on the previous odd year's Insurance Track Survey and the current odd year's population characteristics. In even years, Claritas' insurance market data are updated based on the current even year's population characteristics. For example, both 2014 and 2015 Claritas insurance price data are based on the 2013 Insurance Track Survey. For 2014 insurance price data, Claritas uses 2014 population estimates while using 2015 population estimates for 2015 insurance price data. One concern with Claritas' insurance market data is that the estimates for odd years and the following even years are from the same Insurance Track Survey. We, therefore, use one-year lagged average insurance prices per zip code in our regressions (e.g., using 2014 insurance prices for 2013 insurance prices) and consider it as the appropriate estimate of the given year's average premiums.[26]

[25] Claritas take two-stage approach to produce nationally representative estimate of insurance prices. First, they sample approximately 35,000 households stratified along five household age groups, three race/ethnicity groups, and the nine US census geographic divisions. When producing household-level estimates after the survey is fielded, the sample is further adjusted with population estimates of household income, presence of children, and home ownership.

[26] Another concern with Clarita's insurance market data is the validity of its statistical model that estimates zip code-level homeowners insurance prices from its Insurance Track Survey respondents, as survey respondents may not represent the US national population. We examine the external validity of these data using homeowners insurance price data published by the NAIC. These data are only reported by the NAIC at the state level each year, which is why we do not use them in our main analysis, but this does allow us to compare the prices produced by Claritas to an external source (i.e., insurance regulators). We do so by estimating models with the NAIC's state-level average prices as the dependent variable and the Claritas zip code level insurance prices as independent variables. Overall, we observe a strong statistical correlation between the two data sources (at the 1 percent level) with coefficient estimates that are approximately one, indicating that a $1 change in prices in one sample should be associated with a $1 increase in the other sample. We estimate the model using both one-year lagged and not lagged average prices and find a higher correlation when using one-year lagged average prices, bolstering our strategy to use one-year lagged average prices. We report these results in Appendix Table A2. We also estimate the models using insurance prices that are not lagged, and find consistent results as shown in Appendix Table A5.

For our second data source, we use data from annual statutory statements property insurers file with the NAIC to gather insurance company information. We use data on insurer risk-based capital ratios as well as information from the "State Pages" to provide summary assessments of changes to risk-based capital ratios over time, and to construct state-level control variables in our regression analysis.

We gather zip code level demographic characteristics from the American Community Survey (ACS). Specifically, we use annual estimates from the ACS 5-year data following the US Census recommendation for geographic areas with less than 65,000 population. Due to zip code tabulation area (ZCTA) update, we find 16 zip codes with duplicate ACS demographic information. We drop these zip codes in our analysis. We also obtain data on insurers' rate change requests from S&P Global.[27] Finally, we use data from the Spatial Hazard Events and Losses Database for the United States (SHELDUS) to control for actual catastrophe losses (ASU, 2021).

Our final sample includes 201,080 zip code-year observations from 25,135 unique zip codes (balanced sample). These zip codes have non-missing insurance premiums data from S&P Global as well as socio-economic data from ACS.

IV. RESULTS

A. Summary Statistics and Event Study Style Estimates

We report univariate differences between our treated and control zip codes in Table 1.[28] First, we note that average homeowners insurance premiums are $57.77 higher ($p$-value < 0.01) in

[27] We use insurers' rate requests filed for homeowners multi-peril and homeowners occupied lines. We limit the sample rates to those that have valid requested and accepted rate information. Florida is not included in this database, so we do not have access to their rate change request data. Data from Alabama is missing for most years in our sample aside from 2014 and 2016. Data from Wyoming is missing in 2019 and 2021. When we use these data to construct variables, we impute values for Florida, Alabama, and Wyoming using the average across states in a given year.
[28] We also tabulate the distribution of each variable in Appendix Table A1. We additionally tabulate and report summary statistics and tests of univariate differences between treated and non-treated RCat *states*. We report these in Appendix Table A2.

zip codes with more intense treatment under the new RCat regulation. RCat zip codes also appear to have insurers that use more reinsurance for homeowners business (higher values for *AvgHOReinsShare*) and face higher RBC burdens (higher value of *HighRBCBurdenShare*). There are also important differences in our socio-economic variables. On average, RCat zip codes have larger populations and include more zip codes that belong to MSAs. While RCat zip codes have higher educational attainment and income, they also tend to have higher unemployment rates. The average age of the population in RCat zip codes is slightly lower than in control zip codes.

We next estimate differences in insurance prices between RCat treated zip codes and control zip codes in an event-study style model. Specifically, we estimate a model that is an event-study style version of equation (5):

$$HOPrem_{jst} = \sum_{t}^{T} \beta_t \, Treat_{\,j} X \, Year_t + \boldsymbol{\zeta}_j + \boldsymbol{\tau}_t + \boldsymbol{S}_s + \epsilon_{jst} \tag{6}$$

Everything in this equation is the same as equation (5) except that we replace the *Post* indicator with year indicators and do not include time-varying control variables. The omitted baseline year is one year before the introduction of RCat (2016). We report coefficient estimates on the interaction of *Treat* and year indicators in Figure 4 Panel A. The figure indicates a pre-trend where treatment zip codes report lower insurance prices than control zip codes in year 2014. However, we observe a large price increase post-RCat especially in 2021.

We conjecture that the pre-trend in 2014 is likely due to the insurance price methodology update mentioned in Section III.C. Yet, we assess the sensitivity of our results due to the 2014 pre-trend following Rambachan and Roth (2023). We estimate robust confidence intervals of our average treatment effect during the post-RCat period under different assumptions on how large the post-treatment violation of parallel trends can be and report the results in Figure 4, Panel B. The x-axis reports the underlying assumptions of the post-treatment violation (e.g., a value of 0 imposes exact parallel trends in the post-treatment period as in pre-treatment period and a value of 2 implies that the post-treatment violation of parallel trends is no more than twice the maximum violation in the pre-treatment period). We find that the breakdown point (i.e., the largest bound of the null effect) is 0.6, implying that our results are robust to allowing for violations of parallel trends up to 60% of the maximum violation in the pre-period. If we are willing to restrict post-treatment violations of parallel trends to be no more than 60% as large as the maximal pre-treatment violation, we can infer significant positive average price increase after the RCat reform.

B. RCat and Insurance Prices

We report results from our empirical estimates of equation (5) in Table 2. In column (1), we estimate equation (5) excluding time-varying control variables. In column (2), we include zip code characteristics, including property damage per capital from catastrophes. In column (3), we additionally control for insurance market characteristics. In column (4), we estimate the model in column (3) on a subsample of zip codes located in MSAs. In column (5), we estimate the model in column (3) on a subsample of zip codes with at most $100,000 property damage losses (in 2021 dollars) throughout the sample period.

Overall, the results in Table 2 indicate that homeowners premiums appear to increase following the implementation of RCat for treatment zip codes (i.e., those with higher expected catastrophic losses). Specifically, the coefficient estimate on the *Treat*Post* interaction is positive and statistically significant in all specifications. Economically, the coefficient estimates indicate that annual premiums increase by 0.23 percent in zip codes most impacted by RCat requirements following implementation which is a small economic effect. The statistical significance of the coefficient remains stable after we include controls for zip code demographics (column (2)) and the insurance market conditions (column (3)), although the magnitude is smaller. In terms of dollars, the increase in prices due to RCat are commensurate to \$5.2-\$11.5 across columns (1) to (3). The effect size remains consistent when we estimate the full model with control variables on a subsample of MSAs reported in column (4). Finally, our main result holds even on a subsample of zip codes that do not experience catastrophic losses at any point during our sample period as shown in column (5). The effect size is larger than that of the full model reported in column (3). This finding suggests that the regulatory capital reform is likely a driver for the price increase.

The coefficient estimates of control variables are mostly consistent across models and largely intuitive. On average, zip codes with higher income levels, more mortgaged homes, or more rental units report higher insurance premiums. Median age, unemployment, educational attainment, and catastrophe losses are all negatively associated with average premiums, but the effect size is small. While competition among homeowners insurers (*HomeownersHHI)* drives down insurance premiums in our full sample, the effect size is small. States with larger shares of insurers with a high RBC burden (*HighRBCBurdenShare*) report lower average premiums but those with larger shares of insurers transferring homeowners insurance to reinsurers (*AvgHOReinsShare*) report higher average premiums. States with new insurance commissioners (*New Comm[t-1,t])* report higher premiums, yet states with more homeowners insurers requesting price increases (*ln(No. Affected Policies)* are associated with smaller average premiums; the economic effects of both variables are small.

We test the robustness of our results to our choice of what constitutes a "high risk" zip code based on the NRI's expected annual loss scores. While our initial choice of 75 is based on the top tercile value of the scores, it is important to ensure that our results are not sensitive to this research design choice. Accordingly, we estimate the models reported in Table 2 (columns (3) and (5)) but change our treatment definition. We report these results in Table 3.

We report results for our full sample in columns (1)-(3). We alternatively define our treatment by splitting the sample at the 50th, 60th and 70th percentiles of the NRI distribution in columns (1), (2), and (3), respectively. We observe that our coefficient estimates are consistent in their magnitude and statistical significance, which increase as we choose higher thresholds, suggesting that our results are not solely driven by our choice of treatment definition. Importantly, we observe similar results in columns (4)-(6), where we estimate the same models, but now exclude zip codes from our sample that experience catastrophic property damage at any point during our sample period. Again, these tests support our hypothesis that the price increases are not solely driven by the RCat risk charge instead of actual catastrophe-related claims experience of property insurers.[29]

C. RCat Mechanism—Risk-Based Capital Constraints and Reinsurance

In the next step of our empirical analysis, we examine the mechanisms underlying the link between RCat implementation and insurance prices. Our first mechanism relates directly to RCat's regulatory capital cost. Following the enactment of RCat, insurers will be differentially impacted by this regulation, with some facing a relatively higher "RBC burden" where the denominator of their RBC Ratio (i.e., how much capital an insurer "should" hold based on the risk they take) will increase with this new regulation.[30] We anticipate that insurers with the largest RBC burdens will

[29] To provide further evidence on what is driving the association between the RCat risk charge and prices, we estimate equation (5) after restricting our sample to only treated states. We report these results in Appendix Table A6. We estimate the same models (with the same control variables) as Table 2. Overall, the statistical significance of the results are consistent and effect sizes are larger compared to what we report in Table 2. We interpret these results to indicate that estimating models using a state-level definition of treatment and control may underestimate the true effect of RCat regulation, and importantly, areas with high RCat risk within the RCat state experience price increases more than areas with low RCat risk.

[30] We focus on the denominator only to reflect that if insurers are able to raise prices, as we hypothesize, the numerator of their RBC Ratio will increase as well, making it difficult to disentangle both numerator and denominator effects when observing the ratio on its own. Focusing on the denominator allows us to isolate how impactful RCat implementation is outside of any behavior to alter an insurer's capital position (i.e., the numerator).

be more likely to raise prices in an effort to offset this increase. To test this, we estimate the following model:

$$HOPrem_{jst} = \beta Treat_j \times Post_t \times High\ RBC\ Burden_{st} + \boldsymbol{H}_{jst} + \boldsymbol{\zeta}_j + \boldsymbol{\tau}_t + \boldsymbol{S}_s + \epsilon_{jst} \quad (7)$$

where all variables are defined as in equation (5), but we now include the triple interaction term with *High RBC Burden*. Since our unit of observation is at the zip code level for insurance prices while we only observe insurer financial characteristics at the state level, we calculate *High RBC Burden* at the state-year level. We calculate this variable using the denominator of the RBC ratio (risk-based capital) divided by lagged assets and examine the distribution of this variable among homeowners insurers in each year in the US. Then, we calculate the share of the homeowners insurance market written by insurers in the top tercile of the RBC burden. We define *High RBC Burden* state to be a binary variable equal to one in states where at least either 10%, 20%, or 30% of the state had always been written by insurers in the top tercile of the RBC burden during the pre-period, 2011 to 2016, and zero otherwise.[31] We expect that insurers most impacted by RCat (i.e., those with relatively high RBC burdens) will be more likely to increase prices, which would result in a positive and statistically significant coefficient estimate on the triple interaction term (β > 0).[32]

We report results for our high RBC burden tests in Table 4. The dependent variable is zip-code level homeowners insurance premiums. We include all prior control variables (including those controlling for the rate regulation environment) as well as year, state, and zip code fixed effects. Our results in columns (1)-(3) are for our full sample, while the results in columns (4)-(6)

[31] Market share percentages are based on direct premiums written in homeowners insurance within a state. We test the sensitivity of the variable by creating the High RBC Burden indicator using periods before the informal implementation period, 2014 to 2016, and find consistent results as shown in Appendix Table A7 Panel A.
[32] We note that these models also include the interaction terms *Treat X Post* and *High RBC Burden X Post* which requires us to take the sum of the coefficient estimates on *Treat X Post* and the triple interaction term to examine the full effect, which we report when we discuss these results.

are for our sample excluding zip codes that experienced disasters during our sample period. The main result we focus in this table is the Wald test, which provides information on the overall insurance price effect on treatment zip codes in the post-RCat period, specifically in states where a relatively large portion of the insurers faced high RBC burdens. We note that the overall estimate in all six models presented in Table 4 is positive and statistically significant. Moreover, the magnitude of the coefficient increases as we limit the states to have a higher threshold on the prevalence of insurers with high RBC burden—increasing to over 2 percent when we examine state-years with more than 30% of insurers in the highest RBC burden tercile. The results are stronger when we limit our sample to zip codes that did not experience disasters, continuing to suggest that our results are driven by the regulatory capital reform rather than price responses to actual catastrophes.

Our second proposed mechanism is through reinsurance. Insurers that write catastrophe-exposed property insurance can reduce their exposure and, therefore, their RCat risk-based capital charge, by transferring these policies to an external reinsurer. Insurers that are able to transfer all of their catastrophe-exposed risks to reinsurers do not need to raise prices to offset any increase in RCat. In another extreme, the full cost of RCat will be borne by firms that do not engage in any external reinsurance. Similar to our RBC burden tests, we construct a state-level measure of reinsurance use to test whether reinsurance plays a role in RCat and insurance prices. Specifically, we calculate the percent of insurers that use no homeowners reinsurance in a state-year, and then create indicator variables based on whether a state always had either 10%, 20%, or 30% of property insurers in the state without any reinsurance during the sample period, and zero otherwise. We estimate the same model as in equation (7), except we replace the *High RBC Burden* indicator with *No Reinsurance* indicator. We expect that insurers most impacted by RCat (i.e., those without access to external reinsurance markets) will be more likely to increase prices, which would result in a positive and statistically significant coefficient estimate on the triple interaction term ($\beta > 0$).

We report the results of our reinsurance tests, in Table 5. We again focus on the results of the Wald tests, which provide information on the overall insurance price effect on treatment zip codes in the post-RCat period, specifically in state-years where higher portions of the homeowners insurers did not use homeowners reinsurance. We note that the overall estimate in all six models presented in Table 5 is positive and statistically significant, but the reinsurance effect is nuanced. While the magnitude of the sum of coefficient estimates is the lowest for states where only 10% of firms do not use reinsurance, the magnitude of the estimates does not monotonically increase from 20% to 30%. We observe no statistically significant coefficient on the full effect of no reinsurance when the threshold is 30%. The magnitude of the post-RCat premium increase is between 0.5 percent and 1.7 percent in state-years where at least 10% or 20% of insurers have no reinsurance.[33] This results are stronger when we limit our sample to zip codes that did not experience disasters, with the coefficient estimate of 0.035 (3.6 percent increase in premiums) of the full effect of no reinsurance access in zip codes without catastrophe losses. While the results continue to suggest that our results are driven by the regulatory capital reform rather than price responses to actual catastrophes, we note that the inconsistency in the effect size across models and conjecture the state-level insurers' access to reinsurance may possess measurement error.[34]

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[33] We also highlight that the sample of states with high RBC burdens is not the same as the sample of states with no reinsurance (see Appendix Figure A3).

[34] We test the sensitivity of the variable by creating the No Reinsurance indicator using periods before the informal implementation period, 2014 to 2016, and find consistent results as shown in Appendix Table A7 Panel B.

V. COMPLEMENTARY EVIDENCE FROM FLORIDA

One of the limitations of our aforementioned tests is that we can only provide indirect evidence on how firm-specific factors (e.g., risk-based capital and reinsurance) influence insurers to raise insurance prices following the implementation of the RCat. Accordingly, we turn to the Florida homeowners insurance market, where we can exploit a unique reporting requirement to gain additional insight. The Florida Office of Insurance Regulation requires insurers to report supplemental personal and commercial residential information on a quarterly basis through the Quarterly and Supplemental Reporting system (QUASR).[35] Importantly, insurers report premiums and the number of policies in force at the county level, allowing us to construct a measure of average premiums at the insurer-county-level for homeowners insurance premiums.

We construct a panel data of average insurance premiums of homeowners policies in Florida at insurer-county-quarter levels during 2011-2021. To limit the influence of outliers, we exclude insurer-county-quarter observations where less than ten homeowners insurance policies are written. The final sample includes 132,927 insurer-county-quarter observations from 119 unique insurers (2,948 unique insurer-quarters). We winsorize average insurer-county-quarter premiums and continuous control variables (excluding natural log variables) at 1st and 99th percentile values. We then match insurer-year-level financial characteristics using the NAIC annual statements.

Another advantage of using Florida data is that we can use a more direct proxy of the costs associated with RCat—instead of using the NRI's expected annual losses as our proxy for expected losses, we can use the Florida Public Hurricane Loss Model (FPHLM). In practice, insurers can

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[35] We note that the disclosure is not mandatory and some insurers do not disclose their information due to trade secret concerns. We address the concern that insurers' attrition is the main driver of the result by focusing on periods where insurers participating in QUASR represent most of the insurers writing in Florida.

input granular detail (not just location, but also specific housing characteristics) on the homes they insure into commercially available modeling software to obtain modeled losses. With limited data from insurer regulatory filings, we lack the detail to perform similar calculations even if we had access to the modeling software. Since the FPHLM is public, we are able to access the overall estimates in each county within Florida, even if we lack the level of detail that companies would input.[36]

We first document that hurricane loss estimates differ from the actual property loss experience. The FPHLM provides separate estimates for frame, masonry, and manufactured homes. We use these estimates to calculate our treatment intensity variable. We report a summary of the FPHLM county-level loss costs per $1,000 in quartiles in Figure 5, Panel A.

We compare the FPHLM loss estimate figures with actual property losses over our sample period in Figure 5, Panel B, where we use SHELDUS data to examine actual property losses in Florida counties. We note several important differences between the two, which suggests that, if we want to capture regulatory capital costs as reflected in the RCat regulation, using the modeled loss estimates should yield a more accurate result.

In addition to county-level premiums and the number of insurance policies sold, QUASR also requires insurers to report their county-level "exposure." This allows us to capture an insurer's overall exposure across counties within Florida, which reflects their overall RCat risk charge in Florida. This is important as it is likely that insurers attempt to raise prices across all Florida counties in response to the RCat not just in the specific geographies that have the highest modeled loss estimates. For example, insurers can request to raise insurance price across the geographical

[36] FPHLM estimates are updated periodically. We use the most recent publicly available estimates reported in 2019 downloaded from the weblink: https://fphlm.cs.fiu.edu/files/wind_certification/v7.0Submission/Submission_Document/.

rating territories in a state when filing for rate increase request, which typically reduces the administrative costs for rate filings. In addition, constrained insurers are likely to increase their price in areas with and without catastrophic risks, so long as the price increase is modest and does not hinder its competitiveness in the market. Accordingly, we calculate each insurer's exposure-weighted modeled losses per county-quarter.

With our insurer-county-specific measure of homeowners insurance price, as well as our insurer-specific approximation of each insurer's RCat risk charge, we estimate equation (5), now measured at the insurer-county-quarter-year level. We dichotomize our insurer-specific risk variable (*Hurricane Risk (FPHLM)*) and create a variable, *High Risk*, that is equal to one for firms in the top quartile of risk in the pre-RCat period (2011 to 2016). We use county-level annual ACS variables from the 5-year data to construct socio-economic variables. At this level of observation, we include additional control variables from either QUASR or insurer annual regulatory filings. Specifically, we now control for Citizen's property exposure in each county, which could affect pricing for the private market.[37] We also control for the natural log of RBC burden (*ln(RBC)*), the natural log of percent of homeowners reinsurance as percent of homeowners insurance premiums written (*ln(Reins)*), the natural log insurer assets (*ln(Firm Size)*) and capital ratios (*Liab/Surplus*). We also control for the percent of homeowners insurance premiums written in Florida relative to the fifty states and the District of Columbia (*Florida Focus).*

We report summary statistics including univariate differences between treatment and control observations for our QUASR sample in Table 6.[38] The control and the treatment observations differ in many dimensions. Homeowners insurance written by insurers with high

[37] Citizens Property Insurance Company is a state-run residual insurer for property insurance in Florida. It was formed in 2002 and provides property insurance for homeowners who are unable to obtain insurance through the private market.
[38] See Appendix Table A8 for the distributional statistics of QUASR sample.

hurricane risk exposure report higher average premiums. These high risk insurers write in counties with higher Citizens' exposure, larger population, older median age, higher income, lower unemployment rate, higher educational attainment, higher share of rental homes, and larger number of housings than the control group insurers. Geographical hurricane risks measured both in FPHLM and FEMA along with catastrophe property damage per capita (*PropertyDamageCapita)* are higher for insurers with high risk than the control group insurers. High risk insurers are on average smaller, bears higher RBC burden (and commensurate lower RBC ratios), are more leveraged, use more reinsurance, and are more focused in the Florida market than the control group insurers.

We provide event-study style estimates of premium differences between high risk (i.e., treated) insurers and control insurers, similar to equation (6), in Figure 6 Panel A. We find no pre-trend, as opposed to our main model estimates shown in Figure 4 Panel A, when we utilize the homeowners insurance premiums reported by insurers in Florida (i.e., not survey estimates as in our main model) and the RCat treatment tied to individual insurers' catastrophe risk exposure.[39] Furthermore, we find large and statistically significant premium increase in 2020-2021, which is consistent with our national-level estimates as shown in Figure 4 Panel A. As discussed in Section II, we acknowledge the informal implementation of RCat after 2013 and test for potential "anticipatory" effects of RCat. We estimate the model similar to equation (6), but change the omitted baseline year to 2013 and define insurers' treatment using the 2011-2013 period. The estimated coefficients are shown in Figure 6 Panel B, which show consistent results as in Figure 6

[39] Similar to Figure 4 Panel B, we test the sensitivity of our results from the pre-trend and show the results in Appendix Figure A4. In Panel A, we show the robust confidence intervals of the average treatment effect during the post-RCat period, where the breakdown point is 0.2. As we note, larger number of insurers do not report insurance price data beginning in 2020. In Panel B, we show the robust confidence intervals of the average treatment effect during 2017-2020, with similar breakdown points. These results imply that our results are robust to allowing for violations of parallel trends up to 20% of the maximum violation in the pre-period.

Panel A; we consider this as evidence of no statistically significant anticipatory effect, consistent with our findings from the national-level estimates.

We provide differences-in-differences regression results of our Florida-specific models in Table 7. The dependent variable in all five columns is homeowners insurance premiums, which we calculate as quarterly direct premiums written divided by policies in force in each county for each insurer. We report results for our main model specification in columns (1)-(3), with varying inclusion of control variables. For parsimony, we report coefficient estimates of county-level characteristics in Appendix Table A9.[40] All models include year, quarter, county, and insurer fixed effects with standard errors clustered at the insurer level. Positive coefficient estimates indicate higher homeowners insurance prices while negative coefficient estimates indicate lower homeowners insurance prices.

We first observe that the coefficient estimates on our interaction term between *High Risk* and *Post* is positive and statistically significant in columns (1), (2), and (3). This, generally, suggests that homeowners insurance prices increased for firms with relatively greater exposure to hurricane risks following the implementation of RCat. The results are also economically meaningful, with the average premium increase for firms in the most exposed areas increasing by \$282 to \$333 in the post period, which is around 14% of the average premium reported in QUASR during our sample (\$2,164).[41] The coefficient estimates of insurer-level variables are as expected. Insurers with higher RBC burden and more focus in Florida increase insurance premiums on average, while insurers with more reinsurance or large size decrease premiums.

[40] The coefficients are as expected. Counties with higher income on average report higher insurance prices while the coefficients are negative for age and education attainment.
[41] We estimate the effect of the anticipatory effect during the informal implementation period of RCat and find similar results in all specifications except column (5). The results are reported in Appendix Table A11

Turning to our mechanism tests, we next examine whether an insurer's RCat burden influences price increases following the RCat. Using the QUASR dataset allows us to use firm-specific information in these tests instead of relying on state-level aggregates as we did in our previous tests. We begin with a descriptive comparison of how our *RBC Burden* measure evolves versus the RBC ratio for our sample of Florida property insurers. We regress both *RBC Burden* and *RBC Ratio* on a set of insurer and year fixed effects and then report the coefficient estimates on the year fixed effects (with 2016 being the omitted year) with their 95% confidence intervals in Figure 7.

In Figure 7 panel A, we observe that the coefficient estimates for the post-period in our sample (2017-2021) are positive and statistically significant, suggesting that the RBC burden (risk-based capital over lagged assets) is increasing in the post-RCat period. We contrast this with the evolution of the RBC ratio, with the coefficient estimates plotted in Figure 6 Panel B. We find that the coefficient estimates on the year indicators are statistically significantly negative in the post-RCat period. The figures suggest RCat has a material impact on insurer regulatory capital ratios, and that this manifests in an overall decline in regulatory capital ratios following the enactment of RCat.

We next explore the mechanism of insurer characteristics, specifically focusing on RBC burden and reinsurance use, in triple differences-in-differences models. In column (4) of Table 7, we include a *High RBC* binary variable, that is equal to one if a firm is in the top quartile of the RBC burden distribution during the pre-RCat period of our sample (2011-2016). We interact *High RBC* with our *High Risk* times *Post* to create a triple interaction term to the model reported in column (3) of Table 7. We then perform a Wald test on the coefficient estimates between *High Risk* times *Post* and the triple interaction to determine the overall impact of RCat in the post period for firms with relatively high RBC burdens. The result of this test (reported in column (4)) are positive and statistically significant, with effect size of \$219 (*p-value* < 0.01), indicating that the overall increase in premiums that we observe is partially driven by firms facing regulatory capital constraints.

We next turn to our second mechanism test which is related to whether a property insurer accesses reinsurance markets, which can reduce the effect of RCat. Accordingly, we again construct a triple interaction term to the model reported in column (3) of Table 7, but this time include a low reinsurance indicator variable instead of the high RBC burden indicator. *Low Reins* is a binary variable that is equal to one if a property insurer is in the lowest quartile of homeowners reinsurance use during the pre-RCat period (2011-2016). Once we include and interact the low reinsurance indicator and perform the Wald test on the coefficient estimates between the *High Risk* and *Post* interaction coefficient and the triple interaction coefficient, we see that the overall effect is positive and statistically significant (*p-value* < 0.01) —this finding provides evidence that insurers with low reinsurance use are increasing their prices when they are impacted by RCat to a greater extent than insurers that have access to reinsurance markets. Taken together with our national-level estimates reported in Table 5, these results indicate that access to reinsurance markets plays a large role in determining insurance pricing behavior, particularly through the RCat.[42]

One component of the Florida market that we do not account for explicitly in the results we report in Table 7 is the presence of a state reinsurance program, the Florida Hurricane

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[42] We perform two robustness tests using our Florida sample. First, we use the FEMA Hurricane EAL risk measure as our treatment proxy, for consistency with our national tests. We report these results in Appendix Table A10, Panel A. Second, we estimate the models reported in Table 7 after excluding 2020 and 2021, when a substantial number of insurers in Florida has stopped reporting to QUASR. We report these results in Appendix Table A10, Panel B. In both cases, our results are robust.

Catastrophe Fund (FHCF), that provides reinsurance to property insurers in the state at a rate lower than the private market. In particular, since participation in the FHCF is mandatory for most insurers, our reinsurance mechanism tests in the Florida market may not generalize as there is no equivalent federal program. It may also be worthwhile to explore how access to a government-sponsored reinsurance program influence any RCat-induced price increases, as this could inform regulators and policymakers tasked with administering programs like the FHCF.

We, therefore, use detailed reinsurance cession data from Schedule F—Part 3 of insurer annual statutory filings to determine which Florida insurers report cessions to the FHCF.[43] We test the sensitivity of our results due to FHCF in two different ways. We first control for the insurers' use of FHCF for the model reported in Table 7, column (5). Second, we construct *Low Reins* proxies that are similar to the models we estimate in Table 7, column (5), using FHCF cessions. One issue with FHCF variable is that we only observe FHCF at insurer-level, and do not observe how much of the FHCF cessions are attributable to homeowners insurance market. We overcome the potential measurement error by creating two different measures of FHCF usage: One is based on FHCF cessions divided by Florida premiums and the second is FHCF cessions divided by total unaffiliated reinsurance. The latter captures relative reliance of FHCF versus other unaffiliated reinsurance. We report these results in Table 8. Overall, the results suggest that the FHCF plays an important role in limiting premium increases that insurers may try to pass on to consumers following the implementation of RCat. Specifically, we observe the largest premium increases for firms more exposed to RCat treatment that do not cede premiums to the FHCF relative to other

[43] While the program is mandatory for all Florida insurers, there are exemptions for insurers that are relatively small as well as firms that have substantial business outside of Florida. Each firm's cession is then determined by their exposure within Florida, which can vary substantially by firm.

reinsurers ($914.38, *p-value* =0.038), which implies a significant role of the cost of reinsurance interacted with regulatory capital burden.

VI. CONCLUSION

In this study, we provide empirical evidence consistent with insurers passing on regulatory costs associated with climate risk to consumers. Specifically, we find evidence that homeowners insurance premiums increase in zip codes most subject to the RCat regulatory capital regulation. Overall, the premium increase, while statistically significant, is modest for individual policyholders. The estimated premium increase in areas with the high catastrophe exposures, as defined by the NRI, ranges from $6.91 to $11.5. We additionally provide evidence that our results are concentrated in states where insurers face relatively higher RBC burdens as well as states where insurers have relatively little access to the reinsurance market. We complement our results using detailed insurer-county-quarter-level data in Florida market which enables us to more precisely measure insurer-level mechanisms of our findings. We find consistent results in Florida market as in our national-level estimates, and find stronger results for insurers' reinsurance access interacted with RCat reform.

Our estimates on the national zip code-level homeowners insurance price increase combined with the 30.7 million households with homeowners insurance in RCat-treatment zip codes (2017 estimates of *InsuredHomes* variable), suggest an average annual premium increase between $160 and $353 million, or total $799 to $1,767 million premium increase from 2017 to 2021. We calculate the back-of-the-envelope impact of the estimated total premium increase on insurers' regulatory capital positions. As documented in Figure 1 Panel A, by the end of 2021, insurers report $54.4 billion regulatory required capital for RCat, which grew by $3.7 billion from $50.7 billion in 2017; an increase of capital levels between $930.2 to $2.394.6 million suggests insurers could finance 21.6% to 47.8% of the increased regulatory capital cost due to RCat by increasing homeowners insurance prices. Given that the RCat not only includes homeowners insurance lines but also other property lines, and that approximately 55% of the premiums are written in homeowners insurance lines compared to other property lines such as commercial properties applicable to the RCat, our back-of-the-envelope estimate implies potentially significant homeowners insurance price impact of RCat.

Our finding is of interest not only to researchers but also to policyholders and regulators. A growing literature empirically examines the pricing of climate changes on financial markets interacted with insurance (e.g., Issler et al. 2020), yet not many focus on how insurers adapt to climate risks (Koijen and Yogo 2022). While other financial institutions, such as banks or life insurers, hold assets that may expose them to climate risk, property insurer underwriting operations are directly exposed to climate-related extreme weather events.[44] Importantly, homeowners with mortgages in the US are required to maintain insurance and thereby less elastic to the modest price increase. Understanding how insurers price climate risk is valuable to researchers who will continue to examine these issues moving forward.

From a regulatory perspective, our study has clear implications for insurance regulators as we evaluate the current system of regulation, but also as regulators are adopting changes in the regulation (e.g., adding wildfire as a risk category). Historically, the adoption of the RCat has been discussed since the costly hurricane seasons in 2004-2005. Regulators have been interested in imposing regulatory capital requirements on catastrophic risks, yet it took more than a decade for the implementation in 2017 due to push back from the industry (see Klein and Wang (2009) and

[44] While property insurers tend to avoid underwriting correlated risks (e.g., hurricanes or earthquakes), extreme weather events usually lead to loss events covered under conventional homeowners insurance (e.g., wind damage and fire damage).

NAIC CIPR Newsletter August (2017) for more detailed discussions on the topic).[45] Our study, by examining how changes in catastrophe-related solvency regulation influence insurance pricing, can inform regulators as they consider implementing or altering these regulations moving forward.

[45] Based on historical NAIC meeting minutes, we identify that insurers' major concern was potential duplicative regulatory capital costs, resulting in debates over more than a decade to reach a conclusion with the regulators. For example, the industry was concerned about how the rule will account for the existing underwriting regulatory capital charges for actual losses and within group reinsurance transactions.

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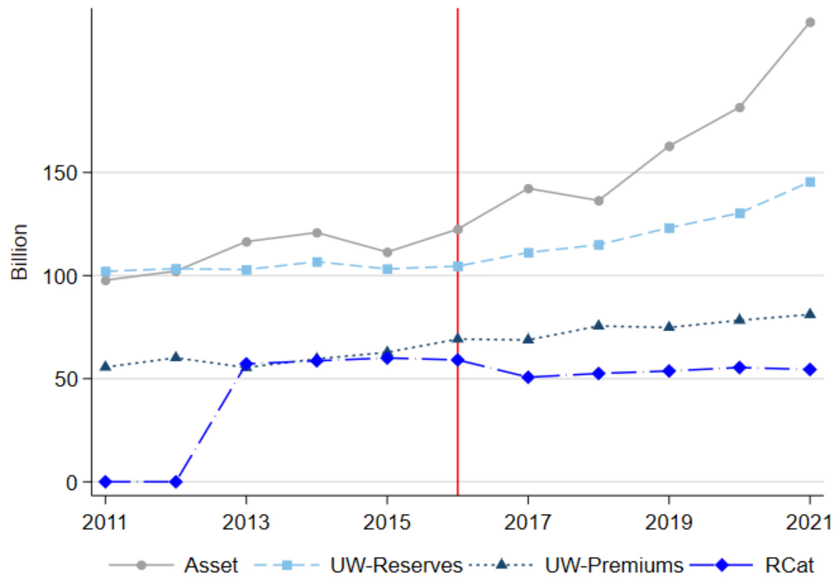
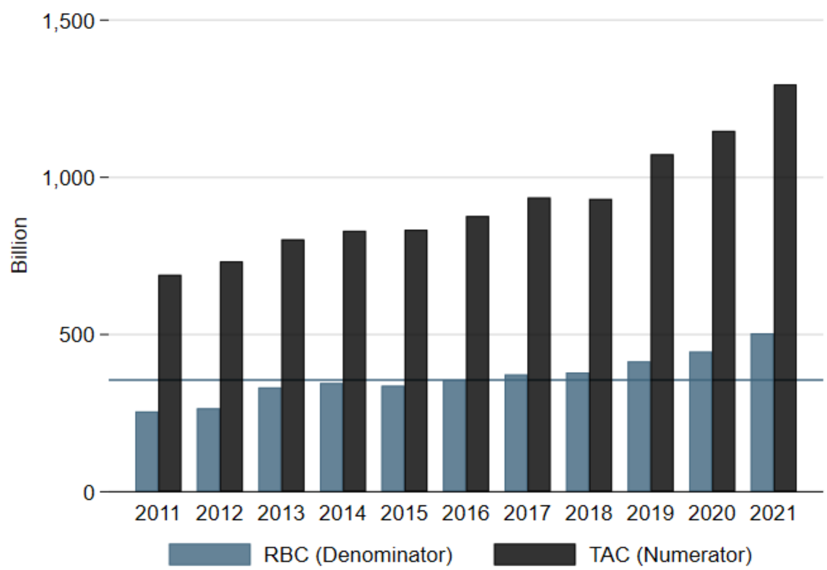
Figure 1: Industry Aggregate RBC

A. RBC Components



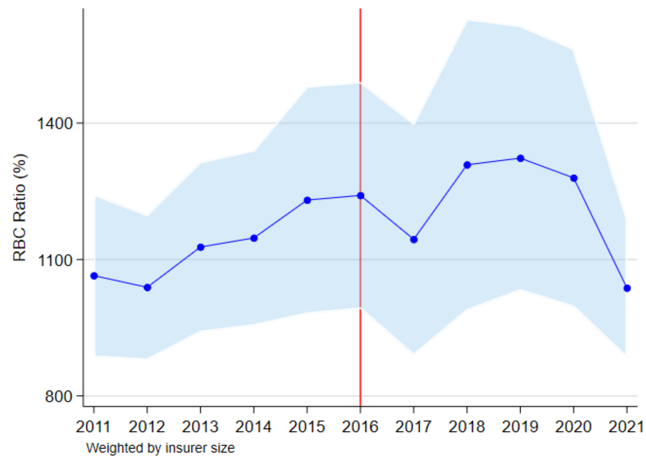
B. RBC Ratio Breakdown



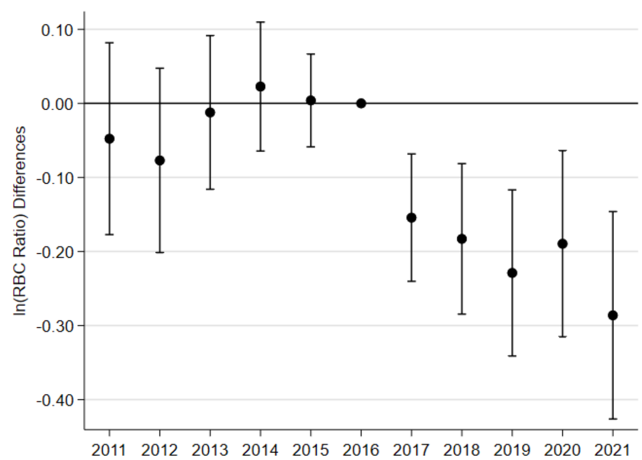
Source: Annual RBC statistics produced by the NAIC.
Notes: The top figure shows industry aggregate Risk-based Capital (RBC) of property and casualty insurers in each year; we show reported values of asset RBC, underwriting (UW) reserves RBC, underwriting (UW) premiums RBC, and catastrophe risk RBC (RCat). For brevity, we add asset related components together (Fixed income, equity, and credit RBC). The bottom figure shows the industry aggregate RBC in grey bars and total adjusted capital (TAC) in black bars each year. The horizontal line marks industry aggregate RBC in 2016 as a reference point.

Figure 2: Homeowners Insurers' RBC Ratios

A. Average RBC Ratios



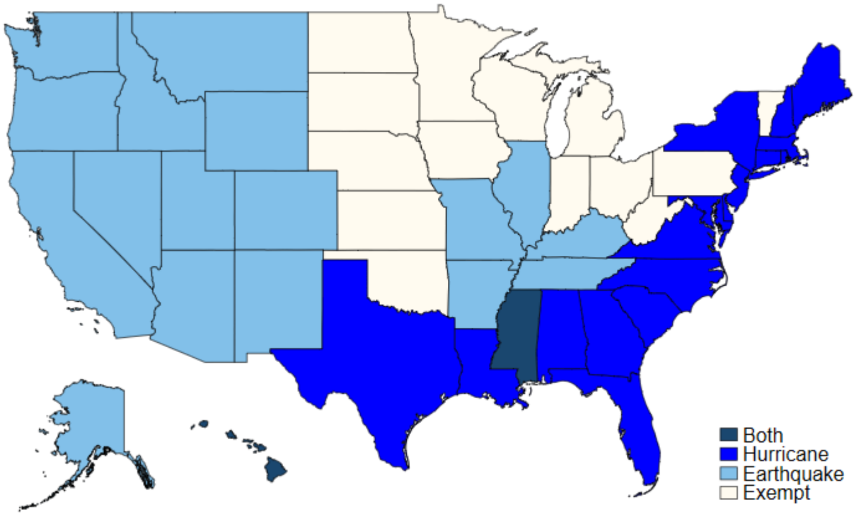
B. Differences in RBC Ratios by RCat



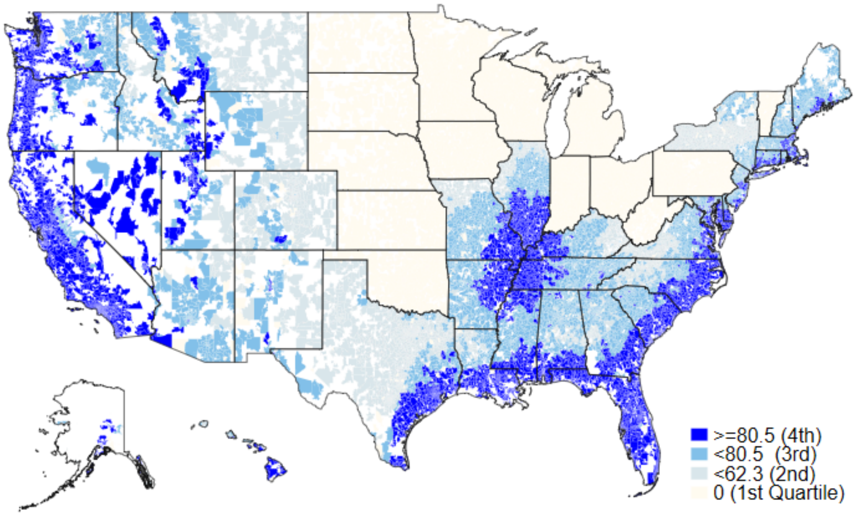
Source: Annual statutory statements of insurers.
Notes: The figures are based on homeowners insurers, i.e., insurers writing positive premiums in homeowners insurance lines in a given year. The top figure shows the average RBC ratios of homeowners insurance in each year along with 95% confidence intervals estimated based on the standard errors of the averages. We weight insurer-year observations using their size of assets. The bottom figure shows differences in the average Risk-based Capital (RBC) ratios (in logarithm values) of homeowners insurers by RCat treatment in each year along with 95% confidence intervals. Specifically, we run a regression of logarithm values of RBC ratios on year indicators, indicator that the insurer is treated under RCat, and year indicators interacted with an indicator that the insurer is treated under RCat, logarithm values of insurer size, insurer fixed effects, and year fixed effects. We define RCat treatment as insurers who write positive premiums in homeowners insurance lines in RCat states throughout the 2011 - 2016 period. Both RBC ratios and insurer sizes are winsorized at the bottom and the top one percentile values. Standard errors are clustered at the insurer level.

Figure 3: Regulatory Catastrophe Risk (RCat)

A. Treatment Defined at the State



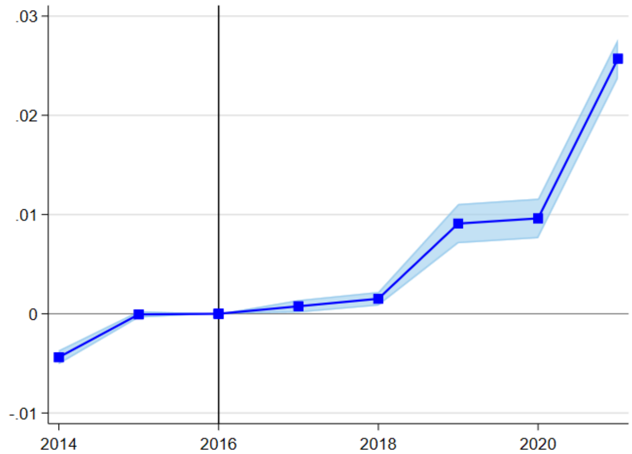
B.Treatment Defined at the Zip Code



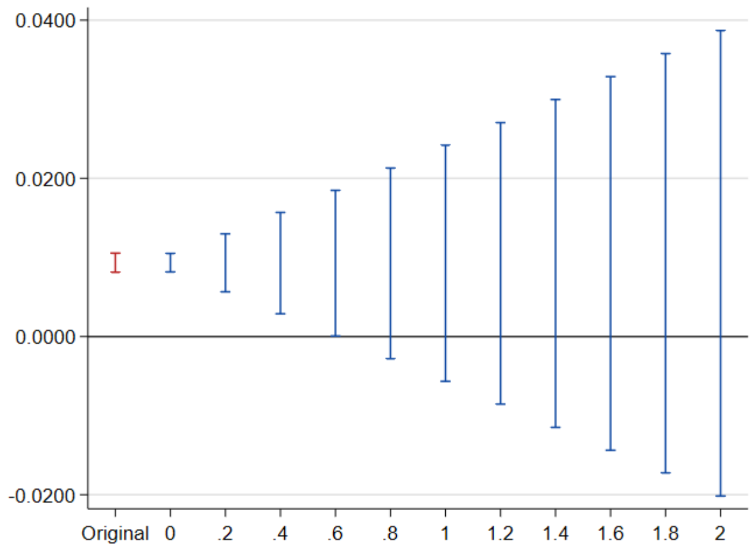
Notes: The figures show the map of U.S. by regulatory catastrophe risk charge. The top figure delineates states by whether or not the state is exempt from regulatory catastrophe risk charge from the Property and Casualty Risk-Based Capital Instructions (2017). The bottom figure shows zip code-level expected annual loss scores from either hurricane or earthquakes, based on the National Risk Index database (from https://hazards.fema.gov/nri/map, pulled on September 1st, 2023). Zip codes are color-coded into four quartiles of the expected annual loss score distribution; we impute the expected annual loss scores to be 0 for states that are exempt from regulatory catastrophe risk charge to be consistent with the Property and Casualty Risk-Based Capital Instructions.

Figure 4: Homeowners Insurance Price Differences by Treatment

A. Full Sample



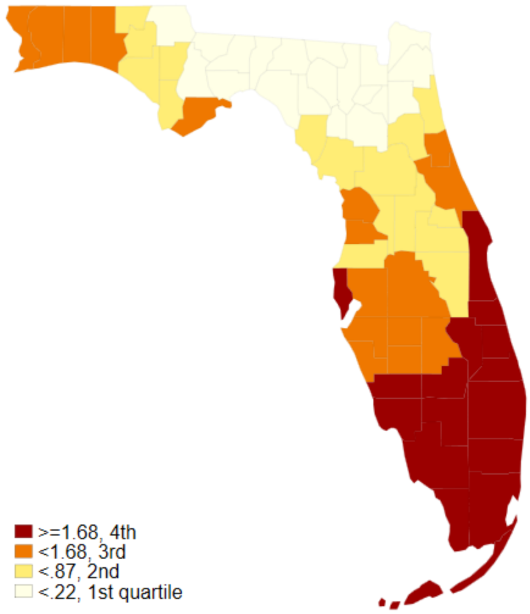
B. Sensitivity Analysis of the Parallel Pre-trend Assumptions



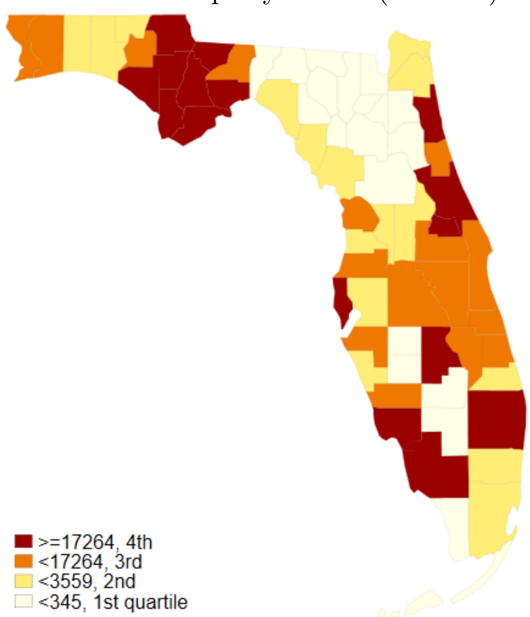
Notes: The top figure show average homeowners' insurance premium (in natural log value) differences by RCat treatment. Specifically, the top figure plots estimates of coefficients from equation (5), which is a regression of the natural log values of average homeowners insurance prices on treatment indicator, year fixed effects, treatment indicator interacted with year fixed effects, state fixed effects, and zip code fixed effects, using 2016 as the omitted baseline year. Treatment equals one for zip codes with expected annual loss scores higher than 75, and zero otherwise. Shaded areas in figures represent 95% confidence intervals of the estimated coefficients. Standard errors are clustered at the zip code level. The bottom figure reports the estimated robust confidence intervals of the average treatment effect during the post-RCat period under different pre-trend violation assumptions following Rambachan and Roth (2023). X-axis represent the value of $\bar{M}$ as in Rambachan and Roth (2023), where a value of $\bar{<} = 2$ implies that the post-treatment violation of parralel trends is no more than twice the maximum violation in the pre-treatment period.

Figure 5: Hurricane Risks and Losses in Florida

A. Estimated Hurricane Risks



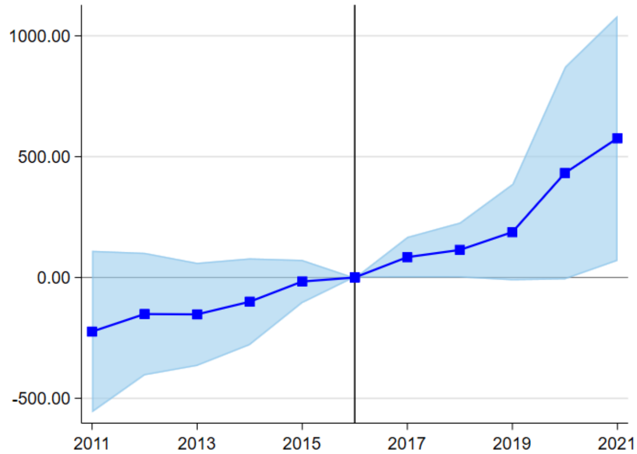
B. Actual Property Losses (in $Mil.)



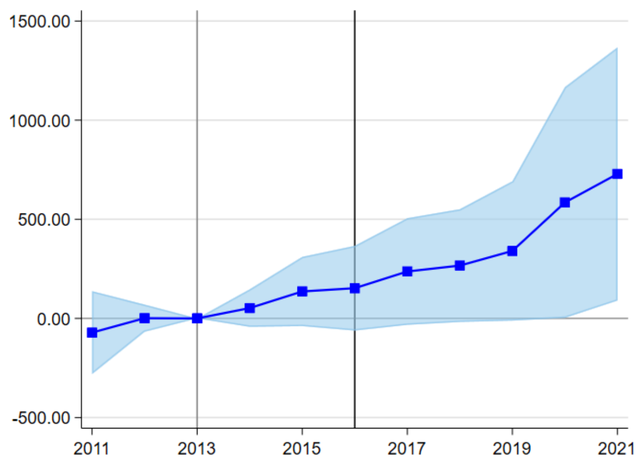
Notes: The top figure shows estimated average hurricane related loss costs per \$1,000 value of framed houses based on exposures measured in 2012 from the Florida Public Hurricane Loss Model (FPHLM). The bottom figure shows total property losses for each county during the sample period (2011-2021) in 2021 million dollars from Spatial Hazard Events and Losses Database for the United States.

Figure 6: Homeowners Insurance Price Differences by Treatment in Florida

A. Post = 2017 and after



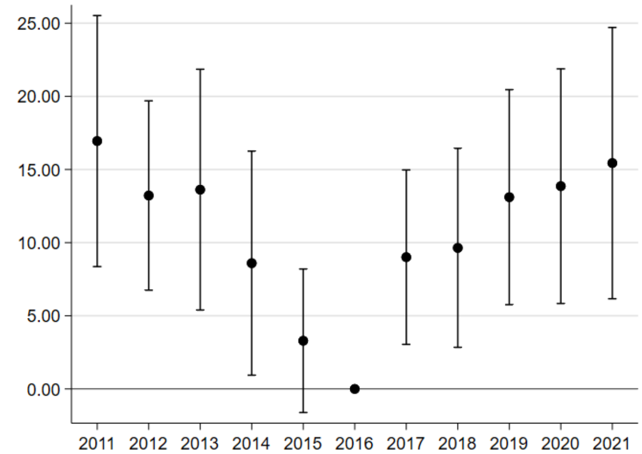
B. Post = 2014 and after



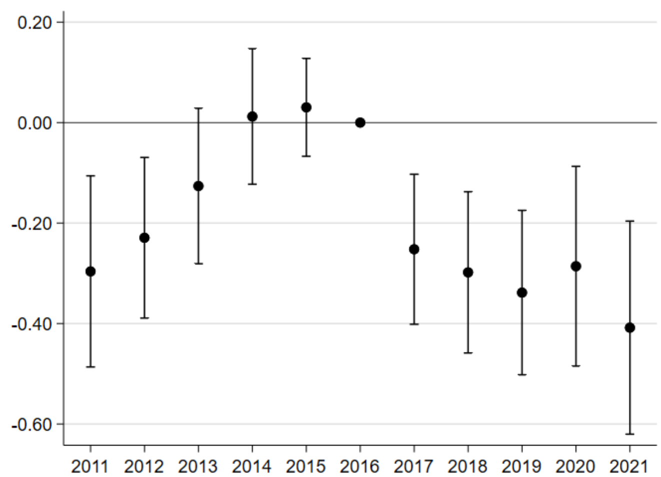
Notes: The figures show average homeowners' insurance price differences by insurer-level hurricane loss estimate treatment. Specifically, the top figure plots estimates of coefficients from equation (6), which is a regression of the log of average homeowners insurance price on treatment indicator, year fixed effects, treatment indicator interacted with year fixed effects, quarter fixed effects, county fixed effects, and insurer fixed effects, using 2016 as the omitted baseline year. Treatment equals one for insurers with their exposure-weighted hurricane risks (FPHLM) at the top quartile during the 2011-2016 period, and zero for others. Shaded areas in figures represent 95% confidence intervals of the estimated coefficients. Standard errors are clustered at the insurance company level. The bottom figure is based on the same regression model, except that 2013 is the omitted baseline year and treatment equals one for insurers with their exposure-weighted hurricane risks (FPHLM) at the top quartile during the 2011-2013 period, and zero for others

Figure 7: RBC of Homeowners Insurers in Florida

A. RBC Burden



B. RBC Ratio



Notes: The top figure shows average RBC burdens in each year compared to the average RBC burden in 2016 among insurers that report to Florida Office of Insurance Regulation's Quarterly and Supplemental Reporting System (QUASR). Specifically, the figure plots coefficients from the event-study style regression of insurer's RBC burden (*Risk-Based Capital/Assets*$_{t-1}$) on insurer fixed effects and year indicators, using 2016 as the omitted baseline year. The bottom figure shows average RBC ratios in each year compared to the average RBC burden in 2016 among insurers that report to QUASR. Specifically, the figure plots coefficients from the differences-in-differences regression of insurer's RBC ratios (*Total Adjusted Capital/Risk-Based Capital*) on insurer fixed effects and year indicators, using 2016 as the omitted baseline year. The spikes show 95% confidence intervals of the estimated coefficients. Standard errors are clustered at insurer levels.

Table 1: Univariate Differences by Zip Code Treatment

	Control		RCat Zip		*Mean*	Total	
	Mean	SD	Mean	SD	*diff.*	Mean	SD
AvgPrice	1,040.44	135.67	1,098.20	148.26	57.77***	1,060.21	142.76
MajorHOShare	3,661.69	5,156.43	3,340.83	5,553.98	-320.86***	3,551.84	5,298.07
HomeownersHHI	745.29	251.97	686.98	291.45	-58.30***	725.33	267.58
AvgHOReinsShare	0.05	0.03	0.09	0.10	0.04***	0.06	0.06
B: Socio-economic							
MSA	0.56	0.50	0.70	0.46	0.14***	0.61	0.49
Population 000s	10.36	13.48	16.65	16.64	6.29***	12.51	14.94
MedianAge	41.99	6.81	41.30	7.34	-0.68***	41.75	7.00
MedianIncome 000s	57.97	20.65	63.08	28.04	5.11***	59.72	23.57
InsuredHomes 000s	2.26	2.76	3.40	3.23	1.14***	2.65	2.98
UnempRate	3.58	2.24	4.13	2.26	0.55***	3.77	2.26
BachelorDegree	12.96	7.21	13.60	8.45	0.64***	13.18	7.66
MortgagedHomes	0.35	0.13	0.35	0.14	0.00	0.35	0.14
RentalHomes	0.23	0.15	0.27	0.16	0.05***	0.24	0.15
Occupied Homes 000s	3.95	5.04	6.05	5.87	2.10***	4.67	5.43
C: Risks							
Cat Risk	27.48	31.01	86.85	7.35	59.37***	47.80	38.01
PropertyDamageCapita	17.20	81.25	29.02	124.08	11.82***	21.25	98.20
HighRBCBurdenShare	0.33	0.12	0.40	0.15	0.07***	0.35	0.14
New Comm[t-1,t]	0.45	0.50	0.34	0.47	-0.11***	0.41	0.49
No. Affected Policies 000s	795.34	623.74	736.74	576.57	-58.61***	775.28	608.64
No. Requesting Insurers	34.45	12.62	28.19	12.28	-6.26***	32.30	12.85
Observations	132,240		68,840		201,080	201,080	

Note: The table reports univariate mean differences between the control and the treatment zip codes. We perform tests of the mean difference assuming unequal variance structures between the control and the treatment. *AvgPrice* is the zip code annual average homeowners' insurance prices (one-year lagged from Claritas estimates), *MajorHoSHare* is the number of homeowners insurance policies written by thirteen major insurers as a share of total households with homeowners insurance, *HomeownersHHI* is market concentration (Herfindahl-Hirschman Index) of homeowners insurance business line in each state, *AvgHoReinsShare* is the average share of homeowners insurance prices transferred to unaffiliated reinsurers, *MSA* is the indicator that the zip code belongs to the metropolitan statistical area, *Population 000s* is the number of population in the zip code in 1,000s, *MedianAge* is the median age of the population in the zip code, *MedianIncome 000s* is the median income of working population in \$1,000s, *InsuredHomes 000s* is the number of households with homeowners insurance per zip code in 1,000s, *UnempRate* is the unemployment rate in the zip code (in percentage), *BachelorDegree* is the percent of population with at least bachelor's degrees, *MortgagedHomes* is the share of homes with mortgages, *RentalHomes* is the share of occupied homes that are rented, *Occupied Homes 000s* is the number of occupied homes per zip code in 1,000s, *Cat Risk* is the value of expected annual loss scores from hurricanes or earthquakes in the zip code, *PropertyDamageCapita* is a property damage per capita from natural disasters in 2021 dollars, *HighRBCBurdenShare* is the share of homeowners insurers with the top tercile of RBC burden, *New Comm*$[t-1,t]$ is the indicator that equals 1 for the year and the year prior to a new insurance commissioner appointment/election and 0 otherwise, *No. Affected Policies 000s* is the number of policies affected by insurers requesting to change its homeowners insurance rate changes in the year in the state, and *No. Requesting Insurers* is the number of insurers requesting to change its homeowners insurance rates in the year in the state.

Table 2: Log Average Homeowners Insurance Price Difference by Treatment

	Base	Mkt Control	Ins. Control	MSAs	No Disaster
	(1)	(2)	(3)	(4)	(5)
Treat X Post	0.0108***	0.0065***	0.0049***	0.0038***	0.0088***
	(0.0006)	(0.0005)	(0.0005)	(0.0008)	(0.0016)
ln(Population)		-0.0402***	-0.0390***	-0.0739***	-0.0165**
		(0.0033)	(0.0033)	(0.0067)	(0.0066)
MedianAge		-0.0004***	-0.0004***	-0.0006***	-0.0002**
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
ln(MedianIncome)		0.0543***	0.0532***	0.0824***	0.0381***
		(0.0019)	(0.0019)	(0.0036)	(0.0044)
ln(OccuHomes)		0.0472***	0.0424***	0.0675***	0.0138*
		(0.0036)	(0.0036)	(0.0072)	(0.0071)
UnempRate		-0.0014***	-0.0013***	-0.0017***	0.0000
		(0.0001)	(0.0001)	(0.0002)	(0.0002)
BachelorDegree		-0.0021***	-0.0020***	-0.0020***	-0.0020***
		(0.0001)	(0.0001)	(0.0001)	(0.0002)
MortgagedHomes		0.0294***	0.0288***	0.0457***	0.0136*
		(0.0038)	(0.0038)	(0.0066)	(0.0082)
RentalHomes		0.0182***	0.0190***	0.0450***	-0.0003
		(0.0041)	(0.0041)	(0.0074)	(0.0087)
ln(PropertyDamageCapita)		-0.0003***	-0.0004***	-0.0004***	0.0003
		(0.0001)	(0.0001)	(0.0001)	(0.0005)
MajorHOShare			0.0000***	0.0000	0.0000***
			(0.0000)	(0.0000)	(0.0000)
HomeownersHHI			-0.0000***	-0.0000	-0.0001***
			(0.0000)	(0.0000)	(0.0000)
HighRBCBurdenShare			-0.0530***	-0.0609***	-0.0228***
			(0.0022)	(0.0031)	(0.0061)
AvgHOReinsShare			0.1536***	0.2396***	-0.1874***
			(0.0235)	(0.0341)	(0.0554)
New Comm[t-1,t]			0.0027***	0.0044***	0.0036***
			(0.0002)	(0.0004)	(0.0006)
ln(No. Affected Policies)			-0.0025***	-0.0030***	-0.0048***
			(0.0001)	(0.0002)	(0.0004)
No. Requesting Insurers			-0.0000	-0.0001***	0.0002***
			(0.0000)	(0.0000)	(0.0000)
Dep.Var. Mean	7.0	7.0	7.0	7.0	6.9
Year FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Zipcode FE	Yes	Yes	Yes	Yes	Yes
Adj. Within R^2	0.004	0.086	0.096	0.087	0.121
N	201,080	201,080	201,080	121,729	20,312

Note: The table report regression results from equation (5). Treatment equals one for zip codes with expected annual loss scores from hurricanes and earthquakes higher than 75 and zero otherwise. Post equals one for years 2017 to 2021 and zero for years 2014 to 2016. See Table 1 for definitions of the variables. Column (1) does not include time-varying control variables. We add zip code-level time-varying zip code characteristics in column (2), add time-varying homeowners insurance market characteristics in column (3). In column (4), we estimate the same model in column (3) for zip codes that are located within metropolitan statistical areas. In column (5), we estimate the same model in column (3) for zip codes that reported at most \$100,000 property damage losses (in 2021 dollars) from natural disasters throughout the sample period. Standard errors are clustered at zip code levels. $*p < 0.1$, $**\ p < 0.05$, $***\ p < 0.01$.

Table 3: Sensitivity of Treatment Threshold

	Full Sample			No Disasters		
Treatment Defined at:	50th	60th	70th	50th	60th	70th
	(1)	(2)	(3)	(4)	(5)	(6)
Treat X Post	0.0028***			0.0048***		
	(0.0005)			(0.0013)		
Treat X Post		0.0045***			0.0079***	
		(0.0005)			(0.0015)	
Treat X Post			0.0065***			0.0124***
			(0.0006)			(0.0019)
Treatment Threshold	66.8	72.6	77.9	66.9	72.6	77.9
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. Within R^2	0.095	0.096	0.096	0.119	0.121	0.124
N	201,080	201,080	201,080	20,312	20,312	20,312

Note: The table report regression results from the model reported in Table 2 column (3) for columns (1) to (3) and Table 2 column (5) for columns (4) to (6). Columns differ in terms of the treatment indicator threshold where the treatment equals one for zip codes with expected annual loss scores from hurricanes and earthquakes higher than the 50th percentile value and zero otherwise in columns (1) and (4), higher than the 60th percentile value and zero otherwise in columns (2) and (5), and higher than the 70th percentile value and zero otherwise in columns (3) and (6). Standard errors are clustered at zip code levels. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Homeowners Insurance Price Difference by Treatment and High RBC Burden Insurers

	Full Sample			No Disasters		
	10%	20%	30%	10%	20%	30%
	(1)	(2)	(3)	(4)	(5)	(6)
Treat X Post ($\beta 1$)	-0.0088***	-0.0031***	-0.0026***	-0.0264***	0.0011	-0.0002
	(0.0034)	(0.0008)	(0.0006)	(0.0060)	(0.0018)	(0.0014)
High RBC X Post	-0.0009			0.0002		
	(0.0010)			(0.0023)		
High RBC X Post		0.0029***			0.0049***	
		(0.0006)			(0.0012)	
High RBC X Post			0.0047***			0.0100***
			(0.0010)			(0.0016)
Treat X High RBC X Post ($\beta 2$)	0.0146***			0.0357***		
	(0.0034)			(0.0063)		
Treat X High RBC X Post ($\beta 2$)		0.0121***			0.0109***	
		(0.0011)			(0.0030)	
Treat X High RBC X Post ($\beta 2$)			0.0227***			0.0245***
			(0.0013)			(0.0044)
Share I(High RBC)	0.931	0.527	0.156	0.944	0.559	0.209
Share I(High RBC) | Treat	0.981	0.667	0.323	0.987	0.656	0.306
Dep.Var. Mean	7.0	7.0	7.0	6.9	6.9	6.9
High RBC Burden: $\beta 1 + \beta 2$	0.006***	0.009***	0.020***	0.009***	0.012***	0.024***
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. Within R^2	0.092	0.094	0.100	0.121	0.124	0.137
N	201,080	201,080	201,080	20,312	20,312	20,312

Notes: The table report regression results from including *High RBC Burden State* indicator interacted with Post indicator and Treatment indicator, respectively, in the model reported in Table 2 column (3) for columns (1) to (3) and Table 2 column (5) for columns (4) to (6). In columns (1) and (4), we define *High RBC Burden State* as states that has at least 10% of its homeowner insurance written by insurers with high RBC burden (i.e., insurers in the top tercile in terms of RBC burden in a given year), during 2011 to 2016. In columns (2) and (5), *High RBC Burden State* is defined using 20% threshold and it is 30% in columns (3) and (6). Standard errors are clustered at zip code levels. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Homeowners Insurance Price Difference by Treatment and Insurers Not Using Reinsurance

	Full Sample			No Disasters		
	10%	20%	30%	10%	20%	30%
	(1)	(2)	(3)	(4)	(5)	(6)
Treat X Post ($\beta 1$)	0.0105***	-0.0020***	0.0072***	-0.0040	-0.0043***	0.0063***
	(0.0015)	(0.0007)	(0.0006)	(0.0061)	(0.0015)	(0.0017)
No Reins X Post	-0.0048***			-0.0122***		
	(0.0008)			(0.0028)		
No Reins X Post		-0.0086***			-0.0083***	
		(0.0007)			(0.0017)	
No Reins X Post			-0.0074***			-0.0220***
			(0.0010)			(0.0019)
Treat X No Reins X Post ($\gamma 2$)	-0.0053***			0.0120*		
	(0.0016)			(0.0064)		
Treat X No Reins X Post ($\gamma 2$)		0.0185***			0.0397***	
		(0.0012)			(0.0043)	
Treat X Low RBC X Post ($\gamma 2$)			-0.0055***			0.0124**
			(0.0014)			(0.0058)
Share I(No Reins)	0.920	0.391	0.164	0.965	0.239	0.075
Share I(No Reins) | Treat	0.899	0.507	0.193	0.934	0.323	0.052
Dep.Var. Mean	7.0	7.0	7.0	6.9	6.9	6.9
No Reins: $\beta 1 + \gamma 2$	0.005***	0.017***	0.002	0.008***	0.035***	0.019***
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. Within R^2	0.096	0.098	0.097	0.121	0.134	0.128
N	201,080	201,080	201,080	20,312	20,312	20,312

Notes: The table report regression results from including *No Reinsurance* indicator interacted with Post indicator and Treatment indicator, respectively, in the model reported in Table 2 column (3) for columns (1) to (3) and Table 2 column (5) for columns (4) to (6). In columns (1) and (4), we define *No Reinsurance* as states that has at least 10% of its homeowner insurance market written by insurers that are not using reinsurance, during 2011 to 2016. In columns (2) and (5), *No Reinsurance* is defined using 20% threshold and it is 30% in columns (3) and (6). Standard errors are clustered at zip code levels. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: QUASR Univariate Differences by Insurer Treatment

	Control		Treat (FPHLM)		*Mean*	Total	
	Mean	SD	Mean	SD	Diff.	Mean	SD
A: Insurance							
AvgPrice	1,923.46	1,175.39	3,035.85	3,041.37	1,112.39***	2,164.70	1,816.04
CitizensExp Mil.	1,725.83	4,789.88	2,058.83	5,148.74	333.00***	1,798.05	4,871.86
B: Socio-economic							
Population 000s	392.77	511.03	479.75	570.36	86.98***	411.63	525.69
MedianAge	43.23	6.58	43.65	6.57	0.42***	43.32	6.58
MedianIncome 000s	48.69	9.10	50.15	8.88	1.46***	49.01	9.07
UnempRate	4.91	1.66	4.76	1.59	-0.16***	4.88	1.64
BachelorDegree	13.71	5.17	14.64	5.05	0.92***	13.91	5.16
MortgagedHomes	0.31	0.07	0.31	0.06	-0.00***	0.31	0.07
RentalHomes	0.26	0.08	0.28	0.08	0.01***	0.27	0.08
Occupied Homes 000s	147.01	181.16	178.83	199.78	31.82***	153.91	185.82
C: Geographic Risks							
Hurricane Risk (FPHLM)	1.14	1.04	1.37	1.13	0.23***	1.19	1.06
Hurricane Risk (FEMA)	94.41	6.39	95.95	5.21	1.54***	94.74	6.19
PropertyDamageCapita	6.61	41.14	7.08	42.66	0.46*	6.71	41.47
D: Insurer							
Insurer Risk (FPHLM)	1.39	0.36	2.19	0.48	0.80***	1.57	0.51
Insurer Risk (FEMA)	97.89	1.05	99.01	0.50	1.13***	98.13	1.06
Firm Size Bil.	2.19	6.63	1.35	4.05	-0.84***	2.01	6.18
RBC Burden	60.80	38.04	76.17	41.44	15.37***	64.13	39.32
RBC Ratio	3,030.57	6,667.77	1,893.59	4,752.54	-1,136.98***	2,784.00	6,319.42
Liab/Surp	156.88	97.38	184.50	97.44	27.62***	162.87	98.05
HO Reins.	32.96	28.28	35.57	26.13	2.61***	33.52	27.85
Florida Focus	11.07	8.04	11.87	8.63	0.80***	11.24	8.18
Observations	104,100		28,827		132,927	132,927	

Notes: The table reports univariate mean differences between the control group and the treatment group insurers reporting to QUASR. Treatment equals one for insurers with their exposure-weighted hurricane risks (FPHLM) at the top quartile during the 2011-2016 period, and zero for others. We perform tests of the mean difference assuming unequal variance structures between the control and the treatment. *AvgPrice* is the quarterly average homeowners insurance prices in each county in Florida, *County No. Insurers* is the number of homeowners insurers reporting to QUASR for each county, *CitizensExp Mil.* is the total exposure of homeowners insurance policies written by Citizens in a given county in a given quarter in millions, *Hurricane Risk (FPHLM)* is the estimated loss costs per $1,000 value of framed houses from the FPHLM, *Hurricane Risk (FEMA)* is the expected annual loss scores from hurricanes from FEMA, *PropertyDamageCapita* is property damage per capita in 2021 dollars from natural disasters in a given county in a given quarter, *Insurer Risk (FPHLM)* is the quarterly-county exposure weighted Hurricane Risk (FPHLM) for each insurer in Florida in each quarter during 2011 - 2016, *Insurer Risk (FEMA)* is the quarterly-county exposure weighted Hurricane Risk (FEMA) for each insurer in Florida in each quarter during 2011 - 2016, *Firm Size Bil.* is the total admitted assets of the insurer in billion dollars, *RBC Burden* is Risk-based capital of the insurer scaled by its beginning-of-the year total admitted assets, *RBC Ratio* is RBC ratio (i.e.,total adjusted capital of the insurer divided by its Risk-based capital), *Liab/Surp* is total liabilities of the insurer divided by its surplus, *HO Reins.* is amount of homeowners insurance premiums transferred to unaffiliated reinsurers in percentages, and *Florida Focus* is the insurer's homeowners insurance premiums written in Florida as a percent of its total homeowners insurance premiums in the U.S. See Table A1 for definitions of the socio-economic variables.

Table 7: Florida Quarterly Insurance Price Difference by Treatment

	Base	County	Insurer	× RBC Burden	× Reinsurance
	(1)	(2)	(3)	(4)	(5)
High Risk X Post ($\beta 1$)	292.6620**	282.8295**	333.6301**	592.1414**	253.8545
	(146.2481)	(142.7765)	(136.0706)	(292.6522)	(158.7716)
Post X High RBC ($\beta 2$)				-136.2291**	
				(61.4051)	
X High Risk ($\beta 3$)				-373.0349	
				(295.0169)	
Post X Low Reins ($\beta 2$)					40.0900
					(65.9152)
X High Risk ($\beta 3$)					232.7600
					(288.9752)
County No. Insurers		-0.9375	-0.6423	-0.4676	-0.4544
		(1.2367)	(1.2369)	(1.2652)	(1.2200)
ln(County Citizens Exposure)		5.3734	4.6268	4.9905	4.2775
		(7.8808)	(8.2738)	(8.1254)	(8.3133)
ln(PropertyDamageCapita)		0.1184	0.0595	0.0670	0.1146
		(0.5347)	(0.5338)	(0.5284)	(0.5270)
ln(County Insurer Exposure)			50.7942	50.2226	49.4617
			(33.4805)	(33.0790)	(32.9423)
ln(RBC Burden)			53.9275**		52.6241**
			(24.3347)		(23.7481)
ln(Reins.)			-65.6304*	-62.8525*	
			(36.7443)	(37.1381)	
ln(Firm Size)			-164.4018**	-103.2461	-162.3159**
			(74.6917)	(69.7276)	(71.0865)
Liab/Surp			0.2993	0.4324	0.3089
			(0.3318)	(0.3405)	(0.3387)
Florida Focus			16.5498**	12.1556*	13.2150
			(8.1107)	(7.0941)	(9.7967)
$\beta 1 + \beta 3$				219.106***	486.615**
Year FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes	Yes	Yes
Other County Controls	No	Yes	Yes	Yes	Yes
Adj. Within R^2	0.005	0.008	0.023	0.027	0.022
N	132,927	132,927	132,927	132,927	132,927

Notes: The table report differences-in-differences regression results. Treatment equals one for insurers with their exposure-weighted hurricane risks (FPHLM) at the top quartile during the 2011-2016 period, and zero for others. Post equals one for years 2017 to 2021 and zero for years 2011 to 2016. Column (1) does not include time-varying control variables. We add county-level time-varying market characteristics in column (2) and add time-varying homeowners insurer characteristics in column (3). In column (4), we include insurer's high RBC burden indicator interacted with the treatment indicator and the post indicator, respectively, to the model in column (3). Insurers whose RBC burden is at the top quartile during the 2011-2016 period are considered to be high RBC burden insurers. In column (5), we include insurer's low reinsurance use indicator interacted with the treatment indicator and the post indicator, respectively, to the model in column (3). Insurers whose reinsurance use is at the bottom quartile during the 2011-2016 period are considered to be low reinsurance users. Standard errors are clustered at insurer levels. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

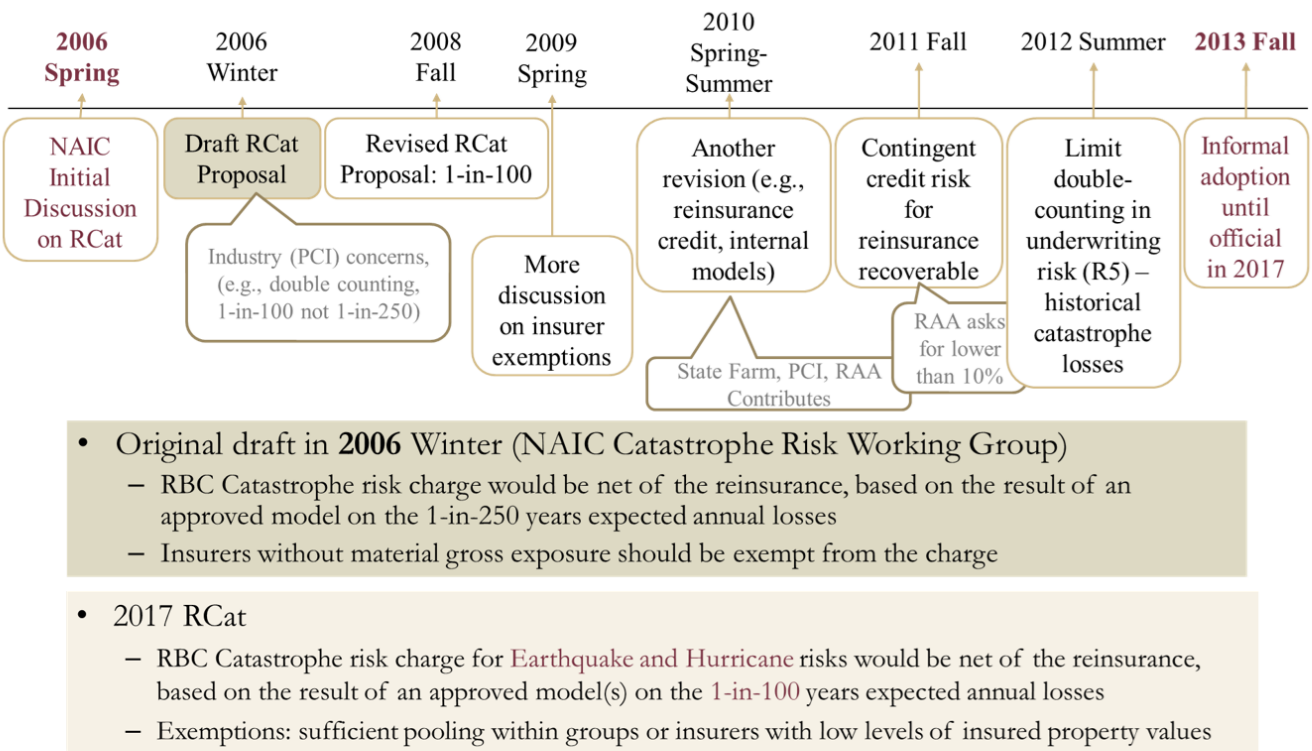
Table 8: Florida Quarterly Insurance Price Difference, Florida Hurricane Catastrophe Fund

	Control FL Cat Fund Use		FL Cat Fund Treatment	
	(1)	(2)	(3)	(4)
High Risk X Post ($\beta 1$)	253.8421	252.2583	275.0562*	101.5804*
	(158.6329)	(163.4347)	(151.5221)	(55.9951)
X High Risk ($\beta 3$)	232.2148	233.6999		
	(289.4558)	(290.1121)		
Post X Low Reins$_{FL.\ Cat/FL\ Prem}$ ($\beta 2$)			-97.2768	
			(65.2968)	
X High Risk ($\beta 3$)			273.6458	
			(275.4972)	
Post X Low Reins$_{FL.\ Cat/Reins}$ ($\beta 2$)				191.3618
				(135.7999)
X High Risk ($\beta 3$)				812.7992*
				(446.6987)
ln(RBC Burden)	53.7468**	52.7022**	49.2961**	63.7486**
	(23.6119)	(23.9428)	(23.7928)	(24.7286)
ln(Reins.)			-66.5973*	-68.9430*
			(35.9132)	(35.0387)
FL Cat/FL Prem	-1.0202			
	(3.1507)			
FL Cat/Reins		-0.1886		
		(1.8153)		
Florida Focus	12.6607	13.1700	16.9049*	4.9339
	(9.6429)	(9.8561)	(8.5460)	(5.7154)
$\beta 1 + \beta 3$	486.057**	485.958**	548.702**	914.380**
Year FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes	Yes
Other County Controls	Yes	Yes	Yes	Yes
Adj. Within R^2	0.022	0.022	0.024	0.036
N	132,927	132,927	132,927	132,927

Notes: In column (1), we report differences-in-differences regression results based on same models as in Table 7 column (5) except we additionally control for insurer's use of Florida Hurricane Catastrophe Fund (FHCF) as percent of total premiums written. In column (2), we report differences-in-differences regression results based on same models as in Table 7 column (5) except we additionally control for insurer's use of FHCF as percent of total reinsurance. In column (3), we report differences-in-differences regression results based on same models as in Table 7 column (5) except we define low reinsurance using the amount of FL Cat Fund as percent of total premiums written (defined during 2011-2016 period). In column (4), we report differences-in-differences regression results based on same models as in Table 7 column (5) except we define low reinsurance using the amount of FHCF as percent of total unaffiliated reinsurance (defined during 2011-2016 period). In both columns (3) and (4), we control for the amount of total unaffiliated homeowners reinsurance as percent of total homeowners premiums. Standard errors are clustered at insurer level in all models. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix

Figure A1: Timeline of RCat Reform



Notes: The figure summarizes NAIC meeting minutes (proceedings) since the initial discussion of RCat in 2006 and the official adoption discussed in 2016. We also summarize the draft proposal and the final proposal of RCat in the boxes below the timeline.

Table A1: Summary Statistics

	Mean	SD	1st	25th	50th	75th	99th
AvgPrem	1,060.21	142.76	735.00	956.00	1,052.00	1,150.00	1,448.00
MajorHOShare	3,551.84	5,298.07	68.70	587.70	1,547.98	4,086.17	30,913.93
HomeownersHHI	725.33	267.58	253.73	563.28	676.46	927.44	1,304.25
AvgHOReinsShare	0.06	0.06	0.02	0.03	0.04	0.07	0.38
B: Socio-economic							
MSA	0.61	0.49	0.00	0.00	1.00	1.00	1.00
Population 000s	12.51	14.94	0.41	1.80	5.49	18.84	66.41
MedianAge	41.75	7.00	25.40	37.00	41.40	45.90	61.30
MedianIncome 000s	59.72	23.57	23.48	43.70	54.46	69.84	147.11
InsuredHomes 000s	2.65	2.98	0.13	0.47	1.30	3.99	12.89
UnempRate	3.77	2.26	0.00	2.20	3.40	4.90	11.70
BachelorDegree	13.18	7.66	2.10	7.90	11.10	16.40	38.30
MortgagedHomes	0.35	0.14	0.06	0.25	0.34	0.44	0.68
RentalHomes	0.24	0.15	0.02	0.13	0.21	0.31	0.78
Occupied Homes 000s	4.67	5.43	0.17	0.70	2.08	7.24	23.22
C: Risks							
Cat Risk	47.80	38.01	0.00	0.00	62.83	80.63	98.72
PropertyDamageCapita	21.25	98.20	0.00	0.01	0.48	4.05	819.44
HighRBCBurdenShare	0.35	0.14	0.09	0.25	0.36	0.43	0.80
New Comm[t-1,t]	0.41	0.49	0.00	0.00	0.00	1.00	1.00
No. Affected Policies 000s	775.28	608.64	17.45	327.10	655.38	1,035.64	2,601.73
No. Requesting Insurers	32.30	12.85	5.00	24.00	32.00	40.00	65.00
Observations	201,080						

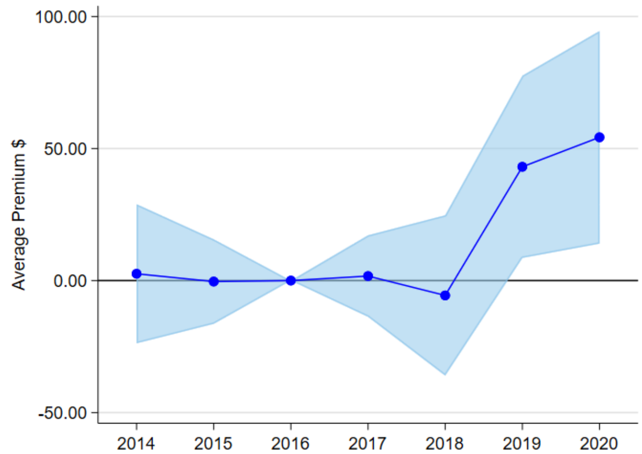
Notes: The table reports summary statistics of zip code-year observations. See Table 1 for definitions of the variables.

Table A2: Univariate Differences by State Treatment

	Control		RCat State		*Mean*	Total	
	Mean	SD	Mean	SD	*diff.*	Mean	SD
AvgPrice	993.35	108.97	1,092.48	145.90	99.13***	1,060.21	142.76
MajorHOShare	3,175.64	3,988.91	3,733.40	5,816.90	557.76***	3,551.84	5,298.07
HomeownersHHI	769.45	174.77	704.03	300.03	-65.42***	725.33	267.58
AvgHOReinsShare	0.03	0.01	0.08	0.07	0.04***	0.06	0.06
B: Socio-economic							
MSA	0.49	0.50	0.66	0.47	0.17***	0.61	0.49
Population 000s	8.20	11.00	14.59	16.10	6.39***	12.51	14.94
MedianAge	42.31	6.46	41.48	7.24	-0.83***	41.75	7.00
MedianIncome 000s	57.53	17.73	60.78	25.85	3.25***	59.72	23.57
InsuredHomes 000s	1.94	2.49	2.99	3.13	1.05***	2.65	2.98
UnempRate	3.27	2.13	4.01	2.29	0.75***	3.77	2.26
BachelorDegree	12.99	6.58	13.27	8.13	0.28***	13.18	7.66
MortgagedHomes	0.36	0.13	0.34	0.14	-0.02***	0.35	0.14
RentalHomes	0.21	0.13	0.26	0.16	0.05***	0.24	0.15
Occupied Homes 000s	3.24	4.32	5.36	5.77	2.12***	4.67	5.43
C: Risks							
Cat Risk	0.00	0.00	70.88	22.51	70.88***	47.80	38.01
PropertyDamageCapita	17.83	77.95	22.90	106.57	5.07***	21.25	98.20
HighRBCBurdenShare	0.30	0.11	0.38	0.14	0.08***	0.35	0.14
New Comm[t-1,t]	0.42	0.49	0.41	0.49	-0.01***	0.41	0.49
No. Affected Policies 000s	750.01	587.61	787.47	618.16	37.46***	775.28	608.64
No. Requesting Insurers	36.10	11.94	30.47	12.87	-5.62***	32.30	12.85
Observations	65,456		135,624		201,080	201,080	

Notes: The table reports univariate mean differences between the control and the treatment state of RCat. We perform tests of the mean difference assuming unequal variance structures between the control and the treatment.

Figure A2: State-level Average Insurance Price Differences by RCat Using NAIC HO Report



Notes: The figure plots differences in average state-level price between RCat states and control states. We use state-level annual data from NAIC Homeowners Insurance Market Report during 2014 - 2020. Specifically, the figure plots coefficients from the differences-in-differences regression of average homeowners insurance prices on year indicators, RCat state indicator and the interactions of year indicators and RCat state indicator, using 2016 as the omitted baseline year. Standard errors are clustered at state levels. Shaded areas represent 95% confidence intervals of the coefficient estimates.

Table A3: External Validity of Zip Code Insurance Prices

Dependent Variable: NAIC's State-level Price				
	(1)	(2)	(3)	(4)
Avg. Premium (Zip)	1.0735***	1.1178***		
	(0.3237)	(0.3875)		
Avg. Premium $(\text{Zip})_{\text{not lagged}}$			1.0735***	1.1016***
			(0.3299)	(0.3820)
Dep. Var. Mean	1,223.8	1,223.8	1,223.8	1,223.8
Avg. Premium (Zip) Mean	1,015.7	1,038.6	1,015.7	1,038.6
Year FE	No	Yes	No	Yes
R^2	0.161	0.167	0.157	0.164
N	175,945	175,945	175,945	175,945

Notes: The table report regression results from estimating the state-level average homeowners insurance prices reported in the NAIC Homeowners Insurance Market Report (2014 - 2020)on the zip code-levelaverage homeowners insurance price from Claritas. NAIC HO Data ends in 2020. Standard errors are clustered at state levels. $*p < 0.1$, $**\ p < 0.05$, $***\ p < 0.01$.

Table A4: Average Price Difference by Treatment

	Base	Mkt Control	Ins. Control	MSAs	No Disaster
	(1)	(2)	(3)	(4)	(5)
Treat X Post	15.6021***	11.0173***	7.3235***	6.0607***	9.4823***
	(0.5768)	(0.4978)	(0.5112)	(0.6988)	(1.5428)
Dep.Var. Mean	1,060.2	1,060.2	1,060.2	1,081.1	1,030.9
Year FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Zipcode FE	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes
Adj. Within R^2	0.010	0.113	0.135	0.125	0.137
N	201,080	201,080	201,080	121,729	20,312

Note: The table report regression results from the same models as shown in Table 2 except the dependent variable is average homeowners insurance price. The model specifications are the same as thos reported in Table 2. Standard errors are clustered at zip code levels. $*p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Not Lagged Price Difference by Treatment

	Base	Mkt Control	Ins. Control	MSAs	No Disaster
	(1)	(2)	(3)	(4)	(5)
Treat X Post	0.0070***	0.0033***	0.0031***	0.0032***	0.0025*
	(0.0005)	(0.0004)	(0.0004)	(0.0005)	(0.0013)
Dep.Var. Mean	6.9	6.9	6.9	6.9	6.9
Year FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Zipcode FE	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes
Adj. Within R^2	0.002	0.075	0.086	0.079	0.082
N	201,080	201,080	201,080	121,729	20,312

Note: The table report regression results from the same models as shown in Table 2 except the dependent variable is natural log of average insurance prices of the year Claritas produce estimates, i.e., not lagged. The model specifications are the same as thos reported in Table 2. Standard errors are clustered at zip code levels. $*p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

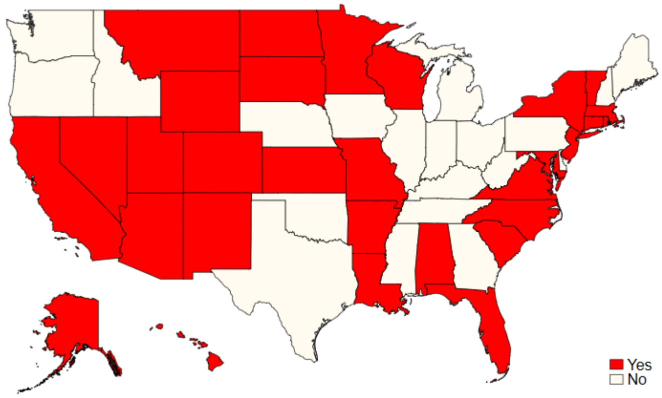
Table A6: Spillover Effect within RCat State

	Base	Mkt Control	Ins. Control	MSAs	No Disaster
	(1)	(2)	(3)	(4)	(5)
Treat X Post	0.0118***	0.0089***	0.0070***	0.0049***	0.0105***
	(0.0007)	(0.0006)	(0.0006)	(0.0009)	(0.0018)
Dep.Var. Mean	7.0	7.0	7.0	7.0	7.0
Share I(Treat)	0.508	0.508	0.508	0.537	0.350
Year FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Zipcode FE	Yes	Yes	Yes	Yes	Yes
Adj. Within R^2	0.005	0.094	0.106	0.089	0.157
N	135,624	135,624	135,624	89,761	12,752

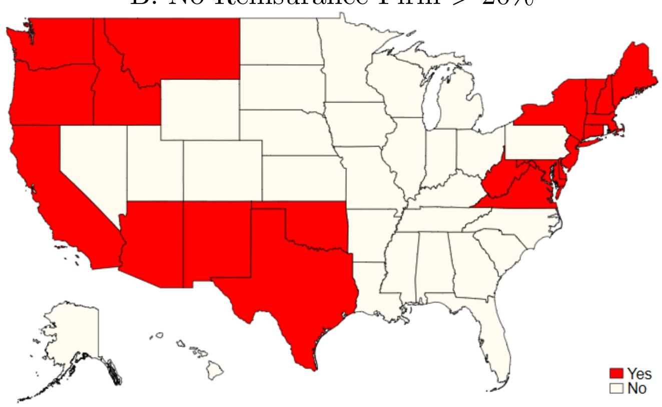
Notes: The table report regression results from equation (5) on a subsample of zip codes within RCat states. Standard errors are clustered at zip code levels. The model specifications are the same as thos reported in Table 2. $*p < 0.1$, $**\ p < 0.05$, $***\ p < 0.01$.

Figure A3: RBC Burden and HO Reinsurance by State

A. High RBC Burden Firm > 20%



B. No Reinsurance Firm > 20%



Notes: The top figure shows the states with at least 20% of its homeowners insurance market written by high RBC burden insurers throughout the pre-period (2011-2016) in red. We define high RBC burden insurers as those in the top tercile (top 33rd percentile) of RBC burden among homeowners insurers in the U.S. in each year. The bottom figure shows the states with at least 20% of its homeowners insurance market written by those not using homeowners' reinsurance throughout the pre-period (2011-2016) in red.

Table A7: Triple Difference Results, State Insurer Characteristics Treatment Defined during 2014-2016

	Full Sample			No Disasters		
	10%	20%	30%	10%	20%	30%
RBC Burden						
	(1)	(2)	(3)	(4)	(5)	(6)
Treat X Post ($\beta 1$)	-0.0088***	-0.0031***	-0.0018***	-0.0264***	0.0011	0.0003
	(0.0034)	(0.0008)	(0.0006)	(0.0060)	(0.0018)	(0.0014)
Treat X High $RBC_{14\text{-}16}$ *X Post* ($\beta 2$)	0.0146***			0.0357***		
	(0.0034)			(0.0063)		
Treat X High $RBC_{14\text{-}16}$ *X Post* ($\beta 2$)		0.0121***			0.0109***	
		(0.0011)			(0.0030)	
Treat X High $RBC_{14\text{-}16}$ *X Post* ($\beta 2$)			0.0165***			0.0224***
			(0.0012)			(0.0044)
Share I(High RBC)	0.931	0.527	0.186	0.944	0.559	0.232
Share I(High RBC) | Treat	0.981	0.667	0.328	0.987	0.656	0.306
Dep.Var. Mean	7.0	7.0	7.0	6.9	6.9	6.9
High RBC Burden: $\beta 1 + \beta 2$	0.006***	0.009***	0.015***	0.009***	0.012***	0.023***
Adj. Within R^2	0.092	0.094	0.101	0.121	0.124	0.139
N	201,080	201,080	201,080	20,312	20,312	20,312

No Reinsurance						
	(1)	(2)	(3)	(4)	(5)	(6)
Treat X Post ($\beta 1$)	0.0105***	-0.0042***	0.0072***	-0.0040	-0.0067***	0.0063***
	(0.0015)	(0.0007)	(0.0006)	(0.0061)	(0.0015)	(0.0017)
Treat X No $Reins_{14\text{-}16}$ *X Post* ($\gamma 2$)	-0.0053***			0.0120*		
	(0.0016)			(0.0064)		
Treat X No $Reins_{14\text{-}16}$ *X Post* ($\gamma 2$)		0.0224***			0.0448***	
		(0.0011)			(0.0041)	
Treat X Low RBC X Post ($\gamma 2$)			-0.0055***			0.0124**
			(0.0014)			(0.0058)
Share I(No Reins)	0.920	0.441	0.164	0.965	0.307	0.075
Share I(No Reins) | Treat	0.899	0.507	0.193	0.934	0.323	0.052
Dep.Var. Mean	7.0	7.0	7.0	6.9	6.9	6.9
No Reins: $\beta 1 + \gamma 2$	0.005***	0.018***	0.002	0.008***	0.038***	0.019***
Adj. Within R^2	0.096	0.100	0.097	0.121	0.139	0.128
N	201,080	201,080	201,080	20,312	20,312	20,312

Notes: In Panel A, we report regression results from the same models as those reported in Table 4, except insurers' RBC burden is defined during the 2014-2016 period. In Panel B, we report regression results from the same models as those reported in Table 5, except insurers' reinsurance use is defined during the 2014-2016 period. Standard errors are clustered at zip code levels. $*p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: QUASR Summary Statistics

	Mean	SD	1st	25th	50th	75th	99th
A: Insurance							
AvgPrice	2,164.70	1,816.04	729.39	1,324.64	1,674.65	2,238.20	12,762.82
County No. Insurers	70.31	13.55	33.00	60.00	74.00	81.00	89.00
CitizensExp Mil.	1,798.05	4,871.86	0.66	21.08	92.39	549.48	29,492.21
TotalDPW 000s	1,619.57	3,405.55	12.92	75.88	335.85	1,502.37	22,428.89
TotalPIF 000s	0.81	1.57	0.01	0.04	0.19	0.80	9.91
TotalExp. Mil.	405.03	792.98	3.41	20.54	92.26	400.72	4,847.40
B: Socio-economic							
Population 000s	411.63	525.69	11.63	73.30	210.50	495.58	2,664.42
MedianAge	43.32	6.58	30.00	39.20	42.90	47.10	65.30
MedianIncome 000s	49.01	9.07	33.51	42.82	48.23	54.74	74.06
UnempRate	4.88	1.64	1.80	3.50	4.90	6.20	9.00
BachelorDegree	13.91	5.16	5.30	9.50	13.30	17.80	27.30
MortgagedHomes	0.31	0.07	0.17	0.27	0.31	0.34	0.47
RentalHomes	0.27	0.08	0.09	0.21	0.25	0.32	0.46
Occupied Homes 000s	153.91	185.82	3.88	28.07	79.24	195.58	853.62
C: Geographic Risks							
Hurricane Risk (FPHLM)	1.19	1.06	0.11	0.30	0.90	1.77	5.06
Hurricane Risk (FEMA)	94.74	6.19	75.31	92.95	97.19	99.09	99.96
PropertyDamageCapita	6.71	41.47	0.00	0.00	0.00	0.10	364.43
D: Insurer							
Insurer Risk (FPHLM)	1.57	0.51	0.77	1.18	1.48	1.91	2.98
Insurer Risk (FEMA)	98.13	1.06	94.60	97.77	98.25	98.82	99.55
Firm Size Bil.	2.01	6.18	0.01	0.08	0.14	0.54	35.46
RBC Burden	64.13	39.32	1.41	39.49	62.68	84.36	218.42
RBC Ratio	2,784.00	6,319.42	228.52	416.99	642.71	1,198.71	34,344.34
Liab/Surp	162.87	98.05	0.36	99.57	155.83	221.22	547.40
HO Reins.	33.52	27.85	0.00	7.49	31.30	51.98	100.00
Florida Focus	11.24	8.18	0.03	1.66	12.32	18.50	26.43
Observations	132,927						

Notes: The table reports summary statistics of quarterly insurer-county observations. *TotalDPW 000s* is total premiums written by homeowners insurers reporting to QUASR in a given county in a given quarter in 1,000s, *TotalPIF 000s* is the total number of policies written by homeowners insurers reporting to QUASR in a given county in a given quarter in 1,000s, *TotalExp Mil.* is the total exposure of homeowners insurance policies written by insurers reporting to QUASR in a given county in a given quarter in millions, See Table 6 for definitions of the rest of the variables.

Table A9: Table 7 Results, County Variables

	Base	County	Insurer	× RBC Burden	× Reinsurance
	(1)	(2)	(3)	(4)	(5)
ln(Population)		-174.0182	-276.1794	-340.5344	-326.1585
		(254.2724)	(260.0161)	(255.1484)	(269.8002)
MedianAge		-18.4880*	-15.8780*	-16.4098*	-16.0302*
		(9.3986)	(9.2632)	(9.1004)	(9.2790)
ln(MedianIncome)		464.9539**	399.1145*	390.8757*	407.9179*
		(219.2448)	(206.4287)	(200.3266)	(208.2472)
ln(OccuHomes)		-183.4557	-126.7833	-80.7761	-103.8217
		(232.7049)	(226.6462)	(218.6465)	(221.9506)
UnempRate		-17.2891	-17.0134	-16.6002	-16.8168
		(12.2437)	(12.1102)	(12.0375)	(12.0863)
BachelorDegree		-17.8626***	-17.8440***	-17.2250***	-17.6528***
		(4.7552)	(4.5881)	(4.4747)	(4.6163)
MortgagedHomes		169.2700	152.6056	100.2157	109.5896
		(336.5690)	(334.0757)	(329.7982)	(330.2103)
RentalHomes		461.6425	284.7964	216.8963	225.7511
		(363.7586)	(364.0487)	(355.0262)	(374.7997)
$\beta1 + \beta3$				219.106***	486.615**
Year FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes
Adj. Within R^2	0.005	0.008	0.023	0.027	0.022
N	132,927	132,927	132,927	132,927	132,927

Notes: The table report coefficients of county characteristics variables of the models reported in Table 7. Standard errors are clustered at insurer levels. $*p < 0.1$, $**\ p < 0.05$, $***\ p < 0.01$.

Table A10: Florida Quarterly Insurance Price, Robustness

	Base	County	Insurer	× RBC Burden	× Reinsurance
Panel A: FEMA Hurricane EAL Risk					
	(1)	(2)	(3)	(4)	(5)
High Risk X Post (β1)	264.5454*	255.0523*	329.3226**	812.3273**	194.5930
	(153.1479)	(149.4760)	(146.1345)	(371.5903)	(151.7367)
Post X High RBC (β2)				-104.0608	
				(65.2339)	
X High Risk (β3)				-667.8534*	
				(376.4077)	
Post X Low Reins (β2)					36.5258
					(68.0775)
X High Risk (β3)					799.5309***
					(184.9827)
$\beta1 + \beta3$				144.474*	994.124***
Adj. Within R^2	0.004	0.007	0.023	0.030	0.025
N	132,927	132,927	132,927	132,927	132,927
Panel B: Exclude 2020 and 2021					
	(1)	(2)	(3)	(4)	(5)
High Risk X Post (β1)	190.8328*	187.0592*	248.7503**	412.2212*	189.1393
	(102.2422)	(100.5447)	(102.8423)	(222.8336)	(117.3247)
Post X High RBC (β2)				-153.6680***	
				(58.2605)	
X High Risk (β3)				-195.8769	
				(226.8713)	
Post X Low Reins (β2)					62.0240
					(55.2681)
X High Risk (β3)					173.3979
					(204.3500)
$\beta1 + \beta3$				216.344***	362.537**
Adj. Within R^2	0.003	0.003	0.013	0.016	0.013
N	117,789	117,789	117,789	117,789	117,789

Notes: In Panel A, we report differences-in-differences regression results based on same models as in Table 7 using different treatment indicator. The treatment equals one for insurers with their exposure-weighted expected annual losses from hurricanes (FEMA) at the top quartile during the 2011-2016 period, and zero for others. In Panel B, we report differences-in-differences regression results based on same models as in Table 7 using a subsample with the sample period ending in 2019. Standard errors are clustered at insurer level in all models. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

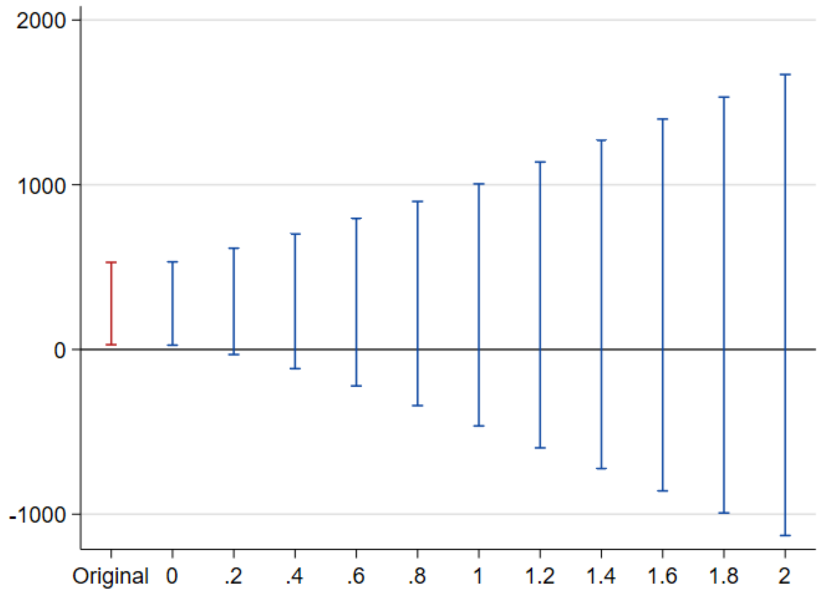
Table A11: Florida Quarterly Insurance Price, Informal Implementation Effect

	Base	County	Insurer	× RBC Burden	× Reinsurance
	(1)	(2)	(3)	(4)	(5)
High Risk$_{<13}$ *X Post*$_{2014}$ (β1)	256.8915*	250.3856*	320.4119**	557.4554**	259.4780*
	(146.0365)	(143.3804)	(130.0478)	(246.9445)	(149.1932)
Post$_{2014}$ *X High RBC*$_{<13}$ (β2)				-130.8646**	
				(58.1877)	
X High Risk$_{<13}$ (β3)				-394.5862	
				(271.5971)	
Post$_{2014}$ *X Low Reins*$_{<13}$ (β2)					0.5412
					(75.8984)
X High Risk$_{<13}$ (β3)					166.5951
					(311.3535)
$\beta 1 + \beta 3$				162.869*	426.073
Adj. Within R^2	0.004	0.006	0.022	0.026	0.021
N	132,927	132,927	132,927	132,927	132,927

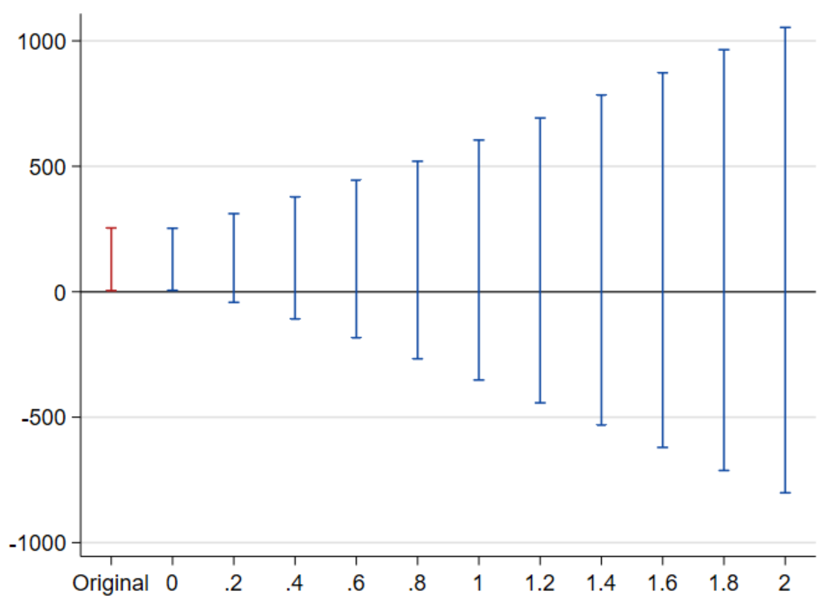
Notes: We report regression results from the same models as those reported in Table 7, except we define the Treatment and the Post indicator differently. Treatment equals one for insurers with their exposure-weighted hurricane risks (FPHLM) at the top quartile during the 2011-2013 period, and zero for others. Post equals one for years 2014 to 2021 and zero for years 2011 to 2013. Standard errors are clustered at insurer levels. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure A4: Florida Homeowners Insurance Price, Honest DiD

A. Average Post-Period



B. Average 2017 - 2019



Notes: The figure reports the estimated robust confidence intervals of the average treatment effect during the post-RCat period under different pre-trend violation assumptions following Rambachan and Roth (2023) as in Figure 4.