Regulatory Capital and Catastrophe Risk

Evan M. Eastman[a]
Florida State University

Kyeonghee Kim[b]
Florida State University

October 2023

Abstract

In this study, we examine the effect of capital regulation on insurers' pricing behavior using homeowners' insurance price data. We leverage a regulatory reform that imposes greater regulatory capital costs for insurers to provide property coverage in catastrophe-prone areas. We first document that the regulatory capital reform had a meaningful impact on insurers—on average, regulatory capital ratios appear to decline by 50 percentage points. Using a difference-in-differences design and homeowners insurance prices, we find empirical evidence that the reform results in price increases, though the magnitude of the increases is restrained. Taken together with the size of the homeowners' insurance market, our back-of-the-envelope calculation suggests the increase in insurance price is commensurate to 7-14% of the increase in regulatory capital costs due to catastrophes. We also find that the increase in price is larger for insurers with greater regulatory capital constraints or less access to reinsurance markets. Overall, our study provides evidence that climate-related regulation costs can passed on to consumers.

Keywords: Property/Casualty Insurance; Regulatory Capital Management; Climate Change
JEL Codes: G20; G22; G28

The authors would like to thank Patty Born, Chia-Chun Chiang, Cameron Ellis, Shaveta Gupta, Moritz Hanika (discussant), Greg Niehaus, Joan Schmit, Justin Sydnor, Ana-Maria Tenekedjieva, Xuesong You, staff at the National Association of Insurance Commissioners and participants at Florida State University, the American Risk and Insurance Association Annual Meeting, and the Southern Risk and Insurance Association Annual Meeting for helpful comments.

[a] Dr. William T. Hold/The National Alliance Program in Risk Management/Insurance, College of Business, Florida State University, Tallahassee, FL, 32306 email: eeastman@business.fsu.edu.

[b] Dr. William T. Hold/The National Alliance Program in Risk Management/Insurance, College of Business, Florida State University, Tallahassee, FL, 32306 email: kkim@business.fsu.edu.

Regulatory Capital and Catastrophe Risk

Abstract

In this study, we examine the effect of capital regulation on insurers' pricing behavior using homeowners' insurance price data. We leverage a regulatory reform that imposes greater regulatory capital costs for insurers to provide property coverage in catastrophe-prone areas. We first document that the regulatory capital reform had a meaningful impact on insurers—on average, regulatory capital ratios appear to decline by 50 percentage points. Using a difference-in-differences design and homeowners insurance prices, we find empirical evidence that the reform results in price increases, though the magnitude of the increases is restrained. Taken together with the size of the homeowners' insurance market, our back-of-the-envelope calculation suggests the increase in insurance price is commensurate to 7-14% of the increase in regulatory capital costs due to catastrophes. We also find that the increase in price is larger for insurers with greater regulatory capital constraints or less access to reinsurance markets. Overall, our study provides evidence that climate-related regulation costs can be passed on to consumers.

Keywords: Property/Casualty Insurance; Regulatory Capital Management; Climate Change
JEL Codes: G20; G22; G28

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/casualty (P&C) 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 for exposures located in catastrophe-prone areas.

In this study, we examine how P&C insurers respond to a change in regulatory capital regulation that requires P&C insurers to hold additional capital when underwriting catastrophic risk. We first document that the reform, which we refer to as "RCat," has a material impact on insurers' risk-based capital (RBC) ratios in the year it was introduced. The RBC ratio is the ratio of an insurer's capital holdings to capital required by regulators and, therefore, a higher ratio indicates a better regulatory capital position. This finding establishes that the regulation change was not mitigated by insurers *ex ante*. We use P&C insurer financial statement data from 2010 to 2020 and find evidence that the RCat risk charge materially impacts RBC ratios. We find that the industry-average RBC ratio drops from 2016 to 2017 and that this decline is driven by an increase in the denominator (i.e., regulatory required capital) rather than a drop in capital levels (numerator). This result appears to be concentrated among insurers writing homeowners coverage, which are the firms most impacted by the regulatory change. Beyond suggesting that the RCat

[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.

represents a material change to risk-based capital regulation, these findings also indicate that despite substantial regulatory lag between the announcement and implementation of RCat, insurers do not appear to alter their capital structure in anticipation of RCat.

We next examine insurer capital management after the reform. Specifically, we study insurers' pricing behavior. While insurance price increases are potentially constrained by regulatory price controls (i.e., rate regulation), insurers can improve their capital positions by increasing insurance prices. We use detailed zip code-level data from 2014-2019 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 level based on catastrophe risk following the RCat guidelines.[2] Controlling for various state- and zip code-specific characteristics that 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 exposure following RCat's implementation in 2017. Our results are robust to various alternative specifications, such as limiting our sample to areas that did not experience catastrophic losses. We also find that the observed increase in prices is robust to different treatment thresholds that we designate as "high risk."

Our next set of analyses focuses on disentangling the drivers of this relationship between RCat and price increases. We propose two potential mechanisms that could be drivers. First, we anticipate that firms with greater regulatory capital constraints 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 liabilities to reinsurers. We find evidence in support of both hypotheses—

[2] As we discuss in greater detail later, we reply 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.

homeowners insurance prices increase following RCat implementation in risky areas more when states have insurers with a greater regulatory capital burden and when fewer insurers have access to external reinsurance markets.

For the final step in our research design, we take advantage of detailed firm-county-quarter level reporting for property insurers in Florida. In addition, we are able to use publicly available data from a hurricane catastrophe model, which is the precise procedure used by insurers in calculating their RCat risk charge. 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. Consistent with our previous tests, we find evidence that this is primarily driven by firms that cannot transfer their property liabilities to reinsurers, but we do not find similar evidence for firms with high regulatory capital burdens.

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) that documents life insurers' pricing behavior associated with financial market frictions. While Koijen and Yogo (2015) exploit the financial frictions arising from regulatory capital requirements and the credit rating system to identify abnormal pricing behavior, we exploit a regulatory reform to document how RBC rules on climate change risks influence insurers' pricing behavior in the homeowners' insurance market.

Second, we contribute to the broad literature exploring how insurers and regulators respond to catastrophic 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.

Third, we contribute to the literature examining the effect of climate change risk in the financial markets (e.g., Jouvenot and Krueger 2020; Ilhan et al. 2020; Mésonnier and Nguyen 2021; Kim and Lin 2022). Most of the studies focus on disclosure requirements to financial institutions while we study a unique regulation that directly affects financial institutions' regulatory capital costs. We extend the literature by examining P&C insurers, who directly underwrite climate change related property risks in their operations. Our study is most related to Oh, Sen, and Tenekedjieva (2022), who find evidence that rate regulation and the state-based nature of insurance regulation results in pricing distortions in the P&C insurance market.

This topic 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, P&C insurer underwriting operations are directly exposed to climate-related extreme weather events.[3] Importantly, homeowners with mortgages in the US are required to maintain insurance and thereby less elastic to the modest price

[3] While P&C 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).

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 pushback from the industry (see Klein and Wang (2009) and NAIC CIPR Newsletter August (2017) for more detailed discussions on the topic).[4] 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.

II. INSTITUTIONAL DETAILS

Regulation in the Property-Casualty Insurance Industry

The U.S. 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).

[4] 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.

One tool regulators use for monitoring insurer solvency is the risk-based capital ratio (RBC ratio), which is uniform across states in the U.S. 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* is based on risk-weighted measures of how much risk an insurer takes and can be considered the minimum amount of capital an insurer should be holding. Specifically, the denominator for P&C insurers can, prior to the implementation of the catastrophe exposure risk charge, be calculated as:[5]

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

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). Firms that drop below minimum RBC ratio thresholds, 200%, may be subject to varying levels of

[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).

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.

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 begins after the 2004-2005 hurricane seasons, wherein the initial proposal faced push back from the industry. The initial proposal in 2006 includes the 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 instantly responded by requesting more detailed guidelines to limit the potential double counting of the current underwriting premiums RBC (R5), that includes actual catastrophe loss exposure, as well as the potential double counting of within group reinsurance transactions. The industry also disagreed with the 1-in-250 years modeled losses. Over the next five years, regulators and interested 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, P&C insurers' RBC is calculated as follows (with changes in **bold**):

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

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 (hence 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).[6]

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	=	1-in-100 years net modeled losses + (1-in-100 years contingent credit risk)*0.048
Net Modeled Losses	=	Direct and assumed modeled losses minus ceded amounts recoverable
Contingent Credit Risk	=	Ceded amounts recoverable minus ceded amounts recoverable with zero credit risk charge (i.e., U.S. affiliates and mandatory pools)
Losses	=	Exclude loss adjustment expenses.

Each catastrophe risks charge is calculated by NAIC-approved commercially available catastrophe modelling vendors.[7] 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.[8] 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,

[6] See, for example, Page 2304 of NAIC Proceedings Fall 2019.
[7] AIR, EQECAT, RMS for earthquake or hurricane and ARA HurLoss or the Florida Public model for hurricane only.
[8] 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 for earthquake risks.

Effect of the RCat on RBC Ratios and Insurers' Responses

Intuitively, the total effect of the RCat on insurers' RBC ratio depends on the difference between RCat and the previous underwriting risk charge related to catastrophic events (R_5) as well as the reduction in underwriting risk charge arising from actual catastrophic losses in a given year (R_{5A}).[9] The detailed breakdown of the RBC formula for each insurer is not a public information—only regulators have access to the information.[10] The NAIC, however, periodically reports aggregate industry values of each of the RBC component. During the 2013-2016 period, the NAIC published 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, we examine the trend of R5 and RCat in the P&C 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

[9] In other words, the difference between the (estimated) modeled catastrophic losses in 100 years (RCat) and past 10 years' historical loss experience from catastrophic events (formerly included as a portion of the R_5 component) plus the actual catastrophic event losses in the given year (now included as portion of the R_{5A} component).
[10] 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.

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.

[Insert Figure 1]

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 shown in billion dollars. We note that both the numerator (total adjusted capital) and the denominator (risk-based capital) of the RBC ratio appear to be increasing across our sample period. 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 the risk-based capital ratio, we calculate the average RBC ratio across insurers. While we do not observe the breakdown of the 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 in each year, weighted by insurer's asset size. We report these results in Figure 2. We use insurer-level reporting of their RBC ratios in Figure 2 since the RBC ratio is a tool regulator use to examine each insurer's financial condition. 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

P&C insurers report lower RBC ratios due to the RCat introduction, despite the adoption date being known well in advance. We also find that the RBC ratio increases in 2018 but declines in 2019. 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 P&C industry offset this increase in capital requirements to some extent yet not fully, as the average RBC ratio is lower after this regulatory change.

[Insert Figure 2]

III. RESEARCH DESIGN

Homeowners Insurance Prices

Building on the institutional background we cover in the previous section, 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 the framework on insurance pricing from Harrington, Niehaus, and Yu (2013) to discuss the capital costs of RCat. 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 premium 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 premium. Capital shocks affect insurers' pricing behavior. For example, Koijen and Yogo (2015) document evidence that life insurance companies price products at discount to increase capital levels in the short run during the financial crisis. A vast literature in the P&C industry document unexplained variation of premiums, 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)). 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 short-term increases in pricing in areas with higher expected claims. 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 not a viable option for many insurers already selling business in catastrophic risk areas, however, since some insurers specialize exclusively in catastrophe-exposed states or lines. Given that RCat affects property lines, we focus on homeowner's insurance. The merit of focusing on homeowners' insurance is that many homeowners are required to purchase and maintain insurance coverage through their mortgage provider, suggesting that the observed insurance premium (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 P&C insurers making up around 15% of total industry premiums written and $82 billion in 2017.

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., Koijen and Yogo 2015; Sastry 2022).

Third, there is an advantage in terms of the identification strategy that enables us to study insurer pricing behavior better than other financing options, even if we do not assume costly external financing. Insurers can improve their capital position using multiple methods: i) external capital financing through issuing equity for stock insurers or issuing surplus notes for mutual insurers (e.g., Berry-Stölzle et al. 2014; Hanley and Nikolova 2021), ii) internal capital financing through capital contributions from affiliated companies if the insurer belongs to an insurance holding group (e.g., Niehaus 2018; Ge 2020), iii) transfer liabilities to another entity through reinsurance to decrease liability positions (e.g., Mayers and Smith 1990; Adiel 1996), or iv) abnormal insurance pricing (Koijen and Yogo 2015). Options i) and ii) are difficult to test empirically since these capital contributions are observed at insurer-level while the RCat is implemented at insurer-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).[11] We view option iii) as unlikely, 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 at the net-of-reinsurance basis. Our study, therefore, aims to empirically test option iv), pricing behavior, using the homeowners' insurance premium panel data.

[11] 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.

Empirical Strategy

Our main empirical test examines whether insurers exhibit different pricing behavior for markets that are subject to RCat. Using detailed zip code level panel data on homeowners' insurance premiums, we estimate differences in homeowners' insurance premium between states subject to the RCat and those not pre- and post-RCat. Our model is the conventional two-way fixed effects difference-in-differences design:[12]

$$HOPrem_{jst} = \beta Treat_{jst} \times Post_t + \boldsymbol{H}_{jst} + \boldsymbol{\zeta}_j + \boldsymbol{\tau}_t + \boldsymbol{S}_s + \epsilon_{jst} \tag{5}$$

where $HOPrem_{jst}$ is the average homeowners' insurance premiums in zip code *j* that belongs to state *s* in year *t*.[13] *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.[14] *Post* is a binary variable that equals one for 2017 and later years, and zero otherwise (i.e., the period following implementation of RCat). $\boldsymbol{H}_{jst-1}$ is a vector of one-year lagged zip code-level control variables. We control for socio-economic characteristics of the zip including population, population density, median age, percent with bachelor's or higher education, median household income, median home value, and unemployment rate. We also control for supply side controls in year *t*, including insurance firm prevalence in the zip code following Ellis, Grace, Smith, and Zhang (2022) and the Herfindahl index based on homeowners insurance premiums in each state.[15]

---

[12] 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 and that we observe parallel trends over time that are similar for the treated and the control group, as shown in Section 4.

[13] We do not take the natural log of *HOPrem* because the distribution does not appear to be skewed (skewness = 0.019). To limit the influence of extreme outliers, however, we replace the bottom 1 percent and the top 1 percent observations with 1st and 99th percentile values.

[14] We estimate this model with alternative definitions to ensure our results are robust to alternative cutoffs.

[15] The Nielson database includes data 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.

We 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.

With zip code and year fixed effects, our estimates capture within zip code variations over time. If RCat results in increases in premiums 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) drive down insurance prices in RCat states ($\beta < 0$).

In addition to our main model reported in equation (5), we perform two tests to attempt to rule out price changes associated with actual catastrophe losses. One concern with our specification and study period is that insurers that experience catastrophic losses may increase price, regardless of the impact of the RCat. Such losses would increase the capital cost, 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 in each county (in 2019 dollars) as a control variable. 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.

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 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).[16] Accordingly, we also include a specification where we control for characteristics of the 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 year *t*.

The next step of our empirical analysis involves an examination of the factors or mechanisms that potential rate increases in response to RCat implementation. Our first mechanism relates directly to the regulatory capital cost of the RCat. 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.[17] We anticipate that insurers with the largest RBC burdens will be more likely to raise prices in an effort to offset this increase. To test this, we estimate the following model:

$$HOPrem_{jst} = \beta Treat_{jst} \times Post_t \times High\ RBC\ Burden_{st} + \boldsymbol{H}_{jst} + \boldsymbol{\zeta}_j + \boldsymbol{\tau}_t + \boldsymbol{S}_s + \epsilon_{jst} \quad (6)$$

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 risk-based

[16] Harrington (2002) considers some forms of rate regulation, such as prior approval, to be stringent, while other types, such as use-and-file, are not considered stringent. 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.

[17] 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).

capital ratio (required regulatory capital) divided by lagged assets and examine the distribution of this variable among homeowners insurers in each year. 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 (i.e., regulatory required capital divided by lagged total assets) during the sample period, and zero otherwise.[18] 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 ($\beta > 0$).[19]

For our second mechanism test, we examine the role that reinsurance use plays in implementing the RCat and whether insurers make any subsequent price changes. 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 their catastrophe-exposed liabilities to reinsurers do not need to raise prices to offset any increase in regulatory capital requirements. However, the full cost of RCat will be borne by firms that do not engage in external reinsurance will either have to accept the capital cost or raise prices to offset the RCat risk charge.

$$HOPrem_{jst} = \beta Treat_{jst} \times Post_t \times No\ Reinsurance_{st} + \boldsymbol{H}_{jst} + \boldsymbol{\zeta}_j + \boldsymbol{\tau}_t + \boldsymbol{S}_s + \epsilon_{jst} \qquad (7)$$

Similar to our RBC burden tests, we construct a state-level measure of reinsurance use to test whether reinsurance plays a role in RCat driving price increases. Specifically, we calculate the percent of insurers that use no property reinsurance in a state-year, and then create indicator

---

[18] Market share is based on direct premiums written in homeowners insurance within a state.

[19] 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 do when we discuss these results.

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.[20] All other variables and fixed effects are as we defined previously. 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 ($\beta > 0$).

Data

Our data are from various sources. First, we use P&C insurance premium market survey data gathered by Claritas and compiled by S&P Global, following Ellis, Grace, Smith, and Zhang (2022). The dataset contains household-level average annual premium and number of homeowners' insurance policies from the top 17 major homeowners insurers at the zip code-level. For our second data source, we use data from annual statutory statements P&C insurers file with the National Association of Insurance Commissioners (NAIC). 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, compiled by S&P Global. We also obtain data on rate change requests from S&P Global.[21] Finally, we use data from the Spatial Hazard Events and Losses Database for the United States (SHELDUS) to control for actual catastrophe losses.

[20] We exclude reinsurance transfers that take place between affiliated firms.
[21] 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 only in 2019. When we use these data to construct variables, the number of requesting insurers and total affected policies are state-year variables, we impute values for Florida, Alabama, and Wyoming using the average across states in a given year.

We define our treatment using the National Risk Index (NRI) from the FEMA website following the RCat guideline.[22] 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 relative figure that measures the dollar amount of economic losses within a certain zip code.[23] 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.[24] While this is not perfectly comparable to the sophisticated cat 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 annual loss scores.

[Insert Figure 3 here]

Within the states, treatment intensity can also 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, 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. Accordingly, we 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, indicating that this may be a more appropriate treatment.

[22] Accessible at: https://hazards.fema.gov/nri/.

[23] 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.

[24] All zip codes located in states exempt from the RCat requirement are not considered as treated areas.

IV. RESULTS

Summary Statistics and Event Study Style Diff-in-Diff

We report summary statistics for our sample of 158,754 zip code-year observations in Table 1. The average annual homeowners premium in our sample is $1,000.50 while the median is exactly $991. Relative to 2014 premiums, the average zip code experienced a 4.24 percentage points increase in premiums. In Figure 4, we report coefficient estimates and confidence intervals of a regression of differences in annual homeowners insurance premiums between treatment and control observations, defined at the zip code level, on fixed effects (state, zip code, and year). In this event study-type test, we observe a notable increase in premiums following the enactment of the RCat risk charge. In our subsequent regression models, we replace the year indicators with a *Post* variable to capture the entire regulatory change in a single variable.

[Insert Table 1]

[Insert Figure 4]

In addition to reporting summary statistics for our entire sample, we report univariate differences between our treated and control zip codes in Table 2.[25] First, we note that average homeowners insurance premiums are $46.94 higher ($p$-value < 0.01) in zip codes subject to the new RCat regulation. This is consistent with these states being subjected to higher catastrophic losses and insurers, therefore, charging higher premiums to compensate. Similarly, RCat zip codes saw a larger increase in premiums compared to 2014, with premiums increasing by around 0.31 percentage points more in RCat states (p-value < 0.01).

[Insert Table 2]

[25] 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 1A.

There are also important differences in our socioeconomic control variables. On average, RCat zip codes have larger and more dense populations. They also tend to have more homes that are valued more highly. While RCat zip codes have higher education 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 those in control states. Finally, it appears that insurers tend to hold weaker capital positions in RCat zip codes, as the RBC ratios operating in treated states are lower. With these statistically significant differences in mind, we control for these factors, as well as fixed effects in our multivariate analysis to attempt to isolate any effect the RCat risk charge has on homeowners insurance premiums.

RCat and Insurance Prices

We report results from our empirical estimates of equation (5) in Table 3. The dependent variable is the average annual homeowners insurance premium. We report standard errors in parentheses beneath each coefficient estimate. All models include year and zip code fixed effects as well as state-level trends. Positive coefficients indicate higher zip code-level premiums while negative coefficients indicate lower zip code-level premiums.

[Insert Table 3]

Overall, the results in Table 3 indicate that homeowners premiums appear to rise following the implementation of RCat for treated 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 four specifications reported in Table 3. Economically, the coefficient estimates indicate that annual premiums increase by $2 to $4 in zip codes most impacted by RCat requirements following implementation. The statistical significance and magnitude of the coefficient remain stable after we control for the state-level risk-based capital burden as well as the amount of property damage associated with catastrophic events (column (3)). Finally, our main result holds even after we exclude zip codes that experience an actual catastrophic loss at any point during our sample period. This finding suggests that the regulatory change and not catastrophic claim payments are driving our result.

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 3 (columns (3) and (4)) but change our treatment definition. We report these results in Table 4.

[Table 4 here]

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, 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 disaster property damage at any point during our sample period. Again, these tests support our hypothesis that the price increases are driven by the RCat risk charge instead of actual catastrophe claims by property insurers.[26]

[26] To provide further evidence on what is driving the association between the RCat risk charge and prices, we provide two additional tests. First, we estimate equation (5) after restricting our sample to only treated states. Second, we estimate equation (5), but exclude control zip codes within treated states. In both cases, we also estimate the models on our full sample and after excluding zip codes that experience actual catastrophe losses. The coefficient estimates when excluding control zip codes are higher (over $4) compared to the within-treated-states models (around $1). We report these results in Appendix Table A2. 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.

RCat Mechanism—Risk-Based Capital Constraints and Reinsurance

Having identified an on-average association between zip codes with greater exposure to catastrophes and a corresponding increase in homeowners insurance prices, we next examine whether we can identify environments driving this effect. We are interested in examining two potential mechanisms: risk-based capital burdens and external reinsurance use.

We first examine insurer risk-based capital burdens. As we describe previously, we expect that markets with more capital constrained insurers due to increases from RCat implementation will be more likely to raise prices in response. We, therefore, create a new variable, *High RBC Burden*, which is equal to one if the state has a high number of insurers (10%, 20%, or 30%) in terms of regulatory required capital levels. We then interact this variable with our treatment times post interaction term (see equation (6)).

We report results for our high RBC burden tests in Table 5. 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) are for our sample excluding zip codes that experienced disasters during our sample period. The main result in this table is the Wald test, which provides information on the overall premium effect on treated 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 5 is positive and statistically significant. Moreover, the magnitude of the coefficient increases as we limit the RBC-burden states to have a higher threshold—increasing to over \$4.50 when we examine state-years with more than 30% of insurers in the highest RBC burden tercile. This result hold when we limit our sample to zip codes that did not experience disasters, continuing to suggest that our results are driven by the regulatory change rather than price responses to actual catastrophes.

[Table 5 here]

Our second proposed mechanism is through reinsurance. As we discuss previously, reinsurance can reduce or entirely eliminate their exposure to the RCat risk charge through reinsurance transactions, where they essentially transfer their catastrophe-exposed property liabilities to an external firm. Some insurers may be unable to access reinsurance markets if they do not have prior experience working with reinsurers or if the cost of purchasing reinsurance is unreasonably high. We expect for these firms, they will transfer the regulatory costs of RCat onto consumers in the form of premium increases.

[Table 6 here]

We report the results of our reinsurance tests, displayed in equation (7), in Table 6. The dependent variable is zip-code level homeowners insurance premiums. We include all previously-discussed control variables as well as year, state, and zip code fixed effects. We, again, report results in columns (1)-(3) for our full sample and in columns (4)-(6) for our sample excluding zip codes that experienced disasters during our sample period. We again focus on the results of the Wald tests, which provides information on the overall premium effect on treated zip codes in the post-RCat period, specifically in state-years where higher portions of the market used no property reinsurance. We note that the overall estimate in all six models presented in Table 6 is positive and statistically significant. Additionally, the magnitude of the coefficient increases as we increase the "no reinsurance" threshold from 10% to 30%. Notably, the magnitude of the post-RCat premium increase is nearly $20 when we define a state-year as "no reinsurance" if at least 30% of insurers have no external reinsurance.[27] This result hold when we limit our sample to zip codes that did not experience disasters, continuing to suggest that our results are driven by the regulatory change rather than price responses to actual catastrophes.

V. A CASE STUDY OF THE FLORIDA PROPERTY INSURANCE MARKET

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 the propensity to raise property insurance prices following the implementation of the RCat. Accordingly, we turn to the Florida 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). Importantly, insurers report premiums and the number of policies in force at the county-level every quarter, allowing us to construct a proxy for homeowners insurance premiums. We use the insurance company codes reported in QUASR to match with the statutory financial information from the NAIC.

Another advantage of using Florida-specific data is that we can also 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 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

[27] 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 A1).

even if we had access to the modeling software. Since the FPHLM is, as defined, public, we are able to access the overall estimates, even if we lack the level of detail that companies would input. The FPHLM makes certain estimates publicly available for estimated losses at the county-level.[28] They provide 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.

[Insert Figure 5]

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 sold property insurance policies, 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, versus only their exposure within a county. This could be important if insurers attempt to raise prices across all Florida counties in response to the RCat, and not just in the specific geographies that have the highest modeled loss estimates. Accordingly, we calculate each insurer's weighted modeled losses per county-quarter, where the weight is by an insurer's reported exposure.

[28] 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/.

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 (2014 to 2016). 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.[29] We also control for the natural log of insurer assets (*ln(Firm Size)*) and capital structure (*Liab/Surplus*). We report summary statistics for our QUASR sample in Table 7.[30]

[Insert Table 7]

We provide empirical estimates of our Florida-specific models in Table 8. The dependent variable in all five columns is homeowners insurance premiums, which we calculate as quarterly direct premiums written divided by policies in force. We report results for our main model specification in columns (1)-(3), with varying inclusion of control variables. 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.

[Insert Table 8]

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,

[29] Citizens Property Insurance Company is a government 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.
[30] We also provide univariate differences between treatment and control insurers in Appendix Table A3.

suggests that homeowners insurance prices increased for firms with relatively greater exposure to hurricane losses following the implementation of RCat as a component of regulatory capital. The results are also material, with the average premium increase for firms in the most exposed areas increasing by $216 to $258 in the post period, which is around 10% of the average premium reported in QUASR during our sample ($2,265).

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 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.

[Figure 6 here]

In Figure 6 panel A, we observe that the coefficient estimates for the post years in our sample (2017-2019) are positive and statistically significant, suggesting that the RBC burden (required regulatory 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, where we observe that the coefficient estimates on the year indicators is not statistically different from zero at any point during our sample period. We interpret this as suggesting that the RCat has a material impact on insurer regulatory capital ratios, but it is not necessarily observable in the overall RBC ratio. A potential explanation is that insurers are taking action outside of increasing prices (e.g., issuing capital) in order to maintain their desired level of regulatory capital in response to the rising amount of required capital imposed by the RCat.

In column (4) of Table 8, we include a *High RBC Burden* 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 (2014-2016). We interact *High RBC Burden* with our *High Risk* times *Post* to create a triple interaction term to the model reported in column (3) of Table 8. 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)), however, are not significantly different from zero, indicating that we do not observe an incremental effect on property insurers in Florida with relatively high RBC burdens.

We, therefore, 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 8, 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 (2014-2016). 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—this finding provides evidence that insurers with low reinsurance use are increasing their prices when they are more impacted by RCat to a greater extent than Florida insurers that have access to reinsurance markets. This finding is also consistent with what we find in our previous tests using national data. Taken together, these results indicate that access to reinsurance markets plays a large role in determining insurance pricing behavior, particularly through the RCat.

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 highest predicted catastrophe exposures, as defined by the NRI, ranges from $2.31 to $4.75. We additionally provide evidence that our results are concentrated in states where insurers face relatively higher RBC burdens as well as

Our estimates on the national zip code-level homeowners' insurance price increase combined with the 31 million households with homeowners' insurance in RCat-treated zip codes, suggest an average annual premium increase between $71 and $146 million, or total $213 to $437 million premium increase from 2017 to 2019. We calculate the back-of-the-envelope impact of the estimated total premium increase on P&C insurers' regulatory capital positions. As documented in Figure 2 Panel A, by the end of 2019, P&C insurers report $54 billion regulatory required capital for RCat, which grew by $3 billion from $51 billion in 2017; an increase of capital levels between $213 and $437 million suggests insurers could finance 7.1% to 14.6% of the increased regulatory capital cost due to RCat by increasing homeowners' insurance premiums. Given that the RCat not only includes homeowners insurance lines but also other property lines, and that only 55 – 58% 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 is not negligible.

Our study makes important contributions to several strands of academic literature and have direct relevance to regulators. From an academic perspective, we contribute to the literature examining how regulated financial firms respond to financial frictions, finding that risk-based capital regulations can have a material impact on consumers (e.g., Koijen and Yogo 2015). We additionally contribute to the growing academic literature examining who bears the cost of climate change. While our regulatory environment is not based on realizations of catastrophes, it can have an impact on markets for homeowners insurance in catastrophe-prone areas and, for terms longer than our study, may have implications on the affordability and availability of insurance. From a regulatory perspective, our study provides evidence for what regulators may expect moving forward with RCat, particularly as modeled wildfire losses are incorporated into the calculation going forward.

REFERENCES

Adiel, R. 1996. Reinsurance and the management of regulatory ratios and taxes in the property-casualty insurance industry. *Journal of Accounting and Economics* 22: 207-240.

Becker, B., and V. Ivashina. 2015. Reaching for yield in the bond market. *Journal of Finance* 70 (5): 1863-1902.

Berry-Stölzle, T. R., G. P. Nini, and S. Wende. 2014. External financing in the life insurance industry: Evidence from the financial crisis. *Journal of Risk and Insurance* 81: 529-562.

Born, P. H., and W. K. Viscusi. The catastrophic effects of natural disasters on insurance markets. *Journal of Risk and Uncertainty* 33: 55-72.

Born, P., J. B. Karl, and R. Klein. 2023. An empirical assessment of regulatory lag in insurance rate filings. *North American Actuarial Journal* Forthcoming.

Born, P. H., and B. Klimaszewski-Blettner. 2013. Should I stay or should I go? The impact of natural disasters and regulation on U.S. property insurers' supply decisions. *Journal of Risk and Insurance* 80 (1): 1-36.

Boyer, M. M., E. Jacquier, and S. Van Norden. 2012. Are underwriting cycles real and forecastable? *Journal of Risk and Insurance* 79 (4): 995-1015.

Callaway, B., and P. H. C. Sant'Anna. 2021. Difference-in-differences with multiple time periods. *Journal of Econometrics* 225: 200-230.

Cummins, J. D., and C. M. Lewis. 2003. Catastrophic events, parameter uncertainty and the breakdown of implicit long-term contracting: The case of terrorism insurance. *Journal of Risk and Uncertainty* 26 (2/3): 153-178.

Ellis, C. M., M. F. Grace, R. A. Smith, and J. Zhang. 2022. Medical cannabis and automobile accidents: Evidence from auto insurance. *Health Economics* 31 (9): 1878-1897.

Ellul, A., C. Jotikasthira, and C. T. Lundblad. 2011. Regulatory pressure and fire sales in the corporate bond market. *Journal of Financial Economics* 101: 596-620.

Ge, S. 2022. How do financial constraints affect product pricing? Evidence from weather and life insurance premiums. *Journal of Finance* 77: 449-503.

Goodman-Bacon, A. 2021. Difference-in-differences with variation in treatment timing. *Journal of Econometrics* 225: 254-277.

Grace, M. F., R. W. Klein, and P. R. Kleindorfer. 2004. Homeowners insurance with bundled catastrophe coverage. *Journal of Risk and Insurance* 71 (3): 351-379.

Grace, M. F., and J. T. Leverty. 2010. Political cost incentives for managing the property-liability insurer loss reserve. *Journal of Accounting Research* 48 (1): 21-49.

Grace, M. F., and R. D. Phillips. 2008. Regulator performance, regulatory environment and outcomes: An examination of insurance regulator career incentives on state insurance markets. *Journal of Banking and Finance* 32: 116-133.

Hanley, K. W., and S. Nikolova. 2021. Rethinking the use of credit ratings in capital regulations: Evidence from the insurance industry. *Review of Corporate Finance Studies* 10: 347-401.

Harrington, S. E. 2002. Effects of prior approval rate regulation of auto insurance. *Deregulating Property-Liability Insurance: Restoring Competition and Increasing Market Efficiency*.

Harrington, S. E., G. Niehaus, and T. Yu. 2013. Insurance price volatility and underwriting cycles. *Handbook of Insurance* 2nd Edition.

Ilhan, E., P. Krueger, Z. Sautner L. T. Starks. 2020. Climate risk disclosure and institutional investors. *Swiss Finance Institute Research Paper* No. 19-66.

Issler, P., R. Stanton, C. Vergara-Alert, and N. Wallace. 2020. Housing and mortgage markets with climate-change risk: Evidence from wildfires in California. *Working Paper*. University of California, Berkeley.

Jouvenot, V., and P. Krueger. 2020. Mandatory corporate carbon disclosure: evidence from a natural experiment. *Working paper.*

Kim, K., and X. Lin. 2022. Underwriting sea level rise risk: Evidence from the insurance industry. Working Paper. Florida State University.

Klein, R. W., and S. Wang. 2009. Catastrophe risk financing in the United States and the European Union: A comparative analysis of alternative regulatory approaches. *Journal of Risk and Insurance* 76 (3): 607-637.

Klein, R. W. 2012. Principles for insurance regulation: An evaluation of current practices and potential reforms. *Geneva Papers on Risk and Insurance—Issues and Practice* 37: 175-199.

Koijen, R. S. J., and M. Yogo. 2015. The cost of financial frictions for life insurers. *American Economic Review* 105 (1): 445-475.

Koijen, R. S. J., and M. Yogo. 2022. New perspectives on insurance. *Review of Financial Studies* Forthcoming.

Leverty, J. T., and M. F. Grace. 2018. Do elections delay regulatory action? *Journal of Financial Economics* 130: 409-427.

Leverty, T., and J. Liu. 2019. Does technology adoption save regulatory compliance costs? Working Paper. University of Wisconsin—Madison.

Mayers, D., and C. W. Smith, Jr. 1990. On the corporate demand for insurance: Evidence from the reinsurance market. *Journal of Business* 63: 19-40.

Meier, U. B. 2006. Multi-national underwriting cycles in property-liability insurance: Part I–some theory and empirical results. *Journal of Risk Finance* 7 (1): 64-82.

Mésonnier, J.-S., and B. Nguyen 2021. Showing off cleaner hands: mandatory climate-related disclosure by financial institutions and the financing of fossil energy. *Working Paper*.

Myers, S. C., and N. S. Majluf. 1984. Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics* 13: 187-221.

Niehaus, G. 2018. Managing capital via internal capital market transactions: The case of life insurers. *Journal of Risk and Insurance* 85: 69-106.

Oh, S. S., I. Sen, and A.-M. Tenekedjieva. 2022. Pricing of climate risk insurance: Regulation and cross-subsidies. *Working Paper*.

Ragin, M. A. and M. Halek. 2016. Market expectations following catastrophes: An examination of insurance broker returns. *Journal of Risk and Insurance* 83 (4): 849-876.

Ragin, M. A. and J. Xu. 2019. An ex post assessment of investor response to catastrophes. *North American Actuarial Journal* 23 (2): 250-275.

Sastry, P. 2022. Who bears flood risk? Evidence from mortgage markets in Florida. *Working Paper*. Columbia University.

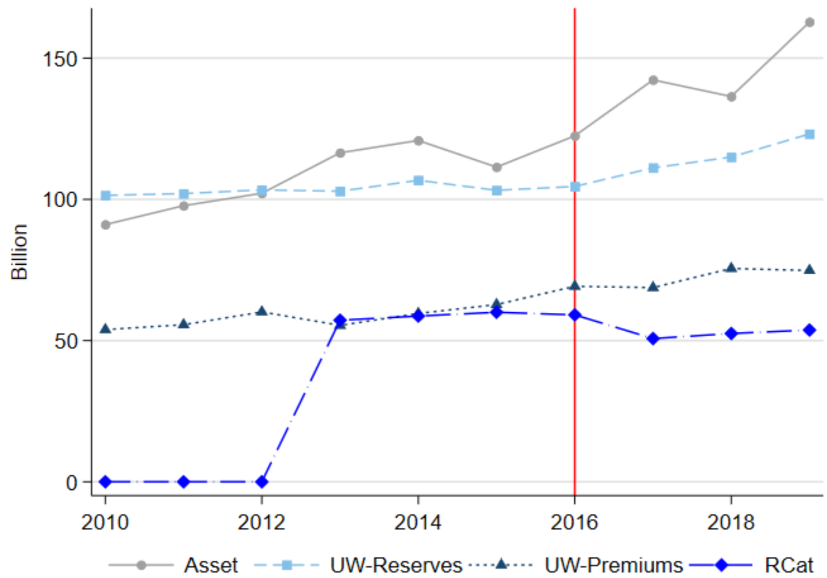
Sun, L., and S. Abraham. 2021. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal Econometrics* 225: 175-199.

Tenekedjieva, A.-M. 2021. The revolving door and insurance solvency regulation. *Working Paper*. Federal Reserve Board of Governors.

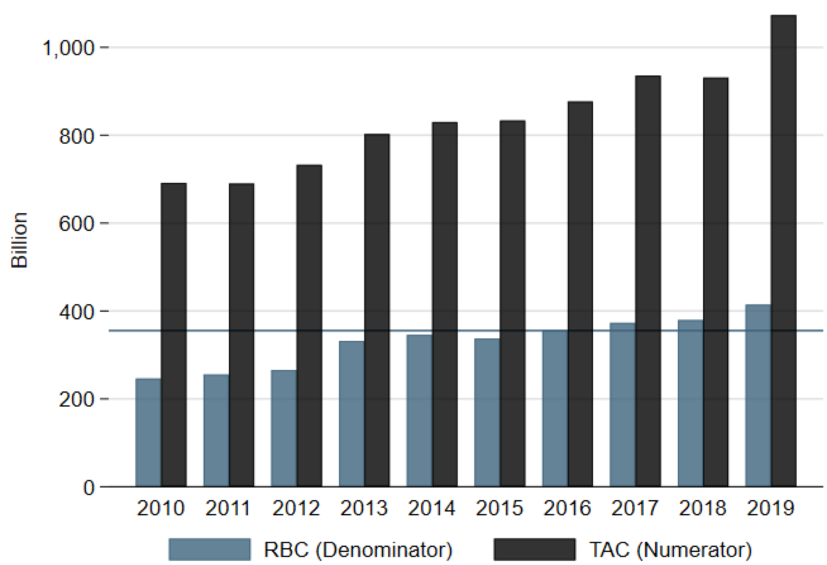
Zuzak, C., M. Mowrer, E. Goodenough, J. Burns, N. Ranalli, and J. Rozelle. 2022. The national risk index: establishing a nationwide baseline for natural hazard risk in the US. *Natural Hazards* 114 (2): 2331-2355.

Figure 1: Industry Aggregate RBC

A. RBC Components

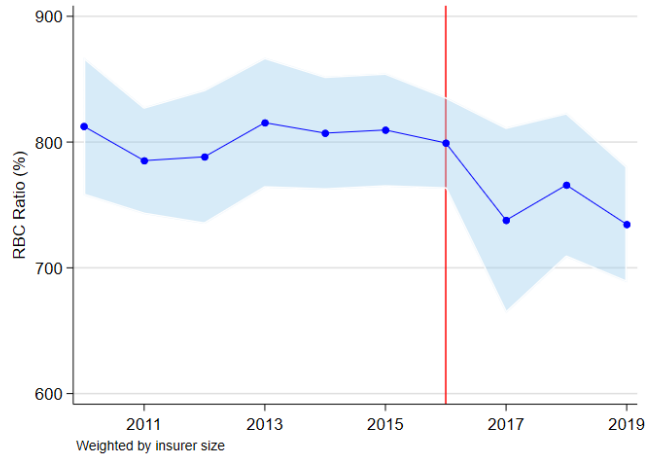


B. RBC Ratio Breakdown



Source: Annual RBC statistics produced by the NAIC.
Notes: The top figure shows industry aggregate 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 contrast the industry aggregate RBC and total adjusted capital (TAC) in each year. The horizontal line marks industry total RBC in 2016 as a reference point.

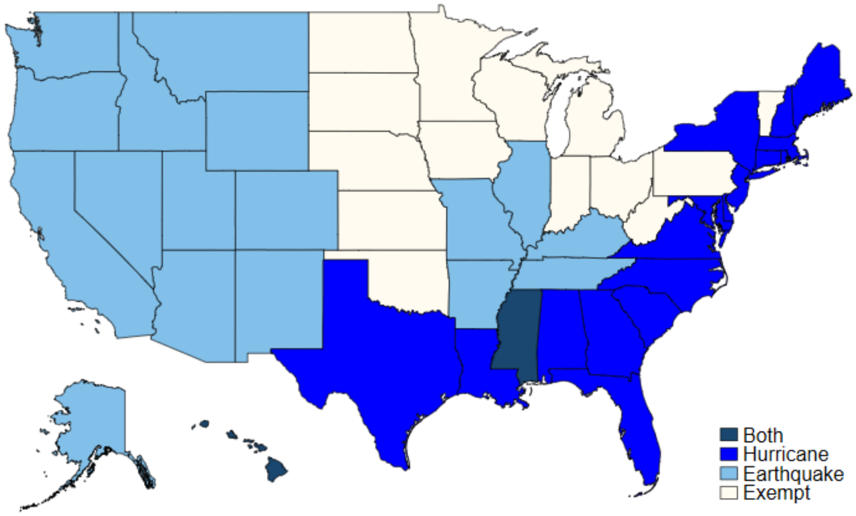
Figure 2: Insurers' Average RBC Ratios



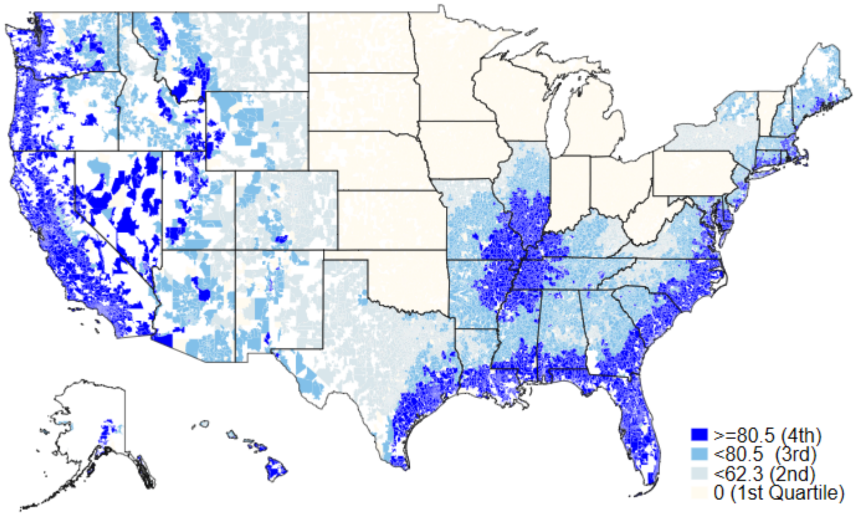
Source: Annual statutory statements of insurers.
Notes: The figure shows average Risk-based Capital (RBC) ratios of property and casualty insurers in each year along with 95% confidence intervals based on the standard errors of the means. The averages and standard errors are weighted by insurer asset size.

Figure 3: Regulatory Catastrophe Risk (RCat)

A. Treatment Defined at the State

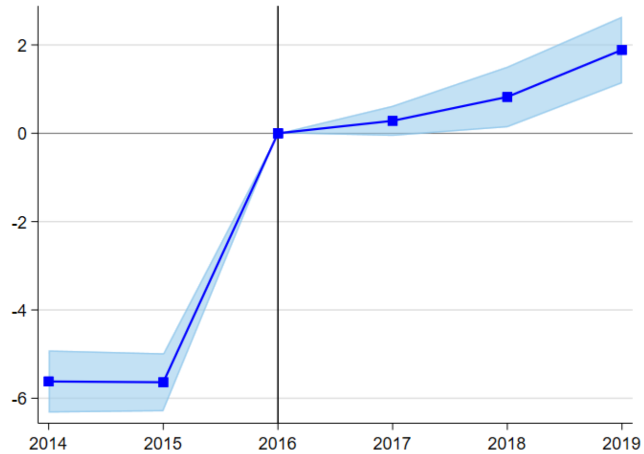


B.Treatment Defined at the Zip Code



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 match with the Property and Casualty Risk-Based Capital Instructions.

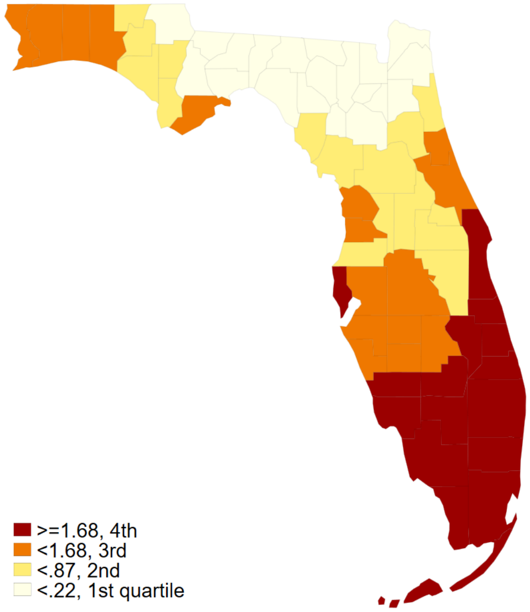
Figure 4: Average Premium Differences by Treatment



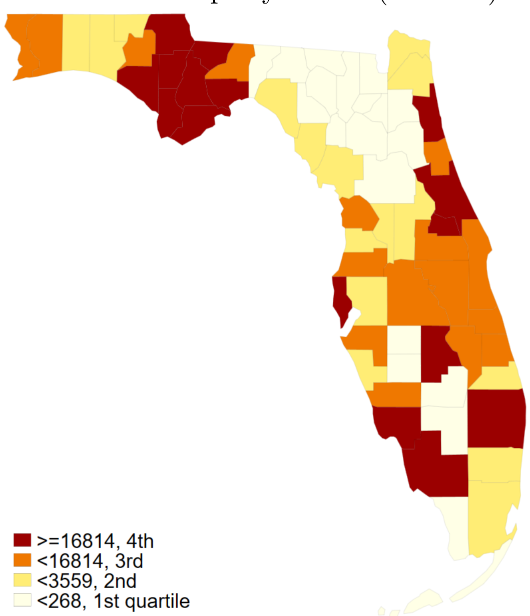
Notes: The figure shows conditional means premium differences in homeowners' insurance by zip code-level RCat treatment. Specifically, the figure plots estimates of coefficients from equation (5), which is a regression of the homeowners insurance premiums on treatment indicator, year fixed effects, treatment 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 state level for the top figure and at the zip code level for the bottom figure.

Figure 5: Hurricane Risks and Losses in Florida

A. Estimated Hurricane Risks



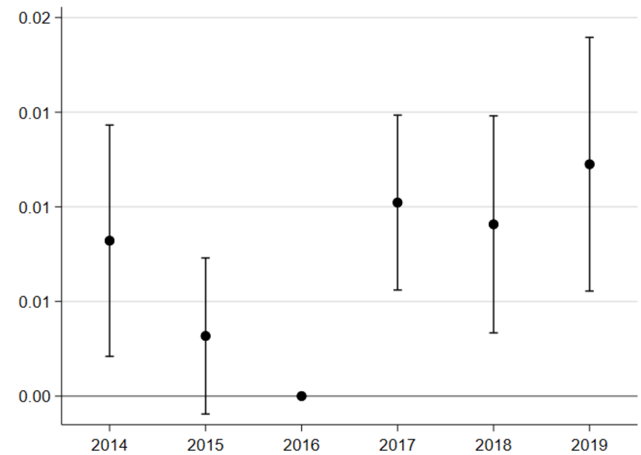
B. Actual Property Losses (in $Mil.)



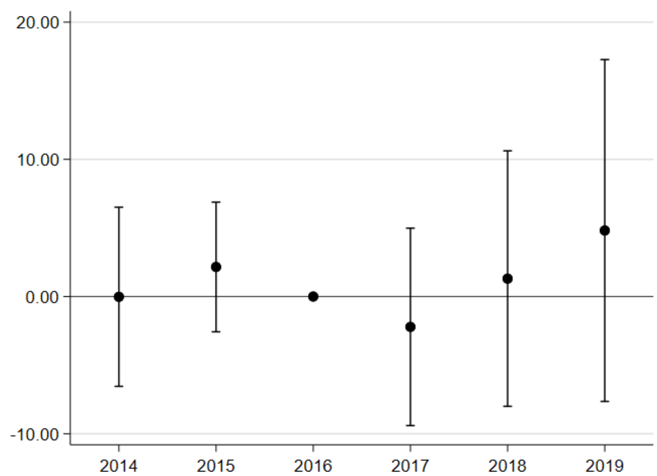
Notes: The top figure shows estimated average hurricane related loss costs per $1,000 value of framed houses based on exposures measured in 2012 from the Florida Public Hurricane Loss Model (FPHLM). The bottom figure shows total property losses for each county during the sample period in 2021 million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

Figure 6: 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 differences-in-differences regression of insurer's *Required Regulatory Capital/Assets*$_{t\text{-}1}$ 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 Florida Office of Insurance Regulation's Quarterly and Supplemental Reporting System (Quasr). Specifically, the figure plots coefficients from the differences-in-differences regression of insurer's *Total Adjusted Capital/Required Regulatory 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: Summary Statistics

	Mean	SD	1st	25th	50th	75th	99th
A: Homeowners' Insurance							
AvgPrem	1,000.50	125.07	692.00	907.00	991.00	1,092.00	1,322.00
MajorHOShare	0.92	0.16	0.75	0.84	0.88	0.95	1.80
HomeownersHHI	742.42	268.59	267.21	577.79	687.57	935.64	1,304.25
AvgHOReinsShare	0.06	0.06	0.02	0.03	0.04	0.07	0.36
B: Socio-economic							
MSA	0.44	0.50	0.00	0.00	0.00	1.00	1.00
Population 000s	12.01	14.79	0.40	1.59	4.96	17.95	65.56
PopDensity 000s	1.19	2.77	0.00	0.03	0.09	0.85	17.79
MedianAge	41.82	5.92	26.80	38.10	41.90	45.40	58.60
MedianIncome 000s	56.79	21.09	24.08	42.70	52.21	65.60	135.38
InsuredHomes 000s	2.60	3.02	0.11	0.42	1.20	3.90	13.06
UnempRate	8.07	4.08	1.60	5.10	7.30	10.20	22.30
BachelorDegree	15.01	7.99	3.58	9.09	12.91	19.13	38.97
C: Risks							
Cat Risk	47.47	38.04	0.00	0.00	62.34	80.50	98.74
PropertyDamageCapita	0.55	3.59	0.00	0.00	0.00	0.00	31.48
HighRBCBurdenShare	0.32	0.14	0.08	0.22	0.32	0.41	0.81
New Comm[t-1,t]	0.43	0.49	0.00	0.00	0.00	1.00	1.00
No. Affected Policies 000s	659.44	563.68	27.82	277.24	511.74	837.29	2,511.14
No. Requesting Insurers	30.30	11.79	7.00	23.00	30.00	37.00	58.00
Observations	158,754						

Notes: The table reports summary statistics of zip code-year observations. *AvgPrem* is the zip code annual average homeowners' insurance premiums, *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, *MSA* is the indicator that the zip code belongs to the metropolitan statistical area, *Population 000s* is a number of population in the zip code in 1,000s, *PopDensity 000s* is a population density in the zip code in 1,000s, *InsuredHomes 000s* is a number of households with homeowners insurance per zip code in 1,000s, *MedianIncome 000s* is the median income of working population in $1,000s, *MedianAge* is a median age of the population in the zip code, *UnempRate* is a unemployment rate in the zip code, *BachelorDegree* is a percent of population with at least bachelor's degrees, *Cat Risk* is the value of expected annual loss scores from hurricanes or earthquakes in the zip code, *PropertyDamageCapita* is a property damage per capital from natural disasters, *HighRBCBurdenShare* is the share of homeowners insurers with the top tercile of RBC burden, *New Comm*$[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: Univariate Differences by Zip Code Treatment

	Control		RCat Zip		*Mean*	Total	
	Mean	SD	Mean	SD	*diff.*	Mean	SD
A: Homeowners' Insurance							
AvgPrem	984.57	119.46	1,031.51	129.85	46.94***	1,000.50	125.07
MajorHOShare	0.91	0.15	0.95	0.18	0.04***	0.92	0.16
HomeownersHHI	762.49	252.02	703.38	294.33	-59.11***	742.42	268.59
AvgHOReinsShare	0.05	0.03	0.08	0.09	0.04***	0.06	0.06
B: Socio-economic							
MSA	0.42	0.49	0.46	0.50	0.04***	0.44	0.50
Population 000s	9.89	13.29	16.13	16.58	6.24***	12.01	14.79
PopDensity 000s	0.99	2.63	1.59	2.97	0.60***	1.19	2.77
MedianAge	42.04	5.61	41.37	6.45	-0.67***	41.82	5.92
MedianIncome 000s	55.36	18.27	59.57	25.46	4.22***	56.79	21.09
InsuredHomes 000s	2.21	2.79	3.36	3.29	1.15***	2.60	3.02
UnempRate	7.59	3.97	9.00	4.13	1.41***	8.07	4.08
BachelorDegree	14.44	7.47	16.12	8.83	1.68***	15.01	7.99
C: Risks							
Cat Risk	27.24	30.94	86.83	7.38	59.59***	47.47	38.04
PropertyDamageCapita	0.58	3.69	0.49	3.38	-0.09***	0.55	3.59
HighRBCBurdenShare	0.30	0.12	0.38	0.16	0.08***	0.32	0.14
New Comm[t-1,t]	0.46	0.50	0.36	0.48	-0.10***	0.43	0.49
No. Affected Policies 000s	651.41	532.79	675.07	619.09	23.66***	659.44	563.68
No. Requesting Insurers	32.21	11.72	26.60	11.02	-5.61***	30.30	11.79
Observations	104,862		53,892		158,754	158,754	

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. See Table 1 for definitions of the variables.

Table 3: Average Premium Difference by Treatment

	Base	Mkt Control	Ins. Control	Rate Control	No Disaster
	(1)	(2)	(3)	(4)	(5)
Treat X Post	4.7493***	2.3370***	2.3137***	2.4916***	2.7155***
	(0.3641)	(0.3101)	(0.2816)	(0.2806)	(0.3187)
ln(Population)		132.1667***	137.8740***	136.3315***	153.0257***
		(7.6313)	(7.8112)	(7.7679)	(9.7873)
ln(PopDensity)		2.2279*	0.2290	0.2333	0.2324
		(1.1686)	(1.1349)	(1.1286)	(1.3225)
MedianAge		-0.6277***	-0.8132***	-0.7014***	-0.9578***
		(0.1847)	(0.1759)	(0.1750)	(0.2220)
ln(MedianIncome)		165.5228***	168.5635***	168.0224***	169.7156***
		(1.2601)	(1.2483)	(1.2439)	(1.4915)
ln(InsuredHomes)		-127.0761***	-137.9270***	-136.7160***	-155.5043***
		(6.8023)	(7.0166)	(6.9846)	(8.6317)
UnempRate		0.2516***	0.3069***	0.3058***	0.3376***
		(0.0419)	(0.0388)	(0.0386)	(0.0449)
BachelorDegree		0.4043***	0.3766***	0.3788***	0.3465***
		(0.0504)	(0.0470)	(0.0469)	(0.0547)
HomeownersHHI			0.0460***	0.0434***	0.0447***
			(0.0022)	(0.0022)	(0.0026)
ln(PropertyDamageCapita)			0.0853	0.0894	
			(0.0922)	(0.0922)	
HighRBCBurdenShare			-85.7700***	-88.5370***	-92.7599***
			(1.3909)	(1.3687)	(1.5810)
AvgHOReinsShare			57.5850***	56.8363***	49.1928***
			(10.9239)	(11.0419)	(12.6008)
MajorHOShare			-101.7083***	-98.8900***	-101.4669***
			(3.2311)	(3.3104)	(3.7451)
New Comm[t-1,t]				-0.7877***	-0.6658***
				(0.1335)	(0.1553)
ln(No. Affected Policies)				-0.1552**	-0.2267**
				(0.0765)	(0.0881)
No. Requesting Insurers				-0.1706***	-0.1667***
				(0.0075)	(0.0086)
Dep.Var. Mean	1,000.5	1,000.5	1,000.5	1,000.5	1,002.0
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	0.318	0.372	0.376	0.369
N	158,754	158,754	158,754	158,754	122,652

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 2019 and zero for years 2014 to 2016. Column (1) does not include time-varying control variables. We add zip code-level time-varying market characteristics in column (2), add time-varying homeowners insurance market characteristics in column (3), and add time-varying homeowners insurance rate regulation characteristics in column (4). In column (5), we estimate the same model in column (4) for zip codes that reported no property damage losses from natural disasters. Standard errors are clustered at zip code levels. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: 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	2.4962***			2.7379***		
	(0.2528)			(0.2896)		
Treat X Post		2.7014***			2.9752***	
		(0.2685)			(0.3058)	
Treat X Post			2.2079***			2.4332***
			(0.2979)			(0.3373)
Treatment Threshold	66.5	72.4	77.7	66.5	72.4	77.7
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	0.376	0.376	0.375	0.369	0.370	0.369
N	158,754	158,754	158,754	122,652	122,652	122,652

Note: The table report regression results from the model reported in Table 3 column (4) for columns (1) to (3) and Table 3 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 5: Average Premium 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 ($\beta 1$)	-5.4145***	-0.3364	1.7402***	-6.4483***	0.1334	2.5885***
	(1.0423)	(0.4079)	(0.3637)	(1.3428)	(0.4760)	(0.4188)
High RBC Burden X Post	10.6664***			11.0022***		
	(0.4220)			(0.5097)		
High RBC Burden X Post		4.9050***			5.1869***	
		(0.2786)			(0.3290)	
High RBC Burden X Post			-1.1933***			-0.5352
			(0.4286)			(0.4855)
Treat X High RBC X Post ($\beta 2$)	7.2899***			9.0008***		
	(1.0986)			(1.4004)		
Treat X High RBC X Post ($\beta 2$)		2.5701***			2.8104***	
		(0.5844)			(0.6678)	
Treat X High RBC X Post ($\beta 2$)			3.0641***			2.0239**
			(0.7156)			(0.7992)
Share I(High RBC)	0.927	0.519	0.157	0.929	0.535	0.169
Share I(High RBC) | Treat	0.981	0.668	0.324	0.983	0.679	0.336
Dep.Var. Mean	1,000.5	1,000.5	1,000.5	1,002.0	1,002.0	1,002.0
High RBC Burden: $\beta 1 + \beta 2$	1.875***	2.234***	4.804***	2.552***	2.944***	4.612***
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	0.333	0.332	0.327	0.324	0.324	0.317
N	158,754	158,754	158,754	122,652	122,652	122,652

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 3 column (4) for columns (1) to (3) and Table 3 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, throughout the sample period. 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 6: Average Premium 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 (β1)	-15.5097***	-6.8878***	-0.6668**	-15.9355***	-6.6229***	0.0232
	(0.6388)	(0.2949)	(0.3073)	(0.7260)	(0.3465)	(0.3526)
No Reins. X Post	1.3679***			1.4736***		
	(0.3682)			(0.4550)		
No Reins. X Post		6.7886***			6.9411***	
		(0.3190)			(0.3714)	
No Reins. X Post			7.2422***			7.3026***
			(0.7251)			(0.8288)
Treat X No Reins. X Post (γ2)	19.8441***			21.1827***		
	(0.7095)			(0.8031)		
Treat X No Reins. X Post (γ2)		18.2438***			18.2738***	
		(0.5808)			(0.6508)	
Treat X Low RBC X Post (γ2)			19.9853***			19.2375***
			(1.0583)			(1.1861)
Share I(No Reins.)	0.920	0.442	0.102	0.926	0.468	0.108
Share I(No Reins.) | Treat	0.903	0.505	0.142	0.900	0.527	0.146
Dep.Var. Mean	1,000.5	1,000.5	1,000.5	1,002.0	1,002.0	1,002.0
No Reins.: $\beta 1 + \beta 2$	4.334***	11.356***	19.319***	5.247***	11.651***	19.261***
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	0.336	0.369	0.350	0.328	0.360	0.341
N	158,754	158,754	158,754	122,652	122,652	122,652

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 3 column (4) for columns (1) to (3) and Table 3 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, throughout the sample period. 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 7: Quasr Summary Statistics

	Mean	SD	1st	25th	50th	75th	99th
A: Insurance							
AvgPrem	2,265.26	2,082.09	651.00	1,311.98	1,676.63	2,290.33	14,135.51
TotalDPW 000s	1,376.42	4,842.54	0.89	14.79	110.19	867.79	18,744.04
TotalPIF 000s	0.67	1.97	0.00	0.01	0.06	0.49	8.91
TotalExp. Mil.	330.21	961.65	0.24	3.91	30.60	235.96	4,456.81
County No. Insurers	70.01	13.04	36.00	60.00	73.00	81.00	89.00
CitizensExp Mil.	0.88	2.58	0.00	0.01	0.04	0.17	14.68
B: Socio-economic							
Population 000s	360.29	512.61	8.63	40.14	175.21	396.38	2,712.95
PopDensity 000s	0.43	0.59	0.02	0.06	0.23	0.49	3.49
MedianAge	43.51	6.41	31.40	39.60	42.80	47.20	66.20
MedianIncome 000s	47.03	8.49	32.20	40.36	46.19	52.57	70.08
InsuredHomes 000s	82.22	105.12	1.61	8.57	45.19	101.37	462.20
UnempRate	10.70	2.98	4.40	8.80	10.70	12.50	18.90
BachelorDegree	13.87	5.43	5.33	8.77	13.89	18.06	27.15
C: Geographic Risks							
Hurricane Risk (FPHLM)	1.11	1.06	0.11	0.22	0.87	1.68	5.06
Hurricane Risk (FEMA)	93.22	7.16	75.14	88.20	96.63	98.79	99.96
PropertyDamageCapita	18.10	117.43	0.00	0.00	0.00	0.14	1,047.95
D: Insurer							
Insurer Risk (FPHLM)	1.62	0.55	0.77	1.20	1.54	1.96	3.44
Insurer Risk (FEMA)	98.25	0.97	94.66	97.81	98.32	98.94	99.60
Firm Size Bil.	1.92	5.72	0.01	0.08	0.14	0.60	33.80
RBC Burden	0.06	0.03	0.00	0.04	0.06	0.08	0.16
RBC Ratio	27.52	57.96	2.41	4.37	6.97	12.41	292.73
Liab/Surp	153.04	86.11	0.27	93.54	146.62	217.24	371.51
HO Reins.	30.29	26.85	0.00	5.23	27.72	46.21	100.00
Florida Focus	67.39	40.28	1.26	15.10	96.36	100.00	100.00
Observations	107,170						

Notes: The table reports summary statistics of quarterly county observations. *AvgPrem* is the quarterly average homeowners' insurance premiums in each county in Florida, *TotalDPW 000s* is total premiums written by homeowners insurers reporting to Quasr in 1,000s, *TotalPIF 000s* is the total number of policies written by homeowners insurers reporting to Quasr in 1,000s, *TotalExp Mil* is the total exposure of homeowners insurance policies written by insurers reporting to Quasr in millions, *County No. Insurers* is the number of homeowners insurers reporting to Quasr, *County Citizens Exposure* is the total exposure of homeowners insurance policies written by Citizens 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 from natural disasters in each county, *Insurer Risk (FPHLM)* is the quarterly-county exposure weighted Hurricane Risk (FPHLM) for each insurer in Florida in each quarter during 2014 - 2016, *Insurer Risk (FEMA)* is the quarterly-county exposure weighted Hurricane Risk (FEMA) for each insurer in Florida in each quarter during 2014 - 2016, *Firm Size Bil.* is the total admitted assets of the insurer in billion dollars, *RBC Burden* is regulatory required capital of the insurer scaled by its beginning-of-the year total admitted assets, *RBC Ratio* is total adjusted capital of the insurer divided by its regulatory required capital, *Liab/Surp* is total liabilities of the insurer divided by its surplus, *Reins.* is total unaffiliated reinsurance for homeowners insurance policies of the insurer as a percent of its total homeowners insurance premiums, 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 1 for definitions of the socio-economic variables.

Table 8: Florida Quarterly Insurer Premiums - Insurer Treatment

	Base	County	Insurer	× RBC Burden	× Reinsurance
	(1)	(2)	(3)	(4)	(5)
High X Post (β1)	258.2592**	255.1870**	216.5791**	307.3312*	65.7416
	(110.0250)	(109.0031)	(98.9804)	(163.6313)	(83.6106)
Post X High RBC Burden (β2)				-144.4883**	
				(70.6112)	
X High Risk (β3)				-140.2737	
				(182.5727)	
Post X Low Reins. (β2)					41.4261
					(53.0730)
X High Risk (β3)					508.8906*
					(282.1027)
County No. Insurers		-3.6655**	-3.1119**	-3.0077**	-2.8112*
		(1.5266)	(1.4709)	(1.4634)	(1.4760)
County Citizens Exposure		26.0299	22.8110	21.6258	21.7215
		(18.3663)	(19.1546)	(19.2617)	(19.2662)
ln(PropertyDamageCapita)		0.4316	0.3587	0.3336	0.3313
		(1.0158)	(1.0000)	(1.0080)	(1.0167)
County Insurer Exposure			98.3486**	98.0826**	96.9966**
			(37.7866)	(37.6401)	(37.2649)
ln(RBC Burden)			-0.4610		
			(33.0916)		
ln(Reins.)			-54.9298*		
			(28.6425)		
ln(Firm Size)			-126.0149*	-122.4052*	-89.8535
			(71.7110)	(70.7964)	(68.2305)
Liab/Surp			-0.2841	-0.0976	-0.0390
			(0.4250)	(0.4388)	(0.4202)
$\beta1 + \beta3$				-284.762	550.317**
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	0.002	0.002	0.017	0.018	0.019
N	107,170	107,170	107,170	107,170	107,170

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 2014-2016 period, and zero for others. Post equals one for years 2017 to 2019 and zero for years 2014 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 2014-2016 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 2014-2016 period are considered to be low reinsurance users. Standard errors are clustered at insurer levels. $*p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix

Table A1: Univariate Differences by State Treatment

	Control		RCat State		*Mean*	Total	
	Mean	SD	Mean	SD	*diff.*	Mean	SD
A: Homeowners' Insurance							
AvgPrem	941.25	95.34	1,028.98	127.65	87.73***	1,000.50	125.07
MajorHOShare	0.90	0.12	0.93	0.18	0.04***	0.92	0.16
HomeownersHHI	784.44	172.79	722.23	302.01	-62.21***	742.42	268.59
AvgHOReinsShare	0.03	0.01	0.07	0.07	0.04***	0.06	0.06
B: Socio-economic							
MSA	0.43	0.49	0.44	0.50	0.01***	0.44	0.50
Population 000s	7.88	10.87	14.00	15.97	6.11***	12.01	14.79
PopDensity 000s	0.63	1.69	1.46	3.12	0.83***	1.19	2.77
MedianAge	42.39	5.19	41.54	6.22	-0.85***	41.82	5.92
MedianIncome 000s	55.38	15.62	57.46	23.23	2.08***	56.79	21.09
InsuredHomes 000s	1.91	2.52	2.93	3.17	1.02***	2.60	3.02
UnempRate	6.83	3.80	8.67	4.07	1.84***	8.07	4.08
BachelorDegree	14.05	6.80	15.47	8.47	1.41***	15.01	7.99
C: Risks							
Cat Risk	0.00	0.00	70.29	23.22	70.29***	47.47	38.04
PropertyDamageCapita	0.68	4.05	0.48	3.35	-0.20***	0.55	3.59
HighRBCBurdenShare	0.27	0.10	0.35	0.14	0.09***	0.32	0.14
New Comm[t-1,t]	0.45	0.50	0.42	0.49	-0.02***	0.43	0.49
No. Affected Policies 000s	627.06	475.85	675.00	600.72	47.93***	659.44	563.68
No. Requesting Insurers	33.99	11.13	28.53	11.69	-5.45***	30.30	11.79
Observations	51,534		107,220		158,754	158,754	

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.

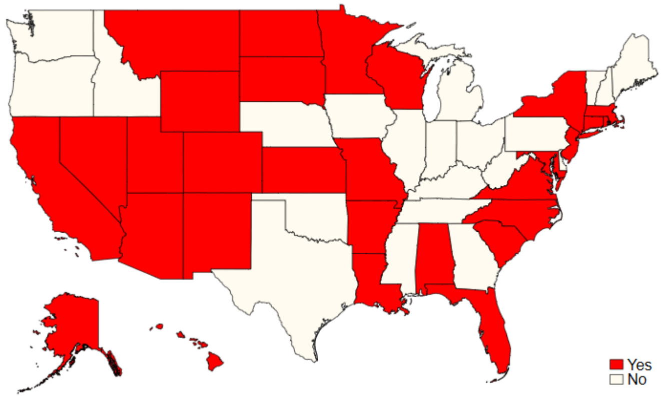
Table A2: The Effect of Treatment within Treated

	Within Treated States		Exclude Control Zips in Treated	
	Full	No Disasters	Full	No Disasters
	(1)	(2)	(3)	(4)
Treat X Post ($\beta 1$)	0.7327**	1.1204***	4.2342***	4.3613***
	(0.2974)	(0.3399)	(0.3453)	(0.4017)
Dep.Var. Mean	1028.980	1027.616	987.390	989.501
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Zipcode FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Adj. Within R^2	0.391	0.385	0.372	0.360
N	107,220	85,488	105,426	81,126

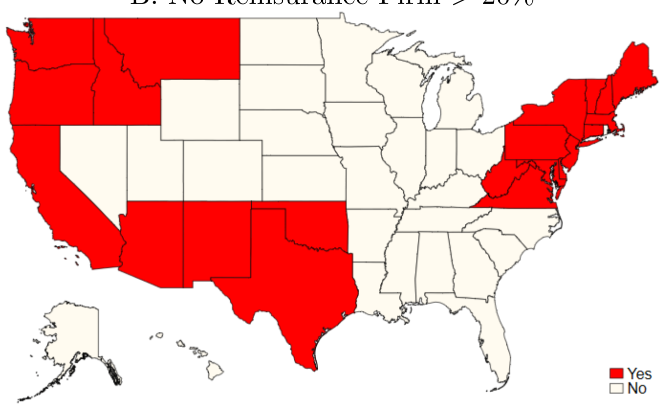
Notes: The table report regression results from the model reported in Table 3 column (4) for columns (1) to (3) and Table 3 column (5) for columns (2) to (4). In columns (1) and (2), we exclude zip codes in exempt states from the RCat. In columns (3) and (4), we exclude zip codes with expected annual loss scores from hurricanes or earthquakes equal to or below 75 in states that are not exempt from RCat. Standard errors are clustered at zip code levels. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure A1: 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 sample period (2014-2019) 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 sample period in red.

Table A3: Quasr Univariate Differences by Insurer Treatment

	Control		Treat (FPHLM)		*MeanDiff.*	Total	
	Mean	SD	Mean	SD		Mean	SD
A: Insurance							
AvgPrem	1,958.36	1,354.76	3,243.00	3,323.12	1,284.64***	2,265.26	2,082.09
TotalDPW 000s	1,382.08	4,707.63	1,358.38	5,249.30	-23.70	1,376.42	4,842.54
TotalPIF 000s	0.71	2.00	0.54	1.90	-0.17***	0.67	1.97
TotalExp. Mil.	335.75	921.95	312.56	1,078.27	-23.20***	330.21	961.65
County No. Insurers	69.35	13.26	72.11	12.09	2.76***	70.01	13.04
CitizensExp Mil.	0.83	2.51	1.01	2.78	0.18***	0.88	2.58
B: Socio-economic							
Population 000s	344.76	501.18	409.79	544.50	65.03***	360.29	512.61
PopDensity 000s	0.41	0.58	0.48	0.62	0.07***	0.43	0.59
MedianAge	43.42	6.39	43.79	6.47	0.37***	43.51	6.41
MedianIncome 000s	46.73	8.47	48.00	8.50	1.27***	47.03	8.49
InsuredHomes 000s	78.76	103.12	93.23	110.52	14.47***	82.22	105.12
UnempRate	10.78	3.00	10.42	2.90	-0.36***	10.70	2.98
BachelorDegree	13.62	5.47	14.66	5.21	1.04***	13.87	5.43
C: Geographic Risks							
Hurricane Risk (FPHLM)	1.07	1.04	1.23	1.11	0.16***	1.11	1.06
Hurricane Risk (FEMA)	92.87	7.32	94.36	6.49	1.49***	93.22	7.16
PropertyDamageCapita	17.99	116.99	18.46	118.81	0.46	18.10	117.43
D: Insurer							
Insurer Risk (FPHLM)	1.42	0.37	2.28	0.50	0.87***	1.62	0.55
Insurer Risk (FEMA)	98.02	0.94	98.99	0.65	0.97***	98.25	0.97
Firm Size Bil.	1.92	5.84	1.94	5.34	0.02	1.92	5.72
RBC Burden	0.06	0.03	0.06	0.04	0.01***	0.06	0.03
RBC Ratio	27.50	58.80	27.57	55.19	0.07	27.52	57.96
Liab/Surp	150.18	81.07	162.15	99.95	11.97***	153.04	86.11
HO Reins.	29.56	26.59	32.61	27.53	3.05***	30.29	26.85
Florida Focus	69.67	39.72	60.13	41.21	-9.54***	67.39	40.28
Observations	81,567		25,603		107,170	107,170	

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 2014-2016 period, and zero for others. We perform tests of the mean difference assuming unequal variance structures between the control and the treatment.