# Financial Stability and Natural Disasters under Endogenous Adaptation *

Koen van den Bosch† Christina Kolerus‡ Joana Pereira§

February 18, 2026

**Abstract**

We examine the effect of natural disasters (ND) on financial stability in insurance and mortgage markets when household adaptation is endogenous to changing financial conditions. We first empirically establish that ND reduce insurers' and banks' solvency and profitability metrics, although the effects for banks are small. Using a novel instrument based on reinsurance market shocks, we show that the sensitivity of bank financials to ND rises with the size of the insurance gap, revealing interaction effects. Using a structural model with heterogeneous households, we then analyze how the responses of banks and insurers following ND dynamically shape moral hazard and credit constraints, affecting investment in physical resilience against ND and therefore long-run financial stability. Consistent with the empirical results, disaster-driven default rates increase when insurance gaps grow. Yet, endogenous household adaptation substantially lowers the long-run financial consequences of ND relative to the counterfactual of no adaptation. We further illustrate the implications of moral hazard and credit constraints for the optimal mix between insurance- and adaptation subsidies when the aim is to reduce defaults. Our micro-founded model highlights how the interplay between regulation, frictions, and household behavior shapes the long-run financial consequences of ND.

*Keywords*: Financial stability; Natural disasters; Household adaptation; Insurance; Banking; Moral hazard; Credit constraints

*JEL Classification*: G21, G22, Q54

*For helpful comments and suggestions, we thank Fabian Valencia, Zamid Aligishiev and seminar participants at the IMF.

†Erasmus University, Rotterdam School of Management, e-mail: vandenbosch@rsm.nl.

‡International Monetary Fund, e-mail: ckolerus@imf.org.

§International Monetary Fund, e-mail: jpereira@imf.org.

# 1 Introduction

Financial regulators and policymakers are tasked with understanding how natural hazards will impact the stability of financial systems and how policies can be designed to help manage increasing disaster risks. First and foremost, this requires grasping how institutions and households will dynamically respond under climate uncertainty. Such endogenous responses are likely first-order in whether and to what extent natural hazards create financial stability risks at different horizons.[1]

In insurance and credit sectors, disasters can create financial risks via two main channels, the *insolvency channel* and the *underinsurance channel*. Regarding the insolvency channel, natural disasters could lead to unexpected claim payouts and borrower defaults, creating financial distress among insurers and banks. Although climate-driven insolvencies are rare, they are increasing in frequency. For example, 15 insurers have become insolvent in the state Florida alone between 2009 and 2022 (Sastry et al., 2023).

Regarding the underinsurance channel, financial risks materialize due to limited risk sharing (Rousová et al., 2023). On the supply side, elevated climate risks have driven insurers to restrict underwriting in high-hazard areas (Sastry et al., 2023), increasing homeowners' insurance premiums dramatically (Ge et al., 2025). These insurance supply reductions could result from insurers hitting binding capital constraints or updating risk models following disasters.[2] On the demand side, Sastry et al. (2024) document pervasive under-insurance, particularly among the most financially vulnerable households, even at actuarially fair premiums and empirically show that financially constrained households further reduce coverage as premiums rise. As a consequence, hardening insurance markets leave households more exposed to disasters which, in turn, implies transferring financial risks from insurance to the household and, in case of mortgage financing, the banking sector.

As such, spillovers emerge: for example, Ge et al. (2025) find that higher premiums from more elevated climate risks increase the probability of mortgage delinquency. In addition, Eastman et al. (2024) document that a 10% increase in average homeowner insurance prices leads to a decrease in house prices of at least 1.2% to 2.1%. These findings highlight that disaster risks can also spillover between sectors as institutions dynamically change their

[1] Cochrane (2021) argues: "We know with great precision what the climate will be for the next five years. Nobody writing insurance in Florida is unaware of the chance of hurricanes. The chances of extreme weather are not going to change unexpectedly in even ten years. Risk is the unknown. This is known." This view implies that climate risks evolve slowly and predictably and financial actors can anticipate them.

[2] The insurance protection gap varies widely across geographies, ranging from 43% in the U.S., 70% in Europe, 80% in Latin America, and 85% in Asia (Swiss Re, 2024).

exposures.

In this paper, we argue that understanding the financial stability consequences of natural disasters requires an approach that considers both the *insolvency channel* and the *underinsurance channel*. Both of these channels are economically relevant on their own, but may also interact as financial institutions change exposures over longer horizons. Moreover, such dynamically changing exposures create financial frictions at the borrower and policyholder level. By affecting collateral and potential retained losses, changes in insurance coverage and loan supply shape moral hazard and credit constraints, which jointly affect adaptation by households.[3] Since adaptation reduces the economic damages from disasters, adaptation in itself is a determinant of climate-related financial fragility. The existing literature thus far has primarily focused on documenting the short- and medium-term financial stability effects of disasters with little attention to the underlying economic channels.

We fill this gap by examining how natural disasters affect long-run financial stability in insurance and mortgage markets in a setup that considers direct effects of disasters on financial institutions, spillovers between insurance and banking sectors, and endogenous adaptation responses by households that result from dynamically changing exposures of financial institutions.

Whether a model that includes dynamic adaptation by institutions and households produces different financial stability effects from disasters than a benchmark model without dynamic adaptation is not obvious. When insurers raise prices following disasters, equilibrium insurance quantities may be lower. Risks then get transferred back to banks and the household. The reduction in household insurance coverage eases moral hazard and thus increasing the incentive of households to invest into risk-management (i.e., to adapt). This would lower the negative impact of disasters on financial stability compared to a model without dynamic adaptation. However, as insurance prices rise, households may become credit constrained and defer adaptation. Similarly, lenders face higher mortgage default rates when households' retained losses are higher - possibly offsetting the above mitigating effects on financial stability - are less likely to extend new loans to households that are under-insured. When households rely on external credit to finance adaptation, this could equally reduce the capacity to adapt. Whether the moral hazard or credit constraint channel dominates is not clear ex-ante.

We start by presenting various motivating empirical analyses that quantify the direct and indirect effects of disasters on financial stability in the insurance and banking sector.

[3] We abstract from government support after disasters which represents a further source of moral hazard.

We establish three key empirical facts. First, natural disasters lower insurer solvency and profitability temporarily. Specifically, a one-standard deviation increase in disaster exposure decreases return on assets by 0.5 percentage points, increases loss ratios by 12.5 percentage points and decreases capital ratios by 3.8% on average. The sensitivity of financials to disasters is especially strong among smaller insurers and insurers that rely less on reinsurance. Profitability and financial stability ratios revert within two and four years, respectively. Second, natural disasters reduce banks' solvency and profitability ratios, but the effects are smaller than for insurers. Bank capital ratios on average remain unaffected following increases in disaster exposure, but foreclosure ratios and non-performing asset ratios increase by 3%, and 1.5% following a one-standard deviation increase in disaster exposure, respectively. Return on assets decrease by 0.01 percentage points after 4 years, suggesting that the effects on banks are negligble compared to insurers. Third, instrumenting local insurance gaps with global reinsurance market shocks, we find that growing insurance gaps amplify the sensitivity of bank financial to disasters. This finding suggests that disaster risk creates spillovers from insurers to banks, highlighting the role of the underinsurance channel.

To understand the long-run financial implications of disaster risk, we analyze the different drivers of climate-driven financial fragility using a structural model. We construct a heterogeneous-agent model to capture the dynamic interactions between insurers, banks, and adaptation by households in the context of rising disaster risk. The key objective of this model is to understand how the decisions of banks, insurers, and insured households unfold in equilibrium, and which policy options could help improve outcomes. Our model allows for dynamic adaptation to climate change. Incentives for households to invest in adaptation are driven by the supply decisions of insurance companies and banks.

We extend the model of Fried (2022) by including the decisions of insurers and banks in the economy. Heterogeneous households derive utility from consumption and housing services. Housing is subject to i.i.d. disaster shocks. In addition, households face undiversifiable idiosyncratic income shocks. Households decide each period how much to invest in productive and adaptive housing capital, a risk-less bond that pays the risk-free rate, and how much insurance coverage to buy. Adaptation reduces the economic damages upon a disaster. Moreover, households can obtain financing through one-period mortgages. Insurers and banks decide on their insurance and loan supply, respectively, with their actions interacting in equilibrium. The model is calibrated using US financial and disaster data, matching US disaster probabilities in the stationary equilibrium.

Our main findings are threefold. First, the underinsurance channel plays an important

role in driving household financial fragility. Insurance coverage — which is strongly correlated with household wealth — declines at higher disaster probabilities. Banks price in disaster risk when households' insurance-adjusted leverage ratio exceeds one, although the risk premium is only significant for larger disaster probabilities. Consistent with the empirical results, our model predicts higher disaster-driven defaults when insurance markets tighten, supporting the importance of the underinsurance channel and its interaction with the insolvency channel for banks. Moreover, disentangling households' wealth distribution, low-wealth households have significantly higher leverage and higher disaster-driven default rates than high-wealth households.

Second, we show that endogenous household adaptation substantially lowers the long-run financial consequences of natural disasters relative to the counterfactual of no adaptation. As disasters become more frequent, making insurance more expensive, households respond by adapting more, which lowers household financial fragility. In the economy without adaptation, default rates increase more sharply in disaster probabilities relative to the economy with adaptation. Without adaptation, households shift to insurance, but take-up equally lowers as insurance becomes more expensive when disaster probabilities increase, keeping households financially fragile. At a disaster probability of 5%, endogenous adaptation lowers aggregate defaults by about 35%.

Third, comparing the effectiveness of both insurance and adaptation policies in reducing defaults and strengthening financial stability, we find that insurance subsidies are more effective than adaptation subsidies in improving financial fragility, yet introduce moral hazard, lowering equilibrium adaptation decisions. Overall, our micro-founded model highlights how the interplay between regulation, financial frictions and household behavior shapes the long-run financial stability effects of natural disasters.

We contribute to the literature in the following ways. So far, it is not clear how the *insolvency channel* and *underinsurance channel* interact dynamically and shape long-run outcomes jointly. Empirically, the channels have mostly been studied in isolation, but conceptually they may mute or amplify each other. When insurers rationally lower insurance supply in response to anticipated elevated disaster risk, making them less financially fragile to this risk, the strength of the two channels are inversely related. When a reduction in insurance supply is a direct consequence of increased insolvency risks, the strength of two channels are positively related. We find evidence of both direct effects on banks and insurers and indirect effects through spillovers, suggesting that the two channels are complementary.

Second, how climate risks affect financial stability is endogenous with respect to adapta-

tion (Battiston et al., 2021). Adaptation lowers expected policyholder losses from disasters, reducing downside risks for insurers - making underwriting climate risks more acceptable - and lowering disaster-driven defaults with banks. Adaptation thus has the potential to reduce insurance gaps while minimizing the direct insolvency risks. The literature has called for approaches that consider such feedback loops.

Third, the literature on the drivers of adaptation is nascent and, so far, those drivers as well as insurance supply were modeled in a rather static way ignoring possible interaction effects with credit markets. For example, the adaptation models of Fried (2022) and Van der Straten (2023) assume that insurance capital is available in fixed quantities. This arguably has resulted in an imperfect understanding of why adaptation rates remain low and, consequently, why some regions have more volatile insurance markets than others.

To illustrate this, consider the typical argument that insurance reduces the incentive to adapt to climate change through moral hazard (Fried, 2022, Annan and Schlenker, 2015). This argument is incomplete in a dynamic context for two reasons. Insurance supply varies dynamically with the level of adaptation. Low adaptation today means lower coverage in the future due to a lower willingness to offer insurance by insurers. In addition, low adaptation could increase claim payouts, threatening the creditworthiness of insurers, and limiting their ability to sell insurance in the future. Such reductions in coverage transfer climate risk back to the household or firm, potentially restoring incentives for adaptation. Moreover, insurance capacity co-moves strongly with bank credit supply (Sastry, 2022, Ouazad and Kahn, 2022). Banks are more reluctant to provide credit if households and firms are not insured. Underinsurance itself could thus be a driver of stressed credit markets. Indeed, Sastry et al. (2023) find that fragile insurers caused a 150% increase in conforming mortgage defaults after natural disasters, highlighting spillovers to the banking sector. Relatedly, Noth and Schüwer (2023) find that insurance payments and public aid do not sufficiently protect banks from disasters, affecting bank stability. As adaptation requires up-front financing, such credit constraints could lower the ability of households and firms to invest in risk management.

These arguments highlight that while providing insurance could reduce adaptation through moral hazard, low adaptation could limit insurance supply, transferring climate risks back to the households and possibly restoring adaptation incentives. However, low insurance coverage does not necessarily improve adaptation due to credit constraints. Persistently low adaptation rates could keep insurability low and lead to insurance traps as the intensity of disasters grows over time. Making adaptation models externally valid requires a setup where

insurance, adaptation, and bank credit co-move dynamically, which is a contribution of this paper.

## 2 Motivating Empirical Evidence

We conduct various empirical analyses to establish whether and how climate risks have affected financial stability in insurance and credit markets, both directly and indirectly, i.e. through spillovers between sectors. Appendix A provides the details on the data sources.

**Fact 1: Natural disasters temporarily reduce insurers' solvency and profitability ratios.**

To test the impact of natural disasters on insurer financials, we broadly follow Jung et al. (2024). While the authors apply a market-based approach to measure U.S. based insurers' stock return sensitivity to physical risk factors, we restrict our analyses to book values. Although not forward-looking, book values have the potential to measure the financial impact of disasters on insurance companies. We focus on US insurers given data availability. As in Jung et al. (2024), we leverage geographical variation in disaster impact and insurer exposure to capture potential effects of disasters on financial outcomes.

We use the local projections approach by Jordà (2005) to dynamically measure the impact of disasters on insurer financials. The setup allows us to compute impulse responses that show the dynamic path of insurer financials after the realization of disasters. We run the following specification for $h \in [0, 9]$.

$$\Delta^{h+1} Y_{i,t-1} = \beta_h \times \log(\text{DisasterExposure})_{i,t} + \alpha_i^h + \tau_t^h + \sum_{l=1}^{L} \gamma_j^h \times X_{i,t-j} + \varepsilon_{i,t}^h, \qquad (1)$$

$Y \in \{\text{Capital Ratio, Return on Assets, Loss Ratio, Capital-to-Surplus}\}$ contains insurer-level financial stability and performance indicators. $\Delta^{h+1} Y_{i,t-1}$ captures the difference between $h$ years ahead and 1-year lagged $Y$. $X_{i,t-j}$ contains lags of $Y$, insurer assets, leverage, and the insurer's overall reinsurance ratio. In addition, we control for insurer- and year fixed effects, denoted by $\alpha_i^h$ and $\tau_t^h$, respectively. We cluster standard errors at the insurer level.

The variable of interest is $\text{DisasterExposure}_{i,t}$. To construct insurers' disaster exposure, we multiply the premium share of an insurer in state $s$ by realized climate damages in this

state (both insured and uninsured damages) and sum across states:

$$\text{DisasterExposure}_{i,t} = \sum_{s \in S} w_{i,s,t} \times \text{Property Damages}_{s,t} \tag{2}$$

where

$$w_{i,s,t} = \frac{\text{DPW}_{i,s,t}}{\sum_{s \in S} \text{DPW}_{i,s,t}}$$

Here, $\text{DPW}_{i,s,t}$ captures the direct premiums written by insurer $i$ in state $s$ in lines of business affected by disasters.[4] $\text{PropertyDamages}_{s,t}$ are monetary loss amounts from natural disasters.

Figure 1 plots the estimated dynamics of insurers' financial stability and performance indicators after disaster realizations. The figure plots $\hat{\beta}_h$ cumulatively alongside 68 and 90 percent confidence intervals. At $h = 0$, the disaster hits. Disaster losses reduce insurer return on assets, risk-based capital ratios, and capital-to-surplus ratios. Specifically, a one-standard deviation increase in disaster exposure decreases return on assets by 0.5 percentage points, increases loss ratios by 12.5 percentage points and decreases capital ratios by 3.8% on average.[5] These estimated effects are economically meaningful and show that natural disasters entail financial stability risks for U.S. insurers. The results also show that the negative effects are temporary: insurer capital ratios recover within 4 years from disaster shocks. Disasters sharply increase loss ratios, but the effect becomes negative 2 years after the disaster realization, suggesting that insurers swiftly adjust risk models and underwriting after disasters (or exit). We find (in untabulated results) that disasters predict future insurance rate increases, which is consistent with improved long-run profitability ratios.

To explore heterogeneity in the effects of disasters on insurer financials, we sort insurers into quantiles based on their size (measured by total assets), reinsurance ratio and the share of homeowners insurance in their total portfolio. The cutoff is the median that varies every year. Moreover, we do a sample split based on observations before and after 2012 to understand whether insurer sensitivity to disasters changed over time. We run equation 1 for each subsample. Figure 2 shows that, first, capital ratios of smaller insurers are more sensitive to disasters. Second, smaller insurers recover less quickly from disasters than larger insurers. Third, financial metrics of insurers which transferred less risks to reinsurance are more sensitive to disasters, with a particularly stark difference in effects on return on assets

[4] We compute weights based on premiums written in the homeowners insurance segment.

[5] At the mean, a one standard-deviation increase in disaster exposure corresponds to a 1.3$bn increase in disaster exposure.

and capital ratios. Fourth, insurers with a lower share of homeowner insurance to total insurance are less affected by disasters. Finally, we find no evidence that the sensitivity of insurer financials to disasters increased over time.

**Fact 2: Natural disasters reduce banks' solvency and profitability ratios, but the effects are smaller than for insurers.**

To understand the impact of disasters on bank financial stability, we run a similar specification as for insurers:

$$\Delta^{h+1} Y_{j,t-1} = \beta_h \times \log(\text{DisasterExposure})_{j,t} + \alpha_j^h + \tau_t^h + \sum_{l=1}^{L} \gamma_j^h \times X_{j,t-j} + \varepsilon_{j,t}^h. \tag{3}$$

$Y \in \{\text{Capital Ratio, Foreclosure ratio, Non-performing assets ratio, Return on Assets}\}$ contains bank-level financial stability and performance indicators. $X_{j,t}$ contains lagged $Y$, lagged log bank assets and lagged leverage. We define disaster exposure for bank $j$ as a scaled version of the measure for insurers:

$$\text{DisasterExposure}_{j,t} = \sum_{c \in C} w_{j,c,t} \times \frac{\text{Property Damages}_{c,t}}{\text{Personal Income}_{c,t}} \tag{4}$$

where

$$w_{j,c,t} = \frac{\text{Loans}_{j,c,t}}{\sum_{c \in C} \text{Loans}_{j,c,t}}$$

While the above insurance metrics are constructed at the state-level, our disaster and loan data for banks are by county $c$ to match the county-level loan data. We scale natural disasters by personal income following (Noth and Schüwer, 2023). For insurers, claims increase linearly in disaster losses conditional on the contract's loss limit not being exceeded. For banks, however, the disaster intensity matters: climate losses affect bank returns primarily when disasters push borrowers beyond a threshold after which they cannot fulfill their obligations.

The variable $\text{Loans}_{j,c,t}$ captures the dollar volume of new mortgage issued to households in state $s$ in year $t$. New loans originated serves as a proxy for local banking activities. For each bank, we take a 5-year rolling average of $w_{j,c,t}$ to mitigate the possibility that shocks to banks' regional activities are not reflective of their total loan portfolio. We include the same controls as for insurers except the reinsurance ratio, which is not applicable to banks. We cluster standard errors at the bank level.

Figure 3 shows the dynamic treatment effect of disasters on bank financial metrics. Bank capital ratios on average remain unaffected following increases in DisasterExposure. Return

on assets decrease by 0.01 percentage points after 4 years, suggesting that the effects on banks are negligble compared to insurers. Foreclosure- and non-performing assets ratio increase by about 3% and 1.5%, respectively, following a one-standard deviation increase in DisasterExposure.

Compared to insurers, the effects on banks are small. Figure 4 provides a comparison between the effects on insurers and banks using both scaled and unscaled disasters, taking into account financial metrics that are available to both banks and insurers. In estimating the effects, we include only size and leverage as controls to ensure that the set of controls included for banks and insurers are the same. On average, effects of disasters on capital ratios and return on assets are negligible for banks compared to insurers.

**Fact 3: Insurance gaps amplify the negative effects of disasters on bank financial metrics.**

To understand how insurance and credit markets interact in the context of climate risks, we analyze how insurance supply shocks spill over to credit markets and change the sensitivity of the banking sector to disasters. Lower insurance coverage makes households more vulnerable to climate shocks. Hence, negative insurance supply shocks could increase disaster-driven households losses, rendering banks more exposed.

We test whether the sensitivity of bank financials to disasters increases when insurance protection declines. Our estimation strategy relies on interacting the above disaster exposure of banks with a measure of insurance protection. However, correctly measuring the insurance gap households are facing is challenging.

We proxy insurance protection by insurers' average non-renewals in a county. Specifically, we compute banks' exposure to insurance gaps by multiplying banks' regional loan shares by local insurance non-renewals and aggregate across counties:

$$\text{InsuranceGap}_{j,t} = \sum_{c \in C} w_{j,c,t} \cdot \text{Non-Renewals Share}_{c,t} \tag{5}$$

where $\text{Non-Renewals Share}_{c,t}$ is the share of homeowners' insurance policies not renewed by insurers in county $c$ in year $t$. While employing non-renewals as insurance gap proxy has some shortcomings - the share of the local population being insured depends on cancellations in prior years, whether households can find substitutes, and on overall coverage limits - , non-renewals have important bell-weather characteristics. They rose significantly in recent years when insurance markets hardened (Figure 5), and increases are heavily concentrated in high-risk costal communities (Figure 6).

We construct a second measure for insurance gaps based on primary insurance rate increases as the proxy for insurance gaps. Strong rate increases, all else equal, proxy for lower insurance coverage, and vice versa. We construct the new proxy by multiplying banks' regional loan shares by local insurance rate changes over the prior 5 years and aggregate across all states:

$$\text{InsuranceGap}_{j,t} = \sum_{s \in S} w_{j,s,t} \cdot \prod_{k=1}^{5} \left(1 + \Delta\text{InsuranceRate}_{s,t-k}\right), \tag{6}$$

where $\text{InsuranceRate}_{s,t}$ is the average of insurers' approved rate change in state $s$ in year $t$, weighted by the affected revenue of the insurers' rate change. The measure $\text{InsuranceGap}_{j,t}$ only considers previous insurance rate changes as contemporaneous rate changes could reflect insurers' response to disasters rather than a persistent insurance gap prior to the disaster. As insurance rate changes are constructed at the state- rather than the county-level, $w_{j,s,t}$ represent state-level bank loan shares.

We then perform a local projections–instrumental variables (LP-IV) approach (Jordà et al., 2024) to quantify spillovers from insurers to banks:

$$\begin{aligned}\Delta^{h+1} Y_{j,t-1} = \beta_1^h \log(\widehat{\text{DisasterExposure}})_{j,t} \times \text{InsuranceGap}_{j,t} + \beta_2^h \log(\text{DisasterExposure})_{j,t} \\ + \beta_3^h \widehat{\text{InsuranceGap}}_{j,t} + \alpha_j^h + \tau_t^h + \sum_{l=1}^{L} \gamma_j^h \times X_{j,t-l} + \varepsilon_{j,t}^h\end{aligned} \tag{7}$$

$X_{j,t-l}$ contains lagged $Y$, lagged bank size and lagged leverage. The variable $\widehat{\text{InsuranceGap}}$ is a bank-level, instrumented proxy for the extent to which disaster exposure of households included in the bank's portfolio is covered by insurance companies. We compute robust standard errors that account for the additional sampling uncertainty introduced in the 2SLS procedure. To ensure we comparability of results across InsuranceGap measures, we restrict the sample to 2018-2022 for both InsuranceGap measures.

Insurance gaps are potentially endogenous with respect to bank financials. For example, regional insurance demand could correlate with unobserved heterogeneity in state regulatory frameworks that also predict bank risk taking. We proceed by instrumenting InsuranceGap based on global reinsurance activity. Reinsurance rates have predictive power for primary insurance conditions for two reasons. First, negative reinsurance supply shocks could limit insurers' risk bearing capacity and lead to reductions in primary insurance supply. Second, reinsurance markets signal market conditions to primary insurers, and lead to a pass-through

from reinsurance to primary insurance markets.

Banks have heterogeneous exposures to reinsurance shocks, depending on insurers' reinsurance ratios and their local market shares, as well as the geographical distribution of banks activities. Our IV captures each bank's exposure to reinsurance rate shocks via the insurance sector:

$$\text{ReinsuranceExposure}_{j,t} = \sum_{s \in S} w_{j,s,t} \cdot \prod_{k=1}^{5} \left(1 + \text{ReinsuranceShock}_{s,t-k}\right), \tag{8}$$

where

$$\text{ReinsuranceShock}_{s,t} = \sum_{i \in I} \underbrace{\frac{\text{DPW}_{i,s,t}}{\sum_{i \in I} \text{DPW}_{i,s,t}}}_{\text{Regional market share}} \times \underbrace{\frac{\text{Ceded premiums}_{i,t}}{\text{DPW}_{i,t}}}_{\text{Reinsurance ratio}} \times \Delta\text{Global Reinsurance rate}_{t} \tag{9}$$

$\text{ReinsuranceShock}_{s,t}$ therefore is a state-level measure that depends on insurers' state market shares, their reinsurance ratio[6], and global reinsurance market shocks. The variable $\Delta\text{Global Reinsurance rate}_t$ captures changes in the index of US property catastrophe reinsurance Rate-on-Line movements. The first-stage regressions become:

$$\text{InsuranceGap}_{j,t} = \alpha_j + \lambda_t + \beta' Z + \sum_{l=1}^{L} \gamma_j \times X_{j,t-l} + \varepsilon_{j,t} \tag{10}$$

$$\log(\text{DisasterExposure})_{j,t} \times \text{InsuranceGap}_{j,t} = \alpha_j + \lambda_t + \beta' Z + \sum_{l=1}^{L} \gamma_j \times X_{j,t-l} + \varepsilon_{j,t} \tag{11}$$

where $Z \in \{\text{ReinsuranceExposure}_{j,t}, \log(\text{DisasterExposure})_{j,t} \times \text{ReinsuranceExposure}_{j,t}\}$ is a vector of instruments.

The validity of the instrument relies on the relevance and exclusion restrictions. In Table 5, we confirm that the measure ReinsuranceShock predicts strongly primary insurance rates. Specifically, reinsurance rates have a pass-through of 45-67% to primary insurance rates. The exclusion restriction relies on reinsurance rates correlating with insurance cancellations and primary insurance rates, but not affecting bank financial stability metrics directly. Even through banks' regional loan exposure may dynamically respond to local insurance coverage, as long as the shocks themselves are exogenous to bank financials, the instrument would satisfy the exclusion restriction (Borusyak et al., 2025). Primary insurers mainly act as pricetakers for global reinsurance services precluding reverse causality.

[6] In constructing insurers' reinsurance ratios, we include premiums ceded to non-affiliated (re)insurers and exclude premiums ceded to affiliated (re)insurers within the same group.

Table 3 provides the results of the first stage regression of both measures. The F-statistics on the instruments confirm that (banks' exposure to) reinsurance rates predicts (banks' exposure to) insurance non-renewals, as shown in columns 1 and 2. Columns 3 and 4 show a negative association between (banks' exposure to) reinsurance rates and (banks' exposure to) primary insurance rates, despite a strong positive association between state-level reinsurance conditions and primary insurance rates. We find that over time banks' loan portfolio shares shifted away from high insurance rates states to low insurance rate states. In addition, banks shifted from states in which insurers have low reinsurance ratios to states in which insurers have high reinsurance ratios. The inclusion of bank fixed effects leads to the first stage coefficient capturing within-bank changes in exposure to primary insurance and reinsurance market conditions over time, which happen to be negatively correlated. Figure B.4 illustrates this result.[7]

Table 4 provides the results of the second-stage regression 7 when using the InsuranceGap measure based on insurance non-renewal rates at different horizons $h$. Overall, we find that the sensitivity of bank financial metrics to DisasterExposure increases with the InsuranceGap for return on assets and foreclosure ratios. Figure 7 plots the second-stage impulse response functions for both measures of InsuranceGap. Each projection captures the change in bank financials following a one standard deviation increase in DisasterExposure at the median 50th, 75th and 90th percentile of Insurance Gap. The values of Insurance Gap based on non-renewal rates at these percentiles are 0.69%, 0.89% and 1.41%, respectively. The values of Insurance Gap based on primary insurance rates at these percentiles are 17.55%, 22.61% and 22.84%, respectively.

For the InsuranceGap measure based on non-renewal rates, we find that when InsuranceGap is at the 90% percentile, foreclosure ratios increase by 15% in year 4 for a one standard deviation increase in DisasterExposure, whereas the effect is close to zero when InsuranceGap is at the median. For the InsuranceGap measure based on primary insurance rates, foreclosure ratios increase by up to 60%, capital ratios decrease by 4% and return on assets decrease by 0.42 percentage points when InsuranceGap is at the 90%.[8] We find negligible or even positive effects when InsuranceGap is at the median. These effects show that the degree to which homeowners are covered by insurance affects the financial exposure of banks to disasters. We find similar spillover effects for write-offs ratio and loss reserves ratios, but not for non-performing asset ratios. The effects however vary across measures

[7] We lag bank county/state shares by 5 years as a robustness.

[8] Given the mean return on assets of 1.03% in the subsample for which insurance non-renewals are available, this corresponds to a deviation of 40.8% from the mean.

for InsuranceGap. Overall, insurance gaps amplify the negative effects of disasters on bank financial metrics.

# 3 A Model with Endogenous Adaptation

So far, we have established that disasters affect the financial soundness of insurers and banks both directly and indirectly, i.e. through spillovers between the two sectors. The temporary nature of most effects suggests a swift repositioning of financial institutions to incorporate risks - further backed by evidence in the literature on disaster responses by insurers (Sastry et al., 2023, Ge et al., 2025). Since the risks insurers and banks face ultimately depend on the behavior of households they insure or lend to, it is important to consider how households' risk exposures change in light of rising climate risks.

To draw implications for long-run financial stability, we propose a macroeconomic heterogeneous-agent model that captures the dynamic interactions between insurers, banks, and households adapting to rising climate risks. The key objective of this model is to understand how the decisions of banks, insurers, and insureds unfold in equilibrium. Our model allows for dynamic adaptation to climate risks. Incentives for households to invest in adaptation are driven by the interrelated decisions of insurance companies and banks on insurance and credit supply. Consequently, climate-driven financial fragility is a function of both the exposure of insurers and banks to disasters, and aggregate adaptation, which itself is a function of insurer and bank supply decisions.

We extend the model of Fried (2022), who develops a macro-economic heterogeneous-agent model to study the interactions between adaptation, U.S. federal disaster policy, and climate change, and incorporate insurance and credit markets. In our adjusted Aiyagari (1994) model, insurers and banks decide on their insurance and loan supply, respectively, with their actions interacting in equilibrium. Households are heterogeneous with respect to idiosyncratic income and climate shocks. Households derive utility from consumption and housing services. Households decide each period how much to invest in productive and adaptive housing capital, a risk-less bond that pays the risk-free rate, and how much insurance coverage to buy. Moreover, households can obtain financing through one-period mortgages. In the model, time is discrete and infinite.[9]

[9] Ultimately, we aim distinguish between idiosyncratic and aggregate climate risk to understand how optimal policy design depends on insurers' ability to diversify climate risk.

## 3.1 Preliminaries

### 3.1.1 Households

The economy features a continuum of heterogeneous households with preferences over non-durable consumption $c_t$ and owner-occupied housing services $\tilde{h}_t^s$. The utility function is given by:

$$U(c_t, \tilde{h}_t^s) = \frac{\left[c_t^{\zeta}\left(\tilde{h}_t^s\right)^{1-\zeta}\right]^{1-\sigma}}{1-\sigma}.$$

Parameter $\sigma > 0$ is the coefficient of relative risk aversion. Households discount the future with discount factor $\beta$ and maximize expected lifetime utility. Each period, the household decides between consumption and investing in productive housing capital $h_t^p$, which is susceptible to disaster damage. Households enjoy owner-occupied housing services from productive housing capital that is not damaged by a disaster, $\tilde{h}_t^s$, using a linear production technology:

$$\tilde{h}_t^s = A^h \tilde{h}_t^p.$$

Variable $A^h$ denotes total factor productivity in the production of housing services. We use "tildes" throughout the paper to denote the value of a variable after the realization of the disaster shock. Hence, variables $h_t^p$ and $\tilde{h}_t^p$ denote household $i$'s values of housing services before and after the realization of the period-$t$ disaster shock, respectively.

Households receive an idiosyncratic endowment $z_{it}$. The log of the household's idiosyncratic endowment is:

$$\log(z_{it}) = \rho \log(z_{it-1}) + \sqrt{(1-\rho^2)}\epsilon_{i,t} \tag{12}$$

where $\epsilon_{i,t} \sim \mathcal{N}(0, \sigma_\epsilon^2)$. The parameter $\rho$ denotes the persistence, and $\varepsilon_{it}$ is a noise process with variance $\sigma_\varepsilon^2$. We take the values for $\rho = 0.98$, and $\sigma_\varepsilon = 0.3$ from Jeske et al. (2013). We use the Rouwenhorst method to approximate the AR(1) process with a five-state Markov chain. The Markov chain has transition probabilities $\pi(\nu_{i,t+1} \mid \nu_{it})$, and unique invariant distribution $\Pi(\nu_{it})$.[10]

[10] The Markov transition matrix $\pi$ and its invariant distribution $\Pi$ are given by

$$\Pi = \big(0.1984,\ 0.2007,\ 0.2014,\ 0.2007,\ 0.1984\big),$$

### 3.1.2 Disasters and adaptation

At the start of period $t$, the household can experience a disaster shock, $e^h_{nt} \in \{0, 1\}$. Value $e^h_{nt} = 1$ indicates that the household is hit by a disaster and $e^h_{nt} = 0$ indicates that the household is not hit by a disaster. Parameter $\gamma_{nt}$ is the probability that the household is hit by a disaster. Let $\psi(e^h_{nt})$ denote the vector of disaster-shock probabilities, where $\psi_{nt}(0) = 1 - \gamma_{nt}$ and $\psi_{nt}(1) = \gamma_{nt}$. Let $\Omega^h$ denote the fraction of the household's property affected by the disasters in period $t$.

To mitigate climate damages, households can invest in adaptation. Variable $a^h_{it}$ captures the household's adaptive capacity, which is equal to adaptive housing capital relative to productive housing capital: $a^h_{it} \equiv \frac{h^a_{it}}{h^p_{it}}$. Only investments in productive housing capital provide households with utility, whereas adaptation capital does not. The law of motion for adaptive housing capital, which is not susceptible to disasters, can be described as:

$$h^a_{i,t+1} = (1 - \delta^a)h^a_{it} + i^a_{it},$$

where $i^a_{it}$ denotes the household's investment in adaptive capital.

We model damaged housing as:

$$h^d_{it} = e_{it}F(a^h_{it})\Omega^h_n h^p_{it} \tag{13}$$

Following Fried (2022), we assume that $F(a^h_{it})$ is decreasing and convex in adaptive capacity and takes the following form:

$$F(a^h_{it}) = \exp(-\theta(a^h_{it})^{\frac{1}{\theta}}),$$

with $\theta > 1$ being the effectiveness of adaptive capacity at reducing disaster damages. Fried (2022) determine the moments that pin down the structural parameter governing the effectiveness of adaptation capital, $\theta$. Disaster-related damages reduce the amount of housing that can be resold. For a given household $i$, the post-disaster housing capital equals:

$$\tilde{h}^p_{it} = h^p_{it} - h^d_{it}$$

---

and

$$\pi = \begin{pmatrix} 0.9413 & 0.0573 & 0.0013 & 0.0000 & 0.0000 \\ 0.0143 & 0.9420 & 0.0430 & 0.0007 & 0.0000 \\ 0.0002 & 0.0287 & 0.9422 & 0.0287 & 0.0002 \\ 0.0000 & 0.0007 & 0.0430 & 0.9420 & 0.0143 \\ 0.0000 & 0.0000 & 0.0013 & 0.0573 & 0.9413 \end{pmatrix}.$$

Housing capital evolves according to

$$h^p_{t+1} = (1 - \delta^h)\tilde{h}^p_t + i^{hp}_t,$$

where $i^h_{it}$ denotes the household's investment in productive housing capital.[11]

**Insurance**. Households can buy insurance $X_{i,t+1}$ at price $P_t$ against next period's disaster damage. If a household experiences a disaster in period $t+1$, then she receives $\min\left[X_{i,t+1}, h^d_{i,t+1}\right]$, which indicates that the payout is constrained by the amount of insurance bought prior to the disaster. If the homeowner does not experience a disaster, then she receives zero. Individual insurance policies get aggregated into the stock of insurance as follows:

$$X_t = \int_i X_{it} di$$

The insurance price consists of an expected loss component and operating cost. Homeowners know the loss amount if a disaster occurs. Consequently, homeowners will rationally never buy insurance that exceeds possible future losses. This means that the expected loss for the insurer is $\gamma$. We assume that the insurance prices is the expected payout plus the expected cost of disbursing the insurance claim, such that the price becomes:

$$P_t = \gamma + \gamma\lambda$$

where $\lambda$ reflects the insurer's operational cost. Under the stationary distribution with idiosyncratic climate risk, the LLN implies that the insurance payouts equal the premiums plus the operational cost.

**Saving**. Households can save through deposits $f_t$ paying a risk-free rate $r^b_t$. **Mortgages**. We follow Jeske et al. (2013) by considering that households can borrow against their housing position using one-period mortgage debt.[12] Households can use credit for investments into housing capital or adaptation capital, and, since assets are fungible, for consumption. Yet, borrowing without collateral increases leverage and increases the mortgage interest rate.

Let $d_{i,t+1}$ denote the household's mortgage that has to be repaid in the next period and $P_d$ the contemporaneous receipt of resources for each unit of mortgage. The price $P_d$ is determined in equilibrium by banks and is a function of the households housing and adaptation choices, acting as collateral, insurance coverage, and the size of the mortgage.

[11] We impose a minimum housing level $\bar{h}^p_{t+1}$ equal to 30% of the lowest grid point of household wealth.

[12] One-period mortgage debt avoids the need the track mortgage balances over time, otherwise introducing another state variable.

The gross mortgage interest rate is given by $R_d = 1/P_d$. Hence, households receive $d_{i,t+1}P_d$ today from the borrowing decision.

In the next period, after undergoing a disaster shock, households may default on their mortgage, which results in households losing their entire housing and the insurance payout is shifted to the bank. The one-period mortgage contract implies that household will default if the value of housing is less than what is owed on the mortgage minus the insurance payment, i.e., $d_{i,t+1} - \min\left[X_{i,t+1}, h^d_{i,t+1}\right] > (1-\delta^h)\tilde{h}^p_{i,t+1}$. Note that households cannot pledge adaptation capital as collateral. In the event of a disaster, the household can fulfill its mortgage obligations using the insurance payment (Gallagher and Hartley, 2017). When defaulting, the insurance payment will be collected by the bank. The default condition shows that households buying more insurance weakly lowers the probability of default.

We impose that households will not borrow to increase consumption today and default tomorrow. This requires a limit on the loan-to-value (LTV) ratio, such that households will not default absent a disaster. The LTV-limit is given by:

$$\frac{d_{i,t+1}}{h^p_{i,t+1}} < 1 - \delta^h \tag{14}$$

The LTV-limit shows that the ratio of next period mortgage debt to housing capital should satisfy an upper bound. The LTV-limit is easier satisfied when the depreciation rate is low as this lowers the probability that the mortgage will be underwater in the next period.

**Household problem** The time-invariant household characteristics are $\Upsilon_i \equiv n$. Cash at hand evolves according to

$$\begin{aligned}\tilde{m}_{it}(h^p_{it}, h^a_{it}, f_{it}, X_{it}, d_{it}, e^h_{it}, \nu_{it}; \Upsilon_i) = {} & w_t z_{it}(1-\tau) + f_{it} + (1-\delta^a)h^a_{it} \\ & + \max\left[0, (1-\delta^h)\tilde{h}^p_{it} + e^h_{it}\min\left[X_{it}, h^d_{it}\right] - d_{i,t}\right]\end{aligned}$$

where $\tau$ is the income tax, which is zero in the baseline economy and non-zero in the policy counterfactuals. The household state variables include the persistent labor productivity shock $\nu_{it}$, cash at hand $\tilde{m}_{it}$, and housing services after the realization of the disaster shock $\tilde{h}^s_{it}$.

The dynamic programming problem for the household equals

$$V(\nu_{it}, \tilde{m}_{it}, \tilde{h}^s_{it}; \Upsilon_i) = \underbrace{\max}_{c_{it}, h^p_{i,t+1}, h^a_{i,t+1}, f_{i,t+1}, X_{i,t+1}, d_{i,t+1}} \Big[ U(c_{it}, \tilde{h}^s_{it}) + \beta \sum_{\nu_{i,t+1}} \pi(\nu_{i,t+1} \mid \nu_{it}) \sum_{e_{t+1}} \Gamma(e_{t+1}) V(\nu_{i,t+1}, \tilde{m}_{i,t+1}, \tilde{h}^s_{i,t+1}; \Upsilon_i) \Big]$$

subject to the budget constraint,

$$c_{it} = \tilde{m}_{i,t} + d_{i,t+1} P_d(h^p_{i,t+1}, d_{i,t+1}, X_{i,t+1}, h^a_{i,t+1}) - h^p_{i,t+1} - h^a_{i,t+1}(1-\eta^{h^a}) - \frac{f_{i,t+1}}{(1+r^b_t)} - P_t X_{i,t+1}(1-\eta^X)$$

the LTV constraint,

$$\frac{d_{i,t+1}}{h^p_{i,t+1}} \leq 1 - \delta^h$$

and non-negativity constraints: $h^p_{t+1} + h^a_{t+1} + f_{t+1} \geq 0, \quad h^p_{t+1} \geq 0 \quad d_{i,t+1} \geq 0 \quad X_{t+1} \geq 0,$ and the stochastic laws of motion for $z_{it}$. $\eta^{h^a}$ and $\eta^X$ denote the subsidy for adaptation and insurance, respectively, which are both zero in the baseline economy.

### 3.1.3 Mortgage lenders

Banks use household deposits as resources for mortgage lending. In equilibrium, banks face a financing cost equal to $1 + r^b_t$ per unit mortgage lending. In addition, banks incur an operational cost $r^w$ per unit of mortgage lending, which captures screening costs, and is expressed as a percentage per unit of mortgage lending.[13] Combined, the effective cost of financing for banks equals $1 + r^b_t + r^w_t$ per unit of mortgage lending.

Banks will only lend to the household if in expectation they make a non-negative profit. In their lending decision, banks take into account the possibility that households may default, in which case they receive the collateral plus insurance payouts, which, by the household default condition, is less than the originally scheduled mortgage repayment.

Banks will extend a loan if and only if:

$$d_{i,t+1} P_d(h^p_{i,t+1}, d_{i,t+1}, X_{i,t+1}, h^a_{i,t+1}) \leq \frac{(1-\gamma) d_{i,t+1} + \gamma \min\left[ d_{i,t+1}, (1-\delta^h)\tilde{h}^p_{i,t+1} + \min\left[ X_{i,t+1}, h^d_{i,t+1} \right] \right]}{1 + r^b_t + r^w_t} \tag{15}$$

Equation 15 indicates that the value of the mortgage today should be equal to the discounted

[13] The inclusion of operational costs ensures that the interest paid on mortgages exceeds the cost of financing for the banks.

repayment that the bank expects on the loan. The numerator captures the expected value of next period's cash flow from lending to the household. With probability $1-\gamma$, the bank gets paid back the entire loan. With probability $\gamma$, the bank receives the value of the destroyed collateral plus the insurance payout if the household defaults or simply $d_{i,t+1}$ when the household does not default. Perfect competition results in equation 15 to hold with equality. Rewriting yields a pricing equation per unit of mortgage:

$$P_d(h^p_{i,t+1}, d_{i,t+1}, X_{i,t+1}, h^a_{i,t+1}) = \begin{cases} \frac{1}{1+r^b_t+r^w_t}, & \text{if } \frac{d_{i,t+1}}{(1-\delta^h)\tilde{h}^p_{i,t+1}+\min\left[X_{i,t+1},h^d_{i,t+1}\right]} \leq 1 \\ \frac{1+\gamma\phi(h,d)}{1+r^b_t+r^w_t}, & \text{otherwise} \end{cases} \tag{16}$$

where $\phi(h,d) = \frac{\min\left[X_{i,t+1},h^d_{i,t+1}\right]+(1-\delta^h)\tilde{h}^p_{i,t+1}}{d_{i,t+1}} - 1 < 0$ denotes the risk premium. Households only pay the financing and operational cost on the mortgage when their *insurance-adjusted leverage ratio* is below or equal to 1. This reflects the situation that even in a disaster, the post-disaster housing value plus insurance payout exceeds the mortgage payment, such that default is never optimal. In this case, the bank does not face default risk and prices only the financing and operational cost. When the ratio is above 1 and a disaster strikes, households may default, such that banks recoup collateral that is less than the amount owed on the mortgage. Consequently, banks price in this risk. The risk premium $\phi(h,d)$ enters the equation negatively since the contemporaneous receipt of mortgage resources today $P_d$ is the inverse of mortgage interest rate.

Note that denominator in the insurance-adjusted leverage ratio captures the value of post-disaster housing rather than the value of pre-disaster housing. The denominator therefore captures what the bank can recoup after a disaster. Even when the unadjusted leverage ratio is below 1, the insurance-adjusted leverage may be above 1. Figure B.6 illustrates this intuition. The contemporaneous borrowing receipt $P^d$ decreases in unadjusted leverage. In addition, conditional on unadjusted leverage, $P^d$ increases in insurance coverage as more insurance makes the loan less risky. When insurers become financially constrained, and insurance prices rise, such that households become under-insured, credit constraints become more severe.

## 3.2 Idiosyncratic Climate Risk

In this section, we assume idiosyncratic climate risk that is i.i.d. across households.

### 3.2.1 Equilibrium

We define a stationary recursive competitive equilibrium. Let $g^h = (\tilde{h}_s, m, \nu, \Upsilon)$ denote the vector of household state variables and household characteristics. Let $\mu_h$ be the invariant cross-sectional distribution over the household states and characteristics.

Given an tax rate, a stationary recursive competitive equilibrium consists of the time-invariant value and policy functions for the households $\{V_h, h'_p, h'_a, X', f', d'\}$, prices $\{r^b, p_n^X\}$ for each $n \in \{1, \ldots, N\}$, subsidies $\eta^{h^a}$ and $\eta^X$, and the stationary distribution $\{\mu_h\}$ such that:

1. **Optimality** Given prices, the labor-income tax, and government policies, the household value function $V_h$ solves the optimization problem in equation (8), and $h'_p$, $h'_a$, $f'$, $x'$ and $d'$ are the associated policy functions.

2. **Market Clearing in the Bond Market**

$$\int \frac{f'}{(1+r^b)}\, d\mu_h = \int P_d(h'^p, d', X', h'^a)\, d'\, d\mu_h$$

3. **Federal Government Budget Constraint**

$$\int \tau z\, d\mu_h = \int \left[\eta^{h^a} h'^a + \eta^X X'\right]\, d\mu_h$$

### 3.2.2 Parameterization

We select various parameters exogenously, whereas others are calibrated endogenously to match several moments.

**Disaster parameters** Based on the relationship between observed climate damages, which are proxied by disaster aid expenditures, and the modeled probability of storms, Fried (2022) infers $\theta = 3.78$. We cannot directly rely on this parameter since our model does not focus on a specific type of disaster but rather any. The adaptation parameter for storms may differ from the adaptation parameter for the average disaster. Since our main interest is not calibrating the adaptation parameter internally, we assume $\theta = 3.78$ and perform sensitivity analyses with larger values of $\theta$.

We approximate the disaster probability parameter as fraction of uninsured homeowners that apply for Federal Emergency Management Agency's (FEMA) disaster aid (Fried, 2022). We consider an average U.S. home ownership rate of 65% (FRED). About 7.7% of U.S. homeowners do not have home insurance (Board of Governors of the Federal Reserve System,

2024). Since the typical insurance policy covers fire- and storm damage, we assume that the fraction of homeowners uninsured against fire and storm risks is equal to the country-wide average fraction of uninsured homeowners of 7.7%. Under-insurance to floods is more severe as roughly 96% of U.S. homeowners is uninsured to floods (Fitch Ratings). We compute the average the disaster probability by disaster type and county over the period 2010-2023. Figure B.5 plots the estimated probabilities by county after winsorizing probabilities at the 1% level. Wildfire probabilities are relatively low, whereas storm probabilities are relatively high. The average probability that a households get hit by a disaster of any type is 2.4%.

We calibrate the severity of the disaster $\Omega$ internally so that the share of housing capital damages by disasters aligns with existing estimates (Zillow Research, 2024, Aon, 2025).

**Housing parameters** We choose the depreciation rates on housing capital $\delta^h$ and adaptation capital $\delta^a$ equal to the average depreciation rates for residential fixed assets and structures respectively (NIPA Tables 1.1 and 1.3). Total factor productivity in the production of housing services, $A^h$, is chosen to equal the ratio of housing services divided by residential capital (NIPA Tables 2.3.5 and 1.1).

**Household parameters** We set the coefficient of relative risk aversion equal to 2. We take the exponent on non-durable consumption in the composite of non-durable consumption and housing services, $\zeta$, and the discount rate $\beta$ from Fried (2022).

**Insurance parameters** The operational cost $\lambda$ is calibrated internally to match the insurance protection gap, i.e., the share of damages not covered by insurance, of 46% reported by Swiss Re (2024). Higher operational costs mean that households receive less insurance coverage for the premiums they pay.

**Mortgage parameters** We calibrate the mortgage administration fee $r^w$ to match a median aggregate leverage of 0.61 (Jeske et al., 2013). A higher $r^w$ result in lower contemporaneous resources today. This results in the budget constraint binding more quickly binds, ultimately lowering housing investments relative to the size of the mortgage and thereby leverage.

## 3.3 Equilibrium outcomes

We solve the model using Howard's policy iteration algorithm. Using the obtained policy- and state transition functions, we compute the stationary distribution and aggregate outcomes. The interest clears the mortgage and deposit market. In the stationary distribution, individual households move around the wealth distribution as they are affected by climate and income shocks, but aggregates remain constant. Table 3 reports the targeted and model

**Table 1**
Parameter values: external calibration

| Parameter | Value | Target |
|---|---|---|
| Disaster probability: $\gamma$ | 0.024 | Calculations |
| Depreciation rate of housing capital: $\delta^h$ | 0.02 | NIPA |
| Depreciation rate of adaptation capital: $\delta^a$ | 0.03 | NIPA |
| TFP in housing services: $A^h$ | 0.14 | NIPA |
| Persistent shock persistence: $\rho$ | 0.97 | Kaplan (2012) |
| Persistent shock innovation variance: $\sigma_\xi^2$ | 0.02 | Kaplan (2012) |
| Coefficient of relative risk aversion: $\sigma$ | 2 | - |
| Effectiveness of adaptation: $\theta$ | 3.78 | Fried (2022) |
| Non-durable consumption exponent: $\zeta$ | 0.85 | Fried (2022) |
| Discount rate: $\beta$ | 0.98 | Fried (2022) |

**Table 2**
Baseline parameter values: internal calibration

| Parameter | No policy | Adaptation subsidy | Insurance subsidy |
|---|---|---|---|
| Disaster severity: $\Omega$ | 0.46 | 0.46 | 0.46 |
| Insurance operational cost: $\lambda$ | 85bps | 85bps | 85bps |
| Mortgage fee: $r^w$ | 4bps | 4bps | 4bps |
| Interest rate: $r_t^b$ | 3.4% | 3.4% | 3.3% |
| Tax rate: $\tau$ | 0% | 0.1% | 0.1% |
| Subsidy for adaptation: $\eta^a$ | - | 1.8% | - |
| Subsidy for insurance: $\eta^X$ | - | - | 15.0% |

**Table 3**
Targeted moments in the baseline scenario

| Moment | No policy | Target |
|---|---|---|
| Insurance gap | 86% | 46% (Swiss Re, 2024) |
| Leverage | 0.29 | 0.61 (Jeske et al., 2013) |
| Fraction of housing destroyed | 0.003 | 0.003 (Zillow Research, 2024, Aon, 2025) |

moments. We hit the empirical targets for the fraction of housing that is destroyed reasonably well, but our model produces a larger insurance gap and lower leverage.

Figure ?? plots the household policy function. Housing, consumption and insurance are an increasing function of cash-on-hand. In contrast, household mortgage take-up decreases in cash-on-hand. Household savings become positive only when mortgage take-up approaches

zero. Table 6 reports the aggregate outcomes for the entire economy and the outcomes across the wealth distribution. The aggregate default rate is 0.25%. Based on the disaster probability of 2.40%, this implies that 10.4% of households who experience a disaster default. Default rates are only positive among low-wealth households who have a default probability of 1.7%. This is implies that 71% of low-wealth households who experience a disaster default. These heterogeneous effects show that while disasters may have small effects in aggregate, they may have sizeable effects within subgroups of the population.

The key driver behind defaults is insurance-adjusted leverage, which is highest among low-wealth households. Low-wealth households decide on low insurance and adaptation relative to their housing and mortgage decisions, leading to a high risk of default upon a disaster. While there is variation in insurance-adjusted leverage across the wealth distribution, the effect on mortgage rates remains small as it gets discounted by the disaster probability (equation 16).

Low-wealth households have highest leverage. To highlight the role of leverage constraints in driving our results, we run the model for different LTV constraints under the set of baseline parameters. Figure 8 shows that leverage regulation plays an important role in driving disaster-driven defaults and shaping household insurance- and adaptation decisions. A tighter LTV constraint lowers disaster-driven defaults. We estimate that default risk on mortgages converges to zero for LTV ratios below 60%. In line with Sastry et al. (2024), tighter LTV constraints correlate with larger insurance gaps, although this pattern is primarily visible among higher-wealth households.

### 3.3.1 Counterfactuals

**Contracting insurance markets**. To understand the impact of insurance capacity reductions on financial fragility in mortgage markets, we construct counterfactual outcomes after an exogenous increase in the insurance price of 50%. We leave the disaster probability unchanged, so that the insurance is priced above the actuarially fair rate $\gamma$. The increase in the insurance price proxies for financial frictions at the insurer side. For example, insurance prices may increase when statutory capital is low (Koijen and Yogo, 2022).

We compute the partial equilibrium effect by comparing outcomes between the baseline and the counterfactual with contracting insurance markets. Panel B in Table 6 shows that when insurance prices increase by 50%, default rates increase from 0.25% to 0.29%. The fraction of damages that are insured drops sharply and approaches zero in aggregate. As insurance is now priced above what is actuarially fair, households' perceive insurance as too

expensive relative to the risk they face, lowering insurance take-up. Consequently, conditional on leverage, insurance-adjusted leverage increases, although this effect is partly offset by higher adaptation.

When the insurance coverage of households lowers, it could increase or decrease adaptation. Under the moral hazard channel, insurance and adaptation are substitutes. Under the credit constraint channel, banks price in low insurance into their mortgage rate. This leads to a lower $P_d$ and more severe credit constraints, possibly lowering adaptation. We find that contracting insurance markets increase adaptation, suggesting that the moral hazard channel is stronger than the credit constraints channel. Even though a higher insurance-adjusted leverage is priced in by banks, it does not lead to a significantly higher interest rate on the mortgage as the probability of a disaster of 2.4% reduces the risk premium. While the increase in adaptation reduces the fraction of housing that is destroyed, it is not sufficient to keep defaults rates low. Overall, the results show that, consistent with the empirical results, contracting insurance markets can increase financial fragility in mortgage markets.

**Frequent disasters**. We construct counterfactuals where we let the disaster probability increase from 1% to 5%. Since the risk-premium charged on loans depends on the disaster probability, increasing the disaster probability implies also larger variation between households with high and low insurance-adjusted leverage. We keep the insurance price actuarially fair.

Figure 9 shows that defaults increase when disaster probabilities increase. As in the baseline scenario, high-wealth households do not default as their leverage remains low. Increasing disaster probabilities makes insurance more expensive and results in banks charging higher mortgages, both directly and possibly indirectly through lower household insurance coverage. In addition, we find that households invest more in adaptation for higher disaster probabilities. This reaction is furthermore heterogeneous given that the slope between adaptation investments and disaster probabilities is steeper for high-wealth households.

**Endogenous adaptation** To understand the role of adaptation in driving the financial consequences of disasters, we shut off adaptation and compare outcomes across varying disaster probabilities with outcomes in the economy with adaptation. Figure 10 plots aggregate outcomes for varying disaster probabilities with and without adaptation. We find that in the economy without adaptation, default rates increase more sharply in disaster probabilities relative to the economy with adaptation. As disasters become more frequent, making insurance more expensive, households respond by adapting more, which lowers household financial fragility. At a disaster probability of 5%, endogenous adaptation lowers defaults by

about 35%. Without adaptation, households shift to insurance, but take-up equally lowers as insurance becomes more expensive when disaster probabilities increase. Overall, these findings highlight that endogenous adaptation lowers the financial stability consequences of natural disasters.

**Changing disaster severity**. We construct counterfactuals by exogenously changing disaster severity $\Omega$. To allow a comparison with the outcomes under varying disaster probabilities, we look for combinations of disaster severity and probability that yield the same expected fraction of the house that is destroyed (in the absence of adaptation), which equals $\gamma$ times $\Omega$. Figure 11 shows the aggregate outcomes when varying $\Omega$ while keeping $\gamma$ equal to its baseline value. We also plot aggregate outcomes when varying $\gamma$ while keeping $\Omega$ equal to its baseline value, of which the results are identical to 11.

We find stark differences in optimal insurance take-up. When expected losses are driven by the disaster probability (frequency), optimal insurance take-up decreases in expected losses. Since the price of insurance equals $\gamma$, insurance affordability decreases in disaster frequency. In contrast, when expected losses are driven by disaster severity (volatility), optimal insurance take-up increases in expected losses. The volatility in future wealth induced by higher disaster severity makes households more risk-averse and increases insurance take-up. In this case, the cost of per unit of insurance remains the same despite expected losses increasing so that affordability does not become a constraint. Defaults increase under both measures of expected loss, but more sharply when the expected loss is driven by frequency. These findings highlight that disaster volatility and disaster frequency can have opposing effects on household insurance take-up.

**Bank pricing regimes**

**Random severity**. Our analysis assumed that while the arrival of a disaster is uncertain, the severity is known up-front. In this section, we relax this assumption by making the severity of the disaster random. Let $F(\Omega)$ denote the cumulative distribution function of the disaster's severity, with support $D = \left[\underline{\Omega}, \overline{\Omega}\right]$. We assume that $\Omega$ is uniformly distributed. The realization of $\Omega$ is independent across households, so that the law of large number applies again, and $F(\Omega)$ is the economy-wide disaster severity. Appendix B.3 describes the extension with random severity.

### 3.3.2 Policy analysis

**Conditional cash transfers** We consider that governments can subsidize insurance or adaptation. We construct two counterfactual scenarios where the government subsidizes

either insurance or adaptation by raising taxes by 0.1%. We compute the subsidies $\eta^{h^a}$ and $\eta^X$ by imposing the equilibrium condition that aggregate taxes paid on income should equal aggregate subsidies granted. We then compare the effects of the subsidies on household behavior and default rates. Table 2 shows that for the 0.1% increase in taxes, one can subsidize 15% of insurance premiums and 1.8% of adaptation investments.

Figure 12 computes changes in aggregate outcomes under both subsidy schemes relative to the baseline. Insurance subsidies are effective in reducing defaults. As insurance is now priced below what is actuarially fair, households increase insurance demand to the point where all possible disaster damages are covered by insurance, significantly reducing their vulnerability. While insurance take-up reduces default rates, it decreases adaptation through moral hazard consistent with (Annan and Schlenker, 2015). In contrast, the adaptation subsidy increases adaptation, reduces the share of housing that is damaged, but does not meaningfully reduce defaults.

**Unconditional cash transfers**

# 4 Conclusion

We examine the effect of natural disasters on financial stability in insurance and mortgage markets when household adaptation is endogenous to changing financial conditions. We first establish that natural disasters reduce financial stability indicators in insurance and banking sectors, both directly and through spillover effects, although the magnitudes are small for banks. In a disaster-adjusted Aiyagari (1994) model, we study the dynamic interactions between households, banks and insurers in light of growing disaster risk. Our models confirms the increased financial fragility effects of under-insurance. Yet, we find that endogenous household adaptation lowers the financial stability consequences of natural disasters relative to no adaptation. We further illustrate the effectiveness of both insurance and adaptation policies in reducing defaults and strengthening financial stability. Overall, our micro-founded model highlights how the interplay between regulation, financial frictions and household behavior shapes the long-run financial stability effects of natural disasters.

# References


**Aiyagari, S Rao**, "Uninsured idiosyncratic risk and aggregate saving," *The Quarterly Journal of Economics*, 1994, *109* (3), 659–684.

**Annan, Francis and Wolfram Schlenker**, "Federal crop insurance and the disincentive to adapt to extreme heat," *American Economic Review*, 2015, *105* (5), 262–266.

**Aon**, "Natural Disaster Losses in the U.S.," Claims Journal Report 2025.

**Battiston, Stefano, Yannis Dafermos, and Irene Monasterolo**, "Climate risks and financial stability," 2021.

**Board of Governors of the Federal Reserve System**, "Economic Well-Being of U.S. Households in 2024," Technical Report, Federal Reserve May 2024.

**Borusyak, Kirill, Peter Hull, and Xavier Jaravel**, "A practical guide to shift-share instruments," *Journal of Economic Perspectives*, 2025, *39* (1), 181–204.

**Cochrane, JH**, "A convenient myth: Climate risk and the financial system," *National Review*, 2021, *17*.

**der Straten, Yasmine Van**, "Flooded House or Underwater Mortgage? The Implications of Climate Change and Adaptation on Housing, Income and Wealth," Technical Report, Tinbergen Institute Discussion Paper 2023.

**Eastman, Evan, Kyeonghee Kim, and Tingyu Zhou**, "Homeowners insurance and housing prices," *Available at SSRN*, 2024.

**Fried, Stephie**, "Seawalls and stilts: A quantitative macro study of climate adaptation," *The Review of Economic Studies*, 2022, *89* (6), 3303–3344.

**Gallagher, Justin and Daniel Hartley**, "Household finance after a natural disaster: The case of Hurricane Katrina," *American Economic Journal: Economic Policy*, 2017, *9* (3), 199–228.

**Ge, Shan, Stephanie Johnson, and Nitzan Tzur-Ilan**, "Climate Risk, Insurance Premiums and the Effects on Mortgage and Credit Outcomes," 2025.

**Jeske, Karsten, Dirk Krueger, and Kurt Mitman**, "Housing, mortgage bailout guarantees and the macro economy," *Journal of Monetary Economics*, 2013, *60* (8), 917–935.

**Jordà, Òscar**, "Estimation and inference of impulse responses by local projections," *American economic review*, 2005, *95* (1), 161–182.

**_ , Sanjay R Singh, and Alan M Taylor**, "The long-run effects of monetary policy," *Review of Economics and Statistics*, 2024, pp. 1–49.

**Jung, Hyeyoon, Robert Engle, Shan Ge, and Xuran Zeng**, "Physical Climate Risk Factors and an Application to Measuring Insurers' Climate Risk Exposure," in "FRB of New York Staff Report No. 1066" 2024.

**Kaplan, Greg**, "Inequality and the life cycle," *Quantitative Economics*, 2012, *3* (3), 471–525.

**Koijen, Ralph SJ and Motohiro Yogo**, "The fragility of market risk insurance," *The Journal of Finance*, 2022, *77* (2), 815–862.

**Krusell, Per and Anthony A Smith Jr**, "Income and wealth heterogeneity in the macroeconomy," *Journal of political Economy*, 1998, *106* (5), 867–896.

**Noth, Felix and Ulrich Schüwer**, "Natural disasters and bank stability: Evidence from the US financial system," *Journal of Environmental Economics and Management*, 2023, *119*, 102792.

**Ouazad, Amine and Matthew E Kahn**, "Retracted: Mortgage finance and climate change: Securitization dynamics in the aftermath of natural disasters," *The Review of Financial Studies*, 2022, *35* (8), 3617–3665.

**Rousová, Linda Fache, Margherita Giuzio, Sujit Kapadia, Hradayesh Kumar, Luisa Mazzotta, Miles Parker, and Dimitris Zafeiris**, "The macroeconomic effects of the insurance climate protection gap," 2023.

**Sastry, Parinitha**, "Who bears flood risk? evidence from mortgage markets in florida," *Evidence from Mortgage Markets in Florida (December 18, 2022)*, 2022.

**_ , Ishita Sen, Ana-Maria Tenekedjieva, and Therese C. Scharlemann**, "The Limits of Insurance Demand and the Growing Protection Gap," *SSRN (May 21, 2024)*, 2024.

**_ , _ , and _** , "When insurers exit: Climate losses, fragile insurers, and mortgage markets," *SSRN (December 23, 2023)*, 2023.

**Swiss Re**, "How big is the protection gap from natural catastrophes where you are?," https://www.swissre.com/risk-knowledge/mitigating-climate-risk/natcat-protection-gap-infographic.html#/ 2024. Accessed: 2025-06-06.

**Zillow Research**, "Housing Market Value Hits $1 Trillion Increase," Zillow Research Report 2024.

**Table 1**

Insurer sample - summary statistics

| | N | Mean | SD | Min | 25th | Median | 75th | Max |
|---|---|---|---|---|---|---|---|---|
| Return-on-Assets | 18,489 | 2.09 | 4.84 | -36.50 | 0.46 | 2.18 | 4.14 | 72.91 |
| Loss Ratio (homeowners segment) | 18,336 | 60.99 | 58.89 | -198.93 | 37.33 | 53.20 | 72.05 | 976.35 |
| Total assets ($mn) | 18,582 | 1,011.29 | 4,075.20 | 0.27 | 24.52 | 95.58 | 379.32 | 76,343.55 |
| Leverage | 18,686 | 0.49 | 0.23 | 0.00 | 0.35 | 0.54 | 0.66 | 1.75 |
| Capital Surplus-to-Assets | 18,483 | 50.56 | 22.86 | -75.13 | 33.25 | 45.33 | 64.47 | 100.00 |
| Retention Ratio | 18,530 | 45.57 | 35.29 | -37.60 | 8.49 | 47.61 | 78.68 | 825.10 |
| Risk based capital ratio | 18,030 | 2,892.26 | 7,332.54 | 72.64 | 309.43 | 505.65 | 1,165.19 | 99,290.98 |
| Log(DisasterExposure) | 18,694 | 18.03 | 2.97 | 0.00 | 17.09 | 18.27 | 19.47 | 24.82 |
| DisasterExposure ($mn) | 18,725 | 781.05 | 3,392.41 | 0.00 | 26.25 | 85.45 | 284.11 | 51,526.43 |

**Table 2**

Bank sample - summary statistics

| | N | Mean | SD | Min | 25th | Median | 75th | Max |
|---|---|---|---|---|---|---|---|---|
| Return-on-Assets (%) | 54,245 | 0.77 | 0.92 | -7.28 | 0.47 | 0.84 | 1.21 | 3.56 |
| Assets ($mn) | 54,245 | 4,322.72 | 62,635.01 | 0.20 | 152.52 | 317.38 | 760.14 | 3,357,716.25 |
| Leverage | 54,245 | 0.89 | 0.03 | 0.75 | 0.88 | 0.90 | 0.91 | 0.98 |
| Foreclosure Ratio (%) | 54,213 | 0.56 | 1.40 | -0.10 | 0.00 | 0.10 | 0.51 | 42.68 |
| Non-Performing Assets Ratio (%) | 54,245 | 0.67 | 0.99 | 0.00 | 0.16 | 0.39 | 0.82 | 27.55 |
| Risk-based capital (RBC) ratio | 54,245 | 10.52 | 2.92 | 1.34 | 8.88 | 9.95 | 11.48 | 24.25 |
| Net Write Offs Ratio (%) | 54,245 | 0.31 | 0.73 | -0.54 | 0.00 | 0.07 | 0.30 | 7.51 |
| Credit Loss Reserves Ratio (%) | 54,245 | 1.50 | 0.80 | 0.25 | 1.03 | 1.31 | 1.74 | 6.31 |
| InsuranceGap (non-renewals) (%) | 18,589 | 0.77 | 0.48 | 0.00 | 0.52 | 0.69 | 0.90 | 14.15 |
| InsuranceGap (ins. rate) (%) | 54,245 | 23.83 | 16.99 | -24.54 | 14.77 | 21.74 | 30.79 | 177.17 |
| ReinsuranceExposure (%) | 54,245 | -0.09 | 2.71 | -10.49 | -1.68 | -0.65 | 1.57 | 16.27 |
| Log(DisasterExposure) | 54,245 | -9.14 | 2.30 | -24.53 | -10.53 | -9.07 | -7.67 | 0.16 |
| DisasterExposure (%) | 54,245 | 0.17 | 1.49 | 0.00 | 0.00 | 0.01 | 0.05 | 117.60 |

**Table 3**

IV - first stage regression results. The dependent variable in column 1 includes bank exposure to insurance policy non-renewals. Column 2 provides the interaction with bank disaster exposure. We regress these endogenous variables on the two instruments (bank exposure to reinsurance shocks and the interaction with bank disaster exposure), next to other controls included in the second stage. The table includes 2- and 3-period lagged Log(RBC Ratio); the first stage results with other outcome variables are qualitatively similar. Standard errors are in parantheses and clustered at the bank level. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

| | InsuranceGap | InsuranceGap × Log(DisasterExposure) | InsuranceGap | InsuranceGap × Log(DisasterExposure) |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| ReinsuranceExposure | 0.092*** | -0.154*** | -1.304*** | 8.923*** |
| | (0.000) | (0.050) | (0.141) | (1.334) |
| ReinsuranceExposure × | 0.002*** | 0.047*** | -0.113*** | 0.843*** |
| Log(DisasterExposure) | (0.000) | (0.004) | (0.012) | (0.111) |
| $Lag_1$(Assets) | 0.003 | 0.042 | 0.115*** | 18.559*** |
| | (0.045) | (0.167) | (0.042) | (0.397) |
| $Lag_1$(Leverage) | -0.022 | -0.771 | 0.921** | -8.387* |
| | (0.200) | (2.350) | (0.467) | (4.406) |
| $Lag_2$(Assets) | 0.309*** | -0.336* | -10.902* | 100.003 |
| | (0.193) | (0.204) | (6.584) | (62.099) |
| $Lag_2$(Leverage) | 0.025 | 3.570 | 1.164** | -15.071*** |
| | (0.224) | (2.597) | (0.573) | (5.401) |
| $Lag_2$(Log(RBC Ratio)) | -0.272 | 0.599* | -10.465 | 144.486** |
| | (0.299) | (0.325) | (7.277) | (68.630) |
| $Lag_3$(Log(RBC Ratio)) | -0.044 | -0.242* | -2.485*** | 27.570*** |
| | (0.184) | (0.137) | (0.911) | (8.591) |
| Log(Disaster Exposure) | 0.021 | 0.770*** | 1.030*** | -10.111*** |
| | (0.135) | (0.015) | (0.384) | (3.623) |
| InsuranceGap Measure | Non-renewals | Non-renewals | Rate Change (C5Y) | Rate Change (C5Y) |
| Observations | 18,589 | 18,589 | 18,589 | 18,589 |
| $R^2$ | 0.07 | 0.01 | 0.01 | 0.14 |
| Year FE | Yes | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes | Yes |
| F-test on Instruments | 523.28 | 480.30 | 46.71 | 28.63 |
| Cragg-Donald Statistic | 601.03 | 601.03 | | |
| Durbin Statistic | 4.66 | 4.66 | | |

**Table 4**

**IV Results** - Dynamic Effects on Bank Performance Indicators and interaction with insurance shocks. For $h \in [0, 6]$, we run regression: $\Delta^{h+1} Y_{j,t-1} = \beta_1^h \widehat{\text{ClimateExposure}_{j,t} \times \text{InsuranceGap}_{j,t}} + \beta_2^h \text{ClimateExposure}_{j,t} + \beta_3^h \widehat{\text{InsuranceGap}_{j,t}} + \alpha_j^h + \tau_t^h + \sum_{l=1}^{L} \gamma_j^h \times X_{j,t-l} + \varepsilon_{j,t}^h$

The 'Interaction' and 'Main' columns show $\hat{\beta}_2^h$ and $\hat{\beta}_1^h$, respectively. T-statistics are in parentheses. We cluster standard errors at the bank level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

| | $\Delta^{h+1}\log(\text{RBC}_{j,t-1})$ | | $\Delta^{h+1}\log(\text{FOR ratio}_{j,t-1})$ | | $\Delta^{h+1}\log(\text{NPA ratio}_{j,t-1})$ | | $\Delta^{h+1}\text{ROA}_{j,t-1}$ | | $\Delta^{h+1}$Net Write-Offs Ratio | | $\Delta^{h+1}$Loss Reserve Ratio | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $h$ | Main | Interaction | Main | Interaction | Main | Interaction | Main | Interaction | Main | Interaction | Main | Interaction |
| 0 | 0.001 | -0.001 | 0.005 | -0.009 | 0.005 | -0.007 | 0.000 | -0.002 | 0.005* | -0.007* | -0.004* | 0.004 |
| | (0.490) | (-0.500) | (0.370) | (-0.520) | (0.360) | (-0.380) | (-0.000) | (-0.230) | (1.520) | (-1.630) | (-1.180) | (1.120) |
| 1 | 0.002 | -0.003* | 0.008 | -0.004 | 0.012 | -0.013 | 0.018** | -0.018* | 0.006* | -0.007* | -0.002 | -0.001 |
| | (1.270) | (-1.370) | (0.500) | (-0.240) | (0.780) | (-0.710) | (2.340) | (-1.890) | (1.740) | (-1.760) | (-0.700) | (-0.120) |
| 2 | 0.001 | -0.001 | -0.023* | 0.032* | 0.002 | -0.002 | 0.022*** | -0.024*** | 0.005* | -0.007*** | 0.004 | -0.005 |
| | (0.350) | (-0.280) | (-1.510) | (1.780) | (0.160) | (-0.140) | (3.030) | (-2.830) | (1.850) | (-2.040) | (1.100) | (-1.170) |
| 3 | -0.002 | 0.002* | -0.023*** | 0.032*** | 0.002 | -0.002 | 0.022*** | -0.025*** | -0.002 | 0.002 | 0.007* | -0.009** |
| | (-1.240) | (1.370) | (-4.910) | (4.720) | (0.640) | (-0.760) | (4.170) | (-4.030) | (-0.690) | (0.810) | (2.480) | (-2.520) |
| 4 | -0.003** | 0.003* | -0.069*** | 0.092*** | -0.015* | 0.014 | 0.003 | -0.006 | -0.005** | 0.005** | 0.005* | -0.008** |
| | (-2.150) | (1.930) | (-5.480) | (6.280) | (-1.550) | (1.170) | (0.780) | (-1.250) | (-2.420) | (2.360) | (1.770) | (-2.360) |
| 5 | 0.001* | -0.001 | -0.086*** | 0.104*** | -0.017** | 0.018** | 0.002 | -0.005 | -0.001 | 0.002 | 0.006** | -0.007** |
| | (1.470) | (-1.110) | (-8.720) | (8.930) | (-2.280) | (2.000) | (0.630) | (-1.140) | (-0.460) | (0.990) | (2.580) | (-2.660) |
| 6 | 0.001* | -0.001 | -0.086*** | 0.104*** | -0.017** | 0.018** | 0.002 | -0.005 | -0.001 | 0.002 | 0.006** | -0.007** |
| | (1.470) | (-1.110) | (-8.720) | (8.930) | (-2.280) | (2.000) | (0.630) | (-1.140) | (-0.460) | (0.990) | (2.580) | (-2.660) |

**Table 5**

Effect of Reinsurance Rate Changes on primary Insurance Rate Changes at the State-Year Level. Insurance Rate Changes captures the annual state-level percentage change in homeowners insurance price. The homeowners insurance price change is a weighted average of the insurers who submitted rate change requests to the state regulator. Reinsurance shock is as defined in equation 9. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

| | $\Delta$ Insurance Rate | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Reinsurance shock | 0.449*** | 0.461*** | 0.604*** | 0.668*** |
| | (0.134) | (0.134) | (0.220) | (0.223) |
| Intercept | 4.822*** | | 0.475 | |
| | (0.220) | | (1.319) | |
| Observations | 1,164 | 1,164 | 1,164 | 1,164 |
| Adjusted $R^2$ | 0.009 | 0.018 | 0.156 | 0.173 |
| Year FE | No | No | Yes | Yes |
| State FE | No | Yes | No | Yes |

**Table 6**
Model outcomes by wealth quintile. In the Insurance contraction scenario, we increase insurance prices by 50% relative to the insurance price in the baseline model.

| | Baseline | | | Insurance contraction | | |
|---|---|---|---|---|---|---|
| **Outcome** | **Agg.** | **Q1** | **Q5** | **Agg.** | **Q1** | **Q5** |
| Default rate | 0.0025 | 0.0170 | 0.0000 | 0.0029 | 0.0178 | 0.0000 |
| Adaptation ratio | 0.0165 | 0.0096 | 0.0178 | 0.0172 | 0.0050 | 0.0215 |
| Insured damages | 0.1358 | 0.0000 | 0.3724 | 0.0095 | 0.0586 | 0.0000 |
| Leverage | 0.2940 | 0.7767 | 0.0438 | 0.3325 | 0.9800 | 0.0500 |
| Leverage (insurance-adjusted) | 0.3477 | 0.9790 | 0.0447 | 0.3974 | 1.2069 | 0.0574 |
| Borrowing receipt ($P^d$) | 0.9650 | 0.9632 | 0.9658 | 0.9652 | 0.9626 | 0.9663 |
| Damages-to-housing | 0.0032 | 0.0042 | 0.0030 | 0.0032 | 0.0048 | 0.0028 |

**Local projections for the path of insurer financials following disaster losses**

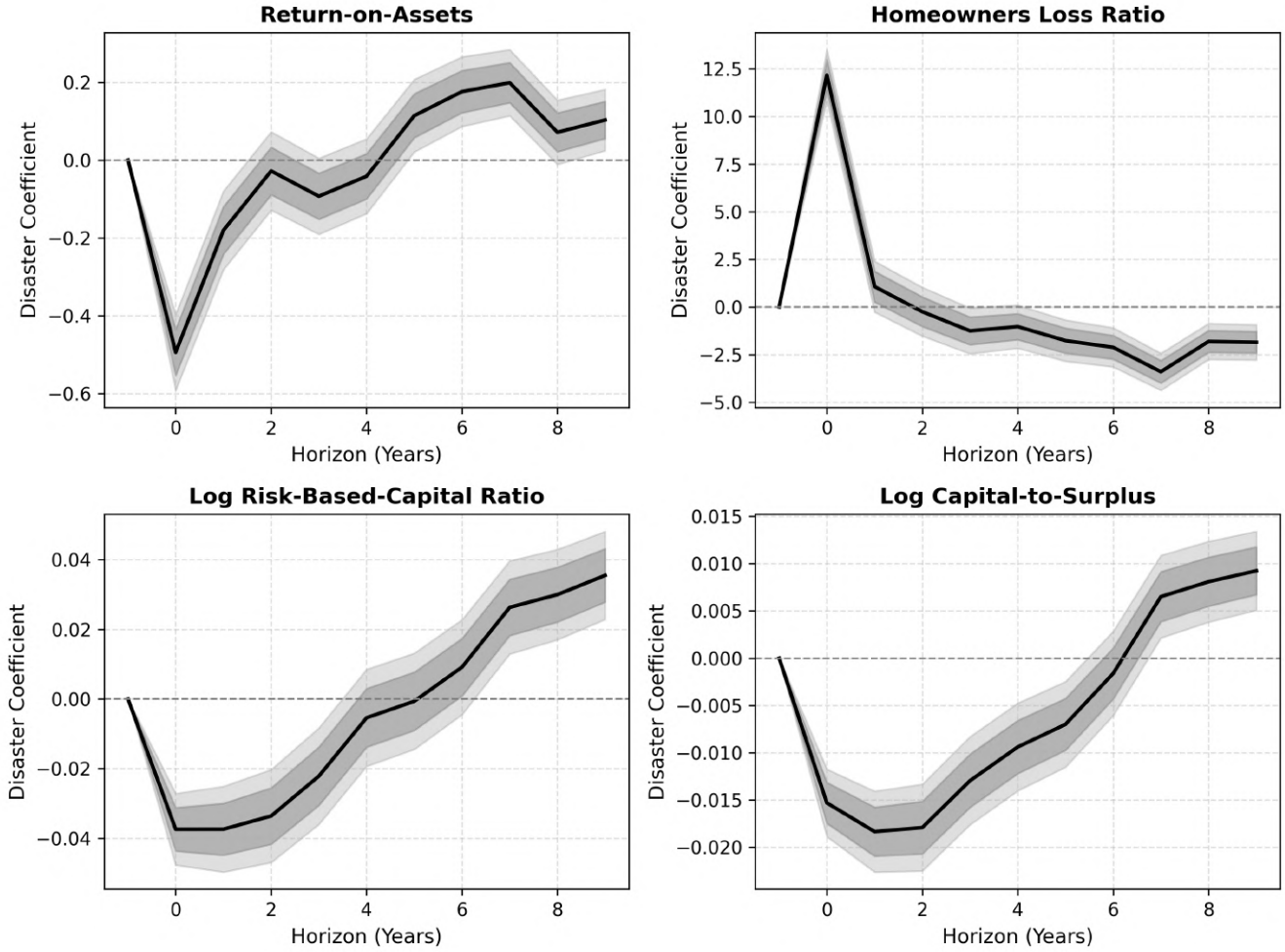



**Figure 1.** The Disaster Coefficient captures the effect of a standard-deviation increase in log(DisasterExposure) on Return on Assets (expressed as a percentage), Homeowners Loss ratio, Log Capital Ratio, and Log Capital-to-Surplus. The dark and light shaded areas reflect 68% and 90% confidence intervals.

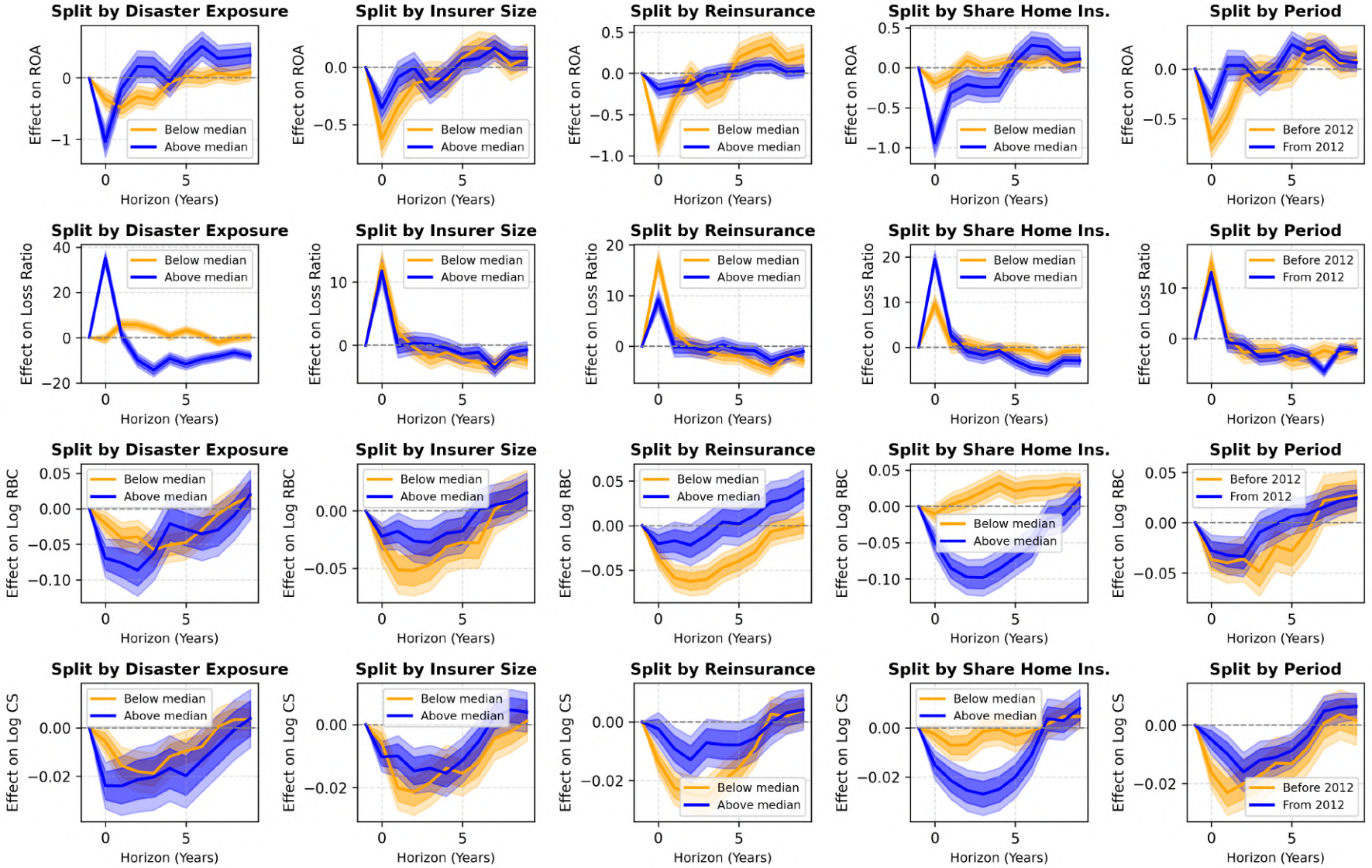



**Figure 2.** The Disaster Coefficient captures the effect of a standard-deviation increase in insurers' log(DisasterExposure) on Return on Assets (expressed as a percentage), Homeowners Loss ratio, Log Capital Ratio, and Log Capital-to-Surplus. Each year, we sort insurers into groups based on whether they are below or above the median based on disaster exposure, insurer size measured by assets, the share of homeowners premiums that is reinsured and the weight of homeowners insurance in their total portfolio. The last column estimates effects separately in the sample before and after 2012.

**Local projections for the path of bank financials following disaster losses - Scaled disasters**

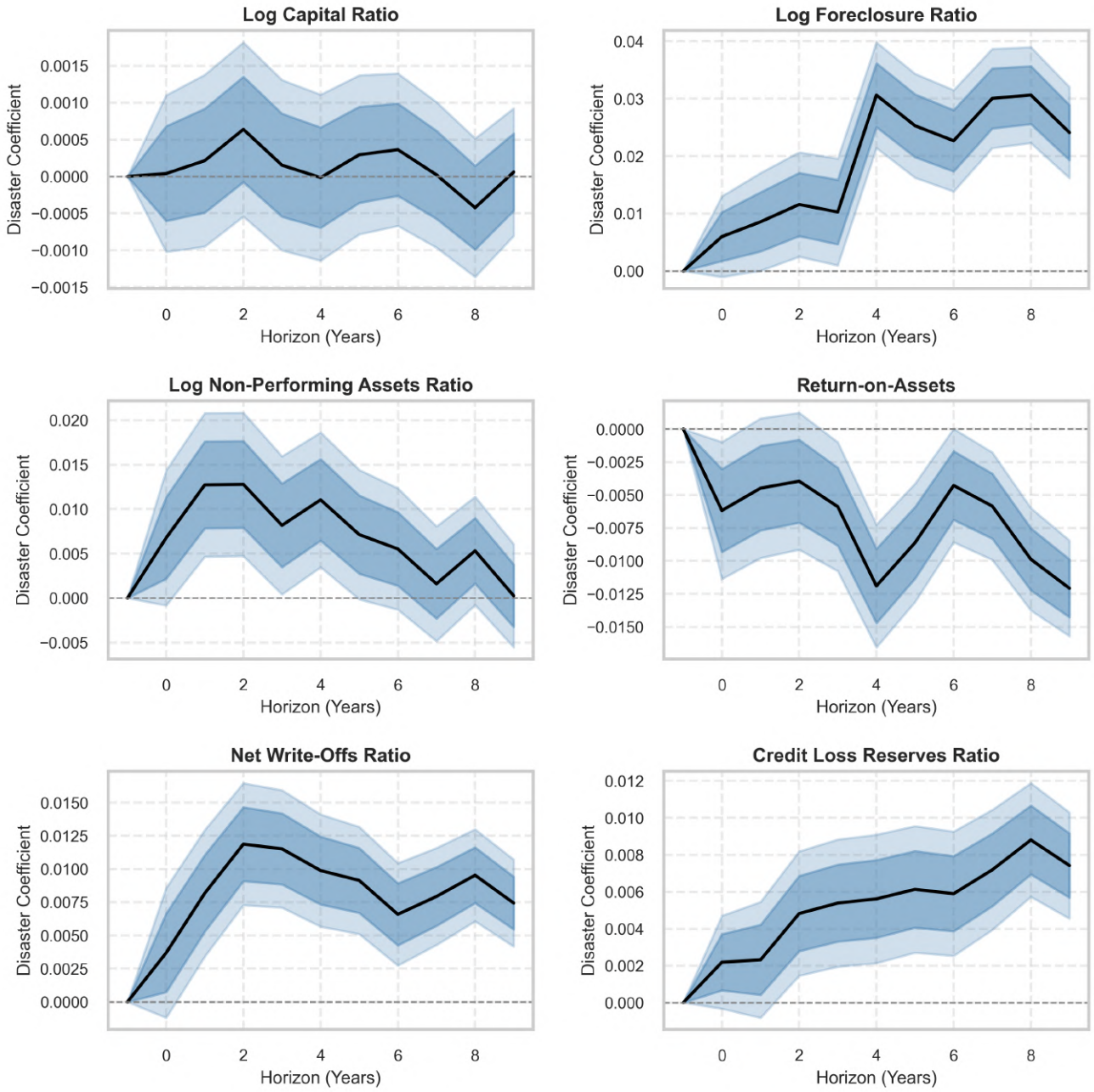



**Figure 3.** The Disaster Coefficient captures the effect of a standard-deviation increase in banks' log(DisasterExposure) on Log Capital Ratio, Log Foreclosure Ratio, Log Non-Performing Assets Ratio, Return on Assets, Net Write-Offs Ratio, Credit loss Reserves Ratio. The dark and light shaded areas reflect 68% and 90% confidence intervals.

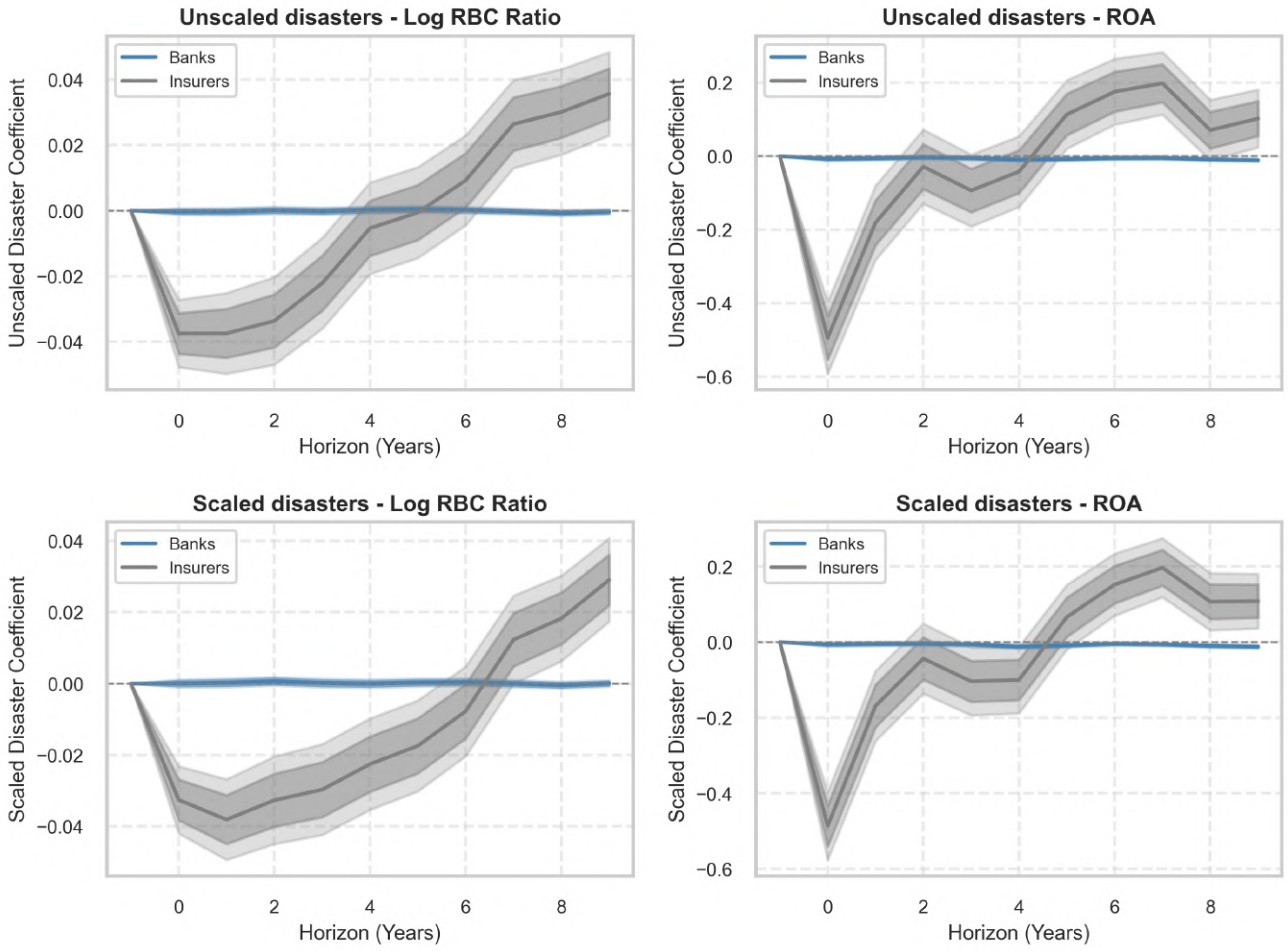



**Figure 4.** The coefficient captures the effect of a standard deviation increase in DisasterExposure on Return on Assets (expressed as a percentage) and Log Capital Ratio. The regression specifications for insurers and banks share the same controls and fixed effects. The dark and light shaded areas reflect 68% and 90% confidence intervals.

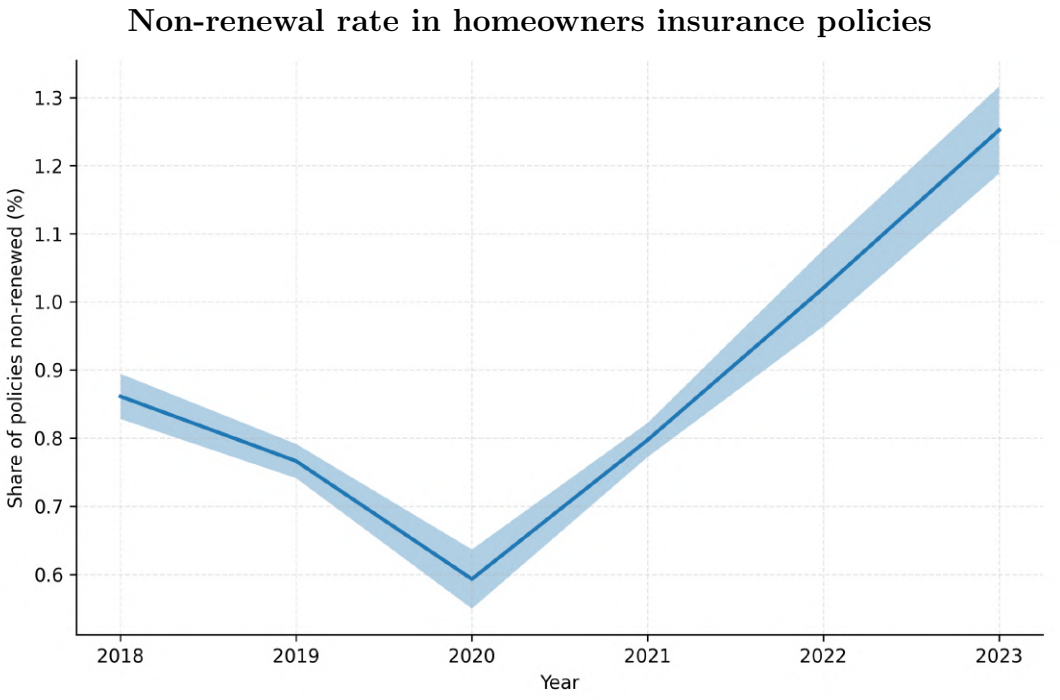



**Figure 5.** The ratio of non-renewed homeowners' insurance policies to outstanding policies averaged across counties. The shaded area reflects 95% confidence intervals.

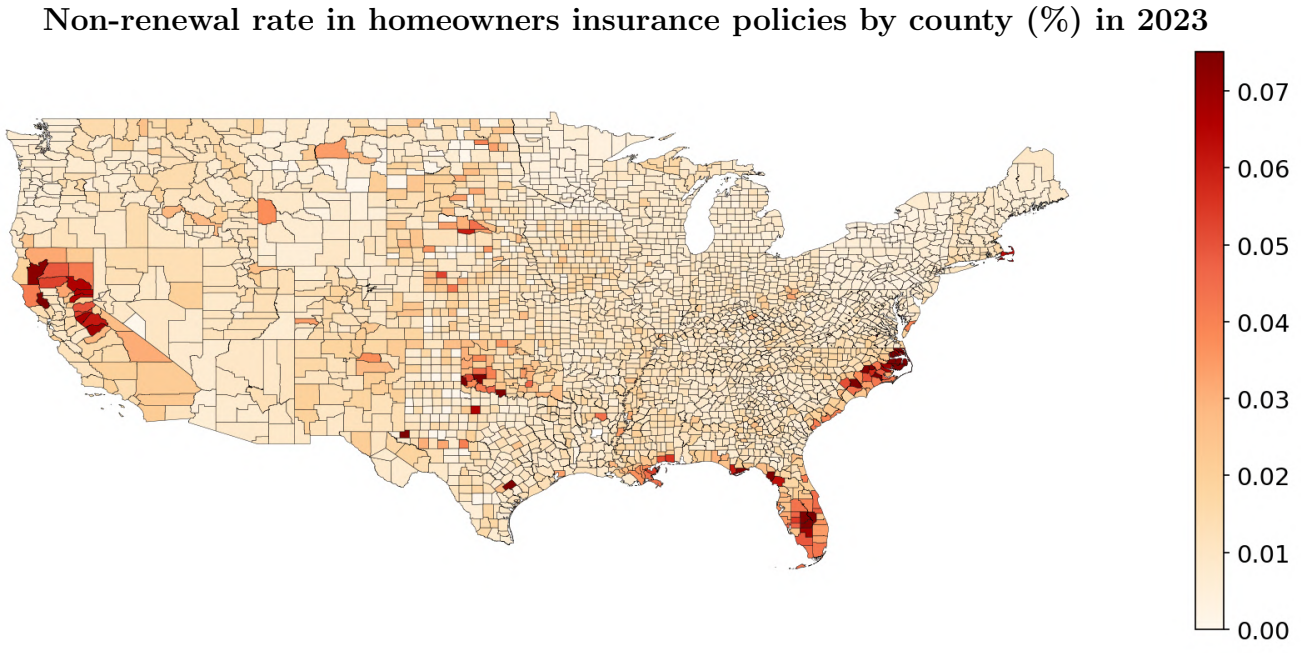



**Figure 6.** The geographical distribution of the ratio of non-renewed homeowners' insurance policies to outstanding policies in 2023.

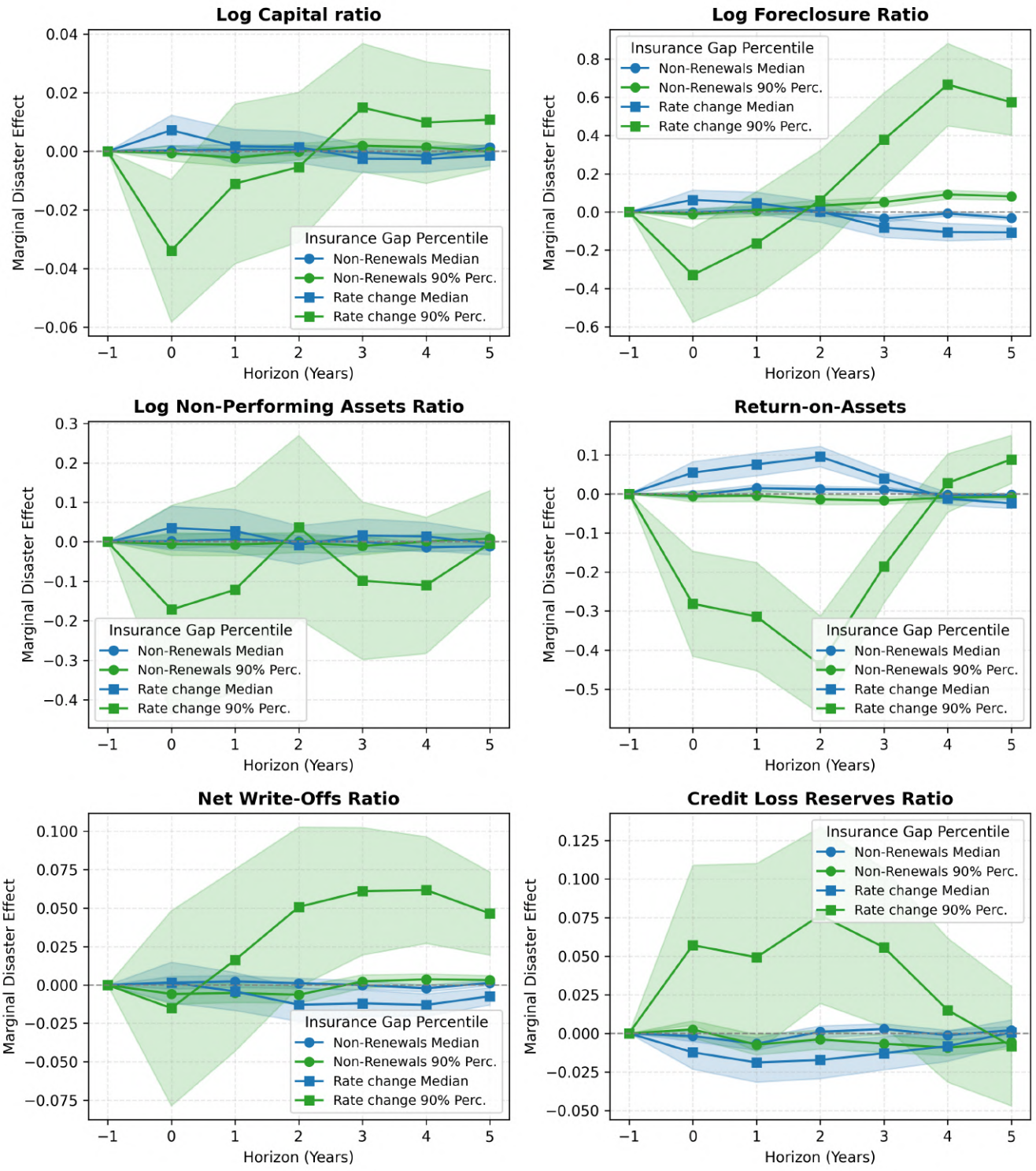



**Figure 7.** The coefficient captures the effect of a standard deviation increase in DisasterExposure on bank financials for different percentiles of Insurance Gap, which captures banks' exposure to (i) counties with insurance non-renewals or (ii) states with primary insurance rate increases. The shaded areas reflect 68% confidence intervals. We provide two-stage robust standard errors clustered at the bank level.

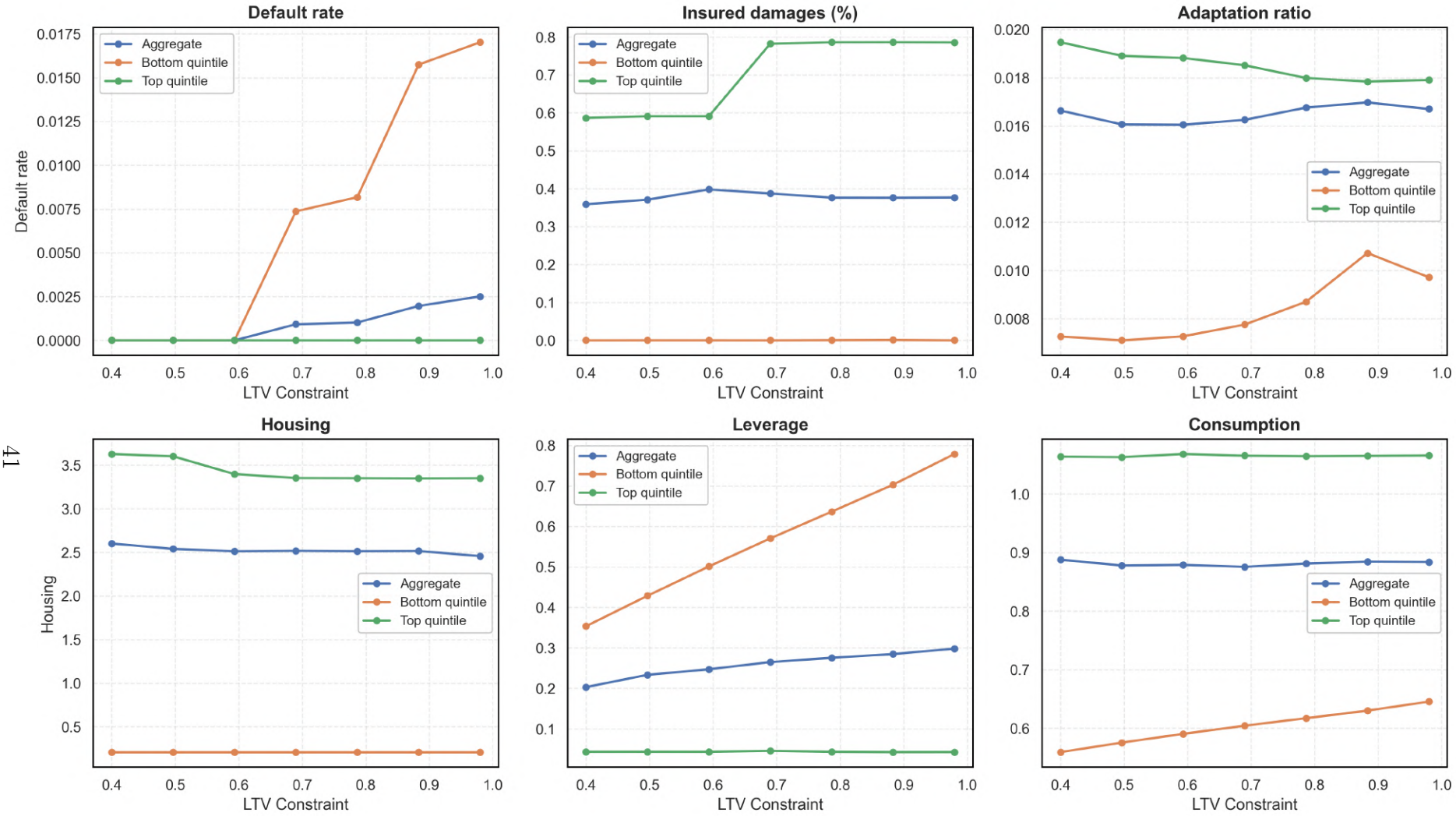



**Figure 8.** We solve the model for different loan-to-value (LTV) constraint using the baseline equilibrium parameters.

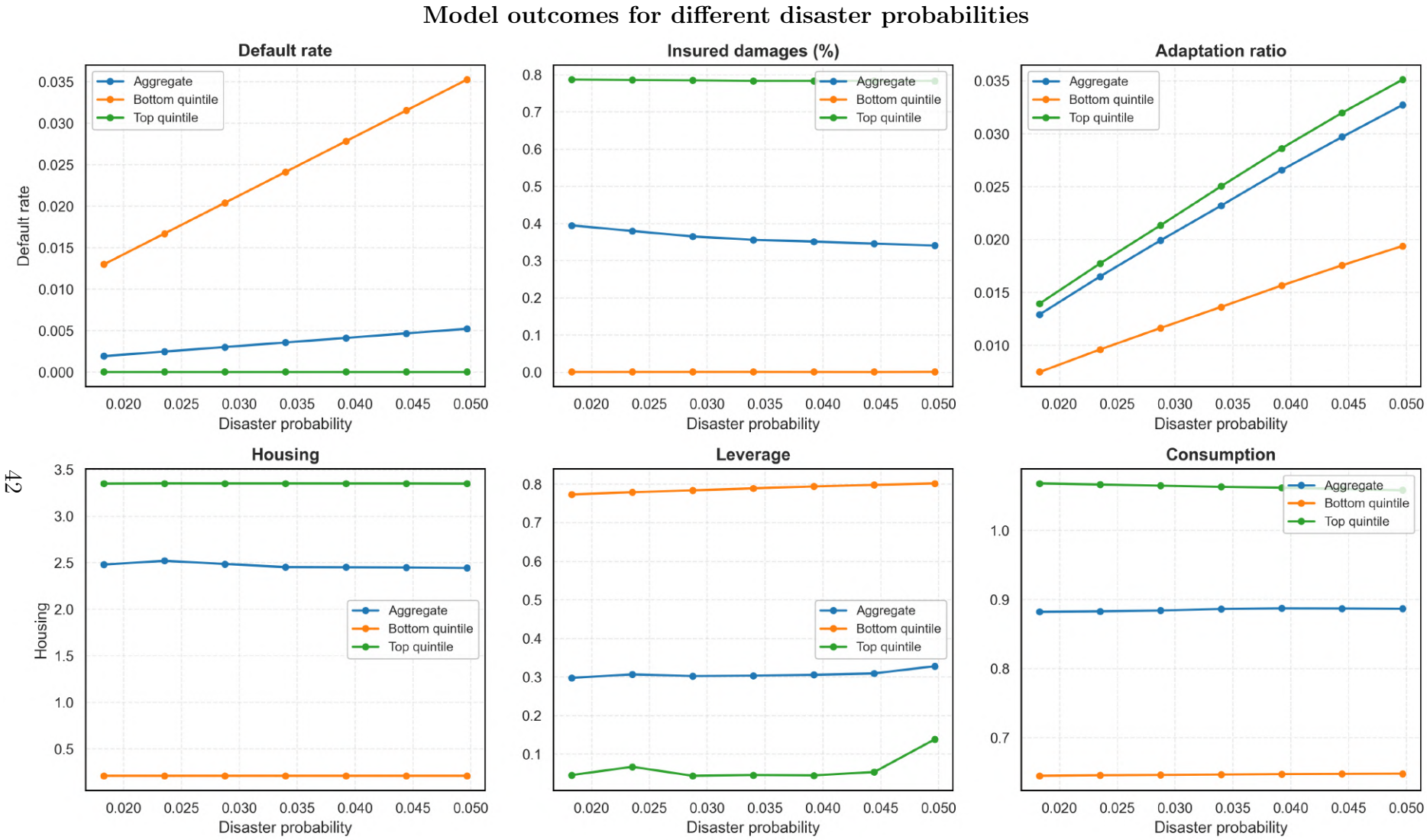



**Figure 9.** We solve the model for different disaster probabilities using the baseline equilibrium parameters.

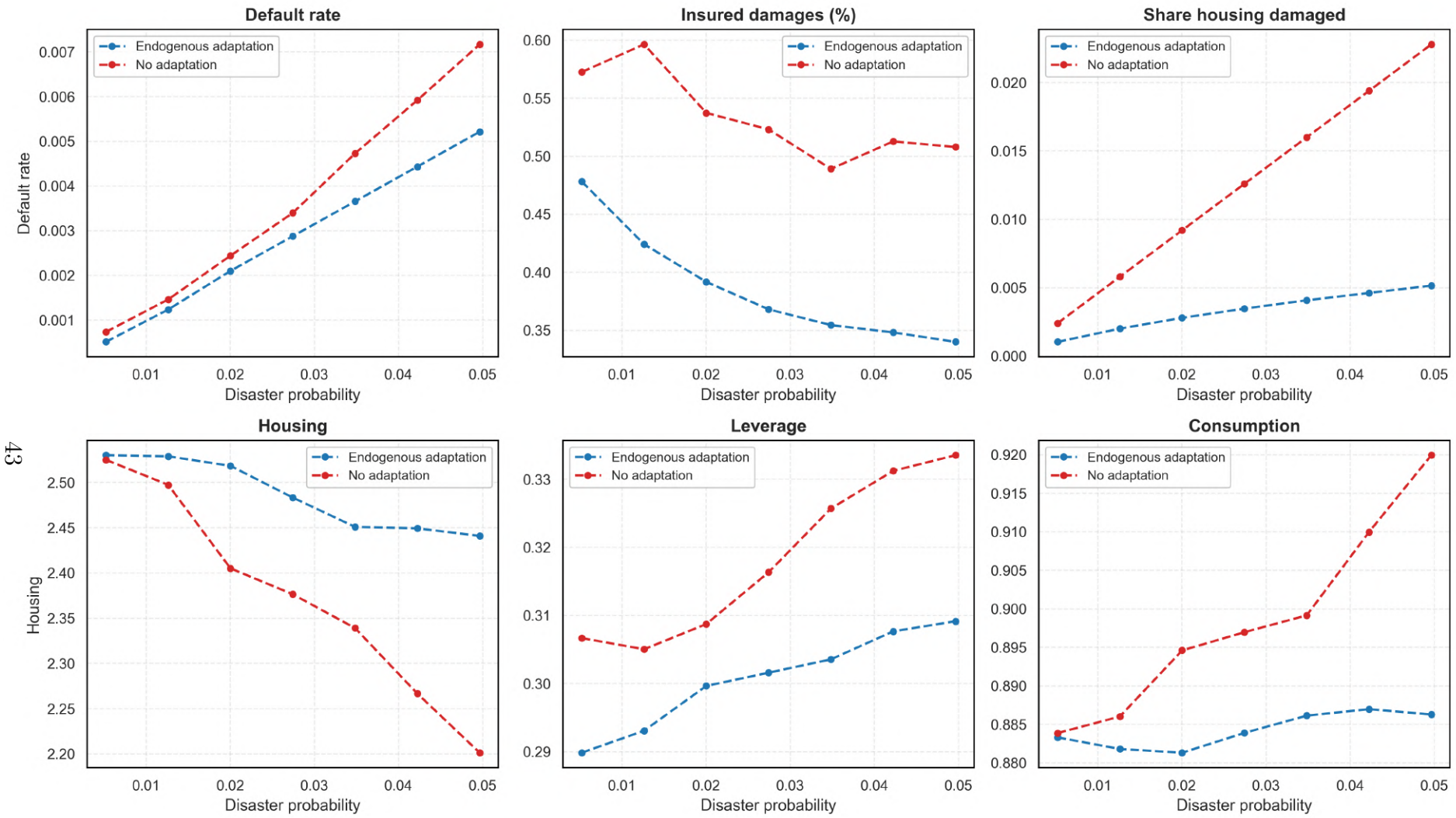



**Figure 10.** We solve the model for different disaster probabilities using the baseline equilibrium parameters. We construct a counterfactual by shutting off adaptation.

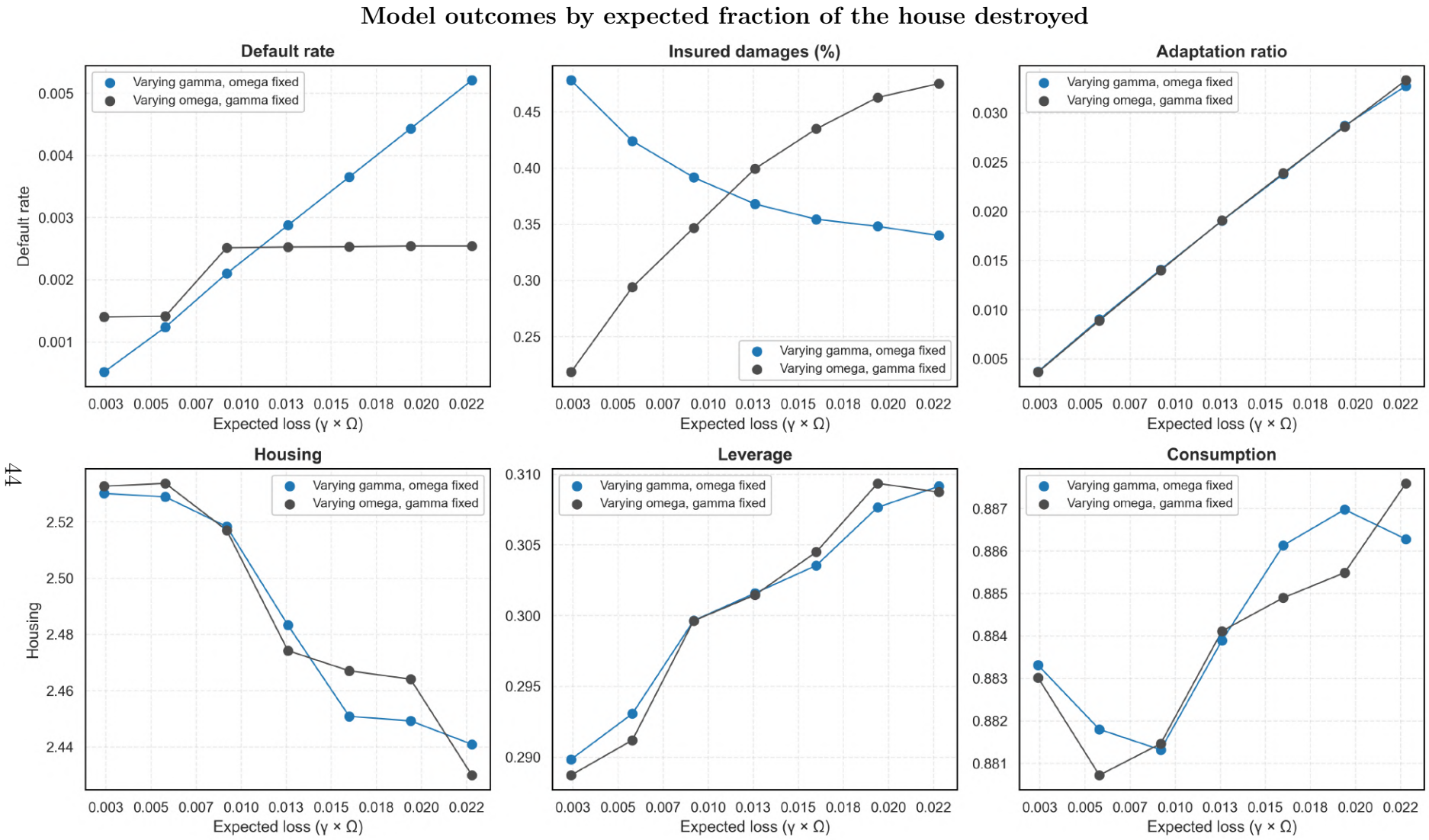



**Figure 11.** We solve the model for different values of the expected fraction of the house destroyed absent adaptation, which is equal to $\gamma$ times $\Omega$. We construct the expected loss values (i) by varying $\gamma$ while keeping $\Omega$ equal to its baseline value, and (ii) by varying $\Omega$ while keeping $\gamma$ equal to its baseline value.

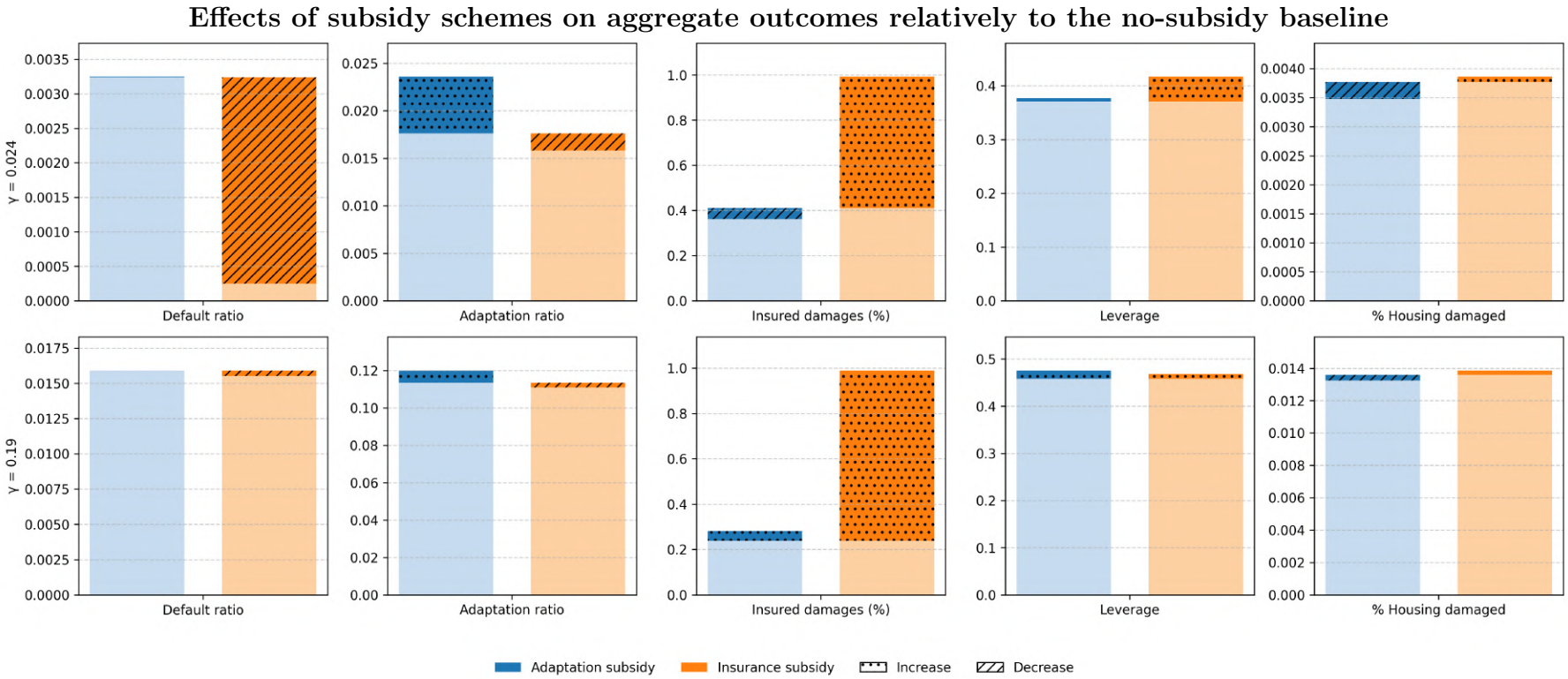



**Figure 12.** We compare three economies: baseline without subsidies, economy with insurance subsidies and an economy with adaptation subsidies. The Figure shows the effect of subsidies on aggregate outcomes relative to the baseline economy without subsidies.

# A Empirics

## A.1 Data construction

**Insurance data**. We obtain U.S. insurer-level data on premiums written and losses incurred from the National Association of Insurance Commissioners (NAIC) through S&P Capital Pro IQ. This data provides an annual breakdown of the business activities per insurer across states. Similarly, we obtain annual insurer balance sheet and profitability indicators from NAIC. As financial stability indicators, we consider the Risk-Based Capital (RBC) Ratio and the Capital-to-Surplus Ratio. As profitability indicators, we consider Return-on-Assets (ROA) and the Loss Ratio in the homeowners' insurance segment.

We obtain data on insurance rate increases from S&P's MI database on Insurance Product filings. Insurers need to file rate change requests to the state regulator when planning to change insurance rates. The Insurance Product filings data provides information on the final rate change of insurers that is approved by the regulator and the revenue affected by the rate change.

**Reinsurance data**. We obtain information on global annual reinsurance price changes from the Guy Carpenter U.S. Property Rate on Line (RoL) Index. It applies to catastrophe reinsurance renewals. The Rate-on-Line captures the prices of reinsurance as reinsurance premiums divided by the reinsurance limit purchased. While the rate information is specific to the U.S., the price changes that the RoL index reflect take place in a global reinsurance market.

NAIC provides information on insurers' reinsurance intensity. We construct insurers' reinsurance ratio as the share of their premiums written in the homeowners insurance segment that is reinsured. We consider only reinsurance to non-affiliated reinsurers.

Our sample consists of 1,252 insurers and runs from 2000 to 2024. Table 1 provides the summary statistics of our insurer-sample.

**Natural disaster data.** For the U.S., we obtain information on the economic losses from disasters from the Spatial Hazard Events and Losses Database U.S. (SHELDUS). We construct a state-level measure of annual disaster losses by summing damages across disaster types and quarters.

**Bank data.** We obtain quarterly bank financial data from Federal Deposit Insurance Corporation (FDIC). As financial stability variables, we consider banks' RBC Ratio and Credit Loss Reserves Ratio. The Credit Loss Reserves Ratio are the reserves for loan and lease credit losses divided by the size of the loan portfolio. As performance variables, we

consider the Foreclosure Ratio (FOR), Non-Performing Assets Ratio (NPA), ROA and Net Write-Offs Ratio. FOR is defined as the volume of foreclosed property scaled by total bank assets. NPA is assets with late payments scaled by total assets. We average the banks' quarterly financials by year to match the reporting period of the annual disaster data.

We obtain bank loan-level data from the Home Mortgage Disclosure Act (HMDA). We use regional bank loan portfolios to construct a measure of the distribution of a bank's business activities across states. We link banks in the HMDA data to FDIC based on mappings that link HMDA's legal entity identifier to FDIC's RSSDID, which is the financial institution identifier assigned by the Federal Reserve. We source this mapping from the Home Mortgage Disclosure Act (HMDA) Lender File of the Federal Reserve Bank of Philadelphia.

Our sample consists of 5,493 banks and runs from 2010 to 2023. Table 2 provides the summary statistics of our bank-sample.

**Insurance non-renewal data** We source insurance non-renewal data from the U.S. Senate Budget Committee (SBC). The data are available from 2018 to 2023, shrinking the sample compared with the baseline regressions. The non-renewal data captures insurer-driven cancellations of homeowners policies.

## A.2 Results

### A.2.1 Unscaled damages

Figure B.1 shows the local projections for banks using unscaled damages rather than damages scaled by personal income as the shock variable.

**Local projections for the path of bank financials following disaster losses - Unscaled disasters**

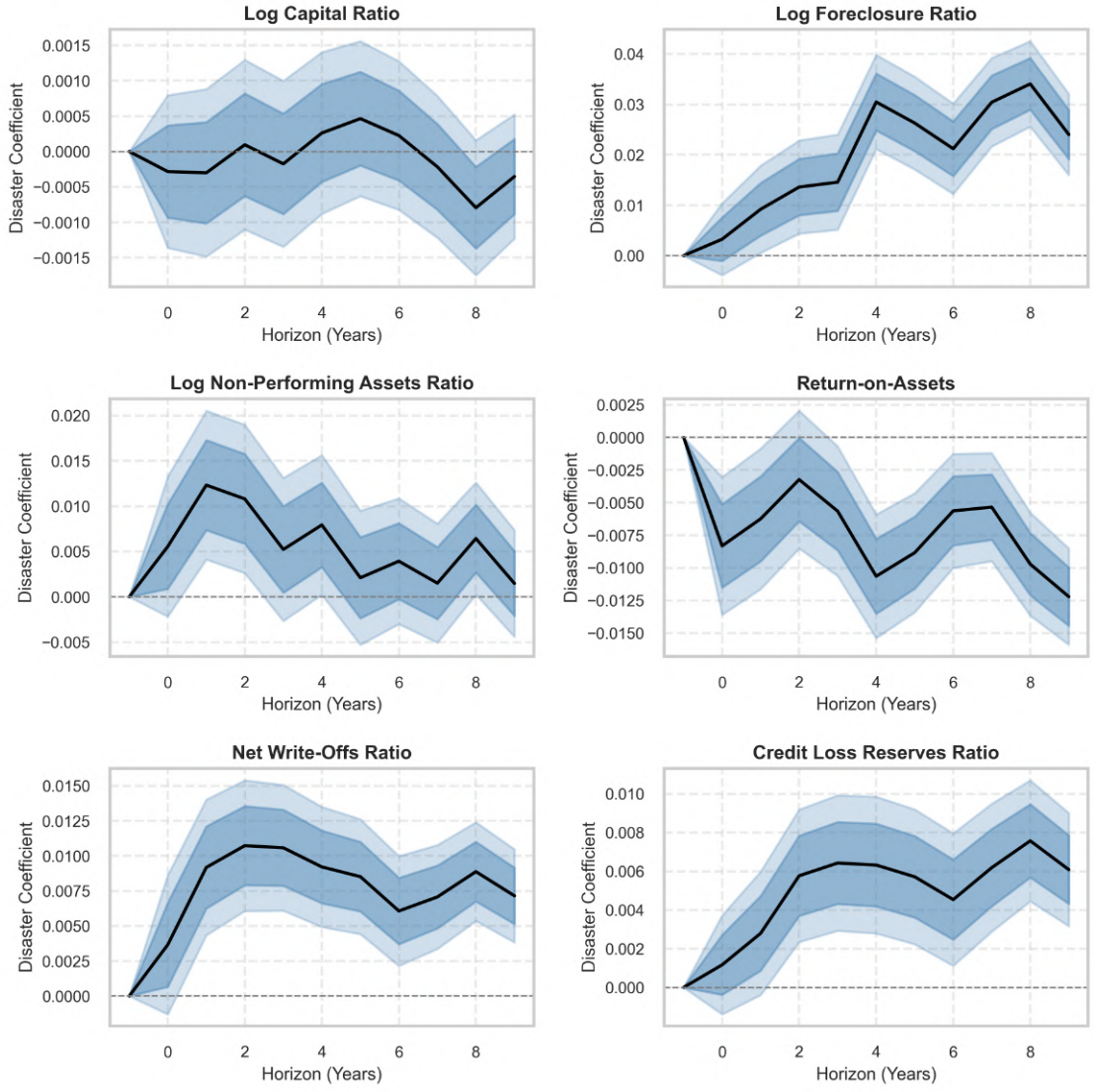



**Figure B.1.** The Disaster Coefficient captures the effect of a standard-deviation increase in banks' log(DisasterExposure) on Log Capital Ratio, Log Foreclosure Ratio, Log Non-Performing Assets Ratio, Return on Assets, Net Write-Offs Ratio, Credit loss Reserves Ratio.

## A.3 U.S. Reinsurance activity by state

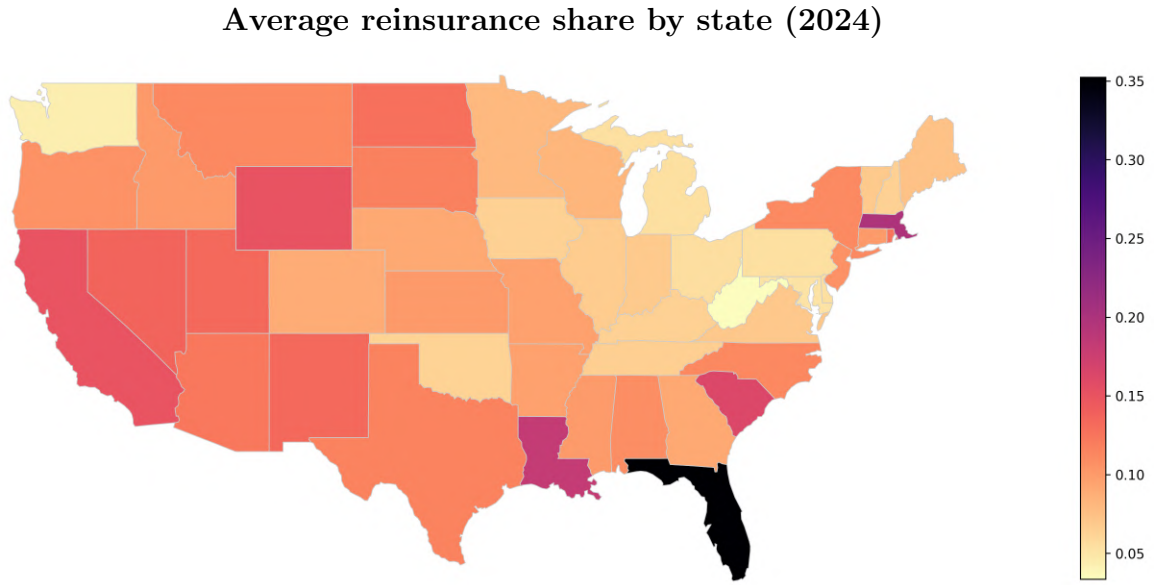



**Figure B.2.** The Figure shows the state-level reinsurance ratio, which captures the average share of homeowners insurance premiums ceded to non-affiliated (re)insurers by insurers active in the state. It is computed by averaging incumbent insurers' homeowners reinsurance ratio weighted by their state-level market share.

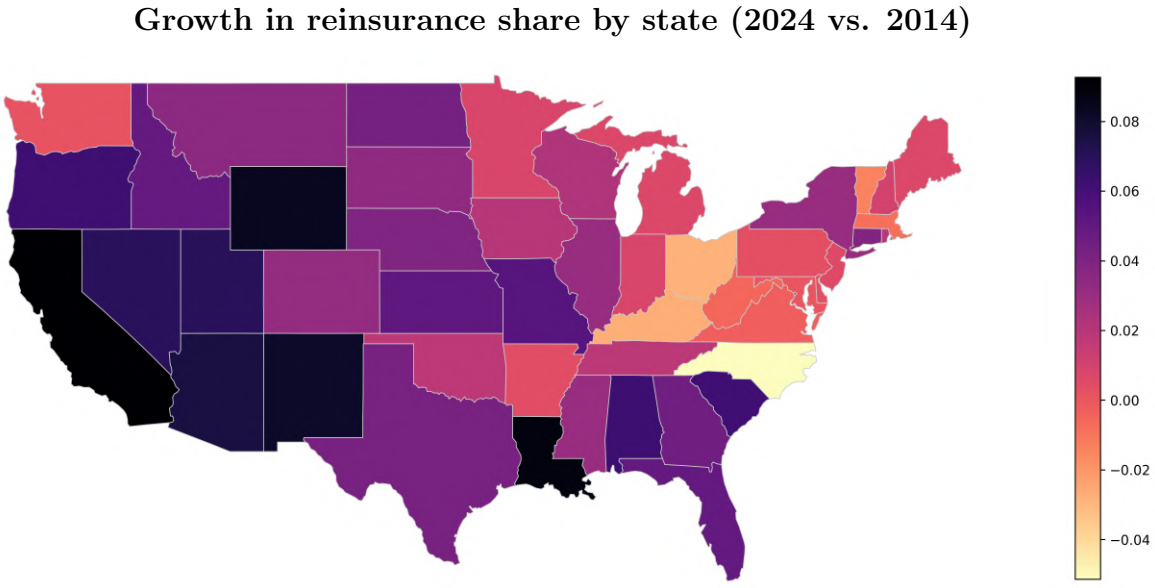



**Figure B.3.** Figure shows the percentage point change in the state average homeowners reinsurance ratio.

## A.4 Time-varying bank state portfolio shares

We explore how bank loan portfolio weights have changed in response to state-level disasters and insurance conditions. To achieve this, we regress the (percentage point) change in bank $j$'s loan portfolio share in state $s$ in year $t$ relative to year $t-5$ on state-level indicator $X$:

$$\Delta^5 \text{Loan Share}_{j,s,t} = \sum_{\tau=2007}^{2024} \beta_\tau \left( X_{s,t} \times \mathbf{1}\{t = \tau\} \right) + \alpha_{j,s} + \lambda_t + \varepsilon_{j,s,t} \tag{17}$$

where $X_{s,t} \in \{$Cumulative Insurance Rate (5Y), Average Reinsurance Ratio (5Y), Cumulative Disaster E
Bank-state fixed effects $\alpha_{j,s}$ capture heterogeneity across banks in specialization or portfolio tilting across states. Year fixed effects $\lambda_t$ absorb common shocks in portfolio weights. Figure B.4 plots the estimated coefficients $\hat{\beta}_\tau$ for each indicator $X_{s,t}$. We plot the effects for a standard deviation change in explanatory variable $X$. We cluster standard errors at the bank-level. The plot shows that, starting from 2014 onwards, banks have increasingly tilted their portfolio away from high disaster- and high insurance rate states. In contrast, banks tilted their portfolios to states in which insurers have high reinsurance ratios. Specifically, in 2023, bank on average reduce their state loan portfolio share by 0.3% for a one-standard deviation increase in cumulative insurance rates in this state over the past 5 years. This standard deviation change corresponds to 19.1%.

# B Model

## B.1 Model assumptions

## B.2 Model illustration and results

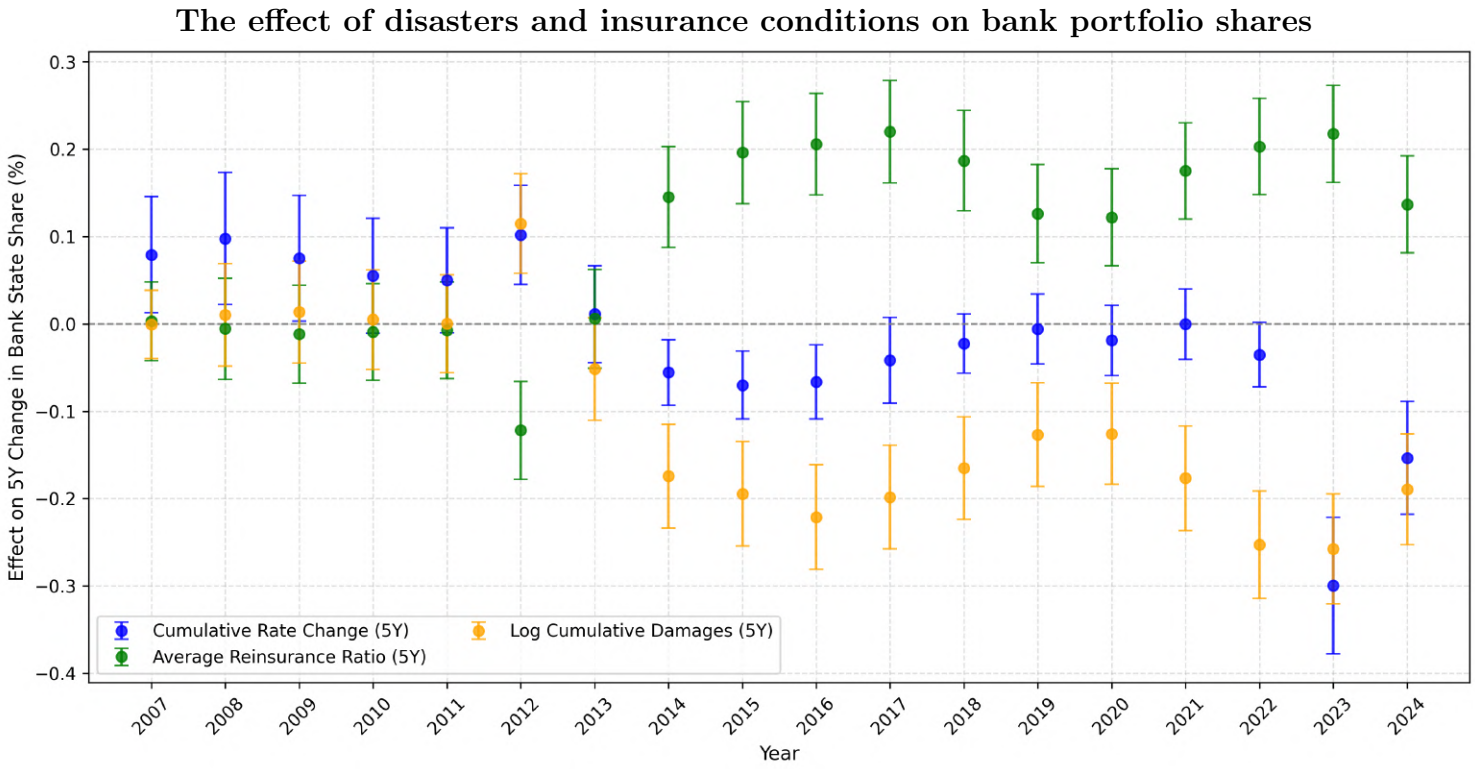



**Figure B.4.** Figure plots the beta coefficients of regression 17. Coefficients capture the average effect of a one-standard deviation change in the explanatory variable on banks' percentage point change in their (state) loan shares in the past 5 years. Error bars represent 95% confidence intervals. We cluster standard errors at the bank-level.

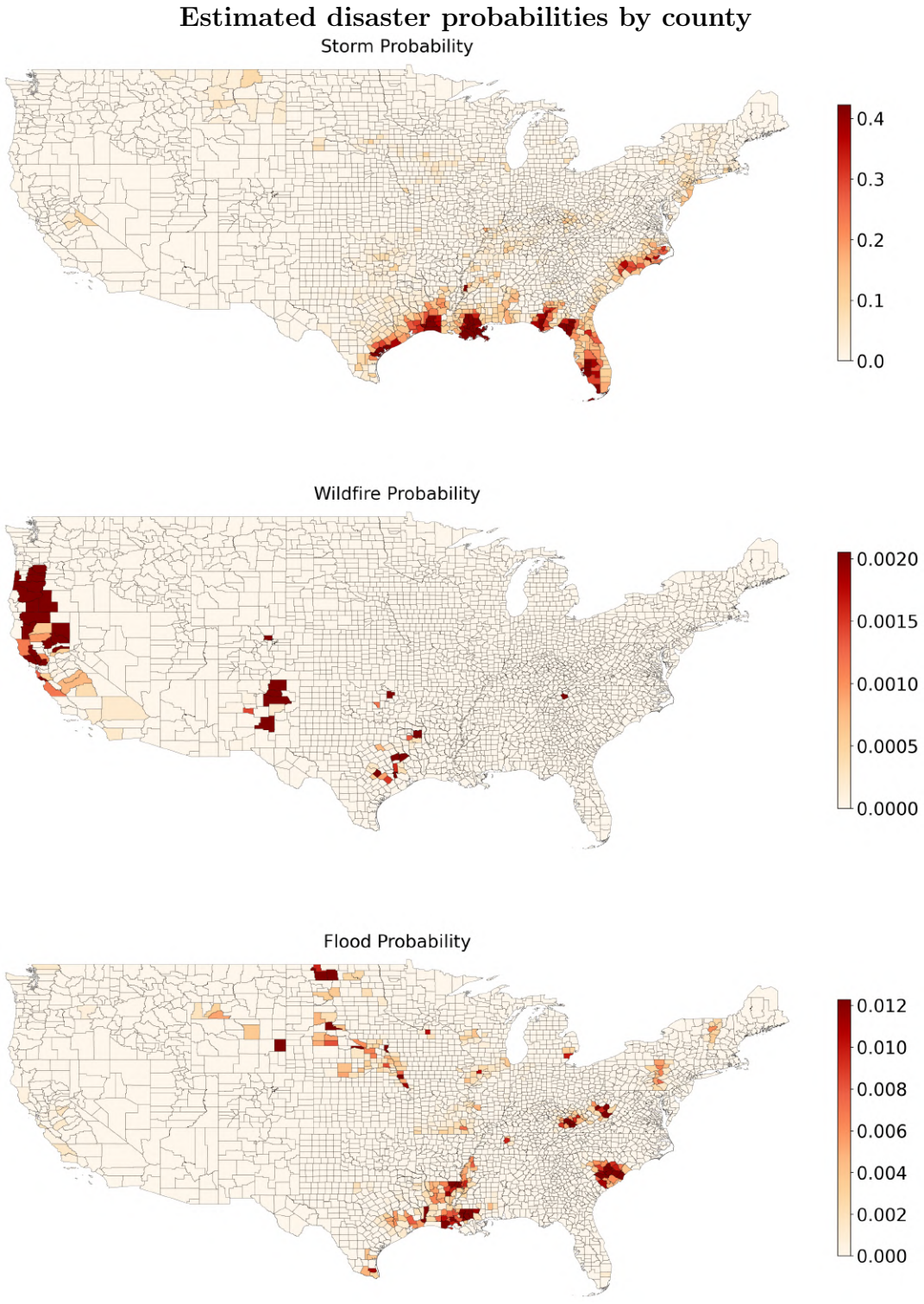



**Figure B.5.** Disaster probabilities are calculated as the fraction of uninsured homeowners that applied for disaster aid.

## Borrowing receipt $P^d$

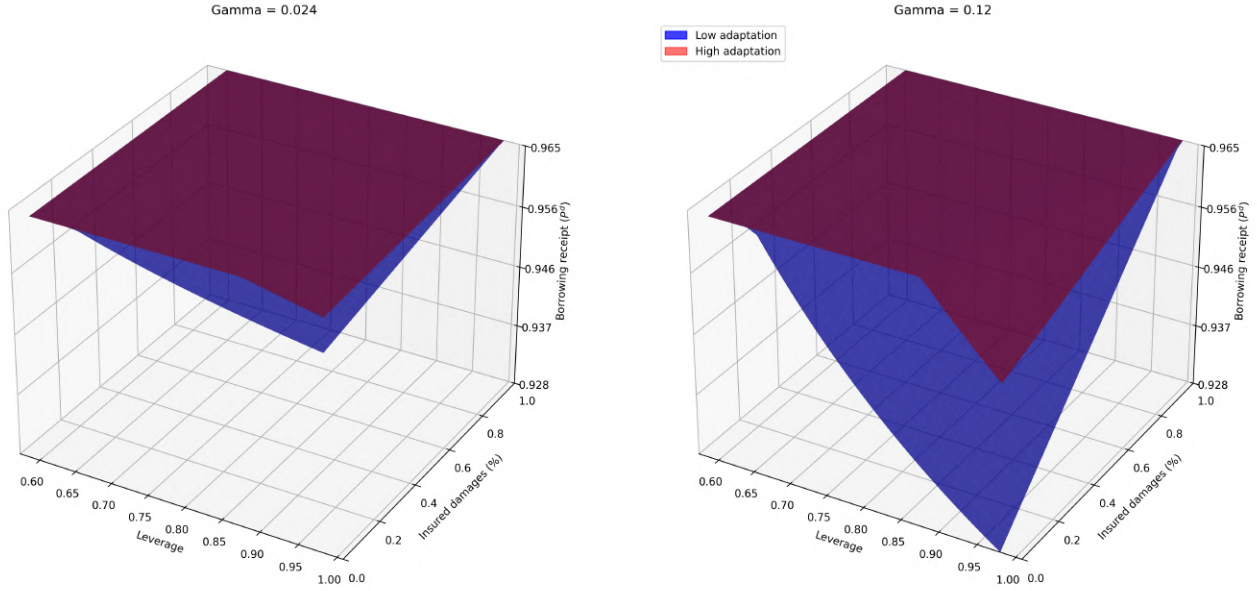



**Figure B.6.** Illustration of borrowing receipt $P^d$ as a function of insurance-adjusted leverage and the protection gap (Insured Damages) for low- and high levels of adaptation, across different disaster probabilities.

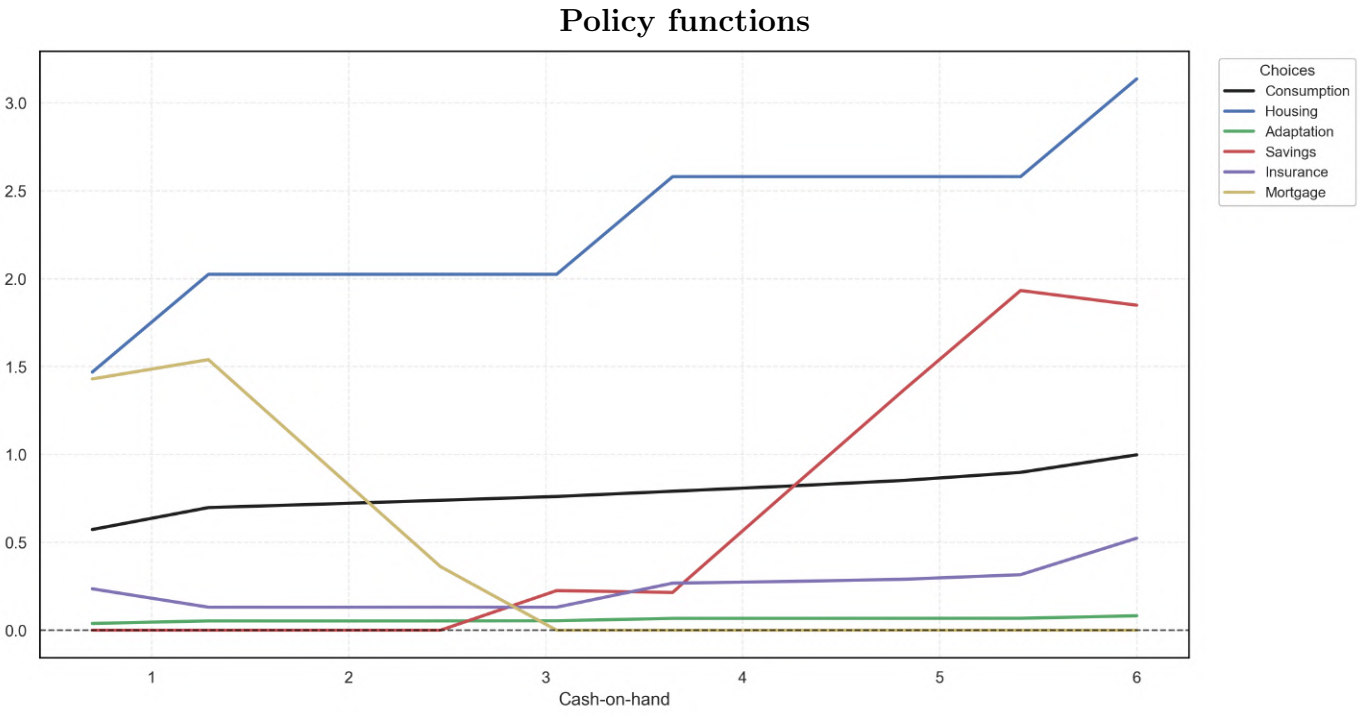



**Figure B.7.** Estimated household policy function as a function of wealth.

## B.3 Random severity

Households will only default if a disaster happens, and when the disaster severity $\Omega$ exceeds a given cutoff $\Omega^*(h^p_{i,t+1}, d_{i,t+1}, X_{i,t+1}, h^a_{i,t+1})$. The cutoff is the point at which the household is indifferent between defaulting and not defaulting, and is given by:

$$\Omega^*(h^p_{i,t+1}, d_{i,t+1}, X_{i,t+1}, h^a_{i,t+1}) = \frac{(1-\delta^h)h^p_{i,t+1} + \min\left[X_{i,t+1}, h^d_{i,t+1}\right] - d_{i,t+1}}{(1-\delta^h)h^p_{it}F(a^h_{it})} \tag{18}$$

This constraint is easier to satisfy when leverage is high, when insurance take-up is low and when adaptation is low, so that the household becomes more riskier for the bank.

Banks will only lend to the household if in expectation they make a non-negative profit. In their lending decision, banks take into account that households will only default if $\Omega > \Omega^*(\cdot)$. Specifically, banks will extend a loan if and only if:

$$d_{i,t+1}P_d(\cdot) \leq \frac{(1-\gamma)d_{i,t+1} + \gamma\left(d_{i,t+1}F(\Omega^*(\cdot)) + \int_{\Omega^*}^{\overline{\Omega}}\left((1-\delta^h)\tilde{h}^p_{i,t+1} + \min\left[X_{i,t+1}, h^d_{i,t+1}\right]\right)dF(\Omega)\right)}{1 + r^b_t + r^w_t} \tag{19}$$

Equation 19 indicates that the value of the mortgage today should be equal to the discounted repayment that the bank expects on the loan. With probability $1-\gamma$, the bank will always receive the mortgage payment in the next period. With probability $\gamma$, the bank will get receive the full mortgage payment if $\Omega \leq \Omega^*(\cdot)$. Whenever $\Omega > \Omega^*(\cdot)$, the bank will receive the post-disaster collateral plus the insurance payout. We can price the mortgage as follows:

$$P_d(\cdot) = \frac{1 + \gamma\left(F(\Omega^*(\cdot)) - 1 + \int_{\Omega^*}^{\overline{\Omega}}\left((1-\delta^h)\tilde{h}^p_{i,t+1} + \min\left[X_{i,t+1}, h^d_{i,t+1}\right]dF(\Omega)/d_{i,t+1}\right)\right)}{1 + r^b_t + r^w_t} \tag{20}$$

Random severity introduces another source of uncertainty beyond income and disaster shocks. The extended dynamic programming problem for the household then becomes:

$$V(\nu_{it}, \tilde{m}_{it}, \tilde{h}^s_{it}; \Upsilon_i) = \underbrace{\max}_{c_{it}, h^p_{i,t+1}, h^a_{i,t+1}, f_{i,t+1}, X_{i,t+1}, d_{i,t+1}} \Big[U(c_{it}, \tilde{h}^s_{it}) + \beta \sum_{\nu_{i,t+1}} \pi(\nu_{i,t+1} \mid \nu_{it}) \sum_{e_{t+1}} \Gamma(e_{t+1}) \int_{\underline{\Omega}}^{\overline{\Omega}} V(\nu_{i,t+1}, \tilde{m}_{i,t+1}, \tilde{h}^s_{i,t+1}; \Upsilon_i) dF(\Omega)\Big]$$

## B.4 Aggregate Climate Risk

So far, we have assumed idiosyncratic climate risk, which allows for comparing aggregate outcomes under the stationary distribution. Consequently, as aggregate variables remain constant, insurers and banks do not face risk. In this section, we introduce aggregate climate risk, which ensures that, upon a random disaster, all households will be affected by the shock, albeit to different degrees given heterogeneous insurance and adaptation decisions. Aggregate variables including insured damages, mortgage decisions and defaults will be no longer constant, which implies time-varying insurer and bank profitability.

The introduction of aggregate climate risk allows us to understand how adaptation decisions change when financial markets tighten. In addition, the setup informs the welfare effects of different subsidy schemes as the benefits of a subsidy not only depend on the short-term benefits for households, but also whether the subsidies drive behavior that help minimize financial sector fragility, which is needed to offer insurance in the long-run.

The model with aggregate climate risk requires modeling the supply decisions of financial institutions in response to disaster realizations. Our analysis focuses on the financial stability of insurance companies. While introducing both insurers and banks in the model with aggregate climate risk would be interesting, modeling both banks and insurance companies makes the model computationally intractable.[14] Furthermore, our motivating empirical analyses reveal that the financial stability effects of natural disasters are largest for insurers and minimal for banks.

### B.4.1 Insurers

There is a continuum of measure 1 perfectly competitive insurers who offer insurance $X_{t+1}$ against next-period disasters to households. Insurers' realized profit per unit of insurance is based on the insurance sold to households in the previous period is given by:

$$\pi^I_{t+1} = P_t - \frac{\int_i \min\left[X_{it}, h^d_{it}\right]}{X_t} - \lambda\gamma \tag{21}$$

As before, $\lambda$ is the operational cost per unit of insurance sold. Prior to going into the period, households present a random loss $\tilde{V}_{t+1}$ per unit of insurance sold, which equals the disaster probability $\gamma$:

$$\mathbf{E}_t\left[\tilde{V}_{i,t}\right] = \gamma$$

[14] This is because the household forecasting rules for credit- and insurance demand would interact.

Even though there is aggregate uncertainty, insurers and households known what the loss will be upon a disaster. Households rationally buy insurance coverage below the loss realization when a disaster occurs. Hence, when a disaster strikes, the entire insurance contract will be exercised, such that the expected loss equals $\gamma$ per unit of insurance. Insurers have to record liabilities $L_t$ on sold insurance coverage for tomorrow's possible disaster. We assume that insurers reserve a share $\alpha$ of their sold insurance coverage, such that liabilities become:

$$L_t = X_t \times \gamma \times \alpha$$

We assume that insurers need to reserve $\alpha = 10\%$ of their maximum loss. We define statutory capital as

$$K_t = \underbrace{A_t - L_t}_{\text{Equity}} - \underbrace{\kappa L_t}_{\text{Required Capital}}$$

where $\kappa$ is the risk charge on liabilities, exogenously determined by regulation.

Households' insurance coverage gets aggregated into an insurance stock as $X_t = \int_i X_{i,t}$. Insurers next-period assets are then given by:

$$A_{t+1} = X_t \pi^I_{t+1} + A_t R^A_{t+1} - C(K_t)$$

Insurers' assets thus consist of the realization on the insurance portfolio, previous period assets that generates an exogenous return $R^A_{t+1}$ minus statutory capital costs.

The term $C(K_t) = e^{-\chi K_t}$ for $K_t > 0$ represent the cost of financial frictions, which is strictly decreasing and convex. $C(K_t)$ is strictly decreasing because insurers benefit from having a large statutory capital, and $C$ is strictly convex because the benefits of having higher statutory capital decreases in the level of capital. This setup generates insurance prices to vary with statutory capital. In states of the world where a disaster occurred, statutory capital is low, making the marginal cost of statutory capital high. This results in high insurance prices when insurers are financially constraint. Conversely, when statutory capital is high, the marginal cost of financial frictions is low, resulting in relatively low insurance prices in states of the world where no disaster occurred.

Insurers choose the insurance quantity $X_t$ to maximize the expected value of next-period assets, which is given by:

$$\begin{aligned} \mathbf{E}_t \left[A_{t+1}\right] &= \mathbf{E}_t \left[\pi^I_{t+1} X_{i,t}\right] + A_t R^A_{t+1} - C(K_t) \\ &= \left(P_t - \mathbf{E}_t \left[\tilde{V}_{i,t}\right] - \lambda\gamma\right) X_{i,t} + A_t R^A_{t+1} - C(K_t) \end{aligned} \tag{22}$$

Taking the first-order condition of 22 with respect to $X_{t+1}$ yields the equilibrium insurance price:

$$P_t = \underbrace{\gamma}_{\text{Expected loss}} \times (1 + \underbrace{\lambda}_{\text{Operational cost}} + \underbrace{(1+\kappa)\alpha\chi e^{-\chi K_t}}_{\text{Risk premium}}) \tag{23}$$

which households take as given. Whenever there would be no aggregate risk, such that reserve decisions do not apply ($\alpha = 0$), the price of insurance equals $\gamma$ as in the economy with idiosyncratic climate risk. In the case of aggregate risk, the insurance price also contains a risk premium, which reflects financial frictions when statutory capital becomes low. Finally, we consider that insurers' assets are capped by $\bar{A}$ as excess profits will be paid out to shareholders.

### B.4.2 Household forecasting

The setup with aggregate risk introduces aggregate insurance demand and the level of the insurers' assets as additional state variables in the household problem. Aggregate insurance demand affect the insurance price by lowering statutory capital for a given level of assets. In addition, low asset values make the insurer constrained for a given level of liabilities.

The trajectory of future insurance prices may already affect the household's decisions today. To form expectations about future insurance prices, households forecast the wealth distribution $\Gamma_t$. Using the wealth distribution, households forecast aggregate insurance demand. Yet, the distribution is a high-dimensional object, endogenous and time-varying. We follow Krusell and Smith (1998) and consider that households form linear, limited-information forecasts based on a small set of moments $I$. In our setup, the aggregate climate shock is i.i.d., which simplifies the algorithm compared to the canonical Krusell and Smith (1998) algorithm, in which the aggregate state of the economy follows a Markov chain.

Households make forecasts separately for the economy where a disaster occurred and one for an economy where no disaster occurred. The law of motion for the aggregate state can be summarized as: $\Gamma' = F(\Gamma, D)$. The indicator $D$ that takes on value 1 if a disaster happens and 0 if not. Then the forecast of the distribution of wealth is:

$$D_t = 0: \quad \log M_{t+1} = \beta^M_{0,ND} + \beta^M_{1,ND} M_t \tag{24}$$

$$D_t = 1: \quad \log M_{t+1} = \beta^M_{0,D} + \beta^M_{1,D} M_t \tag{25}$$

In addition, the forecast of the demand of insurance:

$$D_t = 0: \quad \log X_{t+1} = \beta^X_{0,ND} + \beta^X_{1,ND} M_t \tag{26}$$

$$D_t = 1: \quad \log X_{t+1} = \beta^X_{0,D} + \beta^X_{1,D} M_t \tag{27}$$

Households observe the insurer's statutory capital and also know tomorrow's statutory capital with and without a disaster. Conditional on the forecasted quantity $X_{t+1}$ and next-period statutory capital, households can determine the next-period insurance price in both the disaster and no-disaster state.

The updated dynamic programming problem for the household becomes:

$$V(\nu_{it}, \tilde{m}_{it}, \tilde{h}^s_{it}, \Gamma_t, A_t; \Upsilon_i) = \underbrace{\max}_{c_{it}, h^p_{i,t+1}, h^a_{i,t+1}, f_{i,t+1}, X_{i,t+1}, d_{i,t+1}} \Big[ U(c_{it}, \tilde{h}^s_{it}) + \beta \sum_{\nu_{i,t+1}} \pi(\nu_{i,t+1} \mid \nu_{it}) \sum_{e_{t+1}} \Gamma(e_{t+1}) V(\nu_{i,t+1}, \tilde{m}_{i,t+1}, \tilde{h}^s_{i,t+1}, \Gamma_{t+1}, A_{t+1}; \Upsilon_i) \Big]$$

subject to

$$\begin{aligned} c_{it} &= \tilde{m}_{i,t} + d_{i,t+1} P_d(h^p_{i,t+1}, d_{i,t+1}, X_{i,t+1}, h^a_{i,t+1}) - h^p_{i,t+1} - h^a_{i,t+1}(1 - \eta^{h^a}) \\ &\quad - \frac{f_{i,t+1}}{1 + r^b_t} - P_t X_{i,t+1}(1 - \eta^X), \\ \frac{d_{i,t+1}}{h^p_{i,t+1}} &\leq 1 - \delta^h, \\ h^p_{i,t+1} + h^a_{i,t+1} + f_{i,t+1} \geq 0, \quad h^p_{i,t+1} \geq 0, \quad d_{i,t+1} \geq 0, \quad X_{i,t+1} \geq 0, \\ \Gamma' &= F(\Gamma, D). \end{aligned}$$

Compared to the baseline model, this problem includes additional state variables $\Gamma_t$ and $A_t$ in the household problem, and the law of motion for the aggregate state.