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What's at Stake? Understanding the Role of Home Equity in Flood Insurance Demand

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Why These Findings Are Important

Understanding why so few homeowners purchase flood insurance is important for understanding how increasing flood risk could pose risk to the financial system. This analysis has important implications for understanding the likely impact of climate change on housing markets. If many leveraged households choose not to insure against flooding, then the broader housing finance system, the GSEs that securitize mortgages, and the taxpayers will end up bearing uninsured flood losses.

Key Findings

1. **There is a causal relationship between home equity and flood insurance demand.**

2. **The ability to default deters flood insurance take-up.**

3. **Mandates increase flood insurance take-up.**

How the Authors Reached These Findings

The authors estimated the effect of home equity on the demand for flood insurance. To rule out determinants of insurance demand aside from home equity, such as income and disaster risk, they used the sudden variation in home prices from the housing boom and bust of the 2000s and early 2010s. This cycle created price variation within and across housing markets. The primary drivers of this price variation were changes in land values that were independent of gradual changes in flood risk, economic fundamentals, and demographics. Therefore, this setting is ideal for isolating the effect of home equity on flood insurance demand from that of the value of the physical structure at risk and other confounding factors. Using data from a new state-of-the-art flood risk model, the authors also included flexible controls for risk-dependent trends in flood insurance take-up.

What's at Stake? Understanding the Role of Home Equity in Flood Insurance Demand *

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Abstract

The consequences of climate change will depend on homeowners' incentives to manage their risk. We show that low home equity distorts borrowers' demand for flood insurance by shifting their risk to lenders and federally backed mortgage purchasers. To isolate the causal effect of home equity on disaster insurance demand, we study flood insurance take-up over the housing boom and bust across markets with different price dynamics. Insurance take-up follows rising and falling home equity. Mechanism tests suggest that mortgage default acts as implicit insurance for borrowers with low home equity. Consequently, leveraged households do not fully internalize their climate risk.

JEL: G52, G21, Q54.

Keywords: climate risk, disaster insurance, household finance, home equity, housing cycles, implicit insurance

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1 Introduction

Since 1980, the United States has seen more than $1.7 trillion in damages from major natural disasters, with environmental risk expected to grow over time with climate change (Dahl et al., 2018).[1] The economic costs of climate change in residential real estate markets will depend on how disaster risk is shared and priced by homeowners, lenders, insurers, and governments. Despite growing risk – and historically subsidized premiums – millions of flood-prone properties remain uninsured for flood damage. Identifying the causes of this flood insurance demand gap is critical for understanding how the incentives faced by households will shape the consequences of climate change in real estate markets.

This paper provides the first evidence that low home equity can distort borrowers' disaster insurance demand. We find that flood insurance take-up followed the rise and fall of home prices over the U.S. housing boom and bust of the 2000s. Moreover, the relationship between home prices and flood insurance demand cannot be easily explained by changes in the number or value of homes at risk, demographic changes, flood insurance regulations, or wealth and liquidity effects. Rather, our results suggest a risk shifting channel, where leveraged households have less incentive to purchase flood insurance because mortgage default acts as a form of implicit insurance where their costs of default are the deductible.

These findings suggest that leveraged households do not fully internalize their environmental risk because part of their risk is transferred to lenders instead. Lenders, in turn, can rely on mortgage securitization and credit rationing to reduce their disaster risk exposure (Laux et al., 2017; Ouazad and Kahn, 2019; Keenan and Bradt, 2020; Sastry, 2021; Bakkensen et al., 2023). The government-sponsored enterprises (GSEs) that underwrite residential mortgage securitization do not price disaster risk or enforce mandatory flood insurance purchase outside of floodplains. As a result, taxpayers bear the remaining risk, along with obligations from a host of post-disaster public transfers (Deryugina, 2017; Billings et al., 2019). As long as neither homeowners nor lenders bear the full cost of disasters, homes in risky areas will receive an implicit subsidy, creating a distortion that will grow with increasing climate risk.

We estimate the effect of home equity on the demand for flood insurance from the National Flood Insurance Program (NFIP). The main challenge to establishing such a causal relationship comes from the correlation between equity and other determinants of insurance demand, such as income and disaster risk. To overcome this obstacle, we use the sudden variation in home prices from the housing boom and bust in the 2000s, which drove similar changes in home equity. This cycle created price variation within and across housing mar-

[1] See https://www.ncdc.noaa.gov/billions/.

kets driven primarily by changing land values and independent of gradual changes in flood risk, economic fundamentals, and demographics. Therefore, this setting is ideal for isolating the effect of home equity on flood insurance demand from that of the value of the physical structure at risk and other confounding factors.

We find a large, positive relationship between home prices and flood insurance take-up during this period. For a measure of the housing boom, we use estimated structural breaks in the home price trends of each metropolitan statistical area (MSA) between 2003 and 2005 from Charles et al. (2018). Figure 1 provides a reduced-form depiction of our results in the raw data. The left panel shows that MSAs with larger housing booms saw greater increases in flood insurance take-up between 2002 and 2007, which roughly correspond to the beginning and the peak of the boom. The right panel, in contrast, shows that as housing booms turned into busts from 2007 to 2012, the MSAs with the largest initial booms had the lowest growth in flood insurance policies.

Our difference-in-differences specification exploits variation in the timing and magnitude of housing booms across MSAs and tracks the dynamics of home prices and flood insurance take-up over the boom-bust cycle. The results shows that flood insurance take-up closely follows the dynamics of home prices, has no pretrends, and is robust to controlling for annual income, housing turnover, population, employment, and recent floods. Using data from a new state-of-the-art flood risk model, we also include flexible controls for risk-dependent trends in flood insurance take-up. Using housing boom size and timing as instruments in an instrumental variable (IV) framework, we estimate a home price elasticity of flood insurance take-up around 0.3. We also run a series of robustness checks to verify that the effect reflects voluntary purchases and to address concerns about the exclusion restriction for our instrument.

These results are broadly consistent with a "risk shifting" effect suppressing flood insurance demand. For highly leveraged households, the option of mortgage default or bankruptcy after a disaster can act as a high-deductible substitute for formal insurance, shifting part of the expected flood damage away from them. Since the housing boom and bust might affect other possible drivers of flood insurance demand, we conduct an extensive set of analyses aimed at distinguishing risk shifting from alternative mechanisms. We start by assessing the extent of risk shifting using the empirical distribution of flood claims combined with loan-level data on mortgages. We find that borrowers' incentives from risk shifting strongly align with flood insurance take-up over the boom-bust cycle. Motivated by this finding, we further test three predictions from this mechanism. We find that the home price elasticity of flood insurance take-up is significantly higher in states with borrower-friendly judicial foreclosure laws that reduce the credit consequences of mortgage default. The elasticity is also higher where homes are more exposed to large "tail-risk" flood events that are more likely to push the owners of damaged homes into negative equity. Finally, take-up during the housing bust declines the most for homes built at the peak of the boom — a group that was highly leveraged with little home equity at the market's nadir.

On the other hand, we find little support for wealth effects or changes in liquidity as the main mechanism. The home price elasticity we estimate is an order of magnitude larger than existing estimates of wealth effects on insurance demand. Inconsistent with a wealth shock channel, we estimate a large effect of home equity on extensive margin flood insurance take-up but null effects on intensive margin demand through supplemental coverage and deductible choices. We also find little evidence that homeowners used their increased access to liquidity over the boom to avoid policy lapsation. While we cannot fully rule out these and other possible alternative explanations as contributing somewhat to our main findings, our heterogeneity tests described above and outcomes across intensive and extensive margins point towards an important role for risk-shifting.

This paper provides novel insights into the determinants of flood insurance demand. We are the first to estimate the causal effect of home prices on disaster insurance take-up, revealing an economically important relationship.[2] We also test various mechanisms of how low home equity may limit flood insurance demand, offering new explanations for the insurance gap to complement studies on the role of adverse selection and information frictions (Gallagher, 2014; Mulder, 2019; Wagner, 2021; Mulder, 2021; Collier et al., 2021), affordability issues (Netusil et al., 2021), and disaster aid (Billings et al., 2019; Kousky et al., 2018). Our findings suggest that mortgage default can insure households against climate shocks, albeit at the social cost of reducing incentives to formally insure or invest in adaptation.

Our results also extend the broader insurance literature studying the sources and effects of implicit insurance. Mahoney (2015) finds that bankruptcy acts as implicit health insurance and that a higher cost of bankruptcy induces greater insurance demand, while Gallagher et al. (2020) shows that relying on bankruptcy for implicit health insurance crowds out precautionary saving. Similarly, Finkelstein et al. (2019) find that the availability of uncompensated care to uninsured patients can explain their low willingness to pay for formal health insurance. However, it was less clear whether these incentives documented in health insurance would hold in the real estate context. Recent studies have found mixed evidence of strategic default, but point to "double trigger" events - simultaneous income

[2]Several studies have examined how insurance take-up in the NFIP is correlated with various factors (Kriesel and Landry, 2004; Kousky, 2011; Atreya et al., 2015). Typically, the analysis involves regressions that include home values as one of the covariates but not a formal treatment of unobserved confounding variables.

and equity shocks - as the main drivers of mortgage default (Foote et al., 2008; Guiso et al., 2013; Scharlemann and Shore, 2016; Bhutta et al., 2017; Fuster and Willen, 2017; Gerardi et al., 2018; Ganong and Noel, 2020). In the context of climate risk, we note that natural disasters are classic examples of such double trigger events. Furthermore, they often make homes and neighborhoods uninhabitable for some time, removing one of the key barriers to mortgage default.

Finally, this paper relates to how home prices and equity affect household decisions. An extensive set of studies have shown that high mortgage leverage and negative equity reduce incentives to invest in home improvements and labor search (Melzer, 2017; Donaldson et al., 2019; Bernstein, 2021). A finance literature has also studied risk-shifting behaviors by firms when their financial condition deteriorates or in instances where debt levels are high (e.g. Eisdorfer, 2008; Acharya and Viswanathan, 2011). We show that similar forces can reduce investment in climate risk management. Given a growing literature suggesting that climate change may already be influencing home prices, our estimates will be relevant to ongoing policy discussions around how climate change will affect financial and insurance markets.[3]

The rest of this paper proceeds as follows. Section 2 describes our data and key features of the National Flood Insurance Program and the housing boom and bust. Section 3 explains our empirical design, Section 4 describes the main causal estimates and Section 5 tests for the mechanism, and Section 6 concludes.

2 Data and Background

We construct an MSA-level dataset that contains measures of flood insurance take-up, home prices, and various MSA characteristics, such as flood risk, foreclosure laws, and demographics. Our final estimation sample consists of quarterly observations from 267 MSAs during the years 2001 to 2015. In this section, we introduce our data sources and provide background information about the National Flood Insurance Program and the housing boom and bust.

2.1 The National Flood Insurance Program

Our flood insurance data come from the National Flood Insurance Program (NFIP). The NFIP is a publicly run insurer under the Federal Emergency Management Agency (FEMA)

[3]See the related literature studying how climate and disaster risk are capitalized into home prices (Bernstein et al., 2019; Baldauf et al., 2020; Keys and Mulder, 2020; Murfin and Spiegel, 2020; Ortega and Taspınar, 2018) and how disasters affect housing markets (Boustan et al., 2012, 2020; Gibson and Mullins, 2020; Kousky, 2010; Zivin et al., 2022).

that writes over 95 percent of flood insurance policies in the United States (Kousky et al., 2018). Established in 1968, the NFIP covers 22,000 communities with more than five million policies in force nationwide during the sample period. In each community, FEMA defines the Special Flood Hazard Area (the SFHA, or "100-year floodplain") where the annual flood risk is at least 1 percent. The NFIP sets premiums using a national standard that depends on the property's flood zone designation and structural characteristics (Kousky et al., 2017). Because the flood maps are infrequently updated and NFIP has no means-tested subsidy, the home price changes we studied did not induce any response in insurance pricing (see Appendix Figure A4).

The NFIP, through various federal agencies and GSEs that purchase and insure mortgages, makes flood insurance purchase mandatory on any home that is purchased inside the SFHA with a federally-backed mortgage (henceforth the "mandatory purchase requirement").[4] However, this mandate was not always well enforced (Hecker, 2002). Outside the SFHA, homeowners have no federal requirement to purchase flood insurance. The overall take-up rate in the NFIP has been low, despite premiums often being lower than actuarially fair rates (Michel-Kerjan, 2010).

We obtain policy-level data from the NFIP public database released on OpenFEMA (OpenFEMA). This dataset covers the universe of NFIP policies written since 2009 with variables including property zip code, policy effective date, construction year, and a suite of policy characteristics, such as deductible and coverage limits. We extend our policy data back to 2000 using a similar database of policies shared with the Wharton Risk Center by the NFIP for research purposes. The two datasets contain similar sets of variables, allowing us to construct a consistent and comprehensive record of all NFIP policies written from 2000 to 2015. We aggregate the number of one-to-four family residential policies active at the end of each quarter into a quarterly MSA-level panel of flood insurance take-up for 2001–15. As shown in Table 1, MSAs have on average about 10,500 active policies, of which around 40 percent are located outside the SFHA.

The richness of our flood insurance data allows us to construct separate take-up measures for different subsets of policies. For example, we can calculate take-up for only those policies covering properties outside SFHAs, a feature that allows us to test the effects of home price changes on take-up independent of the mandatory purchase requirement enforced inside SFHAs. We also test other demand-related outcomes, such as the coverage amounts, deductibles, and renewal rates.

[4] For more details on the mandatory purchase requirement, see https://riskcenter.wharton.upenn.edu/wp-content/uploads/2019/10/The-Mandatory-Purchase-Requirement-September-2019.pdf.

2.2 Housing Boom and Bust

The variation we use to estimate the home price elasticity of flood insurance demand comes from the US housing boom and bust over the mid-2000s. During this period, average national home prices increased dramatically, peaking around 2007, before beginning a sharp decline that reached its trough in 2012.

These housing dynamics have inspired an extensive literature on their causes and consequences. Although active debate remains on the original cause of the cycle,[5] a few consistent empirical observations have emerged. The housing price changes were highly heterogeneous across markets, with some seeing sudden price acceleration, and others experiencing smooth changes throughout. More importantly, the sudden variations cannot be explained by any similarly large break in market fundamentals, such as productivity or demographics, that affect house prices (Sinai, 2012). Instead, surveys of home buyers at this time suggest they held strong investment motives and unrealistic beliefs about the long-term growth of property values (Case and Shiller, 2003). Together, these observations led to the widespread view that these dramatic price changes represented growing buyer optimism about future price growth (Kaplan et al., 2020).

This feature of the housing boom and bust—the sudden break in home prices relative to otherwise smoothly changing fundamentals—has been used in a related literature to study the relationship between home prices and other economic outcomes. To illustrate this variation, Figure 2 plots 2001–2005 housing price trends in four markets. In Athens (top left) and Galveston (bottom left), the housing price index increases linearly without any noticeable breaks, whereas a clear break in trend occurs in 2004 in both Tucson (top right) and Naples (bottom right). The latter pattern motivates a procedure, pioneered by Ferreira and Gyourko (2011), to identify a single trend break in each MSA's home price time series during 2001–2005. The structural break instrument is then calculated as the *change* in the slope of the time trend. For markets without a clear break, the procedure still identifies a "break" but with a minimal estimated size. This procedure is used in Charles et al. (2018) to construct the structural break instrument for a broader set of MSAs and eventually to investigate the relationship between educational attainment and labor market opportunities provided by the boom. The authors find that the instrument is economically relevant to changing house prices and highly correlated with the size of each MSA's subsequent housing bust.

Our analysis directly adopts this measure of structural breaks. Figure A1 plots the size and timing of these breaks across our sample of MSAs. Although the method identifies the

[5] See Mayer (2011) for a useful survey of this literature.

most likely break for every MSA, all the pre-2003 breaks are close to zero. Such MSAs effectively form a control group that saw smooth price changes during the period. The majority of large and positive breaks occurred between 2003 and 2005. Figure A2 maps the geographic variation in break size. Although coastal housing markets tended to have larger breaks than inland ones, different coastal markets varied substantially, allowing us to identify the effect of the boom independent of the underlying flood risk level.

As the instrument captures the *change* between the pre- and post-break house price trends, our key identification assumption is that unobserved factors in flood insurance demand continued to evolve smoothly in parallel trends between MSAs with different price trend breaks over the course of the boom and bust. Charles et al. (2018) present a series of empirical tests suggesting that underlying economic conditions and amenities in housing markets run smoothly even across the structural break in the housing market. In particular, the breaks are uncorrelated with pre-boom trends and levels in home prices, post-secondary education enrollment, employment, and wages.

For identification based on MSAs with different break timing or magnitudes, the key assumption is that their flood insurance demand would have continued on parallel trends, as in other difference-in-difference settings. We discuss these assumptions in more detail in Section 3.

2.3 Other Data

Our analysis also uses the following data sources for mechanism tests and regression controls.

Home prices. To measure home prices at the MSA level, we obtain the quarterly House Price Index (HPI) from the Federal Housing Finance Administration. The HPI measures changes in single-family home values using a weighted, repeat-sales methodology on millions of home sales, covering 363 metropolitan areas.

Flood risk. We also obtain a new national flood risk measure from the First Street Foundation (2020). The First Street Foundation Flood Model (FSF-FM) combines hydrological models, fine-resolution land cover and elevation data, and inventories of flood adaptation infrastructure to accurately estimate expected flood depths across the entire continental United States. This property-level measure allows us to construct multiple MSA-level measures that capture different aspects of flood risk in the given MSA. See Appendix C.1 for more details on these measures.

Foreclosure law. One of our mechanism tests relies on variation in foreclosure laws across states. We follow Demiroglu et al. (2014) to classify states as following judicial or nonjudicial foreclosure proceedings.[6] See Appendix C.2 for more details on the background of judicial foreclosure laws.

Additional covariates. For controls in our models, we include MSA-level log annual income, population growth, and the employment rate from the Bureau of Economic Analysis, and we also include residential housing transaction volume and share of foreclosure sales that we calculate using data from CoreLogic.

Loan-level data. To measure how home equity varies across markets over the housing boom-bust cycle, we use the CoreLogic Loan Level Market Analytics (LLMA) database. The LLMA data are from a national sample of loans that include detailed characteristics at origination and monthly data on payments, outstanding balances, and performance over the life of the loans. For every active single-family purchase loan, we measure its outstanding balance and LTV at origination and its outstanding balance in March of 2000, 2007 and 2012 with geography at the CBSA level. Combining these data points with the FHFA HPI and NFIP Flood Claims data, we estimate loan-level flood risk shifting, i.e. the share of expected flood losses exceeding borrower equity. These calculations are described in detail in Appendix C.3.

CoreLogic collects its LLMA data from large mortgage servicers. Our sample includes over 50 million loan-level balance snapshots from 239 CBSAs for a geographically diverse sample. In the first quarter of 2012, the LLMA dataset sample with non-missing geographic information contains 35% of the total value of single-family mortgage purchase originations (Federal Reserve Bank of New York, 2022).

3 Methodology

This section describes our empirical specifications. The first specification uses the housing boom structural breaks as a continuous difference-in-difference treatment to estimate the reduced-form relationship between the housing boom and flood insurance take-up. The second adapts these structural breaks as instrumental variables to estimate the home price elasticity of flood insurance demand. We conclude the section by describing empirical tests to examine the underlying mechanism.

3.1 Housing Boom Event Study

We start with a difference-in-differences event study framework to compare flood insurance take-up across MSAs with different boom intensities and timing. The estimating

[6] See footnote 2 of Table 1 for a complete list of judicial-review states.

equation is

$$lnNFIP_{mt} = \sum_{\tau=-9}^{24} \alpha_\tau (Post^{\tau}_{mt} \times \Delta P_m) + \delta' X_{mt} + \lambda_m + \lambda_t + \varepsilon_{mt}. \quad (1)$$

The main dependent variable $lnNFIP_{mt}$ is the inverse hyperbolic sine (IHS) transformation of the number of NFIP policies in MSA m at quarter t. Our main regressors are a set of interaction terms, together capturing an event time frame starting from nine quarters before the structural break in home prices and extending to 24 quarters after. The variable $Post^{\tau}_{mt}$ is an indicator of the τ-th quarter after the housing boom starts in MSA m.[7] Each indicator is interacted with ΔP_m, the structural break intensity in each MSA, as described in Section 2.2. The model includes a vector of controls, X_{mt}, which contains annual per capita income, home transaction volume, and total NFIP claims in the preceding four quarters, all of which are IHS transformed, population growth, employment rate, and the average FSF-FM risk score interacted with year indicators to control for differential time trends based on risk levels. The model also includes an MSA fixed effect λ_m to control for time-invariant features of the MSA, such as its baseline flood risk and amenities, and a quarter-year fixed effect λ_t to control for national trends in flood insurance take-up.

The α_τs are our coefficients of interest. Together, they capture the dynamics of the outcome variable over the boom-bust cycle, normalized by the initial boom size. The key identifying assumption in Equation (1) is parallel trends: MSAs with different housing boom intensities would have experienced similar changes in flood insurance take-up in the absence of the home price fluctuations around the housing boom and bust. We can partially test this hypothesis by examining whether the pre-boom β_τ coefficients are zero.

We also assess observable differences between housing markets with different cycles to inspect for factors that may be correlated with differential trends around the boom. Table A1 displays measures of flood risk from the Flood Factor model and flood insurance demand in the first quarter of 2001 across terciles of the housing boom structural break. The table shows that housing markets with larger housing booms tended to have greater flood risk and more flood insurance policies before the boom. Despite these level differences, there is no evidence of positive pre-trends in flood insurance take-up in MSAs that experienced larger boom sizes (see Appendix Figure A3 for 2001–2003 take-up trends in the raw data across terciles of the structural break). Nevertheless, one might still be concerned that areas with higher flood risk could have seen an increase in flood insurance demand around the housing boom. That concern motivates our decision to include flood risk controls interacted with

[7] The first indicator, $Post^{-9}_{mt}$, also includes observations earlier than the start of the event time frame. The last indicator, $Post^{24}_{mt}$, also includes those later than the end of the event time frame.

year in all of our baseline specifications, making our estimates robust to differential trends by flood risk.

We also estimate Equation (1) with the IHS-transformed home prices as the outcome variable. Because each β_τ is estimated flexibly, we can assess whether the dynamic effects of the housing boom and bust were similar across both flood insurance take-up and home prices. This provides an additional measure of plausibility to the parallel trends assumption given that any violation would need to match these boom and bust dynamics.

Under the parallel trends assumption, Equation (1) estimates the reduced-form effect of the housing boom and bust on flood insurance demand.

3.2 Instrumental Variables

The housing market structural breaks can be used as instruments to directly estimate the relationship between take-up and home price changes. In this framework, Equation (1) can be reinterpreted as the reduced-form relationship between the outcome and the instrument. We implement a two-stage least square (2SLS) estimation in which the first-stage regression is

$$lnHPI_{mt} = \sum_{\tau=0}^{24} \rho_\tau (Post^{\tau}_{mt} \times \Delta P_m) + \mu' X_{mt} + \gamma_m + \gamma_t + \omega_{mt}. \tag{2}$$

The house price index ($lnHPI_{mt}$) is our endogenous variable. We instrument the IHS-transformed house price index by the set of interaction terms between the event-time indicators and the structural break intensity ($Post^{\tau}_{mt} \times \Delta P_m$), exploiting essentially the same variation in Equation (1). The only difference is that this equation excludes pre-boom interactions, because they do not capture meaningful variation from the boom-bust cycle. The second-stage equation is

$$lnNFIP_{mt} = \beta \cdot \widehat{lnHPI}_{mt} + \delta' X_{mt} + \lambda_m + \lambda_t + \varepsilon_{mt}. \tag{3}$$

$\widehat{lnHPI}_{mt}$ are the instrumented values of the house price index from Equation (2). The equation includes the same set of controls as before.

Equation (3) estimates a single β coefficient that we interpret as the home price elasticity of flood insurance demand.

Exclusion Restriction

For our home price elasticity coefficients to be consistent in the IV framework, the exclusion restriction must hold. Given that the outcome of interest is flood insurance take-up, our first necessary assumption is that the house price trend breaks were uncorrelated with any changes in flood insurance demand outside of the home price channel. This assumption is supported by a body of research that suggests that most other economic fundamentals, including construction costs, were smoothly changing in the markets that saw these sudden price changes (Ferreira and Gyourko, 2011; Sinai, 2012).

Nonetheless, several plausible violations of the exclusion restriction are specific to our setting. We use a variety of approaches to address these concerns, as detailed below[8]:

1. Increased home sales: If new homeowners—especially those subject to the insurance mandate for SFHA properties—have a higher propensity to buy flood insurance, more home sales can mechanically create an increase in take-up. We address this in two ways. First, we control for home transaction volume in all regressions. Second, we separately examine the take-up of non-SFHA policies, which are not required by the insurance mandate. A similar or larger trajectory would suggest the mandate is not a major driver of the take-up response.

2. New construction in risky areas: To explore this possibility, we subset to policies on structures that are built before 2003. If the take-up response is robust among this set of policies, new construction is not likely the main pathway.

3. Home renovations: Renovated homes might have a higher physical replacement cost, prompting homeowners to purchase insurance. To investigate this channel, we examine the amount of building coverage purchased by policyholders as a dependent variable. This is usually commensurate with the insured structure's replacement value, so we would expect to see more coverage being purchased on the intensive margin if home renovations were driving the extensive margin increase in take-up.

4. Labor market conditions: If the housing booms improved labor market opportunities, residents may have become better able to afford flood insurance (Ferreira and Gyourko, 2011; Charles et al., 2019). To account for this possibility, we control for annual MSA income and employment rate in all regressions.

5. In-migration: Because the housing booms might also be associated with greater net in-migration, we control for population growth rate.

3.3 Heterogeneity Tests

The last part of our analysis uses a series of heterogeneity tests to evaluate the risk shifting mechanism as a potential driver of the relationship between flood insurance take-up

[8]For those concerned that the covariates discussed below are bad controls, Figure A5 shows that our results are similar using only MSA and quarter-year fixed effects.

and home prices. The theoretical motivation behind these heterogeneity tests is described by our illustrative model in Appendix B.2.

Our first test stems from the insight that flood insurance demand in MSAs with lower default costs should be more responsive to changes in home equity. We exploit differences in state foreclosure laws that drive variation in default costs. As discussed in Appendix C.2, judicial foreclosure laws raise lenders' costs of pursuing a foreclosure, thus reducing the credit risk of default for households after disasters.

A second prediction is that flood insurance demand in MSAs that have a larger fraction exposed to tail risk flood events that cause negative equity should also be more responsive to changes in home equity. Our measure of tail risk, constructed with the property-level First Street Foundation Flood Model, is described in Appendix C.1.

To formally test these predictions, we extend the 2SLS procedure to estimate heterogeneous effects based on foreclosure laws and flood risk. We do this by adding an interaction term between home prices and an indicator variable for MSAs with judicial foreclosure laws (or above-median flood risk) to the second-stage equation and then instrumenting for it using a corresponding interaction between the structural break instrument and the indicator. For details on this extended framework, see Appendix E.

As a third test of the risk shifting channel, we focus on the flood insurance demand response to the housing bust, comparing the change in take-up between homes built at the peak of the housing boom (2003-2005) to that among homes built before 2003. Homes built during the boom were more likely to be leveraged and to face low or negative equity over the housing bust. Thus, this segment of the housing market should be more responsive to declining home equity during the bust than existing homes. To test this prediction, we employed a first-difference specification to separately estimate effects of home prices on flood insurance take-up for each cohort during the bust. For details on this specification, see Appendix F.

4 Results

4.1 Dynamics of Insurance Choices Over the Boom-Bust Cycle

To investigate the dynamics of our main outcomes over the boom-bust cycle, we start with the difference-in-differences framework. We first estimate Equation (1) over the housing price index. The result is shown in the top panel of Figure 3. Each coefficient corresponds to a quarter relative to the start of a housing boom and estimates the relationship between the size of each MSA's house price trend break and its home price dynamics. As expected, these coefficients trace out a boom-bust cycle with an initial increase, a peak at the end of the third year after the start of the boom, and a subsequent decline. This shows that MSAs with larger structural breaks also experience larger fluctuations in home prices as the housing bubble unfolds. A one-standard-deviation increase in the initial boom size is associated with roughly 15 percent higher home prices at the peak. Little evidence supports a meaningful pre-trend, suggesting that these instruments effectively capture the timing of the sudden breaks in housing price trends.

The bottom panel of Figure 3 shows the results of Equation (1), with flood insurance take-up as the dependent variable. Consistent with the raw correlation in Figure 1, MSAs with larger home price structural breaks saw a larger increase in flood insurance policies. More importantly, the dynamic pattern of take-up closely follows that of house prices, peaking around the same time (three years after the start of the boom) before declining. A one-standard-deviation increase in the initial boom size is associated with a 5 percent higher flood insurance take-up at the peak. No evidence indicates a pre-trend, supporting the validity of the parallel trends assumption.

Figure 3 suggests that the housing boom-bust cycle had similar dynamic effects on both home prices and flood insurance take-up. These closely aligned trajectories suggest a direct relationship between the two, but alternative channels (described in Section 3.2) remain and may explain these changes in take-up. Below, we rule out these other factors as driving our results.

We first show that the increase in take-up was not caused by the mandatory insurance purchase requirement for homeowners with federally-backed mortgages or by new construction in the SFHA. If more properties are transacted and constructed in the SFHA during the boom, it might mechanically drive take-up through the mandate. To test this, we re-estimate Equation (1) over two subsamples of NFIP policies. The first subsample includes only policies written on structures built before 2003[9] and outside SFHAs that have no insurance mandate. For comparison, the second subsample includes only policies written inside SFHAs. These results are shown in Figure 4. The contrast between the two panels is striking: The estimated effect for pre-2003 non-SFHA policies is very similar to the full-sample estimates and much larger than the SFHA subsample estimates. This suggests that our findings are not driven by the insurance mandate or new construction. The small estimated effect inside the SFHA is also consistent with the insurance mandate lowering the elasticity of demand, as a relatively small number of households are on the margin of voluntarily purchasing insurance inside the SFHA.

Next, we also show that the increase in demand was not driven by more home renova-

[9] Figure A1 shows that the vast majority of notable booms occurred in or after 2003.

tions, which could increase the property value at risk of flood damage, leading to higher insurance demand. If this were the case, we would expect homeowners to purchase more building coverage, since 80% of policyholders purchase coverage equal to or greater than the replacement value of their home (Collier and Ragin, 2020).[10] To test this, we estimate Equation (1) on the IHS-transformed average amount of building coverage. These results are shown in Appendix Figure A6. We see little evidence of an increase in the intensive margin of coverage purchased on non-SFHA policies, suggesting that homeowners were not insuring more valuable structures. In contrast, the amount of coverage purchased on SFHA policies did increase over the boom, but did not decline over the bust. This is consistent with SFHA policyholders complying with minimum coverage requirements under the mandatory purchase requirement as mortgage balances increased over the housing boom.[11]

Using the same estimation framework, we examine other margins of the insurance decision to test whether risk preferences or perceptions changed over the course of the boom-bust cycle. Figure A8 shows the estimates of the share of newly enrolled SFHA policies with supplemental contents coverage.[12] A slight increase occurs following the start of the housing boom, but the magnitude is statistically insignificant and very small: A one-standard-deviation increase in boom size is associated with a 0.7 percentage point increase in the share of policies with contents coverage. Figure A9 shows the dynamics of the share of newly enrolled SFHA policies with the standard deductible,[13] which is largely unresponsive to the boom. These results suggest that risk preferences and perceptions are quite stable across the boom-bust cycle.

4.2 Home Price Elasticity of Flood Insurance Demand

In this section, we go from studying the dynamic reduced-form effect of the housing boom and bust on flood insurance demand to directly estimating the home price elasticity of flood insurance demand. Building on our findings, which suggest home prices were the primary channel affecting flood insurance demand, we use our instrumental variable framework to estimate the effect of a given change in home prices on take-up.

[10] The NFIP currently allows for a maximum building coverage of $250,000 for each r family residential structure. In the sample, the average coverage is $133,051 for SFHA policies and $164,286 for non-SFHA ones.

[11] The minimum required coverage is the least of (1) the unpaid principal balance of the mortgage; (2) the maximum available coverage ($250,000); or (3) 100 percent of the replacement value of the structure.

[12] Contents coverage protects the value of personal belongings that might be damaged by flooding. It is separate from the building coverage and not subject to the mandatory purchase requirement. Contents and structure coverage are bundled for non-SFHA policies.

[13] All non-SFHA policies have a standard deductible of $500. SFHA policyholders can choose either the standard deductible or a larger deductible at a different premium.

We estimate the home price elasticity of flood insurance demand using the 2SLS estimator described in Equations (2) and (3). The results are reported in Table 2. The first column displays the estimate based on all policies. The coefficient on the instrumented housing price index is positive and statistically significant at around 0.31. This implies that, on average, a 1 percent increase in home prices is associated with an approximately 0.3 percent increase in flood insurance take-up. In columns (2) and (3), we separately estimate this coefficient for SFHA and non-SFHA policies. Consistent with the patterns in Figure 4, the estimated elasticity of SFHA take-up, around 0.21, is much smaller than that of non-SFHA take-up (0.48). When we further subset to non-SFHA policies on homes built before 2003, we obtain an estimate of 0.33, again showing that the main effects are not due to new construction. All four columns have first-stage F-statistics[14] of over 30, confirming the strength of the instruments, and they include controls for MSA income, home sale volume, and time-varying effects of flood risk.

These estimates reflect the magnitude of the effect of home prices on flood insurance take-up. To put them into context, several studies have estimated an own-price elasticity of flood insurance demand between -0.3 and -0.1 (Kriesel and Landry, 2004; Atreya et al., 2015; Wagner, 2021; Mulder, 2021). In comparison, our estimates suggest that a 1 percent increase in home prices has roughly the same effect on overall take-up as a 2 percent decrease in premiums on overall take-up, or the effect of a 3 percent decrease in premiums on non-SFHA take-up. Kousky (2017) finds that hurricanes are estimated to lead to only 1.5 percent increase in voluntary purchases of flood insurance, which is equivalent to a 4.7 percent increase in home prices. Given the large variability of housing prices in both the short and long run, our results suggest that home prices play a substantial role in flood insurance demand.

4.3 Robustness Checks

We perform several additional analyses to test the robustness of our specifications and measurement of the outcome variable and boom instrument. First, we check that our main difference-in-difference result on total policy count is stable under different sets of controls (see Figure A5). The corresponding 2SLS estimates are also similar across the board, and of the estimates our main specification is the most conservative (see Table A2).

Second, we obtain similar difference-in-difference estimates by examining the count of newly enrolled policies – instead of all active policies – in a given quarter. Because NFIP policies are effective for one year, the number of active policies will respond with a lag

[14] We follow Sanderson and Windmeijer (2016) in calculating the F-statistic to account for multiple endogenous variables.

when existing policyholders want to drop their insurance. In contrast, the number of newly enrolled policies, which include newly written policies and renewals each quarter, might better capture the behavior of homeowners who are actively making insurance decisions. The estimated results on newly enrolled policies are consistent with our results on total policies, albeit with some additional noise due to seasonality (see Figure A7).[15] Table A3 reports the 2SLS estimates based on the number of newly enrolled policies, showing that these estimates are also similar to the main results.

In Table A4, we examine two potential issues in our specification of the boom-bust trajectory. First, our main specification allows for heterogeneity in the start time and magnitude of each housing boom but imposes homogeneity on the boom-bust dynamics across MSAs.[16] To allow for heterogeneous boom-bust dynamics, we interact the original instruments with MSA cohort indicators defined by boom start dates. The regressions based on quarterly and annual cohorts are reported in columns (1) and (2), respectively. These estimates are in general similar to our main estimate but slightly smaller, which could be due to the addition of many weak instruments.

A second potential issue is addressed in columns (3) and (4), which investigate potential misspecification issues related to MSAs with small or negative estimated structural breaks. Such estimates likely represent noise in the structural break estimation procedure rather than actual variation across MSAs. In column (3), we replace all negative values in the boom instrument with zero, which assumes that negative-boom MSAs actually experience no boom or bust. In column (4) we expand this set of no-boom MSAs to include those MSAs in the lowest quartile of positive booms. Both estimates are slightly larger than the main result, which is consistent with a reduction in measurement errors.

To assess whether our results are contaminated by using the two-way fixed effects (TWFE) estimator with staggered treatment timing, we re-estimate our results with the stacked event-by-event estimator following Cengiz et al. (2019).[17] Unlike TWFE with variation in treatment timing, the stacked estimator avoids spurious violation of the parallel trends assump-

[15] Due to strong seasonal patterns in enrollment, we control for MSA-by-quarter-of-year fixed effects in these specifications in place of MSA fixed effects to better account for idiosyncrasies in these patterns across MSAs. The results are noisier but very similar to MSA fixed effects.

[16] Of particular concern is the timing of when each boom turned into a bust. As described in Ferreira and Gyourko (2012), although the beginning of the housing boom was highly heterogeneous across MSAs, the timing of peaks was concentrated between the end of 2005 through the end of 2007. In Equation (2), imposing equality on the ρ_τ coefficients across housing boom cohorts might lead to a misspecified first-stage estimation. This could also cause a violation of the monotonicity assumption under the IV framework if some MSAs experienced home price declines during their busts relative to the pre-boom period. However, the coefficients plotted in the top panel of Figure 3 show that relative home prices in MSAs with larger booms remain well above their pre-boom levels even by the end of the bust, suggesting that the monotonicity assumption generally holds.

[17] See Appendix D for more details on our implementation and results.

tion that can occur with dynamic and heterogeneous treatment effects (Baker et al., 2021).[18] Figure D1 shows that our estimate of the effect of the housing boom on flood insurance take-up is little changed with the stacked estimator. In Table A5, we re-estimate the home price elasticity of take-up, applying the stacked estimator to the 2SLS framework. These estimates are also similar to our main results, again showing little bias from the staggered treatment timing.

5 Testing for the Risk Shifting Mechanism

Our results so far have established a robust and plausibly causal connection between home prices and flood insurance take-up. In this section, we empirically test whether a risk shifting channel might drive our results. When facing major disaster damage, highly leveraged households can default on their mortgage to limit losses, in effect shifting some of their losses to the debt holder. When home equity increased during the housing boom,[19] defaulting became more costly for households, increasing their willingness to pay for disaster insurance.

In the sections below, we first use loan-level data to show that homeowner's equity exposure to flood risk followed home prices in housing booms and busts. We find that, despite the increase in borrowing that accompanied the housing boom, homeowners still saw an increase in home equity which created an economically significant change in their exposure to flood risk. Then, we test three predictions of this mechanism, motivated by the model in Appendix B.2. Our results show that, even among markets or borrowers who experienced similar housing booms, the relationship between flood insurance demand and home prices is driven by subsets of homeowners and markets where we expect the risk shifting mechanism to have the largest effect.

[18] See also discussions of this issue in Sun and Abraham (2020), Callaway and Sant'Anna (2020), and Goodman-Bacon (2021).

[19] Despite a concurrent increase in mortgage debt over the boom, Figure A10 shows that home equity increases with house prices over the course of the housing cycle. Some may be surprised to see this result given that other sources show increasing current LTVs over the housing boom. To see how both LTV and home equity can rise together, consider a homeowner with a $400,000 mortgage on a $500,000 home (and thus $100,000 equity and 80% LTV). Suppose the home price doubles to $1,000,000. The homeowner could borrow an addition $400,000 against their higher home value, thus maintaining the same LTV, and still have doubled their equity. They could borrow up to a 90% LTV – increasing their LTV – and still have higher home equity.

5.1 Flood Risk Shifting: Evidence from Loan-Level Data

We define "flood risk shifted" as the share of expected flood damages that would exceed a homeowner's equity. In a default-triggering flood event, this is the portion of the damage borne by the debt holder rather than the household. Figure 5 shows how flood risk shifted changes as a function of the loan-to-value ratio (LTV), which is calibrated based on the empirical distribution of NFIP flood claims.[20] Our results do not depend on borrowers always defaulting whenever their flood losses exceed their equity. Rather, our measure is meant to show the relative changes in flood risk transfers over time and across groups, which are consistent even when we add higher default thresholds. It is also worth noting again that a post-flood event can act as a "double trigger" – an income shock paired with negative equity – that Ganong and Noel (2020) show drive most negative equity defaults.

As expected, flood risk shifting increases with LTV: The more leveraged the homeowner is, the higher the share of the expected damage is shifted away from them. Such shifting can be substantial, even for owners with moderate LTVs, but particularly for those with LTVs at the higher end. At an 80% LTV, approximately half of expected flood claims would exceed homeowner equity. As a summary statistic of the number of borrowers with substantial risk shifting, we measure the share of borrowers with "low equity", which we define as flood risk shifted exceeding 33% of expected claims.[21]

Figure 6 shows that housing booms increased home equity and decreased flood risk shifting. Using CoreLogic's loan-level data, we calculate the empirical share of borrowers with low equity in MSAs that did not have housing booms (negative or bottom third of structural break measures) against MSAs that did have housing booms in the first quarter of the years 2000, 2007, and 2012.[22] Figure 6 shows that MSAs with and without housing booms had similar levels of flood risk shifting in 2000, but by 2007, the share of owners with high risk-shifting ratios had fallen by 20 percentage points in boom MSAs even as it remained constant in MSAs without booms. By 2012, after the bust, the risk shifting gap had again closed.

These results suggest that the price changes over the course of the housing cycle were large enough to significantly change the risk exposure of leveraged homeowners who might default after a flood.[23] Furthermore, the timing and magnitude of changes in flood risk

[20] Appendix section C.3 describes these calculations in more detail.

[21] The 33% cutoff corresponds to an LTV slightly above 70%, which is where flood risk shifting starts to increase more rapidly with LTV. Appendix Figure A11 shows results consistent with Figure 6 across the full flood risk shifting distribution.

[22] Appendix Figure A11 shows results consistent with Figure 6 across the full flood risk shifting distribution.

[23] The LLMA data do not allow us to track smaller second loans, such as home equity loans, originated after purchase. While such loans could attenuate the decline in risk shifting from housing booms, owners would have to borrow an additional dollar for every dollar in home price appreciation to see no net increase

shifting between MSAs with and without housing booms aligns with the changes in flood insurance take-up in Figure 3. We formalize this risk shifting mechanism in a model in Appendix B. In the following sections, we will test three predictions from the model.

5.2 Default Costs and Tail Risk Exposure Heterogeneity Tests

In this section, we test two MSA-level predictions from the risk shifting mechanism above. First, we test whether there is a stronger relationship between house prices and flood insurance take-up in MSAs with lower default costs than in MSAs with higher default costs. This test exploits differences in the baseline cost of default across states with and without laws that require judicial review of foreclosure proceedings that reduce the credit risk of default for borrowers. In states without judicial review protections, the flood loss threshold where uninsured borrowers would default is higher, weakening the relationship between risk shifting and home equity. Thus, flood insurance demand should be less responsive to changing home prices in states without judicial review if flood risk shifting drives our results.

Figure 7 plots the coefficients from estimating Equation (1) separately in states with and without judicial review over home prices (left panel) and non-SFHA flood insurance take-up (right panel). Despite similar home price trends conditional on the initial break size, flood insurance demand in judicial review states is much more responsive, which is consistent with the risk shifting mechanism.

Next, we test whether MSAs with greater exposure to tail risks see greater increases (decreases) in take-up in response to increases (decreases) in house prices relative to MSAs with lower tail risk. The effect of home equity on insurance demand is increasing in the probability that flood damage will be large enough to induce default. Using flood risk estimates from FSF-FM, we calculate a measure of tail risk exposure for non-SFHA homes (see Appendix C.1 for details). We examine how the effect of home equity varies across MSAs with above-median versus below-median tail risk exposure.[24] Note that all regressions control for the time-varying effect of the *average* risk level. Therefore, any heterogeneity can be attributed to the default-inducing part of the risk—that is, the *tail* risk in the MSA.

Figure 8 plots the coefficients from estimating Equation (1) separately for these two groups of MSAs on home prices (left panel) and non-SFHA flood insurance take-up (right panel). Although we see a slight divergence in price trends between the two groups, the high-

in home equity. Most estimates suggest that over the housing boom households only extracted between \$0.07 (Bhutta and Keys, 2016) and \$0.25 (Mian and Sufi, 2011) in home equity for every \$1 in home price appreciation.

[24] One concern with this variable is that MSAs with higher tail risk might also have higher premiums. Fortunately for our analysis, almost all non-SFHA properties face uniform rates that have changed little over this period, as the NFIP has not developed detailed risk assessments outside of floodplains.

tail-risk group has a much larger flood insurance take-up response,[25] which is consistent with the risk shifting mechanism.

For the two tests above, we formally test the statistical significance of their findings by applying the 2SLS estimator with an additional interaction term between home prices and an indicator of judicial review law or above-median tail risk.[26] These results are shown in Table 3. These estimates confirm the results from our difference-in-differences exercises: MSAs in judicial review states and those with high tail risk both have higher home price elasticities of flood insurance demand. Moreover, the differences are statistically significant and economically large. States with judicial review have a home price elasticity of flood insurance demand of 0.67 versus only 0.3 in states without such laws. MSAs with above-median tail risk have a home price elasticity of flood insurance demand of 0.78, versus 0.45 in states with below-median tail risk. In columns (3) and (4), we also report the estimates on SFHA policies. In sharp contrast to the non-SFHA results, neither margin shows notable differential effects. As discussed, given the mandatory purchase requirement, SFHA homeowners likely face different incentives and have less room for take-up adjustments.

5.3 Household-Level Heterogeneity Test

In this section, we test at the household level whether low-equity borrowers had a particularly strong response to equity changes during the housing boom-bust cycle. The key idea is to compare the change in flood insurance take-up between 2007 and 2012 between homeowners who purchased their homes during 2003-05 near the peak of the housing booms against those who purchased before the housing boom started. While these homeowners all experienced similar housing busts between 2007 and 2012, and thus changes in wealth and local economic conditions, those who bought at the peak of the boom ended up with much lower home equity and thus more flood risk shifting. Under the risk shifting hypothesis, we would expect their flood insurance demand of the 2003-2005 borrowers to decrease more during the bust.

We begin the analysis by verifying that the 2003-2005 cohorts of homeowners experienced a more dramatic increase in flood risk shifting during the bust. Figure 9 measures the share of leveraged homeowners with flood risk shifting ratios exceeding 33%, whom we call "low equity" borrowers, in the first quarters of 2007 and 2012 by loans originated between 2003 and 2005 (lighter bars) versus those originated before 2003 (darker bars). Panel (a) shows that in markets with housing booms, the increase in low equity borrowers was concentrated

[25] The divergence in the first stage is captured in our 2SLS estimator, described in the next paragraph, by interacting the price trend structural breaks with the above-median tail risk indicators.

[26] The precise estimation equations are presented in Appendix E.

among loans originated between 2003 and 2005, while loans originated earlier saw little increase in risk shifting. In contrast, panel (b) shows that in MSAs without housing booms both cohorts experienced similar increases in risk shifting.

We formalize the intuition from Figure 9 with a first-difference regression of the changes in low equity borrowers between 2007 and 2012 over instrumented home price changes interacted with borrower cohort indicators as described in Appendix F, with results shown in Table 4, columns (1) and (2). Column (1) shows that 1% decrease in home prices over the bust led to a 0.55 percentage point increase in low equity borrowers. However, there is substantial heterogeneity in this effect based on home purchase timing. Column (2) shows that the entire increase in the low equity share can be explained by borrowers who purchased between 2003 and 2005, whereas those who bought earlier saw little relative increase in their flood risk shifting.

Motivated by these trends in the home equity data, we compare the flood insurance take-up response during the housing busts for owners of homes built between 2003 and 2005 to the take-up response for owners of homes built before 2003.[27] We use similar specifications as above with log NFIP policies by cohort j and MSA m as the dependent variable.[28] Columns (3) and (4) of Table 4 present these estimates.[29] Column (3) shows that the home price elasticity of overall take-up over the bust is 0.38. Yet, when we separate out the policies on homes built between 2003 and 2005 in column (4), we find that their elasticity increases sharply to 1.4, which is more than four times that of the rest of the policies on older homes. These results parallel the estimates of the share of low equity homeowners and are consistent with the risk shifting mechanism.

To sum up, the household-level test also provides strong support for the risk shifting mechanism because the cohort of home buyers who saw the largest increase in flood risk shifted over the housing bust also had the largest decrease in flood insurance take-up.

[27]We use insurance policies on homes built between 2003 and 2005 as a proxy for likely buyers during the housing boom because we do not observe home purchase year in the flood insurance policy data. This introduces some measurement error into our results because some homes built before 2003 may have been bought during the boom, and some homes built 2003 and 2005 may have been bought later during the bust, likely attenuating the actual difference in flood risk shifting between the two groups relative to our loan-level measures.

[28]It is worth noting that the interaction term captures the effect of flood risk shifting on flood insurance demand separately from the general equilibrium economic effect of housing busts, while controlling for differences in take-up trends between the boom and pre-boom cohorts across MSAs. To control for the effect of increased foreclosures on flood insurance take-up, we include the share of sales through foreclosure in the housing bust specifications.

[29]Table A6 provides similar estimates based on the boom period, as well as a breakdown by SFHA and non-SFHA properties.

5.4 Further Discussion and Alternative Mechanisms

In the previous sections, we find strong evidence consistent with all three predictions of the risk shifting channel, suggesting that it plays an important role in the relationship between home equity and flood insurance take-up. In this section, we assess intensive margin insurance demand responses and consider alternative mechanisms based on changes in wealth or liquidity over the course of the boom-bust cycle.

Risk Shifting and Intensive Margin Responses

In contrast to our results that document the strong effect of the housing boom on extensive margin flood insurance take-up, we find little effect on intensive margin coverage across building coverage purchased, purchase of supplemental contents coverage, and opting into higher deductibles (Figures A6, A8, and A9). These intensive margin null results are consistent with the risk shifting mechanism. As previously mentioned, a large majority of NFIP policyholders purchase building coverage near or above their home's replacement cost or else at the coverage cap (Collier and Ragin, 2020), making it an unlikely margin of adjustment. In addition, a homeowner who anticipates defaulting past some flood damage threshold would be unlikely to partially insure. With respect to other intensive margin decisions, outside the SFHA, contents coverage is bundled with structure coverage and there is only one standard deductible choice. Inside the SFHA, given that almost all mortgaged homeowners are required to buy flood insurance up to their outstanding balance, we do not expect the risk shifting mechanism to apply. However, as discussed below, we would expect wealth or other general equilibrium effects to affect these intensive margins of flood insurance demand.

Liquidity Effect

The housing boom saw a substantial expansion in households' access to liquidity through home equity loans and looser credit conditions (Mian and Sufi, 2011; Bhutta and Keys, 2016). If low flood insurance take-up were driven by households being forced to intermittently forgo flood insurance to manage liquidity shocks, favorable borrowing conditions might increase take-up.

If greater equity eased liquidity constraints, we would expect more policyholders to renew their flood insurance coverage. Over 20 percent of flood insurance policies lapse in their second year (Michel-Kerjan et al., 2012), and policy lapsation has been shown to be driven by liquidity constraints across various insurance settings (Hambel et al., 2017; Gottlieb and Smetters, 2021).

To test the liquidity channel, we estimate Equation (1) with the one-year renewal rates as the dependent variable. Figure A12 shows these results for SFHA (left panel) and non-SFHA (right panel) policies. We see little evidence that the housing boom increased the one-year renewal rate for either group of policies, suggesting that liquidity was not likely the main factor driving the relationship between home equity and insurance demand.[30]

This liquidity channel is also inconsistent with existing evidence on how home equity extraction was used over the housing boom. Both Mian and Sufi (2011) and Bhutta and Keys (2016) find that home equity loans were used to increase spending on consumption and durable goods rather than pay down high interest debt or fund precautionary savings. Furthermore, home equity borrowers had much higher default risk over the housing bust. Given this evidence that households were not using home equity loans to hedge other sources of financial risk, it is unlikely they were using these loans to maintain disaster insurance coverage.[31]

Wealth Effect

Our findings might also be consistent with the "wealth effect puzzle", a pattern found in recent studies where insurance coverage increases with wealth (Armantier et al., 2018; Gropper and Kuhnen, 2021). This effect contradicts the standard theoretical prediction that insurance demand decreases with wealth. To assess the possibility that the same mechanism drives our results, we compare the magnitude of effect from these studies with our estimates, noting the main caveat that the other studies' estimates are based on other insurance types. In Armantier et al. (2018), the implied elasticity of auto insurance spending with regard to home values is 0.07.[32] The home price elasticity of life insurance take-up is 0.08 in Gropper and Kuhnen (2021).[33] Given that our non-SFHA take-up elasticity of 0.48 is much larger

[30] We focus on the one-year renewal rate to capture more policy lapsations due to liquidity conditions rather than household learning about local flood risk. We find similar results using three- and five-year renewal rates as our dependent variables. These results are available upon request.

[31] One may wonder whether the risk-shifting mechanism would also predict an increase in renewal rates. Any homeowner who bought flood insurance in the previous year presumably thought they had enough equity to be worth insuring, which would still be true the next year unless home prices had fallen enough to reduce their equity. Consistent with this channel, Table 4 shows a large decline in flood insurance take-up over the course of the housing bust among homeowners who were most likely to have low or negative equity.

[32] Calculation based on Armantier et al. (2018): Table A8 reports that a $100k increase in home wealth is associated with an increase of 0.31 in the "insurance index". Following the authors' method of calculation on p.21, this implies a 0.31/1.1*(909-812) = $27.34 increase in cost. Using an average home value of $268.52k (Table 3) and average premium of $994.34 (Table 4), we calculate the elasticity to be (268.52/100)*(27.34/994.34) $\approx$ 0.07.

[33] Calculation based on Gropper and Kuhnen (2021): Table 3 shows that a $100,000 increase in housing wealth is associated with a 0.93 p.p. increase in the probability of having life insurance. Using an average home value of $301,387 and an average take-up of 36% (Table 1), the elasticity is (301,387/100,000)*(0.0093/0.36) $\approx$ 0.08.

than both of these estimates, we conclude that the wealth effect is unlikely to be the main driver of our results.[34]

Beyond this comparison of magnitudes, it is worth explicitly listing how our previous results fail to support the wealth effect as a primary driver of our findings:

- Whereas the wealth effect would predict more demand for intensive margin as well as extensive margin coverage, we find little evidence of a positive relationship between contents coverage or deductible choice and home prices (Figures A8 and A9)

- A wealth effect would not predict the higher home price elasticities of take-up in states with judicial foreclosure laws or more tail risk as found in the heterogeneity tests reported in Table 3.

- Comparing columns (1) and (2) of Table 3 to columns (3) and (4), a wealth effect would also not predict that these heterogeneous elasticities would be present for non-SFHA policies where borrowers are typically not required to carry flood insurance but not for SFHA policies where federal law requires most borrowers to carry flood insurance.

- The wealth effect would also not predict that the decline in flood insurance take-up over the housing bust would be concentrated among buyers with higher LTVs, as we show in Table 4.

Other General Equilibrium Effects

Besides the credit, wealth, and risk shifting channels mentioned above, the housing boom and bust caused a host of general equilibrium changes in local economies and housing markets. This study does not rule out all other potential causal channels besides risk shifting between flood insurance demand and home prices. However, we do argue that the pattern of our results convincingly show that risk shifting plays an economically significant role in flood insurance demand.

Of particular importance to our argument is our heterogeneity findings. We find that among MSAs with similar housing cycles, and thus plausibly similar general equilibrium changes, the home price elasticity of flood insurance demand was stronger in precisely the areas or among subsets of owners within MSAs where we would expect the risk shifting effect to be larger. Table 3 shows that the home price elasticity of flood insurance demand was stronger in MSAs with borrower-friendly judicial foreclosure laws or where tail risk made

[34] Note that the home price elasticity of flood insurance spending is trivially equal to our take-up elasticity because all non-SFHA policies face approximately the same premiums.

flood damages exceeding equity more likely. Table 4 shows that the decline in flood insurance take-up over the housing bust was concentrated among borrowers with high LTVs.

Expectations of Home Price Growth and Volatility

A more subtle mechanism that might drive the relationship between flood insurance take-up and home prices over the housing boom and bust are beliefs about future home prices and home price volatility. Case et al. (2012) show that short-run and long-run home price expectations followed the rise and fall of the housing boom and bust. It is possible that even high LTV borrowers bought insurance over the boom to avoid defaulting after a flood and losing future price gains. Conversely, low LTV borrowers may have dropped their coverage in the bust anticipating that they might soon have low or negative equity anyway. On the other hand, price expectations will not affect insurance demand absent a risk-shifting channel. If a borrower does not intend to default after a flood, then whether or not they have flood insurance does not affect their future home price gains. Thus, we see these dynamic considerations as consistent with the risk-shifting channel.

A related point is that beliefs about home price or replacement cost volatility may have shifted with the housing boom and bust. Although we are not aware of survey evidence showing such changes in buyer beliefs over volatility in this period, housing market actors may have anticipated the possibility of a boom-bust cycle or mean reversion in the housing market. Higher volatility would dampen the risk-shifting demand effect at the peak of the boom if some buyers realized that their increased equity might disappear with the next housing cycle. On the other hand, volatility wouldn't affect flood insurance demand without risk-shifting. Following the same argument regarding price expectations, a homeowner's expectations about the spread of future price trajectories should have as little effect on their annual insurance choice as the mean of those paths.

Homeowners may also have believed that replacement costs, and by extension the cost of a flood, became more volatile during the housing boom. First, we see little evidence of a consistent relationship between the boom-bust cycle and coverage in Figure A6. Second, Ferreira and Gyourko (2011) find stable construction costs around housing booms and busts. Third, such general beliefs about volatility could not explain the heterogeneous home price elasticities we find across homeowner cohorts with different LTVs over the housing bust, states with different foreclosure laws, or MSAs with different exposure to default-inducing tail risks. Thus, we see little reason why beliefs about volatility should affect insurance demand outside of a risk shifting channel.

6 Conclusion

We find a significant and positive relationship between home prices and flood insurance take-up over the course of the housing boom and bust of the 2000s. The price variations reflect large changes in home equity for existing homeowners but little difference in their actual structural value at risk. After ruling out alternative explanations, such as new construction or mandatory purchase requirements imposed by the NFIP, our findings suggest that home equity plays a causal role in flood insurance demand. Moreover, the magnitude of the effect is comparable to other primary factors, such as premiums and flood events, in shifting flood insurance demand.

Findings from multiple mechanism tests are consistent with the risk shifting channel, where leveraged homeowners have less incentive to purchase formal flood insurance because mortgage default provides a form of implicit insurance that shifts part of the expected damage away. Using loan-level data, we find direct evidence of such risk shifting changing over the boom-bust cycle that corresponds closely to the trajectory of flood insurance take-up. We also find higher home price elasticities of flood insurance demand in states where default is less costly and in states with higher risk of extreme flood events that might induce mortgage default. In addition, we find a much stronger response to the subsequent housing market bust among the owners of homes built at the peak of the housing boom, the same group with the greatest increase in leverage and flood risk shifting during the housing bust. While we consider alternative channels through liquidity, wealth, or other general equilibrium effects, they ultimately fall short in explaining the patterns and magnitudes of our findings.

These results have important implications for understanding the likely impact of climate change on housing markets. As disaster risk increases over time, more homeowners will face a choice between purchasing insurance or risking default after a flood. The significant elasticity between changes in home prices and flood insurance take-up, combined with continuing low take-up rates in the NFIP, suggests that many leveraged households will choose not to insure. This means that some of their losses will ultimately be borne by the broader housing finance system or the GSEs that securitize mortgages and the taxpayers that support them. Home price declines driven by a bursting "climate bubble" along the coast (Bakkensen and Barrage, 2017; Bernstein et al., 2019; Keys and Mulder, 2020) could exacerbate these dynamics by reducing insurance demand. Our results are also relevant to other disaster insurance markets for wildfire and hurricane coverage that are increasingly under stress.

However, our findings do point to two promising policy interventions. First, expanding the mortgage purchase requirement to high-risk non-SFHA homes may lead owners and lenders to better internalize their flood risk. The SFHA mortgage mandate exists in part for this reason, and our findings suggest that underinsurance due to misaligned incentives in leveraged markets is prominent outside the SFHA. Second, GSEs could start pricing the risk of disaster-induced default into securitization. This would improve lenders' incentive to require borrowers to maintain flood insurance.

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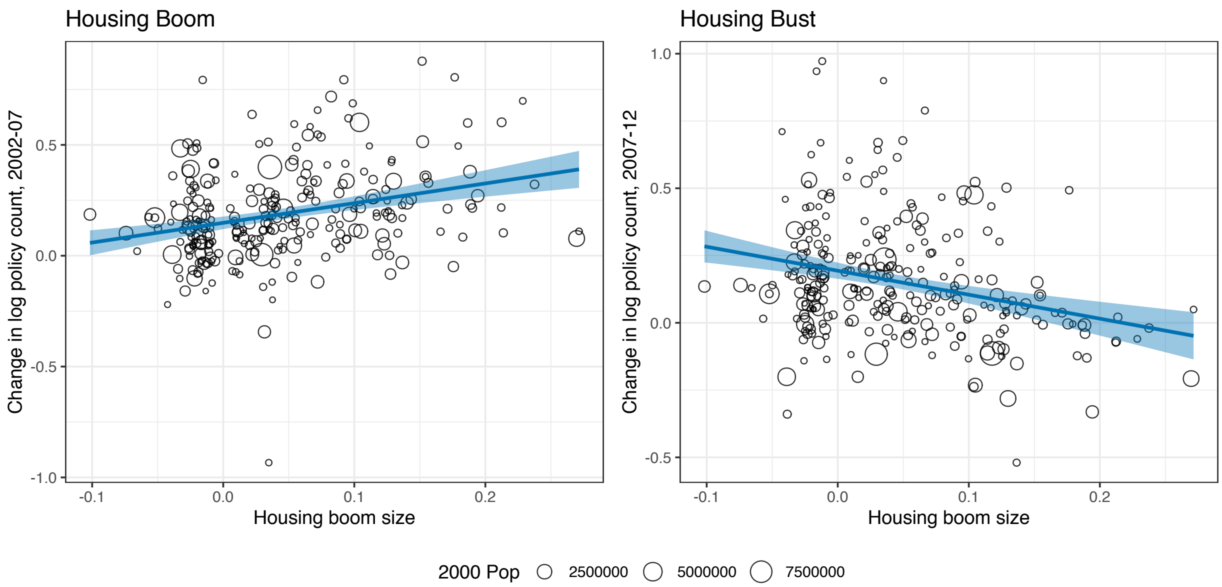
Figures

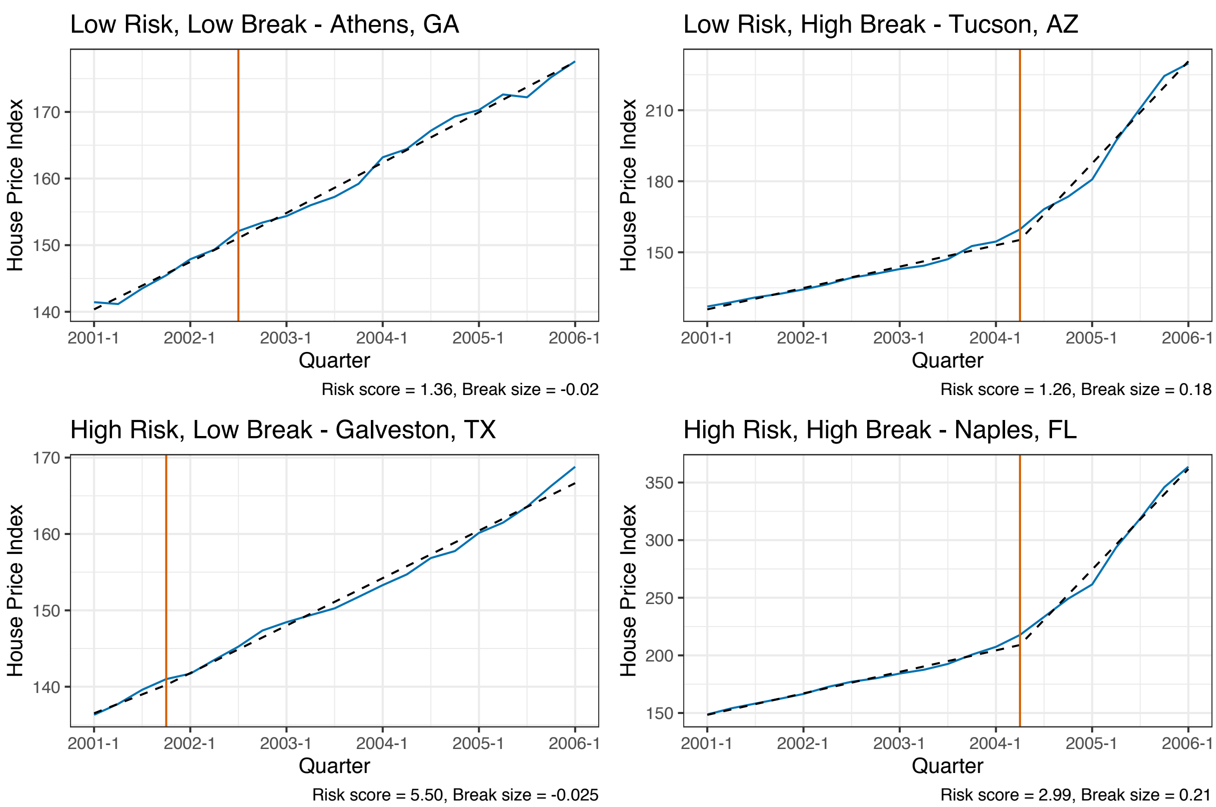
Figure 1: Reduced-Form Relationship Between Boom Size and Take-Up



Source: OpenFEMA policy data and Authors' Analysis

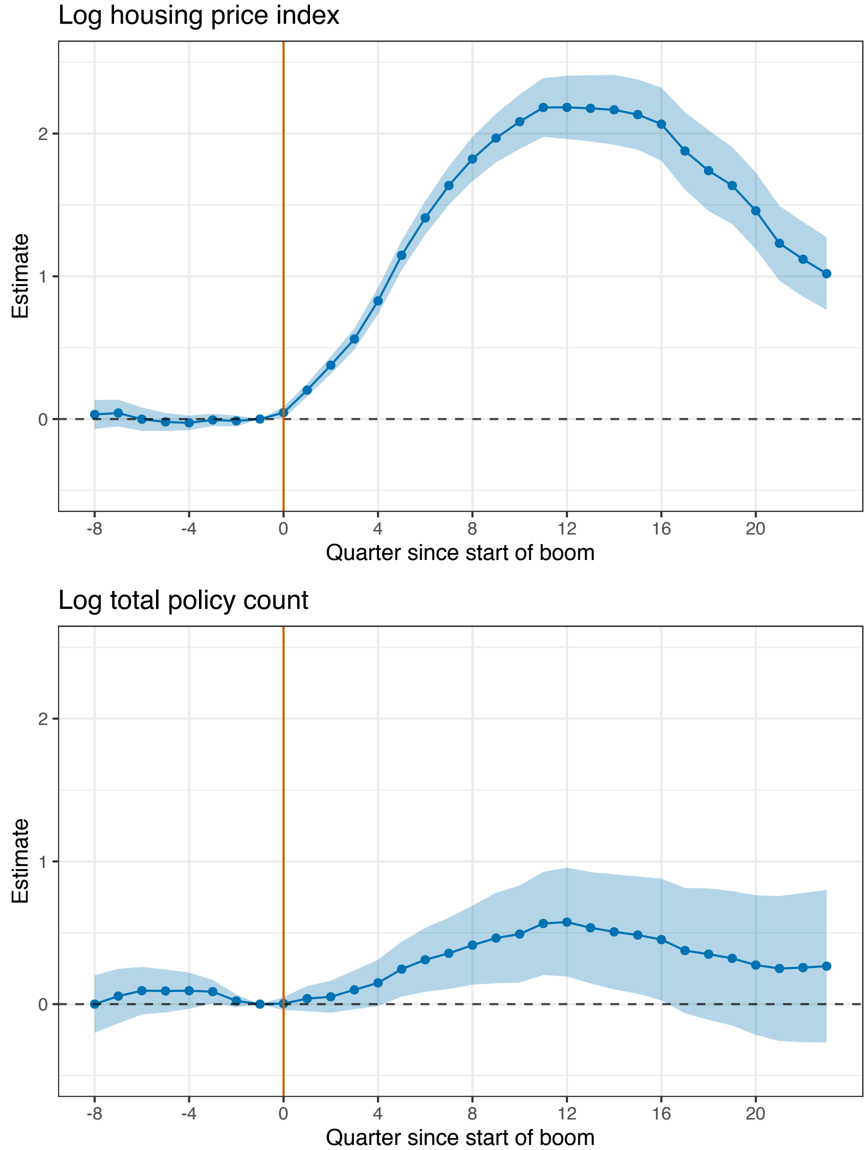
Notes: Each circle represents an MSA. The x-axis displays the size of the housing boom, and the y-axis displays the change in log NFIP policy count between 2002 and 2007 in the left panel and 2007 and 2012 in the right panel. The boom size measure comes from the structural break estimates in Charles et al. (2019).

Figure 2: Examples of Housing Booms



Source: Structural break estimates from Charles et al. (2019) and Authors' Analysis
Notes: This figure shows the quarterly series of the housing price index for four MSAs. The four MSAs each represent a group of MSAs classified based on low/high risk and low/high break. In each panel, the blue solid line presents the house price series, the black dashed line presents the predicted value from the structural break model, and the red vertical line presents the timing of the break. The note below each panel displays the average risk score in the MSA and the estimated break size.

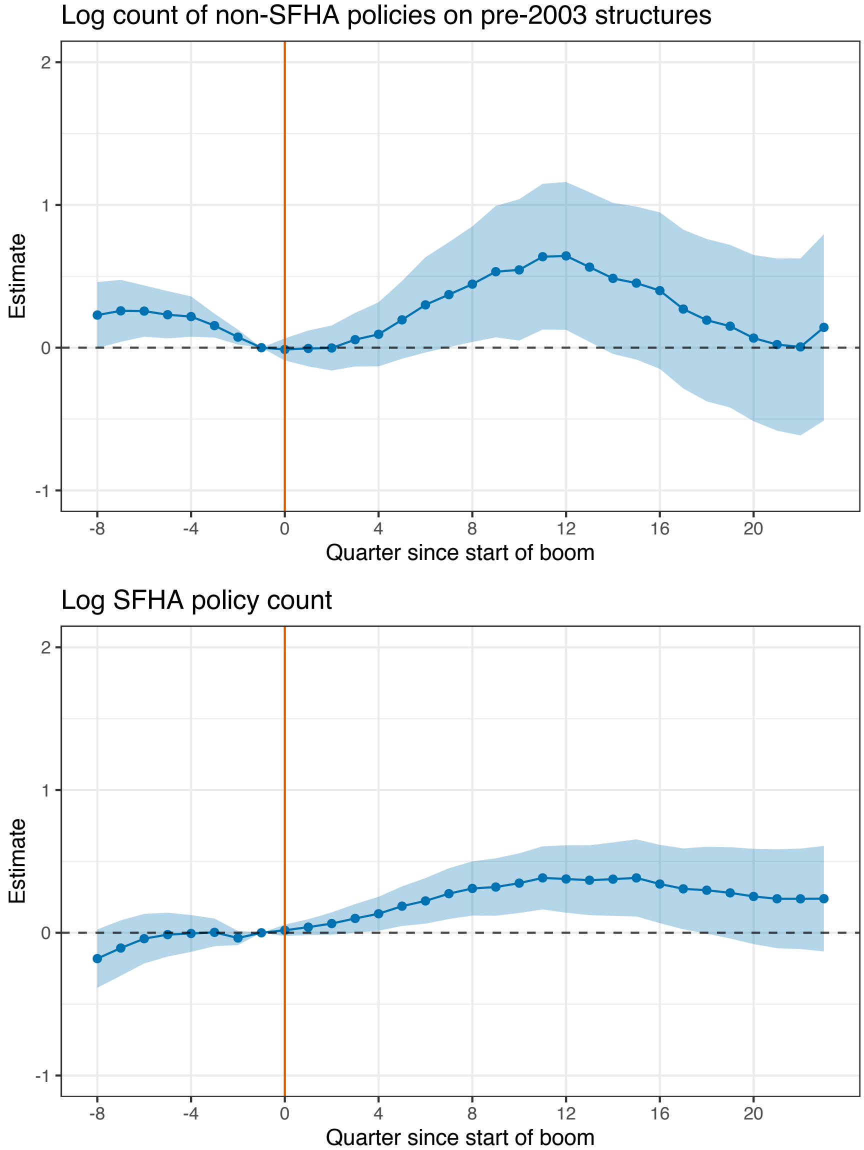
Figure 3: Dynamics of the House Price Index and Insurance Take-Up



Source: OpenFEMA policy data and Authors' Analysis

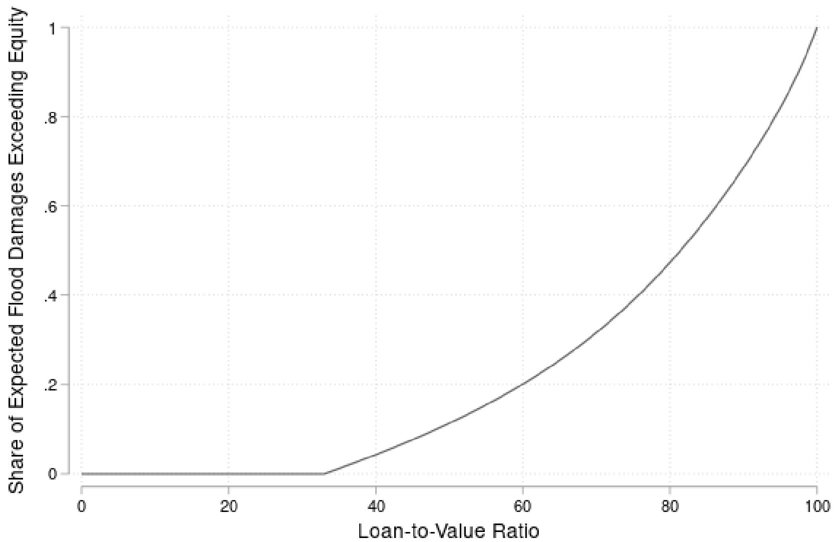
Notes: This figure plots the estimated coefficients and their 95 percent confidence intervals from Equation (1) for HPI (top panel) and total flood insurance policy count (bottom panel). Both dependent variables are IHS transformed. The policy count includes all one-to-four family policies.

Figure 4: Dynamics of Insurance Take-Up in Two Subsamples



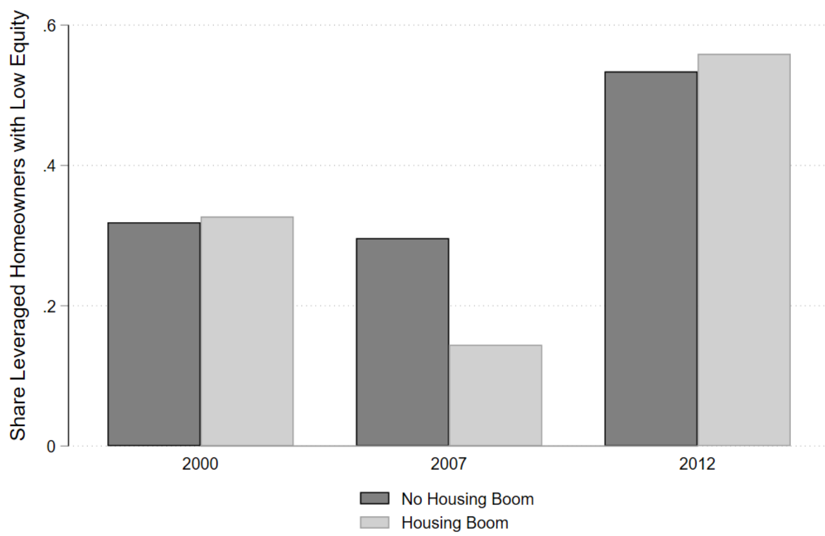
Source: OpenFEMA policy data and Authors' Analysis
Notes: This figure plots the estimated coefficients and their 95 percent confidence intervals from Equation (1) for the count of flood insurance policies written on structures outside the SFHA and constructed before 2003 (top panel) and those inside the SFHA (bottom panel). Both dependent variables are IHS transformed.

Figure 5: LTV and Flood Risk Transfers



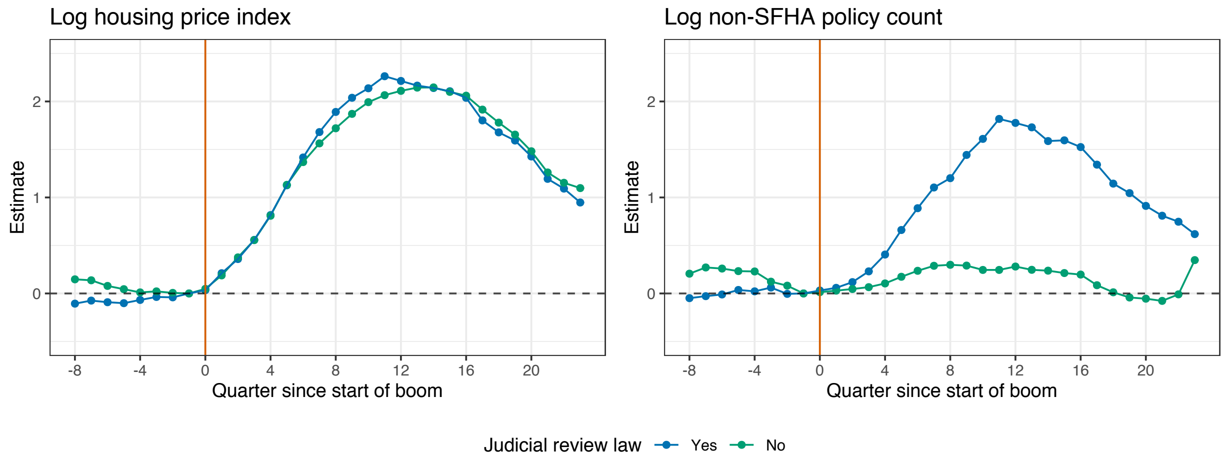
Source: OpenFEMA claims data and Authors' Analysis
Notes: This figure plots the relationship between a homeowner's loan-to-value ratio (LTV) and the size of their flood risk transfer, defined as the share of expected flood damages that would exceed their equity. Calculation details are given in Appendix Section C.3.

Figure 6: Flood Risk Transfers over the Housing Cycle



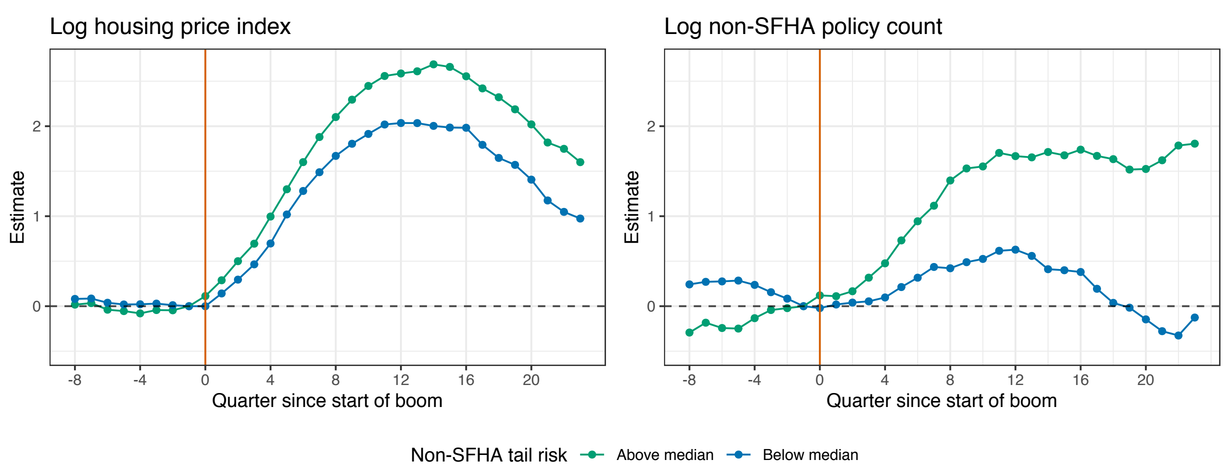
Source: CoreLogic, Inc. LLMA data and Authors' Analysis
Notes: This figure shows the share of leveraged homeowners with high flood risk transfers in the first quarters of 2000, 2007, and 2012 in MSAs with and without large housing booms. High flood risk transfers are defined as more than 33% of expected flood losses exceeding equity.

Figure 7: Heterogeneity by Judicial Review Law



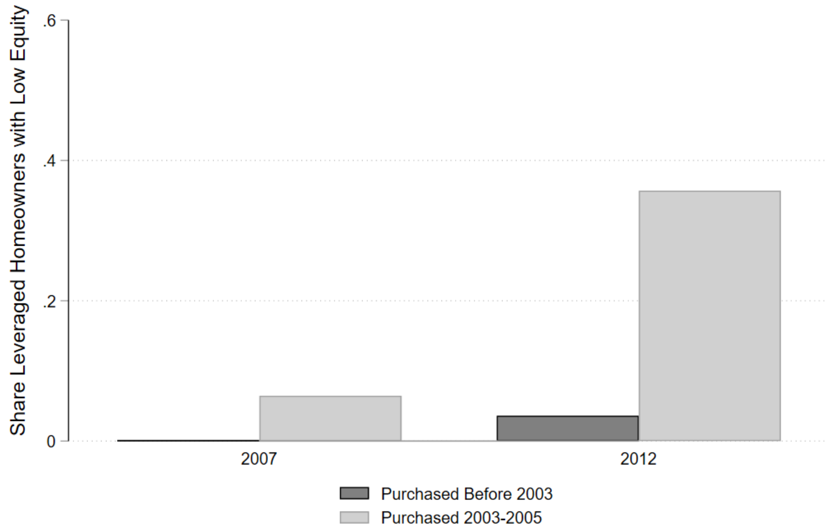
Source: OpenFEMA policy data and Authors' Analysis
Notes: This figure plots the estimated coefficients from Equation (1) for home prices (left panel) and non-SFHA flood insurance take-up (right panel) separately for MSAs in states with judicial review foreclosure laws (green line) or without such laws (blue line). Both dependent variables are IHS transformed.

Figure 8: Heterogeneity by Non-SFHA Risk

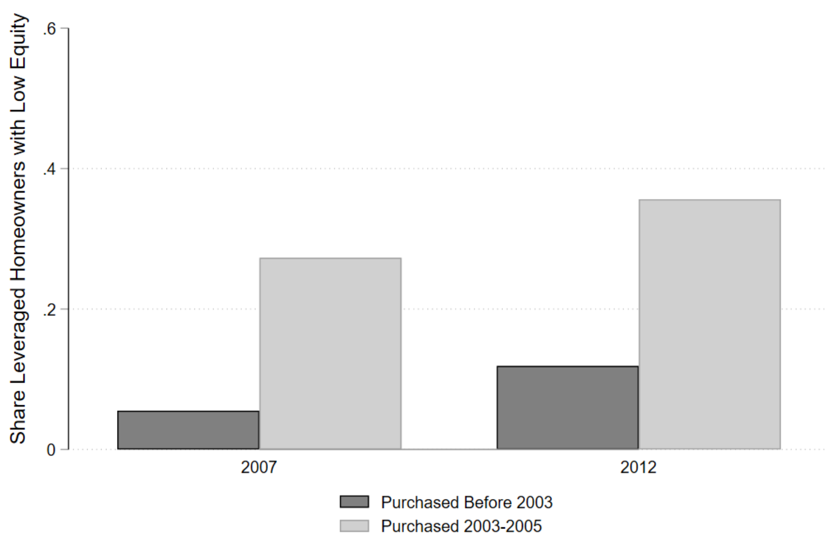


Source: OpenFEMA policy data, First Street Foundation, and Authors' Analysis
Notes: This figure plots the estimated coefficients from Equation (1) for home prices (left panel) and non-SFHA flood insurance take-up (right panel) separately for MSAs in states with above-median (green line) and below-median (blue line) non-SFHA risk as measured by Flood Factor from the First Street Foundation. Both dependent variables are IHS transformed.

Figure 9: Flood Risk Transfers over the Housing Bust



(a) MSAs with Housing Booms



(b) MSAs without Housing Booms

Source: CoreLogic, Inc. LLMA data and Authors' Analysis
Notes: This figure shows the share of leveraged homeowners with high flood risk transfers in the first quarters of 2007 and 2012 in MSAs with (top panel) and without (bottom panel) large housing booms as well as whether the purchase loan was originated between 2003 and 2005 (light grey) or before 2003 (dark grey). High flood risk transfers are defined as more than 33% of expected flood losses exceeding equity.

Tables

Table 1: Summary Statistics

Statistic	Mean	St. Dev.	10th Pctile	Median	90th Pctile
All Policies	10,510.05	31,664.71	282	1,774	23,097
SFHA Policies	6,155.51	21,388.61	136	986	10,753
Non-SFHA Policies	4,354.53	16,081.73	112	646	9,796
Non-SFHA Pre-03 Policies	3,793.74	14,015.92	103	585	8,376
Avg. Premium[1]	0.51	0.19	0.28	0.49	0.76
Non-SFHA Avg. Premium	0.25	0.09	0.17	0.24	0.37
SFHA Avg. Coverage	129,031.20	42,999.41	75,774.87	122,894.70	191,852.10
Non-SFHA Avg. Coverage	160,121.40	37,050.27	107,363.60	163,272.20	206,263.50
% Contents Coverage	0.33	0.21	0.11	0.27	0.69
% Standard Deductible	0.73	0.12	0.57	0.74	0.88
SFHA 1-yr Renewal Rate	0.77	0.20	0.56	0.77	0.94
Non-SFHA 1-yr Renewal Rate	0.75	0.19	0.56	0.75	0.94
Total Claims ($1,000s)[2]	8,693	221,178	0	131	4,045
Break Size	0.04	0.07	−0.03	0.03	0.14
FHFA Housing Price Index	169.89	36.73	132.93	162.34	217.67
Per Capita Income ($1,000s)	36.73	8.64	27.38	35.54	46.77
Population	834,636	1,338,575	138,330	372,086	1,920,919
Population Growth	0.01	0.01	−0.002	0.01	0.02
Employment Rate[3]	0.58	0.08	0.48	0.59	0.68
Home Transaction Volume	12,542.98	21,463.26	684	5,000	32,536
Judicial Review Law[4]	0.52	0.50	0	1	1
Non-SFHA Tail Risk[5]	0.64	0.14	0.49	0.65	0.79

Source: OpenFEMA policy and claims data, Charles et al. (2019), Bureau of Economic Analysis, FHFA Home Price Index, First Street Foundation, CoreLogic Deeds data

Notes: This dataset consists of quarterly observations across 267 MSAs during 2001–2015.

[1] Premium is measured as cost per $100 coverage.

[2] Total claims in the preceding four quarters.

[3] Employment rate is calculated as employed persons divided by total population.

[4] The states with judicial review laws are CT, DE, FL, HI, IL, IN, IA, KS, KY, LA, ME, MD, NJ, NM, NY, NC, ND, OH, PA, RI, SC, VT, WI.

[5] Non-SFHA tail risk is measured by the fraction of properties with 1 percent annual risk among all non-SFHA properties that are at any risk.

Table 2: Home Price Elasticity of Insurance Take-Up

Policy Sample	Dependent variable: log(NFIP Policy Count)			
	All	SFHA	Non-SFHA	Non-SFHA + Pre-2003
	(1)	(2)	(3)	(4)
$\widehat{\log(\text{HPI})}$	0.305***	0.211***	0.483***	0.322**
	(0.077)	(0.060)	(0.154)	(0.141)
log(Income)	0.244	0.128	0.026	−0.072
	(0.276)	(0.258)	(0.404)	(0.373)
log(Sales)	0.002	0.006	0.017*	0.016*
	(0.006)	(0.005)	(0.009)	(0.009)
log(Claims)	0.003***	0.0002	0.007***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
Pop. Growth	−0.226	−0.160	−0.568	−0.045
	(0.545)	(0.551)	(0.740)	(0.673)
Emp. Rate	−0.517	−0.423	0.041	0.761
	(0.587)	(0.551)	(0.832)	(0.775)
Risk × Year indicators	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
First-stage F-stat	40.20	53.68	37.28	37.28
Observations	15,180	15,180	15,180	15,180
Adjusted R^2	0.991	0.992	0.979	0.981

Source: OpenFEMA policy and claims data, Charles et al. (2019), Bureau of Economic Analysis, FHFA Home Price Index, First Street Foundation, CoreLogic Deeds data
Notes: This table presents 2SLS coefficients from Equation (3). Each column indicates a different policy sample over which take-up is measured. Respectively, they are all one-to-four family residential policies, policies inside the SFHA, policies outside the SFHA, and policies on structures built prior to 2003 outside the SFHA. The first-stage regression follows Equation (2), and the corresponding F-statistic is reported in the bottom panel. “Risk × Year indicators” refers to a set of interaction terms between the average risk score in the MSA and indicators for each year. Standard errors (in parentheses) are clustered by MSA. *p < 0.1; **p < 0.05; ***p < 0.01

Table 3: Heterogeneity by Foreclosure Law and Non-SFHA Risk

	Dependent variable: log(NFIP Policy Count)			
Policy Sample	Non-SFHA		SFHA	
	(1)	(2)	(3)	(4)
$\widehat{\log(\text{HPI})}$	0.298*	0.453**	0.194***	0.240***
	(0.168)	(0.179)	(0.074)	(0.072)
$\widehat{\log(\text{HPI}) \times \text{Judicial}}$	0.373***		−0.053	
	(0.119)		(0.066)	
$\widehat{\log(\text{HPI}) \times \text{High Risk}}$		0.326**		0.092
		(0.152)		(0.076)
log(Income)	0.039	−0.050	0.162	0.073
	(0.419)	(0.436)	(0.261)	(0.263)
log(Sales)	0.014	0.018**	0.006	0.006
	(0.009)	(0.009)	(0.005)	(0.006)
log(Claims)	0.007***	0.007***	0.0003	0.0002
	(0.001)	(0.001)	(0.001)	(0.001)
Pop. Growth	−0.606	−0.777	−0.089	−0.130
	(0.739)	(0.760)	(0.544)	(0.549)
Emp. Rate	−0.163	−0.007	−0.380	−0.489
	(0.813)	(0.807)	(0.548)	(0.544)
Risk × Year indicators	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
First-stage F-stat	(25.89, 80.95)	(23.74, 71.36)	(29.11, 81.52)	(28.05, 70.35)
Observations	15,180	15,180	15,180	15,180
Adjusted R^2	0.979	0.979	0.992	0.992

Source: OpenFEMA policy and claims data, Charles et al. (2019), Bureau of Economic Analysis, FHFA Home Price Index, First Street Foundation, CoreLogic Deeds data
Notes: This table presents 2SLS coefficients from Equation (E1) testing for heterogeneous home price elasticities by states with judicial review foreclosure laws in columns (1) and (3), and above median non-SFHA flood risk in column (2). The dependent variable is the IHS-transformed count of non-SFHA policies in columns (1) and (2), and its counterpart for SFHA policies in columns (3) and (4). The first-stage regressions follow Equation (E2), and the corresponding F-statistics are reported in the lower panel. "Risk × Year indicators" refers to a set of interaction terms between the average risk score in the MSA and indicators for each year. Standard errors (in parentheses) are clustered by MSA. *p < 0.1; **p < 0.05; ***p < 0.01

Table 4: Risk Shifting over the Bust: Changes by Home Purchase Timing

	Dependent variable:			
	ΔShare Low Equity		ΔPolicy Count	
	(1)	(2)	(3)	(4)
$\Delta\widehat{\log(\text{HPI})}$	-0.555***	0.008	0.377***	0.333***
	(0.065)	(0.057)	(0.120)	(0.118)
$\Delta\widehat{\log(\text{HPI})}$ × '03–'05 Cohort		-0.921***		1.035***
		(0.064)		(0.272)
First-stage F-stat	91.42	91.42	10.18	94.43
Observations	239	464	252	504
Adjusted R^2	0.795	0.800	0.168	0.192

Source: OpenFEMA policy and claims data, Charles et al. (2019), Bureau of Economic Analysis, FHFA Home Price Index, First Street Foundation, CoreLogic Deeds data

Notes: This table presents coefficients from first-difference specifications as described in Appendix F. Column (1) presents estimates of the change in the share of low equity borrowers as a function of instrumented changes in home prices between 2007 Q1 and 2012 Q1. Column (2) separately measures the low equity share for loans originated between 2003-2005 and those before 2003 with an indicator and home price interaction term for the 2003-2005 cohort. Columns (3) and (4) present estimates on the change in NFIP policy count from the same specifications as (1) and (2), respectively. In the latter two regressions, the cohort indicator represents whether the building was built during 2003-2005. All regressions control for first-differenced log income, log sales, population growth and employment rate, foreclosures, the average risk score, and the interaction of each of the above with the 2003-2005 cohort indicator. *p < 0.1; **p < 0.05; ***p < 0.01

A Additional Tables and Figures

Table A1: MSA Characteristics by Structural Break Size (2001 Q1)

Group	Lowest Boom (N = 88)	Middle Boom (N = 91)	Highest Boom (N = 88)
Structural Break Size			
Mean (SD)	-0.024 (0.015)	0.032 (0.018)	0.13 (0.047)
Median [Min, Max]	-0.021 [-0.102, -0.007]	0.034 [-0.007, 0.065]	0.117 [0.065, 0.271]
SFHA Policy Count			
Mean (SD)	1,870 (4,490)	2,390 (5,200)	13,500 (34,400)
Median [Min, Max]	528 [32.0, 35,500]	791 [5.94, 42,300]	2,220 [27.2, 22,5000]
Non-SFHA Policy Count			
Mean (SD)	2,210 (11,300)	1,260 (2,110)	5,140 (10,800)
Median [Min, Max]	220 [18.8, 103,000]	430 [32.7, 12,100]	1240 [76.8, 79,000]
Average SFHA Building Coverage (in $1,000s)			
Mean (SD)	74.3 (20.8)	82.4 (24.6)	108 (29.5)
Median [Min, Max]	70.6 [28.5, 145]	76.1 [41.4, 158]	108 [48.3, 173]
Average Non-SFHA Building Coverage (in $1,000s)			
Mean (SD)	101 (26.4)	110 (26.3)	130 (28.7)
Median [Min, Max]	97.9 [36.4, 171]	107 [62.3, 185]	130 [67.0, 195]
Average Risk Score, All Properties			
Mean (SD)	1.65 (0.532)	1.76 (0.584)	2.16 (0.874)
Median [Min, Max]	1.50 [1.23, 5.50]	1.63 [1.21, 5.79]	1.86 [1.25, 6.74]
Average Risk Score, SFHA Properties			
Mean (SD)	4.61 (1.15)	4.81 (1.17)	4.70 (1.56)
Median [Min, Max]	4.59 [2.42, 8.33]	4.68 [2.39, 7.63]	4.65 [1.52, 8.82]
Average Risk Score, Non-SFHA Properties			
Mean (SD)	1.51 (0.370)	1.61 (0.549)	1.89 (0.651)
Median [Min, Max]	1.38 [1.20, 3.79]	1.46 [1.16, 5.95]	1.68 [1.22, 5.08]
Population (in 1,000s)			
Mean (SD)	743 (1,100)	734 (1,410)	855 (1,290)
Median [Min, Max]	289 [101, 6,120]	348 [104, 9,380]	386 [125, 9,630]

Source: OpenFEMA policy and claims data, Charles et al. (2019), Bureau of Economic Analysis, FHFA Home Price Index, First Street Foundation, CoreLogic Deeds data

Table A2: Home Price Elasticity of Take-Up in Different Specifications

	Dependent variable: log(NFIP policy count)			
	(1)	(2)	(3)	(4)
$\widehat{\log(\text{HPI})}$	0.390***	0.352***	0.308***	0.305***
	(0.059)	(0.070)	(0.072)	(0.077)
log(Income)		0.228	0.250	0.244
		(0.277)	(0.275)	(0.276)
log(Sales)		0.003	0.002	0.002
		(0.006)	(0.006)	(0.006)
log(Claims)		0.004***	0.003***	0.003***
		(0.001)	(0.001)	(0.001)
Pop. Growth		−0.364	−0.248	−0.226
		(0.522)	(0.531)	(0.545)
Emp. Rate		−0.789	−0.514	−0.517
		(0.597)	(0.581)	(0.587)
Other covariates		Yes	Yes	Yes
Risk × Quad. time trend			Yes	
Risk × Year indicators				Yes
MSA FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
First-stage F-stat	99.78	49.28	44.31	40.20
Observations	15,420	15,240	15,180	15,180
Adjusted R^2	0.990	0.990	0.991	0.991

Source: OpenFEMA policy and claims data, Charles et al. (2019), Bureau of Economic Analysis, FHFA Home Price Index, First Street Foundation, CoreLogic Deeds data

Notes: This table presents 2SLS coefficients from Equation (3). The dependent variable is IHS-transformed total policy count. The first-stage regression follows Equation (2), and the corresponding F-statistic is reported in the bottom panel. Each column represents a different set of controls as indicated by the bottom panel. "Other covariates" include IHS-transformed income, home sales volume, and total NFIP claim amount, as well as population growth and employment rate. "Risk × Quadratic trend" is the interaction between the average risk score for all properties in the MSA and a quadratic time trend. "Risk × Year indicators" are a set of interaction terms between the average risk score and indicators for each year. Column (4) is the preferred specification used in all main results. Standard errors (in parentheses) are clustered by MSA. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table A3: Instrumented Regressions—Newly Enrolled Policy Count

	Dependent variable: log(NFIP Policy Count)		
	All	SFHA	Non-SFHA
	(1)	(2)	(3)
$\widehat{\log(\text{HPI})}$	0.297***	0.190***	0.486***
	(0.078)	(0.060)	(0.152)
log(Income)	0.303	0.203	0.045
	(0.271)	(0.268)	(0.393)
log(Sales)	0.002	0.006	0.018**
	(0.006)	(0.006)	(0.008)
log(Claims)	0.003***	0.0002	0.008***
	(0.001)	(0.001)	(0.001)
Pop. Growth	−0.009	0.001	−0.290
	(0.551)	(0.584)	(0.738)
Emp. Rate	−0.577	−0.445	−0.069
	(0.586)	(0.580)	(0.816)
Risk × Year indicators	Yes	Yes	Yes
MSA × Quarter-of-year FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
First-stage F-stat	37.67	51.33	34.86
Observations	15,112	15,112	15,112
Adjusted R^2	0.988	0.989	0.973

Source: OpenFEMA policy and claims data, Charles et al. (2019), Bureau of Economic Analysis, FHFA Home Price Index, First Street Foundation, CoreLogic Deeds data

Notes: This table presents 2SLS coefficients from Equation (3). The dependent variables are the IHS-transformed counts of newly enrolled policies in categories indicated in the top panel. The first-stage regressions follow Equation (2), and the corresponding F-statistics are reported in the bottom panel. Standard errors (in parentheses) are clustered by MSA. *p < 0.1; **p < 0.05; ***p < 0.01

Table A4: Robustness Checks on the Home Price Elasticity of Take-Up

	Dependent variable: log(NFIP Policy Count)			
Checks	Cohort-Based IV		Boom Measurement	
	(1)	(2)	(3)	(4)
$\widehat{\log(\text{HPI})}$	0.258***	0.278***	0.341***	0.360***
	(0.067)	(0.070)	(0.069)	(0.068)
log(Income)	0.287	0.269	0.212	0.195
	(0.268)	(0.272)	(0.271)	(0.269)
log(Sales)	0.002	0.002	0.003	0.003
	(0.006)	(0.006)	(0.006)	(0.006)
log(Claims)	0.003***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Pop. Growth	−0.206	−0.215	−0.242	−0.250
	(0.539)	(0.539)	(0.541)	(0.539)
Emp. Rate	−0.456	−0.482	−0.562	−0.586
	(0.579)	(0.580)	(0.586)	(0.586)
Risk × Year indicators	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
First-stage F-stat	1531.24	120.93	39.41	42.14
Observations	15,180	15,180	15,180	15,180
Adjusted R^2	0.991	0.991	0.991	0.991

Source: OpenFEMA policy and claims data, Charles et al. (2019), Bureau of Economic Analysis, FHFA Home Price Index, First Street Foundation, CoreLogic Deeds data

Notes: This table presents 2SLS coefficients from Equation (3). The dependent variable is IHS-transformed total policy count. The first-stage regressions follow Equation (2), and the corresponding F-statistics are reported in the bottom panel. Columns (1) and (2) use instruments based on start-of-boom cohorts. In column (1), the first-stage regression uses, as instruments, the interaction between the original instruments with indicators for the start-of-boom quarter. Column (2) switches to the start-of-boom year. Columns (3) and (4) examine potential mismeasurement of boom size and timing for those MSAs with no clear boom. Column (3) sets the structural break of all MSAs with negative boom sizes to zero. Column (4) expands sets the lowest quartile of MSA structural breaks to zero. Standard errors (in parentheses) are clustered by MSA. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Table A5: Instrumented Regressions—Stacked Design

	Dependent variable: log(NFIP Policy Count)		
	All	SFHA	Non-SFHA
	(1)	(2)	(3)
$\widehat{\log(\text{HPI})}$	0.294***	0.188***	0.484***
	(0.078)	(0.060)	(0.152)
log(Income)	0.307	0.206	0.055
	(0.269)	(0.266)	(0.391)
log(Sales)	0.002	0.006	0.017**
	(0.006)	(0.006)	(0.008)
log(Claims)	0.003***	0.0002	0.007***
	(0.001)	(0.001)	(0.001)
Pop. Growth	−0.002	0.005	−0.270
	(0.539)	(0.572)	(0.723)
Emp. Rate	−0.581	−0.444	−0.086
	(0.583)	(0.577)	(0.814)
Risk × Year indicators	Yes	Yes	Yes
MSA-cohort FE	Yes	Yes	Yes
Quarter-cohort FE	Yes	Yes	Yes
First-stage F-stat	39.19	54.53	35.74
Observations	15,180	15,180	15,180
Adjusted R^2	0.988	0.989	0.973

Source: OpenFEMA policy and claims data, Charles et al. (2019), Bureau of Economic Analysis, FHFA Home Price Index, First Street Foundation, CoreLogic Deeds data

Notes: This table presents 2SLS coefficients from the stacked design as described in Appendix D. The dependent variables are IHS-transformed policy counts in categories indicated in the top panel. The corresponding F-statistic in the first-stage regression is reported in the bottom panel. Standard errors (in parentheses) are clustered by MSA. *p < 0.1; **p < 0.05; ***p < 0.01

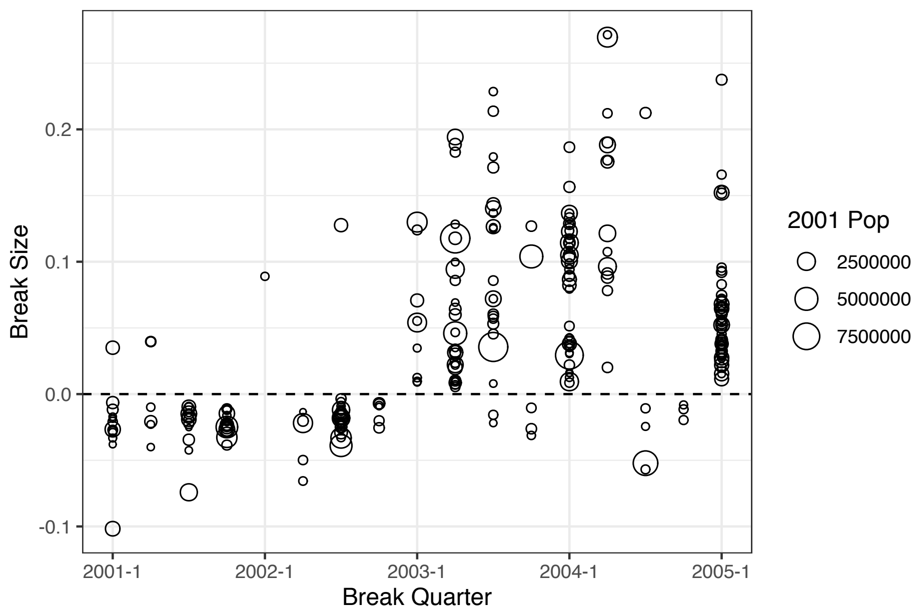
Table A6: Boom vs. Bust: First-Difference Estimates

	Dependent variable: $\Delta\log$(NFIP Policy Count)			
	Boom (2002–2007)		Bust (2007–2012)	
	SFHA	Non-SFHA	SFHA	Non-SFHA
	(1)	(2)	(3)	(4)
$\Delta\widehat{\log(\text{HPI})}$	0.315***	0.353**	0.056	0.670***
	(0.068)	(0.178)	(0.131)	(0.234)
$\Delta\widehat{\log(\text{HPI})}$ × '03–'05 Cohort			0.298	0.777***
			(0.234)	(0.270)
First-stage F-stat	35.52	33.35	108.11	91.23
Observations	251	251	504	504
Adjusted R^2	0.004	0.034	0.048	0.137

Source: OpenFEMA policy and claims data, Charles et al. (2019), Bureau of Economic Analysis, FHFA Home Price Index, First Street Foundation, CoreLogic Deeds data

Notes: This table presents coefficients from first-difference specifications as described in Appendix F. Columns (1)-(2) present boom-period estimates based on the difference between 2002 Q1 and 2007 Q1, while columns (3)-(4) present bust-period estimates based on the difference between 2007 Q1 and 2012 Q1. Columns (1) and (3) feature SFHA policies and columns (2) and (4) feature non-SFHA policies. In columns (3) and (4), we further interact the (first-differenced) housing price index with an indicator of whether the building was constructed near the peak of the boom (2003-05), to estimate differential effects on this "boom cohort". All regressions control for first-differenced log income, log sales, population growth and employment rate, as well as the average risk score. Columns (3)-(4) also control for the first-differenced share of foreclosures among home sales. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

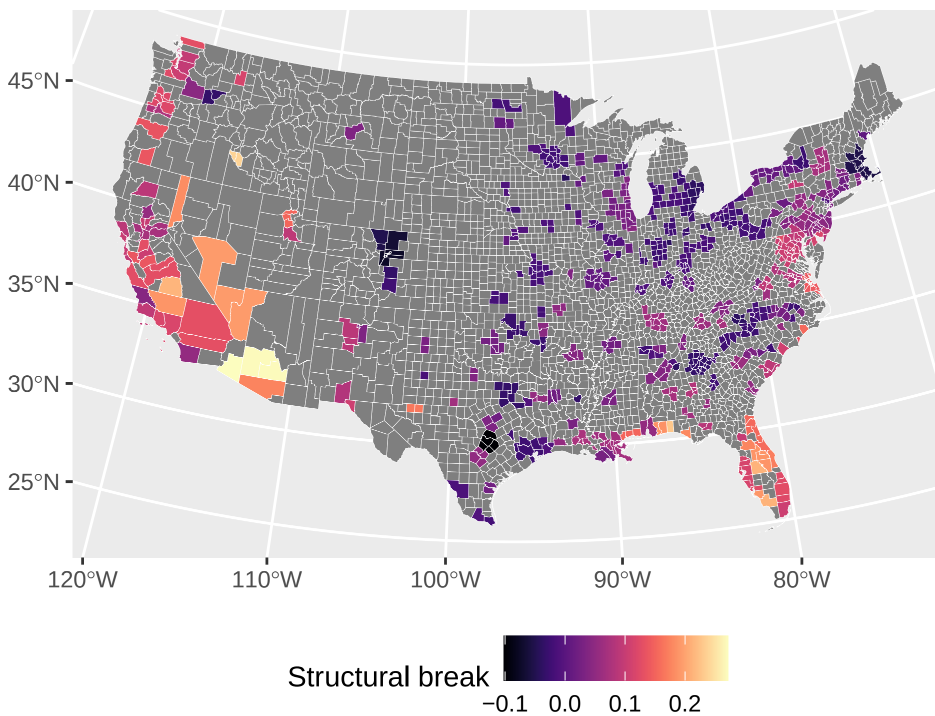
Figure A1: Size and Timing of the Structural Breaks



Source: Structural break estimates from Charles et al. (2019) and Authors' Analysis

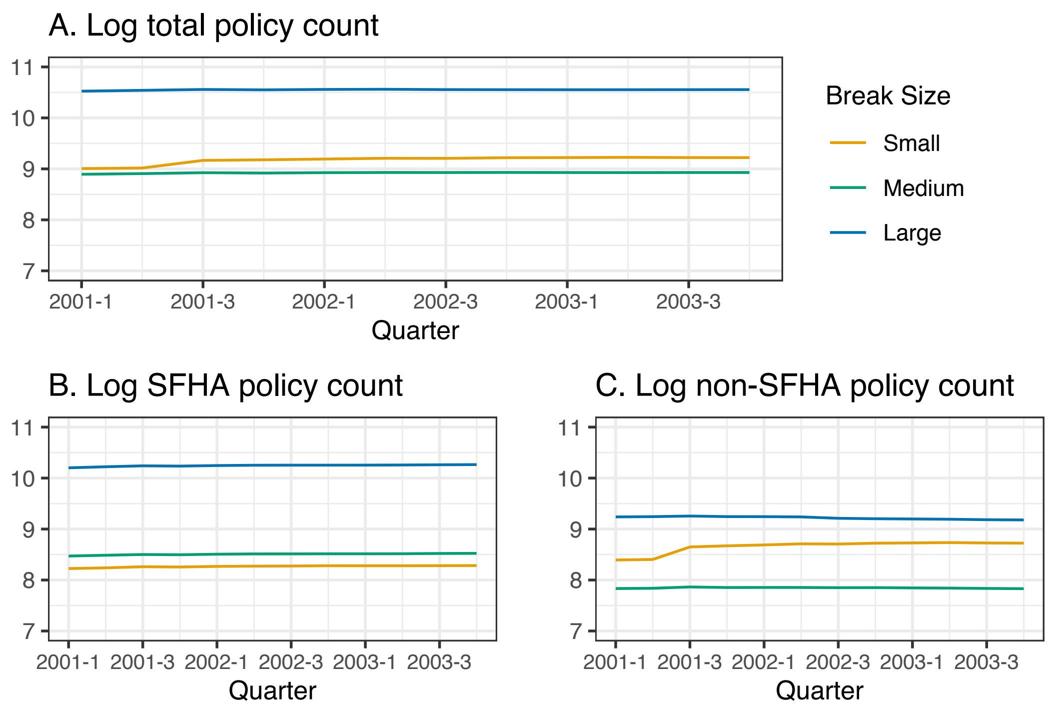
Notes: Each circle represents an MSA. The x-axis displays the quarter of the structural break, and the y-axis displays the size of the break. The size of the circle reflects population size in 2000.

Figure A2: Housing Boom Size Across MSAs



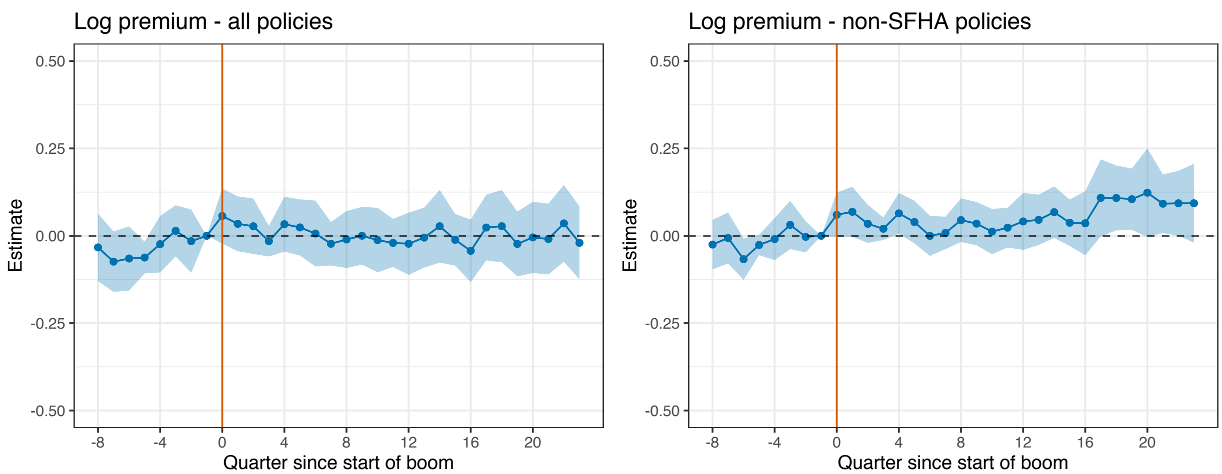
Source: Structural break estimates from Charles et al. (2019) and Authors' Analysis

Figure A3: Pre-Boom Trends in NFIP Take-Up by Structural Break Tercile



Source: OpenFEMA policy data, Charles et al. (2019)
Notes: This figure shows the quarterly time series of NFIP policy in force during 2001–2003 in the raw data. Each color represents one group of MSAs in each structural break tercile. Panel A plots the IHS-transformed total policy count, and Panels B and C plot the IHS-transformed count of SFHA and non-SFHA policies, respectively.

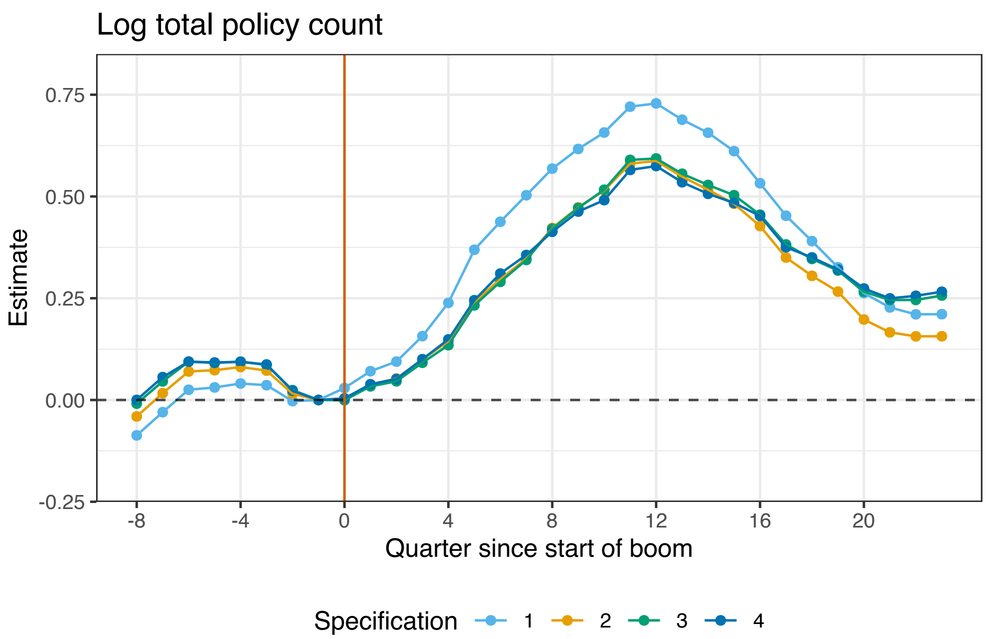
Figure A4: Dynamics of NFIP Premium



Source: OpenFEMA policy and claims data, Charles et al. (2019), Bureau of Economic Analysis, FHFA House Price Index, First Street Foundation, CoreLogic, Inc. Deeds data, and Authors' Analysis

Notes: This figure plots the estimated coefficients and their 95 percent confidence intervals from Equation (1) for premium, measured as cost per $100 coverage, of all policies (left panel) and non-SFHA policies (right panel). Both dependent variables are IHS transformed.

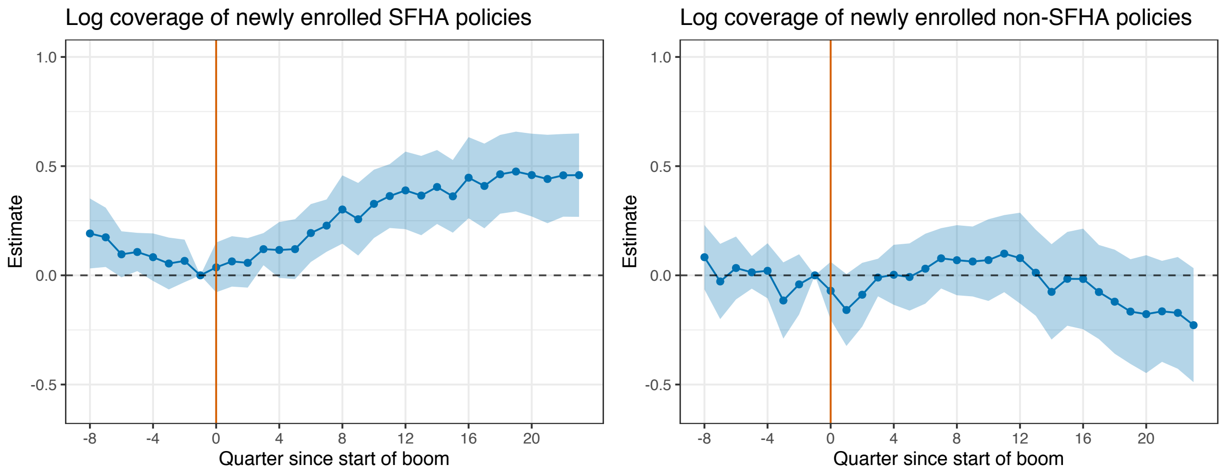
Figure A5: Dynamics of Take-Up Under Different Specifications



Source: OpenFEMA policy and claims data, Charles et al. (2019), Bureau of Economic Analysis, FHFA House Price Index, First Street Foundation, CoreLogic, Inc. Deeds data, and Authors' Analysis

Notes: This figure plots the point estimates for overall take-up from Equation (1) with different sets of controls. Specification 1 includes only MSA and quarter-year fixed effects. Specification 2 adds controls for income and home sales volume. Specification 3 further adds the average risk score interacted with a quadratic time trend. This risk control is replaced with a set of interaction terms between the average risk score and indicators for each year in specification 4, which is also the preferred specification used in all main results.

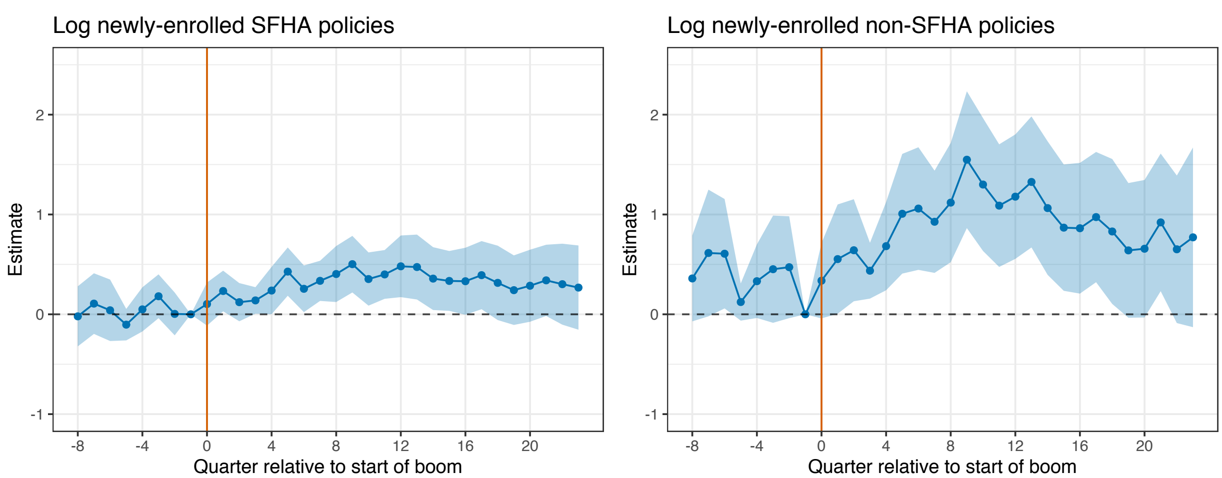
Figure A6: Dynamics of Building Coverage



Source: OpenFEMA policy and claims data, Charles et al. (2019), Bureau of Economic Analysis, FHFA House Price Index, First Street Foundation, CoreLogic, Inc. Deeds data, and Authors' Analysis

Notes: This figure plots the estimated coefficients and their 95 percent confidence intervals from Equation (1) for coverage purchased on flood insurance policies inside SFHAs (left panel) and outside SFHAs (right panel). Both dependent variables are IHS transformed.

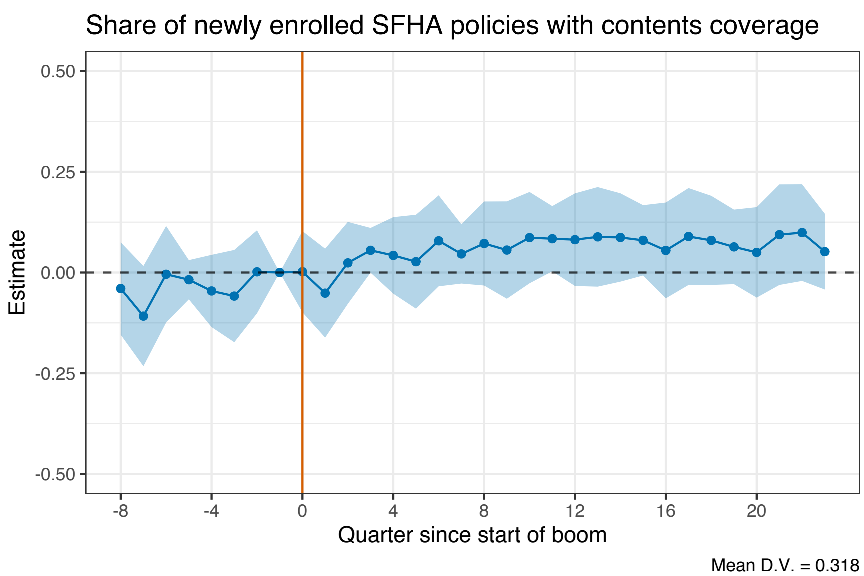
Figure A7: Dynamics of Newly Enrolled Policies



Source: OpenFEMA policy and claims data, Charles et al. (2019), Bureau of Economic Analysis, FHFA House Price Index, First Street Foundation, CoreLogic, Inc. Deeds data, and Authors' Analysis

Notes: This figure plots the estimated coefficients and their 95 percent confidence intervals from Equation (1) for the number of newly enrolled policies inside SFHAs (left panel) and outside SFHAs (right panel).

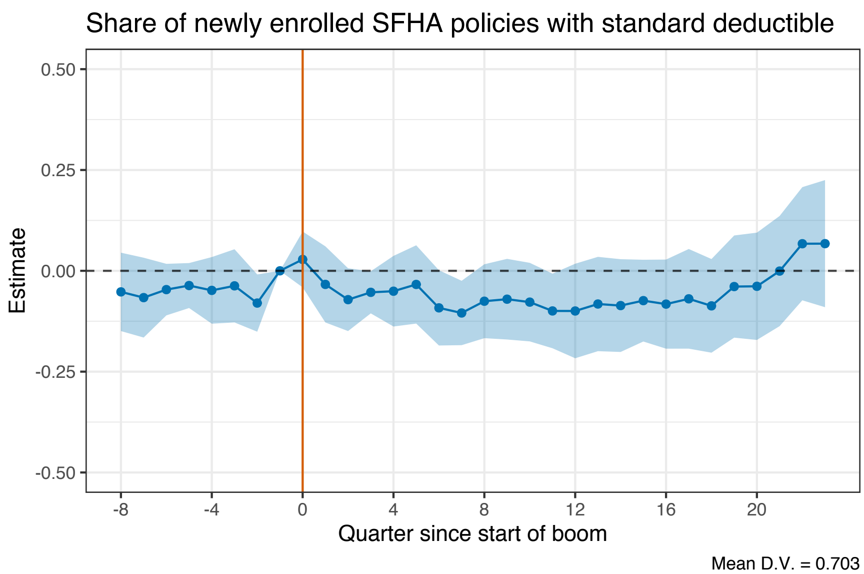
Figure A8: Dynamics of Contents Coverage



Source: OpenFEMA policy and claims data, Charles et al. (2019), Bureau of Economic Analysis, FHFA House Price Index, First Street Foundation, CoreLogic, Inc. Deeds data, and Authors' Analysis

Notes: This figure plots the estimated coefficients and their 95 percent confidence intervals from Equation (1) for the share of newly enrolled SFHA policies that include contents coverage.

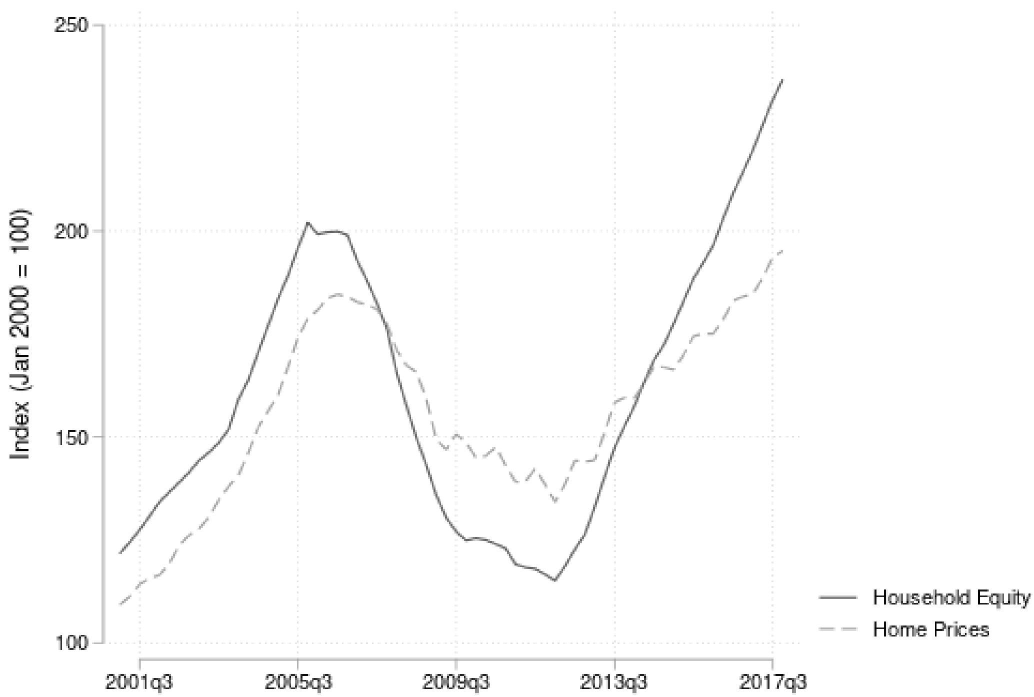
Figure A9: Dynamics of Deductible Choice



Source: OpenFEMA policy and claims data, Charles et al. (2019), Bureau of Economic Analysis, FHFA House Price Index, First Street Foundation, CoreLogic, Inc. Deeds data, and Authors' Analysis

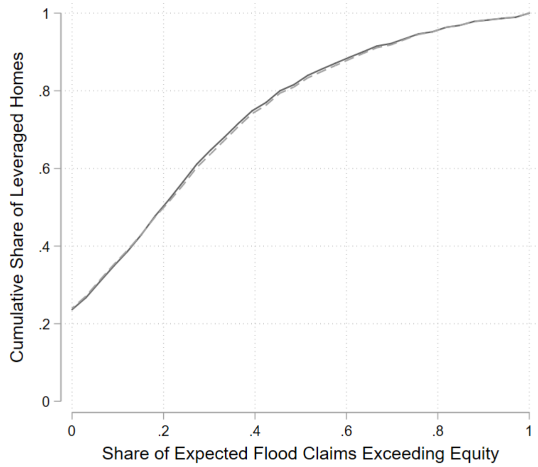
Notes: This figure plots the estimated coefficients and their 95 percent confidence intervals from Equation (1) for the share of newly enrolled SFHA policies with the standard deductible.

Figure A10: Home Prices and Homeowner Equity

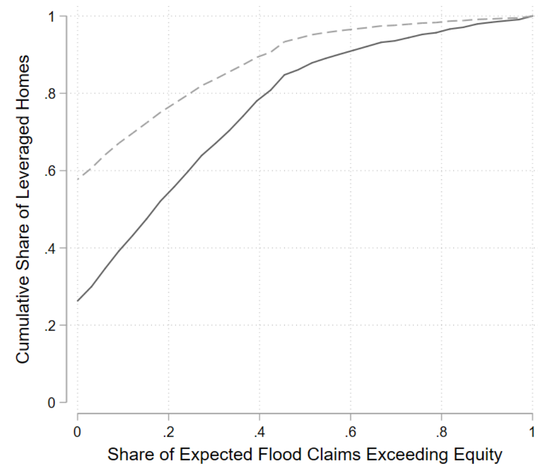


Source: Federal Reserve Board of Governors Quarterly Financial Accounts and S&P Case-Shiller US National House Price Index (Retrieved from FRED)
Notes: This figure plots the household equity (home value minus mortgage debt) and home prices over the sample period.

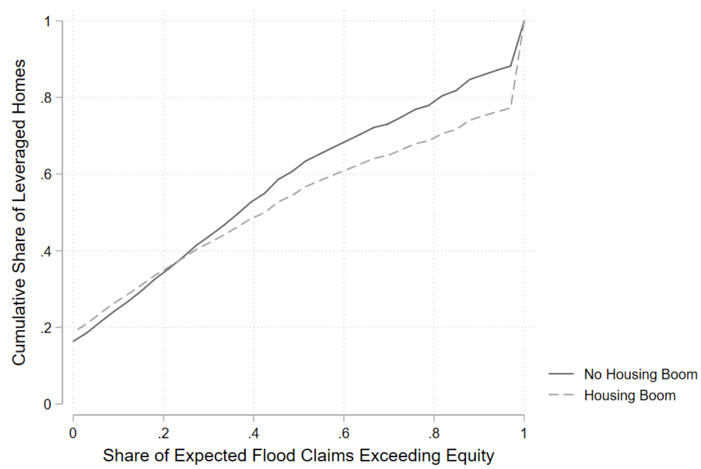
Figure A11: Distributions of Flood Risk Shifting



(a) 2000



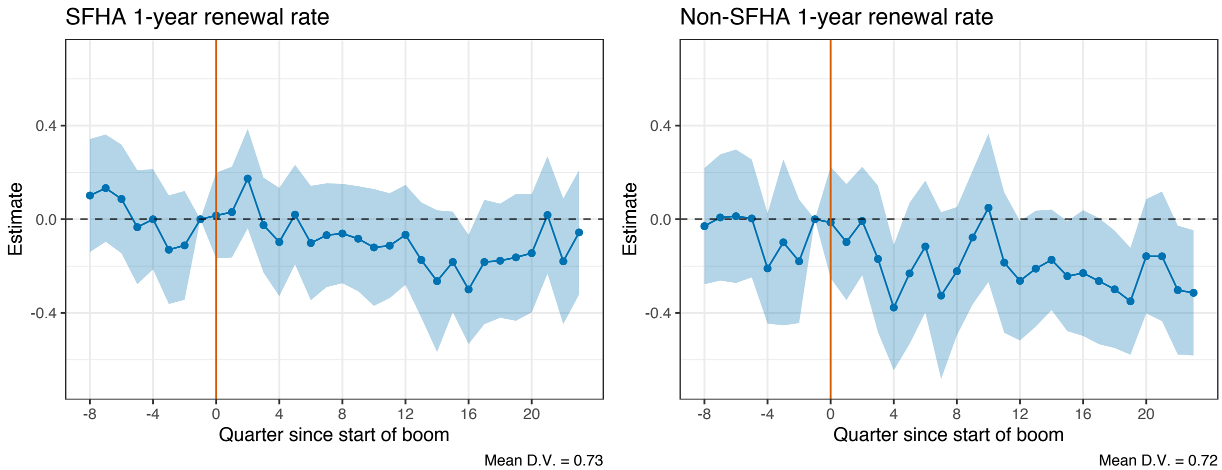
(b) 2007



(c) 2012

Source: CoreLogic, Inc. LLMA data, OpenFEMA claims data, and Authors' Analysis
Notes: Panels show the cumulative distribution function of flood risk shifting by leveraged homeowners between MSAs with and without housing booms in the first quarters of 2000 (top), 2007 (middle), and 2012 (bottom).

Figure A12: One-Year Renewal Rate



Source: OpenFEMA policy and claims data, Charles et al. (2019), Bureau of Economic Analysis, FHFA House Price Index, First Street Foundation, CoreLogic, Inc. Deeds data, and Authors' Analysis

Notes: This figure plots the estimate coefficients and their 95 percent confidence intervals from Equation (1) for one-year renewal rates of policies inside the SFHA (left panel) and outside the SFHA (right panel).

B Framework

We present a theoretical framework to illustrate the role of home equity in disaster insurance demand. We start by describing a baseline model with no relationship between home equity and willingness to pay for insurance. In this simplified model, because disasters damage a building's structure, the other components of home equity—land value and mortgage debt—have no direct effect on demand.

We extend the model to allow homeowners to default on their mortgage debt rather than pay the repair costs from a disaster. Mortgage default provides implicit insurance to leveraged homeowners and creates a positive relationship between their home equity and flood insurance demand.

B.1 Baseline Model

Consider a single-period model with an agent endowed with a property H. The equity value of H is given by $E_H \equiv L_H + R_H - M_H$, where L_H is the land value, R_H is the structure value, and M_H is the outstanding mortgage debt. We assume the agent starts with positive home equity, or $L_H + R_H \geq M_H$.

The model proceeds in three phases: "pre-disaster," "disaster," and "post-disaster." Pre-disaster, the agent receives income $\overline{W}$ and chooses whether to insure their structure against disaster risk. We consider a single insurance contract covering the full value of R_H with no deductible or copay. Denote the purchase decision by $I = 0, 1$ and the price of the insurance P_I.[35]

In the disaster phase, a disaster occurs with probability p and causes damages to the structure. The potential repair cost L is distributed as follows:

$$\begin{cases} L = r \sim f(r), r \in (0, R_H] & \text{with probability } p, \\ L = 0 & \text{with probability } 1 - p \end{cases}$$

If uninsured, the agent must pay the full cost of L. If insured, L is paid by the insurer.

In the post-disaster period, the agent derives linear utility from wealth and home equity:[36]

$$E_H + \overline{W} - I \cdot P_I - (1 - I) \cdot L.$$

The agent maximizes their expected utility. Assuming $P_I \leq W$, the agent will purchase the insurance if and only if expected utility without insurance is lower than utility with insurance:

$$\mathbb{E}\left[E_H + \overline{W} - L\right] \leq E_H + \overline{W} - P_I. \tag{B1}$$

Clearly, the agent's willingness to pay for insurance, denoted $\widehat{P}$, equals their expected repair

[35] In practice, the NFIP caps structure coverage at $250,000. Adding this to the model would not change any of our directional predictions about how home equity affects disaster insurance demand.

[36] We follow much of the insurance literature in defining a utility function over wealth to motivate insurance demand, as in Einav et al. (2010). We abstract away from non-housing assets or risk aversion over home equity because the central point of the model—the directional relationship between home equity and demand for disaster insurance—holds for any weakly concave utility function over wealth.

costs:

$$\widehat{P} = \mathbb{E}(L). \tag{B2}$$

The agent's valuation of disaster insurance is not affected by their home equity because the agent fully internalizes the risk to their structure, which is independent of land value and mortgage debt.

B.2 Insurance willingness to pay with Mortgage Default

We extend the baseline model to allow the agent to default on their mortgage debt after a disaster. When an uninsured agent defaults, they do not pay repair costs L but forfeit their equity E_H and pay a default cost $\widehat{M}$.

Uninsured agents default when $L \geq \widehat{M} + E_H$. Thus, expected utility without insurance is

$$\mathbb{E}\left[E_H + \overline{W} - \min(L, \widehat{M} + E_H)\right].$$

Setting this expression equal to the agent's utility with insurance, which is unaffected by the default option, we derive the agent's willingness to pay for insurance with default:

$$\widehat{P} = \mathbb{E}\left[\min(L, \widehat{M} + E_H)\right] = \mathbb{E}(L) - \overbrace{p \cdot \int_{\widehat{M}+E_H}^{R_H} \Big(r - (\widehat{M} + E_H)\Big) \cdot f(r)dr}^{\textbf{implicit insurance effect}} \tag{B3}$$

The key difference between Equation (B3) and Equation (B2) is the "implicit insurance effect" of default that is subtracted from expected repair costs. The willingness to pay specified in (B3) is strictly less than that in (B2) when the probability of disaster-induced default is nonzero.

Further, we can derive how $\widehat{P}$ changes with respect to E_H:

$$\frac{d\widehat{P}}{dE_H} = p \cdot \Big(1 - F(\widehat{M} + E_H)\Big) > 0. \tag{B4}$$

where $F(\cdot)$ is the cdf of the disaster damages function. This expression shows that the marginal effect of equity on the agent's value of insurance is given by the likelihood of getting a damage level that is high enough for the homeowner to default. Intuitively, the default option provides the agent with a form of informal insurance with a deductible equal to the agent's equity plus default costs. As home equity increases, the loss from defaulting grows, and the value of this implicit insurance becomes less compared to that of formal insurance.

Equation (B4) identifies two factors that should influence the strength of the relationship between home equity and flood insurance demand. Expression (B4) is larger when (i) the default cost $\widehat{M}$ is lower and (ii) default-inducing damage levels are more likely. These observations motivate two empirical tests to assess whether the implicit insurance from default plausibly explains the relationship between home prices and flood insurance take-up in the data:

Risk Shifting Prediction (1). *MSAs with higher default costs should have an attenuated* *relationship between the house prices and flood insurance take-up relative to MSAs with lower default costs.*

Risk Shifting Prediction (2). *MSAs with greater exposure to tail risk should see greater increases (decreases) in take-up in response to increases (decreases) in house prices relative to MSAs with lower tail risk.*

C Additional Variables

C.1 Flood Risk

The First Street Foundation Flood Model (FSF-FM) combines hydrological models, fine-resolution land cover and elevation data, and inventories of flood adaptation infrastructure to accurately estimate expected flood depths across the entire continental United States (First Street Foundation, 2020). Covering 142 million properties, it provides the most comprehensive national account of flood risk to date.

The flood risk measure from FSF-FM has two main differences from FEMA's flood map. First, the majority of FEMA's maps are outdated and do not reflect recent changes in risk levels; 75 percent of them are more than five years old, despite the National Flood Insurance Reform Act of 1994 requirement to update the maps every five years. Second, FSF-FM accounts for potential pluvial or surface water flooding unlike FEMA's maps. As a result, FSF-FM finds a higher flood risk than FEMA for most locations: FSF-FM shows that 14.6 million homes are currently subject to a 1 percent annual flood risk, but FEMA's maps indicate this level of risk for only 8.7 million properties.[37]

The First Street Foundation also provides a "Flood Factor" risk score measure (1–10, representing minimal to extreme levels of risk) based on each property's flood probability and depth profile.[38] For each MSA, we calculate the average risk score of all properties, SFHA properties, and non-SFHA properties. In the regressions, we use the floodplain-specific risk measure[39] interacted with quarter indicators to control for time-varying effects of the average risk level.

We construct an additional measure to characterize non-SFHA tail risk to test the risk shifting channel. One hypothesis under this mechanism is that MSAs with more properties exposed to tail risk will have a larger response to the increase in home equity. As we focus on non-SFHA take-up, we define the following measure of non-SFHA tail risk exposure:

$$\text{Non-SFHA tail risk} = \frac{\text{Number of non-SFHA properties at 1 percent annual flood risk}}{\text{Number of non-SFHA properties at any risk}}.$$

The denominator and numerator capture the extent of the flood insurance market outside the SFHA and the subset of these properties facing severe enough risk that a flood could induce enough damage to cause a mortgage default, respectively.[40] This ratio ranges from 1 to 89 percent across MSAs, with the median at 65 percent.

[37] See https://firststreet.org/flood-lab/published-research/2020-national-flood-risk-assessment-highlights/ for more details.

[38] See https://floodfactor.com/methodology for the Flood Factor methodology.

[39] For example, we use the average risk score for non-SFHA properties when the outcome variable is non-SFHA take-up.

[40] We use the 1 percent annual risk cutoff to proxy for tail risk because properties with at least 1 percent annual risk of shallow flood depth also have a substantial chance of suffering from overwhelming levels of damage.

C.2 Foreclosure Law

The states with judicial review laws are CT, DE, FL, HI, IL, IN, IA, KS, KY, LA, ME, MD, NJ, NM, NY, NC, ND, OH, PA, RI, SC, VT, and WI. These states require court approval for foreclosure sales after mortgage defaults, as opposed to states where lenders may initiate foreclosure outside of the court based on the contract terms of the mortgage.

The main cost of mortgage default to the owner of a heavily damaged or destroyed home with negative equity will be the risk of a foreclosure that negatively effects their long-term credit. Judicial review laws make the process of obtaining a foreclosure sale more costly for lenders because they require lenders to obtain permission through court proceedings. Mian et al. (2015) found that delinquent homeowners were more than twice as likely to enter foreclosure in states with judicial foreclosure laws as in those that allow nonjudicial foreclosures, and Demiroglu et al. (2014) found that borrowers with negative equity are more likely to enter default in judicial foreclosure states. This evidence suggests that flooded homeowners entering default are more likely to reach a settlement with their lender that preserves their credit with the protection of judicial foreclosure.

Other commonly cited borrower protection are state-level non-recourse laws, which prevent lenders from pursuing deficiency judgements in court to recover unpaid mortgage balances after default. We argue that non-recourse laws are unlikely to decrease default costs for disaster-affected homeowners. First, deficiency judgements are notoriously difficult to pursue and can be discharged in bankruptcy (Brueggeman and Fisher, 2011; Guiso et al., 2013). Second, the main effect of recourse laws documented by Ghent and Kudlyak (2011) - increasing the use of deeds in lieu of foreclosure - is unlikely to be perceived as a cost by mortgagors in our setting. Lenders prefer deeds in lieu of foreclosure because they transfer ownership of the distressed property without going through foreclosure. Although borrowers normally rely on the lengthy foreclosure process to remain in their homes longer, this would not be a concern if the home were uninhabitable due to flood damage. Furthermore, the deed in lieu of foreclosure has less negative credit impact, likely making it the preferred mechanism of both parties in our setting.

C.3 Calculating Loan-Level Flood Risk Transferred

We define "flood risk transferred" as the share of expected flood damages that exceed a leveraged homeowner's equity. To calculate this measure, we first estimate the borrower's current equity as a share of their home's structure value for each loan in the CoreLogic LLMA data. Following a similar procedure as in Indarte (2023) whereby we track the loan's current balance in the LLMA data and inflate the property's value by the change in home prices, we use the following equation to estimate the current equity of a loan i in CBSA m originated in quarter t at quarter $k > t$:

$$EQUITY_{ik} = \frac{P_{it} * \frac{HPI_{mk}}{HPI_{mt}} - B_{ik}}{0.66 * P_{it}},$$

where B_{ik} is the current loan balance, P_{it} the original purchase price observed in the LLMA data, and the HPI variables are the FHFA CBSA-level home price index values at t and k. The 0.66 multiplying the purchase period home price converts the measure from equity as a share of total property value to equity as a share of structure value, assuming that land cost made up 34% of the purchase price.[41]

Next, as our proxy for expected flood losses, we use flood insurance claims for building damage among single-family homes from 2001 to 2018 in the OpenFEMA data. Denote claims as a share of insured value by $0 < l \leq 1$ distributed $f(l)$. We calculate flood risk shifted for a loan i in period k as:

$$R_{ik} = \int_0^{EQUITY_{ik}} l * f(l)\, dl + \int_{EQUITY_{ik}}^1 EQUITY_{ik} * f(l)\, dl$$

R_{ik} is expected flood losses falling to the owner if they default whenever damages exceed their equity.[42]

R_{ik} is a noisy proxy for risk-shifting for several reasons: Flood insurance claims do not exactly equal flood damages especially for underinsured homes, we do not observe heterogeneity in flood risk by loan, and the home price indices imperfectly measure changes in property-level prices. This measurement error is an additional motivation, alongside unobserved confounds, for using sudden changes in land value from the housing boom and bust as instrumental variables.

We believe our measure of flood risk shifting provides two key insights in our analysis, as discussed in section 5.3. First, it shows that the magnitude of changes in home equity were large relative to the magnitude of flood insurance claims, plausibly affecting flood insurance decisions. Second, it confirms that homes bought near the peak of the housing boom had much larger changes in their flood risk shifted during the bust than those bought earlier, motivating our heterogeneity test of the risk shifting mechanism.

D Stacked Event-by-Event Estimation

Our implementation of the stacked estimator is adapted from Cengiz et al. (2019). The goal of the estimator is to avoid the biases that can be introduced by two-way fixed effects (TWFE) estimation in settings with heterogeneous treatment effects and variation in treatment timing across units.[43] Because different MSAs experienced their housing booms at different times, our estimation results from Equations (1) and (3) could be affected by these biases.

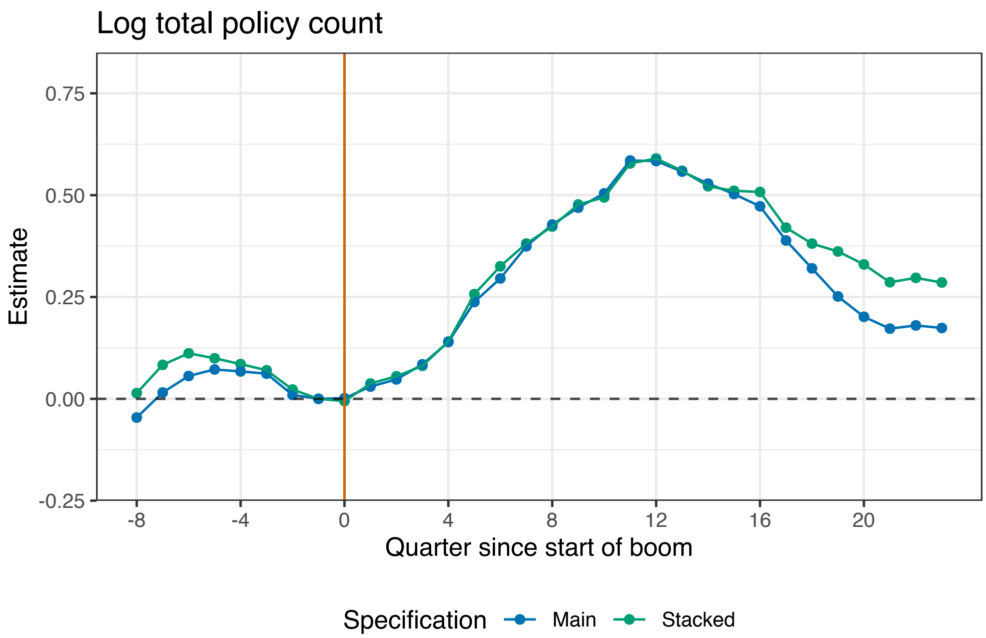
The stacked estimator addresses the TWFE estimator's issues by estimating a separate difference-in-differences regression for each group of MSAs with large housing booms in a specific year. For each group, the only comparison group is the set of MSAs with small or negative estimated structural breaks—those with no housing boom. Thus, each regression used to estimate the pooled treatment effect avoids using treated MSAs with different timing

[41] A 34% land share is the 2000Q1 value in the aggregate land and structure data value data described in Davis and Heathcote (2007) and available at https://www.aei.org/historical-land-price-indicators/. We find similar changes in flood risk shifted over time and across cohorts using different land shares.

[42] For $EQUITY \leq 0$, owners shift all of their flood risk ($R = 0$). For $EQUITY \geq 1$, owners shift none of their risk ($R = 1$).

[43] See the main text for further citations on this literature.

Figure D1: Comparison of main and stacked estimates



Notes: This figure plots our main estimates for overall take-up in green and those from the stacked estimator in blue. They follow Equations (1) and (D1), respectively.
Source: OpenFEMA policy and claims data, Charles et al. (2019), Bureau of Economic Analysis, FHFA House Price Index, First Street Foundation, CoreLogic, Inc. Deeds data, and Authors' Analysis

as comparison groups.

We first define "never-treated" MSAs as those with a negative boom or a boom size in the lowest quartile of positive booms. As discussed in Section 4.2, these values likely represent noise in the estimation rather than actual booms. Our results are similar under other reasonable cutoffs.

Next, we create year-by-year datasets as follows: For each year from 2001 to 2005, we select all MSAs with home price structural breaks in that year and put them together with the no-boom MSAs, which we consider to be a "cohort". We then stack the five cohorts to form the regression dataset. We estimate the following equation:

$$lnNFIP_{mtg} = \sum_{\tau=-9}^{24} \beta_\tau (Post_{mt}^{\tau} \times \Delta P_m) + \delta' X_{mt} + \lambda_{mg} + \lambda_{tg} + \varepsilon_{mtg}, \qquad \text{(D1)}$$

where g denotes the cohort and other notations are the same as before. The only difference between this specification and Equation (1) is that the MSA and time fixed effects are now cohort specific. The stacking design and within-cohort comparison prevent using early-treated MSAs as controls and thus avoid the TWFE problems in the staggered design.

In Figure D1, we plot our main estimates and the estimates from the stacked design together. The two trajectories are almost indistinguishable, especially in the one year before and three years after the boom starts. We also incorporate this approach in the 2SLS framework, where we run the regression using the stacked sample and incorporate cohort-specific fixed effects in both stages. These results are reported in Table A5.

In addition, we find that these patterns and estimates are robust (1) using other reasonable "no-boom" cutoffs and (2) using a "boom" indicator instead of an intensity measure. These results are available upon request. In general, we consistently find that the results under this approach are similar to our main estimation. Therefore, we conclude that our main results are not subject to substantive bias due to the negative weighting problem.

E Additional Notes on Heterogeneity Analysis

E.1 Estimation Equations

In Section 5, we estimate heterogeneous effects based on (1) judicial review law status and (2) non-SFHA tail risk. In this section, we specify and discuss the two-stage least square (2SLS) estimation equations used in those two tests.

In both tests, we estimate the heterogeneous effect based on an indicator variable, $Char$. In the first test, it indicates that the MSA is subject to the judicial review law. In the second, it indicates that the MSA has above-median non-SFHA risk. Formally, our second-stage equation is a version of Equation (3) with an additional interaction term:

$$lnNFIP_{mt} = \beta_1 \cdot \widehat{lnHPI}_{mt} + \beta_2 \cdot \widehat{lnHPI_{mt} \times Char_m} + \delta' X_{mt} + \lambda_m + \lambda_t + \varepsilon_{mt}. \tag{E1}$$

Note that we do not need to include $Char_m$ in the equation because it is absorbed by the MSA fixed effect. β_1 measures the home price elasticity of take-up by the baseline group (MSAs with no judicial review law/below-median risk), and β_2 measures the additional effect for the indicated group. Since $lnHPI$ is an endogenous variable, so is the interaction term. Therefore, we need to instrument for both in the first stage:

$$\begin{aligned} lnHPI_{mt} =& \sum_{\tau=0}^{24} \rho_{1\tau}(Post^{\tau}_{mt} \times \Delta P_m) + \sum_{\tau=0}^{24} \sigma_{1\tau}(Post^{\tau}_{mt} \times \Delta P_m \times Char_m) \\ &+ \mu_1' X_{mt} + \gamma_{1m} + \gamma_{1t} + \omega_{1mt} \\ lnHPI_{mt} \times Char_m =& \sum_{\tau=0}^{24} \rho_{2\tau}(Post^{\tau}_{mt} \times \Delta P_m) + \sum_{\tau=0}^{24} \sigma_{2\tau}(Post^{\tau}_{mt} \times \Delta P_m \times Char_m) \\ &+ \mu_2' X_{mt} + \gamma_{2m} + \gamma_{2t} + \omega_{2mt}. \end{aligned} \tag{E2}$$

In addition to the original set of instruments, we interact each of them with $Char_m$ to create new instruments in these regressions.

E.2 Interpretation

The main challenge in interpreting β_2 is that the characteristic of interest $Char_m$ might not be exogenous. Thus, although β_2 represents the differential effect of home prices for MSAs with this characteristic relative to those without, we cannot causally attribute the entire effect to the characteristic. We can, however, consider the most likely confounders and assess how they might affect the interpretation of β_2.

For the analysis with the judicial review laws, one might be concerned that the statute itself was established in response to the housing market conditions in the state. This is, however, unlikely because most state foreclosure laws were established in the 1930s and few have changed since (Demiroglu et al., 2014). Nevertheless, the judicial review status might still be correlated with other drivers of the relationship between housing prices and insurance take-up. To explore the differences between the MSAs with judicial review laws and those without, we examine the differences between the major characteristics of each

Table E1: MSA Characteristics by Judicial Review Law and
Non-SFHA Extreme Risk (2001 Q1)

Group	*A. Judicial Review Law* No (N=127)	Yes (N=138)	*p*-value
Structural Break IV	0.05 (0.07)	0.03 (0.06)	0.016**
Total SFHA Policies	2,618 (6,304)	8,908 (27,960)	0.011**
Total Non-SFHA Policies	1,539 (4,063)	4,091 (12,029)	0.020**
Average Risk Score (SFHA)	4.64 (1.27)	4.78 (1.33)	0.372
Average Risk Score (Non-SFHA)	1.66 (0.39)	1.67 (0.68)	0.829
1-Yr Renewal Rate (SFHA)	0.76 (0.15)	0.77 (0.18)	0.825
1-Yr Renewal Rate (Non-SFHA)	0.81 (0.19)	0.83 (0.20)	0.400
Population	832 (1,412)	728 (1,141)	0.514
Income	29.0 (5.76)	29.5 (5.44)	0.464
Employment Rate	0.58 (0.08)	0.59 (0.08)	0.335
Home Sales	13,494 (22,755)	10,742 (20,194)	0.308
	B. Non-SFHA Tail Risk		
Group	Below Median (N=133)	Above Median (N=132)	*p*-value
Structural Break IV	0.05 (0.08)	0.03 (0.05)	0.016**
Total SFHA Policies	9,944 (28,574)	1,814 (4,431)	0.001***
Total Non-SFHA Policies	4,806 (12,550)	915 (2,029)	0.001
Average Risk Score (SFHA)	4.35 (1.23)	5.08 (1.27)	<0.001***
Average Risk Score (Non-SFHA)	1.72 (0.56)	1.61 (0.56)	0.106
1-Yr Renewal Rate (SFHA)	0.79 (0.15)	0.74 (0.19)	0.013**
1-Yr Renewal Rate (Non-SFHA)	0.82 (0.18)	0.83 (0.21)	0.738
Population	1,016 (1,632)	540 (704)	0.002***
Income	29.4 (6.23)	29.1 (4.89)	0.593
Employment Rate	0.58 (0.09)	0.60 (0.08)	0.114
Home Sales	14916 (24688)	8986 (17064)	0.025**

Source: OpenFEMA policy and claims data, Charles et al. (2019), Bureau of Economic Analysis, FHFA Home Price Index, First Street Foundation, CoreLogic Deeds data
Notes: This table reports the mean of major characteristics for each group. The last column reports the p-value of the difference in group means. *p < 0.1; **p < 0.05; ***p < 0.01

group in the first quarter of 2001 (see Panel A of Table E1). The two groups have notable differences: MSAs with judicial review laws experienced smaller housing booms and have a greater number of NFIP policies in force. However, the groups are quite comparable in other dimensions. In particular, we detect no systematic differences in factors appears that could amplify or weaken the relationship between housing prices and insurance take-up, such as the overall risk level, income, and household liquidity (as proxied by the one-year renewal rate). Therefore, this gives us more confidence that the comparison between the two groups can provide meaningful evidence on the effect of foreclosure costs.

For the analysis of non-SFHA tail risk, we compare MSAs with above-median non-SFHA tail risk to those below the median. It should be noted that our risk measure is intended to capture the extremity of risk instead of the average level. For the latter, its time-varying effect has already been controlled for in the estimation. There are more qualitative differences in baseline characteristics between the two groups of MSAs (see Panel B of Table E1). The MSAs with above-median tail risk experienced smaller housing booms, have a significantly smaller number of policies in force, and have a smaller population. The SFHAs in these MSAs also have high average risk levels and one-year renewal rates. Nevertheless, these variables are not systematically different for non-SFHA policies, which is more reassuring because our main outcome of interest is non-SFHA take-up. Similarly, the two sets of MSAs have no difference in income levels.

F First-Difference Estimation

To separately examine the changes in flood insurance take-up over the course of the housing boom and bust, we use the first-difference approach following Charles et al. (2018). They show that the structural breaks not only predict the housing boom during 2000–2006 but also the size of the bust during 2007–2012.

For the boom period, we instrument housing price change from 2002 to 2007 using the structural breaks:

$$\Delta_{boom} lnNFIP_m = \beta_0 + \beta_{FD} \widehat{\Delta_{boom} lnH}PI + \delta' \Delta_{boom} X_m + \varepsilon_m. \tag{F1}$$

Here, Δ_{boom} represents the change in the variable between 2002 Q1 and 2007 Q1, which we apply to all variables in the original regression. We also directly control for the risk score. Our key regressor is the change in log housing price index ($\Delta lnHPI$), which we instrument with the break size instrument. The coefficient β_{FD} is the first-difference estimate of how housing price changes during the boom affect flood insurance take-up. The corresponding reduced-form regressions take the form

$$\Delta_{boom} lnNFIP_m = \alpha_0 + \alpha_{FD} \Delta P_m + \gamma' \Delta_{boom} X_m + u_m, \tag{F2}$$

where we regress the first difference in NFIP policy count directly on the structural break size and the same set of first-differenced covariates.

For the bust period, we augment the above specification by adding an interaction term between the housing price change and an indicator for whether the building was built between 2003 and 2005. These homes, which we call the "boom cohort", are likely to see close to zero or negative equity during the bust and hence be most subject to the risk shifting mechanism.

The regression takes the following form:

$$\begin{aligned}\Delta_{bust} lnNFIP_m = &\beta_0 + \beta_{FD}\Delta_{bust}\widehat{lnH}PI + \beta_{FD,BC}\Delta_{bust}\widehat{lnH}PI \times 1(BoomCohort) \\ &+ \delta' \Delta_{bust} X_m \times 1(BoomCohort) + \varepsilon_m.\end{aligned} \tag{F3}$$

Here, Δ_{bust} represents the change in the variable between 2007 Q1 and 2012 Q1, which we apply to all variables in the original regression. We also include an additional control of the share of foreclosures among home sales.