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

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August 19, 2021

Abstract

Millions of homeowners are exposed to increasing financial risk from natural disasters. Yet, many households are uninsured against the costliest disaster: flooding. We show that low home equity is an important driver of low flood insurance take-up. To isolate the causal effect of home equity on flood insurance demand, we exploit price changes over the housing boom and bust. Insurance take-up follows house price dynamics closely, with a home price elasticity around 0.3. Multiple mechanism tests suggest that mortgage default acts as implicit disaster insurance. As a result, households do not fully internalize their disaster risk.

JEL: G52, G21, Q54.
Keywords: disaster insurance, home equity, housing booms and busts, household finance, strategic default

*We thank Ben Collier, Fernando Ferreira, Rhiannon Jerch, Emily Gallagher, Ben Keys, Carolyn Kousky, Howard Kunreuther, Amine Ouazad, Margaret Walls, Joakim Armand Weill, and participants at the Wharton Urban Lunch, Wharton Risk Center Research Seminar, First Street Foundation Flood Lab Workshop, Urban Economics Association Virtual Meeting, Eastern Economics Association Virtual Meeting, Ohio State University PhD Conference in Real Estate Finance, and Federal Housing Finance Agency seminar for helpful comments and suggestions. We thank Brett Lingle for his help with First Street Foundation data. Any remaining errors are our own.

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] Large disasters cause severe financial distress for many households and lead to mortgage delinquency and default.[2] An analysis from CoreLogic finds that the sequence of devastating hurricanes and wildfires in 2017–2018 tripled mortgage delinquency rates in affected areas (Betten et al., 2019).[3] Ouazad and Kahn (2019) find that major hurricanes caused a 1.6 percentage point increase in the probability of home foreclosure. However, millions of flood-prone properties in the country remain uninsured for flood damage, contributing to the mortgage system's exposure to disaster risk. Identifying the causes of this flood insurance demand gap is critical for understanding how climate change will affect households and financial markets.

In this paper, we provide the first empirical evidence for a novel, incentive-based cause of low flood insurance take-up: mortgage default as implicit disaster insurance. After a flood, leveraged homeowners can default and limit their losses, effectively making their home equity their deductible if uninsured. For low-equity households, mortgage default can crowd out demand for formal insurance. Through this mechanism, home equity can have a positive causal effect on flood insurance demand by raising the cost of defaulting.

We estimate the effect of home equity on the demand for flood insurance from the National Flood Insurance Program (NFIP). The main challenge to establish 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 issue, 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 housing market cycle created price variation within and across housing markets 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 each MSA's home price trend from Charles et al. (2018), most of which occurred during 2003 to 2005. 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 over the housing bust from 2007 to 2012, the MSAs with the largest initial booms had the lowest growth in flood insurance policies.

Our formal difference-in-differences specification exploits variation in the timing and magnitude

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

[2] The Federal Reserve estimated that about 40 percent of American adults are not able to cover an unexpected $400 expense by cash or savings (Canilang et al., 2020). However, the typical cost of repair and rebuilding after a disaster is orders of magnitude larger. For example, the average flood insurance claim in 2019 was $52,000 (https://www.fema.gov/data-visualization/historical-flood-risk-and-costs).

[3] Other studies documenting the housing finance impacts of disasters include Anderson and Weinrobe (1986), Morse (2011), Billings et al. (2019), Issler et al. (2019), and Kousky et al. (2020).

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, recent floods, and risk-dependent trends. 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 made by households and to address concerns about the exclusion restriction for our instrument.

We identify two mechanisms that may drive the relationship between home equity and flood insurance demand in our results. First, homeowners with more home equity may have a higher willingness to pay for flood insurance because post-disaster mortgage defaults are more costly (henceforth the "default incentive" mechanism). Second, higher home equity combined with easier credit access during the housing boom may have given households greater liquidity to pay annual flood insurance premiums (henceforth the "liquidity" mechanism). Theoretically, we demonstrate how each mechanism can create a positive relationship between home equity and insurance take-up in a stylized model. We then empirically explore these mechanisms by testing a series of hypotheses.

If home equity increases flood insurance demand by improving access to liquidity, then we expect a negative relationship between insurance lapsation, or nonrenewal, and home prices. Over 20 percent of flood insurance policies lapse in their second year (Michel-Kerjan et al., 2012). Across insurance settings, lapsation has been shown to be driven by liquidity constraints.[4] We find that the relationship between home prices and flood insurance renewal rates is flat, which does not support the liquidity mechanism.

On the other hand, if home equity increases flood insurance demand through the default incentive mechanism, then we would expect a larger effect of home equity in states where default costs are low. We show that the home price elasticity of flood insurance take-up is significantly higher in states with borrower-friendly judicial foreclosure laws. Another prediction by this mechanism is that insurance demand should be more responsive to home equity in areas with greater tail risk exposure, which would induce default. Using a new national database of property-level flood risk, we find that MSAs with more tail risk exposure also have significantly higher home price elasticities of flood insurance take-up. Finally, take-up during the housing bust declines the most for homes built at the peak of the boom, exactly the group with the least home equity at the market's nadir. All of these findings support the default incentive mechanism.

These findings suggest that leveraged households do not fully internalize their environmental risk and that part of their risk is transferred to lenders instead. Lenders, in turn, rely on mortgage securitization to reduce their disaster risk exposure (Laux et al., 2017; Ouazad and Kahn, 2019; Keenan and Bradt, 2020). The government-sponsored enterprises (GSEs) that underwrite residential mortgage securitization do not price disaster risk or enforce mandatory flood insurance purchase outside of floodplains.[5] As a result, the remaining risk is ultimately borne by taxpayers along with

[4] For a discussion of lapsation in broader insurance contexts, see Hambel et al. (2017) or Gottlieb and Smetters (2021).

[5] Even within floodplains, evidence is inconsistent on whether mandatory purchase requirements are well enforced (Hecker, 2002; National Research Council, 2015).

obligations from a host of post-disaster public transfers (see Deryugina (2017) and 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, a distortion that will grow with increasing climate risk.

This paper provides novel insights into the relationship between environmental risk and housing finance. We are the first to estimate the causal effect of home prices on disaster insurance take-up, and our estimates show an economically important causal relationship.[6] 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.[7] We also present and test a mechanism where mortgage default serves as implicit insurance, offering a new explanation for the insurance gap to complement studies on the role of adverse selection and information frictions (Gallagher, 2014; Mulder, 2019; Wagner, 2021), affordability issues (Netusil et al., 2021), and disaster aid (Billings et al., 2019; Kousky et al., 018b). Our findings suggest that, as with macroeconomic shocks, default can insure households against climate shocks (Mitman, 2016), albeit at the social cost of reducing incentives to formally insure or invest in adaptation.

This paper also relates to a larger literature on the effect of home prices and equity on household finance decisions. Our theoretical framework for understanding how home prices can influence insurance demand draws on an extensive set of studies examining the effects of leverage on homeowner incentives to default (Foote et al., 2008; Ferreira et al., 2010; Melzer, 2017; Ganong and Noel, 2020). In our setting, natural disasters often make homes uninhabitable, removing a key barrier to "strategic default." Our empirical analysis builds on the literature studying the impacts of changing home prices over the housing boom and bust on consumption and investment (Charles et al., 2018, 2019; Kaplan et al., 2020b; Mian et al., 2013). These results show that real estate finance has economically significant effects on insurance demand and homeowner disaster risk management.

Finally, our findings extend and are consistent with research on the interactions between implicit insurance from default and demand for conventional insurance. Most relevant to this study, Mahoney (2015) finds that bankruptcy acts as implicit health insurance and a higher cost of bankruptcy induces greater insurance demand. 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. We show that default can also act as implicit disaster insurance, affecting demand for formal flood insurance and shifting environmental risk onto governments and creditors.[8]

The rest of the paper proceeds as follows. Section 2 provides a simple theoretical framework to motivate our empirical analysis. In Section 3, we describe our data and key features of the National Flood Insurance Program and the housing boom and bust. Section 4 explains our empirical design, Section 5 describes our results, and Section 6 concludes.

[6]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.

[7]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 (Gibson and Mullins, 2020; Kousky, 2010; Zivin et al., 2020).

[8]See Dobkin et al. (2018) for an example of how uninsured health costs spill over onto third parties.

2 Framework

In this section, 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 insurance willingness to pay. 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. We derive two empirical tests of the implicit insurance mechanism: the relationship between home equity and flood insurance demand should be stronger in MSAs with (1) lower default costs and (2) more tail risk exposure to extreme flood damages.

To consider an alternative home equity mechanism, we extend the baseline model to have two periods, income shocks, and an insurance renewal decision. In this setting, the positive relationship between flood insurance demand and home equity is primarily caused by liquidity-constrained households using their home equity to smooth negative income shocks and avoid lapsing on their disaster insurance policies. The liquidity mechanism suggests a third empirical test: a positive effect of home equity on flood insurance renewal rates.

2.1 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 the structure value, and M_H 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," respectively. 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.

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[9]:

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

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:

$$\mathbb{E}\left[E_H + \overline{W} - L\right] \leq E_H + \overline{W} - P_I. \tag{1}$$

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

$$\widehat{P} = \mathbb{E}(L). \tag{2}$$

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.

2.2 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:

$$\widehat{P} = \mathbb{E}\left[\min(L, \widehat{M} + E_H)\right] = \mathbb{E}(L) - \overbrace{p \cdot \int_{\widehat{M}+E_H}^{R_H} \left(r - (\widehat{M} + E_H)\right) \cdot f(r)dr}^{\textbf{implicit insurance effect}} \tag{3}$$

The key difference in Equation (3) from Equation (2) is the "implicit insurance effect" of default that is subtracted from expected repair costs. The willingness to pay specified in (3) is strictly less than that in (2) when the probability of disaster-induced default is nonzero.

[9]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.

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

$$\frac{d\widehat{P}}{dE_H} = p \cdot \Big(1 - F(\widehat{M} + E_H)\Big) > 0. \tag{4}$$

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 attractive compared to formal insurance.

Equation (4) identifies two factors that should influence the strength of the relationship between home equity and flood insurance demand. First, a higher value of the default costs $\widehat{M}$ decreases expression (4). Second, when the likelihood of extreme damages large enough to induce default is higher, expression (4) is larger. 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:

Mortgage Default Empirical Test (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.*

Mortgage Default Empirical Test (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.*

2.3 Insurance Renewal with Liquidity Constraints

Next, we consider how liquidity constraints affect the relationship between insurance demand and equity by extending our baseline model to consider the insurance renewal decision across two periods. Each period still has the pre-disaster, disaster, and post-disaster phases, and the choices and shock realizations in each period are denoted with a subscript $t = 1, 2$. Let the first period be as described in the baseline model.[10] Assume that the household buys insurance in the first period, meaning that the inequality in (1) holds.

In the pre-disaster phase of the second period, the agent faces a negative[11] income shock $w_2 \in [0, \overline{W}]$ distributed $g(w)$, for income $\overline{W}_2 = \overline{W} - w_2$. When deciding whether to renew, the agent can also borrow $B_2 \in [0, \delta E_H]$ where $\delta \in (0, 1)$ is a proportional loan limit. The disaster phase is

[10] We present the liquidity and default extensions separately for simplicity. The same empirical predictions hold when the models are combined.

[11] Under a positive income shock, the agent will renew their insurance with certainty.

the same as before with identical damage distribution. Post-disaster, the agent's utility is given by

$$E_H + \overline{W}_2 - I_2 \cdot P_I - (1 - I_2) \cdot L_2 - B_2. \tag{5}$$

The agent maximizes their expected utility subject to the constraints

$$I_2 \cdot P_I \leq \overline{W}_2 + B_2 \quad \text{and} \quad B_2 \leq \delta E_H.$$

Note that their period 1 choice reveals that the insurance is preferred as long as they have enough liquidity to pay for the premium up front. That is, they will renew if and only if

$$P_I \leq \overline{W}_2 + \delta E_H.$$

Thus, the probability of renewal is given by

$$Pr(I_2 = 1) = \int_0^{\overline{W} + \delta E_H - P_I} g(w)dw. \tag{6}$$

Equation (6) is increasing in E_H, suggesting that home equity can affect insurance demand by easing borrowing constraints. The relationship between home equity and renewal suggests the following empirical test of the liquidity constraints mechanism:

Liquidity Empirical Test. *MSAs with larger housing booms (busts) should see an increase (decrease) in flood insurance policy renewal rates.*

3 Data and Background

For our empirical analysis, 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 law, and demographics. Our final estimation sample consists of quarterly observations across 271 MSAs from 2001 to 2017 (see Table 1 for summary statistics). In this section, we introduce our data sources and describe background information about the National Flood Insurance Program and the housing boom and bust.

3.1 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) that writes over 95 percent of flood insurance policies in the United States (Kousky et al., 018a). Established in 1968, it currently covers 22,000 communities with more than five million policies in force nationwide.

In each community, FEMA defines the Special Flood Hazard Area (SFHA, or so-called "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). As the flood maps are infrequently updated and NFIP has no means-tested subsidy, no insurance pricing response exists for the home price changes we study (see Appendix Figure A4).

The NFIP, through the various federal agencies and GSEs that purchase and insure mortgages, makes flood insurance purchase mandatory on any home purchased inside the SFHA with a federally-backed mortgage (henceforth the "mandatory purchase requirement").[12] 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, 2020). This dataset covers the universe of NFIP policies written since 2009 and contains a comprehensive set of variables, including property zip code, policy effective date, construction year, the number of times the policy has been renewed, 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 a similar set of variables, allowing us to construct a consistent and comprehensive record of all NFIP policies written from 2000 to 2018. Next, we aggregate the number of one-to-four family residential policies active at the end of each quarter in each zip code and aggregate them to the MSA level. Thus, we end up with a quarterly MSA-level panel of flood insurance take-up for 2001–2017. As shown in Table 1, each MSA has about 10,500 active policies in our sample, 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 amount of coverage, deductible, and renewal rates. We use these outcomes to implement robustness checks and mechanism tests.

3.2 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,[13] a few consistent empirical

[12] 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.

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

observations have emerged. The housing price changes were highly heterogeneous across markets, with some seeing sudden price acceleration, whereas others experienced 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 represent growing buyer optimism about future price growth (Kaplan et al., 2020a).

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 for both Tucson (top right) and Naples (bottom right). The latter pattern motivates a procedure, pioneered by Ferreira and Gyourko (2017), 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 also identifies a "break" but the estimated size is minimal. 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 break. Figure A1 plots the size and timing of these breaks across our sample of MSAs. Although the method identifies the most likely break for every MSA, all the pre-2003 breaks are close to zero. Such MSAs are effectively a control group that saw smooth price changes over 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 tend to have larger breaks than inland ones, different coastal markets vary substantially, which will allow 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 postbreak 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 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 between 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 4.

3.3 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 homes 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 B.1 for more details on these measures.

Foreclosure law. One of our mechanism tests rely on variation in foreclosure laws across states. We follow Demiroglu et al. (2014) to classify states as following judicial or non-judicial foreclosure proceedings.[14] See Appendix B.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 employment rate from the Bureau of Economic Analysis, and residential housing transaction volume calculated using data from CoreLogic.

4 Methodology

In this section, we formally describe 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 the empirical tests motivated in Section 2 to examine the mechanisms underlying the causal relationship.

4.1 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 intensity and timing. The estimating equation is

$$lnNFIP_{mt} = \sum_{\tau=-9}^{24} \alpha_\tau (Post^\tau_{mt} \times \Delta P_m) + \delta' X_{mt} + \lambda_m + \lambda_t + \varepsilon_{mt}. \tag{7}$$

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

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

quarter after the housing boom starts in MSA m.[15] Each indicator is interacted with ΔP_m, the structural break intensity in each MSA, as described in Section 3.2. 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 and 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 (7) 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 2 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 tend 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 if areas with higher flood risk also saw an increase in flood insurance demand around the housing boom, which motivates our decision to include flood risk controls interacted with year in all of our baseline specifications, making our estimates robust to differential trends by flood risk.

We also estimate Equation (7) 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 (7) estimates the reduced-form effect of the housing boom and bust on flood insurance demand.

4.2 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 (7) can be reinterpreted as the reduced-form relationship between the outcome and the instrument. We implement

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

a two-stage least square (2SLS) estimation where the first-stage regression is

$$lnHPI_{mt} = \sum_{\tau=0}^{24} \rho_\tau (Post^\tau_{mt} \times \Delta P_m) + \mu' X_{mt} + \gamma_m + \gamma_t + \omega_{mt}. \tag{8}$$

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 (7). The only difference is that this equation excludes pre-boom interactions, as they do not capture meaningful variation from the boom-bust cycle. The second-stage equation is

$$lnNFIP_{mt} = \beta \cdot \widehat{lnHPI}_{mt} + \delta' X_{mt} + \lambda_m + \lambda_t + \varepsilon_{mt}. \tag{9}$$

$\widehat{lnHPI}_{mt}$ are the instrumented values of the house price index from Equation (8). The equation includes the same set of controls as before.

Equation (9) 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 were smoothly changing in the markets that saw these sudden price changes (Ferreira and Gyourko, 2017; 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, detailed below:

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, this 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 examine the take-up of non-SFHA policies separately, 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. Similar to earlier, 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 might have become better able to afford flood insurance (Ferreira and Gyourko, 2017; Charles et al., 2019). To account for this possibility, we control for annual MSA income and employment rate in all regressions.

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

4.3 Testing for Home Equity Mechanisms

The last part of our analysis focuses on testing the potential mechanisms driving the relationship between flood insurance take-up and home prices. We describe three empirical exercises motivated in Section 2 to test how home price fluctuations over the boom and bust may have affected flood insurance demand by changing home equity.

Section 2.2 generates two empirical predictions consistent with the mortgage default mechanism. First, flood insurance demand in MSAs with lower default costs should be more responsive to changes in home equity. We find variation in default costs by comparing states with and without judicial review laws.[16] Second, flood insurance demand in MSAs with a larger fraction of properties with tail risk exposure should also be more responsive to changes in home equity. To formally test these predictions, we extend the 2SLS procedure to estimate heterogeneous effects based on foreclosure laws and flood risk, 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 instrumenting for it using a corresponding interaction between the structural break instrument and the indicator. For details on this extended framework, see Appendix E.

To implement our test for the liquidity mechanism described in Section 2.3, we use flood insurance one-year renewal rate as our outcome variable. As shown in Table 1, the non-renewal rate in the second year of coverage is around 25 percent on average in our sample of MSAs. Although lapsation may be driven by several factors, research in other insurance settings supports the hypothesis that negative financial shocks to liquidity-constrained households play a large role (Gottlieb and Smetters, 2021).[17] Thus, if the increase in housing equity increased the overall flood insurance take-up rate by expanding credit access to households, we would expect to see a lower lapsation rate as house prices increase.

[16] See Section 3 for a description of these laws.

[17] See Michel-Kerjan et al. (2012) and Mulder (2019) for studies of lapsation in flood insurance.

5 Results

5.1 Dynamics of Insurance Choices Over the Boom-Bust Cycle

We start with the difference-in-differences framework to investigate the dynamics of our main outcomes over the boom-bust cycle. We first estimate Equation (7) 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 (7) 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 remain, described in Section 4.2, that 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, this might drive take-up mechanically through the mandate. To test this, we re-estimate Equation (7) over two subsamples of NFIP policies. The first subsample includes only policies written on structures built before 2003[18] 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 smaller 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 renovations, which could increase the property value at risk of flood damage, leading to higher insurance demand. If

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

this is the case, we would expect homeowners to purchase more building coverage, since most policyholders purchase coverage equal to the replacement value of their home (Collier and Ragin, 2020).[19] To test this, we estimate Equation (7) on the IHS-transformed average amount of building coverage. These results are shown in Appendix Figure *A*5. 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. This is consistent with many SFHA policyholders being bound by the mandatory purchase requirement, who may have only been holding the minimum coverage necessary to satisfy the requirement.[20] When their home equity increased in the boom, they purchased coverage beyond the minimum requirement.

Using the same estimation framework, we examine other margins of the insurance decision to test whether risk preferences or perceptions changed over the boom-bust cycle. Figure A6 shows the estimates on the share of newly enrolled SFHA policies with supplemental contents coverage.[21] A slight increase occurs following the start of the housing boom, but the magnitude is 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 A7 shows the dynamics of the share of newly enrolled SFHA policies with the standard deductible[22], which is largely unresponsive to the boom. These results suggest that risk preferences and perceptions are quite stable across the boom-bust cycle.

5.2 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.

We estimate the home price elasticity of flood insurance demand using the 2SLS estimator described in Equations (8) and (9). The results are reported in Table 3. 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

[19] 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.

[20] The minimum required coverage is the lesser 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.

[21] 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.

[22] 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.

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[23] of over 30, confirming the strength of the instruments, and 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). In comparison, our estimates suggest a 1 percent increase in home prices has roughly the same effect as a 2 percent decrease in premiums on overall take-up, or 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.

We also separately estimate the effect of housing price changes over the boom and bust periods. Whereas the boom increased home equity, the bust dramatically cut the equity of leveraged homeowners, especially those that bought near the peak of the boom. To compare flood insurance home price elasticities across the boom and bust, we use a first-difference approach where we estimate 2SLS regressions with all variables differenced over two periods (Charles et al., 2018).[24] We take 2002 Q1 to 2007 Q1 to be the boom period and 2007 Q1 to 2012 Q1 to be the bust.

Table 4 reports these results. During the boom, the home price elasticity of take-up is 0.33 for all policies and 0.36 for non-SFHA policies (Panel A, columns (1)–(2)), comparable to the overall estimates. These elasticities are larger during the bust (Panel A, columns (3)–(4)), especially for non-SFHA policies, whose elasticity is twice as large. When we focus on homes constructed between 2003 and 2005 and estimate their take-up elasticity over the bust, both estimates increase sharply to around 1.4. As these homes were bought near the peak of the boom, the owners likely saw their home equity drop to very low, or even negative, levels in the bust. These patterns, therefore, suggest that the effect of an increase and a decrease in home prices on flood insurance demand is asymmetric, and the effect is particularly strong for those with low levels of home equity in the first place.

5.3 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 A8). The corresponding 2SLS estimates are also similar across the board, among which our main specification is the most conservative (see Table A1).

Second, we obtain similar difference-in-difference estimates examining the count of newly enrolled policies in a given quarter instead of all active policies. As NFIP policies are effective for

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

[24]See Appendix C for the regression equations.

one year, the number of active policies will respond with a lag 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 A9).[25] Table A4 reports the 2SLS estimates based on the number of newly enrolled policies, which are also similar to the main results.

In Table A2, 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.[26] 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).[27] Unlike TWFE with variation in treatment timing, the stacked estimator avoids spurious violation of the parallel trends assumption that can occur with dynamic and heterogeneous treatment effects (Baker et al., 2021).[28] 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 A3, 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.

[25] 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.

[26] 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 2007. In Equation (8), 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.

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

[28] See also Sun and Abraham (2020), Callaway and Sant'Anna (2020), and Goodman-Bacon (2021) discussing this issue.

5.4 Mechanisms: Liquidity vs. Default Incentive

Our results so far have established a robust and plausibly causal connection between home prices and flood insurance take-up. This is inconsistent with the frictionless baseline model of disaster insurance demand in Section 2. On the other hand, Sections 2.2 and 2.3 each present a financial friction that can drive this relationship. In this section, we test the empirical predictions derived from each of these mechanisms.

The first mechanism, described in Section 2.3, is that liquidity-constrained homeowners may have extracted their growing home equity with cash-out refinances to purchase and maintain flood insurance. To test this, we examine the one-year insurance renewal rate in the boom period; with the short time frame, we aim to capture mostly lapsation driven by liquidity rather than changing risk perceptions or actual flood experience. If greater equity eased liquidity constraints, we would expect more policyholders to renew their flood insurance coverage, especially at the outset of the boom.

We estimate Equation (7) with one-year renewal rates as the dependent variable. Figure 5 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.[29]

The second mechanism, described in Section 2.2, focuses on the implicit insurance value of mortgage defaults. When facing a large loss from disasters, leveraged households can default on a mortgage rather than pay the full cost of repairs. However, when home equity increased over the housing boom,[30] defaulting became more costly for leveraged households, increasing their willingness to pay for disaster insurance.

Our first test of this mechanism is to exploit differences in the baseline cost of default across states with and without laws that require judicial review of foreclosure proceedings. In the latter states, defaults are more costly for borrowers and thus less viable as a form of implicit insurance. Thus, this mechanism is weaker in such states, and flood insurance demand should be less responsive to changing home prices.

Figure 6 plots the coefficients from estimating Equation (7) 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. This supports the default incentive mechanism.

A second prediction of the default incentive mechanism is that homeowners facing tail risk should be more responsive to home equity in their disaster insurance demand. As shown in Section 2.2, the effect of a change in 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

[29] We find similar results using three- and five-year renewal rates as our dependent variable. These results are available upon request.

[30] A necessary assumption for the default mechanism channel is a positive relationship between home price changes and home equity over the boom and bust. Despite a concurrent increase in mortgage debt over the boom, Figure A10 shows that home equity covaries positively with house prices over the housing cycle.

calculate the following measure of non-SFHA tail risk exposure:

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

The denominator and numerator capture the extent of the flood insurance market outside the SFHA and the subset of properties facing severe enough risk that a mortgage default is potentially relevant after a flood, respectively.[31] This ratio is 1–89 percent across MSAs, with the median at 65 percent.

We examine how the effect of home equity varies across MSAs with different tail risk exposure.[32] Importantly, in all regressions, we 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 7 plots the coefficients from estimating Equation (7) 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 across the two groups, the high-tail-risk group has a much larger flood insurance take-up response,[33] so this finding is also consistent with the default incentive mechanism.

We formally test the statistical significance of these 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.[34] These results are shown in Table 5. 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 0.74 versus only 0.36 in states without such laws. MSAs with above-median tail risk have a home price elasticity of flood insurance demand of 0.83 versus 0.49 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.

In sum, we find strong evidence consistent with the default incentive playing an important role in the relationship between home equity and flood insurance take-up but little empirical support for the liquidity mechanism.

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[31] 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. See Appendix B.1 for more detailed discussions.

[32] One concern with this variable might be that MSAs with higher tail risk 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.

[33] 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.

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

6 Conclusion

We find a significant and positive relationship between home prices and flood insurance take-up over the housing boom and bust of the early 2000s. These price changes reflect a large increase 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.

We explore two potential mechanisms for this effect. First, we test whether higher home equity increased demand by improving homeowner liquidity. We find no evidence that renewal rates increased with home prices, which does not support this mechanism. By contrast, our tests suggest that home equity may have affected demand by changing the implicit insurance value of mortgage default. For leveraged households facing a large flood loss, defaulting allows them to cap their losses at the value of their home equity. Thus, an increase in home equity lowers this implicit insurance value and increases demand for flood insurance. Consistent with this mechanism, we find higher home price elasticities of flood insurance demand in states with judicial review laws, where default is less costly, and in states with higher tail risk, where implicit insurance would be more valuable.

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 the 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.

However, our findings do point to two promising policy interventions. First, expanding the mortgage purchase requirement to high-risk non-SFHAs may lead homeowners 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 themselves 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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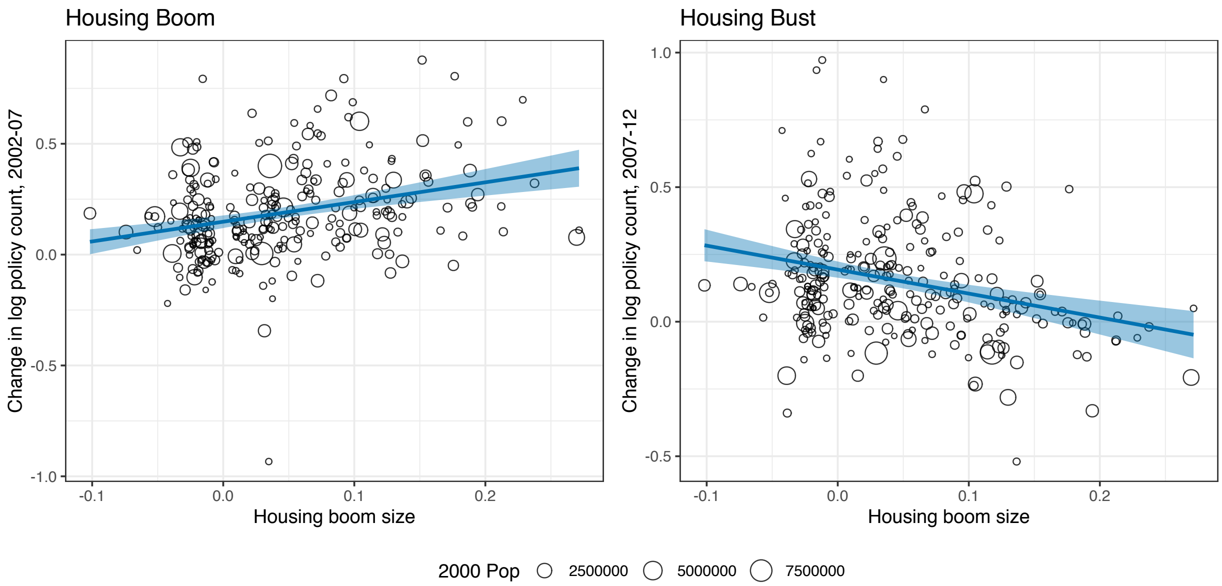
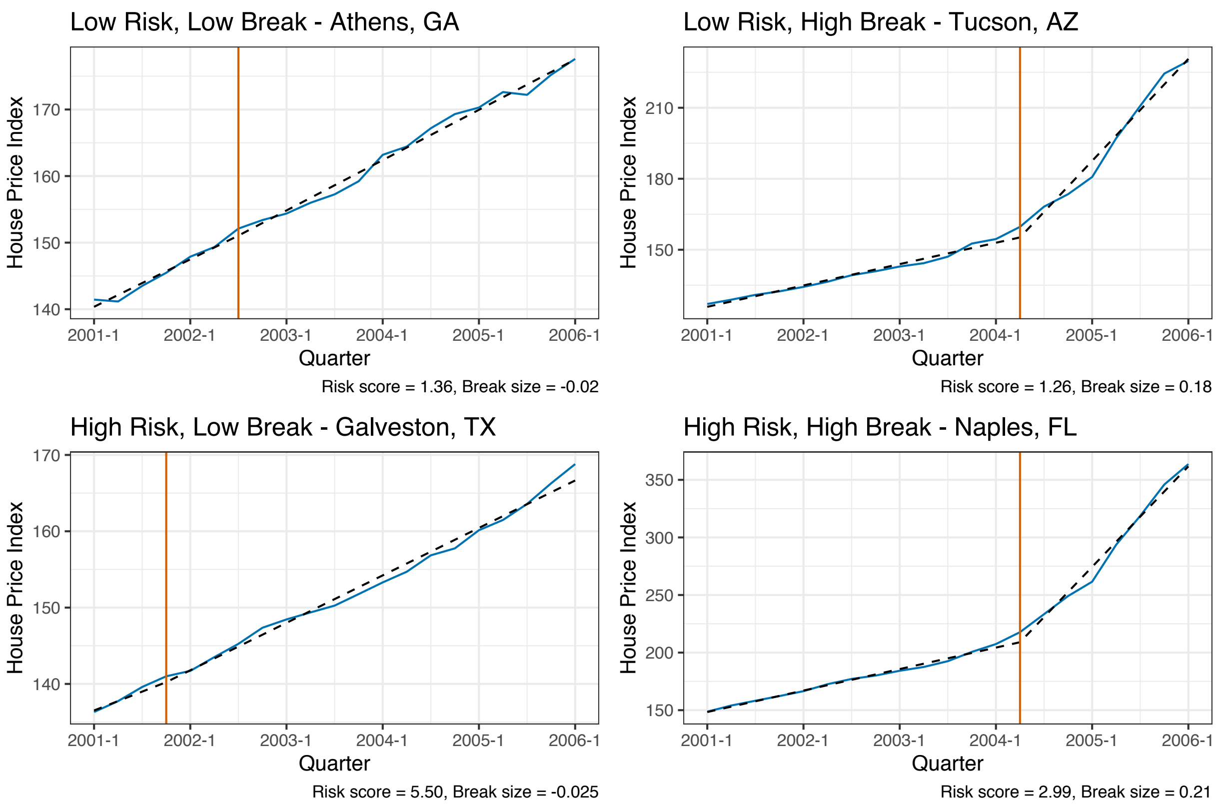
Figures

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



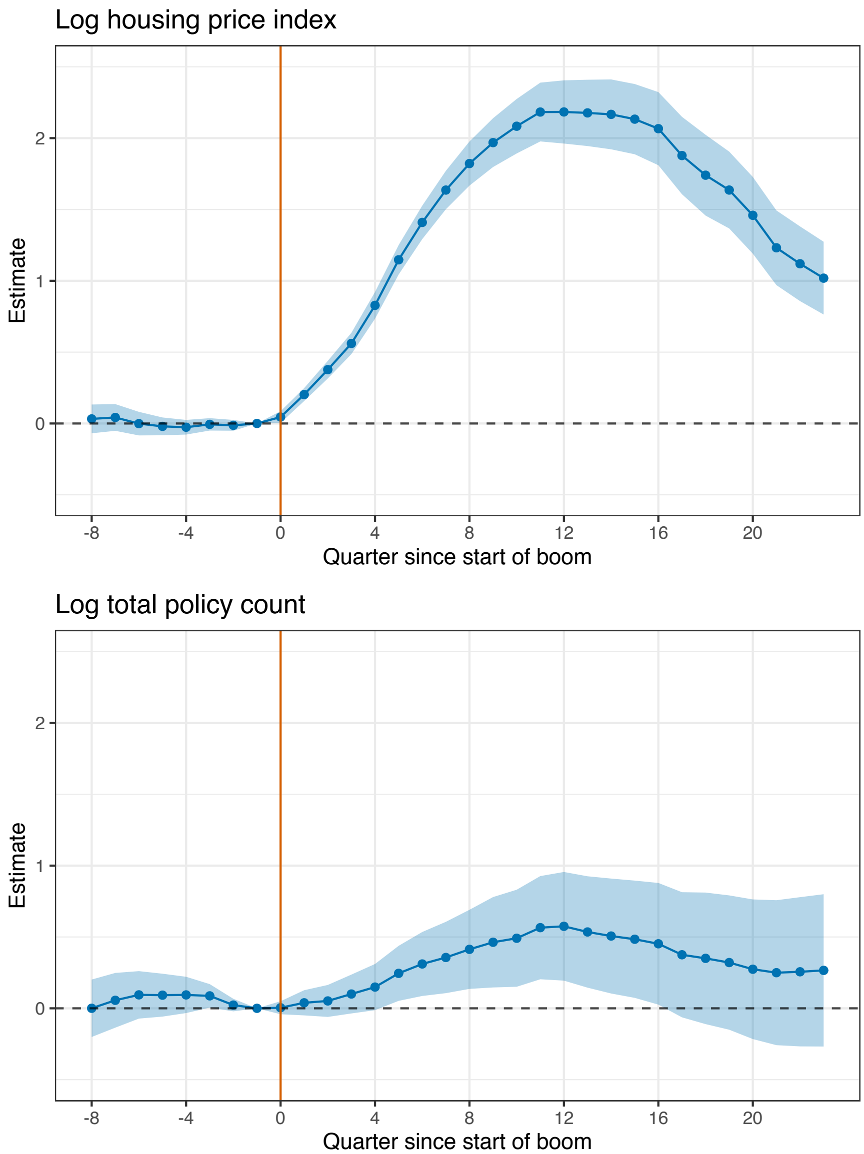
Notes: Each circle represents an MSA. The x-axis displays the size of the housing boom, and the y-axis displays the change in log NFIP policy count between 2002 and 2007 in the left panel and 2007 and 2012 in the right panel. The boom size measure comes from the structural break estimates in Charles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

Figure 2: Examples of Housing Booms



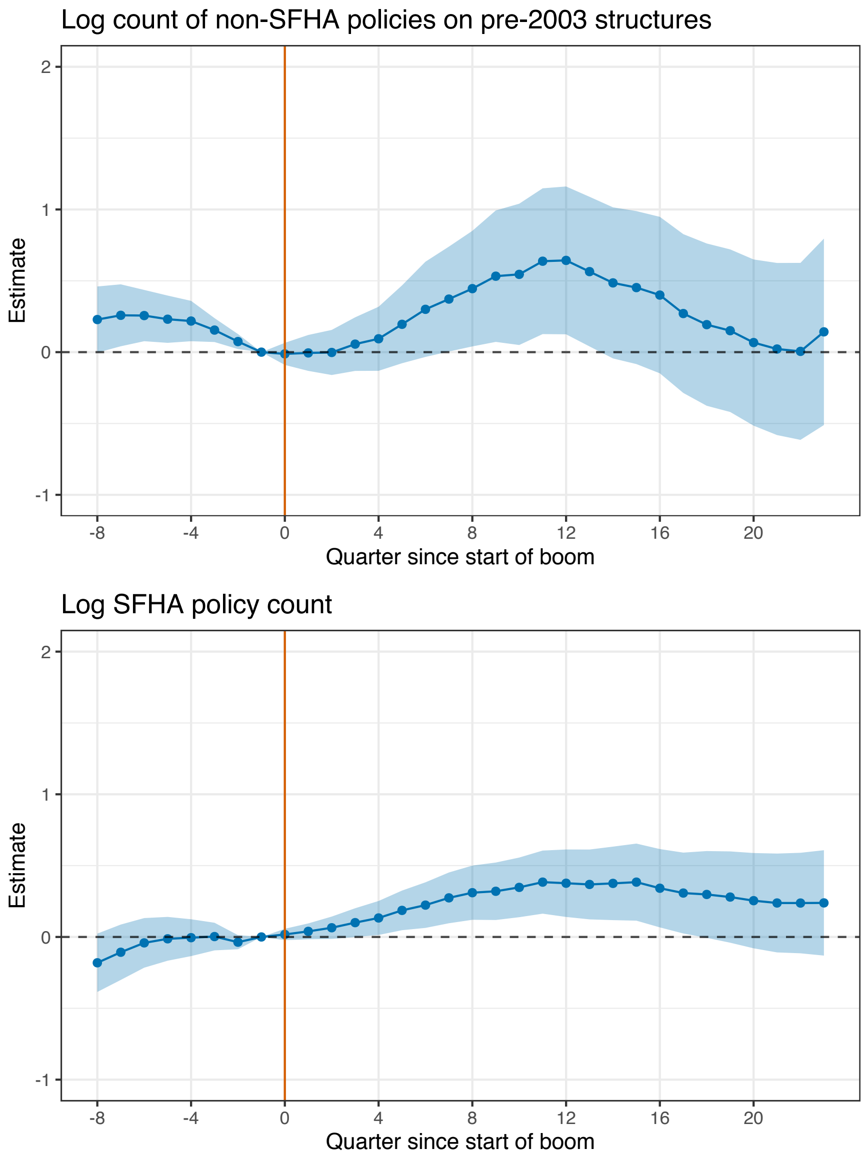
Notes: This figure shows the quarterly series of the housing price index for four MSAs. The four MSAs each represent a group of MSAs classified based on low/high risk and low/high break. In each panel, the blue solid line presents the house price series, the black dashed line presents the predicted value 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



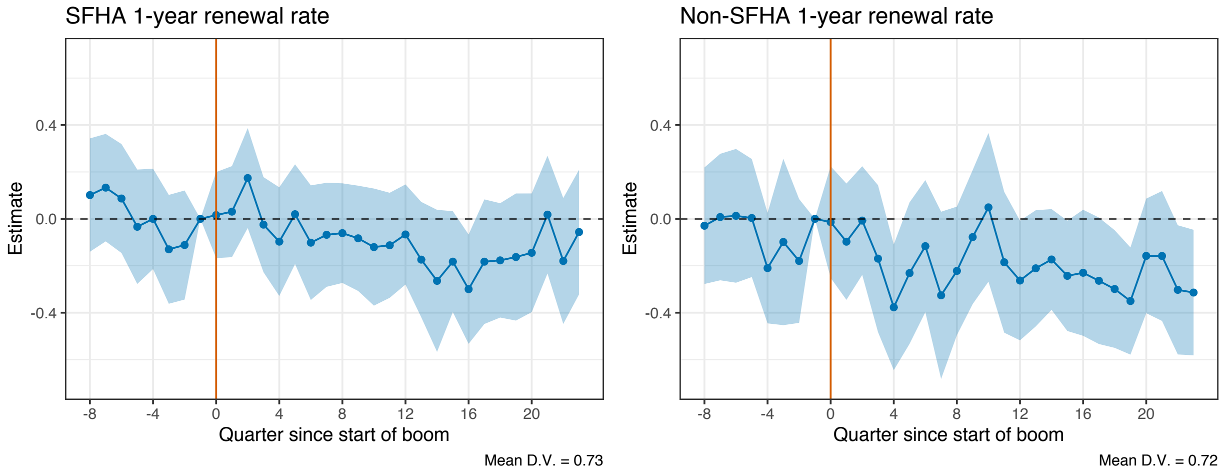
Notes: This figure plots the estimated coefficients and their 95 percent confidence intervals from Equation (7) for HPI (top panel) and total flood insurance policy count (bottom panel). Both dependent variables are IHS transformed. The policy count includes all one-to-four family policies.

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



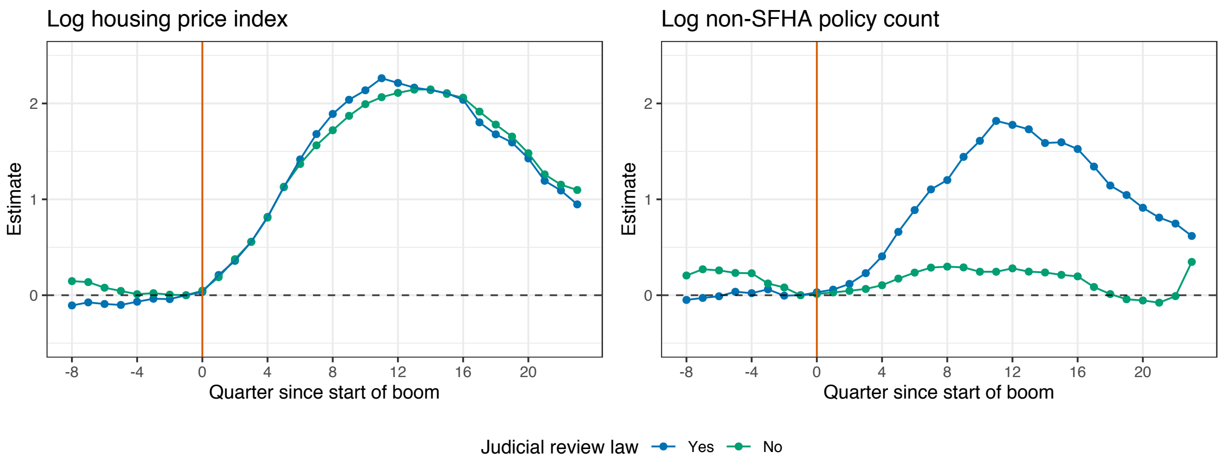
Notes: This figure plots the estimated coefficients and their 95 percent confidence intervals from Equation (7) for the count of flood insurance policies written on structures outside the SFHA and constructed before 2003 (top panel) and those inside the SFHA (bottom panel). Both dependent variables are IHS transformed.

Figure 5: One-Year Renewal Rate



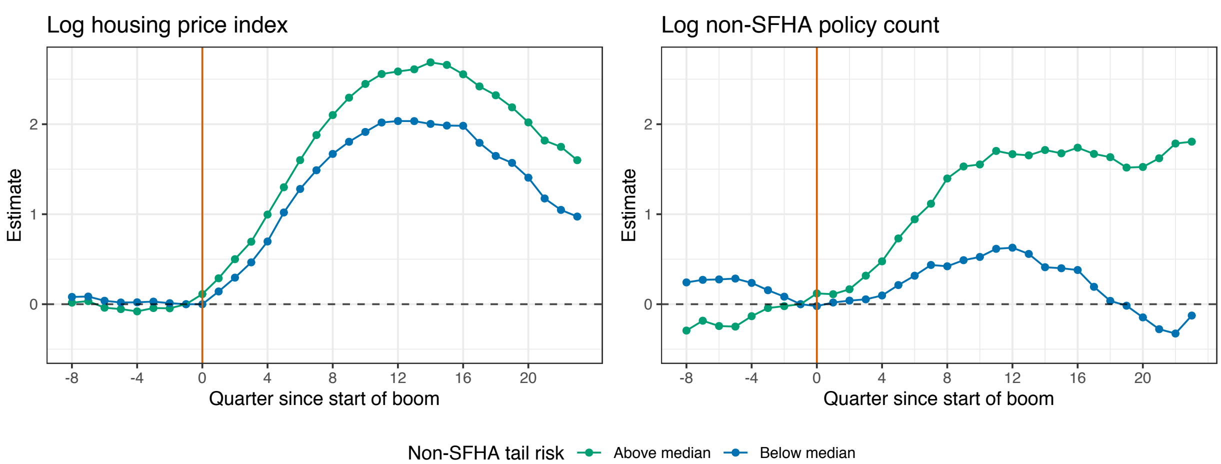
Notes: This figure plots the estimate coefficients and their 95 percent confidence intervals from Equation (7) for one-year renewal rates of policies inside the SFHA (left panel) and outside the SFHA (right panel).

Figure 6: Heterogeneity by Judicial Review Law



Notes: This figure plots the estimated coefficients from Equation (7) 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 7: Heterogeneity by Non-SFHA Risk



Notes: This figure plots the estimated coefficients from Equation (7) 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.

Tables

Table 1: Summary Statistics

Statistic	Mean	St. Dev.	10th Pctile	Median	90th Pctile
All Policies	10,461.58	31,285.15	285	1,783	23,356
SFHA Policies	5,992.94	20,655.23	135	962	10,437
Non-SFHA Policies	4,468.64	16,275.26	119	668	10,014
Non-SFHA Pre-03 Policies	3,841.19	13,984.26	107	594	8,512
Avg. Premium[1]	0.53	0.21	0.29	0.51	0.79
Non-SFHA Avg. Premium	0.26	0.09	0.17	0.24	0.37
SFHA Avg. Coverage	132,222.50	43,715.42	77,640.63	126,393.90	195,819.50
Non-SFHA Avg. Coverage	163,827.90	37,224.75	110,430.00	167,666.20	209,854.20
% Contents Coverage	0.33	0.21	0.12	0.28	0.69
% Standard Deductible	0.71	0.13	0.53	0.72	0.87
SFHA 1-yr Renewal Rate	0.77	0.20	0.56	0.78	0.94
Non-SFHA 1-yr Renewal Rate	0.75	0.19	0.55	0.75	0.93
Total Claims ($1,000s)[2]	9,067	214,941	0	131	4,011
Break Size	0.04	0.07	−0.03	0.03	0.14
FHFA Housing Price Index	173.25	38.69	134.12	165.07	223.88
Per Capita Income ($1,000s)	37.89	9.38	27.71	36.70	48.72
Population	842,666.90	1,349,823	139,313	375,670	1,955,794
Population Growth	0.01	0.01	−0.002	0.01	0.02
Employment Rate[3]	0.59	0.08	0.48	0.59	0.69
Home Transaction Volume	12,590.57	21,496.80	695	5,031	32,805
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

Notes: This dataset consists of quarterly observations across 271 MSAs during 2001–2017.
[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: 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]

Table 3: Home Price Elasticity of Insurance Take-Up

	Dependent variable: log(NFIP Policy Count)			
Policy Sample	All	SFHA	Non-SFHA	Non-SFHA + Pre-2003
	(1)	(2)	(3)	(4)
$\widehat{\log(\text{HPI})}$	0.307***	0.213***	0.483***	0.330**
	(0.077)	(0.061)	(0.154)	(0.142)
log(Income)	0.240	0.125	0.015	−0.076
	(0.278)	(0.260)	(0.407)	(0.375)
log(Sales)	0.003	0.006	0.018**	0.017**
	(0.006)	(0.006)	(0.009)	(0.009)
log(Claims)	0.003***	0.0002	0.007***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
Pop. Growth	−0.240	−0.167	−0.605	−0.046
	(0.557)	(0.563)	(0.757)	(0.687)
Emp. Rate	−0.509	−0.423	0.070	0.757
	(0.590)	(0.554)	(0.834)	(0.775)
Risk × Year indicators	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
First-stage F-statistic	39.10	52.59	36.76	36.76
Observations	15,112	15,112	15,112	15,112
Adjusted R^2	0.991	0.992	0.979	0.981

Notes: This table presents 2SLS coefficients from Equation (9). 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 (8), 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 4: Boom vs. Bust: Long-Difference Estimates

	Dependent variable: $\Delta\log$(NFIP Policy Count)					
	Boom (2002–2007)		Bust (2007–2012)			
	All	Non-SFHA	All	Non-SFHA	All 2003–2005	Non-SFHA 2003–2005
	(1)	(2)	(3)	(4)	(5)	(6)
	A. 2SLS Estimates					
$\Delta\widehat{\log(\text{HPI})}$	0.334***	0.364***	0.384***	0.731***	1.369***	1.452***
	(0.110)	(0.178)	(0.117)	(0.243)	(0.302)	(0.416)
Observations	250	250	250	250	250	250
First-stage F-stat	33.75	33.34	11.96	11.40	11.96	11.40
Adjusted R^2	0.024	0.034	0.170	0.126	0.147	0.123
	B. Reduced-Form Estimates					
Break Size	0.686***	0.745***	−0.662***	−1.247***	−2.358***	−2.478***
	(0.227)	(0.369)	(0.212)	(0.414)	(0.494)	(0.683)
Adjusted R^2	0.070	0.061	0.119	0.111	0.186	0.149

Notes: This table presents coefficients from first-difference specifications. Panel A reports the 2SLS coefficients from Equation (C1), and Panel B reports the corresponding reduced-form coefficients from Equation (C2). Columns (1)–(2) present boom-period estimates based on the difference between 2002 Q1 and 2007 Q1, while columns (3)–(6) present bust-period estimates based on the difference between 2007 Q1 and 2012 Q1. The outcome is the count of all policies in (1) and (3), of non-SFHA policies in columns (2) and (4), of all policies on buildings constructed during 2003–2005 and of non-SFHA policies on those buildings. All regressions control for first-differenced log income, log sales, population growth and employment rate, as well as the average risk score. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 5: Heterogeneity by Foreclosure Law and Non-SFHA Risk

	Dependent variable: log(NFIP Policy Count)			
Policy Sample	Non-SFHA		SFHA	
	(1)	(2)	(3)	(4)
$\widehat{\log(\text{HPI})}$	0.355**	0.493***	0.231***	0.285***
	(0.147)	(0.161)	(0.067)	(0.066)
$\widehat{\log(\text{HPI}) \times \text{Judicial}}$	0.383***		−0.067	
	(0.122)		(0.067)	
$\widehat{\log(\text{HPI}) \times \text{High Risk}}$		0.337**		0.107
		(0.154)		(0.078)
log(Income)	−0.020	−0.090	0.135	0.026
	(0.403)	(0.422)	(0.260)	(0.263)
log(Sales)	0.015*	0.020**	0.006	0.007
	(0.009)	(0.009)	(0.005)	(0.005)
log(Claims)	0.007***	0.007***	0.0002	0.0001
	(0.001)	(0.001)	(0.001)	(0.001)
Pop. Growth	−0.549	−0.702	−0.178	−0.214
	(0.753)	(0.772)	(0.563)	(0.569)
Emp. Rate	−0.197	−0.034	−0.374	−0.520
	(0.840)	(0.833)	(0.555)	(0.551)
Risk × Year indicators	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
First-stage F-statistic	(40.83, 94.55)	(36.09, 92.43)	(45.86, 93.88)	(46.68, 86.08)
Observations	15,112	15,112	15,112	15,112
Adjusted R^2	0.979	0.979	0.992	0.992

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. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

A Additional Tables and Figures

Table A1: Home Price Elasticity of Take-Up in Different Specifications

	Dependent variable: log(NFIP policy count)			
	(1)	(2)	(3)	(4)
$\widehat{\log(\text{HPI})}$	0.389***	0.354***	0.309***	0.307***
	(0.063)	(0.070)	(0.072)	(0.077)
log(Income)		0.223	0.247	0.240
		(0.279)	(0.277)	(0.278)
log(Sales)		0.004	0.003	0.003
		(0.006)	(0.006)	(0.006)
log(Claims)		0.004***	0.003***	0.003***
		(0.001)	(0.001)	(0.001)
Pop. Growth		−0.377	−0.263	−0.240
		(0.534)	(0.544)	(0.557)
Emp. Rate		−0.785	−0.507	−0.509
		(0.600)	(0.584)	(0.590)
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-statistic	97.96	47.54	42.77	39.10
Observations	17,476	15,172	15,112	15,112
Adjusted R^2	0.990	0.990	0.991	0.991

Notes: This table presents 2SLS coefficients from Equation (9). The dependent variable is IHS-transformed total policy count. The first-stage regression follows Equation (8), 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 A2: 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)
$\widehat{\log(\text{HPI})}$	0.262***	0.284***	0.342***	0.361***
	(0.068)	(0.071)	(0.069)	(0.068)
log(Income)	0.281	0.262	0.209	0.191
	(0.270)	(0.274)	(0.273)	(0.271)
log(Sales)	0.002	0.003	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	−0.221	−0.230	−0.256	−0.265
	(0.552)	(0.551)	(0.554)	(0.552)
Emp. Rate	−0.452	−0.479	−0.554	−0.579
	(0.582)	(0.583)	(0.589)	(0.589)
Risk × Year indicators	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
First-stage F-stat	3151.47	130.09	39.03	41.28
Observations	15,112	15,112	15,112	15,112
Adjusted R^2	0.991	0.991	0.991	0.991

Notes: This table presents 2SLS coefficients from Equation (9). The dependent variable is IHS-transformed total policy count. The first-stage regressions follow Equation (8), 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 A3: Instrumented Regressions—Stacked Design

	Dependent variable: log(NFIP Policy Count)		
	All	SFHA	Non-SFHA
	(1)	(2)	(3)
$\widehat{\log(\text{HPI})}$	0.284***	0.196***	0.515***
	(0.075)	(0.069)	(0.150)
log(Income)	0.389	0.242	0.057
	(0.395)	(0.316)	(0.506)
log(Sales)	0.002	0.006	0.016
	(0.007)	(0.006)	(0.010)
log(Claims)	0.004***	−0.001	0.009***
	(0.001)	(0.001)	(0.001)
Pop. growth	−0.932	−1.398*	−0.205
	(0.789)	(0.768)	(1.042)
Emp. Rate	−0.068	−0.217	0.513
	(0.740)	(0.655)	(1.078)
Risk × Year indicators	Yes	Yes	Yes
MSA-cohort FE	Yes	Yes	Yes
Quarter-cohort FE	Yes	Yes	Yes
First-stage F-stat	53.10	62.91	49.34
Observations	46,056	46,056	46,056
Adjusted R^2	0.988	0.991	0.976

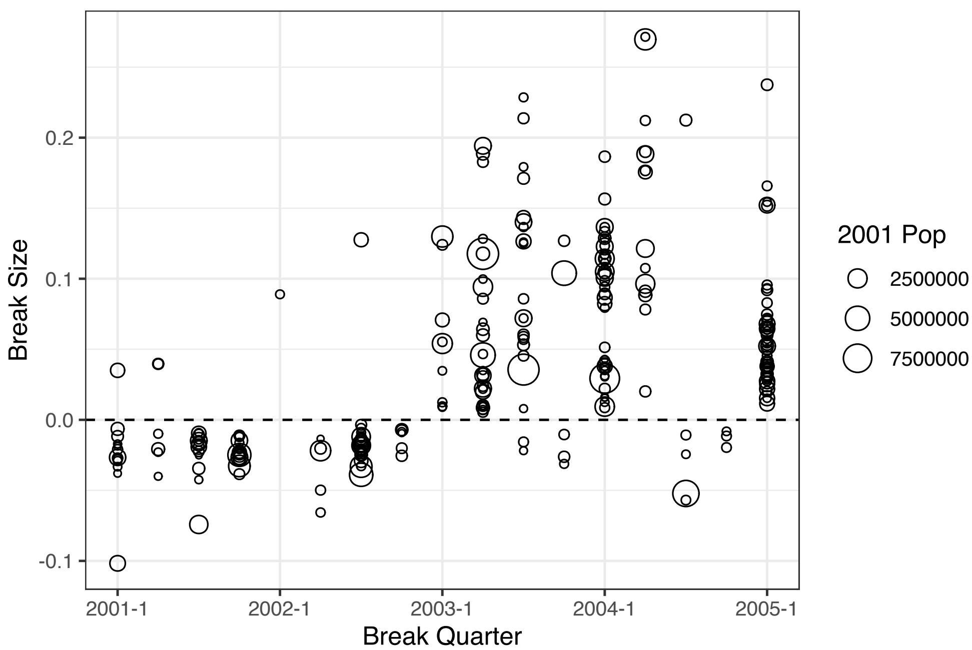
Notes: This table presents 2SLS coefficients from the stacked design as described in Appendix D. The dependent variables are IHS-transformed policy counts in categories indicated in the top panel. The corresponding F-statistic in the first-stage regression is reported in the bottom panel. Standard errors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

Table A4: 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

Notes: This table presents 2SLS coefficients from Equation (9). 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 (8), and the corresponding F-statistics are reported in the bottom panel. Standard errors (in parentheses) are clustered by MSA. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Figure A1: Size and Timing of the Structural Breaks



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. The structural break estimates are from Charles et al. (2019).

Figure A2: Housing Boom Size Across MSAs

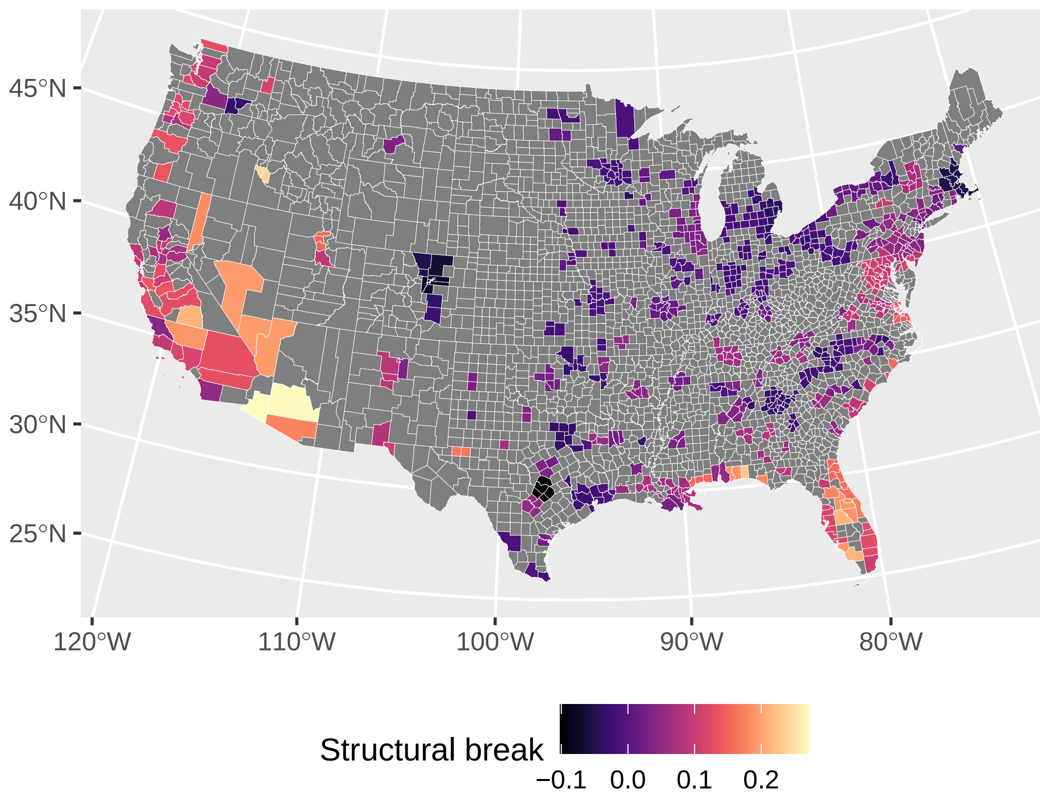
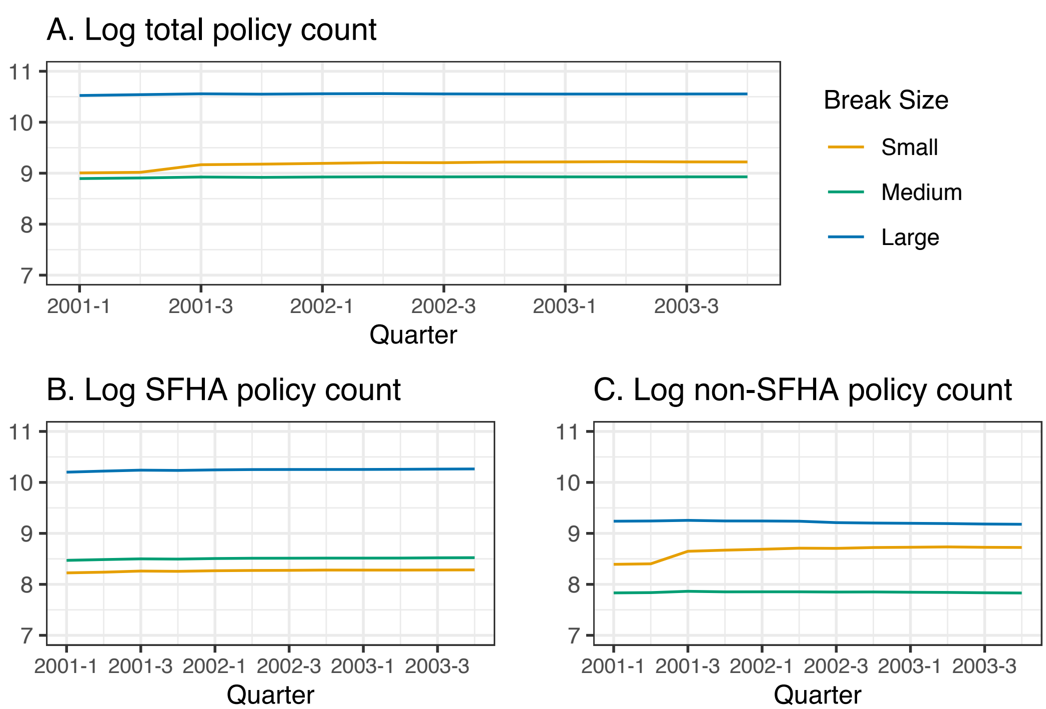
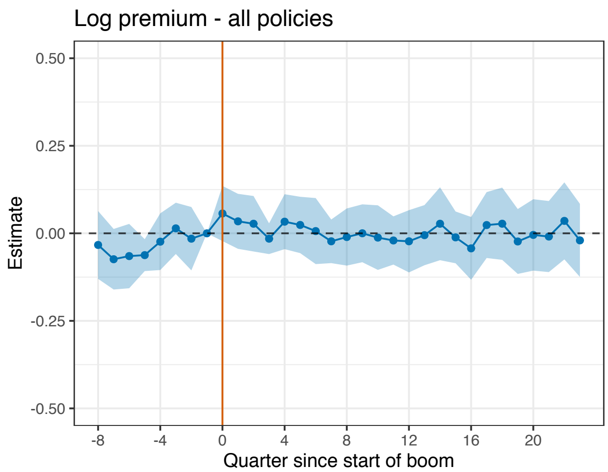


Figure A3: Pre-Boom Trends in NFIP Take-Up by Structural Break Tercile



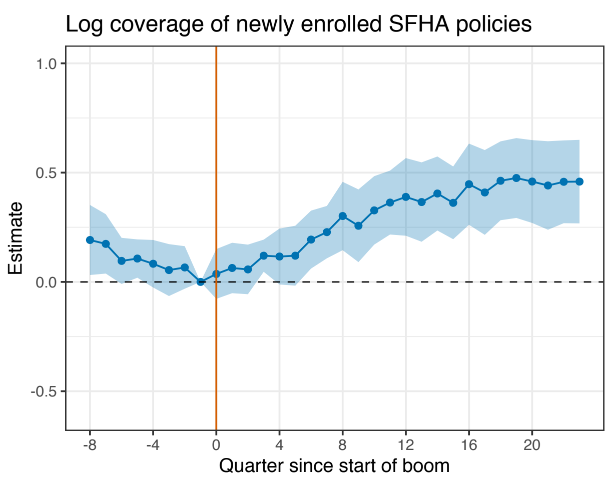
Notes: This figure shows the quarterly time series of NFIP policy in force during 2001–2003 in the raw data. Each color represents one group of MSAs in each structural break tercile. Panel A plots the IHS-transformed total policy count, and Panels B and C plot the IHS-transformed count of SFHA and non-SFHA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

Figure A4: Dynamics of NFIP Premium



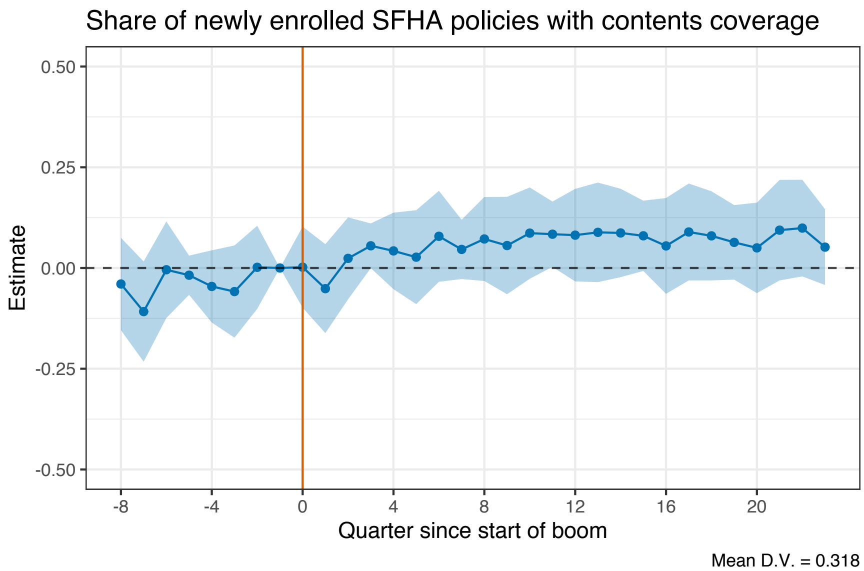
Notes: This figure plots the estimated coefficients and their 95 percent confidence intervals from Equation (7) for premium, measured as cost per \$100 coverage, of all policies (left panel) and non-SFHA policies (right panel). Both dependent variables are IHS transformed.

Figure A5: Dynamics of Building Coverage



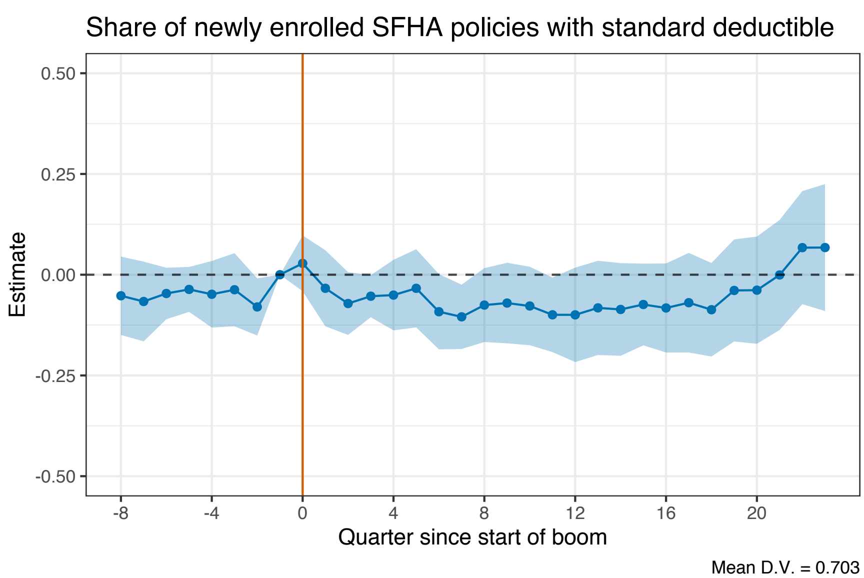
Notes: This figure plots the estimated coefficients and their 95 percent confidence intervals from Equation (7) for coverage purchased on flood insurance policies inside SFHAs (left panel) and outside SFHAs (right panel). Both dependent variables are IHS transformed.

Figure A6: Dynamics of Contents Coverage



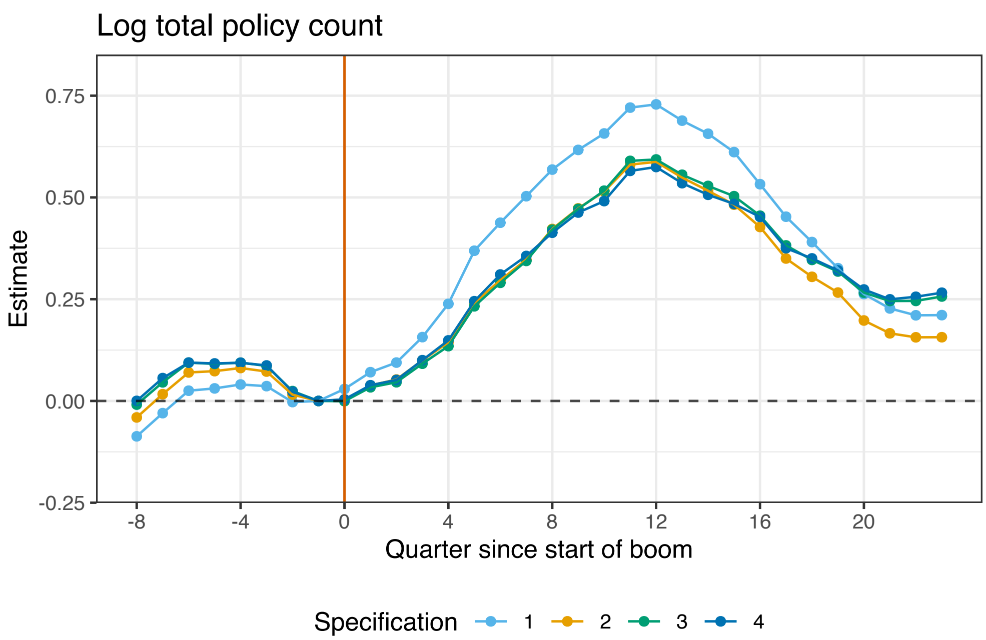
Notes: This figure plots the estimated coefficients and their 95 percent confidence intervals from Equation (7) for the share of newly enrolled SFHA policies that include contents coverage.

Figure A7: Dynamics of Deductible Choice



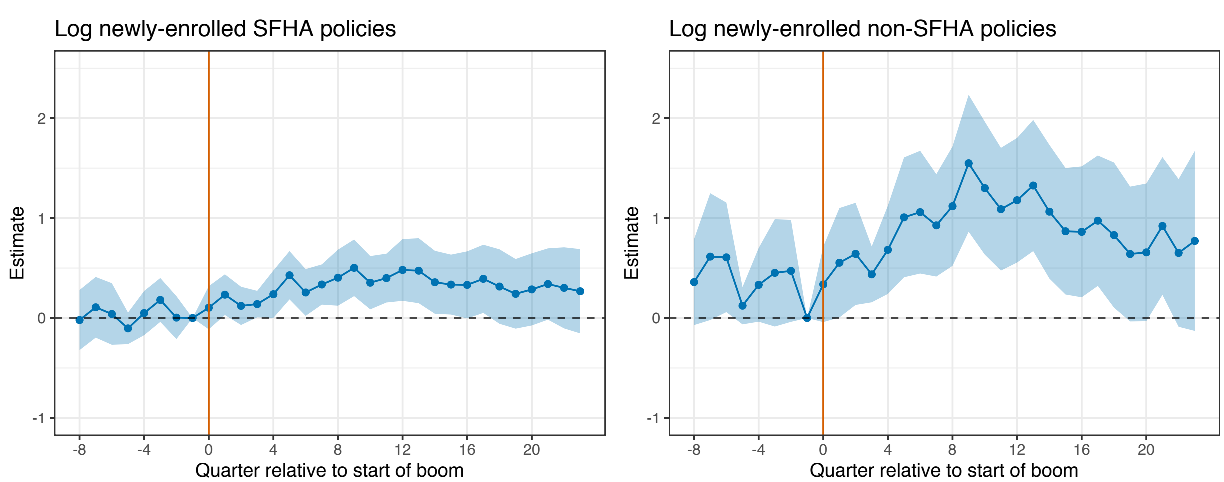
Notes: This figure plots the estimated coefficients and their 95 percent confidence intervals from Equation (7) for the share of newly enrolled SFHA policies with the standard deductible.

Figure A8: Dynamics of Take-Up Under Different Specifications



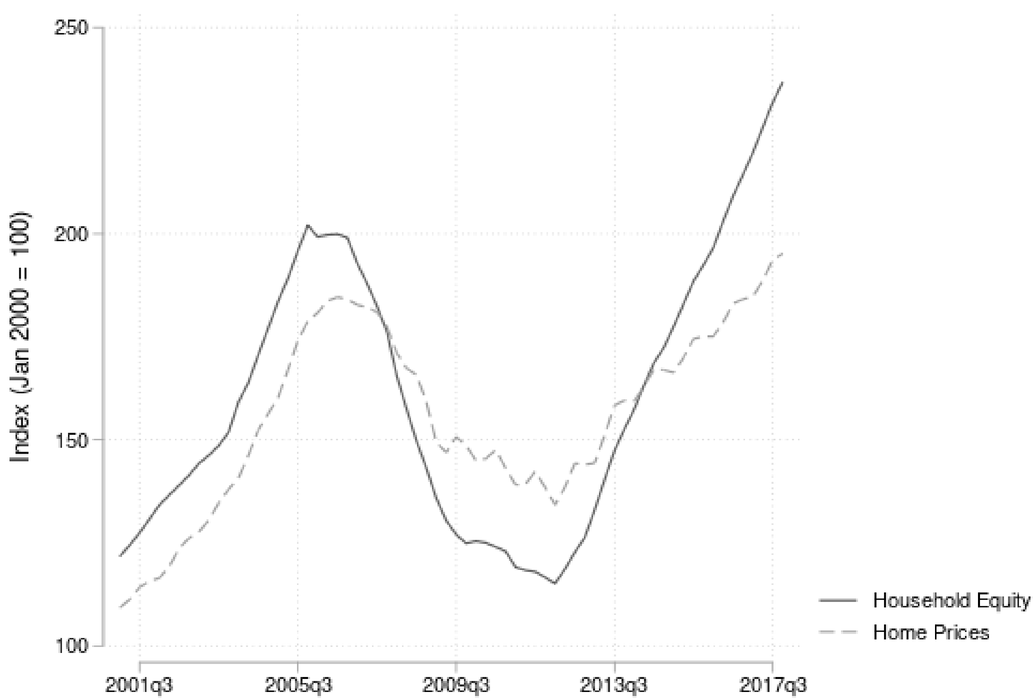
Notes: This figure plots the point estimates for overall take-up from Equation (7) with different sets of controls. Specification 1 includes only MSA and quarter-year fixed effects. Specification 2 adds controls for income and home sales volume. Specification 3 further adds the average risk score interacted 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 A9: Dynamics of Newly Enrolled Policies



Notes: This figure plots the estimated coefficients and their 95 percent confidence intervals from Equation (7) for the number of newly enrolled policies inside SFHAs (left panel) and outside SFHAs (right panel).

Figure A10: Home Prices and Homeowner Equity



Notes: This figure plots the household equity (home value minus mortgage debt) and home prices over the sample period. Sources: Board of Governors Quarterly Financial Accounts and S&P Case-Shiller US National House Price Index (Board of Governors, S&P Dow Jones Indices).

B Data Appendix

B.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 older than five years, 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 more fully than FEMA's estimate. 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 1 percent annual flood risk, but FEMA's maps indicate this level of risk for only 8.7 million properties.[35]

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.[36] 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[37] 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 implicit insurance channel. Under the default incentive mechanism, one hypothesis 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. We classify each MSA as above- or below-median risk according to this measure.

B.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.

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

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

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

These states require court approval for foreclosure sales after mortgage defaults, as opposed to states where lenders may initiate foreclosure based on the contract terms of the mortgage. A judicial review makes the process of obtaining a foreclosure sale more costly and lengthy and affords delinquent borrowers more time to remain in their homes and contest the terms of their mortgage contract in court. Research has found a positive relationship between judicial review laws and rates of strategic default by borrowers with negative equity (see, for example, Demiroglu et al. (2014)), which suggests that this provision makes default a more viable option for borrowers to resolve financial distress. Similarly, as borrowers in judicial review states enjoy greater implicit insurance through default, their flood insurance demand should be more responsive to home equity under our proposed mechanism.

C First-Difference Estimation

To examine changes in flood insurance take-up over the housing bust, we use a 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. Therefore, we can instrument housing price change from 2007 to 2012 using the structural breaks.

The regression takes the following form:

$$\Delta_{bust} lnNFIP_m = \beta_0 + \beta_{FD} \widehat{\Delta_{bust} lnH}PI + \delta' \Delta_{bust} X_m + \varepsilon_m. \tag{C1}$$

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 control for the risk score directly. 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 bust affect flood insurance take-up.

The corresponding reduced-form regressions take the form

$$\Delta_{bust} lnNFIP_m = \alpha_0 + \alpha_{FD} \Delta P_m + \gamma' \Delta_{bust} X_m + u_m, \tag{C2}$$

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

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.[38] Because different MSAs experienced their housing booms at different times, our estimation

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

results from Equations (7) and (9) 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 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 5.2, 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 between 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". The five cohort datasets are then stacked together to form the dataset for regression. We estimate the following equation:

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

where g denotes the cohort and other notations are the same as before. The only difference between this specification and Equation (7) 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 A3.

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 intensity measure. These results are available upon request. In general, we consistently find 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.

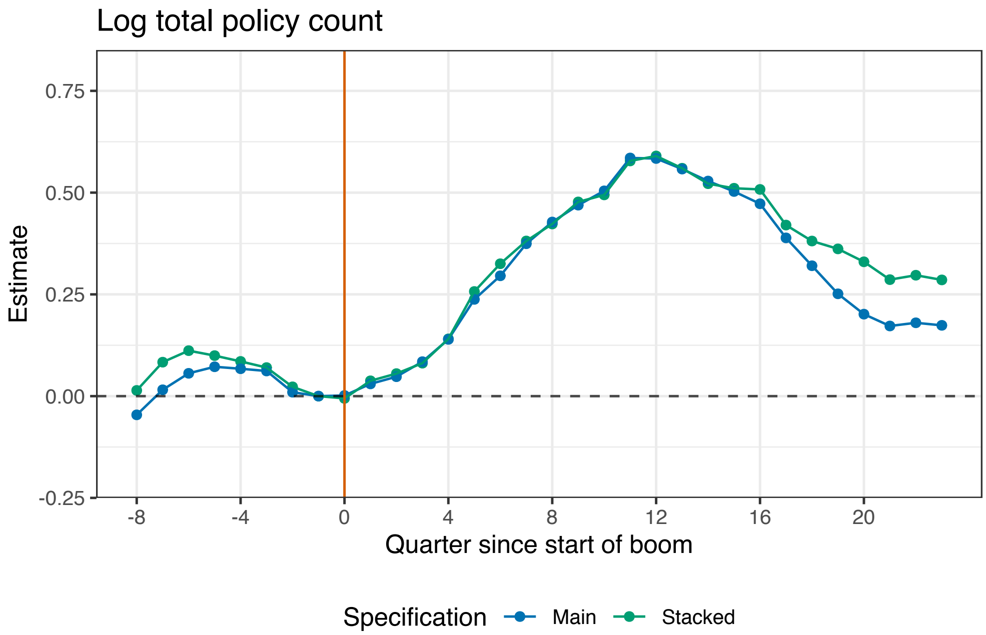
E Additional Notes on Heterogeneity Analysis

E.1 Estimation Equations

In Section 5.4, 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

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 (7) and (D1), respectively.

the MSA has above-median non-SFHA risk. Formally, our second-stage equation is a version of Equation (9) 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.

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

	A. Judicial Review Law		
Group	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	14,916 (24,688)	9,126 (17,161)	0.030**

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

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 on the judicial review laws, one might be concerned that the statute itself is 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 difference in major characteristics for each 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, no systematic difference 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 on 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.