Climate Risk and the U.S. Insurance Gap: Measurement, Drivers and Implications*

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Abstract

This study investigates the prevalence and severity of under-insurance among U.S. households using novel microdata linking homeowners insurance and mortgage information from 2013-2023 nationwide. We document widespread under-insurance on the intensive margin, particularly among borrowers in high climate risk states, with low credit scores, and high loan-to-value ratios. We examine the role played by household credit constraints by showing that households respond to rising premiums by both dropping coverage as well as increasing mortgage debt, suggesting that mortgage credit is used to finance insurance purchases. These results imply that rising premiums change mortgage risks by inducing households drop coverage as well as taking on higher loan balances. Lastly, we study the broader impacts of under-insurance on household financial resilience after natural disasters.

Keywords: Climate Risk, Insurance Protection Gap, Property Insurers, Banks, Mortgages, Household Finance, Financial Stability.

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1 Introduction

Nearly every American household has homeowners insurance. Homeowners insurance helps households rebuild and recover after natural disasters, with over 90% of all its losses being disaster-related.[1] Mortgage lenders typically require borrowers to purchase homeowners insurance as a condition of the loan, making insurance the backbone of the $20 trillion mortgage market.

Despite its importance, very little is known about homeowners insurance and its linkages to the mortgage market. This gap has stemmed from issues with data opacity – insurance data is only consistently available at aggregate state-wide levels; in some places at the county-level, rarely at the zip-code level, and nearly never at the individual loan level. This lack of granular data has made it challenging to understand the dynamics of this market. It is tough to answer even basic questions, such as how many people have adequate insurance coverage? How does coverage vary by the demographics and indebtedness of the individual? And most crucially, what does insurance coverage look like for the most at-risk households, i.e. those living in coastal or fire-prone regions?

These questions have taken on a heightened importance as homeowners insurance markets have begun to unravel, particularly in high climate risk states. In states like California, Colorado, Florida, and Louisiana, there are growing reports about increasing insurance premiums and reduced availability of insurance. A record number of individuals cannot obtain insurance from private insurers, relying on state-provided property insurance. These trends raise the question whether households will have enough financial resiliency to withstand rising climate risks, and whether there will be broader spillovers to other financial institutions or taxpayers.

We utilize a newly-available dataset from BlackKnight McDash which provides a

[1] For example, estimates from SwissRE suggest that over 93% of the total losses are from natural disasters and that this share has risen sharply in the past two decades.

comprehensive picture of both mortgage characteristics and insurance premiums at the loan level nationwide, going back to 2013. This novel data allows us to then connect insurance premiums and coverage with other loan-level borrower characteristics, including credit scores, debt-to-income ratios, loan-to-value ratios, the maturity of the loan, and zip code. To our knowledge, this is the first dataset to connect individual and mortgage characteristics to homeowners insurance contracts at the loan level for the entire United States over a ten-year time period. We combine this information with property-level estimates of climate risk exposures, values at risk, and property characteristics coming from Corelogic Deeds data. We then focus our analysis on understanding the ongoing unraveling of property insurance markets and the implications it has for households, and for the financial system more broadly through its connections to the mortgage market.

We use this novel data to produce three novel facts on household under-insurance. First, we show that households are severely under-insured, on average having only 70% of their replacement costs covered by insurance. There are also significant disparities across states, where some places (like Louisiana, Alabama, and Mississippi) less than 50% of rebuilding costs are insured. This means that if a natural disaster causes a total loss event, the average borrower will likely not have enough insurance claim payouts to completely reconstruct his/her home.

Second, we find that higher credit risk borrowers tend to obtain less insurance coverage at origination. Subprime borrowers with FICO scores less than 620 tend to have a coverage ratio around 65%; borrowers at 780 have coverage ratios of around 70%; and borrowers at 850 have coverage ratios of around 85%. These patterns hold regardless of whether the loan is held on portfolio or backed by FHA/VA or the government-sponsored enterprises. However, the relationship between coverage ratios and credit score are steepest for loans retained on portfolio.

We also find that borrowers with higher loan-to-value ratios obtain less insurance coverage at origination, mimicking the patterns with FICO scores. Borrowers with 70% loan-to-value ratios have insurance coverage ratios of 72%, whereas borrowers with 100% loan-to-value ratios have insurance coverage ratios of 66% on average. We also document a steep discontinuity at loan-to-value ratios of 80%, with coverage ratios declining by 5 percentage points when moving from one side of the boundary to the other. This threshold plays a key role in lending markets– for example the government-sponsored enterprises require that loans with LTVs above 80% obtain private mortgage– but plays virtually no role in *insurance markets*. The discontinuity highlights that there are likely important interconnection between rules in mortgage markets and what drives insurance coverage ratios.

Third, we show that insurance coverage ratios are roughly flat at 70% on average through the life of the loan. We observe that households obtain too little coverage at origination, but that coverage ratios do not change as the loan ages. This is despite the fact that households build up equity as the loan ages and they pay off their loan balances.

The fact that higher credit risk borrowers tend to purchase less insurance suggests that credit constraints are likely an important channel driving insurance demand. On the theoretical side, Rampini and Viswanathan (2013) show that financial constraints create a positive correlation between insurance take-up and wealth. Empirically, this correlation has held across a range of insurance markets, including health insurance (e.g. Finkelstein et al. (2019), Ericson and Sydnor (2018)), crop insurance (e.g. Casaburi and Willis (2018)), flood insurance (e.g. FEMA (2018)), life insurance (e.g. Gropper and Kuhnen (2023)). We build on this literature by evaluating credit constraints *directly*, an analysis we are able to do because our microdata uniquely includes information on both insurance contracts and credit contracts. That is, the data allow us to evaluate for individual borrowers how shocks to insurance costs are *financed* in credit markets.

Households that are downpayment constrained who expect persistently high insurance premiums have strong incentives to *adjust their mortgage contract* at origination. In the short-run, this is because lenders often require that, at origination, borrowers escrow one year of insurance premiums, in addition to the downpayment, property taxes, and other closing costs. Over the longer-term, households expecting persistently high premiums also have incentives to borrow more in the mortgage market. Mortgages are the cheapest type of credit available to households – far cheaper than credit card borrowing, or other uncollateralized borrowing from lenders. This creates two directly testable predictions – rising premiums lead to (1) lower coverage and (2) higher loan balances, measured both as higher debt-to-income ratios and higher loan-to-value ratios. We examine both measures because debt-to-income ratios have a mechanical relationship with insurance premiums, since in the denominator income is defined as net of premiums. This means a rise in premiums, even without a change in the loan balances, will lead debt-to-income ratios to increase.

To quantify and identify this liquidity constraints channel, we require exogenous changes in insurance prices that are independent of household demand for both insurance and credit. We obtain such variation using the following Hausman instrument, inspired by the industrial organization literature (e.g. Nevo (2001), Hausman (1996)). We construct this instrument as follows. First, we limit the sample to a subset of states where insurers face significantly more regulatory hurdles to changing premiums (Oh et al., 2021), what we call *high friction states*. We argue that insurers cannot easily change premiums in response to changing market conditions, whether it is insurance demand or credit demand, either locally or nationally. While there is variation in premiums, the timing is driven by whenever regulators choose to allow insurers to adjust premiums, with the approved premium change often differing substantially from what insurers requested. We then construct the average insurance price for these states in each year, for each FICO category. In the second step, we use this instrument to estimate the effect of premium shocks in *low friction states*. The exclusion restriction here is that insurer pricing in high friction states cannot respond to insurance demand or credit demand in low friction states. This identifying assumption would be violated, for example, if households in low friction states learned something about their own risk from prices in high friction states. Importantly, we show that the instrument is still highly relevant, because pricing frictions in one state impact insurer pricing in other states (Oh et al., 2021).

Using premiums shocks as a shock to liquidity constraints, we estimate the causal effect of quasi-exogenous changes in premiums on three outcome variables: (1) insurance coverage, (2) debt-to-income ratios, and (3) loan-to-value ratios. The liquidity-constraints hypothesis would suggest that rising premiums force households to drop coverage and increase mortgage credit, and indeed this is what we find. A 1% increase in prices is associated with a 0.29% decline in coverage, a 1.875% increase in debt-to-income ratios, and a .236% increase in loan-to-value ratios. These changes in loan-to-value ratios suggests that the increase in debt-to-income ratio is not purely driven by the mechanical relationship between premiums and DTI, where income in the denominator is calculated as net of premiums, but rather is driven by changes in loan balances. These results are consistent with a credit access as an important driver of insurance demand.

In the last part of the paper, we consider the impact of under-insurance on household financial resilience after natural disasters. While it is well-known that higher debt-to-income ratios and loan-to-value ratios are associated with higher default outcomes, there has been limited evidence thus far on the impacts of too little coverage in the homeowners insurance market.[2] To do so, we consider a difference-in-differences design, where we exploit the landfall of Hurricanes Irma and Harvey in 2017. We limit the sample to borrowers in states that were directly affected by the hurricanes,

[2]To the extent such evidence exists, it has been focused on under-insurance in the flood insurance context.

and then consider the impact of the storm on default by whether the household is under-insured. Under-insured status is defined by whether the household has a below-median coverage ratio in the year prior to the storm (2016). We include controls for a rich set of observables, including fixed effects that vary by FICO-quarter, LTV-quarter, and principal balance-quarter. We show that under-insured borrowers are more likely to default after the storm by 38bp relative to fully insured ones, with default rates remaining elevated for the following year.

Our findings suggest that under-insurance is a widespread phenomenon, particularly for the riskiest borrowers and for high climate risk states. We show that access to credit markets are an important driver of under-insurance, with mortgage contracts adjusting to finance rising insurance premiums. These results imply that mortgage market risks are growing, with households taking on more debt at the same time that they take on less insurance coverage. This coverage gap implies that households may have less financial resiliency towards natural disasters, with the costs being passed onto banks, mortgage owners, and taxpayers through enhanced mortgage default. Our liquidity constraint estimates are a crucial first step in mapping out the drivers of under-insurance and the distribution of climate risk throughout the financial system.

While our research can empirically identify the liquidity constraints channel, it is one among the set of possible drivers of underinsurance. The literature has suggested other plausible explanations including supply side rationing (e.g., Oh et al. (2023); Sastry et al. (2024)) household beliefs (Wagner, 2022), or household risk aversion (Arrow (1963), Mossin (1968)). In addition, the expectation of government disaster aid following disasters may also reduce the perceived need for insurance coverage ex-ante. We expect that the emerging new literature exploiting this new dataset will help to shed light on these various channels and their implications for disaster preparedness and recovery.

1.1 Related Literature

This paper contributes to three strands of the literature. First, we add to the literature on the industrial organization of insurance markets. Our work follows the seminal work of estimating demand in insurance by Einav et al. (2010) and Einav and Finkelstein (2023). Several studied applied this framework to the federally-provided flood insurance market (NFIP) and find that consumers have a low willingness-to-pay – below actuarily fair rates and even below the heavily subsidized NFIP rates, leading to low uptake of the product. Wagner (2022) and Collier et al. (2024) attribute the low willingness to pay to households underestimating the risk they are facing, while Liao and Mulder (2021) connect it to households' strategic behavior related to equity ownership. We estimate the demand in a new market – homeowners' insurance – and while we also see under-insurance, we find that liquidity constraints are key drivers of the pattern. Moreover, we show that households finance premium increases by increasing their demand for credit.

Additionally, there is a rich literature that studies the driving forces in the supply side of property and life insurance.Froot and O'Connell (1999) and Jaffee and Russell (1997) study the role of frictions from capital markets; Oh et al. (2023) study the role of insurer pricing regulation across states, Boomhower et al. (2023) study the effect of asymmetric information and use of catastrophe models in the pricing of homeowners insurance. Our paper also relates to the broader insurance literature on supply side frictions and their effects on insurance products and asset holdings (Koijen and Yogo, 2015, 2016, 2022; Ellul et al., 2015, 2022; Ge, 2022; Sen and Humphry, 2018; Sen, 2021; Sen and Sharma, 2020; Barbu, 2021; Tang, 2023; Tenekedjieva, 2021; Oh, 2020; Gennaioli et al., 2021; Egan et al., 2021). Our contribution to this literature is to bring in the role of household demand for insurance, and how mortgage debt can be used to finance insurance premiums.

Second, this paper contributes to the growing literature on the relationship between property insurance, climate risk, and real-estate outcomes. Climate events create financial losses for lenders, and flood insurance payments helps to reduce delinquencies after disasters (Gallagher and Hartley, 2017; Kousky et al., 2020; Billings et al., 2019; Issler et al., 2019; An et al., 2023; Biswas et al., 2023). Several closely related papers consider how the flood insurance market affects mortgage lending. (Sastry, 2022) finds that under-insurance against flood risk leads to credit rationing), and (Ge et al., 2023) finds that changes in flood insurance premiums are capitalized real estate prices. We contribute to this literature by showing that changes in the homeowners' insurance market affect mortgage risk along a number of dimensions, and result in riskier supply of mortgages. Our paper is the first to establish widespread under-insurance in the HO market, with responses to prices on the intensive margin (coverage rate), as opposed to the extensive margin (dropping insurance).[3] Another contemporaneous subset of papers explicitly focuses on the recent increases in the premiums for homeowners' insurance. Mulder and Keys (2024) focuses on quantifying the drivers of rising premiums, in particular the role of rising disaster risk and reinsurance premiums, while we study to what extent rising prices explain low coverage choices and rising mortgage debt. Bakkensen et al. (2024) develops a model on mortgage debt crowding out insurance take-up on the extensive margin, while we show that mortgage debt is actually used to finance insurance payments. Ge et al. (2024) show that rising premiums increase delinquency and prepayment risk throughout the life of the loan. In contrast, we focus on the the impact of premium increases on both insurance and mortgage contracts *when the loan is originated*, allowing us to consider how premiums change

[3]These new patterns contrast with the existing findings likely due to key differences between flood and HO markets. Mortgage lenders only require flood insurance in high risk areas, while HO insurance is always required. This limits homeowners' ability to adjust on the extensive margin. There are other differences as well that play a role. Flood insurance is dominated by a government provider, with little private competition. Flood insurance premiums are heavily subsidized, and have low coverage limits which can leave lenders and households exposed to significant risk even with flood insurance coverage.

household financing decisions and how they may increase the risk of the mortgage as a result. Cookson et al. (2023) find that households in Colorado that were impacted by the Marshall Fire tended to rely on informal crowdfunding networks to rebuild and recover, and that these networks often complemented formal innsurance. Our results on mortgage origination suggest that the new credit is for a riskier, under-insured segment of the market.

Third, our findings speak to the literature on the implications of climate risk for households' finances. Households bear climate risk directly through mortgage markets (Issler et al., 2020), real estate prices (Baldauf et al., 2020; Murfin and Spiegel, 2020; Bernstein et al., 2019), and equity prices (Engle et al., 2020), and indirectly through labor markets (Kruttli et al., 2019) and discounts in municipal bond prices (Goldsmith-Pinkham et al., 2020). The degree to which households are protected from physical climate damage depends on how much of the losses get absorbed from the P&C insurers. Sastry et al. (2024) show that financially fragile insurers contribute to the shift of risk away from the insurance sector and to GSEs and households. This problem is further exacerbated however, if even households relying on high quality insurers are under-insured, as we show in this paper.[4] Our findings on high-risk (and likely less wealthy and more vulnerable) population having even higher rate of under-insurance is particularly concerning in the light that these households are less able to self-insure through savings, and through crowd-funding through their social network (Cookson et al., 2023). Moreover, we show that the insurance demand response of household spill over to the mortgage market as well, with households demanding more credit.

[4]These results are part of a wider agenda on the regional redistribution in financial markets (Ouazad and Kahn, 2021; Lustig and Van Nieuwerburgh, 2010; Hurst et al., 2016).

2 Institutional Details

2.1 Homeowners' Insurance

For most American households, their house represents a significant portion of their wealth. The vast majority of households rely on mortgages to buy homes, and mortgage lenders require that a number of criteria be met for this financing to be provided, including a requirement that borrowers purchase homeowners insurance. As a result, the homeowners insurance product is nearly ubiquitous. Insurers sell homeowners multi-peril insurance coverage to nearly 85% of all U.S. homeowners (Jeziorski et al., 2021). This represents nearly $15 trillion in coverage taken out annually (Oh et al., 2023).

The standard homeowners contract is annual and covers damages from most natural disasters.[5] The insurance contract has three key characteristics: the coverage taken, the deductible choice, and the premium paid. Those purchasing insurance are entitled to claim payouts up to a pre-specified coverage amount if an insured loss event materializes. Coverage amounts are usually dictated by the mortgage lender. For example, any mortgage purchased or securitized by the government-sponsored enterprises require that coverage represents at least 80% of the estimated replacement cost of the house.[6] Deductibles is a clause in the insurance contract that requires insurance companies to only pay for losses that exceeds the pre-specified deductible amount. Lastly, the premium is the annual amount that the insured party must pay to the insurer. It is a function of the risk of the house, and the coverage and deductible choices of the insured. Premiums also reflect other regulatory and operational costs

[5] An important exception is flood risk, which is carved out from standard homeowners insurance contracts and mostly provided through the government-run National Flood Insurance Program.

[6] In addition, the government-sponsored enterprises require replacement cost value coverage (RCV). This policy requires that insurers play the full claim amount (Danko and Merlino, 2024). An alternate policy is the actual cash value (ACV) policy, where insurers are allowed to deduct the depreciation from normal wear-and-tear from from claim payments).

borne by the insurer and passed onto the borrower.

2.2 Mortgage Servicers and Escrow Accounts

Mortgage servicers are usually responsible for managing borrowers' monthly mortgage payments and monitoring that other requirements, such as insurance, continue to be met. The mortgage servicer can sometimes be the originating lender, especially if the mortgage is retained on the lender's balance sheet. For mortgages that are sold or securitized, the ultimate mortgage owner hires mortgage servicers to conduct all monitoring and processing of mortgage payments, and subsequent payments to securitized mortgage pools. Homeowners insurance can be force-placed by mortgage servicer if households do not obtain insurance themselves.

To simplify payments and enforce requirements, most mortgage payments are handled through escrow accounts. Mortgage escrow accounts are separate legal arrangements that are used to collect monthly mortgage payments, homeowners insurance premiums, and property tax payments. The mortgage servicer will send payment requirements to household, and then ensure that payments are made from the borrower's escrow account to the insurance company and tax authorities. Escrow accounts may also include flood insurance and mortgage insurance payments. The majority of of mortgages feature escrow deposit accounts (Anderson and Dokko, 2008), and are required by FHA, Fannie Mae, and Freddie Mac in most circumstances.[7].

When a mortgage is originated, lenders require a number of payments to be made up front– this includes the downpayment, property tax payment, closing costs, and often up to one-year of homeowners insurance payments. These payments are made into the account so that the lender knows that the funds in the account will be enough to cover these additional monthly expenses.

[7]The government-sponsored enterprises at times allow lenders to waive the requirement, but they retain the right to enforce the escrow requirement if the borrower fails to pay his or her property taxes

3 Data

Our analysis combines a number of mortgage and insurance databases to provide the most comprehensive picture of climate risk exposures, values at risk, and insurance take-up (both at the extensive and intensive margins) at the loan/ property level. We obtain a loan-level dataset that includes data on the borrower, property, mortgage, climate risk, and insurance contract. We now describe each dataset in detail, our merge procedure, and methodology.

3.1 Mortgage and Climate Datasets

Credit Risk Insights Servicing McDash (CRISM): Our primary sample comes from CRISM, an anonymous merge between mortgage servicing data and borrower credit profiles. The starting point for CRISM is the Intercontinental Exchange (ICE) McDash data, a loan-level dataset on mortgage origination and performance history. This data is provided to McDash by mortgage servicers, and represents nearly two-thirds of the US mortgage market. The variables include loan amount, loan-to-value ratio, origination month, interest rate, debt-to-income ratio, borrower origination FICO score (from McDash), loan maturity, property value, and the type of mortgage (e.g., FHA, VA, Jumbo, etc.). McDash also includes data on the subsequent performance of the mortgage, from its origination to its final payment. This includes whether the mortgage is current or in delinquency status, as well as events such as prepayment, default or foreclosure. Equifax/CRISM includes an updated credit score. The sample period is from 2011 to 2023.

Equifax then matches the servicing data from BlackKnight McDash to its credit bureau data using a proprietary match procedure. This data includes monthly mortgage payments, as well as a range of other credit market outcomes for the borrower.

CoreLogic Deeds: CoreLogic provides two datasets that contains property-level information. (i) The Deeds data includes property-level information on deed and mortgages for each transaction, as well as other characteristics of the property, such as the structure age and size. (ii) In a separate data file, CoreLogic also reports property tax payments collected by the county assessor office, which is usually the local taxation authority. We employ a fuzzy match to anonymously merge the CoreLogic Deeds data to the McDash loan-level data based on common variables included in both datasets (such as the loan amount). The sample period is from 2011 to 2023.

Climate Data: We also obtain property-level estimates of climate risk using two sources. The first is CoreLogic's climate risk index, which assigns a score for each property which represents its exposure to different hazards. The second is the First Street Foundation's estimates of risk exposure to hurricane, wind, flood, and fire risk, as well as their estimates of rebuilding costs. This climate risk data can be linked to the deeds data using addresses and other geographic coordinates. The First Street Foundation data include an estimate of the rebuilding cost in 2020, using property characteristics and local building cost indexes. We use this measure to validate our independent estimates of rebuilding costs.

3.2 Insurance Datasets

McDash Property Insurance Module: From 2013-2023, we have insurance data made available by BlackKnight McDash to the Federal Reserve system. A subset of mortgage servicers provided information about homeowners insurance to McDash; this includes data on monthly insurance premiums, coverage amounts, deductibles, and information about other insurance policies such as flood insurance. This insurance module can be linked to McDash's mortgage data using loan-level identifiers.

Quadrant Data: We obtain ZIP code level insurance pricing data from Quadrant Information Services from 2011-2020. The data cover over 34,000 ZIP codes across all 51 states in the US. The data is compiled from the rate filings made by the largest insurers operating in a state by market share.[8] The data includes information on premiums, coverage amounts, age of the property, insurance scores, insurer, and ZIP code of the property. The pricing data assumes a $1,000 deductible amount, which is the most common deductible chosen by households.

NAIC aggregate insurance payment data: We also obtain state-level aggregate data from the NAIC of the average insurance payment per policy. This data is compiled from insurers' regulatory filings on the total premiums underwritten, number of policies, and coverage amounts for each state and business line that insurers operate in.

Construction Costs: Insurance companies estimate replacement costs to help households determine how much insurance coverage they need. The point of this measure is to capture the cost of rebuilding the exact same house in the event of a total loss disaster. We use data on local construction costs from the R.S. Means company, a widely used data source in the urban/housing literature (e.g. Glaeser and Gyourko, 2005) that is developed based on detailed surveys of home builders across metropolitan cities nation-wide.

3.3 Final Sample Selection and Key Variables

Our final sample consists of roughly 100 million observations. We employ a number of filters to limit the sample. First, we limit the sample to *purchase mortgages*, dropping loans associated with re-finances. Second, we classify states as being high friction or low friction based on regulatory constraints to adjusting insurance pricing, following the methodology of Oh et al. (2021). For most of our analysis, we consider mortgages *at origination*.

[8]On average, we observe insurance rates for about 16 insurers per state, who collectively hold about 62% of the market share by total premiums in a state.

To assess how insured a given property is, in addition to coverage, we also need estimates on total rebuilding values (also known as replacement costs), which represents what it will cost to rebuild the property to its current state in case it suffers damages. We obtain data on local construction costs from the R.S. Means company, which we then combine with property-level estimates of structure size from the CoreLogic Deeds data. We them use the following formula to obtain reconstruction costs: Replacement Cost $=$ Construction cost per sq. foot $\times$ square feet.[9] We validate our estimate of replacement costs by comparing it with an independent estimate of replacement costs from the First-Street Foundation which we have for 2023–the two estimates are highly correlated ($\approx$ 90%).

Our measure of how insured a property p at time t is then given by

$$\text{Coverage Ratio}_{pt} = \frac{\text{Observed coverage}_{pt}}{\text{Estimated replacement cost}_{pt}}. \tag{1}$$

Our measure of insurance prices for a property p at time t is given by

$$\text{Insurance Price}_{pt} = \frac{\text{premium}_{pt}}{\$100{,}000 \text{ coverage}_{pt}}. \tag{2}$$

4 Three Facts on Insurance Coverage

In this section, we document three new facts about homeowners insurance that motivate our focus on liquidity constraints as a driver of under-insurance.

4.1 Descriptive Facts

When looking at the extensive margin, we find that nearly every mortgage in the McDash Insurance Module has data on homeowners insurance coverage. This matches

[9] This procedure is also used to estimate replacement costs in Sastry (2022).

estimates from the NAIC data which suggests that nearly 80% of owner-occupied housing units had a homeowners insurance policy.[10]

Within the context of homeowners insurance, we find that more than 75% of homeowners insurance policies are associated with an HO-3 policy–the most comprehensive and common type of homeowners insurance, which offers replacement cost coverage for the property and covers all loss events except those that are specifically excluded (usually flood or earthquake; occasionally also fire). In all states, HO-3 represents the majority of policies (see Figure 1). However, there is heterogeneity across states. For example, in Texas, HO-3 policies represent less than 60% of all outstanding policies.

These data suggest that insurance coverage on the *extensive margin* is less of an issue, and that there is similarly less concern about households being under-insured by switching into contracts that cover fewer perils. We therefore focus our attention on looking at the intensive margin of coverage. In that space, we uncover the following five facts.

Fact 1: **Households are under-insured, with significant spatial heterogeneity.**

We find that the average U.S. household has a coverage ratio representing only 70% of the full rebuilding costs. Our measure utilizes construction If a natural disaster causes a total loss event, most borrowers will need to pay significant amount of out-of-pocoket to rebuild their homes. This finding is confirmed by anecdotal evidence from a number of disasters, where it is discovered after-the-fact that households face significant hardship due to being under-insured (e.g., Cookson et al. (2023), and Colorado's 2021 Marshall wildfires).

We see significant heterogeneity in average coverage by geography. In Table 1 we show the five states with highest and lowest insurance coverage. For the most insured

[10]We construct this number by using NAIC state-wide estimates of the number of house-year policy exposures for either dwelling (DW) or homeowners (HO-1 through HO-8) as an estimate of the number of annual homeowners insurance policies. We then scale this by the number of owner-occupied housing units, reported in the Census' American Community Survey. We use the 5-year ACS estimates from 2018-2022.

states (Hawaii, Minnesota, Rhode Island, Massachusetts, Utah), the average coverage ratio is above between 85% and 90%, and in fact we see that the top decile is even over-insured. However, the least insured states (Mississippi, Arkansas, Texas, Alabama and Louisiana) have only 50% coverage rates, and even the 90th percentile is below 80%.

Moreover, the level of coverage is below the GSE eligibility policy of households maintaining at least 80% coverage ratio. This means that both lenders, households, and the government are exposed to under-insurance risk.

Fact 2: **Higher credit risk borrowers have less coverage.**

In Figure 2a we show a binned scatterplot of individual coverage ratios as a function of the loan's FICO score at origination. We see that low FICO (i.e. higher credit risk) borrowers tend to obtain less insurance coverage: Subprime borrowers with FICO scores less than 620 tend to have a coverage ratio around 65%, and borrowers at 780 have coverage ratios of around 70%. These results suggest that under-insurance is particularly high among households who are most vulnerable to large shocks, without the resources to smooth such shocks, and thus likely the ones to benefit most from insurance.

In Figure 2b we show the correlations between FICO score and coverage rates by entity holding the loan, i.e. is the loan retained on the lenders' balance sheet, is it held by FHA/VA thus fully backed by the government at origination), or is it held by the government-sponsored enterprises (GSEs). Several patterns emerge. First, the positive correlation between coverage ratios and credit scores persist regardless of who holds the loan. However, the relationship between coverage ratios and credit score are steepest for loans retained on portfolio. For the portfolio mortgage segment, borrowers with a 620 credit score have roughly 70% coverage, and borrowers at 780 have roughly 80% coverage ratio. In contrast, this difference in credit score is associated with around

5% difference in coverage ratios if the loans are held by GSEs or FHA/VA. Finally, the more risk is retained by lenders, the higher the coverage rate: for a borrower with FICO score of 800, lender loans have average coverage ratio of 90%, loans held by GSEs have coverage ratio of 70% and for FHA/VA, the ratio is 68%. Since it is unclear why households would choose different levels of coverage based on who holds the loan, these pattern imply that household characteristics and mortgage lenders play and important role in the choice of coverage.

In Figure 3, we plot a binscatter of loans' coverage ratios by their loan-to-value (LTV) ratio. We see a negative correlation, with higher LTV (thus riskier loans) having lower coverage rates. For example, borrowers with 70% LTV have coverage ratios of 72%, while borrowers with 100% LTV ratios have coverage ratios of 66% on average. This finding is in similar spirit to Fact 3, where low FICO score households (thus riskier and likely less wealthy) households purchase less insurance. Similarly, this finding goes against Prediction 4 of the standard model that wealthier households would demand less insurance. It also suggests that lenders are unlikely to be engaging in risk management strategies, since one might expect lenders to require the highest risk borrowers to obtain the most coverage.

Most starkly, we see a steep discontinuity at LTV ratios of 80%, with coverage ratios declining by 5 percentage points when moving from one side of the boundary to the other. This drop is equivalent to moving from 40% to 70% LTV, which makes it a very sharp discontinuity. It is difficult to explain this variation by looking at insurance markets alone, since insurers are not impacted by mortgage leverage choice and do not usually price on LTVs. That is, going from 79% to 81% LTV does not immediately seem correlated with any risk factors that would be relevant for insurance markets. However, an LTV of 80% is a key cutoff threshold in mortgage markets. For example the government-sponsored enterprises require that loans with LTVs above 80% obtain private mortgage insurance. The discontinuity implies that mortgage markets play a key role in determining insurance demand. Since households' beliefs are unlikely to be different around the 80% LTV value, it also is less consistent with the hypothesis that under-insurance is mainly driven by inaccurate climate beliefs, or moral hazard from disaster aid. Neither of these channels would imply such a stark discontinuity.

Fact 3: **Insurance coverage stays flat through the life of the loan.**

In Figure 4 we plot a binned scatter plot of coverage ratios by loan age, after controlling for a loan fixed effect. We find that coverage rates do not change after loan origination, and stay roughly flat at 70% on average throughout the life of the loan. In other words, households obtain too little coverage a origination, but that coverage ratios do not change much as the loan ages. This is surprising since households build up their equity as the loan ages and they pay off their loan balances. One might expect that household incentives to insure *increases* as the loan ages, all else equal. Therefore, this pattern suggests that under-insurance is not likely to be driven by strategic behavior by indebted households having limited incentives to hedge .

4.2 Interpreting the Descriptive Facts

Taking the three facts together, the broad patterns suggest that household liquidity constraints play an important role in driving household under-insurance. In this explanation, liquidity-constrained borrowers may be less able to finance rising premiums, and so they respond by decreasing their coverage levels. This story is supported by several of the facts. We will directly test the liquidity constraints hypothesis in the next section by looking at how households react to exogenous changes in insurance premiums.

5 Drivers of Under-insurance

In this section, we seek to understand the drivers of under-insurance, and to what extent liquidity constraints may explain the broad facts.

5.1 Premiums are a shock to liquidity constraints

We first consider exogenous changes in insurance prices as shocks to liquidity constraints. Of course, even unconstrained households will likely adjust coverage as insurance prices change. However, unconstrained households will have limited incentives to adjust mortgage credit. Therefore, we look at the impacts of price changes on both coverage choices and mortgage contracts, together, to provide evidence in support of the liquidity constraints channel. If coverage drops after *exogenous* changes in insurance prices are entirely due to borrowers' elasticity of demand for insurance, then there should be limited impacts on the mortgage contract.

A natural question is why shocks to insurance premiums would exacerbate liquidity constraints. Insurance is paid monthly as a flow over a long period of time, both over the mortgage contract and after households pay off the mortgage. It may not seem like a large upfront fixed cost that exacerbates liquidity constraints. However, an important institutional detail is that mortgage lenders require that households escrow a full year of insurance premiums upfront (or sometimes more). If households are downpayment constrained, this may incentivize them to take on less coverage, as well as adjust their mortgage contract to pay a smaller downpayment (i.e. take out a larger loan). Consider the following hypothetical answer. A borrower has saved \$100,000 to buy a home. If insurance premiums are low requiring only \$1000 upfront, then the majority of this can go to the downpayment. However, if insurance premiums are high requiring \$10,000 upfront, then that means only \$90,000 can go to the downpayment, requiring an additional \$10,000 of the loan.

Another important consideration is that, for most borrowers, the mortgage is the *cheapest* form of borrowing – far cheaper than revolving credit like credit cards, or uncollateralized borrowing. It may also be rational for borrowers to use mortgage finance to finance all future expected changes in insurance premiums over the loan, if they expected to be liquidity constrained in the future or expect interest rates to increase. We consider this a type of liquidity constraint, since expectations of liquidity constraits *in the future* incentivize borrowing today. This may lead borrowers to finance all future insurance premiums with borrowing today.

5.2 Hypotheses

We consider two sets of hypotheses for how premiums shocks impact coverage and mortgage outcomes. The first considers what we might expect if insurance and mortgage decisions are driven by liquidity-constrained borrowers. The second considers what we might expect if decisions are driven by lender risk-management considerations.

Downpayment-constrained borrowers: An increase in insurance prices for such borrowers would, all else equal, likely them to try and reduce their upfront payments by adjusting other dimensions. This can be achieved by taking out less insurance coverage, or paying a lower downpayment. A lower downpayment would translate to an increase in debt through higher debt-to-income and loan-to-value ratios.

Lender risk management: Lenders reaction to an exogenous rise in premiums is more subtle. On the one hand, if these premium shocks are truly exogenous, lenders' should not expect to change the level of coverage that they require borrowers to take out, since fundamental risks have not changed. However, it may have an impact on the mortgage contract. First, there is a mechanical result, whereby the debt-to-income ratio would automatically increase, since the denominator is actually income *net of* *premiums*. So a rise in premiums would mechanically lead to a rise in debt-to-income ratios. However, if premium shocks are large enough to push the mortgage beyond the lender's internal DTI thresholds, then it is possible that lenders may react by forcing borrowers into smaller loans. This would tend to push down debt-to-income ratios and loan-to-value ratios, or lead to no change in these variables at all.

These two classes of explanations yield opposing predictions. By considering the impact on both loan-to-value ratios and debt-to-income ratios, we can see whether loan balances increases on net to accommodate the financing of insurance premiums, or whether lender risk management forces houses to lower their loan balances.

5.3 Empirical Design: IV Approach

We obtain arguably quasi-exogenous changes in insurance prices using the following instrument. First, we limit the sample to a subset of high friction states where insurers face significantly more regulatory hurdles to changing premiums (Oh et al., 2021). This means that, for these states, insurers cannot easily change premiums in response to changing demand conditions, either locally or nationally. While there is variation in premiums, the timing is driven by whenever regulators choose to allow insurers to adjust premiums, with the premium change often differing substantially from what insurers had requested. We construct the average insurance price for these states in each year, for each FICO category. We call this variable $\bar{P}_{HF,c,t}$ where "HF" indicates this is based on the high friction states, and c, t shows that the variable varies by credit score category c and year t.

We then use this instrument to estimate the effect of premiums shocks in *low friction states*. We build off the intuition of the Hausman instruments that are commonly used in the industrial organization literature (e.g. Nevo (2001), Hausman (1996)). They often use prices in other markets to instrument for prices in the current one, the idea being that suppliers which operate nationally may need to adjust prices across many markets optimally, while adjustment in other markets do not necessarily influence demand in the current market. We use a similar intuitions, except we limit our instrument's sample specifically to high friction states, where we argue that prices cannot respond to demand at all (including, for example, national advertising campaigns), satisfying the exclusion restriction of an instrumental variable. This identifying assumption would be violated, for example, if households in low friction states learned something about their own risk from prices in high friction states, or if there was a nation-wide shift in the demand for insurance which was capitalized into prices in high friction states. We argue that such violations are unlikely, given the nature of the challenges to adjusting prices in these states. To help validate this assumption, Oh et al. (2021) show that prices in high friction states are insensitive to risk, both realized losses as well as other measures of ex-ante risk exposures, showing that these variables contain little information or signal about risk.

Importantly, we show that the instrument is still highly relevant, because pricing frictions in one state impact insurer pricing in other states (Oh et al. (2021)). This is true for insurers that operate across states, as well as single-state insurers that compete with multi-state insurers. We consider the following two-stage least squares regression:

$$\text{First Stage:} \log P_{i,c,z,t} = \omega + \eta \log \bar{P}_{HF,c,t} + \theta' W_{i,z,c,t} + \nu_{i,z,c,t} \tag{3}$$

$$\text{Second Stage:} \log Q_{i,z,c,t} = \alpha + \beta \log \hat{P}_{i,c,z,t} + \gamma' W_{i,z,c,t} + \varepsilon_{i,c,z,t} \tag{4}$$

where Q refers to homeowners insurance coverage levels and P refers to prices (premiums per dollars of coverage). The subscript i indexes loans, z indexes ZIP code, c indexes credit score category, and t indexes here. The variable W refers of a vector of control variables which includes ZIP fixed effects, year fixed effects, fico group fixed effects. We also include the First Street Foundation's estimates of expected losses from natural disasters as a measure of climate risk exposure, and our estimates of replacement cost as control variables in W. Our coefficient β can be interpreted as the elasticity of demand for coverage with respect to insurance prices, after controlling for climate risk and the total value-at-risk (the replacement cost)

Table 2 shows the first stage of our instrumental variables regression, which regresses insurances prices at the individual level for mortgage borrowers in low friction states on the instrument which is constructed in high friction states. The $R - squared$ is high, and strongly consistent with the high first-stage F-statistics we obtain (and report in the tables of the second stage).

We also estimate the causal effect of quasi-exogenous changes in premiums on two outcome variables related to the mortgage contract: (1) debt-to-income ratios, and (2) loan-to-value ratios. All regressions are run at mortgage origination, when the terms of the mortgage are set. The liquidity-constraints hypothesis would suggest that rising premiums force households drop coverage and increase mortgage credit,

5.4 Elasticity of Demand

Table 3 shows the results of the two-stage least squares estimation which uses log of homeowners insurance coverage as the outcome variable. Column (1) shows the result without credit score group fixed effects, and Column (2) shows the result with it. Without credit score control groups, we find that on average, a 1% increase in prices is associated with a 0.42% decline in coverage. Including credit score controls in Column (2) shows that this coefficient shrinks to -0.286%, suggesting that there is significant heterogeneity across credit score groups in the elasticity. We denote the first-stage K-P F-Statistic at the bottom of the table, which exceeds the critical values for the weak identification tests of Stock and Yogo.[11] These magnitudes are difficult to compare with other magnitudes in the literature, because such estimates do not exist for homeowners insurance (to our knowledge). The closest market is flood insurance (e.g. Wagner (2019)), but even there the results are difficult to compare because in our context the results are entirely driven by the intensive margin of coverage choice, rather than the extensive margin decision of whether or not to insure at all as in the flood insurance case. This is because mortgage borrowers are forced by lenders to obtain homeowners insurance, so they have limited discretion on the extensive margin.

To interpret this magnitude, we consider that the average insurance price increase over our sample in low friction states is approximately 10% and the average coverage amount is $340,000. Using our estimate in Column (2), our magnitudes suggest that the observed price increases caused households to drop coverage by $9,724.

The other coefficients for the control variables also have intuitive signs and magnitudes. As expected, borrowers purchasing houses with higher replacement costs buy more coverage, and households with higher expected disaster loss also purchase more insurance coverage.

We show the OLS specification (without the instrumented price) in Table A.1

5.5 Mortgage markets

We now turn to the mortgage contract, looking at the impact of rising premiums on debt-to-income ratios and loan-to-value ratios.

Debt-to-Income Ratios: As discussed earlier, rising insurance premiums have a mechanical impact on debt-to-income ratios by changing the denominator. However, another way in which households may finance rising premiums is by adjusting their

[11] We note that the first-stage F-statistics change across specifications because different variables are missing at different rates– because of this change in sample composition, we report the first-stage F-statistic for each regression.

loan size, or changing the downpayment that they pay. Both of these channels would tend to increase debt-to-income ratios. However, lenders may push back by requiring that households obtain smaller loans. Table 4 shows the results of the two-stage-least squares regression which uses debt-to-income ratios as an outcome variable. We find that an exogenous 1% increase in insurance prices leads to a 1% increase in debt-to-income ratios. This result increases in Column (2) after controlling for credit scores to 1.875%. These results could be driven by the direct effect of premiums changing the denominator, by changes in the loan balance, or both.

Loan-to-value Ratios: To understand if the mortgage debt has increased, we complement the result on debt-to-income ratios with a result on loan-to-value ratios. Table 5 shows that loan-to-value ratios significantly increase as insurance prices exogenously change. In Column (1), we find that a 1% increase in insurance prices leads to a 0.6% increase in loan-to-value ratios. With the inclusion of credit score fixed effects, this coefficient becomes closer to 0.236% in Column (2). This shows that the debt-to-income ratio result is not entirely driven by the mechanical effect, and is indeed reflective of an increase in loan balances.

Interestingly both Table 4 and Table 5 show that households with higher climate risk exposure tend to have lower loan-to-value ratios and lower debt-to-income ratios, which could support an interpretation of lenders managing some climate risk exposure by rationing credit, like in Sastry (2022). However, it is clear that such rationing is not triggered in response to exogenous changes in insurance premiums, since the sign goes in the opposite direction, helping to support the contention that the shocks we use to insurance premiums do not contain any signal about underlying risks.

Of course, households cannot obtain bigger loans for free– doing so usually triggers a change in interest rate. In Table A.2, we show that are estimates are similar even after controlling for the interest rate on the mortgage. This might be surprising, but is likely driven by the fact that the majority of our sample was a low interest rate environment that had a limited gradient of interest rates with respect to LTV.

To interpret these magnitudes, we consider that the average debt-to-income ratio in our sample is 38%, and the average loan-to-value ratio is 83%. Our coefficients suggest that the observed 10% increase in prices increased debt-to-income ratios by 7%, and loan-to-value ratios by 2%. If the entirety of this change is driven by the loan balance, this translate to an increase in the loan by roughly $5,719, since the average loan balance in the sample of low friction states was $292,000.

5.6 Premiums and Mortgage Risks

These results suggest that rising premiums impact mortgage risks in three ways, with households dropping coverage, increasing their debt-to-income ratios, and increasing their loan-to-value ratios. All-else-equal, the literature has shown that higher DTI and LTV ratios tend to make the mortgage riskier, both through adverse selection and mortgage hazard explanations. Households that pay a smaller downpayment and have less equity in their homes and have more incentive to strategically default after large natural disasters. Similarly, households with higher debt-to-income ratios may be more liquidity constrained, and also unable smooth disaster shocks, thereby defaulting. There is evidence of both strategic motives and liquidity constraints driving default (e.g. Ganong and Noel (2020)).

While the impact of higher DTI and LTV on mortgage risks is well-known to the literature, the effect of under-insurance on mortgage outcomes is less known. There are only a handful of studies with data on both homeowners insurance and mortgage default. For example, Cookson et al. (2023) report that households in Colorado Boulder impacted by the Marshall Fire were *severely* under-insured, households rely on informal crowdfunding networks to rebuild and recover as a complement to formal insurance payments. Additionally Kousky et al. (2020) show that households without flood insurance outside of flood zones have worse mortgage outcomes. In the last part of the paper, we focus in on the default risk associated with being under-insured.

6 Impacts of under-insurance on Household Resiliency

In this section, we consider the implications of under-insurance. To do so, we exploit the landfall of Hurricane Irma and Harvey in end-August/early-September 2017. The two hurricanes made a landfall within weeks of one another.

To consider the impacts of the hurricane, we first limit the sample to affected counties that were hit by the hurricane, which we identify using the SHELDUS database. This means we are entirely conditioning on areas that were hit.

We then estimate the following specification:

$$Y_{l,z,t} = \alpha + \beta(PostHurricane_t \times UnderInsured_l) + \alpha_{zt} + \gamma' X_{lt} + \epsilon_{l,z,t} \tag{5}$$

The subscript l indexes loans, z indexes ZIP, and t indexes quarter. The dummy $PostHurricane_t$ equals one after September 2017. We define the dummy $UnderInsured_l$ to equal one if the household has a below-median coverage ratio in 2016. In hit counties, the median coverage ratio corresponds to roughly 50%. The key coefficient of interest is β, which represents the difference-in-differences coefficient of the increase in default on under-insured households relative to fully-insured ones. Because such borrowers may be different from eachother in other dimensions, we include a rich set of controls for fico-quarter, LTV-quarter, and principal balance-quarter fixed effects.

A key assumption of the difference-in-differences design is that a conditional parallel trends assumption holds. In our context, that implies that in the absence of the hurricane, conditional on our controls, under-insured borrowers would have similar default outcomes as the more insured group. While this identifying assumption cannot be tested directly, the pre-trends can be evaluated to determine whether this is likely to hold.

Another assumption we must make is that, conditional on observables, under-insured borrowers would have similar default behavior to fully insured borrowers after the hurricane. Or, put another way, β represents the impact of being under-insured, and does not reflect that fact that under-insured borrowers are somehow also unobservably worse than more-insured ones. For example, if under-insured borrowers had systematically less access to credit than fully insured ones, which impacts recovery after storms, this assumption would be violated. While this assumption cannot be tested directly, it can be elicited in part by looking at the pre-trends, since borrowers that are likely to be unobservably worse would also have higher defaults prior to the hurricane. Stated another way, if under-insured borrowers are systematically worse than fully-insured ones, then we might expect that they react to other types of shocks hitting such areas prior to the hurricane, which would lead to visible pre-trends.

Figure 5 shows the results. We plot eight quarter prior to Irma, and find that under-borrowers had similar default patterns to the other borrowers prior to the landfall of the hurricane. This helps to support the identifying assumptions of the difference-in-differences design. In the quarter after the hurricanes' landfall, we see that defaults increase for the under-insured group by roughly 38 basis points; these elevated default levels persist for all four quarters after the storm.

These results suggest that under-insurance systematically reduces household financial resiliency, with knock-on impacts for lenders.

7 Conclusion

This paper provides some of the first loan-level estimates on household under-insurance by connecting state-of-the-art mortgage, climate, tax, and insurance databases at a property level. We show that while nearly all mortgage borrowers have homeowners insurance policies, few households have *enough* coverage. Coverage ratios are the lowest in high climate risk states, and for the poorest borrowers with low FICO scores and high loan-to-value ratios. We show that under-insurance is driven in part by borrowers reacting to rising insurance premiums by reducing coverage. We also provide evidence of this elasticity being driven by liquidity constraints, since borrowers seem to finance premium increases by adjusting their mortgage contract. We employ a novel instrument to show that rising premiums causally result in households dropping coverage and increasing their debt, taking out mortgages with higher debt-to-income ratios and higher loan-to-value ratios. We argue this behavior makes sense because households are often required to escrow a full year of premiums upfront as part of the closing of the mortgage, and that mortgage credit is far cheaper than other sources of credit which borrowers may need to rely on later on to finance insurance premiums, such as credit cards. Lastly, we show under-insurance plays a significant role in household financial resilience by showing mortgage performance after Hurricane Irma is worse for the under-insured. These results suggest that there is a significant coverage gap, with households, lenders, and taxpayers likely facing far more uninsured risk than is realized.

8 Tables and Figures

8.1 Figures

Figure 1: Share of HO-3 Homeowners Insurance Policies by State in 2021

In this figure we compare the share of the standard HO-3 insurance policies to all types of home-owner policies (HO-1, HO-2, HO-3, HO-5 and HO-8) sold in 2021 across states. The source is *Dwelling Fire, Homeowners Owner-Occupied, and Homeowners Tenant and Condominium/Cooperative Unit Owner's Insurance Report Data*.

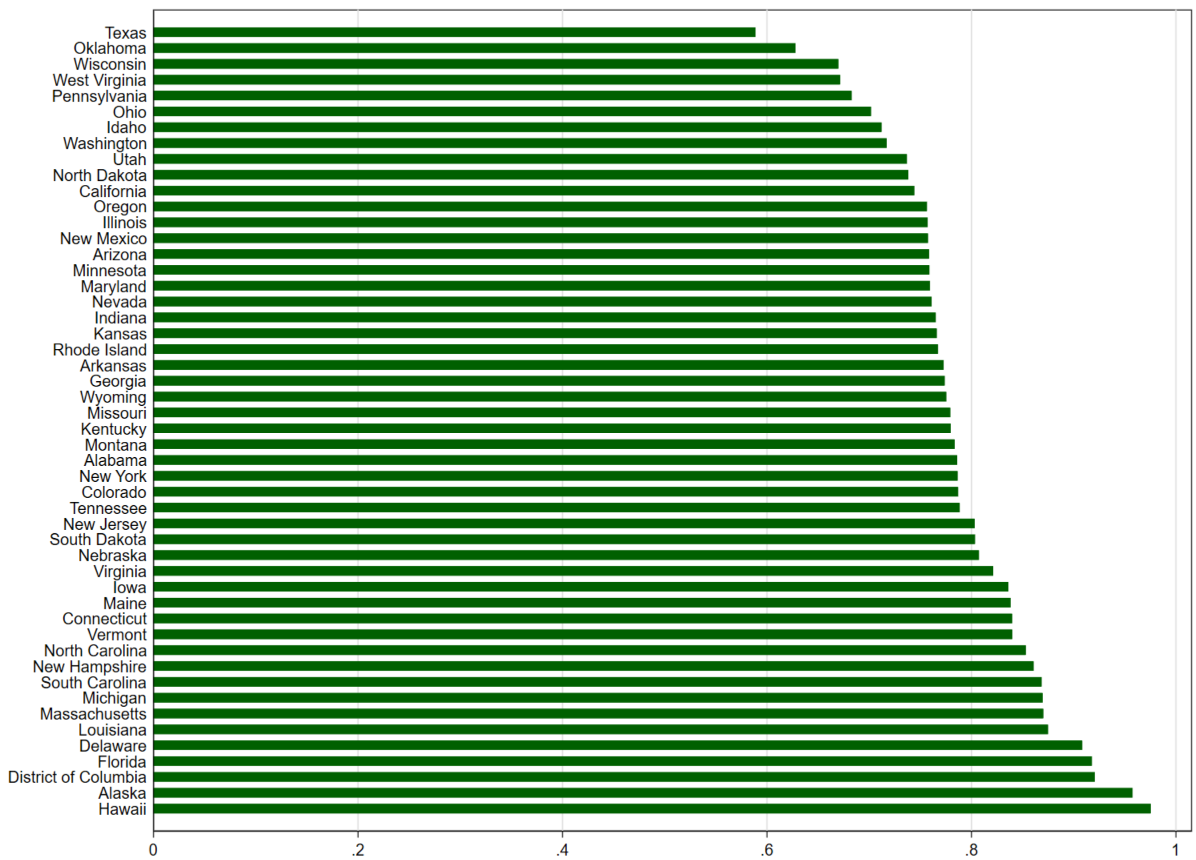
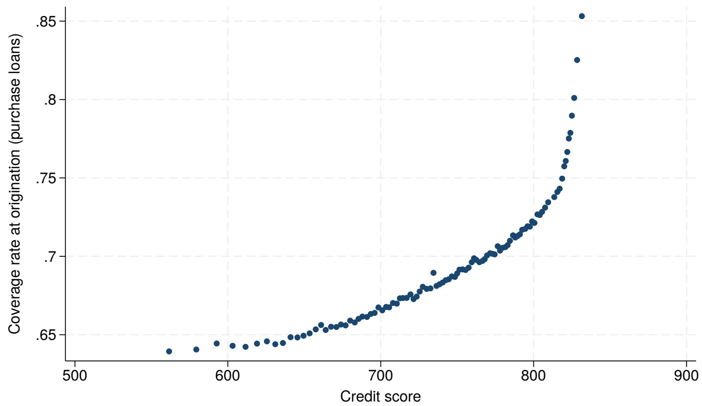


Figure 2: Coverage Ratios by Credit Risk and Investor Type

This figure shows a binned scatter plot of how coverage ratios vary by credit score at origination and investor type. Insurance coverage ratios are defined as insurance coverage divided by estimated replacement costs, obtained by multiplying structure size by a measure of local construction costs from the R.S. Means Company. The data from McDash is limited to purchase mortgages at origination.

(a) Coverage Ratios by Credit Score



(b) Coverage Ratios by Credit Score and Investor Type

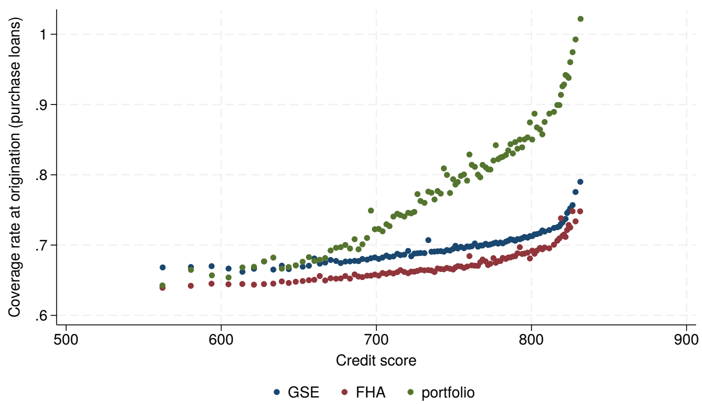


Figure 3: Coverage Ratios by Loan-to-Value at Origination

This figure shows a binned scatter plot of how coverage ratios vary by loan-to-value ratio at origination. Insurance coverage ratios are defined as insurance coverage divided by estimated replacement costs, obtained by multiplying structure size by a measure of local construction costs from the R.S. Means Company. Loan-to-value ratios are the loan amount at origination divided by the property value. The data is limited to purchase mortgages at origination.

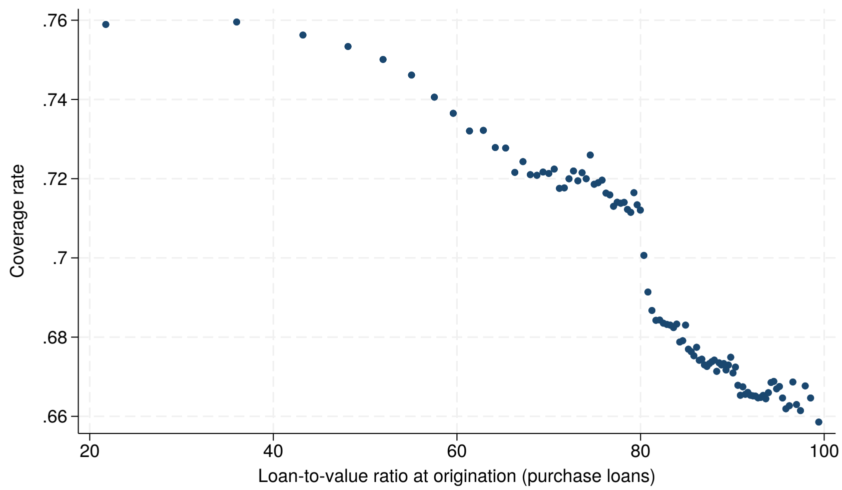


Figure 4: Coverage Ratios by Loan Age

This figure shows a binned scatter plot of how coverage ratios vary by the age of the mortgage, after controlling for a loan fixed effect. Insurance coverage ratios are defined as insurance coverage divided by estimated replacement costs, obtained by multiplying structure size by a measure of local construction costs from the R.S. Means Company. The data is limited to purchase mortgages at origination.

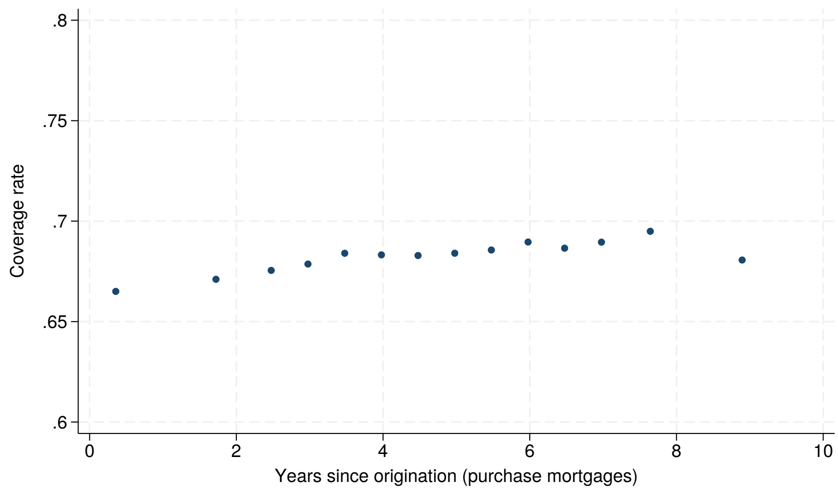
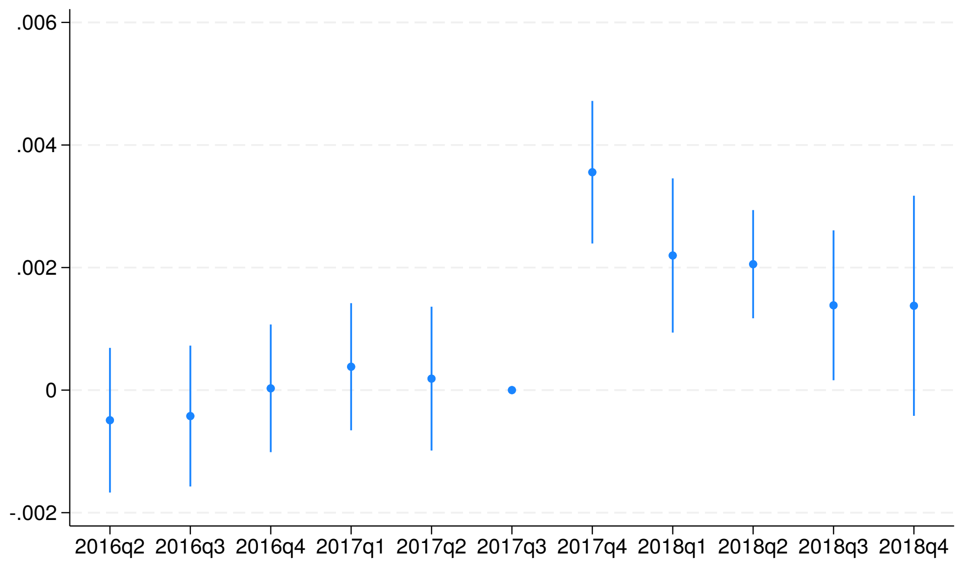


Figure 5: Default after Hurricane Irma/Harvey By under-insurance

This figure shows the dynamic treatment effects of a difference-in-differences regression that estimates the impact of Hurricane Irma/Harvey on 90-day mortgage delinquency. The hurricanes made landfall in late-August/early-September. The sample is limited to households in counties that were hit by the hurricane (as identified in the SHELDUS database). Under-insurance is defined as a dummy variable which equals 1 if households are above the median level of under-insurance. The regression includes controls for FICO-quarter, LTV-quarter, and principal balance-quarter fixed effects. The 95% confidence intervals represent standard errors clustered at the county level.



8.2 Tables

Table 1: Insurance Coverage Ratio by State in 2023

For merged loans in the 2023 McDash insurance module, we estimate the average ratio of insurance coverage to the average rebuilding value of the properties, which we estimate by multiplying structure size by local construction costs from the R.S. Means Company. In Panel A we show the distribution in 2023 for the five states that are the most protected by insurance. In Panel B we show the distribution in 2023 for the five states that are the least protected by insurance. The columns show the insurance coverage ratio's average value, standard deviation, quantiles (10th, 25th, 50th, 75th and 90th), and number of loans we estimate the distribution from.

State	Mean	SD	Q10	Q25	Median	Q75	Q90	N
Panel A: Top Five States by Coverage Ratio								
MA	88.6	34.7	64.2	73.3	84.3	98.3	115.4	79,004
ME	87.1	37.1	60.9	69.5	80.5	95.6	117.9	16,604
RI	83.3	23.0	62.1	71.0	80.8	92.6	106.4	11,924
NY	81.7	30.2	53.8	63.3	75.7	94.2	116.8	220,714
CT	80.3	23.2	60.1	67.5	76.6	88.1	102.8	35,681
Panel B: Bottom Five States by Coverage Ratio								
LA	60.5	20.9	43.0	50.5	58.1	67.3	78.4	38,388
GA	60.3	18.8	44.3	50.8	57.8	66.8	78.2	251,206
TX	60.2	15.9	44.2	51.9	58.9	67.2	77.5	506,149
AL	57.8	33.0	41.0	48.1	55.2	63.3	73.6	83,426
NE	56.9	16.5	40.3	46.9	55.0	64.8	75.8	53,924
WV	56.9	20.5	35.2	45.6	55.6	67.0	78.7	12,700
AR	55.2	28.8	37.8	48.0	55.4	62.1	69.9	69,798

Table 2: First-Stage Effect of Price Changes on Insurance Coverage Demand

This table presents the first stage of a two-stage least squares regression. The sample is limited to purchase mortgages at origination in low friction states, identified in Oh et al. (2021). The dependent variable is insurance price (premiums per $100,000 of coverage), and the instrument is average prices in high friction states for each credit score group in each year. High frictions states are identified in Oh et al. (2021) as states that heavily regulate insurer pricing adjustments. Average annual loss is a property-level measure of climate risk from the First Street Foundation estimating expected losses due to climate-related damages. Replacement cost is obtained by multiplying building size with a measure of local construction costs from the R.S. Means company. Standard errors are clustered at the county level.

	Dep. Var: log price	
	(1)	(2)
log (price)$_{HF}$	0.392***	0.0507***
	(0.0127)	(0.00681)
Average Annual Loss	0.0832***	0.0830***
	(0.0107)	(0.0107)
Log Replacement Cost	-0.316***	-0.315***
	(0.00454)	(0.00454)
ZIP FE	Y	Y
Year FE	Y	Y
Controls	N	Y
Number of Observations	5120621	5120621
Adjusted R-squared	0.596	0.597

Table 3: Second-Stage Effect of Price Changes on Insurance Coverage Demand

This table presents the second stage of a two-stage least squares regression. The sample is limited to purchase mortgages at origination in low friction states (identified in Oh et al. (2021)). The dependent variable is log of the homeowners insurance coverage amount. The independent variable is insurance price (premiums per $100,000 of coverage), which has been instrumented using average prices in high friction states for that credit score group in each year. High frictions states are identified in Oh et al. (2021) as states that heavily regulate insurer pricing adjustments. Average annual loss is a property-level measure of climate risk from the First Street Foundation estimating expected losses due to climate-related damages. Replacement cost is obtained by multiplying building size with a measure of local construction costs from the R.S. Means company. Standard errors are clustered at the county level.

	Dep. Var: log coverage	
	(1)	(2)
Log Price	-0.421***	-0.286***
	(0.0155)	(0.0863)
Average Annual Loss	0.0271***	0.0159**
	(0.00581)	(0.00774)
Log Replacement Cost	0.687***	0.729***
	(0.00701)	(0.0275)
ZIP FE	Y	Y
Year FE	Y	Y
Controls	N	Y
Number of Observations	5120621	5120621
First-stage K-P F-stat	60	55.31

Table 4: Second-Stage Effect of Price Changes on Debt-to-Income Ratios

This table presents the second stage of a two-stage least squares regression. The sample is limited to purchase mortgages at origination in low friction states (identified in Oh et al. (2021)). The dependent variable is log of the mortgage borrower's debt-to-income ratio at origination in McDash. The independent variable is insurance price (premiums per $100,000 of coverage), which has been instrumented using average prices in high friction states for that credit score group in each year. High frictions states are identified in Oh et al. (2021) as states that heavily regulate insurer pricing adjustments. Average annual loss is a property-level measure of climate risk from the First Street Foundation estimating expected losses due to climate-related damages. Replacement cost is obtained by multiplying building size with a measure of local construction costs from the R.S. Means company. Standard errors are clustered at the county level.

	Dep. Var: log DTI	
	(1)	(2)
Log Price	1.073***	1.875***
	(0.0395)	(0.450)
Average Annual Loss	-0.0892***	-0.158***
	(0.0136)	(0.0463)
Log Replacement Cost	0.322***	0.571***
	(0.0133)	(0.139)
ZIP FE	Y	Y
Year FE	Y	Y
Controls	N	Y
Number of Observations	3450943	3450943
First-stage K-P F-stat	866.9	19.90

Table 5: Second-Stage Effect of Price Changes on Loan-to-Value Ratios

This table presents the second stage of a two-stage least squares regression. The sample is limited to purchase mortgages at origination in low friction states (Oh et al. (2021)). The dependent variable is log of the mortgage borrower's loan-to-value ratio at origination in McDash. The independent variable is insurance price (premiums per $100,000 of coverage), which has been instrumented using average prices in high friction states for that credit score group in each year. High frictions states are identified in Oh et al. (2021) as states that heavily regulate insurer pricing adjustments. Average annual loss is a property-level measure of climate risk from the First Street Foundation estimating expected losses due to climate-related damages. Replacement cost is obtained by multiplying building size with a measure of local construction costs from the R.S. Means company. Standard errors are clustered at the county level.

	Dep. Var: log LTV	
	(1)	(2)
Log Price	0.612***	0.236***
	(0.0212)	(0.0596)
Average Annual Loss	-0.0586***	-0.0273***
	(0.00781)	(0.00574)
Log Replacement Cost	0.119***	0.00109
	(0.00798)	(0.0188)
ZIP FE	Y	Y
Year FE	Y	Y
Controls	N	Y
Number of Observations	5108256	5108256
First-stage K-P F-stat	946.3	56.08

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A Additional Tables and Figures

Table A.1: OLS of coverage, debt-to-income, and loan-to-value ratio on price

This table presents the results of an OLS regression. The sample is limited to purchase mortgages at origination in low friction states (Oh et al. (2021)). The dependent variables are log of coverage (Columns 1-2), log of debt-to-income ratios (Columns 3-4), and log of loan-to-value ratios (Columns 5-6). The independent variable is insurance price (premiums per $100,000 of coverage). Average annual loss is a property-level measure of climate risk from the First Street Foundation estimating expected losses due to climate-related damages. Replacement cost is obtained by multiplying building size with a measure of local construction costs from the R.S. Means company. Standard errors are clustered at the county level.

	Dep. Var: log coverage		Dep. Var: log DTI		Dep. Var: log LTV	
	(1)	(2)	(3)	(4)	(5)	(6)
Log Price	-0.254***	-0.249***	0.0469***	0.0228***	0.0335***	0.0192***
	(0.00714)	(0.00725)	(0.00325)	(0.00232)	(0.00181)	(0.00140)
Average Annual Loss	0.0131***	0.0129***	-0.000855	0.000804	-0.0101***	-0.00931***
	(0.00367)	(0.00361)	(0.00162)	(0.00155)	(0.00133)	(0.00120)
Replacement Cost	0.742***	0.740***	-0.0160***	-0.00406	-0.0742***	-0.0672***
	(0.00695)	(0.00685)	(0.00285)	(0.00259)	(0.00170)	(0.00156)
ZIP FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Number of Observations	5120621	5120621	3450943	3450943	5108256	5108256

Table A.2: 2SLS Estimates for Mortgage Outcomes, Controlling for Interest Rates

This table presents the results of an a 2SLS regression. The sample is limited to purchase mortgages at origination in low friction states (Oh et al. (2021)). The dependent variables are log of debt-to-income ratios (Columns 1-2), and log of loan-to-value ratios (Columns 3-4). The independent variable is insurance price (premiums per $100,000 of coverage). Average annual loss is a property-level measure of climate risk from the First Street Foundation estimating expected losses due to climate-related damages. Replacement cost is obtained by multiplying building size with a measure of local construction costs from the R.S. Means company. Interest rates are measured in basis points and are available in McDash. Standard errors are clustered at the county level.

	Dep. Var: log DTI		Dep. Var: log LTV	
	(1)	(2)	(3)	(4)
Log Price	1.061***	1.951***	0.616***	0.237***
	(0.0389)	(0.424)	(0.0212)	(0.0571)
Average Annual Loss	-0.0883***	-0.164***	-0.0588***	-0.0274***
	(0.0135)	(0.0448)	(0.00786)	(0.00552)
Log Replacement Cost	0.320***	0.596***	0.120***	0.00139
	(0.0131)	(0.130)	(0.00800)	(0.0179)
Interest Rate (Basis Points)	0.0168***	0.00825	-0.00405***	0.0000184
	(0.00195)	(0.00539)	(0.000863)	(0.000931)
ZIP FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Controls	N	Y	N	Y
Number of Observations	3450943	3450943	5108075	5108075
First-stage F	893.8	23.50	970.7	62.34