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

Yanjun Liao and Philip Mulder

January 2021 - Working Paper 2021-1
What’s at Stake? Understanding the Role of Home Equity in Flood Insurance Demand
Yanjun Liao\textsuperscript{1} and Philip Mulder\textsuperscript{2}

\textsuperscript{1} Wharton Risk Center
\textsuperscript{2} The Wharton School, University of Pennsylvania

Abstract

Millions of properties in the U.S. are exposed to increasing threats from natural disasters. Yet, a large majority of at-risk homes are uninsured against the costliest disaster: flooding. Floods cause elevated rates of mortgage delinquency and default that can impact the broader housing finance system. In this paper, we explore the connection between homeowners’ stake in their homes and their demand for flood insurance. To isolate the causal effect of home equity on flood insurance demand, we study the response of flood insurance take-up to sudden house price changes over the housing boom and bust in the 2000s. We find that flood insurance take-up follows the dynamics of house prices in each market over the boom-bust cycle, with a home price elasticity around 0.33. A series of heterogeneity and robustness checks suggest that the role of mortgage default as implicit insurance is the most plausible mechanism for this positive relationship. We conclude by discussing the implications of our results for the effects of climate change on real estate and financial markets and for disaster insurance policy.

JEL: G21, G52, Q54

Keywords: disaster insurance, home equity, housing booms and busts, mortgage default

\textsuperscript{1}We thank Benjamin Collier, Fernando Ferreira, Rhiannon Jerch, Benjamin J. Keys, Carolyn Kousky, Howard Kunreuther, Amine Ouazad and participants at the Wharton Urban Lunch, Wharton Risk Center Research Seminar, First Street Foundation Flood Lab Workshop, and Urban Economics Association Virtual Meeting for helpful comments and suggestions. Any remaining errors are our own.
1 Introduction

Since 1980, the United States has seen over $1.7 trillion in damages from major natural disasters\footnote{See \url{https://www.ncdc.noaa.gov/billions/}.}, with environmental risk expected to grow over time with climate change (Dahl et al., 2018). Large disasters cause severe financial distress for many households\footnote{The federal reserve estimated that about 40\% of American adults are not able to cover an unexpected expense of $400 by cash or savings (Canilang et al., 2020). However, the cost of repair and rebuilding after a disaster is often orders of magnitude larger. For example, the average flood insurance claim in 2019 was $52,000 (\url{https://www.fema.gov/data-visualization/historical-flood-risk-and-costs}).} and lead to mortgage delinquency and default. Among others\footnote{Other studies documenting the housing finance impacts of disasters include Anderson and Weinrobe (1986), Morse (2011), Billings et al. (2019), and Issler et al. (2019).}, 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). Ouazad and Kahn (2019) find that major hurricanes caused a 1.6 percentage point increase in the probability of home foreclosure.

Given the substantial welfare loss that could result from these housing finance impacts, it is important to understand how homeowners manage such risks. In this paper, we study how home equity affects households’ demand for disaster insurance. Specifically, we leverage changes to the household’s incentive to default on their mortgage after catastrophic losses. When faced with severe damages, a default can serve as a form of implicit insurance that caps the household’s losses by their home equity. The greater the equity they hold, however, the larger the loss they suffer from defaulting, and hence the more they are willing to pay for disaster insurance. On the other hand, if households can cope with the financial hardship without defaulting, willingness-to-pay for insurance should only be a function of the expected cost to repair the home, but not of home equity.

In this paper, 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 address 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 2003-2005. Figure 1 provides a reduced-form depiction of our results in the raw data: 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.

Our formal difference-in-differences specification exploits variation in the timing and magnitude of housing booms across MSAs and tracks the dynamics of home prices and flood insurance take-up across the boom-bust cycle. The result shows that flood insurance take-up closely follows the dynamics of home prices, has no pre-trends, and is robust to controlling for annual income, housing turnover, 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 0.33. 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.

There are two main explanations for our results. First, homeowners with more home equity have a higher willingness-to-pay for flood insurance because they have lower insurance value from mortgage defaults (henceforth the “default incentive” mechanism). Second, higher home equity combined with easier credit access during the housing boom gave households greater liquidity to pay for the 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 predictions.

If home equity increased flood insurance demand by improving access to liquidity, then there should be a negative relationship between insurance lapsation and home prices. Lapsations caused by policy non-renewal, often after just one year, are common in flood insurance and typically cited as evidence of liquidity constraints in insurance (Hambel et al., 2017). 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 of 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 MSAs with more tail risk exposure also have a significantly higher home price elasticities of flood insurance take-up. Thus, our findings support the default incentive mechanism.

These findings suggest that leveraged households do not fully internalize their environmental risk and part of the 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) who underwrite residential mort-
gage securitization do not price disaster risk or enforce mandatory flood insurance purchase outside of floodplains.\textsuperscript{5} As a result, the remaining risk is ultimately borne by taxpayers along with obligations from a host of post-disaster public transfers (see Deryugina (2017)). 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 change risk.

This paper provides novel insights into flood insurance demand and the relationship between environmental risk and housing finance. We are the first to estimate the causal effect of home prices on flood insurance take-up, to the best of our knowledge\textsuperscript{6}, and our estimates show an economically important causal relationship. Given a growing literature which suggests that climate change may already be affecting home prices, our estimates will be relevant to ongoing policy discussions surrounding climate vulnerability and flood insurance reform.\textsuperscript{7}

A major question in the flood insurance demand literature is why at-risk homeowners under-insure for flooding, with past studies examining the role of adverse selection and information frictions (Mulder, 2019; Wagner, 2019), affordability issues (Netusil et al., 2021), as well as disaster aid (Kousky et al., 2018a). We present and test a new mechanism through which the implicit insurance value of mortgage default also affects household management of disaster risk, thereby offering an additional explanation for the insurance gap.

This paper also relates to a larger literature on housing markets and household finance. Our theoretical framework for understanding how home prices can influence household insurance decisions 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). The empirical analysis builds on the literature on the impacts of changing home prices over the housing boom and bust (Charles et al., 2018, 2019). Our results show that these housing market frictions have economically significant effects on 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 that a higher cost of bankruptcy induces greater insurance demand. Both our findings are consistent with a number of other studies that have shown how the public government and creditors often bear the health costs of underinsured households (see for example Brown and Finkelstein (2008) and Dobkin et al. (2018)). We show that these same mechanisms can affect not only health insurance, but also

\textsuperscript{5}Even within floodplains, there is inconsistent evidence on whether mandatory purchase requirements are well enforced (Hecker, 2002; National Research Council, 2015).

\textsuperscript{6}A number of 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.

\textsuperscript{7}See the related literature studying how climate and disaster risk is capitalized into home prices (Bernstein et al., 2019; Baldauf et al., 2020; Keys and Mulder, 2020; Murfin and Spiegel, 2020; Ortega and Taspinar, 2018) and how disasters affect housing markets (Gibson et al., 2019; Kousky, 2010; Zivin et al., 2020).
disaster insurance and housing markets.

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 a few key empirical features of the National Flood Insurance Program and the housing boom and bust. Section 4 explains our empirical design, and Section 5 describes our results. Finally, we conclude in Section 6.

2 Theory

In this section, we present a simple theoretical framework to illustrate the role of home equity in disaster insurance demand. First, we describe a baseline model where there is 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 earns labor income $W$, purchases a numeraire good for consumption $C$, and chooses whether to insure their structure against disaster risk. We consider a single contract that covers 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 \((1 - p)\) and causes damages with repair cost \(r \in (0, R_H]\) distributed \(f(r)\). If uninsured, the agent must pay the full cost of \(r\) out of their equity value. If insured, \(r\) is paid by the insurer.

In the post-disaster period, the agent sells the house for a final linear consumption value.\(^8\) The agent’s overall utility follows \(U(C) + E_H - r\), where \(U(\cdot)\) is a weakly concave utility function. The agent chooses consumption and insurance to maximize their expected utility:

\[
\max_{C, I} \quad E_H + U(C) - (1 - I) \cdot (1 - p) \cdot \mathbb{E}(r)
\]

Subject to the constraint:

\[C + I \cdot P_I \leq W\]

Denote \(C^I\) as the value of consumption by insurance decision (i.e. \(C^0 = W\) and \(C^1 = W - P_I\)). The agent will choose \(I = 1\) if and only if:

\[U(C^0) - U(C^1) \leq (1 - p) \cdot \mathbb{E}(r)\] \(\quad (1)\)

A first-order Taylor expansion of the left-hand side of (1) allows us to derive an approximation for insurance willingness-to-pay, denoted \(\hat{P}\):

\[
\hat{P} = \frac{(1 - p) \cdot \mathbb{E}(r)}{U'(W)} \quad (2)
\]

Equation (2) says that the agent is willing to pay the expected repair costs scaled by the marginal utility of consumption at their income. In this scenario, without considering any liquidity constraint or mortgage default, 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 \(r\) but forfeit their equity \(E_H\) and pay a default cost \(\hat{M}\).

Uninsured agents default when \(r \geq \hat{M} + E_H\). Thus, expected utility without insurance is:

\[
E_H + U(C^0) - (1 - p) \cdot \left( \int_0^{\hat{M} + E_H} r_D \cdot f(r) dr + \int_{\hat{M} + E_H}^{R_H} (E_H + \hat{M}) \cdot f(r) dr \right)
\]

\(^8\)We follow much of the insurance literature in defining a utility function over wealth to motivate insurance demand. Here, 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.
Setting this above 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:

\[
\hat{P} = (1 - p) \cdot \left( \int_0^{R_H} r \cdot f(r)dr - \int_{\hat{M} + E_H}^{R_H} \left( r - (E_H + \hat{M}) \right) \cdot f(r)dr \right) \cdot \frac{U'(W)}{U''(W)}
\]

(3)

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

Further, we can derive how \( \hat{P} \) changes with respect to \( E_H \):

\[
\frac{d\hat{P}}{dE_H} = \left(1 - \int_0^{R_H} r \cdot f(r)dr - \int_{\hat{M} + E_H}^{R_H} \left( r - (E_H + \hat{M}) \right) \cdot f(r)dr \right) \cdot \frac{U'(W)}{U''(W)} > 0
\]

(4)

where \( F() \) 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, scaled by their marginal utility of consumption. Intuitively, the default option provides the agent with a form of informal insurance that caps out-of-pocket damages if uninsured. 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 \( \hat{M} \) 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 flood 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. Let the first period be as described in the baseline model. Assume that the household buys insurance in the first period and that the following inequality holds: \( P_I \leq (1 - p) \cdot \mathbb{E}(r_2) \). Second period choices and shock realizations are denoted with a \( t = 2 \) index, and home values and risk are constant across the two periods.

In the pre-disaster phase of the second period, the agent faces a negative income shock \( w_2 \in [0, W] \) distributed \( g(w) \), for income \( W_2 = W - w_2 \). The agent can also borrow \( B_2 \in [0, \delta \cdot E_H] \) where \( \delta \in (0, 1) \).

The agent makes their second period decisions after realizing \( W_2 \) but before realizing \( r_2 \). The agent’s choices maximize:

\[
\max_{B_2, C_2, I_2} E_H - B_2 + U(C_2) - (1 - I_2) \cdot (1 - p) \cdot \mathbb{E}(r_2)
\]

Subject to the constraints:

\[
C_2 + I_2 \cdot P_I \leq W_2 + B_2
\]

\[
B_2 \leq \delta E_H
\]

Let \( W^* \) be the lowest income such that the agent renews in the second period and \( \Delta W = W - W^* \) the negative income shock threshold that would cause non-renewal in the absence of borrowing. However, the agent will borrow as much as necessary to prevent lapsation if possible within their borrowing constraints. That is, the agent will renew in the second period if \( w_2 < \Delta W + \delta E_H \).

Thus, the probability of lapsation is:

\[
Pr(I_2 = 0) = \int_{W + \delta E_H - W^*}^{W} g(w)dw
\]

Equation (5) is decreasing in \( E_H \), suggesting that home equity can affect insurance demand by easing borrowing constraints. The relationship between home equity and lapsation suggests the following empirical test of the liquidity constraints mechanism:

**Liquidity Empirical Test.** MSAs with larger housing booms (busts) should see an increase (de-
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 2001-2017 (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 comes 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% of flood insurance policies in the United States (Kousky et al., 2018b). Established in 1968, it currently covers 22,000 communities with over 5 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%. 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 there is no income subsidy, we expect no insurance pricing response to the home price changes we study.

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”). However, this mandate was not always well-enforced (Hecker, 2002). Outside the SFHA, there is no federal requirement for homeowners to purchase flood insurance. The overall take-up rate in the NFIP has been low despite its premiums often being lower than actuarially-fair rates (Michel-Kerjan, 2010). This has often been attributed to affordability issues and low risk perceptions among homeowners (National Research Council, 2015; Wagner, 2019).

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, the year the property was constructed, 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 coverage further 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 1-4 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% are located outside the SFHA.

The richness of our flood insurance data allows us to construct separate take-up measures for subsets of policies with different observable characteristics. For example, we can calculate take-up for only those policies covering properties outside SFHAs, a feature which allows us to test the effects of home price changes on take-up independent of the mandatory purchase requirement enforced inside SFHAs. Moreover, we also test other demand-related outcomes such as the amount of coverage, deductible, and renewal rates. We use these outcomes to implement a number of 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 housing boom and bust that occurred in the United States 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, a few consistent empirical observations have emerged. The housing price changes were highly heterogeneous across markets, with some seeing sudden price acceleration while others experienced smooth changes throughout. More importantly, the sudden variations cannot be explained by any similarly large break in market fundamentals like 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 consensus that these dramatic price changes represent speculative housing bubbles.

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 2001-05 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

\footnote{See Mayer (2011) for a useful survey of this literature.}
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 used 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 structural breaks across our sample of MSAs. Although the method identifies the most likely structural break for every MSA, all of 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 instead between 2003 and 2005. Figure A2 maps the geographic variation in break size. While coastal housing markets tend to have larger breaks than inland ones, there is substantial variation across different coastal markets, 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 post-break house price trends, our key identification assumption is that unobserved factors in flood insurance demand continued to evolve smoothly. 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 structural 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 identification assumption is that their flood insurance demand would have continued on parallel trends, as in other difference-in-difference settings. We discuss our identification assumptions in more detail in Section 4.

3.3 Other Data

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

Home prices. To measure home prices at the MSA level, we obtain the quarterly Home Price Index (HPI) from the Federal Housing Finance Administration (FHFA). 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. See Appendix B.2 for more details on the background of judicial foreclosure laws.

**Additional covariates.** For controls in our models, we include MSA log annual income 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 that compares flood insurance take-up across MSAs with different boom intensity and timing. The estimating equation is:

\[
\ln NFIP_{mt} = \sum_{\tau=-9}^{24} \beta_{\tau}(Post^{\tau}_{mt} \times \Delta P_m) + \delta' X_{mt} + \lambda_m + \lambda_t + \varepsilon_{mt}. \tag{6}
\]

The main dependent variable \(\ln NFIP_{mt}\) 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 9 quarters before the structural break in home prices and extending to 24 quarters after. The variable \(Post^{\tau}_{mt}\) is an indicator of the \(\tau\)-th quarter after the housing boom starts in MSA \(m\). Each indicator is interacted with \(\Delta P_m\), the structural break intensity in each MSA as described in Section 3.2. The model also includes several controls: the vector \(X_{mt}\) contains IHS-transformed annual per capita income and home transaction volume, as well as the average FSF-FM risk score interacted with year indicators to control for

\(^{17}\)See footnote 2 of Table 1 for a complete list of judicial-review states.

\(^{18}\)The first indicator \(Post^{-9}_{mt}\) also includes observations earlier than the start of the event time frame. The last indicator \(Post^{24}_{mt}\) also includes those later than the end of the event time frame.
differential time trends based on risk levels; an MSA fixed effect $\lambda_m$ to control for time-invariant features of the MSA such as its baseline flood risk and natural amenities; and a quarter-year fixed effect $\lambda_t$ to control for national trends in flood insurance take-up.

The $\beta_\tau$’s 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 (6) 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 $\beta_\tau$ 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 prior to 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 2001-03 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. This concern 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 6 with log home prices as the outcome variable. Because the $\beta_\tau$’s are 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 a useful test of the relationship between home prices and flood insurance demand over the housing boom. Given that we do find a similar dynamics between home prices and take-up, 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.

4.2 Instrumental Variables

The housing market structural breaks can be used home price instruments to directly estimate the relationship between take-up and home price changes. In this framework, Equation (6) can be reinterpreted as the reduced-form relationship between the outcome and the instrument. We implement a two-stage least square (2SLS) estimation where the first-stage regression is:

$$
\ln HPI_{mt} = \sum_{\tau=0}^{24} \rho_\tau (\text{Post}_m \times \Delta P_m) + \mu^t X_{mt} + \gamma_m + \gamma_t + \omega_{mt}.
$$

(7)
The home price index \((lnHPI_{mt})\) is our endogenous variable. Here, we instrument the IHS-transformed home price index by the set of interaction terms between the event-time indicators and the structural break intensity \((Post_{mt} \times \Delta P_m)\), exploiting essentially the same variation in Equation (6). 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:

\[
\ln NFIP_{mt} = \beta \cdot \hat{lnHPI}_{mt} + \delta'X_{mt} + \lambda_m + \lambda_t + \varepsilon_{mt}. \tag{8}
\]

\(\hat{lnHPI}_{mt}\) are the instrumented values of the home price index from Equation (7). The equation includes the same set of controls as before.

Equation (8) estimates a single \(\beta\) 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 demand, 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 which suggests that other economic fundamentals were smoothly changing in the markets that saw these sudden price changes (Ferreira and Gyourko, 2017; Sinai, 2012).

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

1. Increased home sales: If the 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 exclusively, 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 above, 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 replacement value, prompting the homeowner to purchase insurance. To investigate this channel, we estimate the dynamics of building coverage purchased by policyholders. The amount of building coverage is usually commensurate with the replacement value. We would expect to see more coverage being
purchased on this intensive margin if home renovations were also causing the extensive margin increase in demand.

4. Higher incomes: If the housing boom improved labor market opportunities, residents may have become better able to afford flood insurance (see for example Charles et al. (2019)). To control for this possibility, we control for annual MSA income in all regressions.

Even in the absence of the exclusion restrictions described above, the difference-in-difference estimates from Equation (6) can still be interpreted as a reduced-form assessment of the effect of housing booms and busts on flood insurance demand. In light of a growing literature which suggests that areas exposed to increasing flood risk under climate change may already be seeing accelerating home price declines (Bernstein et al., 2019; Keys and Mulder, 2020), these reduced-form estimates alone are relevant to policy debates around climate vulnerability and flood insurance reform.

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 below 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.19 Second, flood insurance demand in MSAs with a larger fraction of properties with tail risk exposure should also be more responsive. To formally test the above predictions, we extend the 2SLS procedure to estimate heterogeneous effects based on foreclosure laws and flood risk. We do so by adding an interaction term between home prices and an indicator variable for MSAs with above-median flood risk in the FSF-FM to the second-stage equation and instrumenting for it in the first stage with a corresponding interaction between the structural break instrument and the above-median risk indicator. For details on this extended framework, see Appendix C.

To implement our test for the liquidity mechanism described in Section 2.3, we use the flood insurance renewal rate as our outcome variable. As shown in Table 1, the non-renewal rate in the second year of coverage is around 25% on average in our sample of MSAs. Although lapsation may be driven by a number of factors,20 research in other insurance settings supports the hypothesis that negative financial shocks to liquidity constrained households play a large role (Hambel et al., 2017). Thus, if the increase in housing equity increased the overall flood insurance take-up rate

---

19See Section 3 for a description of these laws.
20See e.g. Mulder (2019) or Michel-Kerjan et al. (2012).
by expanding credit access to households, we would expect to see a lower lapsation rate as house prices increase.

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 (6) over the FHFA 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 the 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% higher home prices at the peak. Moreover, there is little evidence of 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 estimates on flood insurance take-up. Consistent with the raw correlation in the initial scatter plot (Figure 1), MSAs with larger home price structural breaks saw a larger increase in flood insurance policies. More importantly, the dynamical 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% higher flood insurance take-up at the peak. Furthermore, there is no evidence of a pre-trend, which supports the validity of the parallel trends assumption. While these estimates are from our preferred specification, the result is stable with different sets of control variables (see Appendix Figure A4).

The closely-aligned trajectories of the housing price index and NFIP take-up indicate a direct relationship between the two. To support this interpretation, however, we need to rule out alternative channels for the housing boom to affect take-up. One possibility is related to the mandatory insurance purchase requirement for homeowners with a federally-backed mortgage in the SFHA. If more properties are transacted in the SFHA during the boom, this might drive up insurance take-up mechanically through the mandate. A second possibility is that the additional policies were written on new construction caused by the boom.

To assess these possibilities, we re-estimate Equation (6) over two subsamples of NFIP policies. The first subsample includes only policies written on structures built prior to 2003\textsuperscript{21} and outside

\textsuperscript{21}Figure A1 shows that the vast majority of notable booms occurred in or after 2003.
SFHAs where there is 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 take-up inside the SFHA.

A third alternative channel for the increase in demand is through the boom causing more home renovations. Home renovations could increase the value at risk of flood damage, leading to a greater demand for insurance. If 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).22

To test this, we estimate Equation (6) on the IHS-transformed average amount of building coverage. These results are shown in Appendix Figure A5. 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. Such SFHA policyholders may have only been holding the minimum coverage necessary to satisfy the requirement.23 When their home equity increased in the boom, they purchased additional coverage beyond the minimum requirement.

Using the same estimation framework, we also examine other margins of the insurance decision. Figure A6 shows the estimates on the share of newly-enrolled SFHA policies that has any contents coverage.24 There is a slight increase following the start of the housing boom but the magnitude is very small: a one-standard-deviation increase in the boom size is associated with a 0.7 percentage point increase in the share. Figure A7 shows the dynamics of the share of newly-enrolled SFHA policies with the standard deductible25, which is largely unresponsive to the boom. These results suggest that risk preferences and perceptions are quite stable across the boom-bust cycle.

---

22The NFIP currently allows for a maximum building coverage of $250,000 for each 1-to-4-dwelling residential structure. In the sample, the average coverage amount is $133,051 among SFHA policies and $164,286 among non-SFHA ones.

23The 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.

24Contents 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.

25All non-SFHA policies have a standard deductible of $500. SFHA policyholders can either choose the standard deductible or a larger deductible at a different premium.
5.2 Home Price Elasticity of Flood Insurance Demand

In this section, we examine the relationship between home prices and flood insurance take-up directly in an instrumental variable framework. Previously we have shown that, for any given MSA, the initial structural break in the housing price trend predicts the subsequent boom-bust trajectory well (see top panel, Figure 3). We have also ruled out major pathways – independent from changes in home prices – through which the housing boom might affect insurance take-up. These findings form the basis for our IV framework: the initial structural break interacted with event-time indicators are both relevant and valid as instruments for the housing price index.

Formally, we estimate the home price elasticity of flood insurance demand using the 2SLS estimator described in Equations (7) and (8). 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 0.33. This implies that, on average, a 1% increase in home prices is associated with a 0.33% 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 at 0.49. When we further subset to non-SFHA policies on homes built before 2003, we obtain an estimate of 0.36, again showing that the main effects are not due to new construction. All four columns have a first-stage F-statistics\(^{26}\) 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, 2019). In comparison, our estimates suggest a 1% increase in home prices has roughly the same effect as a 2% decrease in premiums on overall take-up, or a 3% decrease in premiums on non-SFHA take-up. Kousky (2017) finds that hurricanes are estimated to lead to only 1.5% increase in voluntary purchases of flood insurance, which is equivalent to a 4.5% increase in home prices. Given the large variability of housing prices in both the short and long run, our results suggest that home equity plays a substantial role in flood insurance demand.

We also conduct a series of robustness checks on the main estimate of the home price elasticity of take-up (column (1), Table 3). Similar to Figure A4 from before, Table A1 shows a comparison of the estimates with different sets of control variables. The estimates all show the same qualitative pattern and our main specification is the most conservative.

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

\(^{26}\)We follow Sanderson and Windmeijer (2016) in the calculation of F-statistic to account for multiple endogenous variables.
housing boom, but imposes homogeneity on the boom-bust dynamics across MSAs. 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 boom peaks was concentrated between the end of 2005 through 2007. Thus, MSAs with later booms might also have shorter booms with more rapid price acceleration which then reversed into the bust. In Equation (7), imposing equality on the $\rho_r$ coefficients across housing boom cohorts might lead to a misspecified first-stage estimation. 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.

The 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. For MSAs with a negative break measure, our specification implies that their housing prices would follow a bust-boom trajectory, which is unlikely to be true in reality. As the vast majority of these negative measures are close to zero (see Figure 1), they likely represent noise in the estimation procedure for MSAs without a clear boom. In column (3), we replace all negative values in the boom instrument with zero and re-estimate the regressions. This yields slightly larger estimates as the home prices evolution is better represented for these MSAs. As we expect the idiosyncratic noise to go in either direction, in column (4) we replace the boom instrument values with zeros for the 25% of MSAs with the smallest structural breaks measured by absolute magnitude. This yields a very small increase in the estimate. In general, these robustness checks have confirmed that our main estimate is robust to alternative regressions that account for major concerns in specification and measurement.

5.3 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 baseline model of disaster insurance demand in a frictionless world, as shown in Section 2. Nonetheless, Sections 2.2 and 2.3 each present a financial friction that can drive this relationship. In this section, we test the empirical predictions from each of these mechanisms.

The first mechanism we investigate is that previously liquidity-constrained homeowners may have extracted their new home equity over the housing boom to purchase and maintain flood

---

27 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.
insurance. To test for this mechanism, we examine the one-year insurance renewal rate in the
boom period. Insurance lapsation is often associated with liquidity constraints (Hambel et al.,
2017). By focusing on the one-year time frame, we aim to capture mostly lapsation driven by
liquidity rather than changing risk perceptions or actual flood experience. The NFIP has a high
rate of lapsation, with only about 75% of policyholders choosing to renew their policies after the first
year. If greater home equity eased liquidity constraints, then we would expect more policyholders
to renew their flood insurance coverage especially at the outset of the boom. Formally, we estimate
Equation (6) over 1-year renewal rates. 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 1-year
renewal rate for both groups of policies, suggesting that liquidity was not likely the main factor
driving the relationship between home equity and insurance demand.

The second mechanism focuses on the implicit insurance value of mortgage defaults. When
facing a large loss from disasters, leveraged households can default on their mortgage rather than
pay the full cost of repairs. However, when home equity increased for homeowners over the housing
boom,30 more of their wealth became exposed to large losses, and hence they would be willing to
pay more for disaster insurance. Our first test of this mechanism is to exploit differences in the cost
of default across states with and without judicial review laws. In states that do not require judicial
review of foreclosure proceedings, 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. This intuition is also borne out in our
model (see Section 2.2). Figure 6 plots the coefficients from estimating Equation (6) separately in
states with and without judicial review over home prices (left panel) and non-SFHA flood insurance
take-up (right panel). Despite having similar home price trends conditional on the initial break size,
flood insurance demand in judicial review states is much more responsive. This provides support
for 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
calculate the following measure of non-SFHA tail risk exposure:

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

---

28 See, for example, Michel-Kerjan et al. (2012) or Mulder (2019) on other factors affecting lapsation in NFIP.
29 We find similar results using 3-year and 5-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 housing boom and bust. Despite a concurrent increase in mortgage debt over the housing
boom, Figure A8 shows that home equity covary positively with house prices over the housing cycle.
The denominator captures the extent of the flood insurance market outside the SFHA, while the numerator captures the subset of properties facing severe enough risk that a mortgage default is potentially relevant after a flood.\textsuperscript{31} This ratio ranges from 1\% to 89\% across MSAs, with the median at 65\%.

This measure allows us to examine how the effect of home equity varies across MSAs with different tail risk exposure.\textsuperscript{32} Importantly, in all regressions we control for the time-varying effect of the average risk level. Therefore, any heterogeneity we find 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 (6) separately for these two groups of MSAs on home prices (left panel) and non-SFHA flood insurance take-up (right panel). Once again, we see a similar relationship between home prices and the initial break size in the two groups, but a much larger response for flood insurance take-up in the high tail risk group. Therefore, this finding is also consistent with the default incentive mechanism.

We formally test the statistical significance of the above findings by applying the 2SLS estimator with an additional interaction term between home prices and an indicator of the characteristic of interest (\textit{i.e.} judicial review law or above median tail risk).\textsuperscript{33} These results are shown in Table 4. Both heterogeneity estimates confirm the results from the difference-in-differences exercises above: 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 0.72 versus only 0.39 in states without such laws. MSAs with above-median tail risk have a home price elasticity of flood insurance demand of 0.84 versus 0.47 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, there is no notable differential effects along either margin. As discussed before, given the mandatory purchase requirement, SFHA homeowners likely face different incentives and have less room for take-up adjustments compared to the non-SFHA homeowners.

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, while there is little empirical support for the liquidity mechanism.

\textsuperscript{31}Here, we use the 1\% annual risk cutoff to proxy for tail risk because properties with at least 1\% 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.

\textsuperscript{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.

\textsuperscript{33}The precise estimation equations are presented in Appendix C.
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. On the other hand, our tests do 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 on their mortgage 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.

However, these 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 under-insurance 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 the incentive of lenders to require borrowers to maintain flood insurance.
References


Dahl, Kristina, Rachel Cleetus, Erika Spanger-Siegfried, Shana Udvardy, Astrid Call- 


First Street Foundation, “First Street Foundationa Flood Model (FSF-FM) Technical Docu- 
06/FSF_Flood_Model_Technical_Documentation.pdf.


Hecker, JayEtta Z, “FLOOD INSURANCE: Extent of Noncompliance with Purchase Require- 


Figures

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

Notes: Each circle represents a 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. 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 Home Price Index and Insurance Take-Up

Notes: This figure plots the estimated coefficients and their 95% confidence intervals from Equation (6) for HPI (top panel) and total flood insurance policy count (bottom panel). Both dependent variables are IHS-transformed. The policy count includes all 1-4 family policies.
Notes: This figure plots the estimated coefficients and their 95% confidence intervals from Equation (6) for the count of flood insurance policies written on structures outside the SFHA and constructed prior to 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 estimates coefficients and their 95% confidence intervals from Equation (6) for 1-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 (6) 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 (6) 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

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Mean</th>
<th>St. Dev.</th>
<th>10th Pctile</th>
<th>Median</th>
<th>90th Pctile</th>
</tr>
</thead>
<tbody>
<tr>
<td>all policies</td>
<td>10,419.28</td>
<td>31,004.83</td>
<td>288</td>
<td>1,799</td>
<td>23,683</td>
</tr>
<tr>
<td>SFHA policies</td>
<td>5,920.52</td>
<td>20,409.55</td>
<td>138</td>
<td>969</td>
<td>10,641</td>
</tr>
<tr>
<td>non-SFHA policies</td>
<td>4,498.77</td>
<td>16,187.19</td>
<td>120</td>
<td>669</td>
<td>10,145</td>
</tr>
<tr>
<td>non-SFHA pre-03 policies</td>
<td>3,864.32</td>
<td>13,901.44</td>
<td>108</td>
<td>597</td>
<td>8,594</td>
</tr>
<tr>
<td>SFHA avg. coverage</td>
<td>133,051.00</td>
<td>43,965.51</td>
<td>78,069.98</td>
<td>127,515.20</td>
<td>197,500.70</td>
</tr>
<tr>
<td>non-SFHA avg. coverage</td>
<td>164,286.60</td>
<td>37,263.33</td>
<td>110,910.30</td>
<td>168,216.20</td>
<td>210,419.00</td>
</tr>
<tr>
<td>% contents coverage</td>
<td>0.33</td>
<td>0.21</td>
<td>0.12</td>
<td>0.28</td>
<td>0.71</td>
</tr>
<tr>
<td>% standard deductible</td>
<td>0.71</td>
<td>0.13</td>
<td>0.53</td>
<td>0.72</td>
<td>0.87</td>
</tr>
<tr>
<td>SFHA 1yr renewal rate</td>
<td>0.77</td>
<td>0.20</td>
<td>0.56</td>
<td>0.78</td>
<td>0.94</td>
</tr>
<tr>
<td>non-SFHA 1yr renewal rate</td>
<td>0.75</td>
<td>0.19</td>
<td>0.55</td>
<td>0.75</td>
<td>0.93</td>
</tr>
<tr>
<td>break size</td>
<td>0.05</td>
<td>0.07</td>
<td>−0.03</td>
<td>0.03</td>
<td>0.14</td>
</tr>
<tr>
<td>FHFA housing price index</td>
<td>173.80</td>
<td>39.39</td>
<td>134.04</td>
<td>165.24</td>
<td>224.74</td>
</tr>
<tr>
<td>per capita income ($1,000s)</td>
<td>37.90</td>
<td>9.37</td>
<td>27.70</td>
<td>36.70</td>
<td>48.73</td>
</tr>
<tr>
<td>population</td>
<td>830,486</td>
<td>1,336,015</td>
<td>137,620</td>
<td>370,454</td>
<td>1,926,284</td>
</tr>
<tr>
<td>home transaction volume</td>
<td>12,438.22</td>
<td>21,318.76</td>
<td>700</td>
<td>4,926</td>
<td>32,310</td>
</tr>
<tr>
<td>judicial review law(^1)</td>
<td>0.51</td>
<td>0.50</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>non-SFHA risk(^2)</td>
<td>0.64</td>
<td>0.14</td>
<td>0.49</td>
<td>0.66</td>
<td>0.79</td>
</tr>
</tbody>
</table>

*Notes:* This dataset consists of quarterly observations across 271 MSAs during 2001-2017.

\(^1\) 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.

\(^2\) Non-SFHA risk is measured by the fraction of high-risk properties among all non-SFHA properties that are at any risk.
Table 2: MSA Characteristics by Structural Break Size (2001 Q1)

<table>
<thead>
<tr>
<th>Group</th>
<th>Lowest Boom (N=88)</th>
<th>Middle Boom (N=90)</th>
<th>Highest Boom (N=90)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Structural Break Size</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean (SD)</td>
<td>-0.024 (0.015)</td>
<td>0.032 (0.018)</td>
<td>0.13 (0.047)</td>
</tr>
<tr>
<td>Median [Min, Max]</td>
<td>-0.021 [-0.102, -0.007]</td>
<td>0.034 [-0.007, 0.065]</td>
<td>0.117 [0.065, 0.271]</td>
</tr>
<tr>
<td><strong>SFHA Policy Count</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean (SD)</td>
<td>1820 (4490)</td>
<td>2400 (5230)</td>
<td>13200 (34100)</td>
</tr>
<tr>
<td>Median [Min, Max]</td>
<td>508 [32.0, 35500]</td>
<td>774 [5.94, 42300]</td>
<td>2220 [27.2, 225000]</td>
</tr>
<tr>
<td><strong>Non-SFHA Policy Count</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean (SD)</td>
<td>2200 (11300)</td>
<td>1260 (2130)</td>
<td>5050 (10700)</td>
</tr>
<tr>
<td>Median [Min, Max]</td>
<td>216 [18.8, 103000]</td>
<td>421 [32.7, 12100]</td>
<td>1150 [76.8, 79000]</td>
</tr>
<tr>
<td><strong>Average SFHA Building Coverage (in $1,000s)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean (SD)</td>
<td>74.4 (20.8)</td>
<td>81.5 (23.4)</td>
<td>108 (30.0)</td>
</tr>
<tr>
<td>Median [Min, Max]</td>
<td>70.8 [28.5, 145]</td>
<td>75.2 [41.4, 146]</td>
<td>108 [48.3, 173]</td>
</tr>
<tr>
<td><strong>Average Non-SFHA Building Coverage (in $1,000s)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean (SD)</td>
<td>102 (26.6)</td>
<td>110 (25.2)</td>
<td>130 (29.6)</td>
</tr>
<tr>
<td><strong>Population (in 1,000s)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean (SD)</td>
<td>736 (1100)</td>
<td>738 (1420)</td>
<td>848 (1270)</td>
</tr>
<tr>
<td><strong>Average Risk Score, All Properties</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean (SD)</td>
<td>1.65 (0.532)</td>
<td>1.76 (0.587)</td>
<td>2.15 (0.868)</td>
</tr>
<tr>
<td>Median [Min, Max]</td>
<td>1.51 [1.23, 5.50]</td>
<td>1.63 [1.21, 5.79]</td>
<td>1.86 [1.25, 6.74]</td>
</tr>
<tr>
<td><strong>Average Risk Score, SFHA Properties</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean (SD)</td>
<td>4.61 (1.14)</td>
<td>4.82 (1.18)</td>
<td>4.67 (1.56)</td>
</tr>
<tr>
<td><strong>Average Risk Score, Non-SFHA Properties</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean (SD)</td>
<td>1.51 (0.370)</td>
<td>1.61 (0.552)</td>
<td>1.88 (0.646)</td>
</tr>
</tbody>
</table>
Table 3: Home Price Elasticity of Insurance Take-Up

<table>
<thead>
<tr>
<th>Policy Sample</th>
<th>Dependent variable: log NFIP policy count</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All</td>
</tr>
<tr>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>$\hat{\log} HPI$</td>
<td>0.328***</td>
</tr>
<tr>
<td></td>
<td>(0.069)</td>
</tr>
<tr>
<td>$\log$ income</td>
<td>0.118</td>
</tr>
<tr>
<td></td>
<td>(0.237)</td>
</tr>
<tr>
<td>$\log$ sales</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
</tr>
<tr>
<td>Risk $\times$ Year indicators</td>
<td>Yes</td>
</tr>
<tr>
<td>MSA FE</td>
<td>Yes</td>
</tr>
<tr>
<td>Year-quarter FE</td>
<td>Yes</td>
</tr>
<tr>
<td>First-stage F-statistic</td>
<td>36.15</td>
</tr>
<tr>
<td>Observations</td>
<td>15,572</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.991</td>
</tr>
</tbody>
</table>

Notes: This table presents 2SLS coefficients from Equation (8). Each column indicates a different policy sample over which take-up is measured. Respectively, they are: all 1-4 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 (7) and the corresponding F-statistic is reported in the bottom panel. “Risk $\times$ 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: Heterogeneity by Foreclosure Law and Non-SFHA Risk

<table>
<thead>
<tr>
<th>Policy Sample</th>
<th>Non-SFHA</th>
<th>SFHA</th>
<th>SFHA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>log HPI</td>
<td>0.389**</td>
<td>0.474***</td>
<td>0.223***</td>
</tr>
<tr>
<td></td>
<td>(0.150)</td>
<td>(0.163)</td>
<td>(0.066)</td>
</tr>
<tr>
<td>log HPI \times judicial</td>
<td>0.328***</td>
<td>−0.054</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.124)</td>
<td>(0.064)</td>
<td></td>
</tr>
<tr>
<td>log HPI \times high risk</td>
<td>0.365**</td>
<td>0.097</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.147)</td>
<td>(0.072)</td>
<td></td>
</tr>
<tr>
<td>log income</td>
<td>−0.086</td>
<td>−0.110</td>
<td>0.055</td>
</tr>
<tr>
<td></td>
<td>(0.356)</td>
<td>(0.373)</td>
<td>(0.196)</td>
</tr>
<tr>
<td>log sales</td>
<td>0.016*</td>
<td>0.020**</td>
<td>0.006</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.009)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Risk \times Year indicators</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>MSA FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year-quarter FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>First-stage F-statistic</td>
<td>(40.07, 98.05)</td>
<td>(28.37, 95.67)</td>
<td>(43.75, 101.07)</td>
</tr>
<tr>
<td>Observations</td>
<td>15,572</td>
<td>15,572</td>
<td>15,572</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.979</td>
<td>0.979</td>
<td>0.992</td>
</tr>
</tbody>
</table>

Notes: This table presents 2SLS coefficients from Equation (A1) 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 (A2) and the corresponding F-statistics are reported in the lower panel. “Risk \times 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
## Additional Tables and Figures

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

<table>
<thead>
<tr>
<th>Dependent variable: log NFIP policy count</th>
<th>All</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>log HPI</td>
<td></td>
<td>0.402***</td>
<td>0.376***</td>
<td>0.331***</td>
<td>0.328***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.061)</td>
<td>(0.065)</td>
<td>(0.066)</td>
<td>(0.069)</td>
</tr>
<tr>
<td>log income</td>
<td></td>
<td>0.020</td>
<td>0.105</td>
<td>0.100</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.233)</td>
<td>(0.237)</td>
<td>(0.238)</td>
<td></td>
</tr>
<tr>
<td>log sales</td>
<td></td>
<td>0.004</td>
<td>0.003</td>
<td>0.003</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.006)</td>
<td></td>
</tr>
<tr>
<td>Other covariates</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Risk × Quadratic trend</td>
<td></td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Risk × Year indicators</td>
<td></td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MSA FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Year-quarter FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>First-stage F-statistic</td>
<td>67.95</td>
<td>41.37</td>
<td>36.59</td>
<td>36.15</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>18,020</td>
<td>15,632</td>
<td>15,572</td>
<td>15,572</td>
<td></td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.990</td>
<td>0.991</td>
<td>0.991</td>
<td>0.991</td>
<td></td>
</tr>
</tbody>
</table>

Notes: This table presents 2SLS coefficients from Equation (8). The dependent variable is IHS-transformed total policy count. The first-stage regression follows Equation (7) 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 and home sales volume. “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

<table>
<thead>
<tr>
<th>Checks</th>
<th>Cohort-based IV</th>
<th>Boom measurement</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>log HPI</td>
<td>0.284***</td>
<td>0.302***</td>
</tr>
<tr>
<td></td>
<td>(0.065)</td>
<td>(0.066)</td>
</tr>
<tr>
<td>log income</td>
<td>0.150</td>
<td>0.130</td>
</tr>
<tr>
<td></td>
<td>(0.220)</td>
<td>(0.227)</td>
</tr>
<tr>
<td>log sales</td>
<td>0.003</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>MSA FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year-quarter FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>First-stage F-stat</td>
<td>3059.58</td>
<td>146.74</td>
</tr>
<tr>
<td>Observations</td>
<td>15,572</td>
<td>15,572</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.991</td>
<td>0.991</td>
</tr>
</tbody>
</table>

Notes: This table presents 2SLS coefficients from Equation (8). The dependent variable is IHS-transformed total policy count. The first-stage regression follows Equation (7) and the corresponding F-statistic is 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 mis-measurement of boom size and timing for those MSAs with no clear boom. Column (3) constrains all MSAs with a negative boom measure to have a flat trajectory across event years, by setting their boom measure to zero. Column (4) does the same for the quarter of MSAs with the smallest absolute values in their boom measure. 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 a 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, while Panels B and C plot the IHS-transformed count of SFHA and non-SFHA policies, respectively.
Figure A4: Dynamics of Take-Up Under Different Specifications

Notes: This figure plots the point estimates for overall take-up from Equation (6) 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 A5: Dynamics of Building Coverage

Notes: This figure plots the estimated coefficients and their 95% confidence intervals from Equation (6) for coverage purchased on flood insurance policies inside the SFHA (left panel) and outside the SFHA (right panel). Both dependent variables are IHS-transformed.
Figure A6: Dynamics of Contents Coverage

Notes: This figure plots the estimated coefficients and their 95% confidence intervals from Equation (6) 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% confidence intervals from Equation (6) for the share of newly-enrolled SFHA policies with the standard deductible.
Figure A8: 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 U.S. National Home 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.

There are two main differences between the flood risk measure from FSF-FM and that from FEMA’s flood map. First, the majority of FEMA’s maps are outdated and do not reflect recent changes in risk levels. In fact, 75% of FEMA’s flood maps are older than 5 years, despite the requirement to update the maps every five years by the National Flood Insurance Reform Act of 1994. 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% annual flood risk, but FEMA’s maps indicate this level of risk for only 8.7 million properties.34

The First Street Foundation also provides a “Flood Factor” risk score measure based on each property’s flood probability and depth profile.35 Flood Factor ranges from 1 to 10, representing minimal to extreme levels of risk. For each MSA, we calculate the average risk score of all properties, SFHA properties, and non-SFHA properties. In the regressions, we use the appropriate risk measure 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 use in a mechanism test. 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 for this test, we define the following measure of non-SFHA tail risk exposure:

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

The denominator captures the extent of the flood insurance market outside the SFHA, while the numerator captures the subset of properties facing severe enough risk that a mortgage default is potentially relevant after a flood. We use this measure to classify each MSA as having above- or below-median tail risk exposure.

35See https://floodfactor.com/methodology for the methodology on Flood Factor.
36For example, we use the average risk score for non-SFHA properties when the outcome variable is non-SFHA take-up.
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.

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 for lenders to obtain a foreclosure sale more costly and lengthy, while affording 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 Note on Heterogeneity Analysis

C.1 Estimation Equations

In Section 5.3, we estimate heterogeneous effects based on (1) judicial review law status and (2) non-SFHA 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 the MSA has above-median non-SFHA risk. Formally, our second-stage equation is a version of Equation (8) with an additional interaction term:

$$\lnNFIP_{mt} = \beta_1 \cdot \hat{\lnHPI}_{mt} + \beta_2 \cdot \hat{\lnHPI}_{mt} \times Char_m + \delta'X_{mt} + \lambda_m + \lambda_t + \varepsilon_{mt}. \quad (A1)$$

Note that we do not need to include $Char_m$ in the equation because it is absorbed by the MSA fixed effect. $\beta_1$ measures the home price elasticity of take-up by the baseline group (MSAs with no judicial review law/below median risk), and $\beta_2$ 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:

\[
\ln HPI_{mt} = \sum_{\tau=0}^{24} \rho_{1\tau} (Post_{mt}^{\tau} \times \Delta P_m) + \sum_{\tau=0}^{24} \sigma_{1\tau} (Post_{mt}^{\tau} \times \Delta P_m \times Char_m) \\
+ \mu_1' X_{mt} + \gamma_{1m} + \gamma_{1t} + \omega_{1mt}
\]

\[
\ln HPI_{mt} \times Char_m = \sum_{\tau=0}^{24} \rho_{2\tau} (Post_{mt}^{\tau} \times \Delta P_m) + \sum_{\tau=0}^{24} \sigma_{2\tau} (Post_{mt}^{\tau} \times \Delta P_m \times Char_m) \\
+ \mu_2' X_{mt} + \gamma_{2m} + \gamma_{2t} + \omega_{2mt}.
\]

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

C.2 Interpretation

The main challenge in interpreting \(\beta_2\) is that the characteristic of interest \(Char_m\) might not be exogenous. Thus, while \(\beta_2\) 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 \(\beta_2\).

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 B1). There are notable differences between the two groups: MSAs with judicial review laws experienced smaller housing booms and have a greater number of NFIP policies in force. However, the two groups are quite comparable in other dimensions. In particular, there appears to be no systematic difference in factors 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 1-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 risk, we compare MSAs with above-median non-SFHA extreme risk to those below 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 B1). The MSAs with above-median risk
Table B1: MSA Characteristics by Judicial Review Law and Non-SFHA Extreme Risk (2001 Q1)

### A. Judicial Review Law

<table>
<thead>
<tr>
<th>Group</th>
<th>No (N=127)</th>
<th>Yes (N=139)</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Structural Break IV</td>
<td>0.06 (0.07)</td>
<td>0.03 (0.06)</td>
<td>0.009***</td>
</tr>
<tr>
<td>Total SFHA Policies</td>
<td>2658 (6360)</td>
<td>8809 (27865)</td>
<td>0.012**</td>
</tr>
<tr>
<td>Total Non-SFHA Policies</td>
<td>1680 (4553)</td>
<td>3933 (11854)</td>
<td>0.039**</td>
</tr>
<tr>
<td>Average Risk Score (SFHA)</td>
<td>4.63 (1.27)</td>
<td>4.77 (1.34)</td>
<td>0.366</td>
</tr>
<tr>
<td>Average Risk Score (Non-SFHA)</td>
<td>1.65 (0.39)</td>
<td>1.68 (0.67)</td>
<td>0.745</td>
</tr>
<tr>
<td>1-Yr Renewal Rate (SFHA)</td>
<td>0.76 (0.16)</td>
<td>0.77 (0.18)</td>
<td>0.484</td>
</tr>
<tr>
<td>1-Yr Renewal Rate (Non-SFHA)</td>
<td>0.81 (0.19)</td>
<td>0.84 (0.20)</td>
<td>0.243</td>
</tr>
<tr>
<td>Population</td>
<td>761 (1183)</td>
<td>789 (1357)</td>
<td>0.853</td>
</tr>
<tr>
<td>Income</td>
<td>28.9 (5.67)</td>
<td>29.6 (5.49)</td>
<td>0.320</td>
</tr>
</tbody>
</table>

### B. Non-SFHA Extreme Risk

<table>
<thead>
<tr>
<th>Group</th>
<th>Below Median (N=132)</th>
<th>Above Median (N=134)</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Structural Break IV</td>
<td>0.05 (0.08)</td>
<td>0.03 (0.05)</td>
<td>0.013**</td>
</tr>
<tr>
<td>Total SFHA Policies</td>
<td>9871 (28479)</td>
<td>1814 (4431)</td>
<td>0.002***</td>
</tr>
<tr>
<td>Total Non-SFHA Policies</td>
<td>4772 (12510)</td>
<td>915 (2029)</td>
<td>0.001***</td>
</tr>
<tr>
<td>Average Risk Score (SFHA)</td>
<td>4.33 (1.24)</td>
<td>5.08 (1.27)</td>
<td>&lt;0.001***</td>
</tr>
<tr>
<td>Average Risk Score (Non-SFHA)</td>
<td>1.72 (0.55)</td>
<td>1.61 (0.56)</td>
<td>0.111</td>
</tr>
<tr>
<td>1-Yr Renewal Rate (SFHA)</td>
<td>0.79 (0.14)</td>
<td>0.74 (0.19)</td>
<td>0.012**</td>
</tr>
<tr>
<td>1-Yr Renewal Rate (Non-SFHA)</td>
<td>0.82 (0.18)</td>
<td>0.83 (0.21)</td>
<td>0.667</td>
</tr>
<tr>
<td>Population</td>
<td>1005 (1628)</td>
<td>544 (703)</td>
<td>0.003***</td>
</tr>
<tr>
<td>Income</td>
<td>29.4 (6.23)</td>
<td>29.1 (4.85)</td>
<td>0.689</td>
</tr>
</tbody>
</table>

**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

experienced smaller housing booms, have a significantly smaller number of policies in force, and a smaller population. The SFHAs in these MSAs also have high risk levels and one-year renewal rates. Nevertheless, these variables are not systematically different for non-SFHA policies, which is more reassuring since our main outcome of interest is non-SFHA take-up. Similarly, there is no difference in income levels across the two sets of MSAs.