What Constrains Insolvency in Property Insurance?

Market Discipline, Capital Regulation, and Catastrophe Exposure

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Abstract

This paper disentangles the roles of capital regulation and credit ratings in mitigating insolvency risk in the U.S. property insurance market. I first investigate the mechanism through which capital requirements affect the insurance market. Using reduced-form evidence and an instrumental variable approach that exploits a 2017 policy change as a quasi-experiment, I find that a $1 million increase in required capital leads insurers to hold $3.34 million more in capital and to raise insurance prices by 0.218 percentage points. These results reveal a direct trade-off between financial stability and consumer affordability. To further explore the underlying mechanisms, I develop a structural model in which insurers make capital and pricing decisions in a competitive market with limited liability and exposure to catastrophic risks. Counterfactual analyses show that tightening capital requirements improves solvency but raises prices. In the absence of capital regulation, the model predicts that the insolvency rate would increase by 0.09 percentage points, while insurance prices would decline by about 5.1%, accompanied by greater risk-taking and market concentration.

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A third counterfactual scenario examines a market without capital regulation but with high credit rating salience. When consumers place greater emphasis on credit ratings, the insolvency rate decreases; however, intensified price competition reduces profitability and increases market concentration. Overall, the findings underscore that capital regulation remains crucial for sustaining market stability, as heightened rating salience alone cannot fully substitute for its stabilizing effects.

In recent years, the frequency and severity of extreme weather events have increased, leading to substantial natural and economic losses. In 2022 alone, global natural disaster damages surpassed $270 billion, with the United States accounting for approximately $140 billion of that total. Property insurance plays a vital role in post-disaster recovery by facilitating reconstruction efforts. However, catastrophic events are also a major driver of insurer insolvencies. For example, following Hurricane Andrew in 1992, eleven insurance companies—ten in Florida and one in Louisiana—became insolvent. Because insurers operate under limited liability, they can declare bankruptcy to avoid excessive losses. When insolvencies occur, State Guaranty Funds intervene to compensate affected policyholders. The combination of limited liability and government-backed bailouts underscores the importance of insurer solvency as a central issue in the property insurance market.

Two primary mechanisms safeguard the solvency of property insurers: market-based discipline and regulatory oversight. Market discipline is administered through credit ratings, which evaluate the financial strength of an insurer and provide vital signals to consumers and reinsurers. Regulatory oversight is enforced through capital requirements, which serve to mitigate moral hazard and risk-seeking behaviors. These regulations also ensure a liquidity cushion to absorb unexpected losses, thereby protecting policyholders. However, the core activities of U.S. insurers are not considered to pose significant systemic risk (a conclusion from Cummins and Weiss (2014)). In an environment with low systemic risk and a robust market discipline mechanism like credit ratings, the appropriate stringency of capital regulation in the property insurance market could reduce distortions from costs of capital.

This idea is bolstered by the empirical observation that most property insurers hold capital levels more than the required amount. This "capital puzzle" raises fundamental questions about whether regulatory capital requirements or credit ratings primarily constrain insurer solvency.

This paper, therefore, seeks to disentangle the roles of these two mechanisms by addressing the following questions: What are the primary constraints on insolvency in the property insurance market, and to what extent can heightened credit rating salience substitute for capital regulation in ensuring solvency while maintaining insurance affordability? Recent debates on U.S. capital regulation have focused on whether the current static, formula-based framework should be replaced by a model-based approach that more accurately reflects insurers' risk exposures. Before such a transition can be meaningfully evaluated, however, it is essential to understand how existing mechanisms—credit ratings and regulatory capital requirements—jointly influence firms' solvency risk. In particular, we must assess the extent to which capital regulation constrains insolvency risk given the presence of credit ratings, which themselves provide market-based discipline. The static, formula-based framework refers to the risk-based capital (RBC) ratio described in Section 1, while the model-based approach relies on predictive models of future losses to determine the level of capital consistent with a target default probability. This paper provides the necessary groundwork for that broader policy discussion by examining the interaction between credit ratings and capital regulation in the property insurance market.

In this paper, I examine how capital requirements and credit ratings interact to shape insolvency risk in the U.S. property insurance market. The paper addresses three central questions: (1) how capital regulation affects insurer solvency and market outcomes, (2) what role capital regulation plays when credit ratings serve as an important source of market discipline, and (3) whether increasing credit rating salience among consumers can effectively substitute for capital regulation in promoting market stability.

I begin by analyzing the mechanisms through which capital regulation influences the insurance market using a reduced-form empirical approach. The analysis centers on a key regulatory trade-off: while tighter capital requirements enhance solvency, they may also increase prices and reduce insurance affordability. To identify this effect, I exploit an exogenous 2017 policy change as an instrument for required capital, addressing the endogeneity of regulatory capital levels. Following the 2017 policy change, property insurers were required to use a 1-in-100-year scenario model to assess catastrophe exposure when calculating required capital. The results show that a $1 million increase in required capital leads insurers to raise held capital by $3.34 million, accompanied by a 0.218 percentage point rise in insurance prices. The increase in capital on hand appears large because the regulatory capital threshold is 200% (see Table 1). Moreover, since capital on hand is stochastic and depends on market valuations, insurers have an incentive to maintain excess capital. These findings highlight the sensitivity of insurers' balance-sheet decisions and pricing strategies to regulatory constraints.

Building on this reduced-form evidence, I develop a structural model in which insurers optimally choose capital and pricing under competition, limited liability, and exposure to catastrophic losses. On the demand side, I specify a logit model in which consumers' insurance choices depend on price and credit ratings. On the supply side, insurers jointly determine capital, pricing, and reinsurance decisions while facing both market discipline and capital regulation. Insolvency triggers state intervention through the State Guaranty Fund, which collects post-event assessments from consumers to pay policyholder claims—introducing an endogenous insolvency cost into the model.

I first construct the moment conditions and estimate the demand system using instrumental variables. Since price levels are unobserved, I recover the baseline prices and the price elasticity parameter from observed price changes during the demand estimation. On the supply side, I estimate most components directly from data, including the credit rating function, required capital function, loss-rate and asset-return distributions, and reinsurance-related parameters. The credit rating and required capital functions are estimated using a generalized additive model, chosen for its robust out-of-sample predictive performance. The remaining unobserved element—the random shocks in insurers' insolvency decisions—is estimated structurally within the supply system using the model's first-order conditions and observed insolvency outcomes.

During the optimization process of the counterfactual analysis, since an insurer's price and the opponents' prices jointly determine the insurance quantity, in each iteration, insurers simultaneously determine their prices, asset allocations, and reinsurance strategies, given competitors' choices. The process converges to a Nash equilibrium when no insurer has an incentive to deviate from its strategy. In the first counterfactual analysis, I investigate how tightening the capital regulation threshold affects market outcomes. Consistent with the reduced-form findings, stricter capital requirements strengthen solvency but raise prices. This counterfactual analysis explores the mechanism of capital regulation by evaluating its impact on the trade-off between solvency and affordability. In a second counterfactual, I isolate the contribution of capital regulation in a market already disciplined by credit ratings. Eliminating capital requirements increases the insolvency rate by 0.09 percentage points while lowering insurance prices by about 5.1%. The absence of regulation also induces greater risk-taking and market concentration. The third counterfactual analysis examines a market without capital regulation but with high credit rating salience. When consumers place greater emphasis on credit ratings, the insolvency rate declines by 0.14 percentage points; however, intensified price competition compresses operating profits and encourages riskier investment behavior, leading to higher market concentration. Taken together, these findings underscore the stabilizing role of capital regulation, even in environments where credit ratings exert substantial market discipline or where consumers are highly attentive to insurers' credit ratings.

This paper contributes to the literature on the roles of capital regulation and credit ratings in the property and casualty insurance industry. The National Association of Insurance Commissioners (NAIC) defines the Risk-Based Capital (RBC) ratio—the primary component of insurers' capital regulation—as a tool that grants regulators the legal authority to intervene in financially distressed insurance companies. Risk-Based Capital (RBC) ratio is a ratio between actual capital and required capital. However, the RBC ratio alone is not intended to serve as a stand-alone measure of financial solvency. Grace et al. (1998) find that RBC ratios are less effective than the Financial Analysis Solvency Tools (FAST) in predicting insurer insolvency. The Financial Analysis Solvency Tools (FAST) is a series of analytical ratios and scoring used by U.S. state insurance regulators to assess the financial condition and solvency of property and casualty insurers. Nevertheless, the combination of RBC ratios and FAST indicators provides stronger predictive power than FAST alone. Similarly, De Haan and Kakes (2010) show that insurers' actual capital holdings are driven more by their underlying risk characteristics than by regulatory solvency requirements, leading most insurers to hold substantially more capital than required. In parallel, other studies examine the role of credit ratings. Basten and Kartasheva (2024) evaluate how regulators and credit rating agencies monitor and discipline the insurance industry's exposure to natural catastrophe (NatCat) risks. They find that many insurers accept rating downgrades and subsequently increase their risk-taking. Eling and Holzmüller (2008) compare capital regulation frameworks for property and casualty insurers across countries and show that New Zealand uniquely integrates rating agencies into its self-supervisory process. Building on this literature, my paper focuses on the interaction between capital regulation and credit ratings, aiming to disentangle the distinct roles of capital regulation play in maintaining solvency within the property insurance market.

Secondly, this paper contributes to the literature on optimal capital requirements in the insurance market. Goussebaïle and Louaas (2022) conducts a theoretical welfare analysis of solvency regulation in the context of catastrophe insurance. Boonen and Jiang (2023) examines the Pareto-optimal reinsurance problem under solvency constraints imposed on reinsurers. The theoretical model in Charpentier and Le Maux (2014) highlights that government-provided insurance becomes more attractive when insurer insolvency risk is taken into account during insurance purchase decisions. Cummins et al. (1993) provides a qualitative discussion of optimal capital requirements. In contrast to these studies, this paper develops a simple theoretical framework and employs structural estimation to quantitatively assess the optimal threshold for capital regulation. By combining theory with empirical analysis, this paper provides a well-supported assessment of optimal capital requirements, grounded in both structural modeling and observed data.

This paper contributes to the extensive literature on the effects of capital requirements in insurance markets. Prior research has established a clear link between capital adequacy and market outcomes. For instance, Eastman and Kim (2023) find that stringent capital requirements lead to increased insurance premiums. Similarly, Gron (1994) shows that an unexpected decrease in financial capacity results in higher prices and profitability. The literature has explored these dynamics across various regulatory landscapes. Barbu (2023) examines the transition from the heterogeneous Solvency I regime to the harmonized Solvency II framework in the European Union, analyzing the impact of differing regulations on product markets and financial stability. In the context of the U.S. life insurance industry, Tang (2022) investigates the competitive dynamics among state jurisdictions. The study finds that while states may lower capital requirements to attract life insurers, this can lead to increased default risks and lower prices, with the associated costs borne by consumers in other states. Furthermore, research has delved into how capital regulations influence the specific investment and operational decisions of insurance companies. Becker et al. (2022) analyze a reform that removed capital requirements for mortgage-backed securities, finding that insurers were subsequently more likely to retain these assets after they were downgraded. Additionally, Niehaus (2018) find that capital flows within insurance groups are responsive to regulatory capital levels, with insurers holding lower risk-based capital receiving greater internal capital contributions. While the aforementioned studies provide crucial empirical insights, this paper builds upon this literature by combining a theoretical model with structural estimation. This approach allows for a direct and quantitative examination of the fundamental trade-off between insurer solvency and the affordability of insurance for consumers.

Finally, this paper contributes to the literature on capital requirements under limited liability. The most closely related studies come from the banking literature. Corbae and D'Erasmo (2021) analyze the impact of regulatory policies on bank risk-taking and market structure, developing and estimating a rigorous theoretical model of bank capital requirements. Malherbe (2020) shows that the capital requirement that restores investment efficiency varies over time—being tighter during booms and looser during recessions. Davydiuk (2017) proposes an optimal dynamic capital requirement that balances efficient lending with liquidity provision, finding that the optimal policy depends on economic growth, credit supply, and asset prices. Building on insights from the banking literature, particularly Corbae and D'Erasmo (2021) and Malherbe (2020), this paper develops a model of capital requirements for insurers operating under limited liability.

In this paper, I begin by reviewing the institutional background in Section 1. I then use a policy change to examine the trade-off introduced by capital regulation between solvency and affordability in Section 3. I find that while capital regulation reduces insolvency in the insurance market, it simultaneously increases the price of insurance. In Section 4, I develop a simple supply and demand model of the insurance market to analyze firms' choices regarding pricing, asset holdings, and reinsurance under limited liability. Section 5 presents the estimation of both the demand and supply sides of this structural model. Based on these estimates, I conduct counterfactual analyses in Section 6. The results indicate that while credit ratings are influential, the absence of capital regulation would result in higher insolvency rates and increased market concentration. Even in markets where consumers are highly sensitive to insurers' credit ratings, capital regulation remains indispensable for maintaining market stability. Finally, I conclude and offer a discussion of the implications.

1 Institutional Background

This section provides institutional background on capital regulation, credit ratings, reinsurance, and state guaranty associations, offering context that will aid readers in understanding the empirical analysis and theoretical models presented in the subsequent sections.

1.1 Capital Regulation

Regulation of the insurance industry in the United States is conducted at the state level. To promote uniformity and establish best practices, state insurance regulators collaborate through the National Association of Insurance Commissioners (NAIC).

A key tool for monitoring insurer solvency, developed by the NAIC, is the Risk-Based Capital (RBC) framework. Insurers are required to maintain capital levels commensurate with their specific risk profiles. Solvency is primarily assessed using the RBC ratio, which compares an insurer's total adjusted capital to its required Risk-Based Capital. The Risk-Based Capital ratio is calculated with the following formula[1]:

$$\text{RBC Ratio} = \frac{\text{Total Adjusted Capital}}{\text{Authorized Control Level Risk-based Capital}}$$

Total adjusted capital refers to the amount of capital a property and casualty insurer holds after all required adjustments. It is expressed as:

$$\text{Total adjusted capital} = \text{Surplus as regards policyholders} + \text{Adjustments}$$

Authorized Control Level Risk-based Capital (ACL RBC) is the regulatory capital require-

[1]For more details, please read https://content.naic.org/insurance-topics/risk-based-capital

ment and is calculated using the following equation.

$$\text{Authorized Control Level Risk-based Capital} = 0.5 \times \text{Total Risk-based Capital}$$

Total Risk-Based Capital (RBC) is a standardized minimum capital requirement for insurers, determined by the inherent risks in their assets and operations. The Total Risk-Based Capital (RBC), developed by the National Association of Insurance Commissioners (NAIC), is stochastic and depends on various risk categories, including asset risk, underwriting risk, and business or credit risk, to establish the required capital level. This framework establishes several action levels based on the ratio of the company's Total Adjusted Capital (TAC) to its calculated Authorized Control Level (ACL) RBC. Each level triggers specific regulatory responses:

Table 1: Risk-Based Capital (RBC) Action Levels and Corresponding Regulatory Actions

RBC Ratio	Regulatory Action
150% to 200%	**Company Action Level:** An insurer falling into this range must submit a comprehensive financial plan to the insurance commissioner detailing how it will improve its RBC ratio.
100% to 150%	**Regulatory Action Level:** At this level, a regulator is required to perform an examination of the insurer and issue a corrective action order specifying necessary improvements.
70% to 100%	**Authorized Control Level:** If an insurer's ratio falls within this range, the state commissioner is authorized, but not required, to take control of the company, which can include rehabilitation or liquidation.
Below 70%	**Mandatory Control Level:** When the ratio is below this threshold, the commissioner is obligated to seize the insurer to protect policyholders.

Notes: This table summarizes RBC action levels and regulatory actions.

1.2 Credit Rating

Credit rating agencies evaluate an insurer's creditworthiness primarily from the perspective of debt investors and counterparties. Their objective is to provide an independent, market-informed assessment of the insurer's financial strength and ability to meet future obligations. These evaluations are generally conservative, as they assess natural catastrophe risks separately and earlier than capital regulations, taking into account both current financial conditions and potential future exposures. Similar to capital regulation, credit rating agencies assess capital adequacy by considering the insurer's exposure to risks associated with underwriting net premiums, asset holdings, subsidiaries, and loss reserves. Major credit rating agencies active in the insurance market include A.M. Best, S&P Global, Moody's, and Fitch.[2]

In my theoretical model, credit rating will affect consumers' choice of insurance. My estimation results suggest that consumers are more willing to choose an insurance company with higher credit rating.

1.3 Reinsurance

To diversify their underwriting risks and lower the capital requirements they must maintain, insurance companies obtain reinsurance from reinsurance firms. In real world, credit rating may affect price of reinsurance. However, because of data limitation, I use a price index which is uniform across insurers to measure the price of reinsurance. This data limitation constrains the model, as it restricts the credit rating channel to influence equilibrium only through its effects on demand. Consequently, insurers in the model have weaker incentives to improve their credit ratings.

1.4 State Guaranty Association

In the U.S., a state-based system of insurance guaranty associations protects policyholders and claimants if an insurance company becomes insolvent. These nonprofit organizations,

[2] For more details, please read *Best's Credit Rating Methodology*, *Insurer Risk-Based Capital Adequacy-Methodology an Assumptions* by S&P Global, *Property and Casualty Insurers Methodology* by Moody's, and *Prism* by Fitch.

mandated by state law, are composed of all insurance companies licensed to do business in a particular state. When an insurer is deemed insolvent, the state guaranty association steps in to continue coverage and pay outstanding claims up to statutory limits. Funding for these payments is primarily sourced from the remaining assets of the failed insurer and through "post-insolvency assessments" levied on the member insurance companies. The amount each solvent insurer is assessed is typically based on its share of premiums written within the state. In many states, these assessed insurers are permitted to recover a portion of these costs over time through offsets on their assessments from consumers. For example, after the insolvency of Florida-based insurer St. Johns Insurance Company in 2022, the Florida Insurance Guaranty Association (FIGA) stepped in to pay out covered claims to affected homeowners.

1.5 Development of Capital Requirement in Property Insurance Market

I use a 2017 policy change to evaluate how capital regulation trades off solvency and affordability. Prior to 2017, the risk exposures R_{5A} and R_{Cat} were grouped under the same category—"underwriting net written premiums risk." R_n represents risk exposure when measuring required capital. However, starting with the 2017 reporting year, insurers with significant exposure to hurricane and earthquake risk have been required to report R_{5A} as "underwriting net written premiums risk net of catastrophic risks" and R_{Cat} as "catastrophe risk" separately. While the RBC ratio is generally calculated using static formulas, the R_{Cat} component is uniquely assessed using a model-based approach. Specifically, catastrophe models are used to estimate the predicted exposure to catastrophic risk. These models employ scenario-based analysis, typically assuming a 1-in-100 year event, which reduces reliance on historical smoothing and increases required capital to better reflect potential future losses. Wildfire risks continue to be included for disclosure purposes and are still not in "catastrophe risk" when calculating required capital. For the development of capital regulation before

2017, please refer to Appendix 8.3.

Credit rating agencies began incorporating catastrophe risk into their capital adequacy models well before regulatory authorities did. For instance, A.M. Best introduced a catastrophe adjustment to the numerator of its capital ratio prior to 2003.

2 Data

The empirical analysis in this paper draws on administrative data from the National Association of Insurance Commissioners (NAIC), the policy-setting organization for state insurance regulators in the United States. The NAIC data are at the individual company level. State-level data on natural disasters are obtained from the Spatial Hazard Events and Losses Database (SHELDUS), while information on rate changes is sourced from the System for Electronic Rates & Forms Filing (SERFF). To measure reinsurance price, I use the Guy Carpenter Global Property Rate on Line Index, which is common to all insurers and varies only over time. Except for natural disasters, insurers' price changes, and the reinsurance price, all other variables are constructed from NAIC statutory filings. The analysis focuses on product lines that the NAIC identifies as exposed to natural disasters: fire, allied lines (including water damage), homeowners multiple perils, commercial multiple perils (non-liability portion), earthquake, and farm owners multiple perils. Government-supported or provided crop insurance (multiple peril crops, private crops) is excluded from the sample. A company's market share within a given state is computed as the ratio of its direct written premiums to the total direct written premiums in that state for the relevant business lines.

I want to study how capital regulation affects solvency and price. Since the required capital can be endogenous and cause issues for identification, I use instrumental variable regressions. The instrumental variable used in this study is a regulatory change implemented in 2017, which requires insurers with significant exposure to hurricanes and earthquakes to calculate catastrophic risks separately from other underwriting risks when determining their

Total Risk-Based Capital. The regulation also mandates the use of scenario-based modeling to estimate future losses. Switching from historical loss data to scenario-based modeling reduces historical smoothing and increases insurers' required capital. I define the treated group as insurers that had exposure to hurricanes and earthquakes prior to 2017. Table 10 lists the regions included in the treated group. Certain states are exempt from this catastrophic risk regulation. Firms are assigned to the treated group if they underwrote policies in the lines of earthquake, homeowners, allied lines, farm owners, or commercial property (non-liability) in catastrophe-prone areas. In contrast, firms with no exposure to these business lines or whose underwriting activities were confined to states not listed in Table 10 are classified as the control group.

The primary sample spans the years 2014 to 2023 and is restricted to property insurers. I define property insurers as firms that wrote insurance in the lines of fire, allied lines, homeowners, earthquake, farm owners, or commercial property (non-liability). Table 11 presents summary statistics. Columns (1) to (3) report the mean, standard deviation, and median of the full sample, respectively. Columns (4) to (7) show the means of the treated and control groups before and after the 2017 regulation.

'Total Adjusted Capital' refers to the total surplus held by an insurer, while 'Direct Written Premiums' represent the total premiums received—commonly used as a proxy for firm size in the insurance industry. The treated group consists of firms that underwrote property insurance related to natural disasters—such as homeowners, commercial property, fire, allied lines, farm owners, and earthquake insurance—prior to 2017. The control group comprises firms without such exposure before 2017. The regulatory change took effect in 2017. The variable '`treatment`' in Table 11 is a binary indicator denoting whether a firm belongs to the treated or control group.

Firms that entered receivership before 2017 are excluded from the sample, as they do not fall into either group. The RBC ratio is defined as the ratio of Total Adjusted Capital to Authorized Control Level Risk-Based Capital, the latter being the minimum regulatory capital required. The surplus represents the capital buffer above the insolvency threshold. All financial variables, except for price change, treatment, and the RBC ratio, are reported in millions of dollars. Price change and the RBC ratio are expressed in percentages. All variables are winsorized at the 95% level.

According to the summary statistics in Table 11, the treated group experienced a substantial increase in regulatory risk-based capital and surplus following the reform, indicating stricter capital requirements and improved solvency post-regulation. Additionally, treated firms tend to be larger in size compared to those in the control group. To address this discrepancy, the empirical analysis in Section 3 includes firm fixed effects and controls for firm size.

3 Capital Regulation Trades off Solvency and Affordability

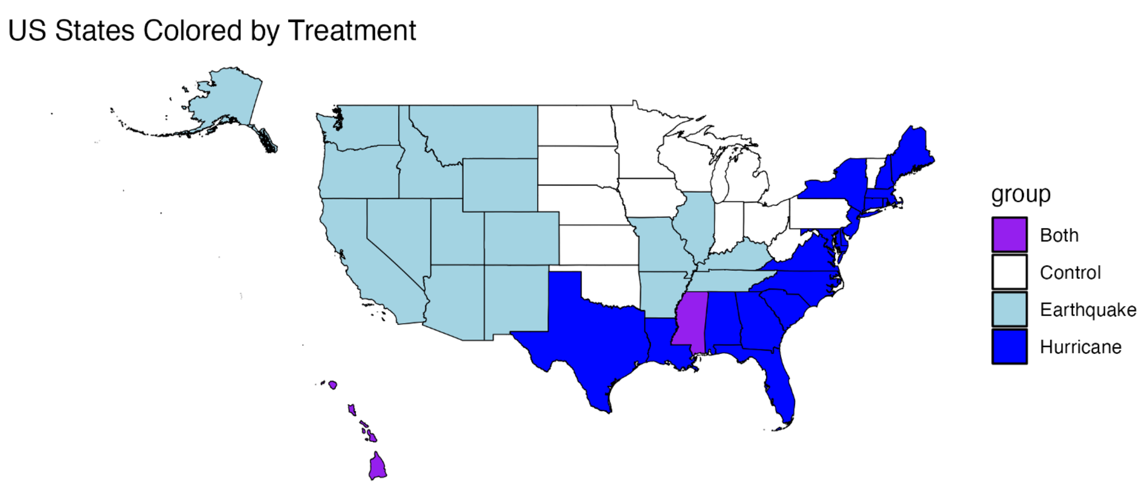
In this paper, I study the mechanism through which capital regulation affects insurers' solvency and the insurance market. This section provides reduced-form evidence to illustrate the empirical relationship between capital regulation, solvency, and affordability. The subsequent sections develop a simple theoretical model in which insurers choose capital, pricing, and reinsurance under limited liability. I then use this model to conduct counterfactual analyses. In the first counterfactual exercise, I tighten capital regulation to evaluate the trade-off between solvency and affordability within the theoretical framework. Empirically, this section examines the trade-off using the 2017 policy reform as an instrumental variable. As detailed in Section 1, the 2017 reform required insurers with substantial exposure to hurricane and earthquake risks to separately report catastrophe and other underwriting risks in their regulatory risk-based capital calculations. A key change introduced by the reform was the shift from historical loss estimation to scenario-based modeling, which increased capital requirements for affected insurers. The identifying variation arises from differences in insurers' exposure to catastrophic events, particularly hurricanes and earthquakes.

To identify the causal effects of this reform, I employ a difference-in-differences (DID) strategy combined with an instrumental variable (IV) approach. The first stage of the IV regression, which utilizes the DID framework, is specified in the following equation.

$$y_{jt} = \beta_0 + \beta_1 \text{treated}_j \times \text{reform}_t + \zeta_j + \zeta_t + \varepsilon_{jt} \tag{1}$$

j indexes insurers, and y_{jt} denotes the dependent variable, which is the regulatory risk-based capital. Treated$j$ is a dummy variable equal to 1 if insurer j wrote at least one policy with exposure to hurricanes or earthquakes in disaster-prone areas (as shown in Figure 1) before 2017, and 0 otherwise. The sample is restricted to property insurers that wrote property insurance during the sample period. Property insurance includes the following product lines: fire, allied lines, earthquake, farmowners, homeowners, and commercial multi-peril. ζj represents insurer fixed effects, and ζ_t represents time fixed effects.

Figure 1: Catastrophe-prone Areas



Notes: The light blue denotes states exposed to earthquake risks. The navy blue areas denote states exposed to hurricane risks. The purple areas denote states exposed to both earthquake and hurricane risks.

The following equation shows the IV regression.

$$y_{jt} = \beta_0 + \beta_1 RBC_{jt} + \zeta_j + \zeta_t + \varepsilon_{jt} \tag{2}$$

The endogenous variable is RBC_{jt}, representing the regulatory risk-based capital. The outcome variable, y_{jt}, includes both the price change and the surplus (i.e., actual capital held). The surplus serves as a proxy for the insurer's distance to insolvency, as greater capital holdings reduce the likelihood of insolvency. The instrumental variable is defined as the interaction term $\text{treated}_j \times \text{reform}_t$.

Table 2 displays the results for the first stage and reduced form of our analysis. The variable of interest, treated×reform, serves as the instrumental variable for the endogenous risk-based capital, as specified in Table 3. The first-stage results, presented in Column (1) of Table 2, show that the policy change led to a \$3.691 million increase in regulatory risk-based capital. In the reduced form, the reform is associated with a \$12.343 million increase in surplus, which measures the distance to insolvency. Concurrently, the price change increased by 0.474 percentage points, suggesting that property insurance became more expensive post-reform. The dynamics illustrated in Figure 2 are consistent with the scale of these regression results.

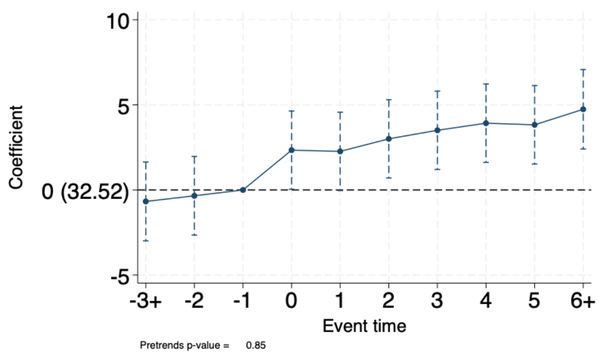
Table 2: First Stage and Reduced Form

	Dependent variable:		
	required capital	surplus	price change
	(1)	(2)	(3)
treated×reform	3.691***	12.343***	0.474***
	(0.569)	(2.591)	(0.100)
	[31.668]	[230.301]	[3.078]
Observations	16,655	16,655	16,655
R^2	0.0453	0.0501	0.0417

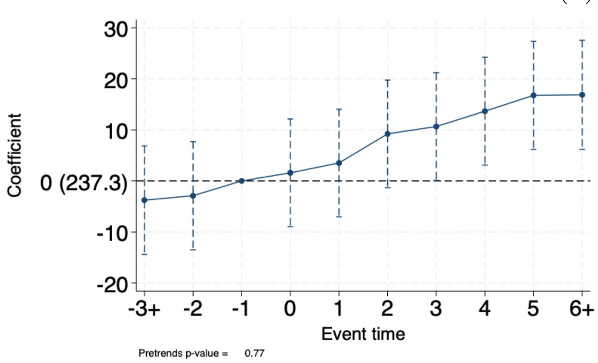
Note: *p<0.1; **p<0.05; ***p<0.01
(standard error), [mean of dependent variable of treated before treatment]

Notes: This table shows regression results of the first stage of instrumental variable regressions. The predictor treated × reform is a difference-in-difference type instrumental variable. Variable required capital will be the endogenous variable in the IV regression. Except for price change, the unit of other variables is a million dollar. The unit of price change is percent.

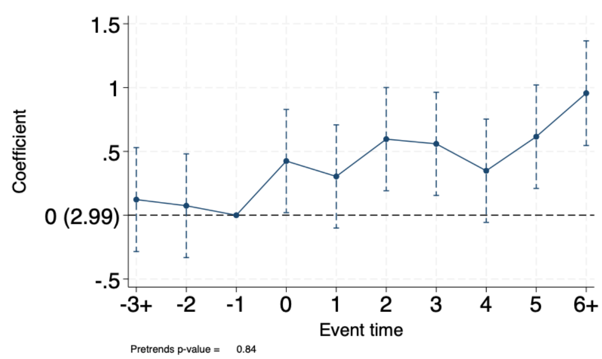
Figure 2: Event study plots of reduced-form specification



(a) RBC



(b) Surplus



(c) Price change

Notes: This figure shows event study plots of reduced-form specification. Panels (a) to (c) correspond to outcome variables "Regulatory capital", "capital on hand", "price change". Results are consistent with Table 2. Except for price change, the unit of other variables is a million dollar. The unit of price change is percent.

Table 3 reports the main results of the IV regressions. The instrumental variable is the interaction term *treated*×*reform*. The outcome variables are the surplus and the price change. The results indicate that a $1 million increase in capital requirements leads to a $3.34 million increase in surplus, implying that insurers become less likely to face insolvency. As shown in Table 11, the RBC ratio (defined as total adjusted capital divided by the authorized control level risk-based capital) generally exceeds 2. Therefore, when the authorized control level risk-based capital rises by $1 million, the corresponding increase in surplus exceeds $1 million. Conversely, column (2) of Table 3 shows that a $1 million increase in risk-based capital raises prices by 0.128 percentage points. Taken together, the results in Table 3 highlight a trade-off between insurer solvency and policy affordability in response to higher capital requirements.

Table 3: IV Regression

	Dependent variable:	
	surplus	price change
	(1)	(2)
required capital	3.344***	0.128***
	(0.549)	(0.033)
Observations	16,655	16,655
R^2	0.400	0.0417
Note:	*p<0.1; **p<0.05; ***p<0.01	

Notes: This table shows regression results of instrumental variable regressions. The instrumental variable is treated×reform. The variable of interest is Risk-based capital. Except for price change, the unit of other variables is a million dollar. The unit of price change is percent.

Since insurers sometimes hold more capital than the total Risk-Based Capital (RBC) requirement, I conduct a robustness check using a subsample of insurers that are more tightly constrained by the regulation. Specifically, these are insurers whose average RBC ratios before the treatment are within one or two standard deviations of the capital requirement threshold. The results from these more binding samples are broadly consistent with those obtained from the full sample. Table 12 presents the first-stage regression results for the binding subsamples. Columns (1) to (3) report results for insurers whose average pre-treatment RBC ratios fall within one standard deviation of the regulatory threshold. Columns (4) to (6) show results for those within two standard deviations. The magnitudes of the coefficients are consistent with those from the full sample. However, for the subsample within one standard deviation, the reduced-form coefficients are somewhat smaller than those in the full sample. This may be because insurers with lower RBC ratios tend to be smaller firms with less exposure to risky underwriting. Consequently, the increase in their required capital is smaller relative to larger insurers. Moreover, smaller insurers may have fewer resources to raise additional capital. Table 13 shows the IV regression results for the binding subsamples. The magnitude of the coefficients is similar to those obtained from the full sample, reinforcing the robustness of the main findings.

Although some insurers may hold capital in excess of regulatory requirements, the stricter capital regulation still affects non-binding insurers. This is because the policy increases the probability of falling below the required threshold, thereby incentivizing insurers to hold additional capital as a buffer. The regulatory reform requires insurers to separately calculate required capital for hurricane and earthquake exposures, and to estimate future losses using scenario-based modeling rather than relying solely on historical losses. As a result, the regulation becomes more binding during periods of increased natural catastrophe activity. Since the policy change coincides with a period of heightened natural disasters, I am unable to fully disentangle the effects of the new capital regulation from those of the catastrophes themselves. However, this limitation is reasonable, as the policy is specifically designed to be most effective when natural catastrophes are more frequent.

4 Model

This section develops a simple theoretical model to illustrate the decisions of property insurers regarding capital, credit rating, pricing, and insolvency. The model incorporates limited liability, capital regulation, and the risk of catastrophe shocks.

4.1 Environment

This is a static model with two markets. The two markets are (1) states that are exposed to hurricane or earthquake risks, and (2) states that have less exposure to hurricane and earthquake. I use m to denote a market. Within each market, risk-averse households, indexed by i, demand property insurance. Property insurers, indexed by j, are risk-neutral and compete by differentiating their products.

Two primary mechanisms monitor and promote insurer solvency. First, the Department of Insurance in each state regularly evaluates the capital adequacy of property insurers. Second, credit rating agencies provide independent assessments of insurers' financial strength by assigning them credit ratings.

In the event of an insurer's failure, a state-level Guaranty Association, funded by assessments on the surviving insurers in that market, compensates the policyholders of the failed firm. Participation in this association is mandated by state law for all solvent insurers.

The model incorporates two sources of uncertainty: the realization of losses, L_{jm}, and the return on risky assets, r_2. Loss rate $L_{jm} \in [0, \infty]$ realizes after solving optimization problems. Loss rates L_{jm} correlate within the same market. I assume the risky asset return r_2 is independent from the loss rate L_{jm}. Risky asset return r_2 can be negative, and has higher mean and variance than the safe asset return r_1.

The following paragraph describes the timeline of the setup.

Timing:

Stage 1: Insurers set price and capital based on regulations.

Stage 2: Regulators assess capital adequacy. Rating agencies assign credit rating.

Stage 3: Consumers decide what insurance products to purchase.

Stage 4: Shocks realize. Some insurers may choose to go bankrupt. If insurers fail, State

Guaranty Funds charge taxes and bail out consumers.

4.2 Demand

The demand model is a simple logit model. The formula below shows the demand model.

$$u_{ijm} = \alpha_1 p_{jm} + \alpha_2 R_j + \xi_{jm} + \varepsilon_{ijm} \tag{3}$$

This formula indicates that consumer i's utility from choosing insurance j in market m depends on the insurance price p_{jm}, the insurer's credit rating R_j, and unobserved product characteristics ξ_{jm}. Consumers care about credit ratings because they are not fully bailed out if the insurer becomes insolvent. The term ε_{ijm} represents idiosyncratic demand shocks, which are assumed to follow an i.i.d. Type I extreme value distribution.

4.3 Supply

Insurers know distribution of losses. However, the randomness of the model (risky asset return r_2 and loss rates L_{jm}) realizes after agents made decisions. Insurers set prices and capital to maximize equity values. We can write

$$\max_{\{p_{jm}, A_{1j}, A_{2j}\}} \mathbb{E}(\Pi_j + A_{1j} + A_{2j}) \tag{4}$$

$$
\begin{aligned}
&s.t.\\
\Pi_j =& \max\{[\sum_m (p_{jm} - L_{jm} - Exp_j) q(\mathbf{p_m}, \mathbf{R}) - p^{re} Q_j^{re} - FC_j + r_1 A_{1j} + r_2 A_{2j} \\
& - \frac{1}{k} \log(\exp(-p^{re} Q_j^{re} k) + \exp(-(\log(1 + \exp(\sum_m (L_{jm} q(\mathbf{p_m}, \mathbf{R})) - d)))k))], \\
& - (A_{1j} + A_{2j}) - \nu_j^d\} && \text{(Profits with limited liability)} \\
R_j =& g(q(\mathbf{p_1}, \mathbf{R}), q(\mathbf{p_2}, \mathbf{R}), \frac{A_{2j}}{A_{1j} + A_{2j}}, A_{1j} + A_{2j}) && \text{(Credit rating)} \\
2 \leq & \frac{A_{1j} + A_{2j}}{\tilde{K}(q(\mathbf{p_1}, \mathbf{R}), q(\mathbf{p_2}, \mathbf{R}), A_{2j})} && \text{(Capital requirement)} \\
Q_j^{re} =& h(q(\mathbf{p_1}, \mathbf{R}), q(\mathbf{p_2}, \mathbf{R})) && \text{(Reinsurance)}
\end{aligned}
$$

Insurers choose price p_{jm}, risk-free asset A_{1j}, risky asset A_{2j}, and reinsurance Q_j^{re} to maximize firm values. $\mathbf{p_m}$ is the price vector including p_{jm} and opponents' prices $p_{-j,m}$. Similarly, $\mathbf{R}$ is the credit rating vector including R_j and opponents' credit ratings R_{-j}. Since this is a static model, the firm value is equal to the sum of profit Π_j and assets in hand. Insurers can choose to hold risk-free assets A_{1j} and risky assets A_{2j}. The profit is defined with limited liability. This means when the realized profit is lower than the loss of capital, the insurer can choose to lose the capital. ν_j^d is a random shock to smooth the insolvency decision. The higher the ν_j^d, the less likely that the insurer will choose to be insolvent. The profit without limited liability is the following expression.

$$
\begin{aligned}
& \sum_m (p_{jm} - L_{jm} - Exp_j) q(\mathbf{p_m}, \mathbf{R}) - p^{re} Q_j^{re} - FC_j + r_1 A_{1j} + r_2 A_{2j} \\
& - \frac{1}{k} \log(\exp(-p^{re} Q_j^{re} k) + \exp(-(\log(1 + \exp(\sum_m (L_{jm} q(\mathbf{p_m}, \mathbf{R})) - d)))k))
\end{aligned}
$$

The profit without limited liability is calculated as total revenue minus claim amounts, operating expenses, payments to reinsurers, and fixed costs, while adding back investment income and recoveries from reinsurance. The following extended expression represents the payment received from reinsurance.

$$
-\frac{1}{k} \log(\exp(-p^{re} Q_j^{re} k) + \exp(-(\log(1 + \exp(\sum_m (L_{jm} q(\mathbf{p_m}, \mathbf{R})) - d)))k))
$$

This expression is a smooth function of $\min\{p^{re}Q_j^{re}, \max\{0, L_{jm}q(\mathbf{p_m}, \mathbf{R}) - d\}\}$, a combination of softmin and softmax functions. k is a smoothness parameter of the function. d is deductible of reinsurance.

Credit rating is equal to a $g(\cdot)$ function which depends on quantity of written premium in risky region $q(\mathbf{p_1}, \mathbf{R})$, quantity of written premium in less risky region $q(\mathbf{p_2}, \mathbf{R})$, quantity of reinsurance Q_j^{re}, share of risky assets $\frac{A_{2j}}{A_{1j}+A_{2j}}$, and total assets $A_{1j} + A_{2j}$. This definition of credit rating is a simplified version of how credit rating agency evaluate credit rating in reality.

Capital requirements mandate that the total capital on hand must be at least twice the authorized control level of Risk-Based Capital (RBC). Let $\tilde{K}(\cdot)$ denote the authorized control level RBC. The function $\tilde{K}(\cdot)$ depends on the quantity of written premium in the risky region, $q(\mathbf{p_1}, \mathbf{R})$, the quantity of written premium in the less risky region, $q(\mathbf{p_2}, \mathbf{R})$, quantity of reinsurance, Q_j^{re}, and risky assets, A_{2j}. This specification of the authorized control level RBC aligns with U.S. regulatory practice, with adjustments made to fit the model.

To compute the optimal choices of prices, assets, and reinsurance, I define a domain in which insurers remain solvent and transform the objective function into the following form.

$$
\begin{aligned}
&\max_{\{p_{jm}, A_{1j}, A_{2j}, Q_j^{re}, R_j\}} \iiint_{D(p_{jm}, A_{1j}, A_{2j}, Q_j^{re}, R_j)} [\sum_m ((p_{jm} - L_{jm} - Exp_j)q(\mathbf{p_m}, \mathbf{R})) - p^{re}Q_j^{re} \\
&- FC_j + \min\{p^{re}Q_j^{re}, max\{0, \sum_m (L_{jm}q(\mathbf{p_m}, \mathbf{R})) - d_j\}\} + r_{1j}A_{1j} + r_{2j}A_{2j}] f dV \\
&- \iiint_{\Omega / D(p_{jm}, A_{1j}, A_{2j}, Q_j^{re}, R_j)} (A_{1j} + A_{2j} + \nu_j^d) f dV + A_{1j} + A_{2j}
\end{aligned}
$$

$$
\begin{aligned}
&s.t. \\
R_j =& g(q(\mathbf{p_1}, \mathbf{R}), q(\mathbf{p_2}, \mathbf{R}), \frac{A_{2j}}{A_{1j} + A_{2j}}, A_{1j} + A_{2j}) && \text{(Credit rating)} \\
2 \leq & \frac{A_{1j} + A_{2j}}{\tilde{K}(q(\mathbf{p_1}, \mathbf{R}), q(\mathbf{p_2}, \mathbf{R}), A_{2j})} && \text{(Capital requirement)} \\
Q_j^{re} =& h(q(\mathbf{p_1}, \mathbf{R}), q(\mathbf{p_2}, \mathbf{R})) && \text{(Reinsurance)}
\end{aligned}
$$

The blue expression is the profit when the insurer is solvent. The purple expression represents the lost capital when it becomes insolvent. I plug in the definition of credit rating and use implicit function theorem to find first-order conditions. Since sometimes the capital requirement may not be binding, I use Karush–Kuhn–Tucker conditions to find solutions to the optimization problem. For detailed derivation of first-order conditions and Karush–Kuhn–Tucker conditions, please refer to Appendix 8.4.

The domain $D(p_{jm}, A_{1j}, A_{2j}, Q_j^{re})$ where insurers are solvent is

$$
\begin{aligned}
&[\sum_m (p_{jm} - L_{jm} - Exp_j) q(\mathbf{p_m}, \mathbf{R}) - p^{re} Q_j^{re} - FC_j + r_2 A_{2j} + r_1 A_{1j} \\
&- \frac{1}{k} \log(\exp(-p^{re} Q^{re} k) + \exp(-(\log(1 + \exp(\sum_m (L_{jm} q(\mathbf{p_m}, \mathbf{R})) - d)))k))] \\
&\geq -(A_{1j} + A_{2j} + \nu_j^d)
\end{aligned}
$$

$M = 2$ in this case because there are only 2 markets: (1) risky markets exposed to hurricane and earthquake, (2) other markets. The domain $D(p_{jm}, A_{1j}, A_{2j}, Q_j^{re})$ is defined as the region where the profits are higher than the loss of capital.

4.4 Welfare

I define welfare as the sum of consumer and producer surplus, net of insolvency costs.

$$
\text{Welfare} = \text{Consumer Surplus} + \text{Producer Surplus} - \text{Insolvency Costs} \tag{5}
$$

Producer surplus represents the total profit earned by producers in the market.

$$\text{Producer Surplus} = \sum_j \Pi_j$$

Consumer surplus is defined as the expected utility in dollar terms. The consumer surplus is normalized to outsider option j'. The following expression is the consumer welfare derived from social surplus function.

$$\text{Consumer Surplus}_t = -\sum_m \sum_i [\frac{1}{\alpha_1} \log(\sum_{k \in D} \exp(\alpha_1 p_{km} + \alpha_2 R_k + \xi_{km}) + cons)] \tag{6}$$

In the event of an insurer's failure, State Guaranty Funds provide a safety net for policyholders by covering their claims. To finance these obligations, these funds levy assessments on the remaining solvent insurers. This paper utilizes data on these guaranty association assessments to approximate the costs of insolvency, which are defined as the claims that insolvent firms are unable to fulfill. It is important to acknowledge that this is not a perfect measure of insolvency costs. The assessments are a transfer to policyholders and are subject to statutory coverage limits, meaning they may not fully capture the total losses incurred. Nevertheless, these assessment data represent the most suitable and currently available proxy for the direct costs of insurer insolvency.

4.5 Equilibrium

I focus on pure strategy subgame perfect equilibrium. The equilibrium is a set of households' insurance choices, insurers' decision $\{p_{jm}, A_{1j}, A_{2j}\}$, such that the following statements hold:

1. Given price p_{jm} and rating R_j, households maximize utility by choosing insurance. Consumers' discrete choice lead to logit demand market shares:

$$S_{jm} = \frac{\exp(\alpha_1 p_{jm} + \alpha_2 R_j + \xi_{jm})}{\sum_{k \in \mathcal{C}} \exp(\alpha_1 p_{km} + \alpha_2 R_k + \xi_{km})} \tag{7}$$

$\mathcal{C}$ is choice set.

2. Given the insurance demand function, $\{p_{jm}, A_{1j}, A_{2j}\}$ solve insurers' optimization problem in equation (4).

3. Market clears: $q^d(\mathbf{p_m}, \mathbf{R}) = q^s(\mathbf{p_m}, \mathbf{R})$.

4. Assessments collected by Guaranty funds are equal to insolvency costs.

5 Estimation

5.1 Demand Estimation

For demand estimation, I first construct moment conditions. The assumption of the moment condition is that the unobserved product characteristics are not correlated with the instrumental variable. Since I do not observe the uninsured, I choose an insurer j that has most observations as the outside option. Therefore, I revise the moment condition as

$$\mathbb{E}([\xi_{jmt} - \xi_{j'mt}][z_{jmt} - z_{j'mt}]) = 0$$

ξ_{jmt} is the unobserved product characteristics and z_{jmt} is the instrumental variable. Furthermore, since I only observe price change and I need to recover time 0 price from the demand estimation, to avoid multicollinearity, I take time difference to construct the moment condition. The final moment condition for demand estimation is

$$\mathbb{E}([(\xi_{jmt} - \xi_{jm,t-1}) - (\xi_{j'mt} - \xi_{j'm,t-1})][(z_{jmt} - z_{jm,t-1}) - (z_{j'mt} - z_{j'm,t-1})]) = 0$$

For instrumental variables, I use claim amount (losses) of the same insurer in another market as the instrument for price. Since insurers may adjust prices if there are losses from another market, the instrumental variable is relevant to prices. Besides, losses of property insurance from other markets are usually related to natural disasters or accidents, which are exogenous to prices. I use a credit rating standard change as the instrument for credit rating. The credit rating standard change is relevant because it will affect values of credit rating. Besides, the trigger of the standard change is a severe hurricane, which is exogenous. In 2005, credit rating standards became stricter after hurricane Katrina. For example, A.M. Best imposed extra stress test for the 2nd following catastrophe event. When evaluate potential catastrophe losses, S&P changed from 100 year to 250 year modeling. Fitch changed from evaluation of single worst event to Tail Value at Risk (TVaR). The Tail at Value at Risk is to evaluate the average losses in worst-case scenarios. Combining TVaR and revision in catastrophe modeling, the insurer will need to hold 10% more capital in order to maintain the same Fitch credit rating, if the insurer had exposure to catastrophe risks. The instrument for credit rating is a difference-in-difference type of instrumental variable. The instrument is $\text{treated}_j \times \text{reform}_t$. The variable reform_t is equal to 1 after year 2006 when the change of credit rating standards happened. Treated_j is defined as the following equation.

$$\text{treated}_j = \frac{\text{property underwriting in treated states}_j}{\text{total underwriting}_j}$$

From the definition above, treated_j is defined as the share of property underwriting in treated states as of the total underwriting. If an insurer has more property underwriting in the disaster-prone regions, then this insurer is more likely to be treated.

Since I only observe price change and revenue market share data, after some algebra, the difference in unobserved product characteristics is defined as

$$\begin{aligned}
&(\xi_{jmt} - \xi_{jm,t-1}) - (\xi_{j'mt} - \xi_{j'm,t-1}) \\
=&(\log \omega_{jmt} - \log \omega_{jm,t-1}) - (\log \omega_{j'mt} - \log \omega_{j'm,t-1}) - \tilde{\alpha}_{1jm}(d_{jmt} - d_{jm,t-1}) \\
&+ \tilde{\alpha}_{1j'm}(d_{j'mt} - d_{j'm,t-1}) - (\log d_{jmt} - \log d_{jm,t-1}) + (\log d_{j'mt} - \log d_{j'm,t-1}) \\
&- \alpha_2[(R_{jt} - R_{j,t-1}) - (R_{j't} - R_{j',t-1})]
\end{aligned}$$

For detailed derivation of the above expression, please see Appendix 8.5. In the equation above,

$$d_{jmt} = \prod_{s=1}^{t} \frac{p_{jms}}{p_{jm,s-1}}$$

This means d_{jmt} is the cumulative price change across years.

$$\tilde{\alpha}_{1jm} = \alpha_1 p_{jm0},$$

$$\tilde{\alpha}_{1j'm} = \alpha_1 p_{j'm0}$$

During the estimation, I directly estimate $\tilde{\alpha}_{1jm}$ and $\tilde{\alpha}_{1j'm}$. Suppose there are 1000 combination of j and m. Since α_1 is common across all $\tilde{\alpha}_{1jm}$ and $\tilde{\alpha}_{1j'm}$, there will be 1000 equations and 1001 unknowns. Therefore, I normalize the time 0 price of the median firm to be 1 and solve for the rest of the α_1, p_{jm0}, and $p_{j'm0}$.

The estimated coefficients are $\hat{\alpha}_1 = -2.3759$ and $\hat{\alpha}_2 = 0.0409$. Price elasticity is computed using the following expression:

$$\text{price elasticity}_{jm} = \alpha_1 \times p_{jm} \times (1 - S_{jm})$$

where p_{jm} denotes the price and S_{jm} represents the market share. The median estimated price elasticity is -2.38. The scale of the price elasticity is similar to the price elasticity estimated in Grace et al. (2004), which find that the elasticity for catastrophe coverage is around -1.9 and the elasticity for non-catastrophe coverage is around -0.4. Figure 5 presents the distributions of the estimated time-0 prices and price elasticities. The small peaks in both tails of the distribution arise because I winsorize extreme time-0 prices to account for the limited number of observations in each estimation.

Table 4: Estimation Results of Demand Parameters

Variable	Coefficient
α_1 (Price Sensitivity)	-2.3759***
	(0.1669)
α_2 (Credit Rating)	0.0409***
	(0.0001)

Note: Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

This table shows estimation results and standard errors of demand estimation.

5.2 Supply Estimation

On the supply side, I estimate the key components required for the counterfactual analysis. The random shocks ν_j^d are inferred based on the Karush–Kuhn–Tucker (KKT) conditions and insurers' insolvency decisions, following an approach similar to the supply-side estimation in BLP. The underlying assumption is that the observed data reflect the optimal decisions of insurers in a competitive market. The quantity of reinsurance, Q_j^{re}, is computed by dividing the observed reinsurance premium by an approximate unit price p^{re}. Note that the unit price p^{re} is assumed to be identical across all insurers. I estimate the parameters of the required capital function $\tilde{K}(\cdot)$ and the credit rating function $g(\cdot)$ using a generalized additive model (GAM). Parameters governing the distributions of losses and returns on risky assets are also estimated from the data. In addition, I estimate the functions determining reinsurance payments and the probability of insolvency directly from observed data. Finally, I use assessments from the Guaranty Association to approximate the social costs associated with insurer insolvency.

Table 5: Supply Estimation

	Parameters or variables	Method
ν_j^d	Random shocks in insolvency decisions	Estimation of supply system (FOC + insolvency decisions)
Q_j^{re}	Reinsurance quantity	Calculate from reinsurance premiums, by dividing p^{re}
L_{jm}, r_2	Parameters of shocks	Estimate from data
$\tilde{K}(\cdot)$, $g(\cdot)$	Policy and credit rating functions	Estimate from data
d, k	Parameters of payments of reinsurance	Estimate from data
	Insolvency social costs	Estimate from Guaranty association assessments
	Insolvency probability	Match with data

Notes: This table shows items that need to be estimated in the supply estimation. The second column shows the parameters and variables to be estimated. The last column explains methods to estimate parameters.

5.2.1 Insolvency Rate

I directly estimate the insolvency rate from the data. On average, there are about 3.3 property insurers became insolvent each year and the average insolvency rate is 0.26%.

5.2.2 Credit Rating Function

I use the following Generalized Additive Model to estimate the credit rating function $g(\cdot)$.

$$g(X_1, X_2, ..., X_4) = \sum_{l=1}^{4} f_l(X_l)$$

$f_l(X_l)$ is a smooth specifier, which is a weighted sum of basis functions. I use a spline with shrinkage to select variables. Only variables that are significant are included in optimization problems. Variables X_1 to X_4 correspond to variables in the credit rating function $g(\cdot)$. These variables are written premium in risky market, written premium in less risky market, reinsurance, expected loss amounts, share of risky assets, and total assets. Please see the credit rating function below.

$$R_j = g(q(\mathbf{p_1}, \mathbf{R}), q(\mathbf{p_2}, \mathbf{R}), \frac{A_{2j}}{A_{1j} + A_{2j}}, A_{1j} + A_{2j})$$

Since the credit rating standards changed in 2005, I estimate the credit rating function separately for the periods before and after the policy change. The out-of-sample accuracy rate from the GAM estimation is approximately 0.50 before the policy change and 0.41 after it. Although these accuracy rates are not particularly high, they represent the best predictive performance obtained in my analysis. Figure 6 illustrates the relationship between the independent variables and credit ratings prior to the standard change. The results suggest that larger total assets are associated with higher credit ratings, while a higher share of risky assets is associated with lower credit ratings. Similarly, Figure 7 depicts the relationship between the independent variables and credit ratings after the standard change. Both Table 15 and Table 16 indicate that the variable 'written premium in less risky markets' is not statistically significant. Therefore, it is excluded from the optimization problem.

5.2.3 Required Capital Function

Similar to credit rating function, I use generalized additive model (GAM) to estimate required capital function $\tilde{K}(\cdot)$. Please see the expression below.

$$\tilde{K}(X_1, X_2, X_3) = \sum_{l=1}^{3} f_l(X_l)$$

Inputs in the generalized additive model are the same as the $\tilde{K}(\cdot)$ function.

$$\tilde{K}(q(\mathbf{p_1}, \mathbf{R}), q(\mathbf{p_2}, \mathbf{R}), A_{2j})$$

Since there was a policy change in 2017, I separately estimate the required capital function for the periods before and after the policy change. The R^2 of the test sample is 96.62% before the policy change and 90.57% afterward. Figures 8 and 9 present the estimation results of the required capital function using a Generalized Additive Model (GAM). The results indicate a positive relationship between the level of risky assets and the required capital, suggesting that firms with higher exposure to risky assets are required to hold more capital. Tables 17 and 18 confirm that all explanatory variables are statistically significant.

5.2.4 Function of Reinsurance

Based on the scatter plots of the quantity of insurance and the quantity of reinsurance presented in Figure 10, I approximate the reinsurance function using multivariable quantile regressions. The following table reports the results of the median (50th percentile) quantile regression. The intercept of the quantile regression is 0.

Table 6: Results of Quantile Regression

	quantity of reinsurance
(Intercept)	0.000
	(0.000)
q in risky market	0.266^{***}
	(0.005)
q in less risky market	0.213^{***}
	(0.010)
Num. obs.	36652
Percentile	0.500

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Notes: This table shows quantile regression results for medians.

5.2.5 Distributions, Payment from Reinsurance, and Insolvency Costs

I estimate the distribution of returns on risky assets and loss rates from the data. The normal inverse Gaussian (NIG) distribution, which has a closed-form probability density function (pdf), fits the empirical distribution of returns on risky assets well. See Figure 11 for the estimated distribution. For detailed parameter estimates and the pdf of the NIG distribution, please refer to Appendix 8.6.

Due to the high frequency of zero-valued observations in loss rates, I estimate their distribution using a hurdle log-normal model. The estimated distributions are displayed in

Figure 12. The results show that the mean loss rate in risky markets is higher than in less risky markets. I define risky markets as those with exposure to hurricane and earthquake risks. Details on parameter estimation and the pdf of the hurdle log-normal distribution can be found in Appendix 8.7.

The reinsurance payment function is also estimated from the data. The original payment function is defined as:

$$\min\{p^{re}Q_j^{re}, \max\{0, \sum_m (L_{jm}q(\mathbf{p_m}, \mathbf{R})) - d\}\}$$

To facilitate differentiation during the optimization process, I approximate the max and min functions using smooth counterparts: softmax and softmin. The smoothed reinsurance payment function becomes:

$$-\frac{1}{k}\log(\exp(-p^{re}Q_j^{re}k) + \exp(-(\log(1+\exp(\sum_m (L_{jm}q(\mathbf{p_m}, \mathbf{R})) - d)))k))$$

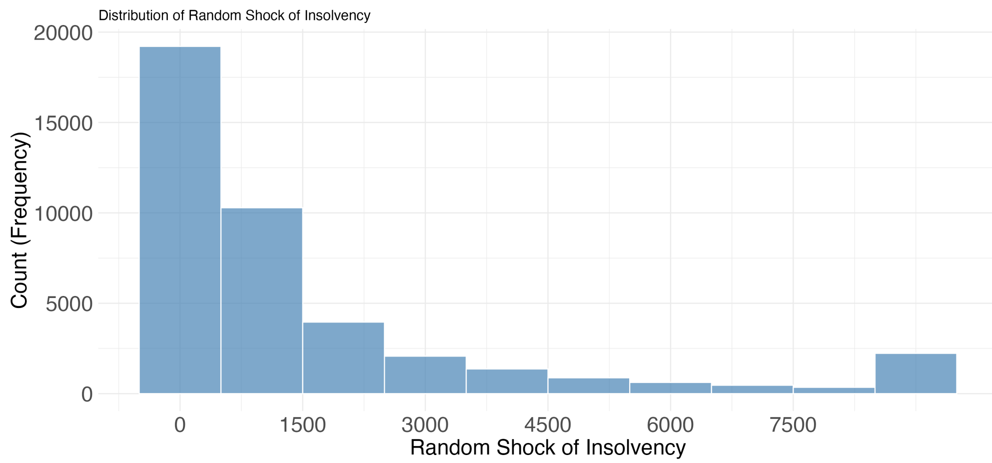
For a detailed derivation of this approximation, please refer to Appendix 8.8. The reinsurance deductible d and the smoothness parameter k are estimated from the data. The results suggest that $k = 5$ and $d =$\$2.26 million.

Finally, I measure the social cost of insolvency using Guaranty Association assessments. These represent the claims left unpaid by insolvent insurers and subsequently borne by the public. On average, each insolvency leads to a societal loss of approximately \$25.095 million.

5.2.5 Random Shocks of Insolvency

I estimate the random shocks of insolvency, ν_j^d, using the Karush–Kuhn–Tucker (KKT) conditions and observed insolvency decisions. This approach parallels the supply-side estimation in BLP. I assume that the insurers' observed choices represent their optimal decisions. When the capital requirement constraint in Equation 4 binds, I jointly solve for the Lagrange multiplier λ and the insolvency shock ν_j^d. When the constraint is not binding, $\lambda = 0$, and I solve for ν_j^d such that the first-order conditions are satisfied. Figure 3 presents the estimated distribution of ν_j^d, with a median value of \$583.62 million.

Figure 3: Estimation Results of Random Shocks of Insolvency



Notes: This figure shows results of estimation of random shocks of insolvency. Winsorization was applied to the results at the 5% level.

During the supply-side estimation, most parameters are identified directly from the data. To estimate the random shocks of insolvency, I rely on a revealed preference approach, assuming that the observed choices represent insurers' optimal decisions in the market. I then recover the insolvency shocks ν_j^d by solving for values that satisfy the Karush–Kuhn–Tucker (KKT) conditions. This procedure allows ν_j^d to capture the discrepancy between the theoretical model and real-world behavior, effectively absorbing model misspecification or unobserved heterogeneity.

6 Counterfactual Policy Analysis

In this section, I conduct counterfactual analyses to evaluate the trade-off between insurer solvency and policy affordability as capital regulation becomes stricter. My theoretical framework allows for a deeper exploration of this trade-off than is possible with reduced-form methods alone. While the reduced-form evidence presented in Section 3 establishes the statistical relationships between capital regulation, insolvency risk, and premiums, it cannot fully capture the underlying economic mechanisms driving these outcomes or predict how insurers and consumers would behave under policy regimes that have not been observed. Second, the structural model enables me to quantify the welfare trade-offs at play. For instance, I can simulate the impact of a heightened regulatory threshold on the equilibrium, observing how it affects insurer failure rates (solvency) and the resulting premium adjustments (affordability). This allows for a quantitative assessment of the costs and benefits of such a policy change from the perspectives of both consumers and insurers.

The initial counterfactual analysis will focus on tightening the existing capital requirements. This exercise will trace out the efficiency frontier between solvency and affordability, providing a nuanced understanding of the potential consequences of various policy choices. Building on these insights, the second part of the counterfactual analysis will then disentangle the roles of capital regulation and credit ratings in mitigating insolvency risk. By simulating a scenario where capital regulation is removed, I can evaluate the extent to which market-based discipline, through credit ratings, can effectively constrain insurer risk-taking. This will shed light on the unique contribution of formal regulation in the insurance market.

6.1 A World with Stringent Capital Requirement

Building on the baseline results, this counterfactual analysis explores the mechanism of capital regulation by evaluating its impact on the trade-off between solvency and affordability. I simulate market outcomes under progressively stricter capital requirement thresholds, κ. Within the model, all agents optimize given the regulatory environment, as consumers maximize utility and insurers maximize firm values. The objective is not to identify a single optimal threshold, $\kappa^\star$, but rather to characterize how equilibrium solvency and affordability levels move in response to changes in κ. This exercise provides direct insight into the costs and benefits of tightening capital regulation.

$$\kappa \leq \frac{A_{1j} + A_{2j}}{\tilde{K}(q(\mathbf{p_1}, \mathbf{R}), q(\mathbf{p_2}, \mathbf{R}), Q_j^{re}, A_{2j})} \qquad \text{(Capital requirement)}$$

Recall that welfare is

$$\text{Welfare} = \text{Consumer Surplus} + \text{Producer Surplus} - \text{Insolvency Costs}$$

Because of computational constraints, I evaluate only several threshold levels and compare the resulting welfare outcomes with those from the original data. In the following table, the capital threshold is set to $\kappa = 6$. At this threshold, approximately 25% of property insurers in the original sample hold capital below this level. After tightening the capital regulation, both solvency and insurance prices increase significantly. This result is consistent with the reduced-form evidence in Section 3, which indicates capital regulation trades off solvency and affordability. In this counterfactual analysis, the higher prices reduce insurance demand, and overall profitability decreases as the demand of insurance is elastic and operation profits of insurers reduce. The number of insurers in the market also increases; however, most entrants are smaller, leading to higher market concentration.

When comparing welfare outcomes, a higher threshold κ leads to lower firm profits, resulting in an decrease in producer surplus. Besides, consumer surplus declines as the threshold κ increases. In the baseline case, the average annual consumer surplus is approximately \$413 million, whereas under a higher threshold κ, it falls to \$226 million. At the same time, because fewer firms become insolvent when κ is higher, aggregate insolvency costs decrease. Since there are many insurers in the market, the magnitude of producer surplus is large relative to consumer surplus and insolvency costs. However, if the model incorporates a free-entry condition, producer surplus becomes zero. In that case, it is more meaningful to focus on aggregate welfare, defined as consumer surplus minus insolvency costs.

Table 7: Higher threshold of capital requirement decreases insolvency and affordability

variables	mean (ori)	mean (counter)	mean diff	median (ori)	median (counter)	median diff
insolvency	0.0024	0.0009	-0.0016	0.0000	0.0000	0.0000
p in risky market	1.0239	8.4142	7.3903	1.0000	2.2565	1.2565
p in less risky market	1.1343	9.4254	8.2911	1.0000	3.5069	2.5069
q in risky market	16.8477	6.6279	-10.2198	3.3140	0.0005	-3.3135
q in less risky market	4.7221	2.9834	-1.7387	0.0006	0.0000	-0.0006
profits	32.3665	20.7606	-11.6059	1.6199	2.4098	0.7899
operation profits	16.9034	0.8055	-16.0979	0.0170	-0.5645	-0.5814
investment profits	18.7767	19.9551	1.1784	1.4423	1.5338	0.0914
risky assets	376.1088	409.1612	33.0524	30.7232	39.7698	9.0465
Q_{re}	5.3624	2.3520	-3.0105	0.5951	0.0486	-0.5464
number of firms in risky market	1193.8808	1562.3955	368.5148	1195.0000	1577.0000	382.0000
number of firms in less risky market	803.2405	1562.3955	759.1550	815.0000	1577.0000	762.0000
HHI in risky market	0.0023	0.0041	0.0018	0.0023	0.0041	0.0017
HHI in less risky market	0.0048	0.0127	0.0079	0.0047	0.0085	0.0038

Notes: This table shows comparison of statistics of original data and counterfactual. The first three columns display mean of variables. The last three columns display median of variables. Columns (1) and (4) show statistics of original data. Columns (2) and (5) show results of counterfactual analysis when threshold of capital requirement is high. Columns (3) is equal to column (2) minus column (1). Similarly, column (6) is equal to column (5) minus column (4). The unit of q and Q_{re} is a million. The unit of profits, operation profits, investment profits, and risky assets is a million dollars.

6.2 A World without Capital Regulation

The second counterfactual analysis disentangles the respective roles of capital regulation and credit ratings in constraining insolvency risk. I examine whether credit ratings alone can effectively prevent insolvency. To isolate the role of ratings, I remove capital regulation from the optimization problem. The resulting optimization problem is given by

$$\max_{\{p_{jm},A_{1j},A_{2j}\}} \mathbb{E}(\Pi_j + A_{1j} + A_{2j}) \tag{8}$$

$$
\begin{aligned}
& s.t. \\
\Pi_j =& \max\{[\sum_m (p_{jm} - L_{jm} - Exp_j) q(\mathbf{p_m}, \mathbf{R}) - p^{re} Q_j^{re} - FC_j + r_1 A_{1j} + r_2 A_{2j} \\
& - \frac{1}{k} \log(\exp(-p^{re} Q_j^{re} k) + \exp(-(\log(1 + \exp(\sum_m (L_{jm} q(\mathbf{p_m}, \mathbf{R})) - d)))k))], \\
& - (A_{1j} + A_{2j}) - \nu_j^d\} && \text{(Profits with limited liability)} \\
R_j =& g(q(\mathbf{p_1}, \mathbf{R}), q(\mathbf{p_2}, \mathbf{R}), \frac{A_{2j}}{A_{1j} + A_{2j}}, A_{1j} + A_{2j}) && \text{(Credit rating)} \\
Q_j^{re} =& h(q(\mathbf{p_1}, \mathbf{R}), q(\mathbf{p_2}, \mathbf{R})) && \text{(Reinsurance)}
\end{aligned}
$$

During the optimization process, since the choice of price p_{jm} and the opponents' prices $p_{-j,m}$ jointly determine the quantity $q(\mathbf{p_m}, \mathbf{R})$, all insurers make their decisions simultaneously each year in the algorithm. After several iterations, if no firm has an incentive to deviate from its chosen price, asset allocation, or reinsurance strategy, the outcome converges to a Nash equilibrium. The quantity of insurance is given by

$$q(\mathbf{p_m}, \mathbf{R}) = \frac{e^{\delta_{jm}}}{\sum_k e^{\delta_{km}}} \cdot N_m$$

where $\delta_{jm} = \alpha_1 p_{jm} + \alpha_2 R_j + \xi_{jm}$. N_m is the market size which is the total quantity of insurance in a market m.

Table 8 reports the results. Without capital requirements, the insolvency rate increases by 0.09 percentage points. Insurance becomes more affordable as prices decrease by about 5.1%. Some insurers adopt riskier strategies by lowering prices and holding more risky assets. Insurers unable to capture sufficient market share experience lower operational profits. In the counterfactual scenario, although more insurers participate with small market shares, market concentration rises, as reflected in an increase in the Herfindahl–Hirschman Index (HHI), particularly in less risky markets.

Table 8: Removing capital requirement increases insolvency and affordability

variables	mean (ori)	mean (counter)	mean diff	median (ori)	median (counter)	median diff
insolvency	0.0020	0.0029	0.0009	0.0000	0.0000	0.0000
p in risky market	1.0409	0.9877	-0.0532	1.0000	1.0300	0.0300
p in less risky market	1.1562	0.9058	-0.2504	1.0000	0.9941	-0.0059
q in risky market	23.0784	13.8387	-9.2397	5.3465	0.0755	-5.2710
q in less risky market	7.4993	10.4378	2.9385	0.0228	0.6883	0.6656
profits	66.1967	41.2910	-24.9056	2.7556	3.9554	1.1998
operation profits	36.4701	6.9860	-29.4841	0.0264	-0.1330	-0.1594
investment profits	32.5734	34.3050	1.7316	2.1329	2.1196	-0.0132
risky assets	662.9585	690.1300	27.1715	47.1503	52.5216	5.3713
Q_{re}	9.4960	5.8026	-3.6935	0.9196	0.3758	-0.5438
number of firms in risky market	1099.8335	1420.5988	320.7653	1105.0000	1400.0000	295.0000
number of firms in less risky market	771.1310	1420.5988	649.4677	761.0000	1400.0000	639.0000
HHI in risky market	0.0021	0.0044	0.0024	0.0020	0.0042	0.0022
HHI in less risky market	0.0043	0.0230	0.0188	0.0044	0.0138	0.0094

Notes: This table shows comparison of statistics of original data and counterfactual. The first three columns display mean of variables. The last three columns display median of variables. Columns (1) and (4) show statistics of original data. Columns (2) and (5) show results of counterfactual analysis when removing capital requirement. Columns (3) is equal to column (2) minus column (1). Similarly, column (6) is equal to column (5) minus column (4). The unit of q and Q_{re} is a million. The unit of profits, operation profits, investment profits, and risky assets is a million dollars.

6.3 A World without Capital Regulation and High Rating Salience

A central question in financial regulation is whether market discipline, driven by vigilant consumers, can serve as a viable substitute for formal government oversight. If the salience of risk indicators like credit ratings were sufficiently high, consumers could theoretically discipline insurers into holding adequate capital, thereby mitigating insolvency risk without the need for binding capital requirements. This would be a first-best outcome, as it would reduce the potential deadweight losses associated with regulatory capital. I test this hypothesis directly within my structural framework.

In the baseline model, the estimated demand coefficient on price is -2.3759, while the coefficient on credit ratings is 0.0409. This indicates that in the current market, consumers are significantly more responsive to price than to an insurer's credit rating. To simulate a world with powerful market discipline, I conduct a counterfactual analysis where I dramatically increase the salience of credit ratings. Specifically, I increase the rating coefficient by a factor of 25 to 1.0225.

Table 9 presents the results for a market without capital regulation but with high credit rating salience. When consumers are more sensitive to credit ratings, the insolvency rate decreases by 0.14 percentage points. Insurers with lower credit ratings tend to reduce prices to attract consumers, resulting in lower average prices compared to a market in which consumers are less responsive to credit ratings. Consequently, the average operating profits in the market decline. To compensate for the reduced profitability, insurers have an incentive to invest in riskier assets. Although the market features a larger number of smaller insurers, those offering lower prices capture a greater market share, leading to an increase in the Herfindahl–Hirschman Index and higher market concentration. Thus, while heightened credit rating salience can mitigate insolvency risk, it may simultaneously contribute to greater market concentration. This result suggests that increasing consumers' rating salience may not be a perfect solution to improving market stability.

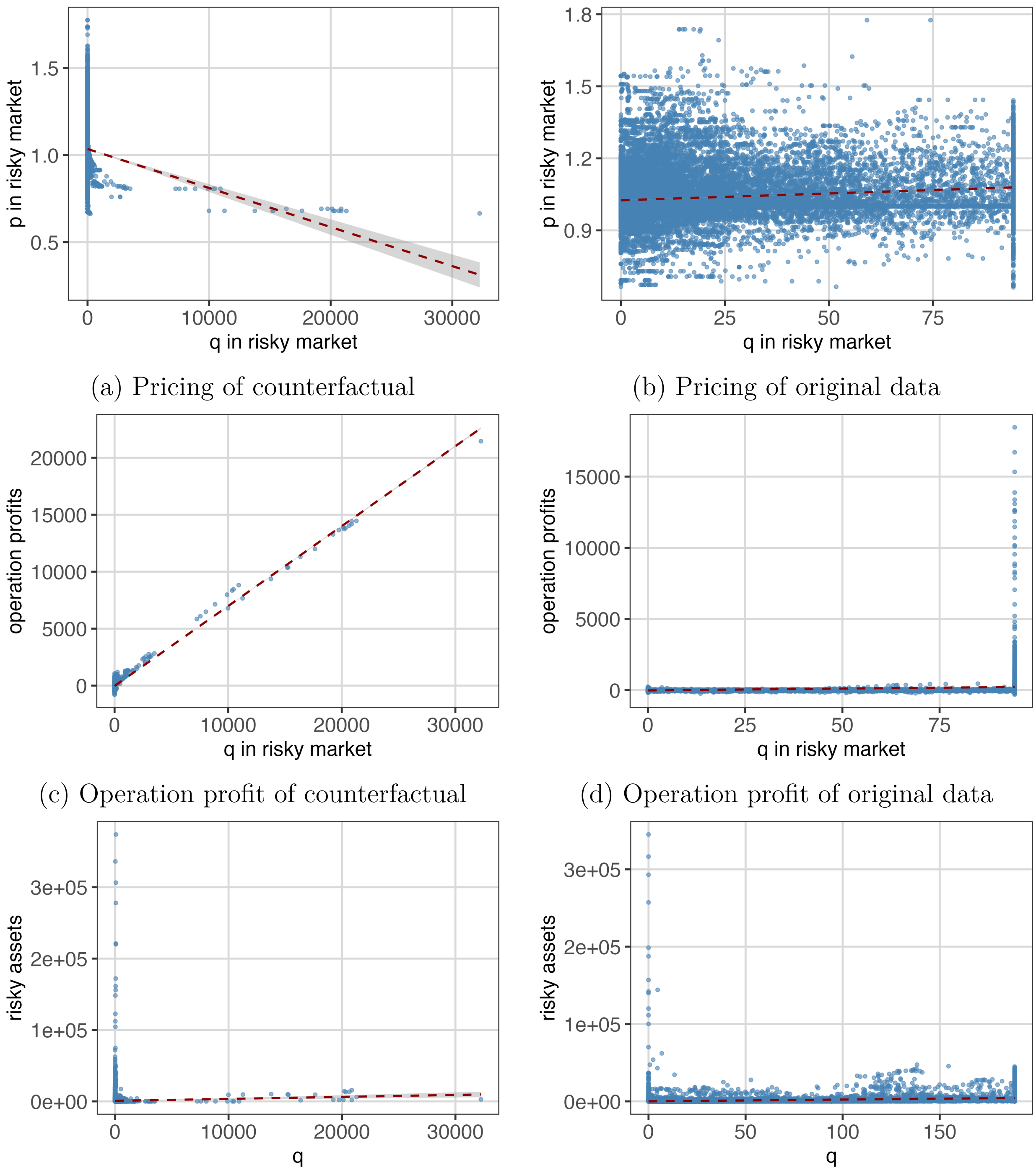
Figure 4 illustrates that the decline in profits is driven by increasing market concentration and aggressive pricing behavior. In Figure 4, panels (a), (c), and (e) show the relationships between the quantity of insurance and price, operational profits, and risky assets in the counterfactual scenario, while panels (b), (d), and (f) present the corresponding relationships in the baseline data. Panel (a) shows that some insurers cut prices to gain larger market shares. For insurers that successfully capture the market, operational profits are higher. Moreover, insurers engaging in more aggressive pricing tend to hold a greater proportion of risky assets.

Table 9: High Rating Salience Improves Solvency and Increases Market Concentration

variables	mean (ori)	mean (counter)	mean diff	median (ori)	median (counter)	median diff
insolvency	0.0022	0.0008	-0.0014	0.0000	0.0000	0.0000
p in risky market	1.0297	0.8954	-0.1343	1.0000	1.0300	0.0300
p in less risky market	1.1442	0.8136	-0.3306	1.0000	0.8360	-0.1640
q in risky market	19.6851	16.3366	-3.3485	4.0859	0.0000	-4.0859
q in less risky market	6.0147	14.8395	8.8248	0.0011	0.0000	-0.0011
profits	45.1599	34.0577	-11.1022	2.1445	0.8386	-1.3059
operation profits	23.7183	8.2000	-15.5183	0.0157	-0.5887	-0.6044
investment profits	24.1664	25.8578	1.6913	1.7740	1.9374	0.1635
risky assets	481.5485	506.3704	24.8219	36.5159	44.7321	8.2163
Q_{re}	6.9286	7.3834	0.4548	0.6513	0.0000	-0.6513
number of firms in risky market	1147.3953	1513.1399	365.7446	1125.0000	1514.0000	389.0000
number of firms in less risky market	779.4315	1513.1399	733.7084	761.0000	1514.0000	753.0000
HHI in risky market	0.0022	0.4473	0.4451	0.0021	0.1721	0.1700
HHI in less risky market	0.0045	0.6708	0.6663	0.0044	0.6264	0.6220

Notes: This table shows comparison of statistics of original data and counterfactual. The first three columns display mean of variables. The last three columns display median of variables. Columns (1) and (4) show statistics of original data. Columns (2) and (5) show results of counterfactual analysis when removing capital requirement. Columns (3) is equal to column (2) minus column (1). Similarly, column (6) is equal to column (5) minus column (4). The unit of q and Q_{re} is a million. The unit of profits, operation profits, investment profits, and risky assets is a million dollars.

Figure 4: Insurers undercut prices in risky market when no capital requirements



(a) Pricing of counterfactual

(b) Pricing of original data

(c) Operation profit of counterfactual

(d) Operation profit of original data

(e) Risky assets of counterfactual

(f) Risky assets of original data

Notes: This figure compares pricing and profits of counterfactual and original data. They are scatter plots to relationship between quantity of insurance and other outcome variables, in order to provide more details of the results. Panels (a) (c) (e) display results of counterfactual analysis after removing capital regulation. Panels (b) (d) (f) display results of original data.

7 Conclusion

In recent years, policymakers have debated whether capital regulation for U.S. property and casualty insurers should transition from a static formula-based framework to a model-based approach. Before making such a shift, it is crucial to deepen our understanding of how capital regulation affects market outcomes and what specific roles it plays in the presence of credit ratings. This paper addresses two central questions: (1) how capital regulation influences insurer solvency and market outcomes, and (2) how capital regulation constrains insolvency when credit ratings are an important market discipline mechanism.

I first provide empirical evidence on the impact of capital regulation on insurer solvency and product affordability. The analysis indicates that while capital regulation strengthens solvency, it also increases insurance prices. Specifically, a \$1 million increase in required capital leads to a \$3.34 million increase in actual capital held and a 0.218 percentage point rise in insurance premiums.

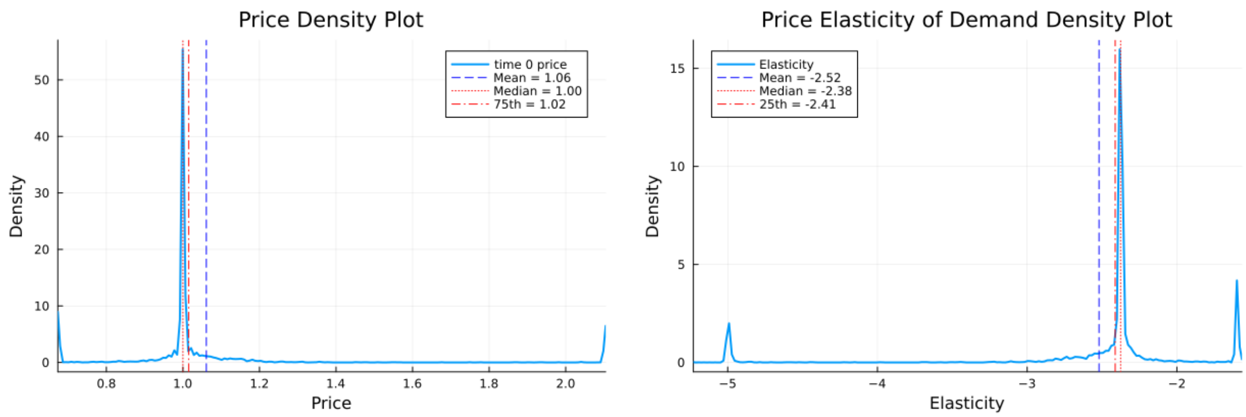
To further investigate these dynamics, I develop a theoretical framework that jointly incorporates capital requirements and credit ratings. Using structural estimation, I conduct counterfactual simulations to inform future policy design. The first counterfactual analysis produces results consistent with the reduced-form evidence: stricter capital requirements improve solvency but also raise prices. The second counterfactual analysis examines the relative roles of capital regulation and credit ratings in mitigating insolvency risk. A key question is whether credit ratings alone can sufficiently discipline insurers. The counterfactual results indicate that, in the absence of capital regulation, the insolvency rate would increase by 0.09 percentage points, while insurance premiums would decrease by about 5.1%. The third counterfactual analysis explores a market without capital regulation but with high credit rating salience. When consumers place greater weight on credit ratings, the insolvency rate declines; however, lower-rated insurers reduce prices to attract customers, which compresses operating profits and incentivizes riskier investment behavior. As a result, market concentration increases despite the lower insolvency rate. This finding suggests that enhancing consumer attention to credit ratings alone may not offer a perfect substitute for capital regulation.

Overall, the findings underscore the critical role of capital regulation in maintaining market stability. Even with robust credit rating mechanisms, capital requirements remain essential to curb excessive risk-taking and preserve solvency in the insurance sector.

8 Appendix

8.1 Figures

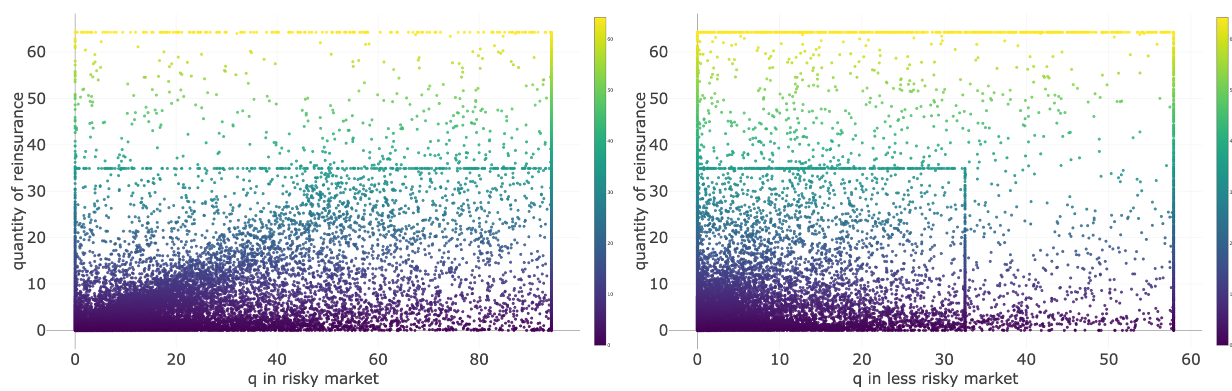
Figure 5: Estimation Results of Price and Elasticity in Demand Estimation



(a) Price (b) Elasticity

Notes: This figure shows results of estimation of price and elasticity. The results are winsorized at the 5% level.

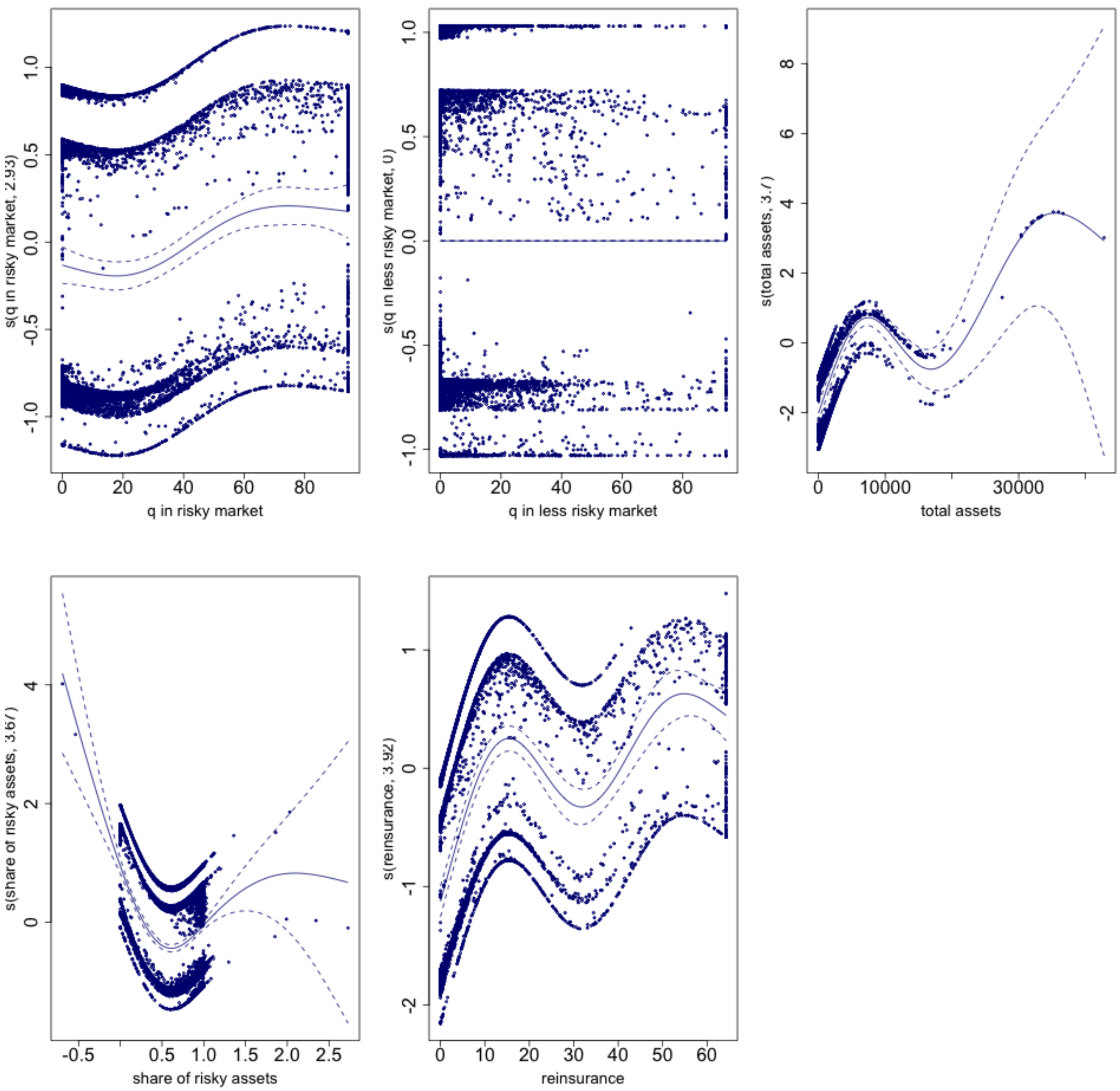
Figure 10: Scatter Plots of Quantity of Insurance and Quantity of Reinsurance



(a) Risky market (b) Less risky market

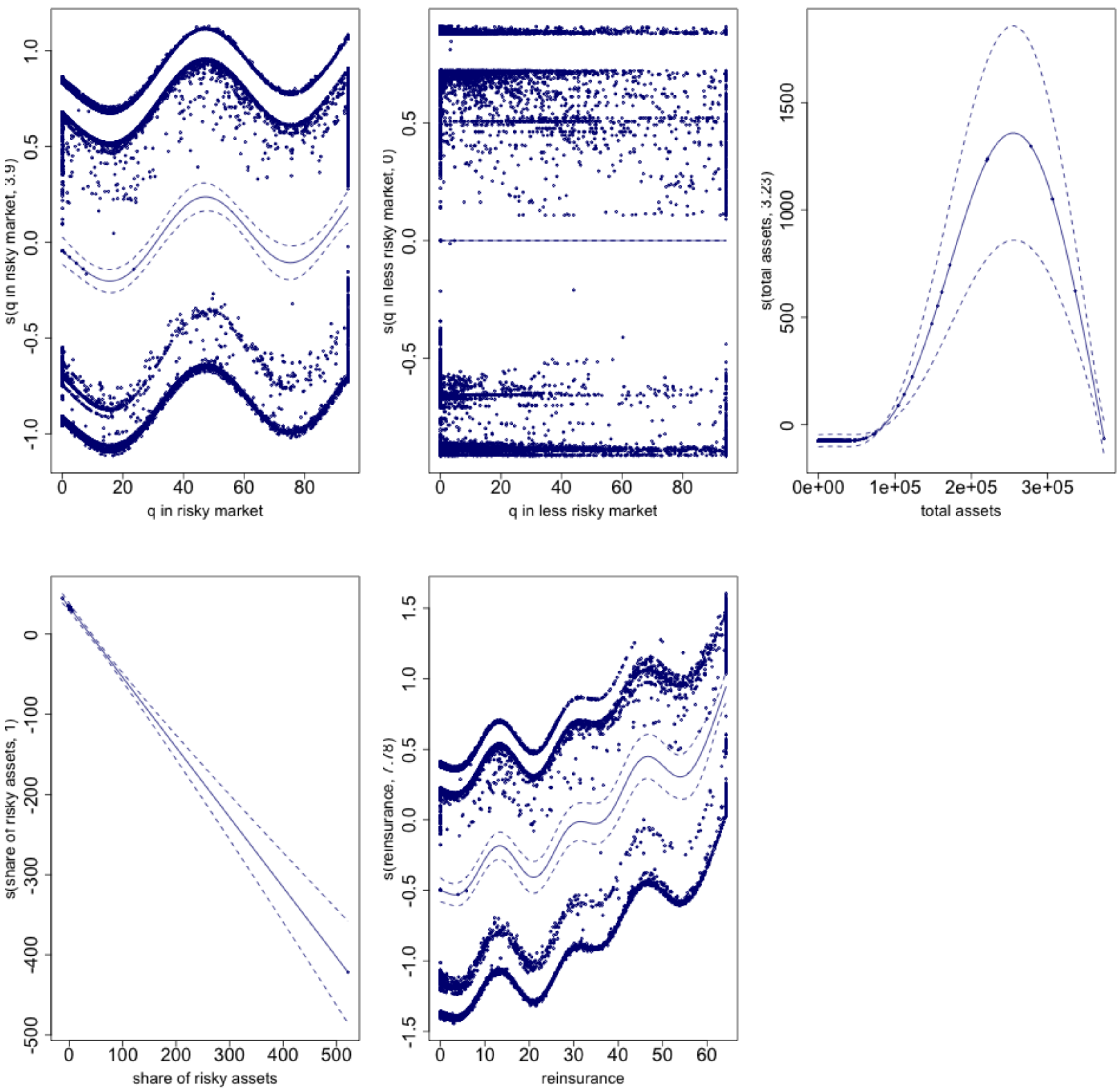
Notes: This figure shows scattered plots of quantity of insurance and quantity of reinsurance. Panel (a) shows quantity in risky markets. Panel (b) shows quantity in less risky markets.

Figure 6: Estimation Results of Credit Rating Function before Year 2005



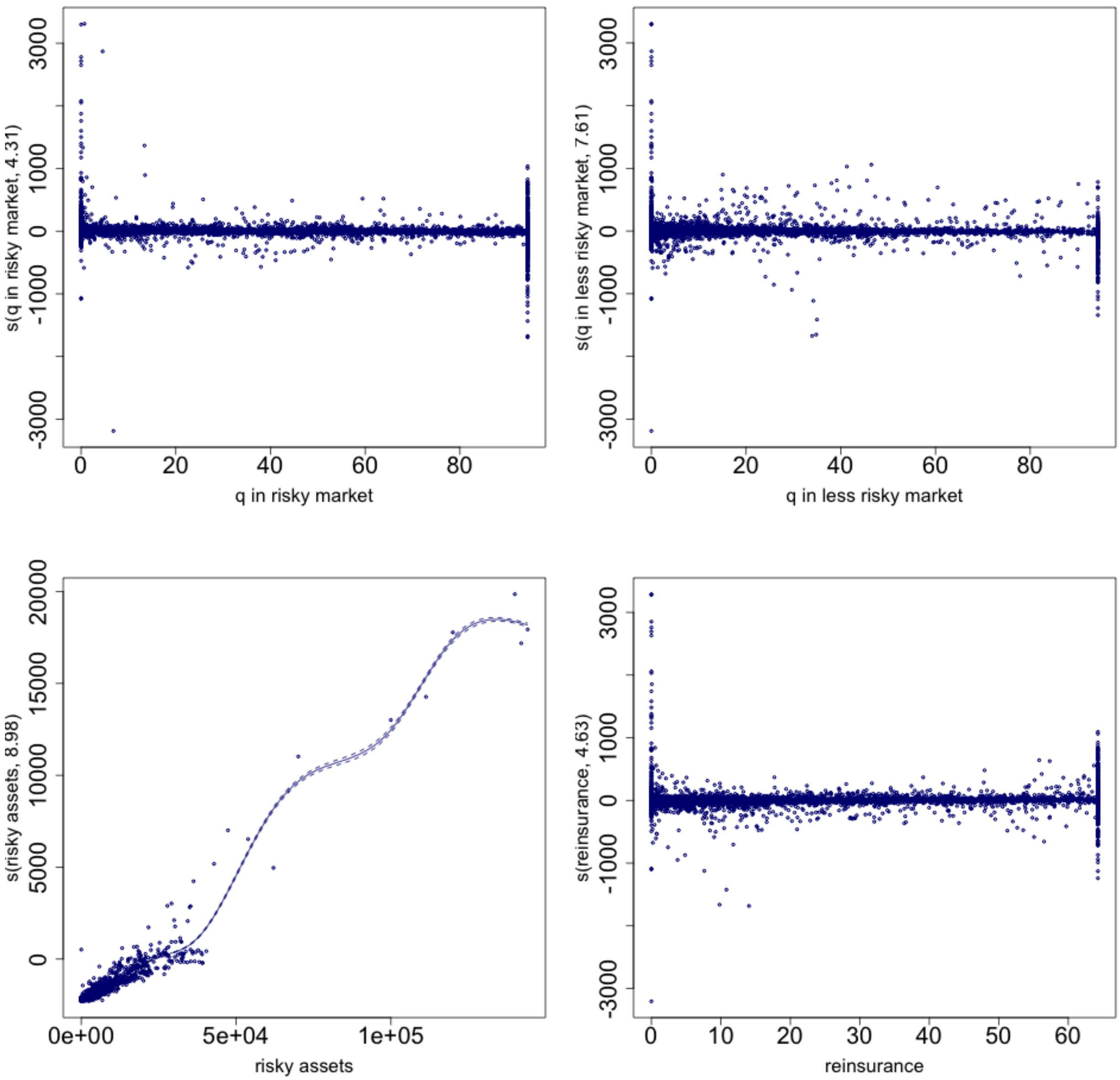
Notes: This figure shows results of estimation of credit rating function before credit rating standard change. The x-axis shows level of variables. The y-axis displays values of the smooth specifier of generalized additive model.

Figure 7: Estimation Results of Credit Rating Function after Year 2005



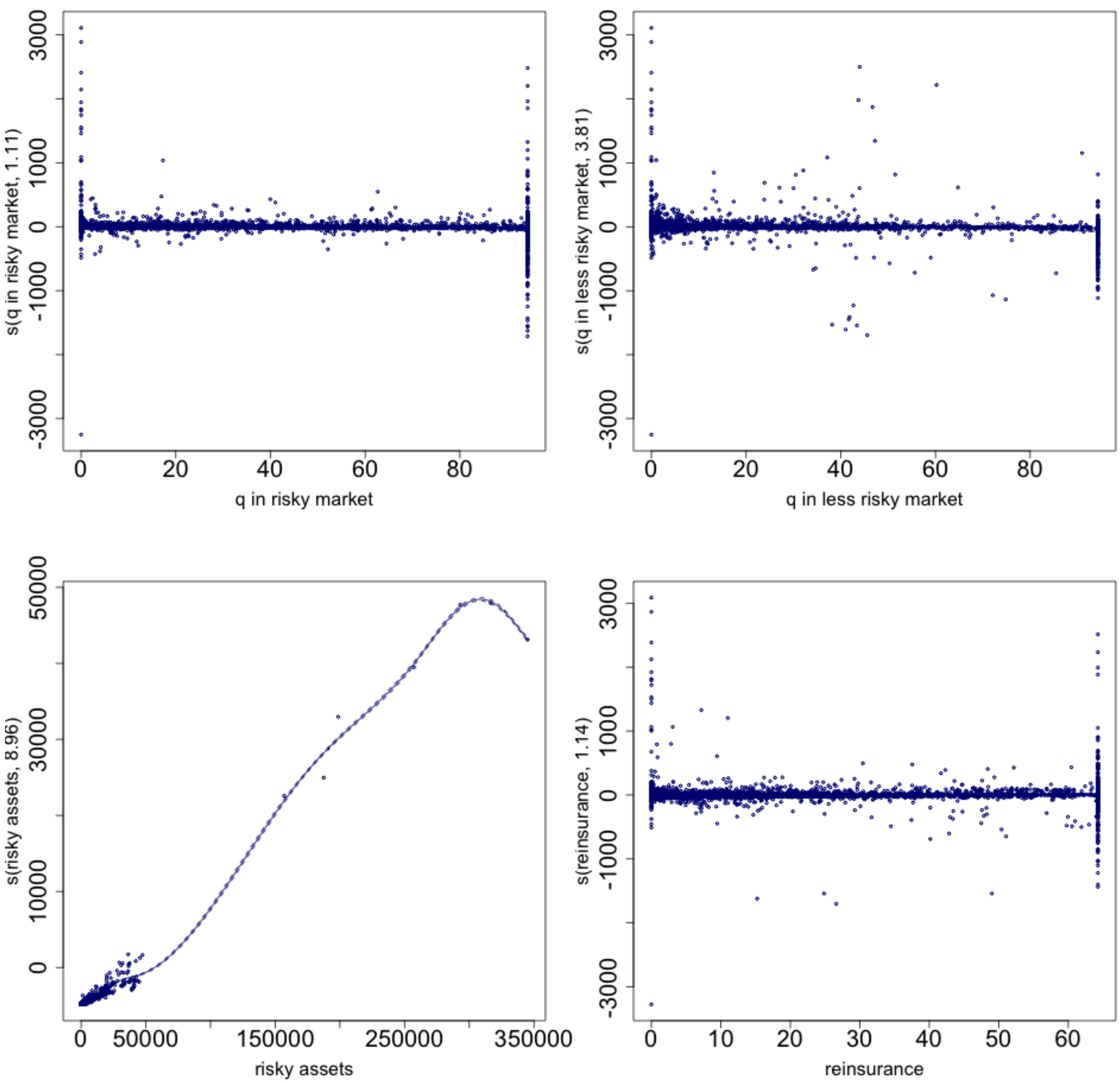
Notes: This figure shows results of estimation of credit rating function after credit rating standard change. The x-axis shows level of variables. The y-axis displays values of the smooth specifier of generalized additive model.

Figure 8: Estimation Results of Required Capital Function before Year 2017



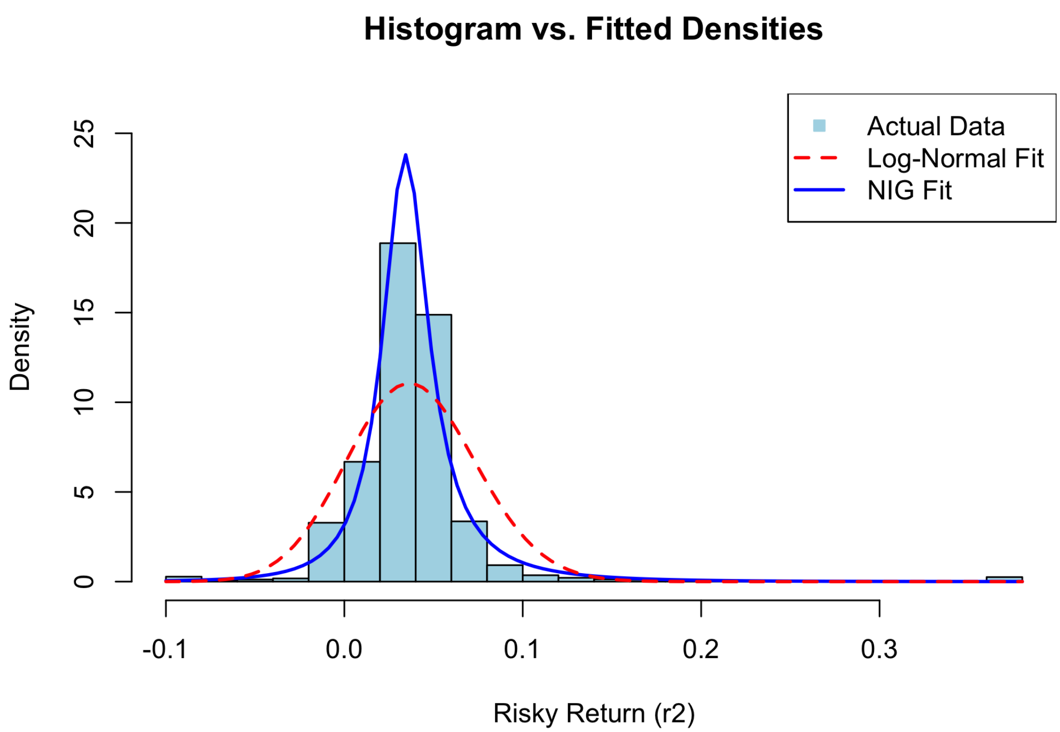
Notes: This figure shows results of estimation of required capital function before policy change. The x-axis shows level of variables. The y-axis displays values of the smooth specifier of generalized additive model.

Figure 9: Estimation Results of Required Capital Function after Year 2017



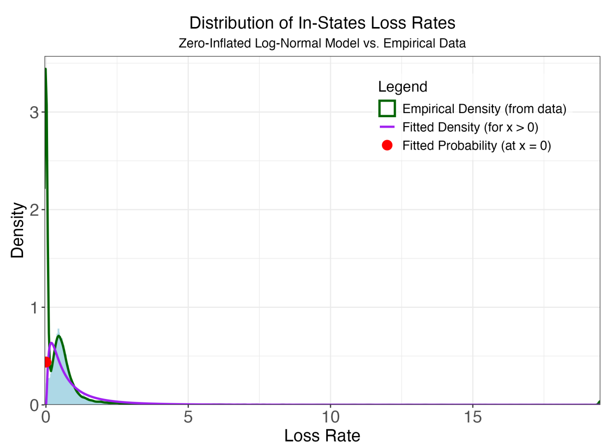
Notes: This figure shows results of estimation of required capital function after policy change. The x-axis shows level of variables. The y-axis displays values of the smooth specifier of generalized additive model.

Figure 11: Estimation Results of Return of Risky Assets

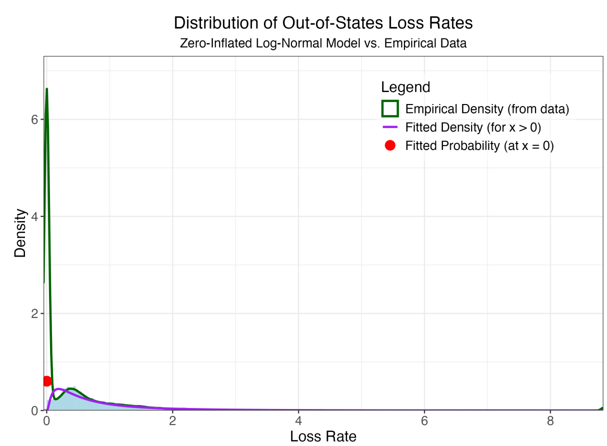


Notes: This figure shows results of estimation of return of risky assets. The normal inverse Gaussian (NIG) distribution fits the data better.

Figure 12: Estimation Results of Loss Rates



(a) Risky market



(b) Less risky market

Notes: This figure shows results of estimation of loss rates. Panel (a) is the loss rate in risky market, which has exposure to hurricane and earthquake. Panel (b) is the loss rate in less risky market.

8.2 Tables

Table 10: Summary of catastrophe-prone areas

Disaster	Catastrophe-prone areas
Hurricane	Hawaii, District of Columbia and states and commonwealths bordering on the Atlantic Ocean and/or the Gulf of Mexico including Puerto Rico.
Earthquake	Alaska, Hawaii, Washington, Oregon, California, Idaho, Nevada, Utah, Arizona, Montana, Wyoming, Colorado, New Mexico, Puerto Rico, and geographic areas in the following states that are in the New Madrid Seismic Zone - Missouri, Arkansas, Mississippi, Tennessee, Illinois and Kentucky.

Notes: This table summarizes the catastrophe-prone areas which I use to define the treated regions.

Table 11: Summary statistics

	Entire sample			Treated		Control	
	mean	sd	median	before	after	before	after
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
total adjusted capital	203.9706	392.1466	50.0268	231.0879	266.4900	109.5418	122.6142
direct premiums written	251.0444	385.7734	72.0020	284.8771	347.2687	98.1380	134.7411
price change	2.5288	5.1154	0.0569	3.0778	3.7489	0.7122	0.9156
net premiums written	146.0623	309.4856	13.4776	166.0407	195.5490	66.8428	84.6467
RBC ratio	72.8135	136.5142	11.3923	68.5824	63.8509	87.3448	85.2334
reserve	162.2866	381.1700	9.0012	186.9741	219.5984	77.0803	87.2492
required capital	28.4768	62.6220	3.2278	31.6679	39.2074	12.9307	15.2807
surplus	203.7210	388.6703	50.1500	230.3006	265.2168	111.8157	123.3460
treatment	0.6225	0.4848	1.0000	1.0000	1.0000	0.0000	0.0000

Notes: This table shows summary statistics. Columns (1) to (3) show the entire sample. Columns (4) to (7) displays means. Columns (4) and (5) are treated group before year 2017 and after year 2017 respectively. Columns (6) and (7) are control group before year 2017 and after year 2017 respectively. Except for price change, RBC ratio, and treatment, the unit of variables is million. The unit of price change and RBC ratio is percent.

Table 12: First stage (binding)

	Dependent variable:					
	required capital	surplus	price change	required capital	surplus	price change
	(1)	(2)	(3)	(4)	(5)	(6)
treated×reform	2.624***	7.308*	0.329**	3.268***	12.617***	0.462***
	(0.975)	(4.140)	(0.158)	(0.715)	(3.206)	(0.126)
Observations	6,055	6,055	6,055	9,835	9,835	9,835
R^2	0.0261	0.0271	0.0233	0.0303	0.0334	0.0280
Note:						*p<0.1; **p<0.05; ***p<0.01

Notes: Columns (1), (2), and (3): Average RBC ratio before treatment is within 1 standard deviation to threshold 2. Columns (4), (5) and (6): Average RBC ratio before treatment is within 2 standard deviations to threshold 2.

Table 13: IV regressions (binding)

	Dependent variable:			
	surplus	price change	surplus	price change
	(1)	(2)	(3)	(4)
required capital	2.785**	0.125*	3.861***	0.141***
	(1.244)	(0.075)	(0.790)	(0.048)
Observations	6,055	6,055	9,835	9,835
R^2	0.380	0.0233	0.404	0.0280
Note:				*p<0.1; **p<0.05; ***p<0.01

Notes: Columns (1) and (2): Average RBC ratio before treatment is within 1 standard deviation to threshold 2. Columns (3) and (4): Average RBC ratio before treatment is within 2 standard deviations to threshold 2.

Table 14: Higher RBC ratios lead to lower probability of insolvency

	Dependent variable:			
	insolvency			
	OLS		*panel linear*	
	(1)	(2)	(3)	(4)
RBC ratio	-0.0001^{***}	-0.0001^{***}	-0.00003^{***}	-0.00002^{***}
	(0.00001)	(0.00001)	(0.00000)	(0.00000)
Constant	0.054^{***}			
	(0.001)			
Observations	61,223	61,223	61,223	61,223
R^2	0.002	0.002	0.001	0.0003
Note:				*p<0.1; **p<0.05; ***p<0.01

Notes: Columns (2) and (3): Control for time fixed effects. Columns (3) and (4): Set insolvency to be 1 when it is 3 years before being insolvent. Column (4): Control for time and firm fixed effects.

Table 15: Estimation Results of Credit Rating Function before Credit Rating Standard Change

	Estimate	**Std. Error**	**t value**	**Pr(> $\|t\|$)**
(Intercept)	3.9741	0.1357	29.3	<2e-16 ***

	edf	**Ref.df**	**F**	**p-value**
s(q in risky market)	2.9300289	4	6.704	2.19e-06 ***
s(q in less risky market)	0.0003405	4	0.000	0.943
s(total asset)	3.6973535	4	79.222	< 2e-16 ***
s(share of risky assets)	3.6749247	4	77.370	< 2e-16 ***
s(reinsurance)	3.9202691	4	113.764	< 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Notes: The last column shows whether each smooth specifier is significant. The edf stands for effective degrees of freedom. It quantifies the complexity or "wiggleness" of the smooth function for a given predictor. The Ref.df, or reference degrees of freedom, is a value used in the calculation of the F-statistic and the corresponding p-value to test the significance of the smooth term.

Table 16: Estimation Results of Credit Rating Function after Credit Rating Standard Change

	Estimate	**Std. Error**	**t value**	**Pr(> $\|t\|$)**
(Intercept)	43.69	14.17	3.083	0.00205 **

	edf	**Ref.df**	**F**	**p-value**
s(q in risky market)	3.8971876	4	19.93	<2e-16 ***
s(q in less risky market)	0.0006075	4	0.00	0.915
s(total assets)	3.2328792	4	87.65	<2e-16 ***
s(share of risky assets)	0.9982281	4	107.50	<2e-16 ***
s(reinsurance)	7.7831365	9	66.09	<2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Notes: The last column shows whether each smooth specifier is significant. The edf stands for effective degrees of freedom. It quantifies the complexity or "wiggleness" of the smooth function for a given predictor. The Ref.df, or reference degrees of freedom, is a value used in the calculation of the F-statistic and the corresponding p-value to test the significance of the smooth term.

Table 17: Estimation Results of Required Capital Function before Policy Change

	Estimate	**Std. Error**	**t value**	**Pr($>|t|$)**
(Intercept)	2250.383	3.961	568.2	<2e-16 ***

	edf	**Ref.df**	**F**	**p-value**
s(q in risky market)	4.309	9	23.23	<2e-16 ***
s(q in less risky market)	7.614	9	61.62	<2e-16 ***
s(risky assets)	8.985	9	63396.95	<2e-16 ***
s(reinsurance)	4.630	9	32.45	<2e-16 ***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Notes: The last column shows whether each smooth specifier is significant. The edf stands for effective degrees of freedom. It quantifies the complexity or "wiggleness" of the smooth function for a given predictor. The Ref.df, or reference degrees of freedom, is a value used in the calculation of the F-statistic and the corresponding p-value to test the significance of the smooth term.

Table 18: Estimation Results of Required Capital Function after Policy Change

	Estimate	**Std. Error**	**t value**	**Pr($>|t|$)**
(Intercept)	4815.984	8.132	592.2	<2e-16 ***

	edf	**Ref.df**	**F**	**p-value**
s(q in risky market)	1.109	9	2.327	2.52e-06 ***
s(q in less risky market)	3.811	9	20.855	< 2e-16 ***
s(risky assets)	8.958	9	99567.155	< 2e-16 ***
s(reinsurance)	1.136	9	2.955	2.91e-07 ***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Notes: The last column shows whether each smooth specifier is significant. The edf stands for effective degrees of freedom. It quantifies the complexity or "wiggleness" of the smooth function for a given predictor. The Ref.df, or reference degrees of freedom, is a value used in the calculation of the F-statistic and the corresponding p-value to test the significance of the smooth term.

8.3 Development of Capital Requirement before 2017

According to Klein (1995), several property-casualty insurers in the United States failed during the 1980s due to deficient loss reserves, inadequate pricing, and overly rapid expansion. The fixed capital requirements in place at the time were insufficient to constrain this rapid growth, which contributed significantly to these failures. In response, the National Association of Insurance Commissioners (NAIC) developed and implemented Risk-Based Capital (RBC) formulas in the early 1990s, allowing capital requirements to vary with firm-specific risk profiles and size. The RBC formula for property and casualty insurers was introduced in 1994. The RBC standards for life and property/casualty (P/C) insurers are based on the Risk-Based Capital (RBC) for Insurers Model Act (Model #312), originally adopted by the NAIC in 1993 and most recently revised in 2011.

Beginning January 1, 2015, the NAIC implemented the Own Risk and Solvency Assessment (ORSA) Model Act, which mandates that insurers conduct and annually report on their enterprise risk management (ERM) practices and capital adequacy. ERM refers to a comprehensive, organization-wide framework for identifying and managing risk exposures.

8.4 Derivation of First-Order Conditions for Supply Estimation

Since $\int\int\int_{\Omega} = \int\int\int_{\Omega/D} + \int\int\int_{D}$, then objective function becomes:

$$
\begin{aligned}
&\max_{\{p_{jm},A_{1j},A_{2j}\}} \int\int\int_{D(p_{jm},A_{1j},A_{2j},Q_j^{re})} [\sum_m (p_{jm} - L_{jm} - Exp_j) q(\mathbf{p}_m, \mathbf{R}) - p^{re} Q_j^{re} - FC_j \\
&- \frac{1}{k} \log(\exp(-p^{re} Q_j^{re} k) + \exp(-(\log(1 + \exp(\sum_m (L_{jm} q(\mathbf{p_m}, \mathbf{R})) - d)))k)) \\
&+ r_1 A_{1j} + r_2 A_{2j}] f_r(r_2) f_{L_1}(L_{j1}) f_{L_2}(L_{j2}) dr_2 dL_{j1} dL_{j2} - \\
&\int\int\int_{\Omega} (A_{1j} + A_{2j} + \nu_j^d) f_r(r_2) f_{L_1}(L_{j1}) f_{L_2}(L_{j2}) dr_2 dL_{j1} dL_{j2} \\
&+ \int\int\int_{D(p_{jm},A_{1j},A_{2j},Q_j^{re})} (A_{1j} + A_{2j} + \nu_j^d) f_r(r_2) f_{L_1}(L_{j1}) f_{L_2}(L_{j2}) dr_2 dL_{j1} dL_{j2} + A_{1j} + A_{2j}
\end{aligned}
$$

Further simplify objective function:

$$\max_{\{p_{jm},A_{1j},A_{2j},Q_j^{re}\}} \int\int\int_{D(p_{jm},A_{1j},A_{2j},Q_j^{re})} [\sum_m ((p_{jm} - L_{jm} - Exp_j)q(\mathbf{p_m},\mathbf{R})) - p^{re}Q_j^{re} - FC_j$$
$$- \frac{1}{k}\log(\exp(-p^{re}Q_j^{re}k) + \exp(-(\log(1+\exp(\sum_m (L_{jm}q(\mathbf{p_m},\mathbf{R})) - d)))k))$$
$$+ r_1A_{1j} + r_2A_{2j} + A_{1j} + A_{2j} + \nu_j^d] f_r(r_2) f_{L_1}(L_{j1}) f_{L_2}(L_{j2}) dr_2 dL_{j1} dL_{j2} - \nu_j^d$$

$$s.t.$$
$$R_j = g(q(\mathbf{p_1},\mathbf{R}), q(\mathbf{p_2},\mathbf{R}), \frac{A_{2j}}{A_{1j}+A_{2j}}, A_{1j}+A_{2j}) \quad \text{(Credit rating)}$$
$$2 \leq \frac{A_{1j}+A_{2j}}{\tilde{K}(q(\mathbf{p_1},\mathbf{R}), q(\mathbf{p_2},\mathbf{R}), A_{2j})} \quad \text{(Capital requirement)}$$
$$Q_j^{re} = h(q(\mathbf{p_1},\mathbf{R}), q(\mathbf{p_2},\mathbf{R})) = \beta_0 + \beta_1 q(\mathbf{p_1},\mathbf{R}) + \beta_2 q(\mathbf{p_2},\mathbf{R}) \quad \text{(Reinsurance)}$$

The domain $D(p_{jm}, A_{1j}, A_{2j}, Q_j^{re})$ where insurers are solvent is

$$[\sum_m (p_{jm} - L_{jm} - Exp_j)q(\mathbf{p_m},\mathbf{R}) - p^{re}Q_j^{re} - FC_j + r_2A_{2j} + r_1A_{1j}$$
$$- \frac{1}{k}\log(\exp(-p^{re}Q^{re}k) + \exp(-(\log(1+\exp(\sum_m (L_{jm}q(\mathbf{p_m},\mathbf{R})) - d)))k))]$$
$$\geq -(A_{1j} + A_{2j} + \nu_j^d)$$

$M = 2$ in this case.

Plug in expression of Q_j^{re} to objective function:

$$\max_{\{p_{jm},A_{1j},A_{2j}\}} \int\int\int_{D(p_{jm},A_{1j},A_{2j})} [\sum_m ((p_{jm} - L_{jm} - Exp_j)q(\mathbf{p_m},\mathbf{R})) - p^{re}(\beta_0 + \beta_1 q(\mathbf{p_1},\mathbf{R}) + \beta_2 q(\mathbf{p_2},\mathbf{R})) - FC_j$$
$$- \frac{1}{k}\log(\exp(-p^{re}(\beta_0 + \beta_1 q(\mathbf{p_1},\mathbf{R}) + \beta_2 q(\mathbf{p_2},\mathbf{R}))k) + \exp(-(\log(1+\exp(\sum_m (L_{jm}q(\mathbf{p_m},\mathbf{R})) - d)))k))$$
$$+ r_1A_{1j} + r_2A_{2j} + A_{1j} + A_{2j} + \nu_j^d] f_r(r_2) f_{L_1}(L_{j1}) f_{L_2}(L_{j2}) dr_2 dL_{j1} dL_{j2} - \nu_j^d$$

$$
\begin{aligned}
& s.t. \\
R_j =& g(q(\mathbf{p_1}, \mathbf{R}), q(\mathbf{p_2}, \mathbf{R}), \frac{A_{2j}}{A_{1j}+A_{2j}}, A_{1j}+A_{2j}) && \text{(Credit rating)} \\
2 \leq & \frac{A_{1j}+A_{2j}}{\tilde{K}(q(\mathbf{p_1}, \mathbf{R}), q(\mathbf{p_2}, \mathbf{R}), A_{2j})} && \text{(Capital requirement)}
\end{aligned}
$$

The domain $D(p_{jm}, A_{1j}, A_{2j})$ where insurers are solvent is

$$
\begin{aligned}
& [\sum_m (p_{jm} - L_{jm} - Exp_j) q(\mathbf{p_m}, \mathbf{R}) - p^{re}(\beta_0 + \beta_1 q(\mathbf{p_1}, \mathbf{R}) + \beta_2 q(\mathbf{p_2}, \mathbf{R})) - FC_j + r_2 A_{2j} + r_1 A_{1j} \\
& - \frac{1}{k} \log(\exp(-p^{re}(\beta_0 + \beta_1 q(\mathbf{p_1}, \mathbf{R}) + \beta_2 q(\mathbf{p_2}, \mathbf{R}))k) + \exp(-(\log(1 + \exp(\sum_m (L_{jm} q(\mathbf{p_m}, \mathbf{R})) - d)))k))] \\
& \geq -(A_{1j} + A_{2j} + \nu_j^d)
\end{aligned}
$$

$M = 2$ in this case.

In this section, I am going break down derivatives by parts. First, I take derivative of the demand function to p_{jm}, we have:

$$
\frac{\partial q_{jm}}{\partial p_{jm}} = N_m \alpha_1 S_{jm}(1 - S_{jm})
$$

Similarly, take derivative of the demand function to R, we have:

$$
\frac{\partial q_{jm}}{\partial R_j} = N_m \alpha_2 S_{jm}(1 - S_{jm})
$$

$$
N_m = \sum_k q_{km}
$$

N_m is market size in market m.

FOC w.r.t p_{j1}:

$$
\iiint_D \left[\frac{\partial G}{\partial p_{j1}} + \frac{\partial G}{\partial R_j}\frac{\partial R_j}{\partial p_{j1}}\right] f \, dV - 2\lambda \left[\frac{\partial \tilde{K}}{\partial q_1}\frac{\partial q_1}{\partial p_{j1}} + \frac{\partial \tilde{K}}{\partial R_j}\frac{\partial R_j}{\partial p_{j1}}\right] = 0
$$

These are expressions of each components.

$$\frac{\partial G}{\partial p_{j1}} = q(\mathbf{p_1},\mathbf{R}) + \frac{\partial q(\mathbf{p_1},\mathbf{R})}{\partial p_{j1}}(p_{j1} - L_{j1} - Exp_j - p^{re}\beta_1) +$$
$$\frac{\frac{\partial q(\mathbf{p}_1,\mathbf{R})}{\partial \mathbf{p}_1}}{\exp(-p^{re}(\beta_0 + \beta_1 q(\mathbf{p}_1,\mathbf{R}) + \beta_2 q(\mathbf{p}_2,\mathbf{R}))k) + \exp(-(\log(1+\exp(L_{j1}q(\mathbf{p}_1,\mathbf{R}) + L_{j2}q(\mathbf{p}_2,\mathbf{R}) - d)))k)} \times H_1$$

where

$$H_1 = (p^{re}\beta_1 \exp(-p^r(\beta_0 + \beta_1 q(\mathbf{p}_1,\mathbf{R}) + \beta_2 q(\mathbf{p}_2,\mathbf{R}))k) +$$
$$\frac{L_{j1}\exp(L_{j1}q(\mathbf{p}_1,\mathbf{R}) + L_{j2}q(\mathbf{p}_2,\mathbf{R}) - d)}{1+\exp(L_{j1}q(\mathbf{p}_1,\mathbf{R}) + L_{j2}q(\mathbf{p}_2,\mathbf{R}) - d)} \exp(-(\log(1+\exp(L_{j1}q(\mathbf{p}_1,\mathbf{R}) + L_{j2}q(\mathbf{p}_2,\mathbf{R}) - d)))k))$$

$$\frac{\partial G}{\partial R_j} = \sum_m \frac{\partial q(\mathbf{p_m},\mathbf{R})}{\partial R_j}(p_{jm} - L_{jm} - Exp_j - p^{re}\beta_1 - p^{re}\beta_2) +$$
$$\frac{1}{\exp(-p^{re}(\beta_0 + \beta_1 q(\mathbf{p}_1,\mathbf{R}) + \beta_2 q(\mathbf{p}_2,\mathbf{R}))k) + \exp(-(\log(1+\exp(L_{j1}q(\mathbf{p}_1,\mathbf{R}) + L_{j2}q(\mathbf{p}_2,\mathbf{R}) - d)))k)} \times H_2$$

where

$$H_2 = (p^{re}\exp(-p^{re}(\beta_0 + \beta_1 q(\mathbf{p}_1,\mathbf{R}) + \beta_2 q(\mathbf{p}_2,\mathbf{R}))k)\left(\beta_1\frac{\partial q(\mathbf{p}_1,\mathbf{R})}{\partial \mathbf{R}} + \beta_2\frac{\partial q(\mathbf{p}_2,\mathbf{R})}{\partial \mathbf{R}}\right)$$
$$+ \frac{\exp(L_{j1}q(\mathbf{p}_1,\mathbf{R}) + L_{j2}q(\mathbf{p}_2,\mathbf{R}) - d)}{1+\exp(L_{j1}q(\mathbf{p}_1,\mathbf{R}) + L_{j2}q(\mathbf{p}_2,\mathbf{R}) - d)} \exp(-(\log(1+\exp(L_{j1}q(\mathbf{p}_1,\mathbf{R}) + L_{j2}q(\mathbf{p}_2,\mathbf{R}) - d)))k) \times$$
$$\left(L_{j1}\frac{\partial q(\mathbf{p}_1,\mathbf{R})}{\partial \mathbf{R}} + L_{j2}\frac{\partial q(\mathbf{p}_2,\mathbf{R})}{\partial \mathbf{R}}\right))$$

$$\frac{\partial \tilde{K}}{\partial R_j} = \frac{\partial \tilde{K}}{\partial (q(\mathbf{p_1},\mathbf{R}))}\frac{\partial q(\mathbf{p_1},\mathbf{R})}{\partial R_j} + \frac{\partial \tilde{K}}{\partial (q(\mathbf{p_2},\mathbf{R}))}\frac{\partial q(\mathbf{p_2},\mathbf{R})}{\partial R_j}$$

The FOC for each decision variable x is given by $\frac{\partial \mathcal{L}}{\partial x} = 0$, which requires applying the chain rule through the implicitly defined function R_j. The derivative of R_j is found using the Implicit Function Theorem: $\frac{\partial R_j}{\partial x} = \frac{\partial g/\partial x}{1-\partial g/\partial R_j}$.

$$\frac{\partial g}{\partial p_{j1}} = g_1(\frac{\partial q_1}{\partial p_{j1}})$$

$$\frac{\partial g}{\partial R_j} = g_1\frac{\partial q_1}{\partial R_j} + g_2\frac{\partial q_2}{\partial R_j}$$

FOC w.r.t p_{j2}:

$$\iiint_D \left[\frac{\partial G}{\partial p_{j2}} + \frac{\partial G}{\partial R_j}\frac{\partial R_j}{\partial p_{j2}}\right] f\,dV - 2\lambda\left[\frac{\partial \tilde{K}}{\partial(q_2)}\frac{\partial q_2}{\partial p_{j2}} + \frac{\partial \tilde{K}}{\partial R_j}\frac{\partial R_j}{\partial p_{j2}}\right] = 0$$

$$\frac{\partial G}{\partial p_{j2}} = q(\mathbf{p_2},\mathbf{R}) + \frac{\partial q(\mathbf{p_2},\mathbf{R})}{\partial p_{j2}}(p_{j2} - L_{j2} - Exp_j - p^{re}\beta_2) +$$
$$\frac{\frac{\partial q(\mathbf{p}_2,\mathbf{R})}{\partial \mathbf{p}_2}}{\exp(-p^{re}(\beta_0 + \beta_1 q(\mathbf{p}_1,\mathbf{R}) + \beta_2 q(\mathbf{p}_2,\mathbf{R}))k) + \exp(-(\log(1+\exp(L_{j1}q(\mathbf{p}_1,\mathbf{R}) + L_{j2}q(\mathbf{p}_2,\mathbf{R}) - d)))k)} \times H_3$$

where

$$H_3 = (p^{re}\beta_2\exp(-p^r(\beta_0 + \beta_1 q(\mathbf{p}_1,\mathbf{R}) + \beta_2 q(\mathbf{p}_2,\mathbf{R}))k) +$$
$$\frac{L_{j1}\exp(L_{j2}q(\mathbf{p}_1,\mathbf{R}) + L_{j2}q(\mathbf{p}_2,\mathbf{R}) - d)}{1+\exp(L_{j1}q(\mathbf{p}_1,\mathbf{R}) + L_{j2}q(\mathbf{p}_2,\mathbf{R}) - d)}\exp(-(\log(1+\exp(L_{j1}q(\mathbf{p}_1,\mathbf{R}) + L_{j2}q(\mathbf{p}_2,\mathbf{R}) - d)))k))$$

$$\frac{\partial g}{\partial p_{j2}} = g_2(\frac{\partial q_2}{\partial p_{j2}})$$

FOC for A_{1j}:

$$\iiint_D \left[(r_1+1) + \frac{\partial G}{\partial R_j}\frac{\partial R_j}{\partial A_{1j}}\right] f\, dV - \lambda\left[2\frac{\partial \tilde{K}}{\partial R_j}\frac{\partial R_j}{\partial A_{1j}} - 1\right] = 0$$

$$\frac{\partial g}{\partial A_{1j}} = \frac{\partial g}{\partial\left(\frac{A_{2j}}{A_{1j}+A_{2j}}\right)}\left(-\frac{A_{2j}}{(A_{1j}+A_{2j})^2}\right) + \frac{\partial g}{\partial(A_{1j}+A_{2j})}$$

FOC for A_{2j}:

$$\iiint_D \left[(r_2+1) + \frac{\partial G}{\partial R_j}\frac{\partial R_j}{\partial A_{2j}}\right] f\, dV - \lambda\left[2\left(\frac{\partial \tilde{K}}{\partial A_{2j}} + \frac{\partial \tilde{K}}{\partial R_j}\frac{\partial R_j}{\partial A_{2j}}\right) - 1\right] = 0$$

$$A_{2j} = A - A_{1j}$$

$$\frac{\partial g}{\partial A_{2j}} = \frac{\partial g}{\partial\left(\frac{A_{2j}}{A_{1j}+A_{2j}}\right)}\left(\frac{A_{1j}}{(A_{1j}+A_{2j})^2}\right) + \frac{\partial g}{\partial(A_{1j}+A_{2j})}$$

Primal Feasibility:

$$2 - \frac{A_{1j}+A_{2j}}{\tilde{K}(q(\mathbf{p_1},\mathbf{R}), q(\mathbf{p_2},\mathbf{R}), A_{2j})} \leq 0$$

Dual Feasibility:

$$\lambda \geq 0$$

Complementary Slackness:

$$\lambda\left(2-\frac{A_{1j}+A_{2j}}{\tilde{K}(q(\mathbf{p_1},\mathbf{R}),q(\mathbf{p_2},\mathbf{R}),A_{2j})}\right)=0$$

8.5 Construct Moment Condition

$\because$ Quantity share $\quad S_{jmt}=\frac{q_{jmt}}{\sum_{k\in\mathcal{C}}q_{kmt}}=\frac{e^{u_{jmt}}}{\sum_{k\in\mathcal{C}}e^{u_{kmt}}}$

$\therefore \log S_{jmt}=u_{jmt}-\log\sum_{k\in\mathcal{C}}e^{u_{kt}}$

$$\begin{aligned}\therefore \log S_{jmt}-\log S_{j'mt}&=u_{jmt}-u_{j'mt}\\&=\alpha_1(p_{jmt}-p_{j'mt})+\alpha_2(R_{jt}-R_{j't})+(\xi_{jmt}-\xi_{j'mt})\end{aligned}$$

Then $\xi_{jmt}-\xi_{j'mt}=\log S_{jmt}-\log S_{j'mt}-\alpha_1(p_{jmt}-p_{j'mt})-\alpha_2(R_{jt}-R_{j't})$

Then if take time difference,

$$\begin{aligned}&(\xi_{jmt}-\xi_{jm,t-1})-(\xi_{j'mt}-\xi_{j'm,t-1})\\=&(\log S_{jmt}-\log S_{jm,t-1})-(\log S_{j'mt}-\log S_{j'm,t-1})\\&-\alpha_1[(p_{jmt}-p_{jm,t-1})-(p_{j'mt}-p_{j'm,t-1})]-\alpha_2[(R_{jt}-R_{j,t-1})-(R_{j't}-R_{j',t-1})]\end{aligned}$$

$\because$ I only observe revenue share in the data $\omega_{jmt}=\frac{p_{jmt}q_{jmt}}{\sum_k p_{kmt}q_{kmt}}$

$$\begin{aligned}\therefore&(\log\omega_{jmt}-\log\omega_{jm,t-1})-(\log\omega_{j'mt}-\log\omega_{j'm,t-1})\\&=\alpha_1[(p_{jmt}-p_{jm,t-1})-(p_{j'mt}-p_{j'm,t-1})]+\alpha_2[(R_{jt}-R_{j,t-1})-(R_{j't}-R_{j',t-1})]\\&+(\xi_{jmt}-\xi_{jm,t-1})-(\xi_{j'mt}-\xi_{j'm,t-1})+(\log p_{jmt}-\log p_{jm,t-1})\\&-(\log p_{j'mt}-\log p_{j'm,t-1})\end{aligned}$$

$\because d_{jmt} = \prod_{s=1}^{t} \frac{p_{jms}}{p_{jm,s-1}}$

$\therefore p_{jmt} = d_{jmt} p_{jm0}$

$$
\begin{aligned}
&\therefore (\log \omega_{jmt} - \log \omega_{jm,t-1}) - (\log \omega_{j'mt} - \log \omega_{j'm,t-1}) \\
=&\alpha_1[(d_{jmt}p_{jm0} - d_{jm,t-1}p_{jm0}) - (d_{j'mt}p_{j'm0} - d_{j'm,t-1}p_{j'm0})] \\
&+ \alpha_2[(R_{jt} - R_{j,t-1}) - (R_{j't} - R_{j',t-1})] + (\xi_{jmt} - \xi_{jm,t-1}) - (\xi_{j'mt} - \xi_{j'm,t-1}) \\
&+ (\log p_{jmt} - \log p_{jm,t-1}) - (\log p_{j'mt} - \log p_{j'm,t-1})
\end{aligned}
$$

Set $\tilde{\alpha}_{1j} = \alpha_1 p_{jm0}$, $\tilde{\alpha}_{1j'} = \alpha_1 p_{j'm0}$, then

$$
\begin{aligned}
&(\xi_{jmt} - \xi_{jm,t-1}) - (\xi_{j'mt} - \xi_{j'm,t-1}) \\
=&(\log \omega_{jmt} - \log \omega_{jm,t-1}) - (\log \omega_{j'mt} - \log \omega_{j'm,t-1}) - \tilde{\alpha}_{1jm}(d_{jmt} - d_{jm,t-1}) \\
&+ \tilde{\alpha}_{1j'm}(d_{j'mt} - d_{j'm,t-1}) - (\log d_{jmt} - \log d_{jm,t-1}) + (\log d_{j'mt} - \log d_{j'm,t-1}) \\
&- \alpha_2[(R_{jt} - R_{j,t-1}) - (R_{j't} - R_{j',t-1})]
\end{aligned}
$$

8.6 NIG distribution

Estimated Parameters:

μ	δ	α	β
0.03366712	0.03188561	7.97037129	0.14520772

Notes: This table displays estimated parameters of Normal Inverse Gaussian distribution.

The functional form of the NIG distribution's PDF, denoted as $f(x)$, is given by:

$$
f(x|\mu, \alpha, \beta, \delta) = \frac{\alpha\delta}{\pi} e^{\delta\sqrt{\alpha^2-\beta^2}+\beta(x-\mu)} \times \frac{K_1\left(\alpha\sqrt{\delta^2+(x-\mu)^2}\right)}{\sqrt{\delta^2+(x-\mu)^2}}
$$

where:

- $\mu \in \mathbb{R}$ is the location parameter.
- $\delta > 0$ is the scale parameter.
- $\alpha > |\beta| \geq 0$ determine the shape of the distribution.
- $K_1(\cdot)$ is the modified Bessel function of the second kind of order 1.

8.7 Hurdle Log-normal Distribution

Estimated Parameters for Hurdle Log-Normal Model

Variable	**p zero** (p_0)	**meanlog** (μ)	**sdlog** (σ)
loss rate in less risky market	0.60429283	-0.6111959	1.01192423
loss rate in risky market	0.43826365	-0.5693463	1.05375027

Notes: This table displays estimated parameters of Hurdle Log-normal distribution.

The model handles a significant number of zero values (a "hurdle") and models the positive values using a log-normal distribution. The probability function $f(x)$ is defined as a piecewise function:

$$f(x; p_0, \mu, \sigma) = \begin{cases} p_0 & \text{if } x = 0 \\ (1 - p_0) \cdot \frac{1}{x\sigma\sqrt{2\pi}} \exp\left(-\frac{(\ln(x)-\mu)^2}{2\sigma^2}\right) & \text{if } x > 0 \end{cases}$$

Where:

- p_0 is the probability of observing a zero value.
- The second part is the scaled PDF of the log-normal distribution for positive values.

8.8 Payment Function of Reinsurance

We want to approximate:

$$\min\{p^{re}Q_j^{re}, max\{0, \sum_m (L_{jm}q(\mathbf{p_m}, \mathbf{R})) - d\}\}$$

The softmin and softmax functions tell us

- $\max(0, B-d)$: $\log(1+\exp(B-d))$
- $\min(A, C)$: $-\frac{1}{k}\log(\exp(-Ak)+\exp(-Ck))$

Then $\min\{p^{re}Q_j^{re}, \max\{0, \sum_m (L_{jm}q(\mathbf{p_m}, \mathbf{R})) - d\}\}$ becomes

$$-\frac{1}{k}\log(\exp(-p^{re}Q_j^{re}k) + \exp(-(\log(1+\exp(\sum_m (L_{jm}q(\mathbf{p_m}, \mathbf{R})) - d)))k))$$

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