Limited Liability and Disaster Underinsurance

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Abstract

We examine the strategic substitution between mortgage debt and disaster insurance. Our model shows that mortgages, which can be defaulted on or placed into disaster forbearance, provide implicit insurance against disaster losses, crowding out formal coverage. Using a novel proprietary dataset linking millions of loan-year observations to property-level insurance, we provide the first direct evidence of this mechanism. Higher loan-to-value (LTV) ratios significantly reduce voluntary flood insurance uptake, while coverage increases with hazard risk and recourse costs. After Hurricane Harvey, uninsured loans were three times more likely to default, underscoring implications for mortgage policy and disaster risk protection.

Keywords: Mortgage, default, flood insurance, natural disasters, incomplete markets.
JEL classifications: G21, G22, D14, Q54, G28.

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1 Introduction

We study how mortgage debt shapes households' demand for flood insurance. Our central message is that mortgages, because they are limited-liability contracts and may be defaulted or placed in forbearance after disasters, provide a form of implicit insurance. This implicit protection reduces the value of holding formal coverage, even when subsidized flood insurance is available below actuarially fair prices. As a result, highly leveraged households often prefer to rely on the insurance embedded in their debt contract rather than purchase disaster coverage.

We formalize this mechanism in a tractable model of insurance and default under an amortizing mortgage. Disasters arrive stochastically; homeowners can choose whether to pay for subsidized coverage; and default carries a finite recourse cost. The model yields a clear characterization of behavior: when balances are low, homeowners maintain coverage; at intermediate balances, they default following a disaster instead of insuring; and with very high balances, they would default immediately. These balance thresholds generate testable predictions: insurance take-up declines with leverage, rises with disaster risk and with stronger recourse, and falls when disaster forbearance is more generous. Perhaps the most striking implication is that, in contrast to the textbook precautionary-savings logic—where greater risk leads households to save more—in the presence of limited liability and incomplete insurance, greater disaster risk can actually encourage borrowing. This connection resonates with the classic insight of Stiglitz and Weiss (1981), but here it operates through insurance demand rather than investment risk-taking.

Using a novel proprietary dataset encompassing millions of loan-year observations across the continental United States, we test the predictions of our model at an unprecedented level of detail. The McDash servicing data link mortgage balances and contract characteristics directly to property-level insurance coverage, allowing us to observe for the first time how leverage shapes households' insurance choices. This granularity provides a new perspective on the financial behavior surrounding the most important asset and liability for U.S. households: their homes and mortgage debt, which account for roughly 66% of household net worth (Board of Governors of the Federal Reserve System, 2023).

In what follows, we use this dataset to zoom in on one product in particular: flood insurance. Flood is not only one of the most damaging natural perils in the United States, but

also one where the gap between risk and coverage is especially pronounced. Despite subsidized premiums through the National Flood Insurance Program (NFIP), voluntary uptake remains remarkably low. For example, Bradt et al. (2021) estimate that outside of FEMA's Special Flood Hazard Areas (SFHAs), only about two percent of households purchase coverage. This widespread underinsurance presents a persistent puzzle that motivates our analysis. We show that limited-liability mortgage debt provides one structural explanation: by lowering the cost of bearing disaster losses through default or forbearance, debt crowds out demand for formal insurance.

The scale of underinsurance is striking when set against actual flood exposure. First Street Foundation (2020) estimate that the number of properties with substantial flood risk is about 1.7 times larger than FEMA's official SFHA maps suggest, with approximately 21.8 million properties facing at least a 0.2% annual probability of flooding. Roughly 80% of homes damaged in recent hurricanes lacked flood coverage (Bradt et al., 2021), and Amornsiripanitch et al. (2025) estimate that 70% of total annual flood losses across single-family residences are uninsured. These facts underscore why explaining low take-up is so important—and why household leverage provides a compelling structural channel.

To test the model's predictions, we estimate regressions of flood insurance uptake on loan-to-value ratios, controlling flexibly for borrower, loan, and neighborhood characteristics. Our key empirical challenge is that mortgage balances may be endogenous: households who are more risk-averse or forward-looking could simultaneously pay down their mortgages faster and be more likely to purchase insurance. To address this, we exploit the mechanical link between amortization schedules and balances. Conditional on the contract terms at origination, remaining time to maturity deterministically maps into the outstanding balance. We therefore use remaining maturity as an instrument for the loan-to-value ratio. This strategy isolates variation in leverage that comes purely from the passage of time under a fixed amortization schedule, and not from unobserved differences in household risk preferences. We complement the IV approach with rich fixed effects. Our baseline specifications absorb ZIP-by-year fixed effects, which flexibly capture local shocks to hazard risk, disaster aid expectations, or insurance market conditions.

The results are consistent with the model's predictions. First, we find that higher mortgage balances significantly reduce the probability of holding voluntary flood insurance: a one

standard deviation increase in LTV is associated with a meaningful decline in take-up. Second, households facing higher underlying flood risk are more likely to insure, confirming that the hazard channel remains important. Third, in states with recourse provisions that raise the cost of default, insurance uptake is higher, consistent with the model's comparative static that stronger penalties for default strengthen demand for coverage. Finally, in the aftermath of Hurricane Harvey, we show that mortgages without flood insurance were roughly three times more likely to default than insured mortgages, confirming that default operates as a substitute form of protection when coverage is absent.

Taken together, these findings confirm the central mechanism of the model: limited-liability debt and disaster insurance are strategic substitutes. Households with low equity rationally substitute away from flood insurance, relying instead on the option to default if disaster strikes. At the same time, higher risk exposure and stronger default penalties increase insurance uptake, just as the model predicts. These results underscore that flood underinsurance is not only a matter of misperceived risk or liquidity constraints, but also a structural feature of mortgage design and its interaction with disaster risk.

The implications extend directly to mortgage policy. If default is functioning as de facto disaster insurance, then programs that expand disaster forbearance or weaken recourse provisions may unintentionally reduce households' incentives to insure. Conversely, linking forbearance relief more explicitly to proof of coverage could strengthen incentives for take-up. Similarly, reforms to the National Flood Insurance Program (NFIP) that change pricing or participation rules will interact with mortgage leverage in shaping demand. Overall, our results suggest that mortgage policy and disaster risk protection cannot be designed in isolation: the structure of debt contracts, disaster relief, and insurance programs jointly determine whether risks remain with households, insurers, or the broader financial system.

1.1 Related literature

The persistently low uptake of flood insurance, despite widespread exposure and subsidized coverage through the NFIP, has motivated a large body of research. Existing explanations emphasize hazard-based factors such as underlying disaster risk, prior experience, expectations of disaster aid, and risk misperception (Botzen, 2021; Gallagher, 2014; Kousky, 2011, 2017). Other studies point to the role of selection in insurance markets (Bradt et al., 2021; Wagner,

2022) or to household-level economic and sociodemographic determinants, including price sensitivity, income, education, and risk attitudes (Browne and Hoyt, 2000; Cai et al., 2020; Mushonga and Mishi, 2022; Robinson and Botzen, 2019).

Closer to our paper, Liao and Mulder (2022) examine how home equity shapes flood insurance demand. Exploiting plausibly exogenous variation in house prices from historical booms and busts, they estimate a home price elasticity of insurance uptake around 0.3 and interpret this as evidence that mortgage default provides implicit insurance for leveraged homeowners. Their analysis, however, relies on metropolitan-level variation in home values and does not directly observe mortgage balances or property-level insurance coverage. By contrast, our data allow us to link loan-level balances directly to insurance take-up and to test a structural mechanism that ties leverage to coverage decisions.

Also related is Sastry et al. (2025), who use McDash data to show that the demand for homeowner insurance is highly price elastic. Emphasizing the role of cash-flow constraints, they find that GSE borrowers with loan-to-value (LTV) ratios above 80%—who are required to purchase mortgage insurance and thus face tighter liquidity—exhibit higher price elasticity. Our study differs in four key respects. First, we focus on voluntary *flood* insurance priced under the subsidized NFIP pricing, where the high stakes make take-up and default particularly salient. Second, we emphasize leverage as the determinant of insurance take-up, whereas they emphasize cash-flow constraints in shaping price elasticity. Third, while they find higher insurance demand (in level, not price elasticity) among high-LTV borrowers, our baseline and instrumented regressions reveal the opposite for flood insurance. Fourth, we extend the analysis beyond purchase originations, using both panel data and a Harvey event study to show that the absence of coverage is associated with higher post-disaster default, consistent with default functioning as de facto insurance. Finally, whereas their analysis centers on the *intensive margin* of coverage (how much insurance is purchased), we study the *extensive margin* of take-up (whether insurance is purchased at all). This contrast reflects institutional design: NFIP policies are capped at $250,000, limiting variation in policy size, while homeowners insurance does not face such a cap.

Our paper contributes to this literature in three ways. First, we provide new theoretical insights into how limited-liability mortgage debt strategically substitutes for formal disaster insurance, with the strength of this substitution mediated by hazard intensity, recourse law,

and forbearance policy. Second, we bring new empirical evidence using a proprietary loan-level dataset that links mortgage balances and characteristics directly to insurance coverage across millions of loans. This level of granularity makes it possible to observe insurance choices at the property level, a major advance over existing approaches that rely on survey data or MSA-level variation. Third, we highlight the broader financial stability implications of flood underinsurance. Using Hurricane Harvey as a case study, we show that uninsured mortgages were three times more likely to default than insured mortgages in the aftermath of the storm. This finding underscores that underinsurance is not only a household-level puzzle but also a channel through which disaster risk can propagate into mortgage markets and the broader financial system.

The remainder of the paper proceeds as follows. Section 2 develops a theoretical framework and derives predictions about how mortgage debt and disaster insurance interact. Section 3 introduces the novel loan-level dataset and describes how we test these predictions in the data. Section 4 presents the main empirical findings and extensions to other forms of voluntary insurance. Section 5 turns to the case of Hurricane Harvey to examine defaults directly and to test the model's core mechanism that insured homes are less likely to default after a disaster. Section 6 concludes.

2 Model

In this section, we develop a theoretical framework to analyze how indebtedness affects the insurance decision.

2.1 Baseline Model

We begin by introducing a parsimonious model of insurance and default for a given mortgage contract, with the timing summarized in Figure 1. Section 2.2 extends the model to heterogeneous homeowners. Section 2.3 incorporates a forbearance policy. Section 2.4 allows homeowners to make endogenous mortgage choices.

Agents Time is continuous and infinite. There is a unit measure of risk-neutral homeowners who discount future utility at the common rate $r > 0$, i.e., their preferences for the accumulated

cash flow process C_t are given by $\mathbb{E}\int_0^\infty re^{-rt}\,\mathrm{d}C_t$.[1] At $t = 0$, each homeowner is given a mortgage loan, which is collateralized by the housing asset.

Asset The house is an indivisible asset that yields the constant utility flow $h > 0$. The house is struck by a disaster at the random time D, which follows an exponential distribution with arrival rate $r\lambda$. Without loss of generality, we assume that the disaster happens only once and imposes permanent damage d to the house such such that its flow utility falls to $h - d$. This assumption is payoff-equivalent to certain processes of decaying damage or certain processes of repeated disasters with lumpy damage.

Mortgage contract A mortgage contract $\mathbf{m} = (B_0, b, T)$ specifies the amount $B_0 \geq 0$ that the homeowner borrows at $t = 0$ and the fixed payment $b \geq 0$ that is made continuously until the loan matures at date T. The unpaid mortgage balance at time t is

$$B_t \equiv e^{rt}B_0 - \left(e^{rt} - 1\right) b, \text{ where } B_T = 0, \tag{1}$$

which is the accrued balance minus the accrued repayment up to t. Repaying B_0 in full over the interval $[0, T]$ implies that the loan is amortized with

$$b \equiv \frac{B_0}{1 - e^{-rT}}. \tag{2}$$

A homeowner can default on the mortgage contract at any time τ before the loan matures. After doing so, she surrenders the house to the lender and incurs the one-time exogenous recourse cost f/r. If the homeowner defaults at the time of disaster, the mortgage lender becomes liable for the damage.

Insurance The consumer can purchase disaster insurance that reduces the disaster damage from d to $d' = d - c$, with premium rate $\lambda^{\text{ins}}c$. At each instant t before default or disaster, the timing of insurance is as follows:

- A homeowner enjoys the house utility flow h.

[1] It is straightforward to extend our analysis to risk-averse agents, but given that our goal is to explain why homeowners do *not* buy insurance, there is little gain to doing so.

- She decides whether to pay $\lambda^{\text{ins}}c$ for insurance; this decision is denoted with the indicator $\mathcal{I}_t \in \{0, 1\}$.
- If a disaster arrives, the house incurs the net damage cost $d - \mathcal{I}_t c$.
- The homeowner decides whether to default or not. If she does, then she incurs the recourse cost f/r, surrenders the house, and leaves the market forever. If she does not default, then she makes the mortgage repayment b (assuming the mortgage has not yet matured), and continues.

To better match the historical setting, we assume $\lambda^{\text{ins}} < \lambda$, implying that the insurance premium is subsidized, like the flood insurance provided by the U.S. government under the National Flood Insurance Program. In other words, homeowners always have a strong incentive to buy insurance in our environment. Nevertheless, we will show that purchasing insurance is not always optimal.

Homeowner's value functions The optimal default time τ and insurance decision $\{\mathcal{I}_t\}$ solve the following:

$$V \equiv \max_{\tau, \{\mathcal{I}_t\}} \left\{ \begin{array}{l} \int_0^\tau re^{-rt} h \, \mathrm{d}t \; - \; \int_0^{\tau \wedge T} re^{-rt} b \, \mathrm{d}t \; - \; e^{-r\tau} f \\ - \; \mathbb{E}_D \left[\int_0^{D \wedge \tau} re^{-rt} \mathcal{I}_t \lambda^{\text{ins}} \, \mathrm{d}t - \mathbb{1}_{D<\tau} \int_D^\tau re^{-rt} \left(d - c\mathcal{I}_D \right) \mathrm{d}t \right] \end{array} \right\}, \tag{3}$$

where: τ is chosen from the set of related stopping times (i.e., τ can be contingent on the realization of disaster);[2] $x \wedge y \equiv \min\{x, y\}$; and $\mathbb{1}_{\mathcal{A}}$ is the indicator for event $\mathcal{A}$. The following proposition characterizes the optimal default and insurance decision.

Proposition 1. *Given the mortgage mortgage contract* $\mathbf{m} = (B_0, b, T)$*, the homeowner optimal strategy of default and insurance is*

$$\tau^* = \left\{ \begin{array}{l} \infty, \textit{ if } B_0 \leq B^{\text{ins}}, \\ D, \textit{ if } B_D \in (B^{\text{ins}}, B^{\text{risky}}], \\ 0, \textit{ if } B_0 > B^{\text{risky}}; \end{array} \right.$$

$$\mathcal{I}_t^* = 1 \textit{ iff } B_t \leq B^{\text{ins}},$$

[2] A stopping time is a random variable that is measurable with a filtration generated by the σ-algebras of events T and T_μ. For example, $\tau = T + 1$ is a stopping time, but $\tau = T - 1$ is not. In words, one cannot default a year before the disaster, because it requires beforehand knowledge of when the disaster will strike.

where the debt limits are given by:

$$B^{\text{ins}} \equiv h - d + \left(1 - \frac{\lambda^{ins}}{\lambda}\right) c + f < B^{\text{risky}} \equiv b - (b - h - f)^{\frac{1}{1+\lambda}} \left(b - B^{\text{ins}}\right)^{\frac{\lambda}{1+\lambda}}.$$

Proposition 1 is illustrated by Figure 2. The homeowner's default strategy and insurance decision are characterized by two thresholds of mortgage balances, B^{ins} and B^{risky}. As long as her mortgage balance is low enough that $B_t \leq B^{\text{ins}}$, the homeowner does not default, even if a disaster happens. Since her mortgage balance is declining over time from B_0 (illustrated in Figure 2), the homeowner never defaults if $B_0 \leq B^{\text{ins}}$, which is the first region of her default strategy in Proposition 1. Otherwise, if a disaster happens and her mortgage balance at time D is such that $B_D \in (B^{\text{ins}}, B^{\text{risky}}]$, then the homeowner will default upon the disaster; this is the second region of her default strategy in Proposition 1. Finally, if her mortgage balance is so large such that $B_t > B^{\text{risky}}$, the homeowner will default at t. As her mortgage balance is declining over time from $t = 0$ forward, in this case we must have $B_0 > B_t > B^{\text{risky}}$, implying that the homeowner immediately defaults at $t = 0$; this is the third region of the default strategy in Proposition 1.

2.2 Heterogenous homeowners

So far we have assumed all homeowners are the same. In this section we extend our analysis to heterogeneous homeowners and derive the population probability of insurance uptake. Suppose now that homeowner i is characterized by

$$\begin{aligned} h_i &= h + \varepsilon_i^h, \\ d_i &= d + \varepsilon_i^d, \\ f_i &= f + \varepsilon_i^f. \end{aligned}$$

Using Proposition 1, homeowner i buys insurance at t if

$$\varepsilon_i \leq B^{\text{ins}} - B_{it}, \text{ where } \varepsilon_i \equiv \varepsilon_i^d - \varepsilon_i^h - \varepsilon_i^f. \tag{4}$$

Let $G(\varepsilon)$ denote the CDF of ε. The probability of insurance uptake by homeowners indebted with mortgage balance B_{it} is then given by

$$\mathcal{P}_{it} = G\left(B^{\text{ins}} - B_{it}\right).$$

The key prediction from this baseline version of the model is that the loan balance crowds out insurance uptake, which is captured by the derivative:

Corollary 1.

$$\frac{\partial \mathcal{P}_{it}}{\partial B_{it}} < 0. \tag{5}$$

2.3 Disaster Forbearance

Mortgages purchased by GSEs often qualify for loan forbearance in the event of a disaster, reducing the need for insurance. For example, Panjwani (2024) estimate that the average forbearance amount per loan after Hurricane Sandy was substantial—approximately $49,000 in net present value . This motivates our extension, which considers the impact of such forbearance programs on homeowners' insurance decisions.

We extend our model to include an exogenous disaster forbearance program. The incentives contained in these programs can be quite interesting. Homeowners who are uninsured are more likely to qualify for forbearance (they must demonstrate "financial hardship" due to the disaster to qualify for the GSE forbearance program[3]). Forbearance reduces the loan balance from B_t to $(1-\theta)B_t$, providing a temporary reprieve.

The fraction of insured homeowners is still given by (4) but with

$$B^{\text{ins}} \equiv \frac{h - d + \left(1 - \frac{\lambda^{\text{ins}}}{\lambda}\right) c + \text{re}}{1 + \underbrace{\theta}_{\text{forbearance}}}. \tag{6}$$

This extension introduces additional testable implications. The relationship between insurance uptake and the various parameters of the model (disaster probability λ, recourse re, and forbearance θ) now hinges on the following signs:

Corollary 2.

$$\frac{\partial \mathcal{P}}{\partial \lambda} > 0, \quad \frac{\partial \mathcal{P}}{\partial \text{re}} > 0, \quad \frac{\partial \mathcal{P}}{\partial \theta} < 0. \tag{7}$$

[3] https://sf.freddiemac.com/faqs/servicing-disaster-relief-policies-faq

Additionally, the sign of the cross-partial derivatives with respect to B and these parameters depends on the sign of $g' \equiv G''(B^{\text{ins}} - B)$:

Corollary 3.

$$\begin{aligned} \frac{\partial^2 \mathcal{P}}{\partial B \partial \lambda} &\quad \text{same sign as} \quad -g' \\ \frac{\partial^2 \mathcal{P}}{\partial B \partial \text{re}} &\quad \text{same sign as} \quad -g' \\ \frac{\partial^2 \mathcal{P}}{\partial B \partial \theta} &\quad \text{same sign as} \quad g' \end{aligned}$$

We can empirically test the signs of these interaction effects to validate the model.

2.4 Endogenous Initial Loan Balance

Finally, we consider endogenous loan balances. Before $t = 0$, homeowners search and match with competitive lenders to find an optimal mortgage contract (B_0, b). In this extended model, homeowners believe that disasters occur at a rate λ, while lenders believe the rate is $\bar{\lambda}$. If $\bar{\lambda} < \lambda$, this can be microfounded with risk-shifting, where mortgage lenders transfer risky loans to GSEs via securitization, as discussed in Bakkensen et al. (2025).

The equilibrium initial loan balance is given by:

$$B_0 = e^{rT} \left[B_0 - \left(1 - e^{-rT}\right)(h + f) \right]^{\frac{1}{1+\lambda}} \left[B_0 - \left(1 - e^{-rT}\right) B^{\text{ins}} \right]^{\frac{\lambda}{1+\lambda}}. \tag{8}$$

While the initial loan balance B_0 is endogenous, its decay over time is not. The loan balance at any time t is:

$$B_t = \frac{1 - e^{-\rho(T-t)}}{1 - e^{-\rho T}} B_0. \tag{9}$$

This insight allows us to use the remaining maturity as an instrumental variable (IV) for the loan balance B_t, addressing potential endogeneity concerns in empirical analysis.

3 Data

To empirically test our model implications, we utilize Intercontinental Exchange's (ICE) McDash® database. Covering the servicing portfolios of the largest residential mortgage servicers in the U.S., the database contains approximately 151 million individual loans with around 5.5 billion records of monthly performance history, or approximately two-thirds of the

entire market. ICE McDash® tracks the performance and characteristics of residential mortgages year by year, from origination to termination such as maturity or foreclosure. Additional variables in this rich dataset include remaining principal balance, appraisal value, loan to value ratio (LTV), and FICO score at origination. We utilize data covering the years 2013 to 2023.

In September 2023, ICE McDash® added a new module to its already rich database: detailed annual insurance data for each loan. The module tracks whether a loan has flood, earthquake, and/or homeowners insurance and, if so, the coverage amount, along with other essential details including whether the insurance is mandatory or voluntary. Whether a loan has insurance data in ICE McDash® depends on whether the servicer agreed to share this data. Fortunately, compliance is high: of the on average 36 million mortgages reported each month, approximately 26 million now include an insurance record. Based on Meyer and Mittag (2017), we correct for potential bias from insurance under-reporting (misclassification) in our robustness exercises.

For our analysis, we focus on conventional term, single-family home, first mortgages that have been active for more than one year. Given the low flood insurance take up rates despite nontrivial flood risk across the U.S., we focus primarily on flood insurance but include other insurance products in additional results. For our flood insurance results, we further restrict our sample to loans where flood insurance is voluntary, that is, loans not in the Special Flood Hazard Areas (SFHAs) defined as properties with at least a 1% annual risk of flooding. Doing so allows us to focus on the household insurance uptake decisions rather than mandate compliance. To exclude loans where flood risk is trivial, we merge our dataset with the First Street Flood Factor, a projection of the cumulative probability of flooding in 2020 to 2050. We drop loans in zip codes with a Flood Factor below 2, representing a less than a 0.2% annual chance of flooding. Finally, we winsorize LTV ratios at the 1st and 99th percentiles. Our final sample contains more than 10.5 million loan-year observations.

Summary Statistics Table 1 provides summary statistics for the main variables in our dataset. The top panel of the table shows results for the sample remaining after we apply the selection criteria listed above, while the bottom panel shows results for the subsample of those loans with voluntary flood insurance uptake. Among our full sample (top panel in Table 1), the mean remaining principal balance is approximately $166,620 with mean appraisal value

at origination of $256,260. As motivated above, the voluntary flood insurance take up is low, with only 0.47% of loans in the sample opting for coverage. Among loans with voluntary flood insurance (bottom panel in Table 1), the median coverage level is $240,000, just below the $250,000 cap on NFIP coverage.[4]

As suggestive evidence of our main model results, loans with voluntary flood insurance have lower LTV ratios and higher home equity relative to the overall sample (Corollary 1). In addition, homes with voluntary flood insurance are located in zip codes with higher average flood risk (Corollary 2). We do additionally note other differences across the two groups, as loans with voluntary flood insurance also have higher average appraisal values and FICO scores at origination. To address these potential endogeneity concerns relating to indebtedness, in addition to including these controls in our main regression specifications, as motivated by Section 2.4, we will include an instrumental variable (IV) specification, using the remaining maturity of the loan as an instrument for the LTV ratio.

4 Empirical Results

4.1 Testing the Model's Main Implication

The primary implication of our model is that an increase in the loan balance reduces the probability of voluntary flood insurance uptake ($\partial \mathcal{P}/\partial B < 0$, Corollary 1). In the model, houses are ex-ante identical, so that higher levels of debt imply lower levels of home equity. To adapt the model's predictions to the data, where home values vary, we look instead at how insurance uptake relates to the LTV ratio. We begin with Figure 3, which plots flood insurance take up (residualized) against the LTV ratio (also residualized). The resulting bin scatter plot shows a pronounced negative relationship, with the trend line indicating that an increase in the LTV ratio from 20% to 80% is associated with a fall in the uptake rate of over 0.1 percentage points (pp), or 20% of its mean value of 0.47pp. Figure 3 thus supports the model prediction that higher indebtedness discourages insurance uptake.

Moving to a more formal analysis, we next estimate a series of a linear probability model where the dependent variable, I_{it}, is a binary variable equal to 1 if a homeowner for loan i

[4]While private flood insurance take up has increased in recent years, it accounts for less than 5% of the residential flood insurance market during our data period (Kousky et al., 2018).

in year t has voluntarily taken up flood insurance, and 0 otherwise.[5] Equation 1 presents our main specification.

$$I_{it} = \alpha + \beta LTV_{it} + \phi' X_i + \Lambda_i + \theta_{ZY} + \epsilon_{it}. \tag{1}$$

The key independent variable of interest, LTV_{it} is the LTV ratio. All regressions control for ZIP code-by calendar year fixed effects (θ_{ZY}), as well as either additional loan-level controls including FICO score at origination and the log appraisal value ($\phi' X_i$) or loan fixed effect (Λ_i).

The results, presented in Table 2, show a consistent and significant negative relationship between the LTV ratio and the probability of voluntary flood insurance uptake. In the simplest specification (Column 1), the LTV ratio is -0.0017, indicating that an increase in the LTV ratio from 0 to 1 is associated with a 17 basis point decrease in the probability of insurance uptake—small, but significant. Compared with the flood insurance take up rate among our sample of 0.47%, a 17 basis point increase represents a 36% relative increase. Columns 2 and 3 show that controlling for FICO score and log appraisal value modestly increases the magnitude of the LTV coefficient, suggesting a slightly stronger insurance crowding-out effect.The coefficients on the two variables themselves are also plausible: individuals with larger homes and stronger personal finances are more likely to buy flood insurance. On the other hand, Column 4 shows that subsuming these variables into a set of loan fixed effects appreciably decreases the LTV coefficient's magnitude, although it remains both statistically and economically significant. In Columns 5 and 6 we restrict the sample to 30-year mortgages. We find our results are robust to the adoption of this more homogeneous subsample.

In Column 7, we address potential endogeneity concerns relating to the initial loan balance and repayment decisions that could be impacted by unobservable factors such as borrower income or wealth. In particular, as motivated by Section 2.4, we use remaining maturity as an instrument for the LTV ratio.[6] Our exclusion restriction assumes that the amount of time that has passed since mortgage origination (or remaining maturity, our instrument) impacts

[5] We use the linear probability model instead of nonlinear binary dependent variable models given concerns such as the incidental parameters problem in maximum likelihood estimators when rich fixed effects are included (Greene, 2004). In addition, common concerns with the linear probability model, such as predictions not bounded between 0 and 1, are not relevant in this context as our aim is to interpret the estimated coefficients rather than use the model for prediction.

[6] Note that we only examine 30 year loans in this specification to avoid potential selection across maturity length.

the flood insurance purchase decision only through the LTV ratio. One potential concern is that homeowners learn about flood risk over the lifetime of their loan. However, in original survey data of residents in coastal Rhode Island, Bakkensen and Barrage (2022) find that recent movers to the area within the past 3 years do not exhibit a different distribution of flood risk perceptions relative to longer-term residents in the same neighborhood. Also, to the extent that flood events increase flood risk perception as has been shown to happen, flood event realizations are random across these locations and over time. Also, previous literature has found that flood risk beliefs fall back to baseline after several years (Atreya et al., 2013; Bakkensen and Barrage, 2022). Thus, longer tenured homeowners should not necessarily perceive higher flood risk. Recall that we exclude loans that are less than one year old, during which time people may learn more about their local flood risk.

The IV estimate in Column 7 indicates a significantly stronger negative relationship, with a coefficient of -0.0039, or 39 basis points, more than twice the initial coefficient in column 1. It is also economically significant relative to the mean flood insurance take up of 47 basis points in this sample. This is a large effect and consistent with the model's predictions.

4.2 Testing Secondary Predictions

In addition to the primary prediction that debt crowds out insurance uptake, our model generates additional predictions regarding uptake (see Corollary 2). Specifically, the model predicts that flood insurance uptake should increase with the disaster rate (corresponding to λ in the model), increase with the cost of default (corresponding to re in the model), and decrease with the amount of forbearance (corresponding to θ in the model). Here, we test these hypotheses by estimating models similar to Equation 1, but add in additional variables across the columns.

In the first column, the coefficient on the flood risk variable, an indicator that the Flood Factor is 3 or larger, is positive and highly significant, suggesting that as the assessed disaster risk increases, the probability of voluntary flood insurance uptake increases as well. This is consistent with the model's prediction that homeowners are more likely to insure against disasters when the risk of such events is higher. However, to avoid absorbing the variation in flood risk, we use state by year (S×Y) fixed effects instead of ZIP code by year (Z×Y) fixed effects, since flood risk is measured at the ZIP code level. This choice allows us to capture

state-level time trends but requires careful interpretation of the flood risk coefficient, as we may be subject to omitted variable bias. For example, areas with higher flood risk might have different socioeconomic characteristics, such as higher income or education levels in coastal communities, that are not fully controlled for by the borrower's FICO score.

Column 2 examines the effect of default costs by including a dummy variable indicating whether the property is located in a recourse state, where mortgage lenders can pursue the borrowers' non-housing assets in the event of default. Our classification of recourse states follows Ghent and Kudlyak (2011). The positive and significant coefficient on the recourse variable suggests that homeowners in recourse states, where the cost of default is higher, are more likely to take up flood insurance. To identify the effect of recourse, we use only year (Y) fixed effects in this specification, as the recourse dummy varies only at the state level, so that state fixed effects would absorb all the recourse-related variation. However, this also introduces the possibility of omitted variable bias, as recourse states may have other unobserved characteristics that influence insurance uptake. Therefore, while the results are consistent with the model's predictions, they should be interpreted with caution.

The third column considers the likelihood of forbearance as measured by a GSE loan indicator, as GSE loans are more likely to qualify for federal disaster forbearance.[7] The coefficient on the GSE indicator is not statistically significant, but its negative sign suggests that GSE loans are associated with a lower probability of insurance uptake, as the model predicts. Overall, the results in the first three columns in Table 4 are consistent with the model's secondary predictions.

4.3 Testing Model Predictions for Interaction Effects

We next test a more nuanced prediction of the model concerning interactions between loan balances and the disaster rate (λ), recourse (re), and the amount of forbearance (θ). According to the model, the signs of the cross-partial derivatives of the insurance probability $\mathcal{P}$ with respect to loan balances (B, proxied in our analysis by the LTV ratio) and each of these factors will depend on the sign of $g' \equiv G''(B^{\text{ins}} - B)$, where G is the distribution of the unobserved idiosyncratic term ϵ. Specifically, the model predicts (recall Corollary 3) that:

[7] The GSE dummy is defined to be one if the mortgage investor is one of the GSEs (Fannie Mae, Ginnie Mae, or Freddie Mac).

- The cross-partial derivatives $\frac{\partial^2 \mathcal{P}}{\partial B \partial \lambda}$ and $\frac{\partial^2 \mathcal{P}}{\partial B \partial \text{re}}$ should have the same sign as $-g'$.
- The cross-partial derivative $\frac{\partial^2 \mathcal{P}}{\partial B \partial \theta}$ should have the opposite sign, i.e., the same sign as g'.

While we cannot determine whether g' is positive or negative (it depends on the specific distribution of ϵ), we can empirically test whether the signs of the interaction terms are consistent with these model predictions. In particular, we can test whether the coefficients on the interaction terms $B \times \lambda$ and $B \times$ re have the same sign, and whether this is the opposite of the sign of the coefficient on the interaction term $B \times \theta$.

Columns 4-6 of Table 4 show the coefficient estimates for the "interaction" specifications. In contrast to columns 1-3, these regressions include full sets of fixed effects, as our focus is now on the interactions, and therefore subsumes the individual variables examined in the previous section. Columns 4 and 5 show that the coefficients on the interaction of the LTV ratio with the disaster rate and the recourse indicator are both negative, matching the model's prediction that they share the same sign.

In column 6, when we interact mortgage balances with the GSE indicator, the empirical results do not align with the model's prediction for forbearance. Our framework suggests that greater access to disaster forbearance through GSE-backed loans (a higher effective θ) should reduce the value of voluntary insurance, leading to a weaker relationship between balances and insurance take-up. In terms of Corollary 3, if g' is pinned down by the negative signs on the LTV×hazard and LTV×recourse interactions, then the LTV×forbearance interaction should be positive. Instead, we find that the $B \times$GSE coefficient is negative, implying that the decline in take-up with higher balances is actually stronger among conforming (GSE) loans.

We interpret this as evidence that, given our model, the GSE forbearance policy is not a dominant factor explaining the low take-up of flood insurance in the data. GSE status captures not only forbearance eligibility but also escrow requirements, servicer mandates, investor overlays, and insurance verification practices, each of which may influence coverage decisions. Moreover, conforming and jumbo borrowers differ systematically in collateral types, geographic distribution, and underwriting standards. Servicer-level differences in escrow management and claims handling may also contribute.

Taken together, these findings suggest that forbearance policy alone is unlikely to be the dominant factor behind the GSE interaction. Instead, the stronger negative LTV–insurance

slope within the conforming segment highlights that "GSE status" reflects a bundle of institutional and compositional features that interact with leverage in complex ways. We therefore treat this as an open question: in future versions of the paper, we plan to revisit the analysis by focusing exclusively on the conforming loan subsample and by adding servicer-by-year and escrow controls, in order to better isolate the role of θ from other GSE mechanisms.

4.4 Testing Model Predictions with Other Insurance Products

Our dataset includes information not only on flood insurance but several other types of insurance as well. In this section, we extend our analysis to test the model's prediction that indebtedness crowds out insurance uptake more generally. We first examine the coefficient on the LTV ratio in predictions of earthquake insurance uptake. We then examine the amount of coverage purchased by those holding earthquake insurance and then the amount of homeowners insurance coverage purchased by homeowners insurance holders (uptake is nearly universal). It is particularly useful to examine insurance products besides flood insurance because, at the intensive margin, there is significant bunching of flood insurance coverage at the regulatory cap of $250,000 set by the NFIP. Neither earthquake nor homeowners insurance is subject to such a cap.

Table 3 presents the results for these supplemental regressions. Column 1 provides results for earthquake insurance uptake. The effect is slightly positive, in contradiction to the model's prediction, and not statistically significant. This may reflect the small number of earthquake policies in effect: comparing the sample sizes of Columns 1 and 2 indicates that fewer than 1 in 20,000 loans has earthquake coverage. Because our data lack the earthquake analogue to the Flood Factor, we have no easy way to restrict our sample to loans in high-earthquake-risk areas.

In the second column, we test the effect of loan balances on the intensive margin of earthquake insurance, namely the log of the earthquake coverage amount. Here, the results are more in keeping with the model's predictions, indicating that an increase in the LTV ratio from 0 to 1 is associated with an 18% decrease in coverage. This regression also shows that the coverage amount rises steadily with the value of the underlying property, with an elasticity of over two-thirds.

The third column examines the relationship between the LTV ratio and the log of the

homeowner's insurance coverage amount. (Comparing the sample sizes for Columns 2 and 3 shows that most loans are attached to a homeowners policy.) The coefficients for the LTV ratio and appraised value are both similar to the ones for earthquake insurance shown in Column 2, with higher LTV ratios predicting significantly less coverage.

Overall, these results confirm that the crowding-out effect of loan balance on insurance extends beyond flood insurance to other types of insurance as well. The consistency of our findings across different insurance products underscores the broader applicability of our model and highlights the importance of considering indebtedness as a factor in homeowners' insurance decisions.

5 Testing Default Mechanism

A central channel in our model is that disasters can trigger strategic default, and that insurance coverage weakens this link. Prior work has established the general connection between natural disasters and higher mortgage default (Bakkensen et al., 2025; Du et al., 2020). More recent evidence highlights the mediating role of insurance. For example, Kousky et al. (2020) and Biswas et al. (2023) show that insurance payouts reduce delinquency risk by offsetting losses. Our analysis builds directly on this insight: unlike most prior work, we observe property-level flood insurance status, allowing us to test whether the presence of insurance dampens the disaster–default channel at the household level.

We focus on Hurricane Harvey, which made landfall in Texas on August 25, 2017. While initially a Category 3 storm, Harvey stalled over southeast Texas and produced the heaviest rainfall from a tropical cyclone in U.S. history, with localized totals exceeding 60 inches. Flood losses drove nearly all of the $125 billion in damages (Blake and Zelinsky, 2018). CoreLogic estimated that roughly 70 percent of residential flood damage was uninsured, with flood insurance penetration just seven percent in Houston (Strochak and Ganesh, 2017). This event provides an ideal setting to examine how lack of coverage translates into higher mortgage default.

Our empirical design exploits over 21.5 million loan-month observations in Texas from 2015–2019. We define treated mortgages as those in ZIP codes where at least 80 percent of housing units received FEMA Individual and Households Program aid; roughly 39 percent of

Texas ZIPs meet this threshold. All other mortgages in the state serve as controls. A necessary caveat is that McDash does not provide the exact property addresses of the collateral due to confidentiality restrictions, and our treatment is assigned at the ZIP level rather than the property level. This limitation implies that our treatment is less precise than would be ideal, and that the control group is not "pure": some control mortgages may still have been affected by Harvey flooding. Later results illustrate this imprecision—defaults increase somewhat even in the control group, though the effect is weaker and much smaller than in treated ZIPs.

We implement a difference-in-differences event study, comparing default rates before and after Harvey across treatment and control areas, and separately for loans with and without flood insurance. Pre-trend tests (Figures 4a–4b) support the identifying assumption of parallel trends.

Table 5 reports the Average Treatment Effects on the Treated (ATET). Among uninsured mortgages, default rates rose by 130 basis points in the two and a half years following Harvey. The increase is much smaller—60 basis points—among insured loans. Put differently, borrowers without flood insurance were roughly three times more likely to default after the disaster. Given a baseline default risk of 900 basis points, this represents a 14.4 percent increase in default likelihood, a large and economically meaningful effect.

Taken together, these results show that insurance directly mitigates the disaster–default channel. They align with the growing literature on insurance as a buffer against disaster-induced mortgage distress, and—despite ZIP-level imprecision—our findings confirm the central mechanism of the model: without coverage, leveraged homeowners turn to default as a substitute form of disaster insurance. This alignment of theory and evidence strengthens the credibility of our overall story.

6 Conclusion

We examine the relationship between mortgage balances and flood insurance uptake. Our findings show that higher loan balances crowd out voluntary flood insurance, while increases in flood risk and stronger recourse provisions raise the likelihood of insurance purchase. This highlights a strategic mechanism that complements existing explanations for low flood insurance penetration: when homeowners hold little equity, they may rely on the option to default

or seek forbearance as a substitute for formal coverage.

These dynamics matter for how disaster risk transmits into household balance sheets and the stability of mortgage markets. As disasters increase in frequency and severity, a substantial share of the U.S. housing stock may remain both high leverage and uninsured against flood risk, creating vulnerabilities for households, lenders, and the broader financial system. Flood risk in housing finance is therefore not only shaped by salience or liquidity constraints, but also by how mortgage design interacts with the incentives to insure.

In future work, we plan to study how changes in government backstops—particularly the winding down of disaster forbearance programs and the evolving role of the National Flood Insurance Program (NFIP) through declining coverage or higher premiums—affect household finance and mortgage market outcomes. Understanding how such reforms shape default risk, household financial stability, and systemic exposure in mortgage markets is crucial for assessing resilience as disaster risks intensify.

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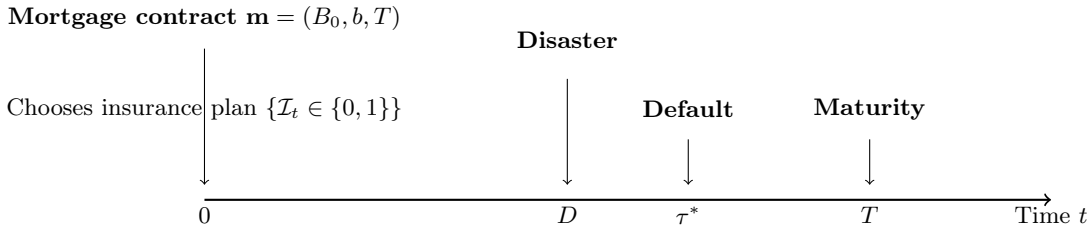


Figure 1: Illustration of the timing of events in the model.

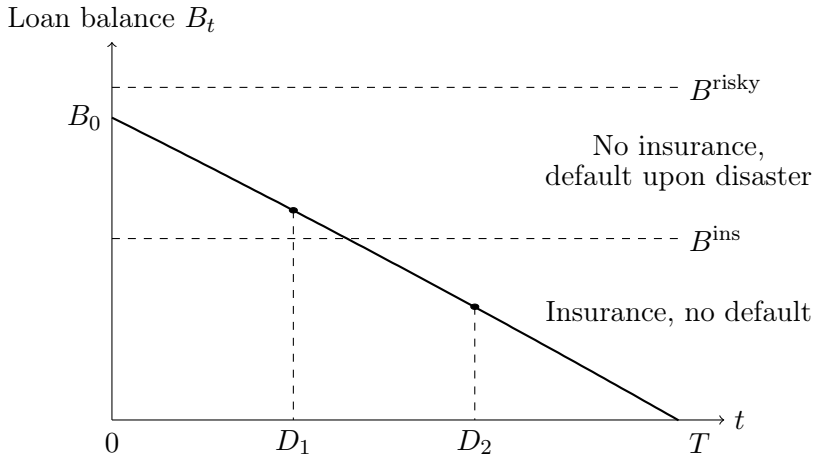


Figure 2: Remaining loan balance, and insurance and default decisions.

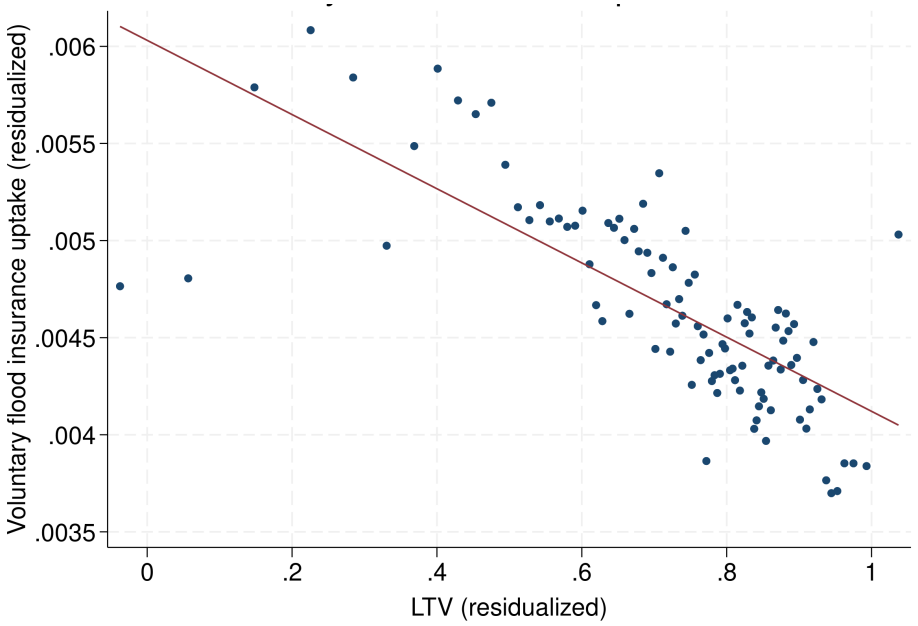
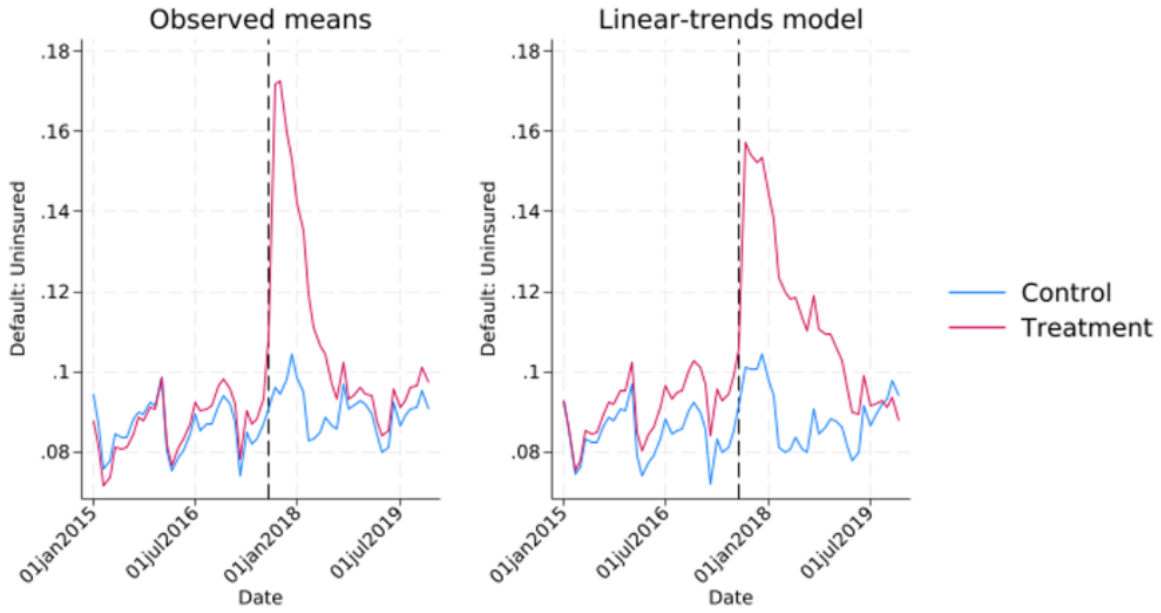
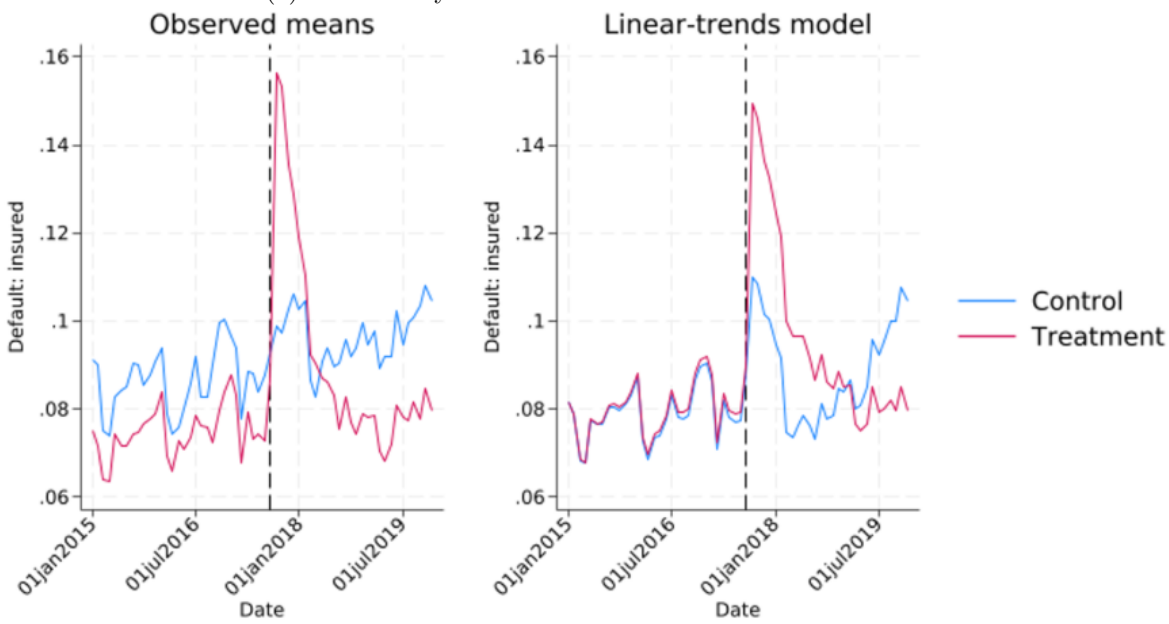


Figure 3: Voluntary Flood Insurance Uptake is Negatively Related to the LTV Ratio
Note: This is a bin scatter plot of residualized voluntary flood insurance uptake and residualized LTV ratios. Controls include FICO score, appraisal amount and a full set of Zip Code × year interactions.



(a) Event study for borrowers without flood insurance



(b) Event study for borrowers with flood insurance

Figure 4: Event studies of the effect of Hurricane Harvey on mortgage default. Both figures plot the default frequency of mortgages before and after Hurricane Harvey (August 2017) in affected (red) and unaffected (blue) three-digit ZIP codes in Texas. The left panels plot the observed means, while the right panels normalize using a linear-trends model where both treatment and control groups are normalized to the same point at the beginning of our data period. The difference-in-differences regressions include zip code fixed effects and month fixed effects. See data descriptions in Section 5.

Table 1: Summary Statistics

	Mean	Std	p10	Median	p90
All loans with no flood insurance mandate					
Remaining Principal Balance (thousand $)	166.62	135.27	40.80	130.57	340.70
Appraisal Value (thousand $)	256.26	223.52	80.48	185.00	510.00
Loan to Value Ratio	0.71	0.22	0.40	0.76	0.93
Home Equity (thousand $)	78.96	113.63	9.43	39.78	190.95
FICO at Origination	718.91	62.85	639.00	724.00	797.00
Flood Factor (ZIP level)	2.91	1.16	2.07	2.50	4.18
Flood Insurance Uptake Dummy (%)	0.47	6.85	0.00	0.00	0.00
Loans with voluntary flood insurance uptake = 1					
Remaining Principal Balance (thousand $)	171.32	131.76	45.04	136.65	346.84
Appraisal Value (thousand $)	272.04	220.46	89.00	203.00	530.00
Loan to Value Ratio	0.68	0.22	0.36	0.72	0.92
Home Equity (thousand $)	93.60	122.85	11.71	51.40	219.92
FICO at Origination	726.16	61.84	641.00	735.00	799.00
Flood Factor (ZIP level)	4.20	2.13	2.20	3.30	8.01
Flood Insurance Coverage (thousand $)	197.39	63.39	100.00	240.00	250.00

Table 2: Crowding-Out Effect of the LTV Ratio on Voluntary Flood Insurance Uptake.

	Voluntary Flood Insurance Uptake = 1						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LTV	-0.0017***	-0.0018***	-0.0019***	-0.0004**	-0.0018***	-0.0004**	-0.0039***
	(-10.91)	(-10.32)	(-10.76)	(-2.44)	(-9.73)	(-2.40)	(-8.52)
FICO at origination		0.0093***	0.0072***		0.0073***		0.0065***
/ 1000		(14.34)	(11.04)		(10.94)		(9.52)
log Appraisal Value			0.0014***		0.0013***		0.0014***
			(14.33)		(13.04)		(13.25)
Constant	0.0060***	-0.0007	-0.0067***	0.0048***	-0.0063***	0.0048***	
	(50.02)	(-1.40)	(-10.26)	(42.94)	(-9.48)	(42.21)	
Fixed effects	ZxY	ZxY	ZxY	L, ZxY	ZxY	L, ZxY	ZxY
Sample					30yrmtg	30yrmtg	30yrmtg
N	10,656,103	9,361,891	9,361,891	9,751,703	8,959,640	9,314,892	8,958,268
R2	0.044	0.044	0.044	0.774	0.045	0.775	
F stat (for IV)							132.44

Note: The table presents the results of a linear probability model where the dependent variable is a dummy indicating whether voluntary flood insurance was taken up (equal to 1). The key independent variable is the LTV ratio, scaled to the $[0, 1]$ interval. The analysis uses annual ICE McDash® data from the period 2013-2023, with the sample restricted to single-family term loans without a mandatory flood insurance requirement. Loans in their first year since origination are excluded, as are loans with a Flood Factor below 2. Z, Y and L refer to ZIP code, year and loan effects, respectively. The final three columns further restrict the sample to mortgages with a 30-year maturity. The last column employs an instrumental variable (IV) approach, where the log of the remaining loan balance is instrumented with the remaining maturity in months. The F-statistic for the first stage is reported for this IV column. All standard errors are shown in parentheses and are clustered at the ZIP code level. Significance levels are indicated as follows: *** $p < 0.001$, ** $p < 0.05$, * $p < 0.01$.

Table 3: Crowding-Out Effect of the LTV Ratio on Earthquake and Homeowner Insurance Uptake and Coverage

	Earthquake Ins. Uptake	log(Earthquake Coverage)	log(Homeowners Coverage)
LTV	0.0000	-0.1803***	-0.1417***
	(0.96)	(-4.63)	(-732.72)
log Appraisal Value	-0.0000***	0.6831***	0.6297***
	(-4.12)	(35.08)	(6712.46)
FICO at origination	0.0005***	0.076	0.0036***
/ 1000	(13.44)	(0.54)	(5.36)
Constant	-0.00005	1.8857***	2.2959***
	(-1.56)	(12.98)	(3545.91)
Fixed effects	ZxY	ZxY	ZxY
N	47,394,658	2,059	46,778,550
R2	0.010	0.891	0.714

The table presents the results of three linear models with different dependent variables. In Column 1, the dependent variable is a dummy indicating whether earthquake insurance was taken up. In Column 2, the dependent variable is the log of earthquake coverage (among policyholders), and in Column 3 the dependent variable is the log of standard homeowner's coverage (among policyholders). The analysis uses annual ICE McDash® data from the period 2013-2023, with the sample restricted to single-family term loans. Loans in their first year since origination are excluded. Z and Y refer to ZIP code and year effects, respectively. Parentheses contain t-statistics, with the underlying standard errors clustered by loan. Significance levels are indicated as follows: *** $p < 0.001$, ** $p < 0.05$, * $p < 0.01$.

Table 4: Crowding-Out Effect of the LTV Ratio on Voluntary Flood Insurance Uptake when Accounting for Flood Risk and Default Costs

	Voluntary Flood Insurance Uptake = 1					
	(1)	(2)	(3)	(4)	(5)	(6)
LTV	-0.0022***	-0.0029***	-0.0019***	-0.0010***	-0.0011***	-0.0010**
	(-12.41)	(-17.09)	(-10.54)	(-6.1276)	(-6.0919)	(-2.3126)
log Appraisal Value	0.0023***	0.0017***	0.0014***	0.0005***	0.0003***	0.0021***
	(33.06)	(26.84)	(14.15)	(5.2260)	(2.7844)	(8.4479)
FICO at origination	0.0061***	0.0047***	0.0074***	0.0000***	0.0000**	0.0000**
/ 1000	(9.17)	(7.31)	(11.06)	(9.1713)	(2.3090)	(12.4381)
Flood Factor	0.0036***					
	(52.55)					
Recourse		0.0052***				
		(72.61)				
GSE loan			-0.0002			
			(-1.48)			
High Flood Factor × LTV				-0.0030***		
				(-6.3475)		
Recourse × LTV					-0.0012***	
					(-3.9019)	
GSE loan × LTV						-0.0012**
						(-2.5359)
Constant	-0.0208***	-0.0090***	-0.0066***	-0.0067***	-0.0061***	-0.0057***
	(-35.19)	(-17.18)	(-10.15)	(-10.3083)	(-9.7084)	(-8.3674)
Saturated interactions	No	No	No	Yes	Yes	Yes
Fixed effects	SxY	Y	ZxY	ZxYxHighFF	ZxYxre	ZxYxGSE
N	9,196,449	9,396,121	9,361,891	9,361,891	9,361,272	9,338,461
R2	0.011	0.002	0.044	0.044	0.044	0.052

The table presents the results of a linear probability model where the dependent variable is a dummy indicating whether voluntary flood insurance was taken up (equal to 1). In addition to the LTV ratio, key independent variables include flood risk disaster rate as measured by the Flood Factor dummy, default costs as measured by a state-level recourse dummy (with recourse states classified as in Ghent and Kudlyak (2011)), and the likelihood of forbearance (represented by the GSE indicator). We allow these variables to enter the regression directly and as interactions with the LTV ratio. The regressions use annual ICE McDash® data from the period 2013-2023, with the sample restricted to single-family term loans without a mandatory flood insurance requirement. Loans in their first year since origination are excluded, as are loans with a Flood Factor below 2. S, Z and Y refer to state, ZIP code and year effects, respectively. The regressions in Columns 4-6 include interactions of the variable in question with the log appraisal value and FICO score. We do not report these coefficients, but they are available on request. Parentheses contain t-statistics, with the underlying standard errors clustered by loan. Significance levels are indicated as follows: *** $p < 0.001$, ** $p < 0.05$, * $p < 0.01$.

Table 5: Impact of Flood Insurance Status on Post-Harvey Mortgage Default

	Mortgage default		
	Uninsured	Insured	All
	(1)	(2)	(3)
ATET	0.018***	0.006*	0.017***
	(0.001)	(0.004)	(0.001)
Constant	0.093***	0.081***	0.106***
	(0.001)	(0.002)	(0.001)
N	14,227,071	478,140	21,545,719

The table presents the Average Treatment Effect on the Treated (ATET) results of three differences in differences (DiD) regressions of the effect of Hurricane Harvey on mortgage default rates. Treatment is defined as being in a 5 digit zip code with more than 80% of housing units in the county received individual or household assistance program aid from FEMA. Column 1 displays estimated ATET coefficient for uninsured borrowers, Column 2 displays for borrowers with flood insurance, and Column 3 for both uninsured and insured borrowers. Parentheses contain standard errors. Significance levels are indicated as follows: *** $p < 0.001$, ** $p < 0.05$, * $p < 0.01$.

A Appendix

B Model: Details

The proof is similar to Bakkensen et al. (2025), where there exist B^{ins} and B^{risky} where the homeowner never defaults when $B_t < B^{\text{ins}}$; defaults at the disaster date D when $B_D \in (B^{\text{ins}}, B^{\text{risky}}]$; default immediately when $B_t > B^{\text{risky}}$. The evolution of B_t is

$$\dot{B}_t = -r\left(b - B\right), \text{ where } B_T = 0.$$

Given the deterministic mortgage maturity, the HJB equation for V is given by

$$\left(1+\lambda\right) rV\left(B\right) = \max_{\mathcal{I}^{ins},\mathcal{I}^{sol}\in\{0,1\}} \left\{ \begin{array}{c} r\left(h - b - \mathcal{I}^{ins}\lambda^{ins}c\right) - r\left(b-B\right)V'\left(B\right) \\ +r\lambda\left[\mathcal{I}^{sol}\left(h - d - B + \mathcal{I}^{ins}c\right) - \left(1-\mathcal{I}^{sol}\right)f\right] \end{array} \right\}.$$

It is obvious that $\mathcal{I}^{ins} = 1$ only if $\mathcal{I}^{sol} = 1$. Guess and verify that there exists B^{ins} such that

$$\begin{aligned} \mathcal{I}^{ins} &= 1 \text{ iff } B \leq B^{\text{ins}}, \\ \mathcal{I}^{sol} &= 1 \text{ iff } B \leq B^{\text{ins}}. \end{aligned}$$

Express

$$V\left(B\right) = \left\{ \begin{array}{l} V_{ins}\left(B\right) \text{ if } B \leq B^{\text{ins}}, \\ V_{sol}\left(B\right) \text{ if } \in (B^{\text{ins}}, B^{\text{risky}}], \end{array} \right.$$

where the smooth-pasting condition is given by

$$\begin{aligned} V_{ins}\left(B^{\text{ins}}\right) &= V_{sol}\left(B^{\text{ins}}\right), \\ V'_{ins}\left(B^{\text{ins}}\right) &= V'_{sol}\left(B^{\text{ins}}\right). \end{aligned}$$

Then the HJB equation becomes

$$\begin{aligned} \left(1+\lambda\right) rV_{ins}\left(B\right) &= r\left(h - b - \lambda^{ins}c\right) - r\left(b-B\right)V'_{ins}\left(B\right) + r\lambda\left(h - d - B + c\right), \\ \left(1+\lambda\right) rV_{sol}\left(B\right) &= r\left(h-b\right) - r\left(b-B\right)V'_{sol}\left(B\right) - r\lambda f. \end{aligned}$$

It is straight-forward to verify that the closed-form solution is

$$\begin{aligned} V_{ins}(B) &= v_\lambda - B + \frac{\lambda - \lambda^{ins}}{1+\lambda} c, \\ V_{sol}(B) &= \frac{h - b - \lambda f}{1+\lambda} + \frac{1}{1+\lambda}\left(\frac{b-B}{b-B^{\text{ins}}}\right)^{\lambda}(b-B), \end{aligned}$$

where B^{ins} solves the smooth-pasting condition, implying

$$\begin{aligned} & v_\lambda - B^{\text{ins}} + \frac{\lambda - \lambda^{ins}}{1+\lambda} c = \frac{h - b - \lambda f}{1+\lambda} + \frac{b - B^{\text{ins}}}{1+\lambda}, \\ \Rightarrow \quad & B^{\text{ins}} \equiv h - d + \left(1 - \frac{\lambda^{ins}}{\lambda}\right) c + f. \end{aligned}$$

Finally, at the default threshold

$$V\left(B^{\text{risky}}\right) = -f \Rightarrow \frac{h - b - \lambda f}{1+\lambda} + \frac{1}{1+\lambda}\left(\frac{b - B^{\text{risky}}}{b - B^{\text{ins}}}\right)^{\lambda}\left(b - B^{\text{risky}}\right) = -f$$

implying

$$B^{\text{risky}} \equiv b - (b - h - f)^{\frac{1}{1+\lambda}}\left(b - B^{\text{ins}}\right)^{\frac{\lambda}{1+\lambda}}.$$

When the initial balance is endogenous in Section 2.4, similar to Bakkensen et al. (2025) the homeowner maximizes the initial balance up to the debt limit $B_0 = B^{\text{risky}}$, which solves the fixed point

$$B_0 = B^{\text{risky}} = \frac{B_0}{1 - e^{-rT}} - \left(\frac{B_0}{1 - e^{-rT}} - h - f\right)^{\frac{1}{1+\lambda}}\left(\frac{B_0}{1 - e^{-rT}} - B^{\text{ins}}\right)^{\frac{\lambda}{1+\lambda}},$$

where we have used the fact that $b = \frac{B_0}{1 - e^{-rT}}$. It reduces to equation (8) in the main text.