Measuring Insurer Vulnerability to Catastrophe Risk

Vaibhav Anand
St. John's University

Yu-Luen Ma
University of North Texas

Yayuan Ren
Illinois State University

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Abstract

We develop an empirical measure of U.S. property-liability insurers' vulnerability to catastrophe risk. Using underwriting outcomes and property damage data from 1991 to 2021, we first estimate state–line sensitivities that quantify how unexpected disaster damages translate into insured losses. Sensitivity varies widely across lines and states: homeowners and allied lines, and the Gulf and Southeastern states, show the strongest transmission. Loss ratios rise sharply in high-damage years, but decline only modestly in low-damage years. Combining sensitivities with insurers' portfolio compositions, we construct an insurer-level vulnerability metric and find that vulnerability is highly skewed. Insurers in the top quintile are roughly four times more exposed than the next group, and their vulnerability has grown by 50 percent over time. While most insurers manage catastrophe exposure through diversification, highly vulnerable insurers, typically smaller and concentrated, rely heavily on reinsurance. Our metric also reconciles prior evidence on diversification and reinsurance: while concentration lowers reinsurance demand on average, for vulnerable insurers, reinsurance usage increases with geographic concentration.

JEL: G22, G32, Q54, L25

Keywords: Catastrophe risk, property-liability insurance, reinsurance, diversification

Insurers play a central role in financing catastrophic losses and maintaining economic resilience. However, the growing frequency and severity of natural disasters, coupled with rising exposure in high-risk areas, have created serious challenges for the industry—from modeling and pricing these risks within regulatory limits to maintaining solvency (Boomhower et al., 2024). These pressures have led to insurer failures and market exits (Aseervatham et al., 2017; Sastry et al., 2023), reducing catastrophe-risk coverage and creating spillovers for households (Eastman et al., 2024; Keys and Mulder, 2024), governments (Cole et al., 2010; Boyer and Nyce, 2013), and financial markets (Born and Viscusi, 2006; Sastry et al., 2023). These developments underscore the importance of

Anand: anandv@stjohns.edu; Ma: yu-luen.ma@unt.edu; Ren: yren2@ilstu.edu. We are grateful for helpful comments by Ty Leverty, Justin Sydnor, Justin Waller, and by participants at the ARIA Annual Meeting 2024, World Risk and Insurance Economics Conference 2025, China Conference on Insurance and Risk Management 2025, and the University of Georgia's Terry Research Seminar. Authors have no conflict of interest to declare.

understanding insurers' exposure to catastrophic shocks; however, there is no systematic metric to measure or monitor insurers' vulnerability to such events.

This paper develops a data-driven approach to quantify the vulnerability of U.S. property-liability insurers to catastrophe risk. Using underwriting outcomes and disaster losses from 1991 to 2021, we first estimate state-line-level sensitivities to unexpected property damages from natural disasters, i.e., the rate at which property damages translate into insured losses. We then combine these sensitivities with each insurer's underwriting portfolio composition to construct a vulnerability metric that captures the insurer's overall exposure to catastrophe risk. Our measure has several distinctive features. First, our approach is comprehensive and empirical, as it is built from granular data that capture the full complexity of insurers' exposures. Second, unlike existing proxies that assume which states or lines are catastrophe-prone, our measure is fully data-driven and dynamic, responding to evolving loss experience of insurers rather than relying on fixed classifications. Third, our approach provides a bottom-up understanding of how insurers' underwriting choices translate into their vulnerability to catastrophe losses, offering quantitative guidance for state-line risk diversification. Finally, our approach is both transparent and flexible. The methodology can be extended and modified to incorporate alternative settings regarding the underlying distribution of property damages (such as specific perils, time periods, risk tolerance level) and risk transfer mechanisms (reinsurance or alternative risk financing) for a variety of risk management applications.

Our analysis provides several key insights. First, we demonstrate that the sensitivity of loss ratios to catastrophe losses varies widely across business lines and states. In general, property lines are highly sensitive to disasters, whereas liability lines remain largely unaffected. We show that the most sensitive lines are homeowners and allied lines, which are about twice as sensitive to catastrophe losses as commercial multi-peril lines and nearly five times as sensitive as auto physical damage lines. Within these lines, sensitivities differ sharply across states, with Gulf and Southeastern states showing the highest transmission of catastrophe damages to insured losses. For instance, homeowners insurance sensitivity in Florida is nearly twice that in California and Texas, about four times that in Pennsylvania, and eight times that in New York. These results complement recent household-level evidence on cross-state variation in how insurers pass catastrophe-risk pricing through to homeowners (Keys and Mulder, 2024). Moreover, we find that loss ratios rise sharply in years when states experience abnormally high property damages but decline only modestly in years with below-average losses. These quantitative findings, previously unavailable using existing proxies, offer practical guidance for insurers to create diversified risk portfolios and to better manage their exposure to catastrophe risk.

Second, we find that the distribution of firm-level vulnerability is highly skewed: insurers in the top quintile are roughly four times more vulnerable than those in the next quintile. The vulnerability metric of top quintile insurers has increased by more than 50 percent since the early 1990s, while that of other quintiles has remained largely stable. These findings suggest that elevated vulnerability is concentrated among a small fraction of insurers. As a robustness test, we show that our vulnerability metrics remain significantly associated with insurer failure after controlling for

exposure to catastrophe-prone states and lines, portfolio concentration, and other financial variables. Moving from the fifth to the ninety-fifth percentile of vulnerability corresponds to roughly a two- to six-fold increase in the odds of failure. Consequently, our measure can serve as a useful tool for identifying insurers at elevated risk of insolvency in the event of catastrophe shocks.

Third, we also investigate how insurers manage catastrophe exposure through diversification and reinsurance. Our results indicate that most insurers primarily manage increasing catastrophe risks through enhancing portfolio diversification**,** spreading exposures across states and business lines to reduce the impact of disasters. In contrast, the most vulnerable insurers, typically smaller and concentrated carriers, rely heavily on reinsurance. They cede a greater share of premiums to reinsurers, which lowers their vulnerability by about 40 percent; however, their vulnerability metrics still remain nearly three times higher than that of their less vulnerable peers.

Lastly, our analysis reconciles previous evidence on the negative relationship between concentration and reinsurance (Mayers and Smith, 1990; Cole and McCullough, 2006). Using our vulnerability measure, we disentangle two opposing effects of concentration: while concentration can enhance underwriting expertise and thereby reduce the demand for reinsurance, it can also increase exposure to catastrophe risk, increasing the need for reinsurance. Our analysis shows that whereas more concentration reduces reinsurance demand in general, for vulnerable insurers, geographic concentration actually increases reinsurance demand.[1] This suggests that insurers with limited scope for spatial diversification rely more heavily on financial risk transfer. These findings have important implications for the stability and resilience of the insurance sector. The most vulnerable insurers face a twofold risk: their concentrated portfolios make them more likely to absorb a disproportionate share of catastrophe losses, while their heavy reliance on reinsurance leaves them exposed to potential supply shocks in the reinsurance market**.**

This paper contributes to the growing literature on the resilience of the insurance sector to catastrophe losses. Most literature in this space examines insurers' exposure to catastrophe risk. Cummins et al. (2002), Dionne and Desjardins (2022), and Powell et al. (2022) develop frameworks to evaluate the insurance industry's capacity to absorb catastrophic losses.[2] These studies rely on the co-movement between industry and insurer losses to measure each insurer's exposure to catastrophe risk. However, their approach does not directly account for the underwriting mechanisms that drive differences in vulnerability across insurers. Jung et al. (2023) propose a climate beta, a market-based measure that captures how insurers' stock returns respond to physical climate risk. Other studies have relied on premium exposures in sensitive geographic areas and business lines as proxies for climate risk exposure (Ge and Weisbach, 2021; Ge, 2022).[3] While often straightforward to

[1]This is consistent with previous studies that found insurers in catastrophe-prone areas tend to purchase more reinsurance (Powell and Sommer, 2007; Drexler and Rosen, 2022).

[2]Cummins et al. (2002) examine the financial capacity of insurers to cover catastrophic loss events. They use the correlation between insurer-level and industry-level losses to model an individual insurer's exposure to catastrophe risk. Dionne and Desjardins (2022) build on Cummins et al. (2002) and show that the insurance industry's capacity improved in the last twenty years on account of increased reinsurance capital access. Powell et al. (2022) examine this financial capacity after taking into account the risk transfer through state level guarantee funds.

[3]Jung et al. (2023) estimates the climate beta for publicly traded insurers and extend it to non-public insurers by predicting their exposure based on portfolio characteristics. Ge and Weisbach (2021) examine how catastrophe-

implement, these proxies rely on fixed definitions of catastrophe-prone regions and lines and may not capture risk variation within them.

Our work advances the literature by proposing a new, data-driven measure of insurers' vulnerability to catastrophe risk. Unlike prior studies that require specific assumptions or stock market reflections, our approach directly builds on insurers' underwriting performance and realized natural disaster losses. Our measure requires no assumptions about the distribution of losses or the relative riskiness of states and lines, and it is applicable to all insurers, including both public and private entities. Moreover, it allows us to take insurers' risk-mitigation efforts into account when assessing their actual vulnerability to catastrophe risk. To our knowledge, this is the first study to develop an insurer-level measure of catastrophe vulnerability that explicitly incorporates their underwriting performance and diversification. Our resulting metric provides granular, actionable insights for portfolio management, capital allocation, and solvency assessment, enabling insurers and regulators to better evaluate and manage catastrophe risk.

Our study also adds to the research examining the trade-off between operational hedging through diversification and financial risk transfer via reinsurance—the two primary tools in insurers' risk management. Diversification reduces exposure to correlated losses, while concentration can improve underwriting expertise.[4] Reinsurance, on the other hand, provides both risk transfer and access to reinsurers' specialized knowledge (Anand et al., 2021). Prior studies document mixed evidence on this trade-off: Mayers and Smith (1990) and Cole and McCullough (2006) find that more concentrated insurers purchase less reinsurance, suggesting that expertise motives dominate risk-transfer needs, whereas Anand et al. (2021) and Drexler and Rosen (2022) show that concentrated portfolios often rely more on reinsurance.[5] Our vulnerability measure allows us to separate the portfolio's catastrophe risk from the benefits of specialization. We find that while concentration generally reduces reinsurance demand, it has the opposite effect among insurers with high catastrophe vulnerability: greater geographic concentration increases reinsurance demand, indicating that limited scope for operational hedging increases reliance on financial risk transfer.

Finally, this paper contributes to the growing literature on how insurers and governments respond to natural disasters in regions with high catastrophe risk. Prior studies show that, following major catastrophes, insurers often reduce insurance supply (Born and Viscusi, 2006), raise premiums or refine pricing (Carrillo et al., 2022; Boomhower et al., 2024; Keys and Mulder, 2024), or even withdraw from catastrophe-prone markets (Aseervatham et al., 2017; Cole and Fier, 2025).[6]

related insurer losses affect investment portfolio choices. Ge (2022) study how financial constraints caused by catastrophic losses influence insurance product pricing. While Ge and Weisbach (2021) and Ge (2022) use insurers' total state-level exposure, Jung et al. (2023) focus on premiums earned in homeowners and commercial multi-peril lines in Florida, California, and Texas.

[4] Elango et al. (2008) suggest that sufficient geographic spread may be needed to benefit from product diversification.

[5] Anand et al. (2021) shows that within a line, more geographic concentration results in more reinsurance purchases. Drexler and Rosen (2022) shows that more concentrated insurers rely more on non-proportional reinsurance contracts.

[6] In Florida, for example, the government has faced pressure to enact a series of legislative and regulatory interventions aimed at expanding subsidization of homeowner insurance, ensuring insurance availability, and constraining insurers' rates (Grace and Klein, 2009).

Our analysis provides empirical insights into how both insurers and policymakers might respond effectively to catastrophe losses. We find that while the majority of insurers manage catastrophe risks through diversification, the most vulnerable insurers tend to be small, geographically concentrated carriers that depend heavily on reinsurance. Our results also show that diversification can substantially reduce an insurer's vulnerability. These findings suggest that public policies should encourage diversification and promote the participation of large national carriers that are better positioned to spread risk geographically.

While our methodology is comprehensive and accounts for insurers' granular underwriting performance at the state–line level and their diversification across states and business lines, several limitations should be acknowledged. First, we rely on past loss experience and property damage data to estimate the sensitivity of insurance lines to catastrophe risk. Consequently, our approach does not account for future changes in catastrophe losses or insurers' underwriting strategies that could alter the relationship between insurance losses and property damages. Nonetheless, our analysis provides a credible method of estimating vulnerabilities over a shorter horizon, during which this relationship can reasonably be assumed stable. Second, when evaluating state-line sensitivities, we link direct loss and catastrophic property damage and account for reinsurance at a constant ratio within each line of business. Because reinsurance data are reported only at the line level rather than the state–line level, we cannot explicitly model reinsurance decisions at a finer level. We therefore assume that reinsurance ratios are uniform within each line of business across all states in which the line is written. Third, we define unexpected damage as the deviation of a year's damages from the long-run rolling historical average. Accordingly, the damages are unexpected relative to the historical experience, rather than to insurers' own expectations. However, our methodology is flexible and can be extended and modified to accommodate alternative assumptions on the underlying distribution of property damages, such as the time period and the risk tolerance level.

The paper is structured as follows. Section 1 discusses the data and methodology for sensitivity and vulnerability estimation. Section 2 presents and discusses the estimated sensitivity results at the property-liability insurance market, line of business, and state-line level. Section 3 estimates and discusses the insurer-level vulnerability. Section 4 examines the risk management strategies of insurers and discusses the tradeoff between reinsurance and diversification. Section 5 discusses the robustness of vulnerability metric. Section 6 concludes.

1 Empirical framework

Most insurance companies operate in multiple states and underwrite a range of insurance lines. To fully assess an insurer's vulnerability to catastrophe risk, it is important to account for differences across product lines and geographic areas, as each may have a unique sensitivity to natural disasters. For example, a loss event of similar scale might sharply raise loss ratios in homeowners insurance in one state (such as Louisiana), yet have a smaller effect on homeowners insurance in another state (such as Texas), or on another line in the same state (such as auto physical damage). These

differences may result from various factors, including state regulatory frameworks, competitive environments, and variation in disaster modeling skills. In states with strict regulations on underwriting and pricing, premium rates may not reflect the true level of risk.[7] Similarly, certain insurance lines may be more sensitive to natural disasters. These state- and line-level factors influence the degree of loss transfer from natural disaster-related property damages to insurance portfolios. Thus, evaluating an insurer's catastrophe risk requires considering not only the exposure to disaster-prone states or lines but also the sensitivity of each state-line to natural disaster losses.

1.1 Methodology

Natural disasters cause property damages, which translate into insured losses. However, this translation varies across lines of business and states. An insurer's underwriting risk depends on its exposure to each state–line, the sensitivity of each state–line to catastrophic damages, and the potential catastrophic damages in each state. We measure vulnerability by capturing variations in exposure at the state–line level and the sensitivity of loss ratios to disaster-related damages.

We first estimate the sensitivity of the loss ratio in a line of business to catastrophic property damages in each state. We define catastrophic damages as abnormal shocks to property damages compared to the historical average for that state. We allow the sensitivity to vary by state–line, and separately estimate sensitivity to positive shocks (damages above average) and negative shocks (damages below average). This approach allows loss ratios to respond differently in bad years versus good years. Specifically, we estimate the following regression for each state–line:

$$lossratio_{islt} = \beta_{sl}^{+} D_{st}^{+} + \beta_{sl}^{-} D_{st}^{-} + year_t + \alpha_i + \epsilon_{it} \tag{1}$$

where $lossratio_{islt}$ is losses incurred divided by direct premiums earned by insurer i in line l and state s in year t. The main variables of interest are D_{st}^{+} and D_{st}^{-}, representing positive and negative abnormal property damages, respectively. We define D_{st}^{+} as:

$$D_{st}^{+} = \frac{Damage_{st} - \overline{Damage}_{st,30yr}}{\sqrt{Var(Damage_{st})_{30yr}}} \cdot \mathbf{1}_{Damage_{st} > \overline{Damage}_{st,30yr}} \tag{2}$$

where $Damage_{st}$ is total property damage due to natural disasters in state s in year t, $\overline{Damage}_{st,30yr}$ is the 30-year average damage for the state, and $Var(Damage_{st})_{30yr}$ is the standard deviation of damages over the last 30 years. The indicator variable, $\mathbf{1}_{Damage_{st} > \overline{Damage}_{st,30yr}}$, equals 1 if annual damages exceed the 30-year average, and 0 otherwise. Similarly, we define D_{st}^{-} when $Damage_{st} < \overline{Damage}_{st,30yr}$. We follow Ge and Weisbach (2021) in defining abnormal damages D_{st} as the deviation from the 30-year average damages, normalized by their standard deviation. This measure is equivalent to a z-score, indicating how many standard deviations a year's dam-

[7] California, for example, requires prior approval of rates, limits the use of catastrophe models in pricing, restricts fine territorial rating, and prohibits the inclusion of reinsurance costs in rate filings. In Florida, homeowners insurance pricing is heavily influenced by regulatory constraints and political oversight.

ages are away from the average. Thus, D_{st} captures unexpected changes in damages not likely reflected in insurance premiums. We construct this measure using the Spatial Hazard Events and Losses Database for the United States (SHELDUS), which provides estimates of economic losses from natural disasters at county, state, and national levels since 1960.

The coefficient β_{sl}^{+} represents the effect of a one standard deviation increase in abnormal property damages on the loss ratio in a given state–line. Similarly, β_{sl}^{-} reflects the impact of a one standard deviation decrease. Higher β_{sl}^{+} indicates more property damages translate into insured losses, while higher β_{sl}^{-} suggests greater savings in loss ratios when damages are below average.

To estimate the sensitivity of line l in state s, we estimate equation (1) separately using observations from each state–line combination. Because our estimation relies on variation in unexpected damages and loss ratios within a specific state–line over time, we do not include year fixed effects. We control for time trends by including a linear year term, $year_t$. We also include insurer fixed effects (α_i) to account for insurer-specific characteristics that do not change over time. Since each regression is state–line specific, separate state or line fixed effects are not needed.

We then compute $Vulnerability$, which is the summation of β_{ls} weighted by an insurer's premium share in a line and a state, ω_{ilst} and the average abnormal damages in the state as follows:

$$Vulnerability_{it} = \sum_{ls} \beta_{ls}^{+} \omega_{ilst} \overline{D_s^{+}} + \sum_{ls} \beta_{ls}^{-} \omega_{ilst} \overline{D_s^{-}} \tag{3}$$

where $\overline{D_s^{+}}$ is the expected value of positive abnormal damages in the state s. $Vulnerability_{it}$ reflects the overall vulnerability of an insurer i's underwriting performance to catastrophe risk in a year t.

1.2 Data

We obtain insurer, line, state, and year-level data from the National Association of Insurance Commissioners (NAIC) annual financial statements for 1991–2021. These data allow us to calculate insurers' loss ratios at the state–line level annually. Data on property damages due to natural disasters come from the Spatial Hazard Events and Losses Database for the United States (SHELDUS), which provides estimates of economic losses at the state–year level from 1960–2021.[8]We perform our analysis by aggregating financial data of affiliated insurers at the insurer group level. We restrict our analysis to lines with at least USD 100,000 in direct premiums annually and non-negative losses, excluding insurers with negative policyholder surplus or negative reinsurance purchased. We exclude federal flood and crop insurance lines from our sample. We also exclude reinsurers.[9] We winsorize our observations with loss ratios and unexpected property damages above the 99th percentile. Our final sample comprises 1,706,180 insurer-line-state-year observations from 2,494 unique insurers, including 838 insurer groups and 1,656 single unaffiliated insurers.

[8]Since our property damage data ends in 2021, we estimate sensitivity using underwriting performance until 2021.
[9]We define reinsurers as insurers that assume more reinsurance from non-affiliates than direct premiums written.

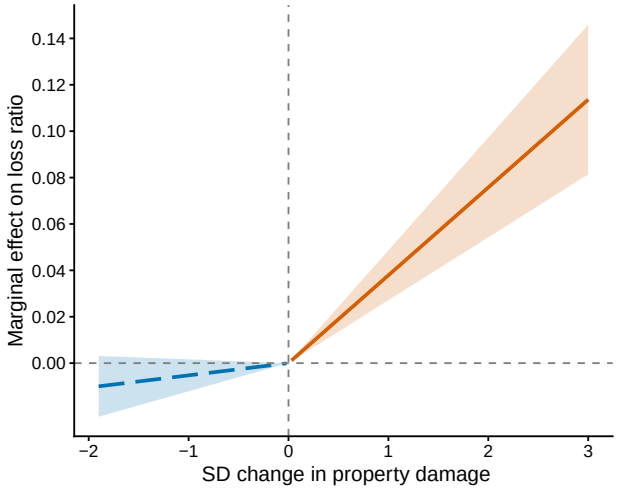
2 Results of estimating sensitivity

In this section, we present the results of estimating the sensitivity of underwriting performance to abnormal property damages. When natural disasters cause significant property damage, these losses are translated into insurance losses, and the sensitivity quantifies this rate of translation. We estimate and present sensitivities at three levels. First, we report the overall sensitivity of the property-liability sector by pooling all state-line-year observations across insurers. Second, we estimate sensitivities for each line of business, pooling observations across all states, to highlight differences at the line level. Finally, for our main analysis, we estimate sensitivities for each state-line pair separately.

2.1 Overall sensitivity of loss ratios

We estimate the overall sensitivity by pooling all insurer-state-line-year observations between 1991–2021. Appendix Section A.1 provides more details on the regression specification and results. Figure 1 plots the marginal effects of sensitivity to positive abnormal damages (solid line) and negative abnormal damages (dashed line). The figure shows that loss ratios are more sensitive to positive abnormal damages. This suggests that when there are large unexpected damages in a state, the loss ratio increases. However, in a year with unexpectedly smaller damages, the loss ratios do not decrease as much. This result also supports our approach of estimating the effect of damages separately for positive and negative shocks.

Figure 1: Effect of abnormal property damages on U.S. property-liability insurers' loss ratios

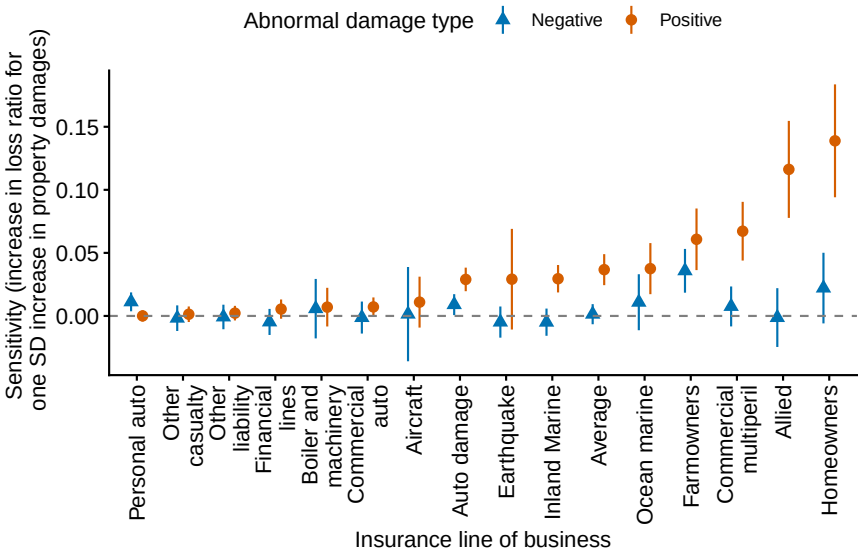


Notes: The figure plots the estimate of overall loss ratio sensitivity to abnormal damages based on the regression model: $lossratio_{islt} = \beta^{+} D^{+}_{st} + \beta^{-} D^{-}_{st} + \alpha_i + \lambda_l + \theta_t + \epsilon_{islt}$ where $lossratio_{islt}$ is the loss ratio of insurer i in line l and state s in year t. D^{+}_{st} and D^{-}_{st} are the measure of positive and negative unexpected losses in state s in year t based on the SHELDUS data. The specification controls for insurer-, line-, and year-level fixed effects. The regression is estimated by pooling all observations across all insurers, lines, and states for the period 1991—2021. The solid line (dashed line) plots the marginal effects based on β^{+} (β^{-}). The error ribbons represent the 95% confidence interval. The standard errors are two-way clustered at the insurer and state level.

2.2 Line level sensitivity

We now present the result of estimating the average sensitivity of each line of insurance across all states. We estimate a version of equation 1 for each line of business separately. Figure 2 shows the sensitivity of different lines of insurance to unexpected property damages. The figure plots the point estimates of the sensitivity of a line of business to a one-standard-deviation increase in property damages. The error bars show the corresponding 95% confidence interval. The estimates are based on the sample pooled across all states in which a line operates. The figure shows how property damages due to natural disasters are transmitted to insured losses across different lines of insurance.

Figure 2: Effect of abnormal property damages on loss ratios by line of business



Notes: The figure plots the estimate of overall loss ratio sensitivity to abnormal damages based on the regression model: $lossratio_{islt} = \beta_l^+ D_{st}^+ + \beta_l^- D_{st}^- + \alpha_{is} + \theta_t + \epsilon_{islt}$ where $lossratio_{islt}$ is the loss ratio of insurer i in line l and state s in year t. D_{st}^+ and D_{st}^- are the measure of positive and negative unexpected losses in state s in year t based on the SHELDUS data. The specification controls for insurer-state and year fixed effects. The regression is estimated separately for each line of business by pooling all observations across all states for the period 1991—2021. The circles (triangles) markers plot the point estimates of sensitivity β_l^+ (β_l^-) for each line. The error bars represent the 95% confidence interval. The standard errors are two-way clustered at the insurer and state level.

The figure offers three key insights. First, positive and negative shocks affect loss ratios differently. Line-level loss ratios are more sensitive to positive abnormal damages. Second, unexpected catastrophic damages do not affect all lines equally. Homeowners and allied lines, commercial multiperil, farmowners, marine (inland as well as ocean), and physical auto damage are the most sensitive lines, whereas nearly all liability lines, including personal and commercial auto, are among the least sensitive lines of business. This is overall not surprising and is consistent with the expectation that property insurance lines are more sensitive to catastrophe risk than are liability lines as property insurance contracts are designed to cover property damages. These two results also validate our

approach of measuring sensitivity separately by line of business and by the direction of abnormal damages.

Third, the quantitative estimates of line level sensitivities offer insight into the relative magnitudes of the proneness of different lines of insurance. We find that there is a significant variation in the magnitude of sensitivity between property and liability lines, as well as within property lines. Homeowners insurance is nearly twice as sensitive as commercial multiperil and five times as sensitive as auto damage, and 25 times as sensitive as commercial auto liability. The sensitivity of most liability lines is not significantly different from zero, both statistically and economically. In Appendix Section A.2, we show that while sensitive property lines, such as homeowners and commercial multiperil, capture a meaningful share of the market, low-sensitivity lines account for a much larger share. In principle, this market size and sensitivity variation suggests that aggregate industry exposure to catastrophe risk can be mitigated by diversification. A key question we examine in this paper is whether some firms are more focused on the lines and geographies most sensitive to abnormal damages. These firms, if unable to diversify, will likely be more vulnerable to catastrophe risk than their more diversified peers.

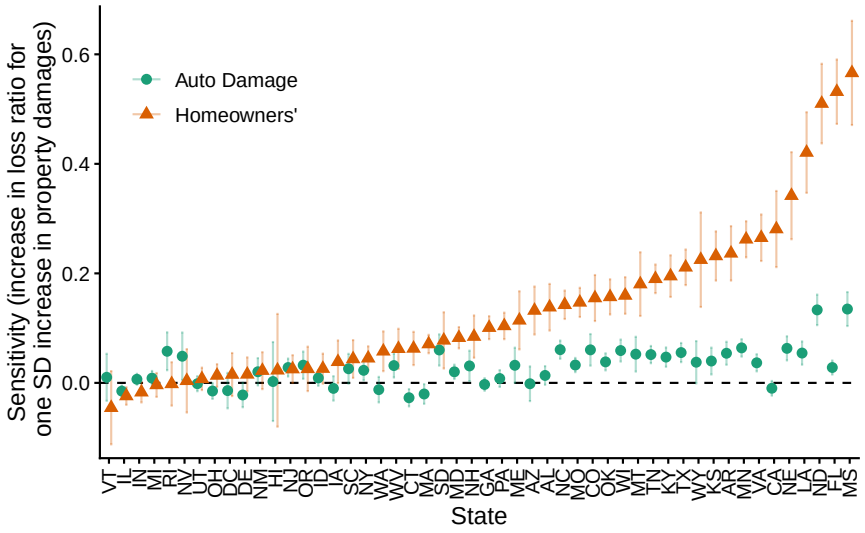
2.3 State-Line level sensitivity

So far, we have examined the overall sensitivity of lines of business across all states. In this section, we examine the state-line level sensitivity by estimating the equation (1). Sensitivities within a line are likely to differ by state. For example, homeowners insurance line is highly sensitive on average, but may not be uniformly sensitive across states. Figure 3 compares the sensitivity of homeowners insurance (Panel a) and auto physical damage insurance (Panel b) across all the states. There is significant variation in the sensitivity of homeowners insurance across states, ranging from a loss ratio increase of more than 0.50 in Mississippi and Florida to a modest effect on loss ratio in Illinois, Indiana, and Michigan for one standard deviation in the increase in abnormal property damages. In contrast, for the physical auto damage line, another property insurance line, the sensitivity varies from 0.13 in Mississippi and North Dakota to -0.02 in Massachusetts.

In Appendix Section A.3, we present the cross-state variation of sensitivities for the six largest insurance lines across the U.S. In addition to a substantial variation between states, the mapping also shows that the sensitivities may be correlated with the geographic location of the states. This suggests there may be limited scope for insurers or policyholders to mitigate these sensitivities. We also find that some large lines, such as auto insurance, remain largely unaffected by unexpected physical damages even when written in highly exposed regions.

Several factors could explain the variation in risk sensitivity across states. First, the distribution of risk is not uniform across states. For instance, an insurance portfolio may carry significantly higher risk in Florida compared to Texas due to its physical location and geographic features. This likely affects the impact of unexpected extreme weather events; a one-standard-deviation event in Florida might be far more devastating than a similar event in Texas. Ex-post moral hazard is another likely contributing factor. For the same loss event, the ultimate claim sizes may be higher in certain states

Figure 3: State-level sensitivities for homeowners and auto physical damage lines



Notes: The figure plots the estimated sensitivities of underwriting performance to abnormal property damages for homeowners and auto physical damage insurance lines. The circles denote auto physical damage and the triangles denote homeowners insurance. Each point represents a state-line-level sensitivity estimate (β_{sl}) obtained from the regression model in equation (1), estimated separately for each state and line of business for the period 1991–2021. The x-axis lists states ordered by homeowners insurance sensitivities. Error bars represent 95% confidence intervals based on clustered standard errors at the insurer level.

than in others. For example, in Florida, the popular press and trade literature often attribute this increased claim amount to higher rates of ex-post litigation. Additionally, ex-ante moral hazard could play a role, where policyholders in high-risk areas may not invest sufficiently in preventive measures. Adverse selection could also contribute to this variation, where the distribution of risk within a state may not be uniform, leading to a concentration of high-risk policies underwritten in certain states. This non-uniform distribution can skew the overall risk profile for insurers operating in that state. Finally, regulatory factors and business environment may hamper insurers' ability to price policies that accurately reflect the risk of unexpected large losses.

Overall, this analysis suggests that insurers writing traditionally more sensitive lines can write across multiple states and diversify their catastrophe risk. Similarly, regional insurers that are geographically concentrated by design can write multiple lines in a concentrated geographic area to diversify their risk. In the next section, we estimate the overall vulnerability to shed light on how insurers manage their physical risk.

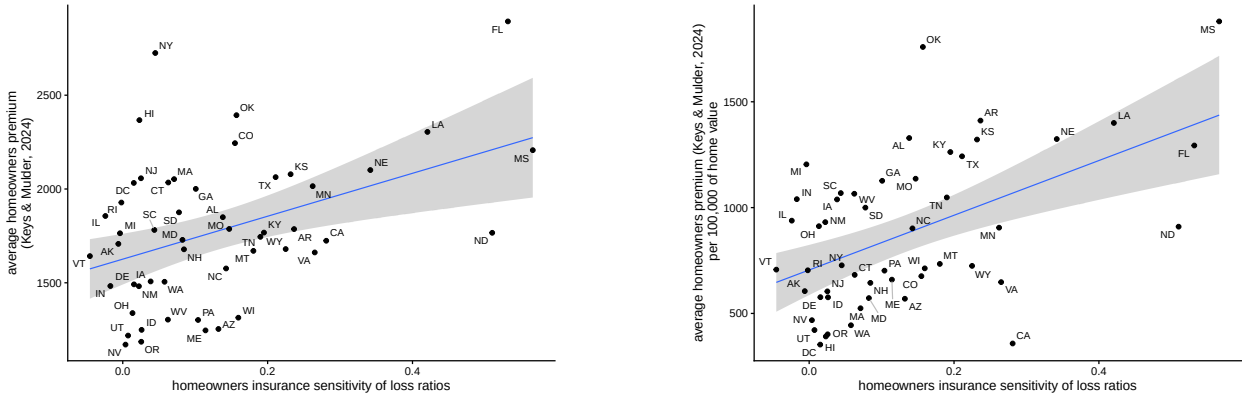
Loss ratio sensitivity and homeowners premiums

Our estimated loss ratio sensitivities help explain cross-state variation in homeowners insurance premiums. We use the county-level homeowners premium data from Keys and Mulder (2024), which provide average premiums paid by households in each U.S. county from 2014–2024. For each

state, we compute a population-weighted average premium across its counties.

Figure 4 plots these state-level premiums against the estimated sensitivity of the homeowners line in that state. Panel (a) presents the relationship using raw average premiums. Panel (b) normalizes premiums by county-level median home values, expressed as premiums per $100,000 of home value.[10] Across both specifications, we find a positive relationship: states with higher sensitivity of loss ratios to abnormal damages have higher premiums. This relationship suggests that our measure captures the information used by insurers in their risk pricing decisions, providing a validation of our metric.

Figure 4: Homeowners premiums and loss ratio sensitivity



(a) Average homeowners premium by sensitivity

(b) Premium per $100,000 of home value by sensitivity

Notes: These figures plot the relationship between homeowners insurers' loss ratio sensitivity to abnormal damage shocks and homeowners premiums at the state level. Panel A uses population-weighted average homeowners premiums from Keys and Mulder (2024). Panel B scales premiums by median county-level home values, expressed per $100,000 of home value. State-level sensitivities are estimated from our baseline specification using homeowners loss ratios. The fitted line and shaded region show the linear trend and its 95% confidence interval.

3 Estimating vulnerability

Our next step is to estimate the overall vulnerability of an insurer's underwriting portfolio. We do this by accounting for the line-state-level sensitivity and the share of direct premiums written in the corresponding line-state. This measure denotes the absolute change in loss ratio if every state in the insurer portfolio experiences an average level of deviations in positive and negative abnormal property damages in a year, i.e.,

$$\overline{D}_s^{\pm} = \frac{\sum_t D_{st}^{\pm}}{T},$$

[10] Median home values are taken from the American Community Survey (ACS) conducted by the U.S. Census Bureau.

where T is the total number of years in the sample. We estimate the average vulnerability of an insurer's portfolio as

$$\textit{Vulnerability}_{it} = \sum_{ls} \beta_{ls}^{+} \omega_{ilst} \overline{D_s^{+}} + \sum_{ls} \beta_{ls}^{-} \omega_{ilst} \overline{D_s^{-}} \tag{4}$$

where $\overline{D_s^{+}}$ is the expected value of positive abnormal damages in the state s, β_{ls}^{+} represents the sensitivity of line l in state s to positive abnormal damages, and ω_{ilst} accounts for the size of exposure in each state and line. The estimated measure, $\textit{Vulnerability}_{it}$, reflects the average vulnerability of an insurer i's underwriting performance to catastrophe risk in a year t, which it measured as the average effect of unexpected property damages on the overall direct loss ratio of insurer i based on its portfolio composition in year t.

Figure 5(a) shows the distribution of estimated vulnerabilities of all insurers for the year 2021. The figure shows that vulnerability is clustered around zero. The average vulnerability is 0.025. Given the average loss ratio of 0.56 across all insurers, this suggests that for an average insurer, the increase in loss ratio due to unexpected property damages is roughly 4.5%. However, there is significant variation across insurers. The 50th, 75th, and 95th percentile insurers have vulnerabilities of 0.011, 0.03, and 0.14, which denote an average increase in loss ratio of 2%, 5.3%, and 25.5%, respectively.

Figure 5(b) shows the average vulnerability for all insurers during 1991—2021. The markers show the average, the solid line plots the best-fit trendline, and the shaded band represents the corresponding 95% confidence interval. The average vulnerability increased by around 50% over the years. It ranges from under 0.018 during the early 1990s to around 0.029 since 2015. The figure also shows some volatility around an increasing trend. In particular, there is a sharp increase in average vulnerability from 2006 to 2008. The sharp rise coincides with a major policy intervention in Florida's homeowners segment after the 2004–05 hurricanes.[11]

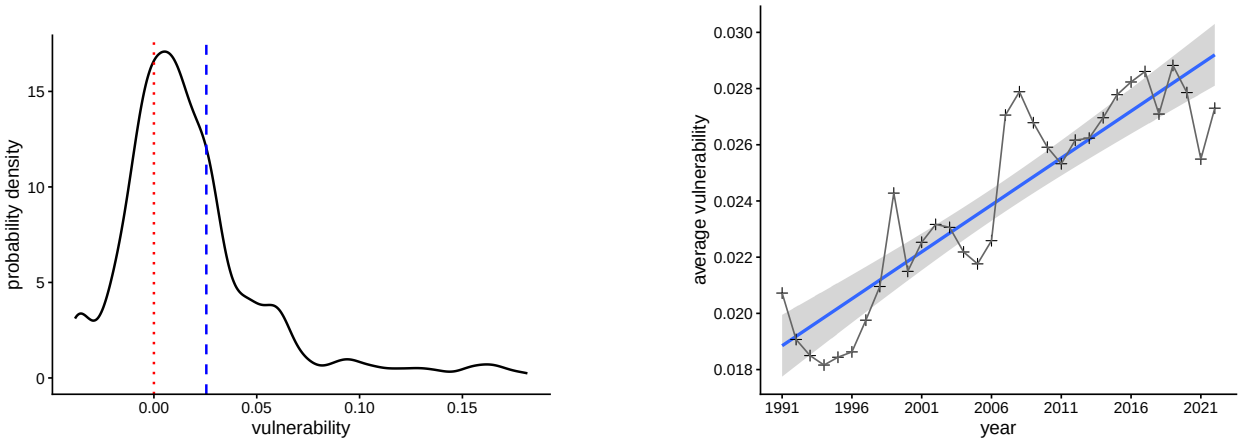
Next, we examine the differences in vulnerability across insurers. We classify insurers each year into quintiles of vulnerability such that the total direct premiums written are equal across quintiles.[12] Figure 6(a) shows the average vulnerability of insurers in five different buckets based on the quintile levels of vulnerability. The average vulnerability in the five categories ranges from -0.012 in the first quintile to 0.023 in the fourth quintile and 0.085 in the fifth quintile.[13] This suggests that unexpected property damages are associated with a slight decrease in loss ratios for

[11] House Bill 1A (2007) expanded the Florida Hurricane Catastrophe Fund and froze the rates for Citizens Property Insurance. The bill had the effect of reducing the price of state reinsurance and encouraged the entry of thinly capitalized, single line insurers that assumed large concentrations of coastal risk (Born and Klimaszewski-Blettner, 2013; Medders et al., 2014).

[12] Weighting by premiums written ensures that each quintile represents an equal share of the market's underwriting activity, rather than an equal number of firms, which is more appropriate given the skewed size distribution of insurers.

[13] A negative vulnerability reflects an insurer whose portfolio is weighted toward state–line segments where loss ratios tend to improve more in low-damage years than they deteriorate in high-damage years. Because our measure captures the average expected effect of abnormal damage shocks (rather than a forecast of losses), an insurer can exhibit a small negative value if its exposure is concentrated in markets with relatively strong downside responsiveness (β^{-}) and limited upside sensitivity (β^{+}). These values do not imply that the insurer "benefits" from catastrophes; they simply reflect the historical asymmetry in how loss ratios respond to abnormal damages.

Figure 5: Summary of vulnerability



(a) Distribution of vulnerability for all insurers, 2021

(b) Vulnerability over time

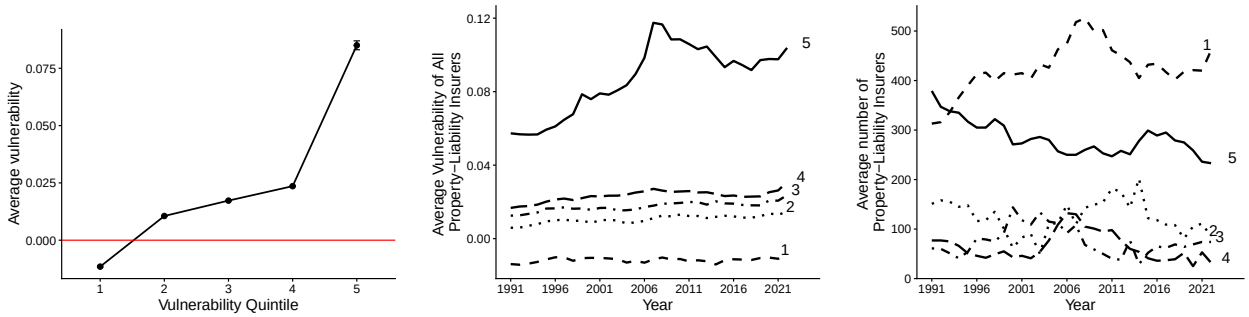
Notes: The figures plot the distribution of the middle 95% range (Panel A) and over time average trend (Panel B) of estimated vulnerabilities of insurers. In Panel A, the dotted line marks a vulnerability of zero and the dashed line marks the average vulnerability. Panel B plots the average of vulnerabilities for all insurers in a year for the period 1991–2021. The linear line and shaded band are the best-fit trend line and corresponding 95% confidence interval.

insurers in the first quintile. On the other hand, unexpected property damages increase loss ratios by 0.085 for the most vulnerable firms in the fifth quintile, an increase roughly four times that for insurers in the fourth quintile. These results suggest that insurers in the most vulnerable quintile are likely to be disproportionately exposed to more sensitive states and lines.

Figure 6(b) and (c) plot the average vulnerability and the number of insurers in each quintile by year. The figure shows that over the years, the average vulnerability in lower quintiles (quantiles 1 to 4) has remained stable, whereas the fifth quintile has experienced a sharp rise beginning in the mid-2000s and has since plateaued. Over the same period, the number of insurers in the fifth quintile declines from about 400 to 250. The combination of fewer firms and higher average vulnerability suggests that the increase in aggregate exposure is likely driven by greater risk concentration among a smaller set of insurers rather than a broad-based rise in vulnerability across the industry. This is consistent with the period following the 2006–08 regulatory and market changes discussed earlier, when underwriting in catastrophe-sensitive states became increasingly concentrated among specialized carriers.

These figures also suggest that not only are the most vulnerable insurers underwriting proportionately more sensitive lines, but they have also increased their risk over the years. However, as Figure A.1 and the discussion in Section 2.2 show, insurers can underwrite across a mix of states and lines to manage their vulnerability. The wide gap between insurers in the fifth and fourth quintiles suggests that insurers in the most vulnerable category likely do not manage their exposure to physical risk using diversification across states and lines of business.

Figure 6: Summary of vulnerability by quintile



(a) Vulnerability by quintile

(b) Vulnerability in each quintile by year

(c) Number of insurers in each quintile by year

Notes: Panel A plots the average vulnerability in each vulnerability-quintile. Panels B and C plot the average vulnerability and number of insurers, respectively, in each quintile by year. Quintile 1 includes insurers with the lowest vulnerability, while quintile 5 includes insurers with the highest vulnerability. The vulnerabilities are estimated based on the equation 3 using the state-line level premiums and sensitivities.

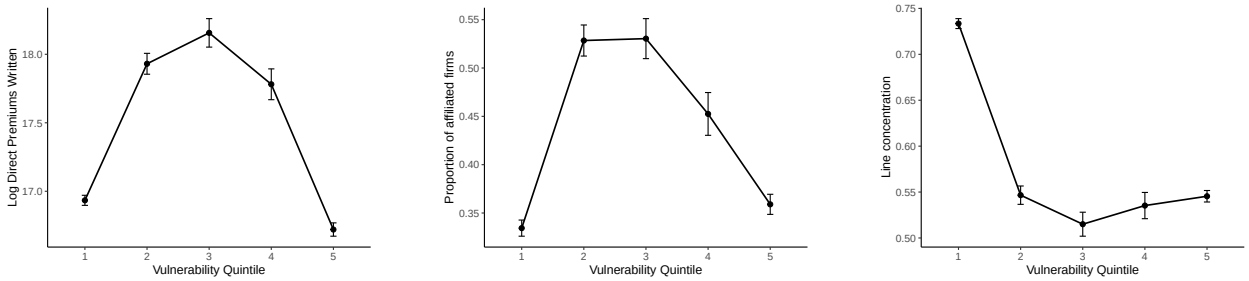
3.1 Characteristics of Vulnerable Firms

How are more vulnerable firms different from less vulnerable firms? Figure 7 plots average size (Panel a), proportion of affiliated insurers (Panel b), investment income (Panel d), return on equity (Panel e), and concentration by line (Panel c) and state (Panel f) for insurers in each vulnerability quintile.[14] Panels (a) and (b) indicate that larger and affiliated insurers tend to have medium vulnerability, whereas firms with the lowest and highest vulnerabilities are smaller and likely unaffiliated. This pattern likely reflects differences in business focus: smaller firms that focus on specific niche lines may have lower vulnerability, while those writing in riskier states face higher vulnerability due to the limited scale needed to diversify across less sensitive lines or states. Panels (c) and (f) provide further evidence supporting this hypothesis. Panel (c) shows that firms with lower vulnerability, on average, exhibit a higher line-level concentration, which suggests that those focusing on select niche lines mitigate exposures by avoiding more sensitive lines or states rather than extensive diversification. In contrast, firms with higher vulnerability–those in quintile 2 or higher—have a lower line concentration, implying that firms operating in more sensitive lines seek to diversify across multiple lines. However, Panel (f) shows that although more vulnerable firms diversify across lines of business, they maintain a high state-level concentration. This likely reflects strategic or regulatory constraints that limit their geographic diversification, resulting in greater concentration within certain states despite broader line-level diversification. Finally, panels (d) and (e) show that profitability, in particular the investment returns, is lowest for Q5 insurers.

We formally examine the differences between more and less vulnerable firms by regressing the vulnerability index on the financial and operational characteristics of the firms. Specifically, we estimate the following regression:

[14]Investment income is the ratio of investment gains to policy holder surplus. Return on equity is the ratio of net income before interest and tax by policyholder surplus.

Figure 7: Characteristics of vulnerable insurers



(a) Log Direct Premiums Written

(b) Proportion of Affiliated Insurers

(c) Line Concentration

(d) Investment Income

(e) Return on Equity

(f) State Concentration

Notes: The figure plots average insurer characteristics by quintiles of portfolio vulnerability. For each quintile, the markers show means and the error bars denote 95% confidence intervals. The figure reports in Panel (a) log of direct premiums written; Panel (b) proportion of firms affiliated to a group; Panel (c) and (f) line and state level Herfindahl-Hirschman Index (HHI), respectively; Panel (d) investment gain divided by policyholder surplus, and Panel (e) income before tax and dividend divided by policyholder surplus.

$$\begin{aligned}\text{vulnerability}_{it} = \beta_1 \text{statehhi}_{it} + \beta_2 \text{linehhi}_{it} + \beta_4 \text{logdpw}_{it} + \beta_5 \text{leverage}_{it} \\ + \beta_6 \text{isaff}_{it} + \beta_7 \text{uwge}_{it} + \beta_8 \text{invge}_{it} + \beta_9 \text{lossratio}_{it} + \theta_t + \epsilon_{it} \quad (5)\end{aligned}$$

where $vulnerability_{it}$ is the estimated vulnerability of insurer i in year t, $statehhi_{it}$ is the Herfindahl–Hirschman Index (HHI) of the insurer's geographic concentration across states, and $linehhi_{it}$ is the HHI of the insurer's concentration across lines of business. The interaction term $statehhi_{it} \times linehhi_{it}$ captures the combined effect of geographic and line concentration. $logdpw_{it}$ is the natural logarithm of direct premiums written, $leverage_{it}$ is the ratio of direct premiums written to policyholders' surplus, $isaff_{it}$ is an indicator variable equal to one if the insurer belongs to an insurance group (affiliate) and zero otherwise, $uwge_{it}$ is the underwriting gain-to-surplus ratio, $invge_{it}$ is the investment gain-to-surplus ratio, and $lossratio_{it}$ is the ratio of incurred losses to direct premiums. θ_t denotes year fixed effects, and ϵ_{it} is the error term.

Table 1 reports the results from estimating equation 5. The findings are consistent with the

Table 1: Insurer characteristics associated with vulnerability

Dependent Variable:	vulnerability		
Model:	(1)	(2)	(3)
state_hhi	0.017***	0.049***	0.019***
	(0.003)	(0.018)	(0.003)
line_hhi	−0.019***	−0.101***	−0.027***
	(0.003)	(0.019)	(0.004)
state_hhi × logdpw		−0.002*	
		(0.001)	
state_hhi × is_aff			−0.007
			(0.005)
line_hhi × logdpw		0.005***	
		(0.001)	
line_hhi × is_aff			0.021***
			(0.006)
logdpw	0.0010	−0.0007	0.001*
	(0.0006)	(0.0007)	(0.0006)
leverage	0.005***	0.005***	0.005***
	(0.0007)	(0.0007)	(0.0008)
is_aff	0.004	0.004	−0.005
	(0.003)	(0.003)	(0.005)
uwge	−0.008**	−0.009**	−0.009**
	(0.004)	(0.004)	(0.004)
invge	−0.129***	−0.130***	−0.130***
	(0.011)	(0.011)	(0.011)
lossratio	−0.008***	−0.008***	−0.008***
	(0.002)	(0.003)	(0.002)
Observations	30,268	30,268	30,268
R^2	0.092	0.096	0.096

Notes: The table shows the results of estimating equation 5. $vulnerability_{it}$ is the estimated vulnerability of insurer i in year t, $state_hhi_{it}$ is the Herfindahl–Hirschman Index (HHI) of the insurer's geographic concentration across states, and $line_hhi_{it}$ is the HHI of the insurer's concentration across lines of business. $logdpw_{it}$ is the natural logarithm of direct premiums written, $leverage_{it}$ is the ratio of direct premiums written to policyholders' surplus, is_aff_{it} is an indicator variable equal to one if the insurer belongs to an insurance group (affiliate) and zero otherwise, $uwge_{it}$ is the underwriting gain-to-surplus ratio, $invge_{it}$ is the investment gain-to-surplus ratio, and $lossratio_{it}$ is the ratio of incurred losses to direct premiums. Sample includes all property-liability insurers during 1991–2022. All specifications include year fixed effects and are weighted by log direct premiums written. Standard errors clustered at the insurer level are in parentheses. Significance levels are: ***: 0.01, **: 0.05, *: 0.1

preliminary patterns observed in Figure 7. We find that more vulnerable insurers tend to have higher geographic concentration, whereas greater line-level concentration is associated with lower vulnerability. This pattern suggests that firms focusing on specific lines generally underwrite less sensitive lines. In contrast, firms operating in more sensitive lines tend to diversify across multiple lines but remain geographically concentrated. The coefficient on the interaction term between state HHI and size (and affiliation indicator) is negative, though not always statistically significant. This indicates that larger insurers tend to concentrate their activities in less exposed states. In contrast, the interaction term between line HHI and size (and affiliation indicator) is positive, indicating that larger (and affiliated) firms are more likely to focus on more exposed lines. These results imply

that larger firms, which may be better equipped to manage sensitive portfolios, are more willing to assume risk in certain lines while avoiding exposure to more sensitive states. The findings highlight the potential influence of state regulation in shaping insurers' underwriting decisions (Born and Viscusi, 2006).

The coefficients on the two profitability measures—underwriting gain and investment gain—are negative, although statistically significant only for the latter. This suggests that insurers with higher vulnerability tend to have lower investment income. Consistent with this, Panel B of Figure 7 shows that return on equity is lower for firms in higher vulnerability quintiles. Taken together, these results indicate that more vulnerable firms have lower profitability, likely driven by reduced investment income. We also find that, after controlling for insurer size, greater vulnerability is associated with higher leverage. The estimates also show that insurers with higher vulnerability are associated with lower loss ratios. It is likely that insurers operating in more vulnerable lines and states adopt higher premium loadings and tighter underwriting standards that may keep their average loss ratios lower.[15]

Overall, our analysis suggests that more vulnerable firms—those operating in sensitive lines and states—tend to focus on fewer states while managing vulnerability by diversifying across multiple lines within the states in which they operate. These firms are often smaller than their less vulnerable peers and exhibit lower profitability, driven primarily by reduced investment income.

3.2 Spatial distribution of vulnerability

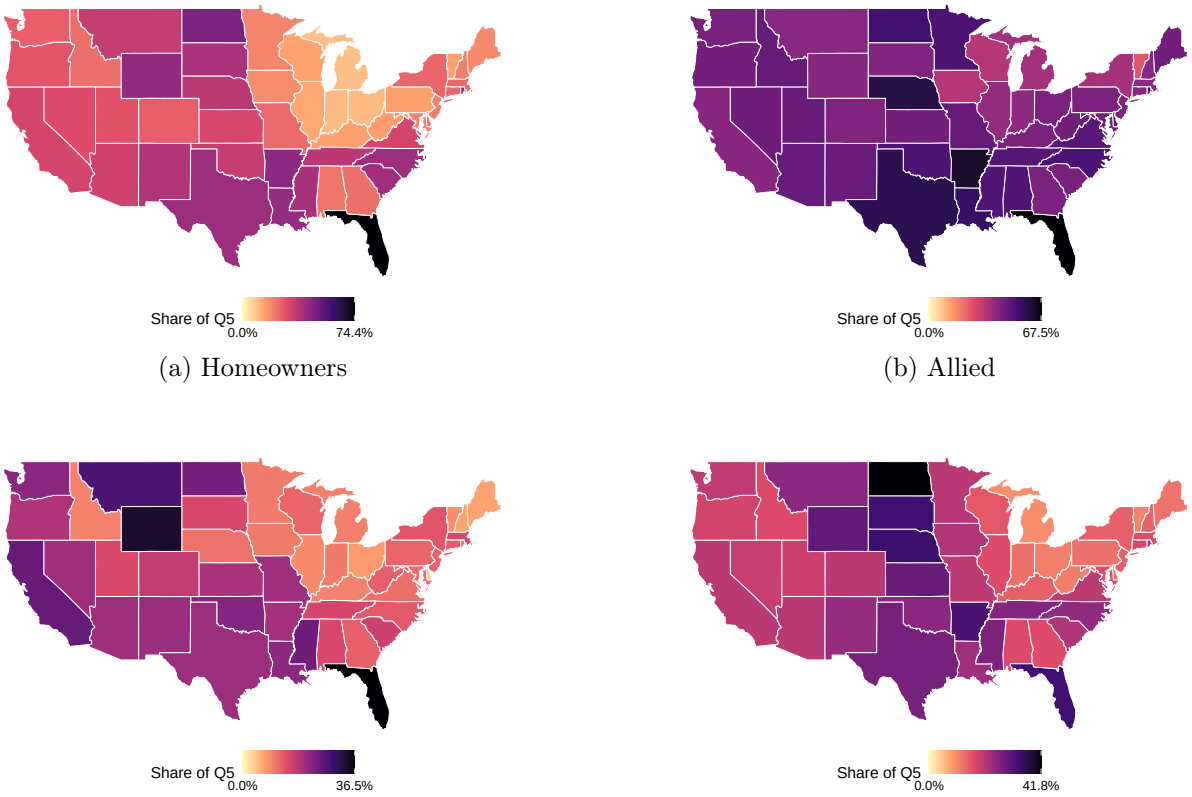
A key question of interest to regulators and policymakers is whether a state's insurance safety net is exposed to catastrophe risk through the composition of insurers writing in that state. Vulnerability can arise from in-state hazard exposure (e.g., hurricanes in Florida, wildfires in California) and from cross-state spillovers when insurers active in a state also hold concentrated catastrophe exposure elsewhere. Our vulnerability measure captures both channels at the insurer level, allowing us to examine how much of each state's market is served by the most vulnerable insurers.

Figure 8 maps, for each state, the share of premiums written by insurers in the highest vulnerability quintile (Q5). The panels report results for (a) Homeowners, (b) Allied, (c) Commercial Multiperil, and (d) total Property and Liability. Darker shading denotes a larger Q5 share; lighter shading denotes a smaller Q5 share. The statistic represents a within-state fraction: premiums written by Q5 insurers in a state divided by total premiums written in that state for the same line.

Figure 8 provides several insights. An intuitive insight is that states with higher catastrophe exposure–Florida, Texas, and California–exhibit a higher share written by the most vulnerable insurers. For example, in Homeowners, nearly three-quarters of Florida's market is written by Q5 insurers. By contrast, most Midwestern and Northeastern states display a relatively small footprint of vulnerable insurers. However, vulnerable insurers are not confined to the usual coastal markets of Texas and Florida; their presence extends broadly across other states. In fact, the figure shows

[15] This also follows from our design that ensures that the vulnerability measure reflect insurers' sensitivity to abnormal shocks in property damages, not the average level of their loss ratios.

Figure 8: Share of each state's total premiums written by Q5 insurers



(a) Homeowners

(b) Allied

(c) Commercial Multiperil

(d) All Property and Liability

Notes: The figure plots the share of portfolio in each state that is written by insurers with the highest vulnerability quintile (Q5) in 2021. The darker shade indicates a higher share written by vulnerable insurers, and the lighter shade indicates a lower share.

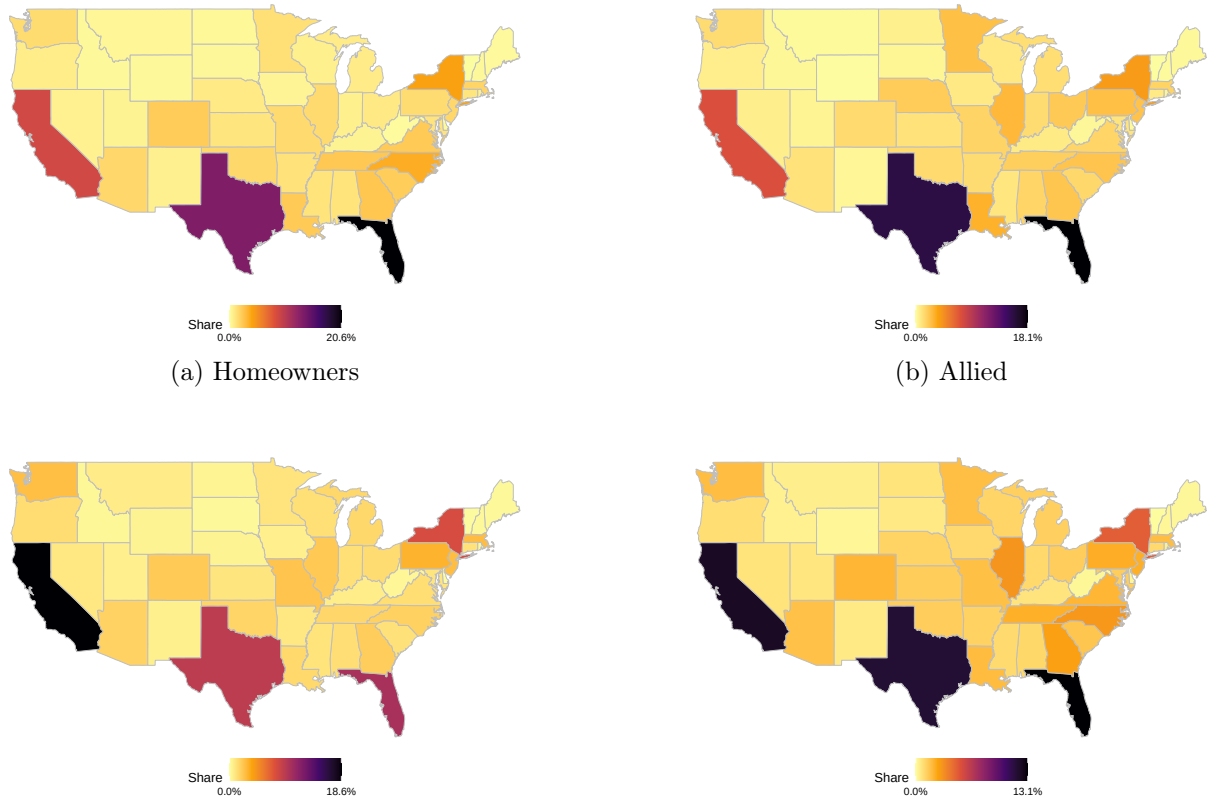
that a fairly large share of premiums is written by vulnerable insurers in non-coastal states. For example, vulnerable insurers account for a substantial portion of the portfolio across the Great Plains region–from the Dakotas to Texas. In Homeowners and Commercial Multiperil, the Dakotas, Montana, and Wyoming show relatively high shares. Similarly, the Allied line exhibits a higher share written by high-vulnerability insurers in most states. This underscores the need to monitor vulnerable insurers and their geographic footprint, as it may not be limited to the states traditionally considered catastrophe-prone.

3.3 Portfolio composition of highly vulnerable insurers

In this section, we examine where the most vulnerable insurers concentrate their underwriting activity. Specifically, we document the geographic and line-of-business composition of insurers in the highest vulnerability quintile (Q5), identifying the states and product lines that account for the

bulk of their exposure.[16]

Figure 9: Distribution of Q5 insurers' portfolios across states



(a) Homeowners

(b) Allied

(c) Commercial Multiperil

(d) All Property and Liability

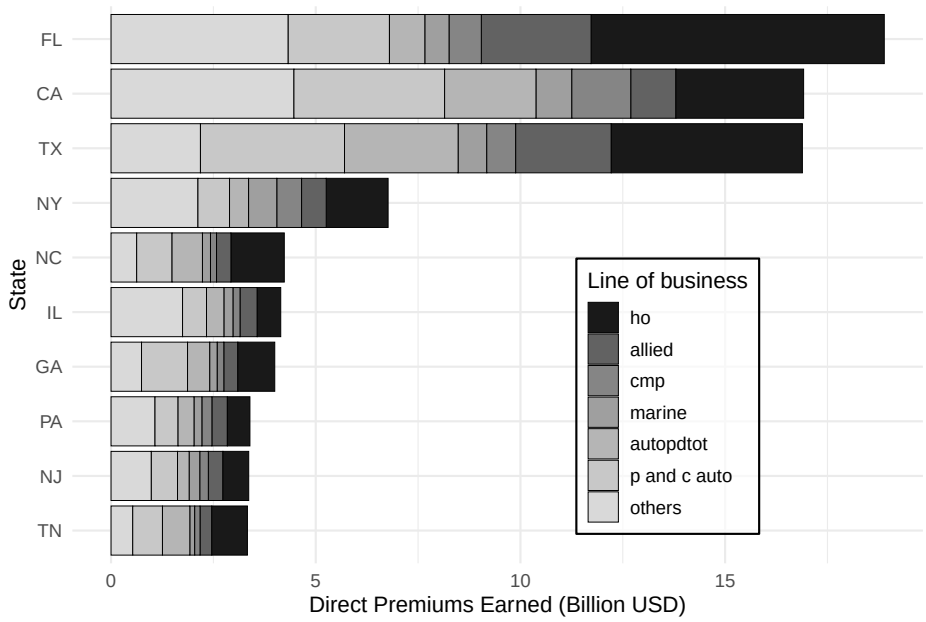
Notes: The figure plots the state-wise share of premiums written by insurers in the highest vulnerability quintile (Q5) in 2021. Dark shades indicate a higher share of premiums and lighter shades indicate a lower share.

Figure 9 maps the fraction of Q5 insurers' total premiums written in each state in 2021. Each panel reports one line of business–(a) Homeowners, (b) Allied, (c) Commercial Multiperil, and (d) all Property and Liability. Darker shading indicates that a larger fraction of the Q5 portfolio for that line is written in the state; lighter shading indicates a smaller fraction. The map shows a between-state composition measure of Q5 insurers' portfolio, not a within-state market share. Figure 10 plots the distribution of portfolios held by insurers in the highest vulnerability quintile (Q5) in the ten largest states. The bars show total direct premiums earned, segmented by major lines of business.

Figure 9 and Figure 10 show that the geographic distribution of Q5 insurers' portfolios is typically concentrated, with some variations across lines. Nearly half of the Q5 premiums are written in three states: Florida, Texas, and California. Florida and Texas dominate the homeowners and

[16] In Appendix Section B, we take a closer look at the top 20 most vulnerable insurers to characterize their size, age, and portfolio composition in greater detail.

Figure 10: Distribution of Q5 insurers' portfolios across states and lines of business



Notes: The figure shows the distribution of total direct premiums earned by insurers in the highest vulnerability quintile (Q5) across the ten largest states in 2021. Each bar represents the total premiums earned in a given state, segmented by line of business—Homeowners (*ho*), Allied, Commercial Multiperil (*cmp*), Inland, and Ocean *marine*), Total Auto Damage (*autopdtot*), Private and Commercial Auto Liability (*p and c auto*), and others, including Financial lines, Boiler and Machinery, Aviation, Earthquake, and other liability and casualty *(others)*. The stacked bar length reflects total exposure in billions of dollars.

allied lines, while California dominates the commercial multiperil. Most interior states individually account for a smaller fraction of Q5 premiums. This distribution aligns with conventional practice in the literature, which proxies catastrophe exposure using portfolio weights in Florida, California, and Texas. However, although these three states dominate Q5 exposures, they represent only about 40–50 percent of the Q5 portfolio. The remaining substantial share is distributed across interior markets, primarily in the Eastern and the Southeastern states. This means that relying solely on the "big three states" as proxies for catastrophe exposure likely understates the true vulnerability. It also suggests that sources of risks are more spread out, because shocks outside the traditional high-risk states can still materially affect these vulnerable insurers.

4 Risk Management by Insurers

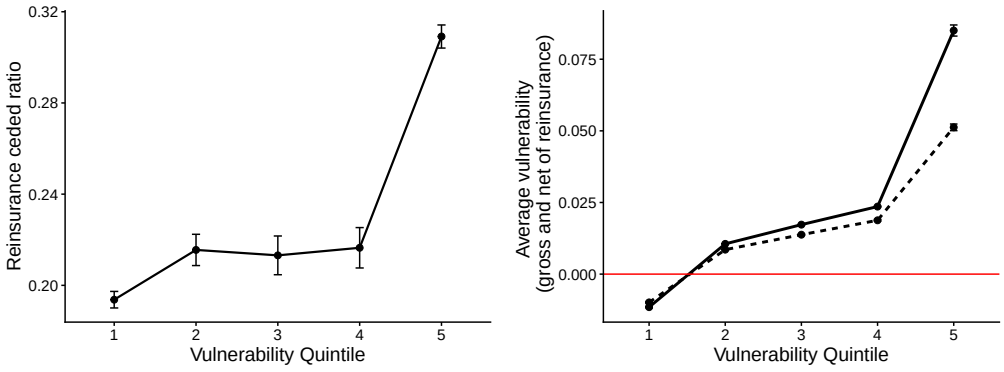
In this section, we use the vulnerability metric to examine how insurers manage catastrophe risk in their portfolio, with a focus on reinsurance and diversification strategies. In particular, we assess how reinsurance affects vulnerability and explore the tradeoff between the two risk management strategies.

4.1 Effect of Reinsurance on Vulnerability

So far, our analysis has focused on the direct written portfolio when estimating sensitivity and vulnerability. These calculations reflect the vulnerability of an insurer's directly written business. However, insurers can transfer part of this risk to other insurers through reinsurance. Although our measure incorporates risk management via diversification across lines and states, it does not capture risk transfer through reinsurance. In this section, we document that more vulnerable insurers purchase more reinsurance, and assess the extent to which reinsurance reduces their vulnerability.

Figure 11 plots the average reinsurance ratio across vulnerability quintiles (Panel a) and the effect of reinsurance on vulnerability (Panel b). The reinsurance ratio is defined as total reinsurance ceded to non-affiliates divided by total direct premiums written in a given year. To compute net vulnerability, we replace the gross portfolio weights in equation 3 with portfolio weights based on net premiums written, after adjusting for reinsurance ceded to and assumed from non-affiliates in each line.[17]

Figure 11: Reinsurance purchase and its effect on vulnerability



(a) Reinsurance ratio (b) Vulnerability net of reinsurance

Notes: Panel (a) reports the average reinsurance ratio estimated as the ratio of reinsurance ceded to nonaffiliates to direct premiums written. Panel (b) plots the average 'gross' vulnerability before reinsurance (solid line) and net vulnerability after reinsurance (dashed line).

Panel (a) shows that insurers in the highest vulnerability quintile cede, on average, 30.9% of their premiums to reinsurers. In contrast, insurers in quintiles 2, 3, and 4 each cede around 21.5%, while those in the lowest quintile cede 19.4% of their premiums to reinsurers. This pattern indicates that the most vulnerable insurers have a substantially higher demand for reinsurance and likely depend more heavily on it for risk management relative to their less vulnerable peers.

Panel (b) shows that, after accounting for reinsurance, the vulnerability of insurers in the top

[17]To estimate net portfolio weights for each state–line combination, we first calculate the ratio of non-affiliated reinsurance ceded and assumed in each line. Because our data do not report these ratios at the state–line level, we assume that reinsurance ratios within a line of business are constant across all states where that line is written. We then estimate net premiums written in each state–line combination by applying these ratios to adjust for ceded and assumed reinsurance.

quintile declines by 40%—from 0.085 to 0.051—while vulnerability in the fourth and third quintiles fall by around 19%. For the lower quintiles, the change is negligible, and for the least vulnerable insurers, vulnerability actually increases slightly. These results suggest that the most vulnerable insurers rely on reinsurance to a greater extent than their peers to reduce their vulnerability to catastrophe risk. This is likely because their ability to manage such risk through geographic diversification is limited. A key implication is that because the most vulnerable insurers rely more on reinsurance than diversification, they are hit hardest after large catastrophes and more exposed to rising reinsurance costs, exacerbating the premium impact on households (Keys and Mulder, 2024). In the next section, we take a closer look at these two risk management decisions. Specifically, we examine how reinsurance decisions are associated with diversification and how catastrophic vulnerability of insurers affects this interaction.

4.2 Reinsurance Demand and Diversification

How do insurers manage catastrophic exposure in their underwriting portfolios? Insurers can reduce exposure in high-risk areas, purchase reinsurance to cede risky exposure, or diversify across less-exposed states and lines of business. We investigate how insurers actually implement these strategies–whether they rely more on financial hedging through reinsurance or operational hedging through diversification. In practice, underwriting, diversification, and reinsurance decisions are likely made jointly, making it challenging to isolate the effect of an exogenous change in one margin on the other. Our objective is therefore not to establish causality, but to examine the trade-off between financial and operational hedging by examining the association between reinsurance purchases and diversification, and how vulnerability to catastrophe risk shapes that relationship.

We begin by estimating a baseline specification used in the prior literature, which examines the relationship between reinsurance usage and concentration:

$$rein_{it} = \gamma statehhi_{it} + \eta linehhi_{it} + \zeta X_{it} + \theta_t + \epsilon_{it} \tag{6}$$

where $rein_{it}$ is the reinsurance ratio, and $statehhi_{it}$ and $linehhi_{it}$ are state and line level HHI, respectively, of insurer i in year t. Rest of the controls and fixed effects are same as in specification shown in Equation (5). Column 1 of Table 2 presents the estimation results. Consistent with prior literature, the negative coefficients on both concentration measures suggest that insurers with higher geographic and line concentration purchase less reinsurance (Mayers and Smith, 1990; Cole and McCullough, 2006).

Next, we modify this baseline specification by adding our vulnerability measure:

$$rein_{it} = \beta vul_{it} + \gamma statehhi_{it} + \eta linehhi_{it} + \zeta X_{it} + \theta_t + \epsilon_{it} \tag{7}$$

Table 2, column 2, reports the results. The coefficient on vulnerability is positive and statistically significant: insurers with greater exposure to catastrophe risk cede more premiums to non-affiliated

Table 2: Effect of concentration and vulnerability on reinsurance usage

Dependent Variable:	reinsurance ratio		
Model:	(1)	(2)	(3)
state_hhi	-0.037^{***}	-0.058^{***}	-0.067^{***}
	(0.012)	(0.012)	(0.012)
line_hhi	-0.043^{***}	-0.020	-0.020
	(0.013)	(0.013)	(0.014)
vulnerability		1.210^{***}	0.748^{***}
		(0.090)	(0.259)
vulnerability × state_hhi			0.600^{**}
			(0.277)
vulnerability × line_hhi			-0.059
			(0.312)
Observations	30,268	30,268	30,268
R^2	0.17	0.22	0.22

Notes: The table shows the results of estimating equations 6, 7, and 8 in Columns 1, 2, and 3, respectively. Reinsurance ratio is the total reinsurance ceded to non-affiliates divided by direct premiums written. $vulnerability_{it}$ is the estimated vulnerability of insurer i in year t, $statehhi_{it}$ is the Herfindahl–Hirschman Index (HHI) of the insurer's geographic concentration across states, and $linehhi_{it}$ is the HHI of the insurer's concentration across lines of business. Other variables included in the regression but not shown in the table include: $logdpw_{it}$, natural logarithm of direct premiums written; $leverage_{it}$, ratio of direct premiums written to policyholders' surplus; $isaff_{it}$, an indicator variable equal to one if the insurer belongs to an insurance group (affiliate) and zero otherwise; $uwge_{it}$, the underwriting gain-to-surplus ratio; $invge_{it}$, the investment gain-to-surplus ratio; and $lossratio_{it}$, the ratio of incurred losses to direct premiums. The sample includes all property-liability insurers during 1991–2022. All specifications include year fixed effects and are weighted by log direct premiums written. Standard errors clustered at the insurer level are in parentheses. Significance levels are: ***: 0.01, **: 0.05, *: 0.1

reinsurers. Geographic and line concentration remain negatively associated with reinsurance usage, consistent with earlier findings. Mayers and Smith (1990) note that concentration creates opposing incentives for reinsurance: while higher concentration increases underwriting risk and therefore the demand for risk transfer, it also indicates greater specialization, which reduces reliance on the real services provided by reinsurers. Both Mayers and Smith (1990) and Cole and McCullough (2006) interpret negative coefficients on concentration as evidence that more focused insurers have less need for both risk management and the real-services provided by reinsurers.

However, these studies do not explicitly account for the vulnerability of the specific lines and states in which insurers operate. If higher concentration is also associated with greater exposure to catastrophe risk, the net effect on reinsurance demand could differ from previous findings. To explore this, we estimate a modified specification that interacts vulnerability with both concentration measures:

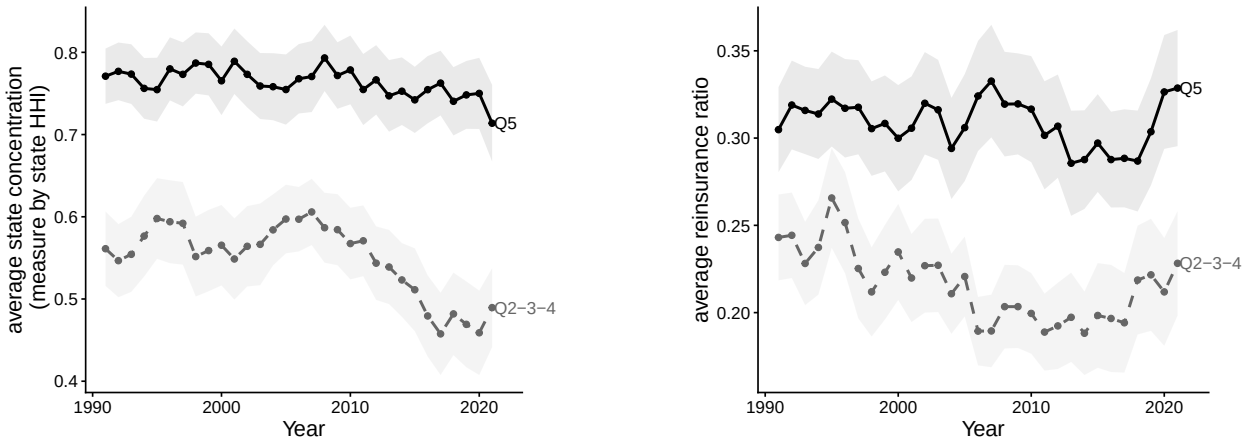
$$\begin{aligned} rein_{it} =& \beta_0 vul_{it} + \beta_1(vul_{it} \times statehhi_{it}) + \beta_2(vul_{it} \times linehhi_{it}) \\ &+ \beta_3 statehhi_{it} + \beta_4 linehhi_{it} + \beta_5 logdpw_{it} \\ &+ \beta_6 leverage_{it} + \beta_7 is_aff_{it} + \beta_8 roe_{it} + \beta_9 lir_{it} + \theta_t + \epsilon_{it} \end{aligned} \tag{8}$$

The results in column 3 of Table 2 show that the interaction between vulnerability and state con-

centration is positive and statistically significant, while the interaction between vulnerability and line concentration is negative but not statistically significant. The main effects of state and line concentration remain negative, though only significant for the state. These results suggest that the relationship between reinsurance demand and geographic concentration is contingent upon an insurer's vulnerability to catastrophe risk. Specifically, when vulnerability is high, greater geographic concentration is associated with higher reinsurance demand.

We also observe this trade-off when comparing the time series patterns of state concentration and reinsurance purchase between more and less vulnerable insurers. Figure 12(a) shows a growing divergence over time in the geographic concentration of highly vulnerable insurers (Q5) relative to those in the middle vulnerability group (Q2–Q4). Panel (b) further shows that Q5 insurers consistently cede a larger share of their premiums to non-affiliates, highlighting their greater reliance on reinsurance as a risk-management tool.

Figure 12: Geographic concentration and reinsurance use by vulnerability



(a) State concentration (HHI)

(b) Reinsurance ratio

Notes: The figure plots average state concentration (Panel a) and average reinsurance ratio (Panel b) for insurers in the highest vulnerability quintile (Q5) and those in the middle vulnerability group (Q2–Q4) during 1991–2021. State concentration is measured by the Herfindahl–Hirschman Index (HHI) across states, and the reinsurance ratio is calculated as the ratio of reinsurance ceded to non-affiliates to direct premiums written. Error ribbons are based on 95% confidence intervals around mean in each year.

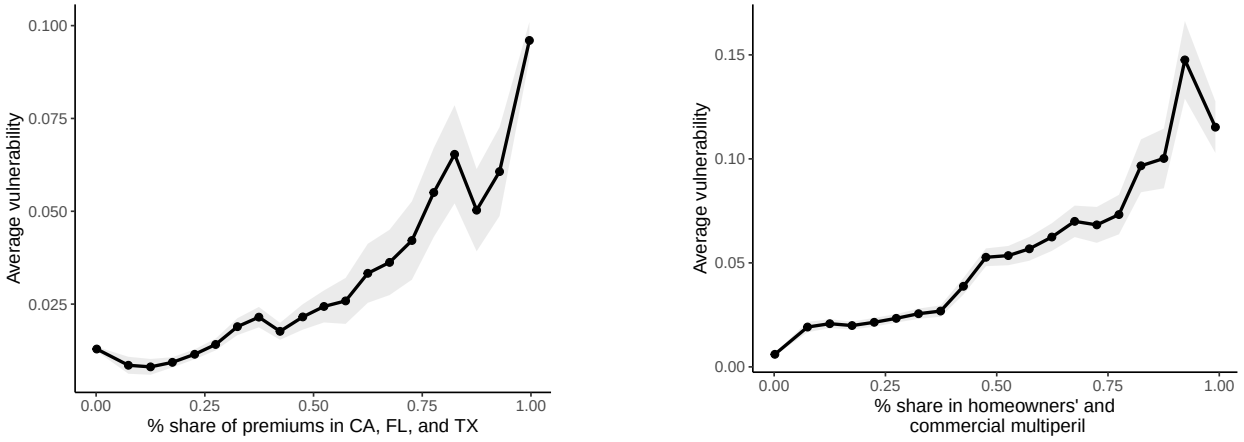
This finding adds to the reinsurance–diversification literature in two key ways. First, it demonstrates that the negative association between concentration and reinsurance demand documented by Mayers and Smith (1990) and Cole and McCullough (2006) is not uniform but varies systematically with exposure to catastrophe risk. Geographic concentration in highly vulnerable portfolios increases the need for risk transfer through reinsurance. Second, by incorporating a direct, insurer-specific measure of catastrophic vulnerability, our analysis captures a new dimension of catastrophe risk exposure that prior work has not explicitly modeled. This approach enables us to distinguish whether concentrated insurers buy less reinsurance because their specialization enhances their ability to bear risk, or because they simply operate in less vulnerable markets. Our results suggest that

when concentration coincides with high vulnerability, insurers rely more heavily on reinsurance as a risk management tool.

5 Robustness Test: Added Information in Vulnerability Index

In this section, we test whether the vulnerability metric provides additional information about an insurer's risk, beyond what is conveyed by simple exposure measures, such as the share of premiums written in catastrophe-prone states or lines. Figure 13 shows the relationship between our metric and the traditional exposure measures. The figure illustrates the correlation between the vulnerability index and insurers' exposures to Florida, Texas, and California (Panel a), as well as to the homeowners and commercial multiperil lines (Panel b)–states and lines commonly used in the literature as proxies for catastrophe risk (Ge and Weisbach, 2021). The results show a strong positive correlation between vulnerability and exposures in high-risk states and lines. The relationship is also nonlinear, suggesting that the vulnerability index likely contains information beyond what exposure measures alone provide. In this section, we evaluate whether the vulnerability index provides incremental information about insurers' exposure to catastrophe risk beyond the standard state- and line-based exposure proxies.

Figure 13: Average vulnerability by premium share in sensitive states and lines



(a) Vulnerability by state exposure

(b) Vulnerability by line exposure

Notes: The figure shows binned scatter plots of average insurer vulnerability by share of direct premiums written in California, Florida, and Texas (Panel A) and by share of direct premiums written in Homeowners and Commercial Multi-Peril (Panel B). The markers show means and the error bars denote 95% confidence intervals.

One way to assess the additional information captured by the vulnerability index is to examine whether it explains the riskiness of insurers' operations after controlling for common measures of catastrophe-risk exposure. We do this by testing whether the vulnerability index is associated with higher probability of an insurer becoming defunct in subsequent years. Specifically, we evaluate whether the vulnerability index retains a statistically significant role in explaining insolvency risk

even after controlling for insurers' exposure to catastrophe-prone states and lines, geographic and line-level concentration, and other financial and operating characteristics associated with failure.

We obtain the list of insurers that became defunct from S&P Capital IQ for the period 1993–2025.[18] We define a variable, $defunct$, equal to 1 if an insurer becomes defunct in the following year or later. Our sample includes all insurer groups and unaffiliated single insurers with direct written premiums exceeding USD 10 million.[19] To examine whether insurers with higher vulnerability are more likely to become defunct, we estimate a logistic regression of insurer failure on the vulnerability index and relevant controls:

$$\text{logit}\big(\Pr(defunct_{it}=1)\big) = \beta\, vul_{it} + \gamma' X_{it} + \zeta' Z_{it} + \theta_t + \epsilon_{it}, \tag{9}$$

where $defunct_{it}$ is an indicator variable, which is 1 if the insurer i goes defunct next year or later. vul_{it} is the vulnerability of the insurer in year t. X_{it} is a vector of six exposure variables, which are the shares of direct premiums written in each of the three states–California, Florida, and Texas, as well as in each of the three lines of business–homeowners, allied, and commercial multiperil. Z_{it} is a vector of control variables which include log of direct premiums written, leverage measured as the premiums divided by policyholders' surplus, return on equity, underwriting income, investment income, indicator variable that is 1 if the insurer is affiliated to a group, reinsurance ratio, and the state and line level concentration measured by the Herfindahl–Hirschman index (HHI). The coefficient β measures the relationship between the vulnerability index and the probability of insurer failure, after accounting for financial and exposure characteristics. θ_t includes year fixed effects to control for common shocks in a year. We cluster standard errors at the insurer level.

Table 3 presents the results from estimating equation (9). Column (1) reports the effect of vulnerability without additional controls. Column (2) adds controls for financial characteristics and exposure to sensitive states and lines. Column (3) further includes interaction terms for state and line exposures. Column (4) estimates the effect of financial and exposure-related factors in the absence of the vulnerability measure. The coefficient on *vulnerability* is positive and statistically significant across all specifications. This result suggests that the vulnerability measure provides a meaningful explanatory power for insurer failure even after controlling for financial and exposure-related characteristics. The coefficient on the vulnerability index implies that moving from the 5th to the 95th percentile of vulnerability in our sample (from -0.04 to 0.14) is associated with nearly two- to six-fold increase in the odds of insurer failure, depending on the specification.[20]

[18] S&P Capital IQ classifies insurers as defunct when they have ceased active operations, typically due to receivership, bankruptcy, liquidation, or acquisition by another entity. To restrict the sample to truly inactive firms, we exclude insurers classified as defunct that continue to report financial data to the NAIC after the reported defunct year.

[19] We impose this minimum size threshold to exclude trivially small insurers that may be winding down operations for reasons unrelated to financial distress. Our results are robust to alternative thresholds of USD 5 million and USD 50 million.

[20] During 2021, the 5th and 95th percentiles of the vulnerability in our sample are -0.038 and 0.140, respectively, implying an increase of $\Delta vul = 0.178$. Given estimated coefficients of 4.35 to 10.69, the corresponding change in the log-odds of failure is $\beta \times \Delta vul = 0.77$ to 1.9, which results in a change in odds ratio of $\exp(0.77) = 2.2$ to $\exp(1.9) = 6.7$.

Table 3: Effect of vulnerability on insurer failure

Dependent Variable:	defunct			
Model:	(1)	(2)	(3)	(4)
vulnerability	4.35***	5.28**	10.69***	
	(1.1)	(2.6)	(4.1)	
logdpw		0.09	0.12	0.11
		(0.10)	(0.10)	(0.10)
leverage		0.09	0.09	0.09
		(0.06)	(0.06)	(0.06)
roe		−0.86	−0.74	−0.75
		(0.79)	(0.80)	(0.78)
uwge		−0.19	−0.36	−0.29
		(0.84)	(0.85)	(0.83)
invge		−1.2	−1.4	−1.4
		(1.5)	(1.5)	(1.5)
is_aff		−0.26	−0.27	−0.27
		(0.29)	(0.30)	(0.29)
state_hhi		0.46	0.42	0.46
		(0.38)	(0.39)	(0.38)
line_hhi		0.54	0.64	0.76
		(0.50)	(0.53)	(0.48)
reins ratio		0.87*	0.92**	1.03**
		(0.44)	(0.45)	(0.44)
% in FL		0.88*	1.16***	1.33***
		(0.50)	(0.45)	(0.37)
% in TX		0.56	0.35	0.63
		(0.61)	(0.73)	(0.60)
% in CA		0.17	0.19	0.30
		(0.45)	(0.49)	(0.45)
% in homeowners		−2.25***	−2.32**	−0.60
		(0.86)	(1.0)	(0.44)
% in cmp		−0.87	0.07	−0.65
		(0.69)	(0.77)	(0.67)
% in allied		−1.71*	−2.82	−0.92
		(0.98)	(2.0)	(0.82)
state × line interaction	No	No	Yes	No
Observations	18,061	18,061	18,061	18,061

Notes: The table shows the results of estimating equation 9. The dependent variable, $defunct_{it}$, equals 1 if insurer i becomes inactive in or after year $t+1$, and 0 otherwise. $vulnerability_{it}$ is the estimated vulnerability of insurer i in year t. $logdpw_{it}$ is the log of direct premiums written; $leverage_{it}$ is the ratio of direct premiums written to policyholders' surplus; roe_{it} is return on equity; $uwge_{it}$ and $invge_{it}$ are the underwriting and investment gain-to-surplus ratios, respectively; is_aff_{it} equals 1 if the insurer belongs to a group and 0 otherwise; $state_hhi_{it}$ and $line_hhi_{it}$ are Herfindahl–Hirschman indices of state and line-of-business concentration; $reinsratio_{it}$ is reinsurance ceded to non-affiliates divided by direct premiums written; and the shares in Florida (FL), Texas (TX), and California (CA) and in the homeowners, commercial multi-peril, and allied lines measure exposure to those states and lines. All specifications include year fixed effects and are weighted by log direct premiums written. Standard errors clustered at the insurer level are in parentheses. Significance levels are ***: 0.01, **: 0.05, *: 0.1.

6 Conclusion

As property-liability insurers face growing insurance losses from natural disasters, it has become increasingly important to assess and monitor their exposure to catastrophe shocks. This paper

develops a systematic, data-driven method to quantify the vulnerability of property-liability insurers to catastrophe risk. Using granular underwriting and disaster loss data from 1991–2021, we estimate state-line-level sensitivities to unexpected disaster losses and combine them with each insurer's underwriting portfolio to construct an insurer-level vulnerability metric.

Our analysis shows that sensitivities vary widely across lines and states, with property lines and coastal states exhibiting the highest transmission of disaster-related damages to insured losses. The state–line-level sensitivities estimated using our framework can provide practical guidance to insurers in calibrating portfolio diversification, adjusting underwriting exposure in high-sensitivity markets, and evaluating solvency under varying catastrophe scenarios.

Using the vulnerability metric, we find that a small subset of insurers accounts for most of the vulnerabilities of the sector, and their exposure has grown significantly over time. The vulnerability metric remains associated with insurer failures, even after accounting for exposure to catastrophe-prone states and lines, portfolio concentration, and other financial variables, underscoring its potential value beyond the traditional proxies of insurers' catastrophe risk exposure used in the literature.

Our analyses also provide insights into how insurers manage catastrophe exposure through diversification and reinsurance. We demonstrate that most insurers manage their catastrophe exposure by diversifying across states and lines of business. In contrast, the most vulnerable insurers, typically smaller and more geographically concentrated, rely heavily on reinsurance to buffer against large losses. Our estimates indicate that reinsurance usage can reduce the vulnerability by around 40 percent for the most vulnerable insurers, yet their exposure remains substantially higher than that of diversified peers. Our analysis also provides insights into the negative relationship between concentration and reinsurance purchases highlighted in prior literature. We show that while concentration generally reduces the reinsurance usage, among highly vulnerable insurers, limited diversification is associated with higher reinsurance purchase. Overall, these results highlight the resilience of diversified national carriers and the vulnerable position of concentrated local insurers that rely heavily on reinsurance. An important implication of our results is that public policies that promote participation by large national carriers and encourage geographic diversification can enhance the stability of catastrophe insurance markets.

This paper provides a transparent and practical framework for insurers, regulators, and researchers to assess, monitor, and mitigate catastrophe vulnerabilities. The proposed metrics offer quantitative guidance for portfolio diversification, capital planning, and regulatory oversight, and can be readily adapted across perils, time periods, and risk-transfer mechanisms. Future research can extend this framework by incorporating forward-looking climate projections, more detailed reinsurance structures, and alternative risk-transfer mechanisms such as catastrophe bonds and insurance-linked securities.

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Appendix

Measuring Insurer Vulnerability to Catastrophe Risk

A Estimating Sensitivity

A.1 Overall sensitivity of loss ratios

Specifically, we estimate the following regression:

$$lossratio_{islt} = \beta^{+} D_{st}^{+} + \beta^{-} D_{st}^{-} + \alpha_i + \lambda_l + \theta_t + \epsilon_{islt} \tag{A.1}$$

where α_i, λ_l, and θ_t are insurer, line, and year level fixed effects. Table A.1 shows the results of regression estimates.

Table A.1: Effect of abnormal damages on U.S. Property-Liability loss ratios: Pooled Sample

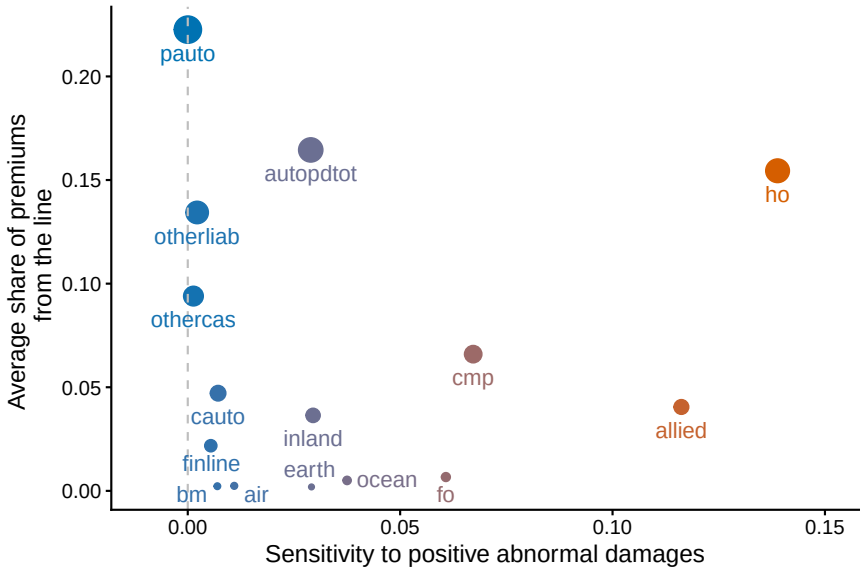
Dependent Variable:	*Loss ratio*
Positive Abnormal Damages	0.380***
	(0.005)
Negative Abnormal Damages	0.005
	(0.003)
Insurer-Line-State-Year Fixed Effects	Yes
Observations	1,706,180

Notes: The table shows the results from estimating the regression models in Equation A.1. The regression is estimated by pooling all observations across all insurers, lines, and states for the period 1991—2021. Significance Level: ***: 0.01, **: 0.05, *: 0.1

A.2 Line level sensitivity and market share

Figure A.1 shows the line-level sensitivities to positive abnormal damages in the context of each line's relative size in the U.S. property–liability insurance market. The horizontal axis plots the estimated sensitivity, while the vertical axis measures the average share of industry premiums written in that line since 2015. The figure shows that among the most sensitive lines, homeowners, allied, and commercial multiperil are also among the larger lines for the industry, implying that catastrophe-related property damages can meaningfully affect a sizable portion of the market. In contrast, some of the largest lines—such as private passenger auto liability and physical damage, other liability, and other casualty—display relatively low sensitivities to abnormal damages. This dispersion in both size and sensitivity across lines suggests that the aggregate industry loss exposure to catastrophe risk can be mitigated by diversification: large premium volumes are often concentrated in lines with lower catastrophe sensitivity, while highly sensitive lines tend to comprise a smaller share of total premiums. A key question to examine next is whether some firms are more focused on lines and geographies that are most sensitive to abnormal damages. Such firms, if unable to benefit from diversification, will be more vulnerable to catastrophe risk than their more diversified counterparts.

Figure A.1: Line size and sensitivity to positive abnormal damages



Notes: The figure plots the sensitivity of each line of business to positive abnormal damages (x-axis) against the average share of industry premiums written in that line since 2015 (y-axis). Sensitivities are estimated from the regression model $lossratio_{islt} = \beta_l^+ D_{st}^+ + \beta_l^- D_{st}^- + \alpha_{is} + \theta_t + \epsilon_{islt}$, where $lossratio_{islt}$ is the loss ratio of insurer i in line l and state s in year t. D_{st}^+ measures positive unexpected losses in state s in year t based on the SHELDUS data. The specification controls for insurer-state and year fixed effects, and the regression is estimated separately for each line of business, pooling all observations across states for the period 1991–2021. The size of each bubble reflects the average share of industry premiums written in that line.

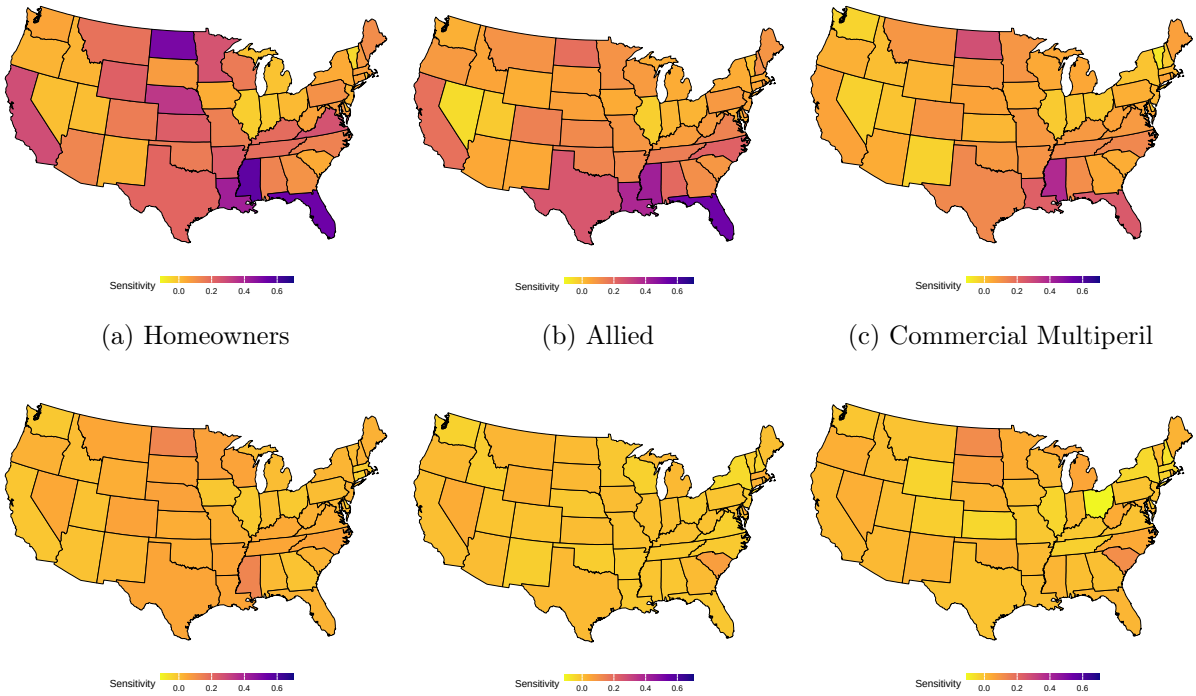
A.3 Mapping the state-line level sensitivities

Figure A.2 plots the line level sensitivities by state on the geographic map for 51 contiguous states in the U.S. Panels (a), (b), and (c) plot the sensitivities for the three most sensitive lines—homeowners, allied, and commercial multiperil. Panels (d), (e), and (f) plot the sensitivities for the three largest remaining lines—auto physical damage, personal auto liability, and commercial auto liability. The figures show significant variations in sensitivity across states. They also suggest that this sensitivity may be correlated with the geographic location of the states. So, it is likely that there are limited actions insurers or policyholders can take to reduce this sensitivity. Figures (d), (e), and (f) provide additional evidence that some lines may be immune to unexpected physical damages even when they are underwritten in highly exposed states.

B A Closer Look at Top 20 Vulnerable insurers

In this section, we examine some outliers in the spectrum of insurer vulnerability to understand who they are and how they manage risk. Table B.2 reports the 20 insurers with the highest vulnerability over 2018–2022, along with basic financial information, the premium shares in Homeowners,

Figure A.2: State-level sensitivities for various insurance lines



(a) Homeowners (b) Allied (c) Commercial Multiperil

(d) Auto Damage (e) Personal Auto (f) Commercial Auto

Notes: The figure plots the estimates of state-line-level sensitivities for six lines of business for 51 contiguous states in the US. Sensitivities are estimated from the regression model: $lossratio_{islt} = \beta_l^+ D_{st}^+ + \beta_l^- D_{st}^- + \alpha_i + year_t + \epsilon_{islt}$, where $lossratio_{islt}$ is the loss ratio of insurer i in line l and state s in year t. D_{st}^+ measures positive unexpected losses in state s in year t based on the SHELDUS data. The specification controls for insurer fixed effects and includes a linear term for year trends. The regression is estimated separately for each state and line of business the for the period 1991–2021. The darker shade indicates a higher sensitivity, and ligher share indicates a lower (or negative) sensitivity of a line in a state.

Commercial Multiperil, and Allied, and the three states with the largest premium shares.[21] The table highlights key characteristics of these firms. First, they are both small in size and relatively young, with an average net premium written of 135 million, compared to the industry average of 726 million. Moreover, except for two firms, all were established after 1990. In terms of geographic and product-line distribution, the majority of these insurers exhibit substantial exposure to Florida and to homeowners insurance. Fifteen of the 20 firms derive most of their premiums from Florida; six have significant exposure in Louisiana; and three have substantial shares in Mississippi or Texas. On average, these 20 firms derive 80% of their total premiums from homeowner insurance, compared with an industry mean of only 10%. Notably, three firms are exclusively focused on homeowners insurance. This concentration is also reflected in their mean Herfindahl-Hirschman Index of 0.80 for state exposure and 0.76 for product-line exposure, both well above the industry averages of 0.60 and 0.66, respectively.

Third, these insurers rely heavily on reinsurance to manage risk. Their average reinsurance-to-premium ratio is 0.66, compared with an industry average of only 0.24. Lastly, these firms are also highly leveraged and financially fragile. From 2018 to 2022, their average leverage ratio was 4.01, more than twice the industry average of 1.83. Only five firms reported a positive return on equity (ROE) during this period; seven are no longer active today.[22] This finding suggests that insurers highly vulnerable to climate risk face substantial insolvency risk, underscoring the need for heightened regulatory oversight.

The above findings point to Florida's homeowners insurance market as the segment most vulnerable to climate risk.[23] This result is unsurprising, given that Florida is the state most exposed to hurricanes in the United States. Florida's homeowners market has evolved into a specialized ecosystem in which large national carriers write little to no business, deterred by high catastrophe exposure, elevated litigation costs, heavy dependence on reinsurance, and regulatory constraints on pricing that together undermine profitability. In their place, the market is dominated by small Florida-domiciled specialists (e.g., Universal, Tower Hill, Slide)[24] alongside Citizens, the state residual market (Kousky and Medders, 2024).[25] These domestic carriers operate as concentrated monolines—effectively "all-in" on one peril and one state.[26] Domestic carriers rely heavily on private

[21] We require that each of the top three states have a minimum premium share of 15%.

[22] Gulfstream Property & Casualty Insurance Company was liquidated in 2021. Avatar Property & Casualty Insurance Company, St. Johns Insurance Company, FedNat Insurance Company, Southern Fidelity Insurance Company, Excalibur National Insurance Company and Americas Insurance Company (a subsidiary of Assure Holding Corp Group) were liquidated in 2022.

[23] Cole and Fier (2025) provide a detailed account on the evolution of structure and profitability of Florida's homeowners market.

[24] Regional insurers may have a competitive advantage given their deep local roots and a loyal customer base. They may also have developed a deep understanding of its unique risk landscape by operating in a state for a long time, enabling them to build sophisticated risk models tailored to local conditions and price risk more accurately.

[25] Citizens Property Insurance Corporation (Citizens) is Florida's state-run residual market for property insurance. It provides property insurance coverage to Floridians who cannot find affordable coverage in the private market. In practice, although intended as an insurer of last resort, Citizens frequently becomes one of the largest players in the market when private insurers withdraw.

[26] Insurers face several challenges when expanding and operating across multiple states. A key challenge is the requirement for increased capital resources to sustain expanded operations, in addition to expenses involved in

reinsurance supplemented by the Florida Hurricane Catastrophe Fund (FHCF), a state-backed, low-cost, mandatory program that reimburses a portion of hurricane losses.[27] While the FHCF provides a stabilizing layer, its coverage is limited to specific risk tranches, leaving firms exposed to private reinsurance cycle volatility above that layer.[28] Moreover, both the FHCF and Citizens concentrate on undiversified Florida hurricane risk and may face funding pressure after severe seasons, potentially necessitating bonding and broad assessments. Subsidization can also weaken price signals and sustain fragile balance sheets. Taken together, this structure—small, concentrated carriers supported by government programs and volatile reinsurance—raises concerns about the system's resilience and long-run sustainability.

Our vulnerability metric can serve as a monitoring tool for regulators to identify insurers with high climate risk exposure and, consequently, elevated insolvency risk. Moreover, our findings in Section 3.2 and Section 4.2 suggest that a reasonable degree of diversification may substantially reduce an insurer's vulnerability to catastrophic loss. From a policy perspective, this implies that Florida may need to reform its current insurance ecosystem to make its risk more insurable and attract large national carriers that are better positioned to diversify risk.

obtaining licenses and establishing new distribution channels in each state. Another challenge is the complexity of insurance regulations from state to state. Since insurance is regulated at the state level, each state has its own regulatory framework. Insurers that operate across states will need to navigate unfamiliar compliance requirements and filing systems, which can be both time-consuming and costly.

[27] The Florida Hurricane Catastrophe Fund was established in 1993, after Hurricane Andrew. Details of FHCF can be found at https://fhcf.sbafla.com/

[28] In 2022, the state introduced an additional layer of support through the Reinsurance to Assist Policyholders (RAP) program, which was designed to further share the financial burden of insurance companies regarding hurricane losses.

Table B.2: Top 20 Vulnerable insurers: concentration, premium mix, and geography

Rank	Company/Group Name	Founding Year	NPW	ROE	Concentration		Leverage	Rein	% Premium in			Top States (Premium > 15%)
					State	Line			HO	CMP	Allied	
1	Avatar Property & Casualty Ins. Co.*	2008	29.04	−0.39	1.00	0.74	3.88	0.63	0.85	0.04	0.10	FL
2	Slide Insurance Company*	2022	221.20	0.06	0.97	0.90	9.43	0.54	0.90	0.00	0.10	FL
3	People's Trust Insurance	2008	97.89	0.01	1.00	0.63	3.69	0.60	0.74	0.00	0.25	FL
4	Tower Hill Insurance	1972	158.90	−0.12	0.96	0.72	2.91	0.62	0.83	0.04	0.09	FL
5	St. Johns Insurance Company	2003	31.53	−0.55	0.91	0.83	7.93	0.91	0.91	0.00	0.08	FL
6	Weston Insurance Company	2012	10.95	−0.33	0.73	0.86	2.58	0.91	0.10	0.00	0.82	FL, TX
7	Safepoint Insurance Company	2013	16.05	−0.12	0.85	0.45	3.88	0.69	0.51	0.03	0.41	FL
8	HCI Group Inc.	2007	341.00	−0.14	1.00	0.79	2.86	0.38	0.89	0.00	0.11	FL
9	Capitol Preferred Insurance	1998	57.09	−0.60	0.70	0.60	4.93	0.73	0.72	0.00	0.26	FL
10	Universal Insurance Holdings	1997	982.60	−0.26	0.71	0.89	4.12	0.33	0.94	0.00	0.06	FL
11	Gulfstream Property & Casualty Ins. Co.*	2005	34.22	−0.56	0.57	0.78	4.98	0.78	0.87	0.00	0.08	FL
12	FedNat Insurance Company*†	1992	239.40	−0.34	0.56	0.73	3.46	0.68	0.86	0.00	0.10	FL, TX
13	Frontline Insurance Group	1998	223.80	0.01	0.63	0.60	5.51	0.70	0.74	0.04	0.15	FL, NC
14	Southern Fidelity Insurance Company*†	2005	113.90	−0.41	0.44	0.58	3.25	0.37	0.70	0.00	0.30	FL, LA
15	Cypress Group Holdings, Inc.	1998	32.12	−0.21	0.52	0.66	3.41	0.48	0.81	0.00	0.09	FL, TX
16	Amfirst Holdings Group	1999	5.26	0.16	1.00	1.00	0.19	0.71	1.00	0.00	0.00	MS
17	Property Insurance Company of America	2021	1.61	0.01	1.00	1.00	1.72	0.85	1.00	0.00	0.00	MS
18	Gulf State Insurance Group	2016	9.61	−0.08	0.63	0.83	3.07	0.74	0.86	0.00	0.07	LA, MS
19	Excalibur National Insurance Company*	2016	8.10	−0.40	1.00	1.00	5.23	0.62	1.00	0.00	0.00	LA
20	Assure Holding Corp Group*	1963	1.77	−0.02	0.98	0.66	3.14	0.93	0.78	0.00	0.20	LA

Notes: NPW denotes net premiums written (USD, millions). ROE is return on equity. "State" and "Line" show concentration measured as HHI. "Leverage" is the ratio of direct premiums written by policyholder surplus. "Rein" is reinsurance ceded to non-affiliates divided by direct premiums written. "HO," "CMP," and "Allied" report the fraction of the firm's premiums in those lines. "Top 3 States" lists any state where the firm writes more than 15% of its premiums.

* Indicates that the insurer is no longer active in the market.

† Assure Holding Corp Group is the parent company of Americas Insurance Company (AIC) and Quality Casualty Insurance Company (QAIC). QAIC was incorporated in 2001, purchased by AIC in 2013 and liquidated in 2021. AIC was liquidated in 2022.