The Insurance Protection Gap *

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Abstract

In a world of rising climate risk, how well insured are U.S. households? What is their willingness to pay for insurance, and what do their choices imply for the future of insurance markets? We provide the first quantification of the "insurance protection gap"—the extent of households' exposure to uninsured property losses, and the first estimates of households' demand elasticities. We utilize newly available, individual-level data on homeowners insurance contracts spanning the entire United States over more than a decade. We first show that the insurance protection gap is large, particularly among financially vulnerable lower income households. Second, exploiting quasi-exogenous regulatory shocks to insurance pricing, we show that demand elasticities vary significantly across households. Low income households exhibit particularly low willingness-to-pay, even when insurance prices are below actuarially fair rates. We then show, both theoretically and empirically, that financial constraints offer a plausible explanation for these patterns. In particular, a household's ability to adjust mortgage debt significantly influences its willingness to pay for insurance. High-income households, facing relatively slack borrowing constraints, are able to increase their mortgage debt and maintain insurance coverage. In contrast, low-income households that are closer to binding debt limits have limited ability to adjust their borrowing and instead respond by substantially reducing their insurance coverage. Our estimates imply that between 17% to 31% of households would hit binding loan-to-value (LTV) constraints and be forced to reduce coverage substantially, if prices were to continue growing at historical rates moving forward, meaning insurance markets may shrink even as the financial risks from natural disasters continue to increase. Our findings inform key policy choices, including the appropriate degree of price regulation and the design of public interventions aimed at addressing these insurance market challenges.

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Over the last fifty years, property damage from natural disasters has dramatically risen. In the United States, an estimated 35 million homes, or one-third of the housing stock, has high exposure to natural disaster risk.[1] Property insurance is the primary way that households financially protect their homes in the face of escalating climate risks. Insurance payments are used by households to repair and rebuild homes damaged by natural disasters, helping to preserve household wealth. However, there are mounting concerns that the most vulnerable households may not have sufficient insurance coverage. Under-insurance could make households more financially exposed to catastrophic shocks, and creates risks for lenders and taxpayers if disasters precipitate household default. Despite intense public concern, there is limited systematic evidence about the extent to which financially vulnerable households are under-insured, the factors influencing their coverage choices, and the implications for their financial resiliency.

Public discourse around under-insurance has honed in on a key explanation: *affordability*. Homeowners insurance premiums have risen faster than inflation.[2] Many policymakers believe that homeowners have to drop insurance coverage because it is simply too expensive to maintain.[3] While a popular view, the affordability hypothesis is difficult to reconcile with traditional models of insurance (Arrow, 1963, Mossin, 1968). In these models, as risks rise, both insurance premiums and households' willingness-to-pay also rise. An implicit assumption of these models is that individuals who value insurance can frictionlessly borrow more to finance rising premiums, allowing them to maintain full insurance. The affordability hypothesis can be better reconciled with models of insurance demand that emphasize financial constraints (Rampini and Viswanathan, 2013, Ericson and Sydnor, 2018). In these models, even households that value insurance would be forced to drop coverage as premiums rise because of binding credit constraints. While households would prefer to increase debt and maintain coverage, binding constraints prevent them from doing so. Taken together, these two broad classes of theories have different predictions for how shocks to insurance premiums influence both household demand for insurance coverage and debt.

[1] Based on estimates from CoreLogic, see CNBC, "Nearly one-third of U.S. homes are at high risk of natural disaster", Jan. 27, 2021.

[2] The Insurance Research Council estimates that the cost of homeowners insurance outpaced inflation in the last two decades. See here.

[3] For example, a press release from the Department of Treasury Report states: "Homeowners insurance is becoming more costly and less accessible for consumers as the costs of climate-related events pose growing challenges to both homeowners and insurers alike." See "U.S. Department of the Treasury Report: Homeowners Insurance Costs Rising, Availability Declining as Climate-Related Events Take Their Toll" (Jan. 16, 2025) here.

However, empirically evaluating the effects of rising premiums and credit constraints poses two key challenges. The first comes from gaps in the available data. Homeowners insurance data is typically only consistently available at aggregate state-wide levels; occasionally at the county-level; rarely at the ZIP-code level; and nearly never at the individual loan level.[4] Most importantly, the data rarely include granular information on both household insurance and debt choices. We are able to address this challenge by making use of a newly available granular dataset which contains detailed insurance contract-level information for individual mortgage borrowers. We then merge this data to household mortgage contract information, along with rich information about borrower, property, and climate risk characteristics. The second challenge is an econometric one. To evaluate how borrowers choose debt and coverage, we require both exogenous shocks to premiums as well as exogenous shocks to credit. We address this issue by leveraging a range of natural experiments that deliver shocks to premiums, cost of credit, and financial constraints, allowing us to estimate key elasticities that determine how insurance and debt contracts evolve in tandem.

Our paper provides the first comprehensive analysis of how households jointly choose homeowners insurance coverage and mortgage debt. We make three contributions. First, we document that under-insurance is a widespread phenomenon, particularly among the most financially vulnerable. Second, we find that financial constraints impact household coverage choices.[5] Less credit constrained households respond to rising premiums by raising mortgage debt and maintaining insurance coverage levels, consistent with Arrow (1963) and Mossin (1968). However, credit constrained households are significantly more sensitive to rising premiums, dropping coverage more and raising debt less because of binding credit constraints, consistent with Rampini and Viswanathan (2013) and Ericson and Sydnor (2018). Together these two sets of results show that households with spare debt capacity can finance rising premiums by borrowing, while credit constrained households are forced to drop coverage. Third, we show household financial resiliency worsens because of both rising household debt and lower insurance coverage. Under-insurance makes households more exposed to catastrophe shocks, which we show increases serious mortgage delinquency, particularly among the most financially vulnerable. In addition, it is well-known that higher debt levels (e.g., debt-to-income and loan-to-value ratios) impact household resiliency to a wide range of shocks (Bhutta et al., 2017, Ganong and Noel, 2020,

[4]To the extent that individual-level data has been made available, it is often limited to a subset of households that have been directly hit by a disaster.

[5]We use the terms financial constraints, credit constraints, and borrowing constraints interchangeably.

Gupta and Hansman, 2021). Together these significantly increase default risks in the mortgage market.

To conduct our analysis, we construct a novel comprehensive dataset that combines information, at the loan level, on homeowners insurance, mortgage contracts, borrower characteristics, property characteristics, and climate risk from 2013-2022 for households across the U.S. We start by using a first-of-its-kind dataset from ICE McDash that compiles information from mortgage servicers on both homeowners insurance and mortgage contracts for individual borrowers at origination, as well as mortgage performance. We merge this with a range of additional datasets from McDash, CoreLogic, Equifax, and R.S. Means, to bring in rich borrower and property-specific information, including credit scores, income, replacement costs, and expected climate losses.

Our paper proceeds in five parts. In the first part of the paper, we present five new facts on household under-insurance, which motivates our focus on financial constraints in the subsequent sections of the paper. We find that the average U.S. household is under-insured, with only 70% of rebuilding costs covered by the insurance contract. The under-insurance gap is especially pronounced among the most financially constrained households, those with lower incomes and credit scores. Furthermore, coverage choices are insensitive to climate risk for lower income borrowers, but vary with climate risk for higher income borrowers. This suggests that financial constraints may outweigh risk considerations in determining insurance coverage for lower income borrowers. We also show that higher insurance prices are correlated with increased levels of both under-insurance and household debt, suggesting an important role for mortgage credit in financing insurance premiums. Lastly, we show under-insurance is strongly associated with higher mortgage delinquencies, suggesting that it impacts household financial resiliency.

We interpret the facts through the lens of a standard consumption-savings model featuring insurance coverage choice and borrowing constraints. We derive several predictions about how households jointly choose insurance coverage and debt in the presence of borrowing constraints. The model serves as an organizing framework that brings together the insights of the textbook frictionless models of Arrow (1963) and Mossin (1968) along with the models of financial frictions Rampini and Viswanathan (2013), which we use to guide our subsequent empirical tests that consider how shocks to insurance prices and interest rates impact coverage and credit demand.

In the second part of the paper, we estimate the sensitivity of household coverage to insurance prices. To estimate this coverage demand elasticity, we require plausibly exogenous changes in insurance prices that are independent of household demand. We obtain such variation using the following Hausman instrument, inspired by the industrial organization literature (e.g., Nevo (2001), Hausman (1996)). In certain "high friction" states, insurance regulation prevents insurance companies from changing premiums in response to changing national or local market conditions, including rising risks, changing insurance demand, or changing credit conditions. While there is variation in premiums, the timing is driven by when regulators allow insurers to adjust premiums, with the approved premium change often differing substantially from what insurers require. As a result, losses in high friction states cannot be addressed by raising prices in high friction states, likely making prices in high friction states below the actuarially fair rate.[6] Oh et al. (2021) show that multi-state insurers cross-subsidize losses in high friction states by adjusting premiums in low friction states. Thus insurance prices in high friction states can instrument for prices in low friction states. The instrument is relevant because of the cross-subsidy, and it is plausibly exogenous because regulators in high friction states limit adjustments in response to demand conditions in low friction states.

Under the frictionless benchmark model of Arrow (1963) and Mossin (1968) demand is completely inelastic when insurance prices are actuarially fair. In addition, higher income borrowers have more elastic demand than lower income borrowers at all price levels because they are less risk averse. We have three pieces of evidence that are inconsistent with the predictions of the benchmark model. First, our IV estimate shows that borrowers are not inelastic, with a 1% increase in prices leading the average borrower to reduce coverage by -0.107%. Second, we estimate that demand elasticities are nearly the same in both high friction states (where prices are at or below actuarily fair on average) and low friction states (where prices are above actuarily fair on average), suggesting that the NPV of the insurance contract is unlikely to explain this elasticity. Last, we find that lower income borrowers are far more elastic than higher income borrowers. This highlights the possible role of financial constraints. In fact, we find that lower income households are nearly two-times more likely to have binding LTV or DTI constraints than higher income households, suggesting that they may adjust coverage more because they have limited debt capacity.

[6]The average combined loss ratio, the ratio of costs (losses and expenses) to premiums, in high friction states is persistently around 100% between 2018-2022.

In the third part of the paper, we examine whether households adjust debt in response to exogenous changes in insurance premiums. To the extent that households are unconstrained, we would expect to see households that value insurance to adjust debt, in line with standard benchmark models. This implies that there is a cross-price elasticity of debt with respect to insurance prices. To estimate this elasticity, we must address the key econometric challenge that insurance prices may be endogenous to household credit demand. We obtain plausibly exogenous variation with the same Hausman instrument as earlier, which uses prices in high friction states to instrument for prices in low friction states. We find that exogenous increases in insurance prices lead to significant increases in both debt-to-income ratios as well as LTV ratios. The debt adjustment is nearly two times larger for higher income households, suggesting that the relatively unconstrained households are better able to finance rising premiums with debt. This result is line with the earlier finding that higher income households had lower coverage demand elasticities.

Taking the results together, we see that constrained households drop coverage and have limited debt adjustments, whereas unconstrained households maintain coverage and increase debt. The differences we find between constrained and unconstrained households show that any insurance coverage demand elasticities must account for the debt capacity of the borrower. Our estimates imply that in a counterfactual scenario where the higher income households could not access debt markets, their coverage demand elasticities would be over 2.4 times higher.

Furthermore, the increase in debt is substantial for unconstrained households. The average annual insurance price increase was 2.15% over the ten-year period (with the rate of growth being significantly larger over the last few years). Therefore, the additional premium burden over the life of the loan would amount to $14,100, relative to a counterfactual where insurance premium growth remained flat. At these growth rates, our elasticity estimates imply that unconstrained households increase LTVs by 2.16 pp, which amounts to an increase in loan balances by close to $5,000. In other words, these estimates imply that 35% of the nominal expected burden is being financed in the mortgage market.

In the fourth part of the paper, we formally estimate how exogenous changes in the cost of mortgage credit influence insurance demand. Higher rates make it more costly to finance insurance premiums by borrowing more. Obtaining quasi-exogenous variation in cost of credit is typically

challenging because mortgage rates are often correlated with other unobserved determinants of household demand, such as their risk aversion, risk exposure, or beliefs about climate risk. We evaluate two shocks to credit costs that deliver variation that is plausibly exogenous to these unobserved borrower characteristics.

The first shock exploits a government-sponsored enterprise (GSE) policy requiring borrowers with loan-to-value (LTV) ratios above 80% to obtain private mortgage insurance (PMI), which on net increases households borrowing costs (Bhutta and Keys, 2022).[7] To conduct this test, we limit the sample to GSE-eligible mortgages within narrow LTV bands around 80%, and include rich borrower controls and ZIP-year fixed effects. Our identifying assumption is that other unobserved household characteristics that impact coverage demand elasticities are smooth through the 80% LTV threshold. We find that borrowers just above the 80% LTV threshold are nearly 50% more elastic in their demand for insurance coverage than observably similar households just below the 80% LTV threshold.

Second, we analyze the effect of higher mortgage rates on insurance demand, exploiting the instrument of Fonseca and Liu (2024). Our identifying assumption is that the market-wide average mortgage rate is independent of both (i) unobserved household characteristics as well as (ii) household expectations about changing macroeconomic conditions that also determine insurance demand. We argue that (ii) is likely to hold because our empirical strategy uses rich borrower controls and ZIP-year fixed effects, which compares two borrowers originating their mortgage in the same ZIP code and year, who are similar on key observables (e.g., income and rebuild cost), but originate their mortgage in different months with different market rates. We find that going from a 3% to 7% interest rate on their mortgage makes households nearly eight times more elastic in their demand for insurance coverage. These tests highlight how credit markets shape coverage demand elasticities by making it more expensive for households' to finance premiums by borrowing.

In the fifth part of the paper, we seek to estimate the causal effect of under-insurance on household financial resiliency. We measure resiliency by whether a borrower becomes seriously delinquent within the first 3-5 years of the mortgage. To estimate this causal effect, we exploit plausibly exogenous changes in insurance coverage driven by changes in the market mortgage rate. We consider within

[7] We note that mortgage insurance does not protect the borrower, and is not a substitute for homeowners insurance.

ZIP-year variation and compare borrowers that have similar replacement costs, climate risk, incomes, credit scores, LTV, DTI, and interest rate, but different coverage amounts that are driven by different policy rates at the time of origination. The identifying assumption is that, conditional on these controls and fixed effects, changes in the market rate are plausibly exogenous to other unobserved variables that simultaneously determine both household insurance coverage at origination and the likelihood of default over the next 3-5 years of the mortgage. We find that households with less coverage are significantly more likely to default on their mortgage. Our estimates imply that a 1% decrease in coverage increase 3-year delinquency by 12bp and 5-year delinquency by 21bp. A back-of-the-envelope calculation suggests that if constrained households had obtained the same coverage levels as unconstrained households, they would have 2.2pp lower delinquency rates.

We conclude by discussing the broader implications of our findings. It is likely that as climate-related risks rise, insurers will need to raise premiums to remain solvent. Our results imply that, if prices were to continue growing at historical rates moving forward, our estimates imply that between 17% to 31% of households would hit binding LTV constraints and be forced to reduce coverage substantially, meaning insurance markets may shrink even as climate risks rise. Furthermore, these changes will reduce household financial resiliency in two ways: by increasing household leverage, and by increasing under-insurance. Finally, there are significant distributional implications. Unconstrained households are increasing debt, while constrained households are reducing coverage. Taken together, the results suggest that the coverage gap is likely to grow in size, posing significant challenges for the most financially vulnerable households and the insurance market more broadly.

Related literature. This paper contributes to three strands of literature. First, we add to the literature on the determinants of households' demand for insurance. Our work starts from the seminal benchmark models of Arrow (1963) and Mossin (1968), who show that household insurance demand is a function of their risk aversion and risk exposure when markets are frictionless. This implies a negative correlation between measures of household income/ wealth and insurance coverage. In contrast, Rampini and Viswanathan (2013) show that insurance demand is heavily influenced by the presence of credit constraints, and that such constraints predict a positive correlation between wealth and insurance coverage. We estimate these coverage-income correlations for homeowners insurance, and, guided by these theories, explore empirically what drives these patterns. We follow

the empirical approach of Einav et al. (2010) and Einav and Finkelstein (2023) to estimate demand elasticities and, to our knowledge, are the first to estimate these parameters for the homeowners insurance market.[8] In addition, we are the first to study the joint choice of debt and insurance, and in doing so empirically identify a cross-price elasticity of mortgage credit with respect to insurance premiums. Lastly, we also show coverage demand elasticities depend on financial constraints and the cost of credit.

Second, our paper contributes to the small but growing new literature studying homeowners insurance markets. Thus far, this literature has focused on the supply-side of insurance, primarily on the determinants of pricing. For example, studies have documented the role played by capital market frictions (Froot and O'Connell, 1999, Jaffee and Russell, 1997), state-level price regulations (Oh et al., 2023), informational asymmetries (Boomhower et al., 2023), trust and claims' validity (Gennaioli et al., 2021), reinsurance pricing (Mulder and Keys, 2024), disaster risk Blonz et al. (2024), and mortgage market frictions (Sastry et al., 2024). Beyond pricing, newer studies have documented insurer quantity rationing, with evidence that insurers ration on both the intensive margin (Cookson et al., 2025) and the extensive margin (Sastry et al. (2024)). To our knowledge, we are the first to explore the drivers of household demand for homeowners insurance. Furthermore, our work draws from the supply-side literature in our empirical strategy for estimating key parameters related to household demand.

Third, our findings speak to the literature on climate risk and household financial resiliency. Thus far the literature has focused on mortgage default (Issler et al., 2020, Sastry, 2022, Ge et al., 2024, Biswas et al., 2023), post-disaster resiliency (Gallagher and Hartley, 2017, Cookson et al., 2023), house prices declines (Baldauf et al., 2020, Murfin and Spiegel, 2020, Bernstein et al., 2019).[9] While it is widely believed that homeowners insurance plays a critical role in household recovery after disasters, the literature has not studied this aspect, primarily because of lack of data.[10] We

[8]There are some estimates of demand elasticities on the extensive margin for flood insurance in Wagner (2022), Collier et al. (2024), and Liao and Mulder (2021). Flood insurance covers flood damage and is only required for mortgages in flood zones, creating limited take-up nationwide (Amornsiripanitch et al., 2024). In contrast, homeowners insurance is required for all mortgages, with nearly 90% of all homeowners purchasing homeowners insurance.

[9]They also bear indirect exposures through labor markets (Kruttli et al., 2019) and discounts in municipal bond prices (Goldsmith-Pinkham et al., 2020).

[10]This question has been more studied in the context of flood insurance, but less so for homeowners insurance. There is evidence that households without flood insurance are significantly more likely to default on mortgages after major flood events (Kousky et al., 2020).

contribute to this literature by showing that households are significantly under-insured on the intensive margin, and that coverage choices matter for household default outcomes. In addition, our finding that the most financially vulnerable households have the highest rates of under-insurance is particularly important for understanding the distributional implications of rising climate risk.

A key finding of our paper is that households increase their borrowing to finance insurance purchases. In that sense, we also contribute to the very large literature on the drivers of mortgage debt (e.g., Adelino et al. (2016), Bhutta and Keys (2022), DeFusco and Paciorek (2017), Defusco et al. (2019)). This literature has shown that higher debt is strongly associated with worse default outcomes (e.g., Greenwald (2018), Gupta and Hansman (2021)). This suggests that rising leverage is a separate channel through which premiums worsen household financial resiliency. Leverage makes the mortgage riskier more broadly, not just in times of natural disasters. To the extent that premiums continue to rise because of rising climate risk, our results predict this will worsen household financial resiliency through two channels: leverage and under-insurance.

1. Institutional Background, Data, and Facts on Underinsurance

1.1. Institutional Background

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), representing over $15 trillion in coverage taken out annually (Oh et al., 2023).

Homeowners Insurance: The standard homeowners contract is annual and covers damages from most natural disasters.[11] Around 90% of homeowners insurance claims are for property damage caused by weather events.[12] The insurance contract has two key characteristics: coverage and premiums.[13] Those purchasing insurance are entitled to claim payouts up to a pre-specified coverage

[11] 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.

[12] Insurance Information Institute. "Facts + Statistics: Homeowners and renters insurance". III.org; Munich RE: "Climate change is showing its claws".

[13] Another feature of insurance contracts are deductibles, which is the amount the borrower must pay before insurers

amount if an insured loss event materializes. The premium is the amount that the insured party must pay to the insurer. It is usually paid every month, and is a function of the risk of the house, and the coverage choices of the insured. Premiums may also reflect other regulatory and operational costs borne by the insurer, which are passed onto households.

Mortgage servicers: Mortgage servicers are usually responsible for collecting borrowers' monthly mortgage payments on behalf of the lender and monitoring that other requirements, such as insurance and property tax payments, are met. To simplify payments and enforce requirements, most tax and insurance payments are collected and paid using escrow accounts. Mortgage escrow accounts are separate legal arrangements that are used to hold any partial mortgage payments and payments toward homeowners insurance premiums and property taxes. The majority of mortgages feature escrow deposit accounts (Anderson and Dokko, 2008), and are required by FHA, Fannie Mae, and Freddie Mac in most circumstances.[14] This feature of mortgage lending enables the data provider ICE McDash to obtain micro data on both the mortgage and the homeowners insurance contract, because mortgage servicers monitor both contracts together for each individual.

Upfront escrow requirements: When a mortgage is originated, servicers estimate the annual tax and insurance outlays associated with the mortgage, establish a monthly payment sufficient to meet those payments, and collect a reserve equal to no more than 1/6 the annual expected escrow expenses.[15] Because homeowners insurance is paid annually for the year ahead, the servicer collects the entire homeowners insurance payment as part of the initial escrow balance.

1.2. Data

We construct a novel granular database that integrates a wide number of mortgage and insurance datasets to provide a comprehensive joint picture of mortgage and insurance markets. Our extensive database provides loan-level information on the insurance contract (e.g., coverage, premium), mortgage contract, borrower characteristics, households' debt and mortgage performance, property characteristics, and climate risk exposures. The dataset spans from 2013 to 2023, encompassing

start paying for insured events. In the data, there is little variation in deductibles and deductibles are orders of magnitude smaller than coverage amounts, with most contracts ranging between $500 and $2000 dollars. In case of catastrophic losses, the amount by which households are underinsured would matter a lot more than the deductible amount they would need to pay, even at the higher end of deductible levels.

[14]The GSEs 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.

[15]https://www.consumerfinance.gov/rules-policy/regulations/1024/17/

households across the United States. To our knowledge, we are the first to bring together such wide ranging aspects of mortgages, insurance contracts, and property characteristics covering the entire U.S. for over a decade at a granular level.

Specifically, our analysis combines the following six databases to obtain a loan-level dataset that includes data on the borrower, property, mortgage, and insurance contract for single-family home *purchase mortgages* originated on or after 2013. We describe each database briefly below, with more details and the merge procedure described in Appendix A.

1.2.1. Data Sources

(1) ICE McDash Mortgage Modules: We start by using the ICE McDash loan-level dataset on mortgage origination and performance history that is widely used in the mortgage literature. McDash collects these data from mortgage servicers, with the data representing nearly two-thirds of the U.S. mortgage market. The key variables include loan amount, loan-to-value (LTV) ratio, origination month, interest rate, debt-to-income (DTI) ratio, borrower origination credit score, loan maturity, property value, and the type of mortgage (e.g., FHA, VA, jumbo, etc.). We merge this with McDash's mortgage performance modules, which contain data on each loan's performance history from its origination to its final payment. This includes whether the mortgage is current or in delinquency status, and records events such as prepayment, delinquency, default or foreclosure.

(2) ICE McDash Property Insurance Module: To jointly study insurance choices, we exploit a newly available granular dataset which contains detailed contract-level information on homeowners insurance for individual mortgage borrowers. The database, introduced in 2024, is sourced from ICE McDash and addresses a key gap in the literature as historically insurance data could not be linked to mortgages at a loan-level. The dataset covers mortgages from 2013 to 2023 and provides information on monthly insurance premiums, coverage amounts, and deductibles. ICE McDash collects these data from a subset of mortgage servicers. Table C.1 discussed in Appendix A shows that the sample of mortgages in the McDash insurance module is broadly representative of all McDash loan originations across a range of borrower characteristics.

(3) Equifax data: To incorporate borrower income information, we use modeled primary-borrower income from Equifax's Personal Income Model (PIM), which uses characteristics from a borrower's credit bureau profile to predict their personal income. These data are linked to the

loan-level McDash data using Credit Risk Insights Servicing McDash (CRISM).[16]

(4) CoreLogic Deeds Module: Next, we bring in property characteristics, such as the geographic coordinates, structure age, and size of the property, using the CoreLogic Deeds database, which compiles property characteristics from tax assessment records. We merge these data to the loan-level data using a fuzzy matching algorithm we have developed based on address (ZIP code), origination date, loan amount, loan purpose, and loan type. We validate this merging procedure using the proprietary FR Y-14 data at the Federal Reserve which contains confidential borrower-level data on both the loan contract and property address.

(5) CoreLogic Climate Module: We also integrate key measures of property-level climate risk from the CoreLogic Climate module. Specifically, we use average annual losses (AAL), which represents the annual expected losses of different types of climate-related hazards for the property. Importantly, CoreLogic's climate module is also widely used by lenders and insurance companies.[17]

(6) R.S. Means Construction Costs: Finally, to understand the extent to which households are under-insured, we incorporate data on local construction costs from R.S. Means company, which is widely used in the urban and housing literature (e.g., Glaeser and Gyourko, 2005) that is developed based on detailed surveys of home builders across metropolitan cities nation-wide.

Figure C.1 provides a high-level summary of the data construction, and Appendix A provides further details. We next describe the construction of our key variables.

1.2.2. Measurement of Key Variables

Coverage Adequacy and Under-insurance: To assess how insured a given homeowner is, we compare the coverage taken with the replacement cost of the property, defined as the amount it would cost to rebuild the exact same property in case of a total loss event.[18] Specifically, we define Coverage Ratio for property p at time t as:

$$\text{Coverage Ratio}_{pt} = \text{Coverage}_{pt}/\text{Replacement cost}_{pt}. \tag{1}$$

[16] CRISM is an anonymous match between ICE-McDash mortgage servicing records and borrowers' credit files. The Personal Income Model was calibrated on an anonymous subsample of credit profiles using earnings income reported by employers.

[17] For example, the *Wall Street Journal* writes: "CoreLogic, paid by the insurer to advise it on risks, said in an interview it first warned State Farm four years ago of a heightened danger in the Los Angeles neighborhoods that were hit by the latest fires." See Wall Street Journal, "State Farm Was All In on California", February 6, 2026.

[18] We use the terms replacement cost, reconstruction cost, and rebuild costs interchangeably.

If coverage equals rebuild cost, then a homeowner can expect insurance payments to cover all potential rebuilding costs, whereas if coverage is below rebuild cost, the homeowner is responsible for any repair costs that exceed the coverage limit. Thus, a coverage level below replacement cost indicates that the household is under-insured.

Our measure of coverage comes from the McDash Insurance module. The coverage variable we observe in our data refers to basic policy limits for the structure.[19] To estimate replacement costs, we multiply local per square foot construction costs for an average quality home, which we take from R.S. Means, and the structure size, which we obtain from CoreLogic Deeds. Thus, Replacement Cost = Construction cost per square foot × Total square feet.[20] While insurers likely use more complex proprietary methodologies to estimate rebuilding costs,[21] we follow a simpler procedure to mimic the process often recommended to homeowners by insurers when they are deciding on coverage amounts.[22] Insurers recommend that households determine coverage based on the rebuild costs rather than house prices to assess resiliency against losses. While the two are highly correlated,[23] land values and local amenities (or disamenities) affect house prices but may not impact reconstruction costs after a disaster, making rebuild cost the relevant measure.[24]

Insurance Price: We define the price of insurance as the monthly insurance premium per $100,000 of coverage for property p at time t, which we obtain from the McDash Insurance module.

$$\text{Insurance Price}_{pt} = \text{Monthly Premium}_{pt}/\$100{,}000 \text{ coverage}_{pt}. \tag{2}$$

[19] Some homeowners may choose to add-on extended coverage, but they can only do so if their basic coverage is at least equal to 100% of their replacement cost. Klein (2018) writes that extended coverage cannot be provided unless "the basic coverage is at least as great as the estimated replacement cost of the property." Similarly, the insurance consulting firm Marsh McLennan also writes "When you insure your home to 100% of its replacement cost value, some insurance companies will offer the benefit of extended replacement cost. This provision will pay beyond your policy limit should the amount at the time of loss not be adequate," available here. See Appendix Section A.2 for more detail.

[20] This procedure is based on Sastry (2022).

[21] Replacement costs may be a function of a number of variables, including local construction costs, square footage, year built, the quality of materials used to build the home, and other home features.

[22] The methodology we follow is based on how insurers recommend households should estimate their replacement costs. For example, the insurance trade group Insurance Information Institute (III) writes: "For a quick estimate of the amount of insurance you need, multiply the total square footage of your home by local, per-square-foot building costs. (Note that the land is not factored into rebuilding estimates.)". See Insurance Information Institute, "How Much Homeowners Insurance Do You Need", available from III.

[23] At origination, for the ZIP-year level, the regression slope is a statistically significant 83%, with an R^2 of 36%. At the individual level the slope is 67%, with an R^2 of 40%.

[24] For example, the insurance trade group III writes: "In every case, you'll want the limits on your policy to be high enough to cover the cost of rebuilding your home. The price you paid for your home—or the current market price—may be more or less than the cost to rebuild." See Insurance Information Institute, "How Much Homeowners Insurance Do You Need", available from III.

Climate Risk: Our property-level climate risk exposure measure uses Corelogic's AAL – expected climate losses of the property – as a share of the property's rebuild cost. Because the measure is subject to model risk and has a highly skewed distribution, we identify high climate risk properties as those in the top decile of this AAL measure.[25]

High and Low Friction States: Homeowners insurance premiums are subject to extensive regulations in the U.S. at the state level. Regulators actively monitor insurers' pricing decisions and prescribe a wide range of pricing rules and guidelines. Oh et al. (2021) show that these practices lead to stark differences in pricing restrictions across states. We exploit the regulatory constraints to adjusting insurance prices to obtain exogenous variation in insurance pricing. To do so, we classify states as being high friction (highly regulated) or low friction (less regulated), following the methodology of Oh et al. (2021).[26]

1.2.3. Key Data Features

We highlight two features of the data which motivate our analysis.

Timing. First, our analysis focuses on understanding the drivers of coverage choices and mortgage debt at *origination*.[27] We focus on origination because most of the variation in coverage arises at the time of origination, while changes in coverage ratios over the remaining life of the mortgage are limited. Figure C.5 shows a binned scatter plot of coverage ratios by loan age, after controlling for a loan fixed effect. Coverage ratios stay roughly flat at 70% throughout the life of the loan, likely reflecting the automatic inflation adjustments commonly built into homeowners' insurance contracts. This shows that households typically choose insurance coverage at the same time they are setting their mortgage terms. On average, they obtain less coverage, and the under-insurance resulting from that initial coverage decision persists throughout the life of the loan.

Key summary statistics for our final dataset is in Table 1, which we discuss in more detail below. Our dataset has roughly 3.2 million observations, with 1.8 million coming from low friction states, and 1.5 million from high friction states. Appendix A also provides additional descriptive facts.

[25] We validate this measure by verifying that is strongly correlated with the probability of filing a claim and claim severity using aggregated ZIP-year level data. See Appendix A.

[26] In this paper, they classify states into three groups: high, medium, and low friction. In our context, we combine medium and low friction states together.

[27] We keep loans for which the first observation occurs within the first two years of the loan. We do so because insurance is not part of the origination information in McDash, but part of the monthly performance data. Over 85% of first observations fall within the first year.

Variation in insurance coverage. Second, we focus on the demand-side drivers of coverage choices. This is motivated by the fact that borrower characteristics explain a large part of the underlying variation in insurance coverage. We examine several broad types of loan-level variables, which could potentially explain the variation in coverage ratios and prices, including ZIP-year fixed effects, rebuild costs, climate risk, the mortgage contract, and the insurance contract. We find that ZIP-year fixed effects, along with borrower characteristics, explain more than 70% of the variation in coverage.[28] In contrast, climate risk or insurance-contract related variables have a lower explanatory power. Therefore, our analysis focuses on estimating demand-side drivers of coverage and debt at mortgage origination. Appendix A.3 provides more details on this analysis.

1.3. Five Novel Facts on Homeowners Insurance Coverage

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

1.3.1. *Fact 1:* The average American household is under-insured.

We start by estimating insurance coverage ratios, and find that the average American household is substantially under-insured. Table 1 shows that the average coverage ratio nationally is 69%. This means that the average household has less than 70% of their rebuild cost covered by insurance. In fact, nearly 61% of households have coverage ratios below 70%. Furthermore, more than 10% of households are *severely* under-insured having only 50% of their rebuild cost covered by insurance. Figure 1 shows how underinsurance varies spatially. At the state level, income and coverage ratios have a 77% correlation. In contrast, climate risk and coverage ratio have a -18% correlation. These broad patterns suggest that household income plays an important role in coverage choices, with higher income states having on average higher coverage ratios.

1.3.2. *Fact 2:* Borrowers that are more likely to be financially constrained have less coverage.

We next dig deeper into the prevalence of under-insurance by considering how under-insurance varies by borrower characteristics. Figure 2 shows how coverage ratios relate to borrower credit scores and borrower incomes.[29] We find a strong positive correlation between credit scores and

[28] We also find that these characteristics explain 60% of the variation in insurance prices.
[29] Credit scores are measured using FICO score at origination from ICE McDash.

coverage ratios (Figure 2a). Going from the lowest ventile of credit scores (650) to the highest ventile of credit scores (800) is associated with an increase in coverage ratios of 10 pp, i.e. coverage ratios rise from 64% to 74%. The relationship is quite linear. Figure 2b shows a similar pattern when plotting coverage ratios as a function of the primary borrower's income. Here the difference in the cross-section of borrowers is even starker. Going from the lowest ventile of income ($20K) to the highest ventile of income ($120K) is associated with a 30 pp increase in coverage ratios, from 60% to 90%. These results suggest that under-insurance is particularly high among the lowest-income and most financially constrained households. Such households are also far more likely to be vulnerable to large shocks, lacking the financial resources of their own to smooth such shocks. Paradoxically, these are the exact households most likely to benefit from insurance, and the ones that standard models (Arrow, 1963, Mossin, 1968) would suggest should have the highest demand for insurance.

1.3.3. *Fact 3:* Climate risk matters for coverage choices, but only for unconstrained borrowers.

The heterogeneity across the cross-section of borrowers raises questions about the role of climate risk, particularly if there is income-based sorting into high-climate-risk areas. To explore this, we analyze the relationship between severe under-insurance (coverage ratios below 50%) and borrower characteristics, while controlling for borrower's climate risk exposure.

For borrowers with higher income and higher credit scores, the data aligns with traditional economic theory: households facing higher climate risk tend to obtain more coverage and are less likely to be severely underinsured (Figure 3b and Figure 3a).

In contrast, lower-income and lower-credit-score households exhibit different behavior: climate risk appears to have minimal influence on coverage choices. For example, households with annual primary borrower incomes below $40k show similar rates of severe under-insurance, regardless of their climate risk exposure. Surprisingly, at the lowest income levels (around $20k annually), households in high-risk areas are more likely to be severely under-insured compared to those in low-risk areas. Similarly, borrowers with lower credit scores (around 650) in high-risk areas tend to have less coverage than their counterparts in low-risk areas.

In short, lower-income households in high climate risk areas are particularly vulnerable and are the most likely to be severely under-insured. This suggests that financial constraints may outweigh

risk consideration in determining insurance coverage, consistent with the broad patterns implied by Figure 1 at the state level.

These stylized facts underscore the need to systematically understand the drivers of under-insurance for low income households, in particular the role played by binding cash flow constraints.

1.3.4. *Fact 4:* Higher insurance prices are associated with more under-insurance and household indebtedness.

We now consider how insurance prices correlate with coverage and debt choices. Figure 4 shows that insurance prices are negatively correlated with coverage: households with higher insurance prices are more likely to be under-insured (defined as having below 70% coverage). In the cross-section, households with the lowest insurance prices (those at \$20) are the least likely to be under-insured (with only 40% under-insured). However, at the higher end of the price range (at \$80), the proportion of under-insured households increases to 80%.

Figure 4b and Figure 4c show that households with higher prices are more likely to have higher DTI and LTV ratios. In particular, for households with the lowest insurance prices (at \$20), 66% are likely to have very high DTIs, and 55% are likely to have high LTVs. However, for households with high insurance prices (at \$80), nearly 72% have high DTIs, and over 75% have high LTVs.

1.3.5. *Fact 5:* Households with less coverage have higher delinquency rates.

We lastly look at the broad correlation between coverage choices and serious mortgage delinquency, defined as more than three consecutive months of missed mortgage payments within the first five years following mortgage origination. Figure 5 shows that there is a strong positive relationship between coverage ratios and mortgage delinquency. Households with a coverage ratio of only 45% have a 10% likelihood of becoming seriously delinquent. The serious delinquency rate falls to 6% for households with the highest coverage ratios.

1.3.6. Interpreting the Descriptive Facts

The broad patterns across the five facts show a clear correlation between household income and coverage. Taken together, these facts are consistent with a model where households value insurance, but exhibit financial constraints that prevent them getting full insurance coverage. We do not interpret these facts as casual relationships, but use them to motivate our focus on financial constraints as an important driver of insurance and debt choices throughout the rest of the paper.

2. Framework: Insurance and Credit Demand with Borrowing Constraints

In this section, we provide a single conceptual framework that brings together the insights of the textbook Arrow (1963) and Mossin (1968) models along with the newer settings of Rampini and Viswanathan (2013) that consider financial constraints.[30] Our framework introduces insurance choice into a standard dynamic consumption-savings model with borrowing constraints. The model generates predictions for how households jointly choose insurance coverage and debt, and comparative statics on how these choices depend on insurance prices and vary with borrowing constraints. The goal of the model is to provide an organizing framework to motivate and interpret our empirical tests throughout the rest of the paper.

2.1. Insurance Coverage Demand: Unconstrained Benchmark

We consider a dynamic partial equilibrium model of a risk-averse individual with utility function U who uses homeowners insurance to protect her house against disaster risk. Each period there is a chance that the house may be fully destroyed by a disaster event, denoted by a binary random variable y with 1 indicating the event of total loss. The probability of loss is known and is given by the parameter $\phi = E[y]$. M is the value of the housing consumption per period, and is taken as exogenous.[31] The individual chooses to insure a fraction $k \in [0, 1]$ of the house at the beginning of the period at the insurance price of p. If a loss occurs, the individual receives the payment kM.

To set ideas, we begin with a benchmark case where households do not face borrowing constraints and insurance prices are assumed to be actuarially fair.

The individual chooses consumption, insurance, and savings to maximize her discounted lifetime utility subject to a budget constraint:

$$\max_{\{c_t, k_t, S_t\}} E_0 \sum_{t=0}^{\infty} \beta^t U(c_t), \tag{3}$$

subject to:

[30] Our model builds on Liu and Myers (2012), replicating their results on constraints but also adding several additional propositions related to optimal debt choice. For related literature on insurance demand with liquidity constraints, see Ericson and Sydnor (2018), Rampini and Viswanathan (2013), and Gollier (2003).

[31] We abstract from the housing choice to focus on the partial equilibrium effects of financial constraints and insurance demand. In this model, in each period, the individual stands to gain M in wealth if there is no shock, or if she is fully insured.

$$S_t = w_t - c_t - pk_t, \tag{4}$$

$$w_{t+1} = (1+r)S_t + (1-y_{t+1})M + y_{t+1}k_tM \tag{5}$$

where $U(.)$ is an increasing and concave utility function. The variables w_t, c_t denote wealth and consumption at period t. The parameter β is the discount factor. The variable S_t is savings (if positive) or borrowing (if negative). r is the risk-free per-period interest rate.

The budget constraint in Equation 4 says that savings or borrowing in period S_t is the individual's wealth minus consumption minus the insurance payment. The law of motion for wealth in Equation 5 says that, the next period wealth w_{t+1} is any earnings on savings (or payments on borrowings), plus the residual value of the house depending on the realization of the disaster given by y_{t+1}.

The individual's problem can be rewritten as the following Bellman equation:

$$V(w_t) = \max_{c_t, k_t, S_t} U(c_t) + \beta E_t[V(w_{t+1})], \tag{6}$$

subject to the constraints (2)–(4), and the transversality condition given by

$$\lim_{t\to\infty} \beta^t w_t = 0. \tag{7}$$

The first-order conditions with respect to c_t and k_t show that the optimal consumption and insurance coverage are chosen according to:

$$U'(c_t) - \beta(1+r)E_tV'(w_{t+1}) = 0 \tag{8}$$

$$E_t[V'(w_{t+1})(-(1+r)p + y_{t+1}M)] = 0. \tag{9}$$

We obtain the following propositions for how the unconstrained household optimally chooses insurance coverage.

Proposition 1A. The unconstrained household optimally chooses full insurance coverage ($k = 1$) when insurance price is actuarially fair.

Proposition 1B. The unconstrained household is completely price inelastic ($dk/dp = 0$) when insurance price is actuarially fair.

See Appendix B for the detailed proof. Intuitively, full insurance is optimal at fair prices because it enables risk averse households to fully offset losses from the disaster shock, allowing them to smooth consumption over time and across states. Because households are risk averse, at actuarially fair prices, they will continue to maintain full coverage and not be sensitive to small price changes. This is a similar logic to what is obtained in static frameworks of Arrow (1963) and Mossin (1968).

2.2. Insurance Coverage Demand: Borrowing Constraints

We now consider the case where borrowers also face a borrowing constraint i.e.

$$S_t \geq s. \tag{10}$$

The parameter s denotes the minimum net wealth position allowed by credit markets. For example, when $s = 0$ borrowing is not possible, whereas $s = -\infty$ implies that there is no borrowing constraint.

With this constraint, the first-order conditions with respect to c_t and k_t are now:

$$U'(c_t) - \beta(1+r)E_t V'(w_{t+1}) - \lambda_t = 0 \tag{11}$$

$$E_t[V'(w_{t+1})(-(1+r)p + y_{t+1}M)] - \lambda_t p = 0 \tag{12}$$

where λ_t is the Lagrange multiplier on the borrowing constraint. We obtain the following propositions for how the constrained household optimally chooses insurance coverage:

Proposition 2A. When the borrowing constraint binds, the household optimally chooses lower than full insurance coverage ($k < 1$) under an actuarially fair insurance price.

Proposition 2B. When the borrowing constraint binds, the household is price elastic ($dk/dp < 0$) under an actuarially fair price.

See Appendix B for the detailed proof. Intuitively, the individual would have liked to borrow more to finance full insurance and smooth consumption across states and time but is unable to do so because the borrowing constraint starts to bind. With the borrowing constraint binding, the individual must consume more from her wealth, which leads insurance coverage to fall. This intuition is similar to the logic in richer models of financing constraints and hedging, as in Rampini and Viswanathan (2013).

Combining Propositions 1A and 2A we obtain that at actuarially fair prices, a household with a binding borrowing constraint ("constrained household") chooses less insurance than the household that does not face borrowing constraints ("unconstrained household"). We now show that this result holds regardless of whether insurance prices are actuarially fair.

Proposition 2C. All else equal, the unconstrained household, u, chooses higher insurance coverage than the constrained household, c, ($k_t^u > k_t^c$) at all levels of insurance prices.

Intuitively, this result reflects the fact that the constrained household would have liked to borrow to finance more insurance coverage, but the binding constraint leads it to have lower coverage. See Appendix B for the detailed proof.

2.3. Demand for Debt

Given the importance of financial constraints for insurance coverage choices, we now derive predictions about how household debt optimally adjusts in response to changes in insurance prices. We obtain the following result:

Proposition 3A. All else equal, the unconstrained household's borrowing is increasing in insurance prices ($dS/dp < 0$) if the household has low coverage demand elasticity (dk/dp is small). The result holds at all levels of insurance prices, including when prices are above actuarially fair.

Proposition 3B. All else equal, the constrained household's borrowing is insensitive to insurance prices ($dS/dP = 0$). The result holds at all levels of insurance prices, including when prices are above actuarially fair.

See Appendix B for the detailed proof. Intuitively, households that are unconstrained and value insurance sufficiently (i.e. have low price elasticities) would only be willing to drop coverage up to a point. This implies that their total outlay towards insurance would rise, requiring them to finance rising premiums in part by increasing borrowing. To illustrate the point further, consider the extreme case where household is completely inelastic. In that case, the borrower would maintain the same coverage levels, and would need to finance the entire increase in prices by increasing borrowing and reducing consumption. On the other hand, if the household is perfectly elastic, they would drop coverage in tandem with prices changes, without having to adjust debt or consumption.

2.4. Empirically Testing the Model's Predictions

The model has a number of testable implications. To summarize the propositions, the model predicts that that constrained households obtain less insurance coverage and have more elastic insurance coverage demand than unconstrained ones. Furthermore, the model suggests that constrained households' debt choices are less sensitive to changes in insurance prices than unconstrained ones.

To bring the model to the data, we note that in the model, households optimally choose insurance coverage k and savings/borrowing S, taking prices p and interest rates r as exogenously given parameters. Therefore, to test the model's predictions, we cannot simply rely upon the correlations in Section 1.3 – we require *exogenous* variation in insurance prices. Our empirical design in the subsequent sections will explain how we obtain such variation.

In addition, to explore the model-implied heterogeneity by financial constraints, we require a proxy for whether the borrower is financially constrained. We use a simple approach, classifying households as "financially constrained" if they have below-median income levels. This is motivated by Figure 6, which shows that higher income households have significantly higher debt capacity than lower income households. In fact, lower income households are nearly two-times more likely to have binding LTV or DTI constraints than higher income households, suggesting that income is strongly correlated with debt capacity.

In Sections 3 and 5, we test Propositions 1A, 1B, 2A and 2B, and 2C, providing some of the first estimates in the literature for households' insurance coverage demand elasticities, and hetereogeneity in elasticities by whether the contract is (i) actuarially fair, and (ii) whether borrowing constraints are likely to bind. In Section 4, we consider Propositions 3A and 3B, estimating cross-price elasticities for household debt with respect to insurance prices. Lastly, to provide additional tests of the financial constraints hypothesis that does not rely on income as a proxy for financial constraints, we consider additional shocks coming from changes in interest rates. These tests are reported in Section 5.

3. Elasticity of Demand for Homeowners Insurance

In this section, we exploit plausibly exogenous variation in insurance prices to estimate households' coverage demand elasticities and test the model's predictions regarding the role of borrowing constraints in households' coverage choices.

3.1. Empirical Design

Estimating demand elasticities is challenging because of the classic simultaneity bias inherent in equilibrium price-quantity outcomes, whereby prices and quantities are jointly determined through the interaction of supply and demand forces. Thus, any observed price-quantity relationships inherently reflect both insurers' cost structures (supply elasticity) and consumers' willingness to pay (demand elasticity). To isolate a demand elasticity, we require exogenous supply shocks that shift the supply curve independently of demand conditions. With such variation, we can estimate demand elasticities and more directly test the model's predictions, which takes prices as exogenous.

We obtain arguably quasi-exogenous changes in insurance prices by instrumenting insurance prices in low price regulation (low friction) states with insurance prices in high price regulation (high friction) states. Our instrument builds off the intuition of the Hausman instruments that are commonly used in the industrial organization literature (e.g., Nevo (2001), Hausman (1996)), where the prices in a given market are instrumented with the prices in other geographic market segments.[32] We implement a similar idea by using prices in *other* states as instruments with one key difference: we only use prices in high friction states, where insurers face significantly more regulatory hurdles to changing premiums in response to changes in expected losses or demand conditions (Oh et al., 2021). While there is still variation in premiums, the timing is driven by when regulators allow insurers to adjust premiums. Moreover, the premium change often differs substantially from what is implied by insurers' actuarial assessments. As a result, price changes in high friction states are unlikely to reflect demand conditions in low friction states, as we explain in more detail below.

We construct the instrument as follows. First, we limit the sample to a subset of high friction states, as in Oh et al. (2021). We compute the average insurance price for these states for each year and for each of the four credit score categories. We call this variable $\bar{P}_{HF,c,t}$ where "HF" indicates that the average 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*, which we refer to as $P_{i,c,z,t}$.

We consider the following two-stage least squares regression:

[32] They posit that suppliers, which operate nationally, may need to adjust prices across many markets in response to national supply shocks, and that prices in other markets are exogenous to demand conditions in the current market.

$$\text{First Stage: } \ln P_{i,c,z,t} = \omega + \eta \ln \bar{P}_{HF,c,t} + \theta' W_{i,c,z,t} + \nu_{i,c,z,t} \tag{13}$$

$$\text{Second Stage: } \ln \text{coverage}_{i,c,z,t} = \alpha + \beta \widehat{\ln P_{i,c,z,t}} + \gamma' W_{i,c,z,t} + \varepsilon_{i,c,z,t} \tag{14}$$

where *coverage* refers to the insurance coverage chosen and P refers to insurance prices (premiums per dollar of coverage). The subscript i indexes loans, and z indexes ZIP code. W refers to a vector of control variables, which include ZIP-year fixed effects as well as controls for climate risk exposure, replacement cost, borrower income, and borrower credit score. Our measure of climate risk is a dummy variable for whether the property is in the top decile of expected annual climate losses.

The coefficient β can be interpreted as the elasticity of demand for coverage with respect to insurance prices. An estimated $\beta < 0$ would suggest that households are price elastic, or in the notation of the model, that $dk/dp < 0$.

3.2. Identifying Assumptions

For this instrument to be valid, we require both that (i) prices in high friction states are a relevant instrument for prices in low friction states, and (ii) prices in high friction states are exogenous to demand in low friction states. We consider each of these assumptions in turn.

Relevance: A natural question is why insurance prices in low friction states are correlated with prices in high friction states. The key logic is that regulatory pricing constraints in high-friction states cause insurers to operate at persistent financial losses. This leads them to raise prices in low-friction states. We describe this key idea in two steps. First, Figure C.6a shows that insurers' combined ratios are on average 100% in high friction states. That is, the amount insurers pay out in claims and operational expenses is roughly equal to what they earn in insurance premiums. Moreover, losses are *persistent* in high friction states, with high combined ratios ranging between 95%-110% throughout the sample (Figure C.6b).[33]

Second, insurers typically operate in multiple states and offset exposures in high friction states by adjusting premiums in low friction states (Oh et al., 2021).[34] This cross-subsidy can be directly seen through insurers' combined ratios, with insurers in low friction states being on average highly

[33] Combined ratio is a widely used metric to measure insurers' underwriting profitability.

[34] Note that Oh et al. (2023) find that insurers cross-subsidize homeowners insurance across states to smooth financial frictions induced by losses. The idea that insurance prices may deviate from fundamentals has also been shown more broadly in other insurance markets across a range of studies (Koijen and Yogo, 2015, Froot and O'Connell, 1999, Ge, 2022, Gao et al., 2024).

profitable (combined ratios are close to 85%). This suggests that premiums are above actuarially fair rates in low friction states, and likely below or close to actuarially fair rates in high friction states. Table 2 shows the first stage of our IV regression, where insurances prices in low friction states are regressed on prices in high friction states, as in Equation 14. The R^2 is high, consistent with the high first-stage F-statistics we obtain (reported in the tables of the second stage), indicating that the relevance condition holds strongly (Stock and Yogo, 2005). The first-stage coefficient η is also highly statistically significant indicating that prices in high friction states strongly relate to prices in low friction states.

While the sign of the first stage coefficient does not affect the validity of the IV or our interpretation of the second stage results, it is worth noting that both positive and negative signs would be consistent with a regulation-based explanation for the cross-state pricing relationship. One possibility is that price increases in high friction states alleviate insurers' financial constraints, allowing them to lower prices in low friction states (negative coefficient). Another possibility, which is what we observe, is that price increases in high friction states are associated with price increases in low friction states (positive coefficient). This may arise if despite price increases, insurers continue to face persistent losses, suggesting that rate increases in high friction states are not sufficient to bring prices to actuarially fair levels.[35] This, coupled with growing risks due to development in high-risk areas and climate losses, indicates that insurance contracts in high friction states likely continue to remain below actuarially fair, consistent with Figure C.6b. In other words, prices likely do not rise by enough to render insurers profitable, requiring them to increase prices further in low friction states.

Another question is whether our instrument might be weak for households facing single-state insurers. However, this is unlikely for two reasons. First, single state insurers have a small market share (10% in the US overall). Second, even single-state insurers in low friction states may be

[35]There is significant anecdotal evidence in support of this interpretation. For example, the *Wall Street Journal* writes about California, a high friction state: " [State Farm's] own actuaries repeatedly said the California subsidiary's premiums weren't high enough and its outside consultants warned of the seriously escalating risk of a devastating fire. [...] 'Our California homeowners insurance product line has not been rate adequate since 2007,' the company said on its website. For years, its in-house calculations had been warning that its rate increases were much lower than what was needed to balance its risks. "Yet State Farm repeatedly asked the state for a fraction of the increases that would be needed to bring its rates up to the necessary levels. In 2021, State Farm asked California regulators to approve a 6.9% rise in home-insurance rates, less than a quarter of the 31% increase its own in-house calculations showed was needed to cover the risks of its policies, state filings show. In 2022, it again asked for 6.9%, rather than the 23% rate its own math indicated was needed. "Insurers in general kept rate requests low to navigate California's tough price controls." See Wall Street Journal, "State Farm Was All In on California—Until It Pulled the Plug Before the Fires", February 6, 2026.

affected by premiums in high friction states because they compete with multi-state insurers, and may be raising prices at the same time. Collectively, these factors help explain our strong first stage.

Exogeneity: The second assumption we require is that prices in high friction states are unrelated to demand in low friction states. To establish exogeneity, we start by showing that prices in high friction states are unresponsive to measures of risk in these states. We consider two measures of risk: a dummy for whether the property is in the top decile of expected losses, and lagged ZIP-level loss ratios, which is a common measure of risk defined as total losses divided by total premiums. Table C.2 shows that insurance prices in low friction states are significantly higher (by nearly 8%) for high risk properties that are in the top decile of expected annual losses. However, in high friction states, prices are completely insensitive to risk, with average annual losses having nearly a zero pass-through to prices. The results are similar using the second measure of risk, loss ratios. Table C.3 shows that premiums in low friction states are responsive to lagged loss ratios, but this is not the case in high friction states. In other words, unlike low friction states, price changes in high friction states occur for non-fundamental reasons. Given that prices do not even reflect actuarial risks in high friction states, it is highly unlikely that prices respond to demand shocks, especially from other states.

Furthermore, Oh et al. (2023) show that prices in low friction states respond to conditions in high friction states through a financial constraints channel. Specifically, losses in high friction states affect insurers' marginal costs leading to insurers wanting to change prices everywhere. But they are only able to do so in low friction states, where raising rates is relatively easier. In other words, the evidence shows that it is the supply curve that shifts not the demand curve.

One might be concerned that exogeneity may be violated due to a learning channel. One example could be if households in low friction states learn about local risks from observing changes in prices in high friction states. We note that such a channel does not bias our estimate of demand. To the extent that a household learns from random variation in prices, this is part of their demand elasticity. What we require is that our variation in premiums is exogenous to demand – i.e. insurers in high friction states are not adjusting prices endogenously. In practice, Oh et al. (2023) show that such cross-state learning patterns are largely absent. Moreover, a learning hypothesis predicts that demand for coverage would rise as high friction prices go up, which if anything pushes against

finding that demand curves slope downwards.

3.3. Estimated Demand Elasticities

Table 3 shows the main results. We estimate that the average borrower has a price elasticity of -0.44, meaning that a 1% increase in insurance prices leads to a 0.44% reduction in coverage. The elasticity drops further to -0.107 after controlling for borrower characteristics. The drop in elasticity between columns (1) and (2) provide the first indication that borrower credit constraints, as proxied by credit score and income, play a considerable role in affecting borrowers' demand elasticities. The OLS estimates are shown in Table C.4. Our OLS estimates are highly similar in magnitude to our IV estimates. This could be because changing prices in low friction states also require explicit regulatory approval, which makes it harder for prices to immediately respond endogenously to demand changes.

3.3.1. Heterogeneity of the estimates

In line with the conceptual framework in Section 2, we next examine the heterogeneity of the elasticity estimates on three dimensions: (i) by whether the contract is actuarially fair; (ii) by proxies for borrower constraints; (iii) by climate risk.

(i) Actuarial fairness of the insurance contract. Insurance contracts in high friction states are on average more likely to be below or close to being actuarially fair, in particular much more so than contracts in low friction states.[36] In our conceptual framework, Propositions 1A and 1B predict that unconstrained households facing actuarially fair prices choose full insurance and have inelastic coverage demand, whereas constrained households facing actuarially fair prices under-insure and have elastic coverage demand.

We show in Table 1 that households in high friction states are not fully insured (with coverage ratios at roughly 70%), which is inconsistent with Propositions 1A. Furthermore, Table C.5 reports the demand elasticities for high friction states using an OLS estimation.[37] Given that in these states price changes are unrelated to shifts in expected losses and demand conditions, an OLS specification can help recover the demand elasticities because insurers cannot simultaneously adjust supply in response. The results in Table C.5 show that even with prices below or at actuarial fair levels,

[36]This comes from the data on combined ratios, which are a measure of insurer profitability. Loss ratios in high friction states are persistently close to 1, while in low friction states they are under 1(Figure C.6b).

[37]Because the price of insurance in high-friction states adjusts quasi-exogenously, we argue that variation in the price is not driven by fundamentals of risk or demand. That is, variation in price reflects variation in how generous the contract is, even though it remains below the actuarily-fair price.

households are elastic. These results are inconsistent with Propositions 1A and 1B for unconstrained households, but are in line with Propositions 2A and 2B for constrained households. We therefore argue that these patterns strongly support a borrowing constraints hypothesis.

Lastly, we note that demand elasticities are similar in high and low friction states. This suggests that the broader patterns of the estimated demand elasticities are unlikely to be driven by the generosity of the insurance contract.

(ii) Borrower constraints. Recall that Proposition 2C in the conceptual framework in Section 2 predicts that constrained households have lower coverage levels and more elastic coverage demand than unconstrained households. Consistent with this prediction, Figure 2b shows that lower income households have less coverage. Additionally, to test this prediction, we estimate heterogeneous elasticities of demand for different income groups, our proxy for borrowing constraints. Table 4 columns (1) and (2) show that elasticities of lower income households are more than double those of higher income ones (-.19 vs. -.08), consistent with the model's predictions.

(iii) Climate risk. We next consider how elasticity of demand varies by the household's exposure to climate risk. Table 4 columns (3) and (4) show that low climate risk households are more elastic than high climate risk ones. This captures the fact that higher risk households, all else equal, have a higher willingness-to-pay for insurance than lower risk households.

Overall, the fact that lower income borrowers are more price elastic strongly suggests that households with fewer financial resources respond to rising premiums by dropping coverage. It also suggests that, all-else-equal, households with more financial resources are better able to accommodate price increases, thus they have to drop coverage to a lesser degree. In the next section, we examine how plausibly exogenous shocks to insurance prices affect households' debt choices, evaluating the next set of predictions from the model.

4. Impact of Insurance Prices on Household Debt

The conceptual framework shown in Section 2 shows that debt plays an important role in supporting households' purchases of insurance coverage. We now test the model's predictions empirically.

4.1. Econometric Concern

Proposition 3A implies that households with spare debt capacity can finance large insurance price shocks by increasing their borrowing levels at origination. In addition, Proposition 3B implies that constrained households' debt choices are insensitive to insurance prices. To test these predictions, we need to estimate a cross-price elasticity of demand of mortgage debt with respect to insurance prices. The ideal experiment would randomly assign different insurance prices across households and examine how their demand for credit changes.

In this setting, the OLS regression of a household's mortgage debt on its insurance prices will likely be biased for a number of reasons. One key omitted variable of concern is the borrower's unobservable risk type– borrowers with high idiosyncratic default risk, or high climate risk, may both have higher insurance premiums and demand higher debt. In this case, the OLS estimate would be higher than the true treatment effect of higher premiums, because it would also capture the effect of riskier borrowers' demand for more mortgage debt. On the other hand, borrowers with higher unobservable risk types may not actually be able to borrow more as lenders may screen more tightly or ration credit (Sastry, 2022). If so, higher premiums would be associated with smaller loan size. In other words, the OLS estimate would be lower than the true treatment effect of higher premiums, because it would also capture lender screening and credit rationing. The intuitions are similar if households and lenders learn about disaster risk probabilities from insurance prices – households would have incentives to increase debt, and lenders would have incentives to ration debt. This discussion highlights that the selection effect of unobservable risk does not present a clear prediction on what the sign of the bias should be because the demand effect and the supply effect go in opposite directions. What is clear, is that a simple correlation between insurance premiums and the level of debt chosen would also capture such selection effects and therefore would be difficult to interpret.

A related concern is that insurance companies can endogenously react to both changing unobservable risk types and changing loan demand. For example, insurers may know that lenders have lax credit standards in some areas, which can enable households to buy more coverage because they are less cash-constrained; they therefore have incentives to adjust prices optimally given this knowledge. Such endogenous supply adjustments would also bias the estimate, because the correlation with premiums and debt levels would also reflect insurance supply elasticities.

4.2. Instrumental Variables Specification

To address these endogeneity issues, we employ the same instrumental variables strategy as in Section 3. In this strategy, we exploit variation in insurance prices that are driven by changes in high friction states, where regulatory frictions prevent insurers from adjusting prices particularly in response to demand shocks. Importantly, in this setting, the fact that insurers in high friction states cannot adjust prices in response to demand shocks also implies that they do not respond to credit conditions in low friction states. We can therefore use prices in high friction states to instrument for prices in low friction states.

We consider the following two-stage least squares regression:

$$\begin{aligned} \text{First Stage: } \ln P_{i,c,z,t} &= \omega + \eta \ln \bar{P}_{HF,c,t} + \theta' W_{i,c,z,t} + \nu_{i,c,z,t} \\ \text{Second Stage: } \ln Debt_{i,c,z,t} &= \alpha + \beta \widehat{\ln P_{i,c,z,t}} + \gamma' W_{i,c,z,t} + \varepsilon_{i,c,z,t} \end{aligned} \tag{15}$$

The first stage, instrument, and control variables are the same as defined in Section 3. The coefficient η represents the pass-through of premium shocks in high friction states to low-friction states, and the estimates are reported in Table 2. In this specification, the second stage uses measures of household debt as outcome variables. The coefficient estimate of interest is β, which is the cross-price elasticity of debt with respect to insurance prices and captures how measures of debt change as insurance prices change.

Measures of debt. We consider two related measures of debt that are commonly used in the literature and by mortgage lenders. The first is the household's debt-to-income ratio (DTI), which considers a household's total monthly debt burden as a proportion of the borrower's monthly income. Debt-to-income ratios are used by lenders to assess a consumer's ability to repay their mortgage (Greenwald, 2018). DTI ratios above 31% are considered to be particularly high (Holden et al., 2012), with lenders often unwilling to offer loans above 45% DTI (Bosshardt et al., 2024).

In the McDash dataset, this variable is a "back-end" DTI, which means that it includes all types of monthly debt payments and insurance payments at the time of mortgage origination.[38] Specifically, the numerator includes the following three items. (i) Debt, which includes the mortgage payment, but importantly also other household debt (e.g., auto loans, revolving credit card debt,

[38] In contrast, a front-end DTI would just consider mortgage debt and exclude other debt obligations.

student loans, etc); (ii) premiums, which include household's homeowners insurance, flood insurance, and mortgage insurance premiums; as well as (iii) property tax payments. The denominator is a household's monthly income.

One benefit of using the DTI ratio is that it captures the impact of rising premiums on nearly all sources of household debt at the time of mortgage origination. That is, we can capture the full suite of loan contracts that households can use to finance rising premiums, both current premiums as well as expected future premiums. However, the downside of this measure is that rising insurance premiums also mechanically increase DTI ratios (through an increase in premiums), even if households do not actually adjust debt contracts. That said, the relationship between DTI and insurance premiums is of key importance, since even a mechanical increase in DTI would carry implications for the risk of the mortgage. In our analysis, we can infer the actual size of the endogenous debt adjustment by removing the part of the effect coming from mechanical changes in the DTI ratio.

The second measure of debt is households' loan-to-value ratios (LTVs). LTV ratios are the ratio of the mortgage loan amount to the house price, and are commonly used by lenders to measure household leverage.[39] The benefit of using this measure is that there is no mechanical relationship between rising insurance premiums and LTV ratios. However, the downside of this measure is that it will only capture mortgage debt adjustments–adjustments of other types of debt (e.g., credit card), for example, will not be reflected. Therefore, both DTI and LTV, together help clarify the extent to which households adjust their borrowing to finance rising insurance prices.

4.3. Identifying Assumptions

The key idea of the IV approach is that we seek to obtain exogenous variation in the supply of insurance so that we can estimate the causal effects of insurance prices on household credit demand. From that standpoint, we require similar identifying assumptions as in Section 3. For relevance, we require that prices in high friction states are relevant for prices in low friction states. However, our exclusion restriction requires the following assumptions: (1) that prices in high friction states are exogenous to insurance demand in low friction states, and (2) that prices in high friction states are exogenous to lending markets in low friction states. Under these two exogeneity assumptions, we can interpret the IV estimates as the causal effect of insurance prices on household debt.

[39]The denominator is either the transaction sale price or the appraised value.

However, to interpret the coefficient β as a credit demand (household-driven) elasticity, rather than a credit supply (lender-driven) elasticity, we require an additional identifying assumption that the elasticity of supply with respect to changes in insurance premiums is less than or equal to zero. That is, if there is any causal impact of higher insurance premiums on credit supply response, it would be a tightening of credit. We identify two main channels for insurance premiums to endogenously affect mortgage credit supply. First, although our measure of changes in insurance premiums is orthogonal to a household's true risk, lenders may learn about borrower risk from insurance premiums. In this case, a higher premium would signal higher risks to the lender, which could induce credit tightening. Second, as discussed earlier, as premiums increase, even without other adjustments, a household's DTI ratio would increase. Lenders may interpret this as an increase in the mortgage's default risk, thereby also inducing credit tightening. Supporting these conjectures, Ge et al. (2024)) show that a rise in insurance premiums after origination directly increases mortgage default risk. Both these channels imply that any endogenous lender adjustments are more likely to bias our credit demand estimates downwards.

To help interpret the coefficients as demand elasticities, we also consider whether there are heterogeneous effects by borrower characteristics. Lower income households are more likely to be at the maximum LTV and DTI thresholds than higher income households. If lenders were to relax (and not tighten) credit standards in response to an exogenous rise in premiums, we expect to see larger debt adjustment among lower income households but not among higher income households.

4.4. Results

Table 5 shows the results of the IV regression with the counterpart OLS results shown in Table C.6. Columns (1) and (2) shows the results for DTI ratios as an outcome variable; all specifications control for rebuild costs and climate risk, while the second specification also adds controls for borrower income and credit scores. The results in column (1) imply that an exogenous 1% increase in insurance prices leads to a 1.05% increase in DTI ratios. This result increases slightly in column (2) after controlling for borrower income and credit scores to 1.217%. These results could be driven by the mechanical effect of premiums changing the total debt in the numerator, or by actual changes in the loan balance, or both. However, in practice, insurance premiums represent less than 2% of a household's monthly debt payment. With no other endogenous adjustments, a 1% increase in

insurance prices therefore should lead to a 2 bps increase in DTI ratios. This suggests that nearly the entirety of the effect we estimate comes from endogenous credit adjustments.

The last two columns in Table 5 show similar results for loan-to-value ratios. Loan-to-value ratios significantly increase with exogenous changes in insurance prices. In column (1), we find that a 1% increase in insurance prices leads to a 0.6% increase in loan-to-value ratios. In column (2) after controlling for borrower income and credit scores, this coefficient becomes closer to 0.7%. In Table C.7, we show that are estimates are robust to controlling for the interest rate on the mortgage.

4.4.1. Heterogeneity of the estimates

We next consider how debt adjustment differs by the type of borrower by showing heterogeneous effects by borrower income and climate risk. The results are reported in Table 6 (columns (1) and (2)). Proposition 3A of our model predicts that unconstrained households' debt choices are sensitive to insurance prices. In contrast, Proposition 3B predicts that constrained households' debt choices are insensitive to insurance prices. Consistent with these predictions, we find that higher income households' credit demand is more sensitive to insurance prices than lower income households'.

Recall that higher income households also exhibited lower coverage elasticities than lower income ones (Table 3). Collectively, these results, are consistent with the model's predictions about how borrowing constraints influence the joint choice of insurance coverage and debt: lower income households (that are constrained) drop coverage more in response to rising premiums, and higher income households (that are unconstrained) raise debt and drop coverage by a lower amount.

We also find that borrowers with high climate risk make bigger debt adjustments than borrowers with low climate risk (columns (3) and (4)). These same borrowers also had lower coverage elasticities, as shown earlier, suggesting that they choose to borrow more to finance insurance premiums rather than dropping coverage. This trade-off makes sense as insurance is likely more valuable in high climate risk areas. Overall, our results are also more in line with a credit demand interpretation than a credit supply interpretation.

Interpretation of Magnitudes: To interpret these magnitudes, we consider the following back-of-the-envelope calculation. Over the course of our sample, insurance prices (per dollar of coverage) grew at an average rate of 2% annually.[40] Our estimates suggest that the observed

[40]We use the growth rate over the entire sample; the annual growth rate is significantly higher at 7% in the recent

2% increase in prices raised loan-to-value ratios by 2.16 percentage points for the unconstrained group (2% $\times$ 1.078). This translates to an increase of \$4,960 in the loan balance (since the average loan balance in the sample of low friction states was \$230,000). To benchmark this number, we compare the implied increase in the loan balance to the additional cost the household would bear due to the increase in insurance prices. At a 2% annual growth rate, households would need an additional \$14,100 over the total life of the loan to pay for insurance. This suggests that 35% of this expected burden is financed in credit markets. Borrowing to finance future insurance payments makes sense if households expect to be less cash-flow constrained in the future, and if households face additional costs to access mortgage credit, which is one of the cheaper forms of borrowing, following origination.[41] We also ask if prices were to continue growing at historical rates moving forward, what fraction of currently unconstrained households would start to hit binding loan-to-value limits. Our estimates imply that between 17% to 31% of previously unconstrained would hit LTV constraints. If so, they would also be forced to reduce coverage substantially in the same way as constrained households.

5. Drivers of Coverage Demand Elasticities: The Role of Borrowing Costs

While the estimates obtained so far are broadly consistent with borrowing constraints explaining how households jointly choose coverage and debt, our empirical approach primarily relies on splitting borrowers by their income levels to proxy for borrowing constraints. A challenge of this approach is that high and low income households may differ on other unobservable dimensions besides borrowing constraints, which could independently explain the heterogeneity of our estimates. For example, high and low income borrowers may have different beliefs, preferences, or risk tolerance. To provide tighter evidence on the borrowing constraints mechanism, in this section, we consider additional tests that focus on shocks to constraints directly.

Through the lens of the model, the ideal test of borrowing constraints would consider shocks to the constraint $S > s$, such as exogenous increases or decreases in the borrowing limit s. Because of empirical challenges to obtaining such variation, instead, we consider a related question, of how household elasticities are influenced by plausibly exogenous shocks in the interest rate (r). We

sample since 2018.

[41] This could also occur if they expect the house price to appreciate.

argue that one measure of household cash-flow constraints concerns their cost of credit. Higher interest rates make it more expensive for households to finance insurance price increases using debt. This may force households to reduce coverage today for a given price change, thus making them more elastic. Our conceptual framework in Section 2 therefore suggests that interest rates are an important driver of household insurance demand.

Identification challenge: To estimate the impact of cost of credit on insurance coverage demand elasticities, we would in principle look at the fully interacted specification that regresses insurance coverage on insurance prices, interest rates, and the interaction of prices and interest rates. However, the econometric challenge with the OLS specification is that there are likely many unobserved borrower-level variables that are correlated with both insurance prices and interest rates, which could determine coverage outcomes at the individual level. For example, households with less financial sophistication could have higher insurance prices, higher interest rates, and may demand less insurance. In this case, both interest rates and insurance prices are endogenous. To estimate the causal effect of interest, we therefore require variation in both insurance prices and households' cost of credit that are plausibly exogenous to these unobserved borrower characteristics.

As earlier, we address the first endogeneity concern with insurance prices by using prices in high friction states. For this instrument, we rely on the same two identifying assumptions as in Section 3: (i) that prices in high friction states are relevant to prices in low friction states, and (ii) that they are exogenous to demand conditions in low friction states.

To address the endogeneity issue with a household's own interest rate, we consider two complementary approaches to obtain plausibly exogenous shocks to interest rates. The first test exploits a discontinuity in mandatory GSE mortgage insurance requirements that directly affect borrowing costs. The second test analyzes the effects of plausibly exogenous market-wide interest rate fluctuations.

5.1. Required Mortgage Insurance Discontinuity

We now consider the first test which exploits a GSE rule that requires households with conforming mortgages to purchase private mortgage insurance (PMI) if their loan-to-value ratios at origination exceed 80%. PMI protects the lender if the household defaults on the mortgage, but the premium is

paid by the borrower every month.[42] While it is true that high-LTV borrowers with PMI may obtain a small reduction in interest rates (e.g., 1-5bp) because the insurance makes them less risky to the lender, this benefit is far lower than the cost of mortgage insurance they must pay. For example, Bhutta and Keys (2022) estimate that PMI, which is quoted as a share of the loan balance, is roughly equivalent to a 50-80 bps increase in the interest rate. We verify this by checking that overall mortgage payments, including PMI payments, are higher directly above the 80% LTV threshold compared to directly below.

We expect that households above the 80% LTV requirement will likely be more cash-flow constrained due to the mortgage insurance payment, making it more expensive for them to accommodate a given shock to the price of insurance by adjusting debt. That is, all else equal, we expect that households just above the 80% LTV threshold who have to pay mortgage insurance will have more price elastic demand for insurance than households that are just under the 80% LTV constraint.

We implement this test by estimating a 2SLS specification, with the following second stage:

$$\begin{aligned}\ln \text{coverage}_{i,c,z,t} = \alpha + \beta_1 \widehat{\ln P_{i,c,z,t}} + \beta_2 I(LTV > 80\%)_{i,c,z,t} + \\ + \beta_3 \widehat{\ln P_{i,c,z,t} \times I(LTV > 80\%)_{i,c,z,t}} + \gamma' W_{i,c,z,t} + \varepsilon_{i,c,z,t}\end{aligned} \tag{16}$$

where we expand Equation 14 by including $I(LTV > 80\%)$, a dummy variable that indicates whether the loan has an LTV ratio that exceeds 80% at origination, and its interaction with prices.

As earlier, to avoid issues with simultaneity bias in prices, we limit the sample to low friction states and use prices in high friction states as an exogenous instrument for a household's price in low friction states. Because both insurance prices P and the interaction $P \times I(LTV > 80\%)$ are endogenous, we rely on two instruments: price in high friction states $\bar{P}_{HF,c,t}$ as well as $\bar{P}_{HF,c,t} \times I(LTV > 80\%)$, where for the interacted instrument we rely on the identifying assumption that $\bar{P}_{HF,c,t} \times I(LTV > 80\%)$ is exogenous. The first stage results are shown in Table C.8.

The key idea of this test is that within narrow LTV bands and accounting for observable borrower characteristics and ZIP-year fixed effects, the primary difference between borrowers just above vs. just below the 80% LTV threshold is in their cash-flow constraints, which drives variations in their sensitivity to insurance pricing. We therefore implement the test by limiting the sample to narrow

[42]The incidence of lender-paid PMI is exceedingly rare, but even in these situations, lenders pass on the costs to borrowers through higher interest rates, and thus PMI costs are borne by the borrower (Bartlett et al., 2022).

bands of the 80% LTV threshold. We consider two bandwidths: first mortgages within 10 points of 80% (that is between 70-90% LTV), and mortgages within 5 points of 80% (between 75-85% LTV). Our specification includes a dummy variable that controls for the main effect of being above versus below 80% LTV. The coefficient of interest is the parameter β_3, which captures the additional role played by the mortgage insurance requirement on households' coverage elasticity.

5.1.1. Identifying Assumptions

One concern about this approach is that there may be unobservable differences between borrowers just above and below 80% LTV that are unrelated to the cash flow constraint channel but also determine household insurance demand. We argue that many traditional determinants of insurance demand, such as household risk exposures, discount factors, sophistication, risk preferences, and beliefs about risks and climate change are likely to vary smoothly through the 80% LTV cutoff, particularly after we include our rich controls and ZIP-year fixed effects. Practically speaking, there is little evidence in the literature that households with 79% LTV are systematically different in these dimensions than households with an 81% LTV, holding fixed the ZIP-year, rebuild cost, property-level climate exposure, income, and credit score.

That said, the concern about unobserved differences is particularly important because it is well known in the mortgage literature that there is significant bunching in the data directly below the 80% LTV cutoff (DeFusco and Paciorek, 2017). The existence of bunching suggests that there may be sorting of households around the threshold based on unobserved characteristics.

However, the sorting pattern does not invalidate our interpretation of the estimates. Rather, it reinforces our ability to measure the causal impact of cash-flow constraints on household demand elasticities. This is because the type of households that bunch just below the 80% LTV cutoff are likely to be *less* cash flow constrained as they have the resources to pay slightly larger down payments, thereby avoiding the need for mortgage insurance.[43] In fact, the existence of such a sorting pattern implies that the quantitative difference in cash-flow constraints between households above and below the 80% LTV threshold may exceed the direct cost difference of PMI. However, qualitatively, the two groups still differ on the key dimension we are interested in estimating.

Furthermore, unobservable differences between the two groups of borrowers does not necessarily

[43] In the lens of the model, these are households with slightly *higher* levels of w_0.

pose a problem for our identification strategy. If the unobservable differences only impact the level of coverage demanded, then our coefficient estimate of interest β_3 will not be biased. However, if the unobservable characteristics do impact household insurance price sensitivities, then this would pose a threat to identification. Therefore, our key identifying assumption is that, within narrow LTV bands, any unobserved differences between borrowers above and below 80% LTV threshold unrelated to cash-flow constraints are fully accounted for by controlling for the main effect and do not impact households price sensitivities.

5.1.2. Results

Table 7 shows the main two-stage least squares results, with the first stages reported in Table C.8. We find that β_3 is negative and statistically significant. That is, households with LTV ratios just above the threshold are significantly more price elastic than households below the threshold. This result holds for both the bandwidths we consider. The economic magnitudes are large. Borrowers with LTV ratios below 80% have an estimated elasticity of -.114% elasticity, whereas borrowers with LTV ratios above 80% have an estimated elasticity of -.174%. That is, borrowers just above the 80% LTV threshold are nearly 50% more elastic than households just below the 80% LTV threshold.

Interestingly, we find a strong positive coefficient for the main effect of higher LTV ratios, β_2. In theory, at extremely low prices (when $lnP = 0$), households just above the LTV threshold would take on more coverage than those just below the threshold. However, when faced with more realistic prices they take on lower amounts of coverage given that they are more price elastic. This explains why higher LTV households have lower levels of observed coverage.

Taken together, our results suggest that downpayment-constrained borrowers that are required to pay mortgage insurance are more price elastic, meaning that they drop coverage more in response to a given price shock. This helps support the important role played by cash-flow constraints in determining households' demand for insurance.

5.2. Market-wide Cost of Credit Shock

We now consider our second empirical test for how households' coverage demand elasticities vary with interest rates. As earlier, we require variation in a household's interest rate that is exogenous to other unobserved determinants of household demand for insurance, such as household sophistication, beliefs, discount rates, risk preferences, or risk type. We make progress by using the market-wide

mortgage interest rate (Freddie Mac's Primary Mortgage Market Survey, or PMMS, rate) along with a ZIP-year fixed effect and rich borrower controls, as in Fonseca and Liu (2024), rather than using a household's own interest rate. This test compares two households that are the same on observables, both of whom originate their mortgage in the same ZIP code in the same year, but differ in the month of the year that they originate the mortgage. That is, one household obtains the mortgage at a point in the year when overall market rates are relatively higher, and the other obtains the mortgage at a point in the year when the market rate is relatively lower. We then estimate whether those two households have different demand elasticities.

We implement this test by estimating the following specification, which is the reduced form of a two-stage least squares regression (Angrist and Pischke, 2009):

$$\begin{aligned}\ln \text{coverage}_{i,c,z,t} = \alpha + \beta_1 \ln \bar{P}_{HF,c,t} + \beta_2 \text{market rate}_t \\ + \beta_3 \ln \bar{P}_{HF,c,t} \times \text{market rate}_t + \gamma' W_{i,c,z,t} + \varepsilon_{i,c,z,t}\end{aligned} \tag{17}$$

where, as earlier in Equation 14, the subscript i indexes borrowers, z indexes a ZIP code, c indexes credit score category, and t indexes time. The variable *coverage* is a household's coverage, $\bar{P}_{HF}$ is prices in high friction states, and market rate is the PMMS rate for 30-year fixed-rate mortgages. Controls W include a household's credit score, income, climate risk, rebuild cost, and ZIP-year fixed effects.

5.2.1. Identifying Assumptions

For the market rate instrument to be valid, we require that it is both relevant to a household's own interest rate, and that it is exogenous to other unobserved household characteristics that determine both their demand for insurance and their interest rates.

Relevance: Relevance of the market rate instrument is straightforward– an increase in the average, market-wide mortgage rate is strongly related to households' mortgage interest rates.

Exogeneity: We argue that the market rate is exogenous to other unobserved individual characteristics that determine household insurance demand. The market rate is determined by the Fed's policy rate, which adjusts in response to economy-wide macroeconomic conditions, the slope of the yield curve, and other factors. The average market-wide mortgage rate is unlikely to be correlated with the unobserved characteristics at the individual level that may simultaneously

determine household insurance demand and their own interest rate (such as an individual household's risk aversion, sophistication, beliefs, etc.).

While the market rate is not driven by unobservables that vary at the individual level, there are other concerns that may arise about how macroeconomic conditions may move with the market-wide mortgage rate. We argue that the use of ZIP-year fixed effects along with our rich controls for borrower and property characteristics alleviate many of these channels. Broadly speaking, we argue that these controls absorb other changes in the local or global economy that impact both insurance demand and interest rates. We go through each of these concerns in detail now for comprehensiveness.

Concern 1: Inflation and macroeconomic expectations. Most obviously, the mortgage rate does not move randomly – it is often a function of contemporaneous changes in inflation and other macroeconomic conditions. High inflation today or Fed policy changes could both influence households expectations of future inflation. This poses a key problem– if households expect construction costs to rise, or labor markets to deteriorate, each of these could impact their demand for insurance coverage. There could also be variation across borrowers in how they form expectations for a given change in the mortgage rate.

For this concern to impact our identification of demand, it would require that two borrowers in the same ZIP code originating mortgages at different points of the year form different macroeconomic expectations in response to changes in the average mortgage rate. Evidence from the macroeconomics literature suggest that such large high frequency changes in household expectations are unlikely. The literature finds that households do not change their inflation expectations as the Fed changes policy rates (Lamla and Vinogradov, 2019, Coibion et al., 2020), or even if the Fed changes its inflation target (Coibion et al., 2023).[44] Regarding the concern about cross-sectional heterogeneity in expectation formation, the literature shows that these minimal household adjustments are true across demographic variables. That said, we also rely on our rich set of borrower controls to hold fixed other dimensions of borrower heterogeneity.

Concern 2: House Prices. A related concern is that higher interest rates could lead to a change in expected or actual house prices. If households expect a change in interest rates to cause house prices to appreciate, for example, they may choose higher coverage levels. In this channel,

[44] Coibion et al. (2023) shows that borrowers expectations remain the same for a full year after the Fed inflation target announcements.

it is the change in house price expectations that changes insurance demand, not the cost of credit. Again, we argue that our use of rich controls with ZIP-year fixed effects also helps with this concern. For house price expectations to confound our estimates, households originating their mortgages in the same ZIP code with the same rebuild cost form different expectations of future house prices based on when in the year their mortgage was originated.[45]

Concern 3: Market Timing. Another concern might be that more sophisticated borrowers can time the market, choosing to originate their mortgage when rates are lower. This would induce negative borrower selection, whereby riskier and less sophisticated borrowers originate when policy rates are higher. While there is evidence of households timing the market, such as for example with their choice of refinancing, the literature suggests that it is very difficult to time the market *within the same year*. Mortgages can take nearly 1-3 months to close, and even professional forecasters can struggle to forecast market rate changes within the same year (Larsen and Martinez, 2024).

Concern 4: Supply-side of insurance. Another concern might be that changes in inflation or interest rates could influence the supply-side of insurance, with insurers optimally adjusting prices or rationing insurance. The concern that inflation could influence the supply-side of insurance is less of an issue here. While in principle insurers would optimally adjust prices as inflation changes, in practice it is hard to do so in high friction states. Oh et al. (2021) show that in high friction states, insurers cannot immediately adjust premiums even in response to changing risks or macroeconomic conditions because of regulatory obstacles to changing insurance prices.

5.2.2. Results

Table 8 shows the results. We find that households' demand elasticities are increasing in interest rates. In other words, when mortgage rates are exogenously higher, borrowers are more elastic and drop coverage at a higher rate in response to premiums increasing. Comparing columns 1 and 2 we find that the results are quantitatively similar with and without borrower controls for income and credit score. At the average interest rate in the sample (4%), column 1 shows that households are significantly elastic, with a demand elasticity of -.03. This effect is quantitatively large relative to the baseline household demand elasticity we estimate (= -.10, see column 2 of Table 3). To quantify how the coverage demand elasticity varies with market rates, we use the estimates in column 2. We

[45] Rebuild costs are highly correlated with house prices at origination. At the ZIP-year level the regression slope is a statistically significant 83%, with an R^2 of 36%; at the individual level the slope is 67%, with an R^2 of 40%.

find that going from a market rate of 3% to 7% makes households nearly eight times more elastic in their demand for insurance coverage ($\beta_1 + \beta_3 * (7\% - 3\%)$).

6. Impact of Underinsurance on Mortgage Default

The results from Section 3 and 4 show that rising premiums could impact mortgage risks by inducing households to drop coverage and by increasing household debt. It is well-known in the mortgage literature that households with higher debt have significantly higher probabilities of default, either due to strategic default motives, liquidity constraint channels, or adverse selection channels (Foster and Van Order, 1984, Bhutta et al., 2017, Ganong and Noel, 2020, Gupta and Hansman, 2021). This is the first channel through which higher premiums at origination change mortgage risks. The second channel through which rising premiums increase mortgage risk is by leading households to under-insure. However, to our knowledge, there is no systematic evidence on the direct effect of under-insurance on default risk.[46] We posit that under-insurance directly increases mortgage default risk. This could occur due to large-scale disasters causing extensive property damage that exceed coverage limits. In these scenarios, households that cannot pay for repairs out of pocket, or do not want to pay, have strong incentives to default on the mortgage.

6.1. Econometric Concern and Empirical Specification

This hypothesis suggests that households with more coverage should have lower default rates. However, a simple correlation between coverage and default would not yield the treatment effect of coverage because, as shown earlier, households with more cash constraints are likely to have less insurance coverage (Section 4). Thus, any correlation between coverage and default could be due to unobserved household cash constraints, rather than the causal effect of coverage. In this case, households with more coverage are positively selected, because they have less cash constraints.

To obtain the causal effect of coverage on mortgage default, we require plausibly exogenous variation in insurance coverage that is unrelated to other unobservables that impact household default outcomes, including an individual's unobserved cash constraints and unobserved ability to

[46] In part, this is due to lack of data on both insurance and mortgage markets. For example, Cookson et al. (2023) report that households in Colorado Boulder impacted by the Marshall Fire were *severely* under-insured, with many households relying on informal crowdfunding networks to rebuild and recover, often as a complement to formal insurance payments. Additionally, in the flood insurance context, Kousky et al. (2020) show that households without flood insurance outside of flood zones have worse mortgage outcomes after flood events.

smooth shocks. We exploit plausibly exogenous changes in insurance coverage driven by changes in the market mortgage rate. Specifically, we consider the following two-stage least squares regression using the market mortgage rate as an instrument for coverage:

$$\text{First Stage: } \ln \text{coverage}_{i,z,t} = \omega + \eta \text{ market rate}_t + \gamma W_{i,z,t} + \nu_{i,z,t} \tag{18}$$

$$\text{Second Stage: Serious Delinquency}_{i,z,t} = \alpha + \beta \widehat{\ln \text{coverage}}_{i,z,t} + \gamma' W_{i,z,t} + \epsilon_{i,z,t} \tag{19}$$

where the subscripts refer to household i in ZIP code z originating the mortgage at time t. *Coverage* is the dollar amount of coverage chosen by the household at origination. Serious delinquency$_{izt}$ is a dummy variable which equals one if the originated loan went seriously delinquent within the first 3-5 years of origination. Serious delinquency refers to more than three consecutive months of missed mortgage payments.[47] In all specifications, the vector W controls for the mortgage contract (LTV ratio, DTI ratio, individual loan interest rate), household characteristics (credit score and log income), replacement costs, and climate risk controls. W also include ZIP-year fixed effects. For robustness, in some specifications, we also control for the insurance price, to partial out any potential independent effect of price on delinquency that does not operate through coverage choices (Ge et al., 2024).

6.2. Identifying Assumptions

For market rate to be a valid instrument for insurance coverage, it must both be relevant to insurance coverage, and must be orthogonal to any unobserved variation in the error term that is correlated with coverage and also determine household delinquency.

Relevance. The relevance condition holds because, as we show in Section 5.2, shocks to households' credit cost, coming from changes in market interest rates impact households' elasticity of demand for coverage. Higher rates make it costlier for households to finance insurance premium increases using debt, thereby forcing them to get lower coverage.

Exogeneity. We argue that changes in the market rate are plausibly exogenous to other unobserved individual characteristics that simultaneously determine both insurance demand and the likelihood of default after conditioning on our rich set of controls. The controls include individual characteristics that capture credit constraints, cash-flow constraints, and unobserved financial

[47] Note that delinquencies in the first few years of the mortgage are especially costly for lenders, even if they do not result in default, since early on interest rates constitute a larger portion of the the mortgage payments.

resources (credit score, incomes, etc.), as well as the property characteristics (rebuild costs, climate risk). In addition, we also control for mortgage contract characteristics (LTV and DTI ratios). Our specification therefore compares borrowers within the same ZIP-year that have similar replacement costs, climate risk, incomes, credit scores, LTV, DTI, and interest rate, but different coverage amounts that are driven by different policy rates at the time of origination.

The market rate is determined by the Fed policy rate, which adjusts in response to economy-wide macroeconomic conditions, the slope of the yield curve, and other idiosyncratic factors such as interest rate volatility, liquidity of mortgage-backed securities, and originator capacity. That is, market-wide changes in the interest rate are unrelated to characteristics that vary across individuals that may impact both coverage and default, such as climate risk beliefs, risk aversion, household financial sophistication.

However, the use of a market rate variable raises other potential concerns about the exclusion restriction related to other macroeconomic conditions which move in tandem with mortgage rates. We argue that our use of ZIP-year fixed effects and rich borrower controls alleviates many of these concerns. We discuss these concerns in great detail in section 5.2 but summarize the broad points again here. First, we cite evidence from the macroeconomics literature that households' expectations of inflation do not significantly respond to changes in the Fed policy rate (which influences mortgage rates) (Lamla and Vinogradov, 2019, Coibion et al., 2023, 2020). We also argue that house prices expectations are unlikely to vary significantly for two households with the same rebuild costs after including ZIP-year fixed effects. Lastly, we cite evidence that it is difficult to time the mortgage market because high frequency changes in the mortgage rate are difficult to forecast, and mortgages can take 1-3 months to close.[48]

While many of the arguments for exogeneity are similar as in 5.2, there are two additional concerns which we must address. The first is the concern that households originating mortgages in a high rate environment will have higher monthly payments, and therefore lower residual income, than households originating mortgages in a low rate environment. This reduction in financial resources could assert an independent effect on default that is also correlated with coverage, potentially biasing our estimates. In addition, changes in the market rate will also induce changes in mortgage contract

[48]The difficulty of forecasting rates can also be demonstrated by lender behavior. Lender mortgage rate menus are typically contemporaneous, and the option to lock in a mortgage rate with a lender typically only lasts for 1-2 months.

features, including the loan-to-value ratio and debt-to-income ratio, which also impact household residual income. To alleviate these concerns, we control for individual loan contract features (LTV, DTI, interest rate, etc.) along with household income, so that we compare households with similar mortgage contracts and similar levels of residual income.

6.3. Results

Table 9 shows the results of our two-stage-least-squares specification. First, note that we obtain high first-stage K-P F-statistics (between 265 and 516) across all specifications, indicating a strong relationship between coverage and interest rates – consistent with our findings in Section 4. Second, we see that the instrumented coverage has a statistically significant negative effect on serious delinquencies, implying that households with low coverage are significantly more likely to default on their mortgage. This result holds for serious delinquency over both a 3-year (columns 1-2) and a 5-year (columns 3-4) horizon since mortgage origination. Our estimates imply that a 1% increase in coverage (e.g., a $3,000 increase in coverage limit) decreases 3-year delinquency by 12bps and 5-year delinquency by 21bps. All specifications include ZIP-year fixed effects and control for property characteristics, individual characteristics, and the mortgage contract. Our results also hold after controlling for the direct effect of changes in insurance premium on delinquency in columns 2 and 4.

6.3.1. Heterogeneity of the estimates

Table 10 shows how the pass-through of coverage to delinquency varies by the type of borrower by showing heterogeneous effects by borrower income. As expected, we find that under-insurance matters much more for lower income borrowers than higher income borrowers. For low income borrowers, a 1% decrease in coverage increases 5-year delinquency by nearly 45bp, while for high income borrowers, we do not find a statistically significant effect of coverage on serious delinquency. This treatment effect heterogeneity makes intuitive sense, since higher income households likely have other resources with which they can smooth disaster shocks, while lower income households likely rely more heavily on homeowners insurance to smooth shocks.

To interpret these magnitudes, we consider the counterfactual delinquency rate of constrained households if they had obtained the same coverage levels as unconstrained households. In our data, unconstrained households have roughly 10% more coverage amounts than constrained households, as

measured by income (Figure 2a).[49] The estimate in column (1) of Table 10 implies that constrained households would have a 2.2 pp lower delinquency if they obtained the coverage levels of unconstrained households.

Overall, these results highlight a new channel for mortgage delinquency risk which operates through households being under-insured. This channel is different from some other mechanisms in the literature that link insurance to mortgage default. For example, the literature shows that large unexpected costs or transfers, such as receiving Medicaid coverage (e.g., Indarte and Bornstein (2017)), insolvency of insurers (Sastry et al. (2024), or unexpected hikes in premiums (Ge et al. (2024)) change household debt and delinquency. In contrast to this literature, we show how insurance price shocks *at loan origination* lead to dropped coverage and higher levels of debt, which increase delinquency risk over the entire life of the loan. Taken together, the results show that insurance coverage plays a key role in households' financial resiliency.

7. Conclusion

This paper provides some of the first loan-level national estimates on household under-insurance by connecting state-of-the-art mortgage, climate, and insurance databases at a property level. While nearly all mortgage borrowers have homeowners insurance policies, we show that the average household does not have *enough* coverage. Coverage ratios are the lowest for borrowers with low incomes and low credit scores. We use a range of natural experiments to show that rising premiums cause constrained households to drop coverage, while unconstrained households maintain coverage and increase their debt, taking out mortgages with higher debt-to-income ratios and higher loan-to-value ratios. Lastly, we show under-insurance impacts mortgage default, particularly among constrained borrowers. These results suggest that rising premiums are leading to greater leverage and under-insurance, particularly among the most financially vulnerable households. Taken together, rising premiums are leaving households dangerously exposed to rising climate-related risks.

[49] That is, low income households had 65% coverage ratios, and high income households had 72%. This represents a 10% change in coverage amounts.

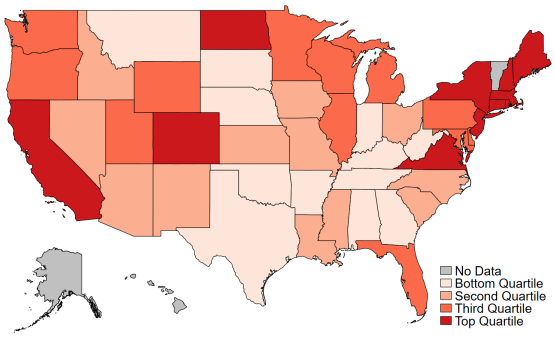
Tables and Figures

Figures

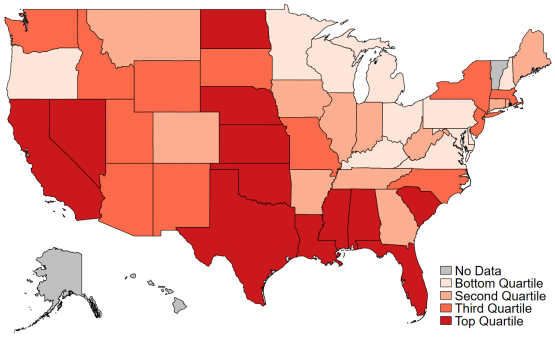
Figure 1: Spatial Distribution of Coverage, Risk and Income Across the U.S.

The maps show state-level variation in insurance coverage ratios (panel a), climate risk (panel b), and average borrower income (panel c), respectively. Coverage ratio is defined as insurance coverage amount divided by the estimated replacement costs, obtained by multiplying structure size and local construction costs from the R.S. Means Company. Insurance coverage data are from ICE-McDash, high climate risk are homes in the top decile by CoreLogic's AAL measure, and average borrower income is from Equifax. The figure is based on the main analysis sample, outlined in Section 1.2.

(a) Coverage Ratio



(b) Climate risk



(c) Borrower Income

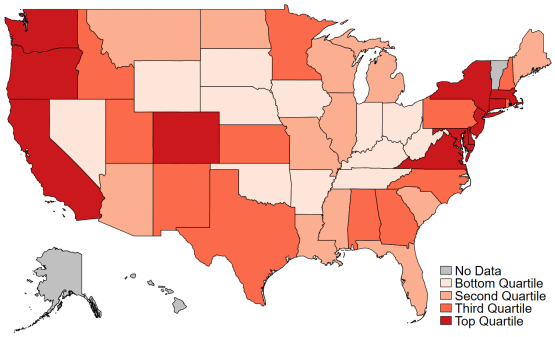
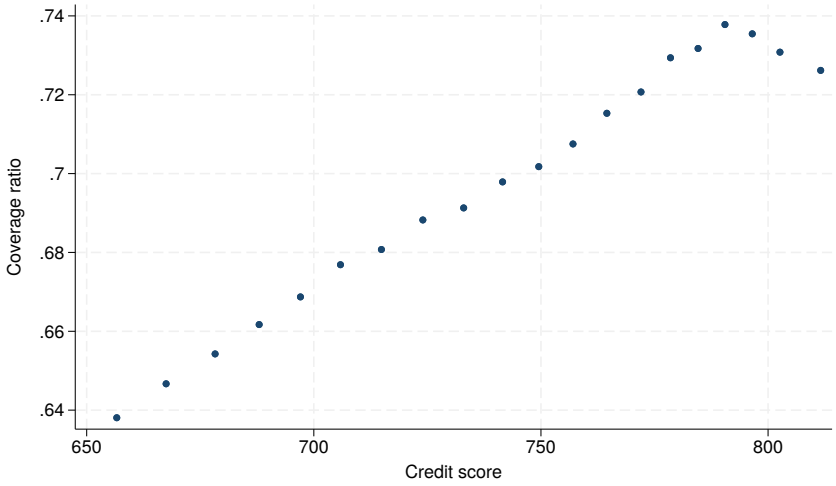


Figure 2: Coverage Ratios by Borrower Credit Score and Income

This figure shows a binned scatterplot of coverage ratios by borrower credit score (panel a) and income (in thousands) (panel b). Coverage ratio is defined as insurance coverage amount divided by the estimated replacement costs, obtained by multiplying structure size and local construction costs from the R.S. Means Company. The figure is based on the main analysis sample, outlined in Section 1.2.

(a) Borrower Credit Score



(b) Borrower Income

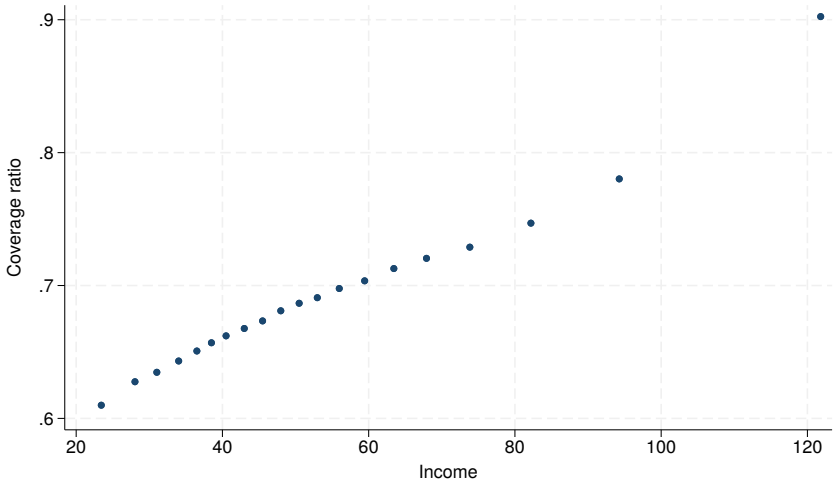
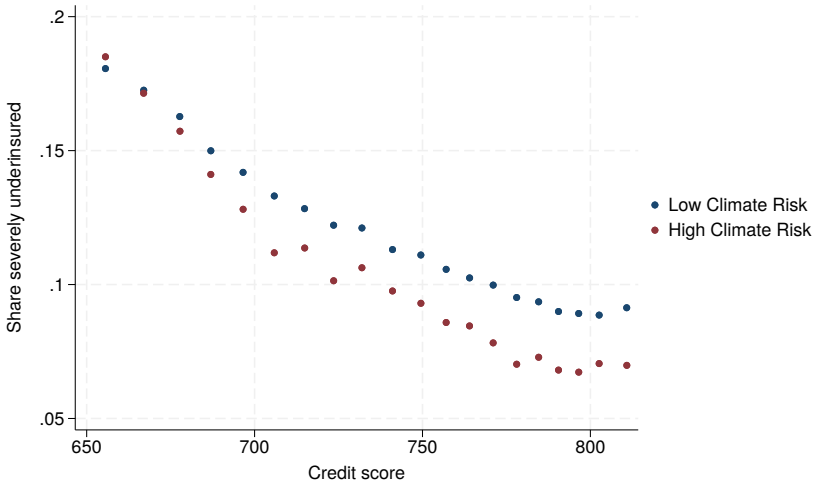


Figure 3: Severe Under-insurance by Borrower Income, Credit Score, and Climate Risk

This figure shows a binned scatter plot of the share of severely under-insured borrowers (coverage ratio of less than 50%) by borrower's credit score (panel a) and by income (in thousands) (panel b). The relationship is plotted separately for high and low climate risk properties, where "high climate risk" indicates those in the top decile of climate risk by CoreLogic's AAL measure. Coverage ratio is defined as insurance coverage amount divided by the estimated replacement costs, obtained by multiplying structure size and local construction costs from the R.S. Means Company. The figure is based on the main analysis sample, outlined in Section 1.2.

(a) Borrower Credit Score



(b) Borrower Income

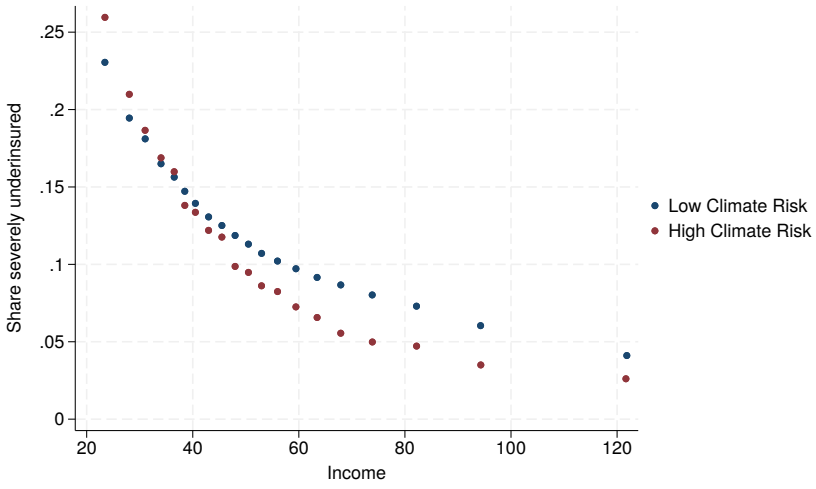
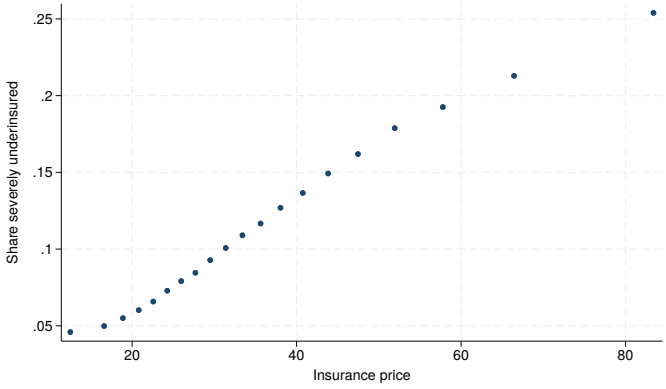


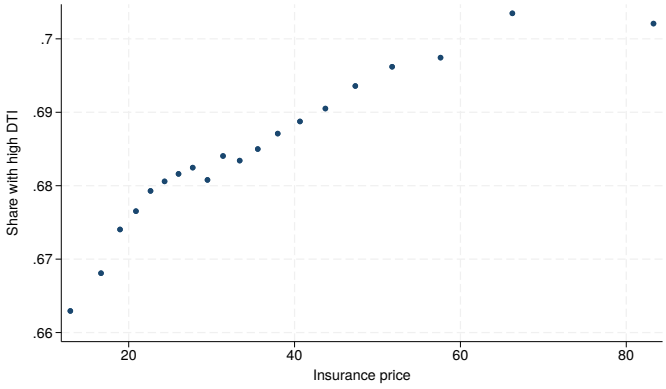
Figure 4: Severe Under-insurance and Household Debt by Insurance Prices

This figure shows a binned scatterplot of insurance prices and the share of severely underinsured borrowers (panel a), the share of high DTI ratio loans (panel b), and the share of high LTV ratio loans (panel c). Insurance price is measured as the monthly premium per $100,000 of coverage. Severely underinsured indicates a coverage ratio below 50%, where coverage ratio is defined as insurance coverage amount divided by the estimated replacement costs, obtained by multiplying structure size and local construction costs from the R.S. Means Company. High DTI loans have a DTI ratio over 31% at origination. High LTV loans have an LTV ratio over 80% at origination. The figure is based on the main analysis sample, outlined in Section 1.2.

(a) Share of Severely Under-insured Mortgages



(b) Share of Mortgages with High DTI Ratio



(c) Share of Mortgages with High LTV Ratio

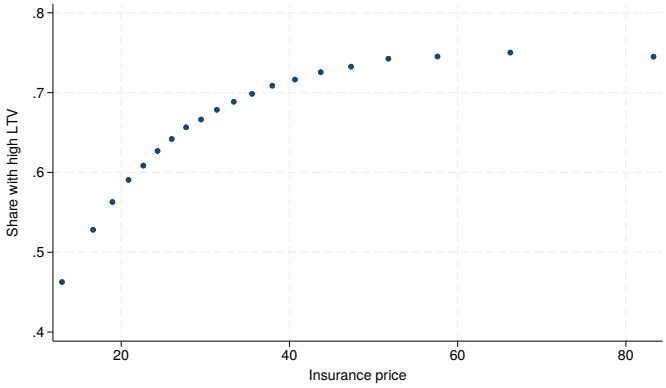


Figure 5: Mortgage Delinquencies by Coverage Ratios

This figure shows a binned scatter plot of serious mortgage delinquency over a 5-year horizon from origination by coverage ratio. Coverage ratio is defined as insurance coverage amount divided by the estimated replacement costs, obtained by multiplying structure size and local construction costs from the R.S. Means Company. The 5-year delinquency rate measures the probability of the loan becoming at least 90-days delinquent during the 5 years following origination. The figure is based on the main analysis sample, outlined in Section 1.2, which we limit further to loans with origination dates before 2018, so we observe a full five years of performance data following origination.

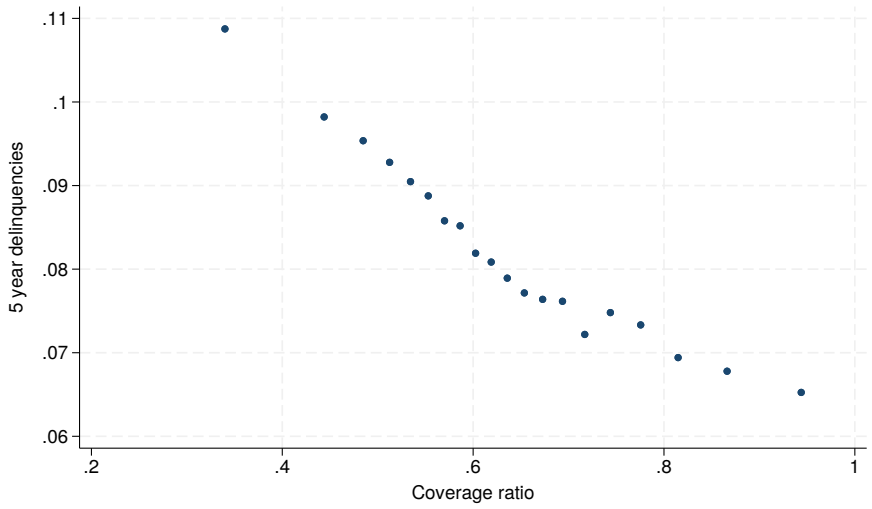
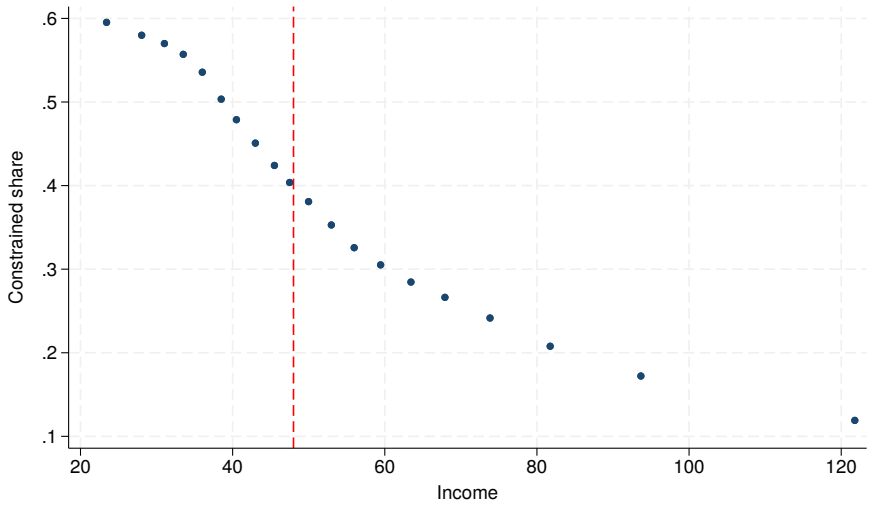


Figure 6: Mortgage Market Constraints and Borrower Income

This figure shows a binned scatter plot of borrower income (in thousands) and a measure of mortgage market borrowing constraints. We define borrowers to be constrained if they are either at the binding LTV constraint (LTV exceeds 95%) or at the binding DTI constraint (DTI exceeds 45%). The figure shows the constrained share, i.e. the fraction of borrowers in a given income ventile that are constrained. The red vertical line indicates the median income in the sample.



Tables

Table 1: Summary Statistics

This table presents the summary statistics for the main analysis sample, outlined in Section 1.2. High climate risk refers to properties in the top decile of climate risk by CoreLogic's AAL measure. Coverage amount is from ICE-McDash. Coverage ratio is defined as insurance coverage amount divided by the estimated replacement costs, obtained by multiplying structure size and local construction costs from the R.S. Means Company. Share underinsured refers to fraction of borrowers with insurance coverage ratios below 70% and share severely underinsured refers to fraction of borrowers with insurance coverage ratios below 50%. Insurance price is the monthly insurance premium per $100,000 of coverage. Share with high DTI refers to the fraction of borrowers with debt-to-income ratios above 31%. Share with high LTV refers to the fraction of borrowers with LTV ratios above 80%. Interest rate is the rate on the mortgage loan. The market interest rate is the monthly average of the primary mortgage market survey (PMMS) 30-year mortgage rate. We group states into two types: high and low friction, following the classification in Oh et al. (2021). High friction are states in the top tercile of regulatory friction and low friction are all the remaining states.

	All States		Low Friction		High Friction	
	(1) Mean	(2) SD	(3) Mean	(4) SD	(5) Mean	(6) SD
Share with high climate risk	0.096	0.29	0.089	0.28	0.11	0.31
Coverage Amount	275152.4	140191.1	272149.1	140297.1	278880.7	139969.7
Coverage Ratio	0.69	0.20	0.69	0.20	0.68	0.19
Share underinsured	0.61	0.49	0.61	0.49	0.61	0.49
Share severely underinsured	0.12	0.33	0.12	0.32	0.13	0.33
Annual Insurance Premium	1123.6	605.3	1138.3	632.2	1105.4	569.8
Insurance Price	38.1	20.7	39.1	21.9	36.9	19.1
Annual Income	54.0	23.5	54.2	23.6	53.7	23.3
Building Size (Sq. Feet)	1968.7	817.2	1984.2	823.3	1949.5	809.3
Loan Amount	233331.4	136840.8	234202.9	137573.6	232249.5	135918.0
DTI Ratio	35.9	9.52	35.7	9.59	36.2	9.42
LTV Ratio	86.9	13.0	86.7	13.2	87.2	12.6
Credit Score	733.2	51.7	734.0	51.9	732.2	51.4
Share with high DTI	0.69	0.46	0.68	0.47	0.70	0.46
Share with high LTV	0.66	0.47	0.66	0.47	0.67	0.47
Interest Rate	4.07	0.63	4.06	0.62	4.09	0.63
Market Interest Rate	3.95	0.49				
N	3271262		1811792		1459470	

Table 2: First-Stage Results: Instrumenting Insurance Prices in Low Friction States using High Friction States

This table presents the first stage of the two-stage least squares regression shown in Equation 13. The analysis uses the sample of low friction states. The dependent variable is log insurance price (monthly premiums per $100,000 of coverage), and the instrument is the log of average prices in high friction states for each credit score group in each year. High and low friction states are as defined in Section 1.2. Specifications include controls for property and borrower characteristics where indicated. Property-level controls include a dummy for whether the property is classified high climate risk (average annual loss is in the top decile), and the property's replacement cost. Borrower controls include log income and credit score. All specifications include ZIP-year fixed effects. Standard errors are clustered at the county level. The sample is as outlined in Section 1.2, but limited to the sample of loans in low friction states. Note: *p<0.1; **p<0.05; ***p<0.01.

	$\ln P_{iczt}$	
	(1)	(2)
$\ln \bar{P}_{HF,ct}$	0.358***	0.116***
	(0.0132)	(0.00538)
ZIP-Year FE	Y	Y
Property Controls	Y	Y
Borrower Controls	N	Y
Number of Observations	1791932	1791932
Adjusted R-squared	0.629	0.635

Table 3: Second-Stage Results: Coverage Demand Elasticity Estimation

This table presents the second stage of the two-stage least squares regression shown in Equation 14. The analysis uses the sample of low friction states. The dependent variable is log coverage amount. The independent variable is log insurance price (monthly premiums per $100,000 of coverage), instrumented using average prices in high friction states for each credit score group in each year. High and low friction states are as defined in Section 1.2. Specifications include ZIP-year fixed effects and controls for property and borrower characteristics, as indicated. The exact list of control variables is as outlined in Table 2. Standard errors are clustered at the county level. The sample is as outlined in Section 1.2, but limited to the sample of loans in low friction states. Note: *p<0.1; **p<0.05; ***p<0.01.

	ln coverage$_{izct}$	
	(1)	(2)
$\widehat{\ln P_{izt}}$	-0.438***	-0.107***
	(0.0190)	(0.0208)
ZIP-Year FE	Y	Y
Property Controls	Y	Y
Borrower Controls	N	Y
Number of Observations	1791932	1791932
First-stage F	739.9	462.2

Table 4: Second-Stage Results: Heterogeneity in Coverage Demand Elasticity by Income and Climate Risk

This table shows heterogeneity in the second stage estimates of the two-stage least squares regression shown in Equation 14. We present the results for two sub-samples: those with above versus below median income (Columns 1 and 2), and those in the top decile of climate risk versus all others (Columns 3 and 4). The analysis uses the sample of low friction states. The dependent variable is log coverage amount. The independent variable is log insurance price (monthly premiums per $100,000 of coverage), instrumented using average prices in high friction states for each credit score group in each year. High and low friction states are as defined in Section 1.2. Specifications include ZIP-year fixed effects and controls for property and borrower characteristics, as indicated. The exact list of control variables is as outlined in Table 2. Standard errors are clustered at the county level. The sample is as outlined in Section 1.2, but limited to the sample of loans in low friction states. Note: *p<0.1; **p<0.05; ***p<0.01.

	ln coverage$_{izct}$			
	By Income		By Climate Risk	
	(1) Low Income	(2) High Income	(3) Low Risk	(4) High Risk
$\widehat{\ln P_{iczt}}$	-0.192***	-0.0817***	-0.108***	-0.0868
	(0.0244)	(0.0252)	(0.0207)	(0.114)
ZIP-Year FE	Y	Y	Y	Y
Property Controls	Y	Y	Y	Y
Borrower Controls	Y	Y	Y	Y
Number of Observations	838569	933953	1631325	148200
First-stage F	384.3	250.4	536.7	12.38

Table 5: Second-Stage Results: Elasticity of Mortgage Debt with respect to Insurance Prices

This table presents the second stage of the two-stage least squares regression shown in Equation 15. The analysis uses the sample of low friction states. The dependent variables in columns 1 and 2 are the log of the loan's DTI ratio and in columns 3 and 4 the log of the loan's LTV ratio, both taken as of origination. The independent variable is log insurance price (monthly premiums per $100,000 of coverage), instrumented using average prices in high friction states for each credit score group in each year. High and low friction states are as defined in Section 1.2. Specifications include ZIP-year fixed effects and controls for property and borrower characteristics, as indicated. The exact list of control variables is as outlined in Table 2. Standard errors are clustered at the county level. The sample is as outlined in Section 1.2, but limited to the sample of loans in low friction states. Note: *p<0.1; **p<0.05; ***p<0.01.

	ln DTI_{izct}		ln LTV_{izct}	
	(1)	(2)	(3)	(4)
$\widehat{\ln P_{izct}}$	1.050***	1.217***	0.608***	0.695***
	(0.0412)	(0.0648)	(0.0232)	(0.0407)
ZIP-Year FE	Y	Y	Y	Y
Property Controls	Y	Y	Y	Y
Borrower Controls	N	Y	N	Y
Number of Observations	1791932	1791932	1791932	1791932
First-stage F	739.9	462.2	739.9	462.2

Table 6: Second-Stage Results: Heterogeneity in Elasticity of Mortgage Debt with respect to Insurance Prices by Income and Climate Risk

This table presents heterogeneity in the second stage estimates of the two-stage least squares regression shown in Equation 15. We present the results for two sub-samples: those with above versus below median income (Columns 1 and 2), and those in the top decile of climate risk versus all others (Columns 3 and 4). The analysis uses the sample of low friction states. For all specifications, the dependent variable is the log of the loan's LTV ratio at origination. The independent variable is log insurance price (monthly premiums per $100,000 of coverage), instrumented using average prices in high friction states for each credit score group in each year. High and low friction states are as defined in Section 1.2. Specifications include ZIP-year fixed effects and controls for property and borrower characteristics, as indicated. The exact list of control variables is as outlined in Table 2. Standard errors are clustered at the county level. The sample is as outlined in Section 1.2, but limited to the sample of loans in low friction states. Note: *p<0.1; **p<0.05; ***p<0.01.

	$\ln \text{LTV}_{izct}$			
	By Income		By Climate Risk	
	(1) Low Income	(2) High Income	(3) Low Risk	(4) High Risk
$\widehat{\ln P_{izct}}$	0.529***	1.078***	0.649***	1.654***
	(0.0365)	(0.0653)	(0.0345)	(0.527)
ZIP-Year FE	Y	Y	Y	Y
Property Controls	Y	Y	Y	Y
Borrower Controls	Y	Y	Y	Y
Number of Observations	838569	933953	1631325	148200
First-stage F	384.3	250.4	536.7	12.38

Table 7: The Effect of Required Mortgage Insurance Discontinuity on Coverage Elasticities

This table presents the second stage of the two-stage least squares regression shown in Equation 16. The dependent variable is log coverage amount. The independent variables are log insurance price (monthly premiums per $100,000 of coverage), instrumented using average prices in high friction states for each credit score group in each year; a dummy variable indicating whether the loan's LTV ratio exceeds 80%; and log price × LTV dummy, instrumented with average prices in high friction states × LTV dummy. We limit the sample to two narrow bands around the 80% LTV threshold. Column 1 limits the sample to loans with LTV ratios between 70%- 90%, and column 2 limits the sample to loans with LTV ratios between 75%- 85%. High and low friction states are as defined in Section 1.2. Specifications include ZIP-year fixed effects and controls for property and borrower characteristics, as indicated. The exact list of control variables is as outlined in Table 2. Standard errors are clustered at the county level. The sample is as outlined in Section 1.2, but limited to the sample of loans in low friction states. Note: *p<0.1; **p<0.05; ***p<0.01.

	ln coverage$_{izct}$	
	70-90% LTV	75-85% LTV
	(1)	(2)
$\widehat{\ln P_{izct} \times I(LTV > 80\%)_{izct}}$	-0.0527***	-0.0598***
	(0.00845)	(0.0130)
$\widehat{\ln P_{izct}}$	-0.143***	-0.114***
	(0.0276)	(0.0379)
$I(LTV > 80\%)_{izct}$	0.176***	0.196***
	(0.0296)	(0.0456)
ZIP-Year FE	Y	Y
Property Controls	Y	Y
Borrower Controls	Y	Y
Number of Observations	585430	358570
Adjusted R-squared	0.651	0.646
First-stage F Stat	131.0	99.08

Table 8: The Effect of Market-wide Interest Rate Shocks on Coverage Elasticities

This table presents the results of the regression shown in Equation 17. The dependent variable is log coverage amount. The independent variables are log insurance price (monthly premiums per $100,000 of coverage) in high friction states for each credit score group in each year; the market rate; and the interaction between the two variables. The market rate is the monthly average of the primary mortgage market survey (PMMS) rate for 30-year fixed-rate mortgages. High and low friction states are as defined in Section 1.2. Specifications include ZIP-year fixed effects and controls for property and borrower characteristics, as indicated. The exact list of control variables is as outlined in Table 2. Standard errors are clustered at the county level. The sample is as outlined in Section 1.2, but limited to the sample of loans in low friction states. Note: *p<0.1; **p<0.05; ***p<0.01.

	ln coverage$_{izct}$	
	(1)	(2)
ln $\bar{P}_{HF,ct}$	-0.121***	0.0200*
	(0.0120)	(0.0110)
market rate$_t$	0.0357***	0.0336***
	(0.0102)	(0.0101)
ln $\bar{P}_{HF,ct}$ × market rate$_t$	-0.00904***	-0.00825***
	(0.00271)	(0.00267)
ZIP-Year FE	Y	Y
Property Controls	Y	Y
Borrower Controls	N	Y
Number of Observations	1791932	1791932

Table 9: Second-Stage Results: Effect of Underinsurance on Mortgage Delinquency

This table presents the second stage of the two-stage least squares linear probability regression shown in Equation 19. The dependent variable is an indicator equal to one if the borrower ever becomes seriously delinquent during the first 3 years following origination (columns 1 and 2) or during the first 5 years following origination (columns 3 and 4). Serious delinquency refers to more than three consecutive months of missed mortgage payments. For columns 1 and 2 (3 and 4), we limit the sample to loans with origination dates before 2020 (2018), so we observe a full three (five) years performance data following origination. The independent variable is log coverage amount, instrumented using the market rate at the time of origination. High and low friction states are as defined in Section 1.2. Specifications include ZIP-year fixed effects and controls for property and borrower characteristics, as indicated, with the exact list as outlined in Table 2. All specifications include additional controls for the mortgage contract (LTV ratio, DTI ratio, individual loan interest rate). Some specifications also control for insurance price, where indicated. Standard errors are clustered at the county level. The sample is as outlined in Section 1.2, but limited to the sample of loans in low friction states. Note: *p<0.1; **p<0.05; ***p<0.01.

	Serious Delinquency (3Y)		Serious Delinquency (5Y)	
	(1)	(2)	(3)	(4)
$\widehat{\ln \text{coverage}}_{izt}$	-0.116***	-0.121***	-0.208***	-0.214***
	(0.0383)	(0.0394)	(0.0545)	(0.0553)
ZIP-Year FE	Y	Y	Y	Y
Property Controls	Y	Y	Y	Y
Borrower Controls	Y	Y	Y	Y
Mortgage Controls	Y	Y	Y	Y
Insurance Price Control	N	Y	N	Y
Number of Observations	1292577	1292577	765160	765160
First-stage F	265.9	301.4	482.3	516.3

Table 10: Second-Stage Results: Effect of Underinsurance on Mortgage Delinquency - Heterogeneity by Income

This table presents the heterogeneity in the second stage estimates of two-stage least squares linear probability regressions shown in Equation 19. We split the main sample into those with above and below median income. The dependent variable is an indicator equal to one if the borrower ever becomes seriously delinquent during the first 3 years following origination (columns 1 and 2) or during the first 5 years following origination (columns 3 and 4). Serious delinquency refers to more than three consecutive months of missed mortgage payments. For columns 1 and 2 (3 and 4), we limit the sample to loans with origination dates before 2020 (2018), so we observe a full three (five) years performance data following origination. The independent variable is log coverage amount, instrumented using the market rate at the time of origination. High and low friction states are as defined in Section 1.2. Specifications include ZIP-year fixed effects and controls for property and borrower characteristics, as indicated, with the exact list as outlined in Table 2. All specifications include additional controls for the mortgage contract (LTV ratio, DTI ratio, individual loan interest rate). All specifications also control for insurance price, as indicated. Standard errors are clustered at the county level. The sample is as outlined in Section 1.2, but limited to the sample of loans in low friction states. Note: *p<0.1; **p<0.05; ***p<0.01.

	Serious Delinquency (3Y)		Serious Delinquency (5Y)	
	Low Income	High Income	Low Income	High Income
	(1)	(2)	(3)	(4)
$\widehat{\ln \text{coverage}}_{izt}$	-0.221***	-0.0454	-0.446***	-0.0158
	(0.0733)	(0.0328)	(0.101)	(0.0407)
ZIP-Year FE	Y	Y	Y	Y
Property Controls	Y	Y	Y	Y
Borrower Controls	Y	Y	Y	Y
Mortgage Controls	Y	Y	Y	Y
Insurance Price Control	Y	Y	Y	Y
Number of Observations	653663	622440	409096	343169
First-stage F	171.2	257.8	224.7	361.3

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A. Additional Details on Data

This appendix provides additional details on the data sources, the process to construct the final sample, and high-level analysis and descriptions of key variables.

A.1. Data Construction

Our main dataset is the ICE-McDash mortgage and insurance modules, which combine data on both mortgages and homeowners insurance for mortgage borrowers whose insurance payments are escrowed. While the ICE-McDash (hereafter "McDash") mortgage data are commonly used in academic research, the insurance module is a newly available dataset that was only recently made available starting in 2024.

Sample representativeness. McDash collects homeowners insurance information for a subset of mortgages, based on whether specific servicers have agreed to report insurance contract details to ICE-McDash and whether borrowers escrow insurance. To ensure that our sample is representative of the broader McDash universe of mortgages, we compare borrower incomes, loan amounts, back-end debt-to-income ratios, loan-to-value ratios, and credit scores for loans in the insurance module with loans in the overall McDash samples. Table C.1 shows that the loans in the McDash insurance module are broadly representative of the loans in McDash's mortgage origination module across a range of borrower characteristics. For example, average credit score is 735 in our insurance module vs. 737 in the overall McDash; LTV ratio is 86 (insurance) vs. 85 (overall); DTI ratio is 35.8 (insurance) vs. 35.1 (overall), loan amount is $243K (insurance) vs. $257K (overall), and annual income is $55K (insurance) vs. $51K (overall). This makes us comfortable that the insurance module is broadly representative of the McDash mortgage sample.

Key details of database merges. Figure C.1 provides a high-level schematic of how we combine loan-level information on mortgage, insurance, and borrower characteristics, with property-level databases. Below we provide further details. We start with merging the McDash insurance and mortgage modules. Next, we merge in Credit Risk Insights McDash (CRISM), which includes Equifax's Personal Income Model. We retain the credit profile of the primary borrower, only for matches with over a 80% confidence rate, as determined by McDash.

Next, we merge CoreLogic Deeds data using a fuzzy matching algorithm based on common

variables available in both datasets (namely the zip code, origination date, loan amount, loan purpose (refinance/purchase), and loan type (i.e. FHA, VA, etc)). These merge fields generate about a 50% match rate and have a duplication rate of under 5%. We drop duplicate matches. We additionally validated this match algorithm using the Federal Reserve's FR Y-14 data, which allows for an exact address match. We find that unique matches using our match algorithm were accurate in over 95% of cases. A match with the mortgage deeds using Y14 data also has about the same match rate as the McDash data, suggesting that mortgage deeds records-keeping - and not our match algorithm - is the main driver of sample attrition.

Using the CoreLogic unique property identifier, we next merge in property-level tax and climate risk data. The tax data cover property characteristics used for tax assessments, including the structure size, among other things. With these core merges, we have, for each loan, the mortgage and insurance contract, borrower characteristics, and property characteristics. Because for years 2013 to 2023, insurance data are only updated in December, we use the insurance information as of the first December after origination date to provide us a picture of the key insurance contract terms at origination. We also retain mortgage performance data only for December for subsequent observations on the same loan, to remain consistent with insurance data updates.

Finally, we bring in data on construction costs at the location and year levels. The final merged sample consists of roughly 75 million observations, which include both information as of mortgage origination and subsequent information on mortgage performance at a monthly frequency. We limit the merged sample to single-family home *purchase mortgages* originated on or after 2013, dropping loans associated with re-finances. As described in Section 1.2, we also limit the main sample to the time of mortgage origination.

A.2. Measurement of Coverage

The coverage variable we observe in our data refers to basic policy limits for the structure. Some homeowners may choose to add-on extended coverage, but they can only do so if their basic coverage is at least equal to 100% of their replacement cost. For example, Klein (2018) writes that extended coverage cannot be provided unless "the basic coverage is at least as great as the estimated replacement cost of the property." Similarly, the insurance consulting firm *Marsh McLennan* also writes "When you insure your home to 100% of its replacement cost value, some insurance companies

will offer the benefit of extended replacement cost. This provision will pay beyond your policy limit should the amount at the time of loss not be adequate," available here. Extended benefits are not intended to substitute for basic coverage choices. Therefore, we argue that our measure of coverage accurately captures underinsurance.

To support our claim, we independently verify our estimates with external sources. A number of independent sources also find that the average household is under-insured by nearly 20-30%, matching our estimates. For example, Klein (2018) claims that while prior to 1990 most insurance contracts guaranteed full coverage by default, in the last 30 years the market has moved towards wide-spread under-insurance. Similarly, Nationwide Insurance estimated that households were on average under-insured by 22%, and that two-thirds of Americans are under-insured (see Nationwide's estimates quoted in PropertyCasualty360 (2021)). Similarly, CoreLogic also estimates that nearly two-thirds of Americans are under-insured, and that they are under-insured by an average of 27% (see CoreLogic quoted in Newbrook Insurance Agency (2022)).

A.3. Broad Data Description

Given the novelty of our data, we provide a broad description of the sample, looking at trends over time, correlations across space, and explanatory power of different variables and characteristics.

A.3.1. Summary Statistics

We start by showing the evolution of premiums and coverage over the entire same period. Figure C.2b shows that annual premiums have increased substantially. The median household had a premium of about $800 in 2013, which increased to roughly $1500 in 2023 at the end of the sample (87% increase). The increase at the 75th percentile is from $1200 to about $2000 (67% increase), rising faster than the rate of inflation. These patterns are consistent with other papers showing rising premiums in the recent period (Mulder and Keys, 2024). During the same period, we also see coverage levels increase, but at a much slower rate (Figure C.2a). The median household increased coverage from $217,000 in 2013 to $284,000 in 2023 (31% increase). Similarly households at the 75th percentile increased coverage from $295,000 to $375,000 (27% increase).

The patterns in the time series mask significant variation in the cross-section. Figure C.3 plots a histogram of coverage ratios over the sample. The vast majority of the households have coverage ratios below 1, i.e. their coverage limits are below the rebuilding cost of their homes. Table 1 shows

that the average coverage ratio is around 70%, and that households with one standard deviation less coverage have a coverage ratio of about 50%.

Next, we examine the spatial distribution of coverage ratios in Figure 1, along with the distribution of income and climate risk. Two patters emerge. First, the states in the top quartile by income (between $56,000 and 85,000 per year in Figure 1c) are also states with the highest coverage ratios (above 73% from Figure 1a). Second, states with the highest climate risk are *not* the ones with the most coverage. For example, Texas is one of the riskiest states, with 24% of its properties classified as high risk. Yet its average coverage ratio is only 62%, putting it in the bottom quartile. Similarly, Maine is very low climate risk state, with less than 2% of its properties being high risk – yet it has among the highest average coverage ratios in the country, at 82%. At the state level, income and coverage ratios have a 77% correlation. In contrast, climate risk and coverage ratio have a -18% correlation. These broad patterns suggest that household income plays an important role in coverage choices, with higher income states having on average higher coverage ratios.

A.3.2. Explaining the Variation in Coverage Ratios and Insurance Prices

We next provide examine which types of loan-level variables drive the variation in coverage ratios and insurance prices. We consider the following broad categories of variables. zip-year fixed effects, housing (rebuild costs), climate, mortgage contract, and insurance contract. In Figure C.4a, we find that zip-year fixed effects alone explain 40% of the variation in coverage choices. Adding our proxy for rebuild costs increases the R^2 by another 30%. Rebuild cost's high explanatory power and its high correlation with house prices further help validate our use of this proxy. We also find that mortgage variables have high explanatory power: together with zip-year fixed effects, they increase the R^2 to 77%. Interestingly, climate variables or insurance-contract variables do not explain as much of the variation. Finally, the full set of variables explain 85% of the variation in coverage choices. Taken together, the results suggest that mortgage variables, which include several types of borrower characteristics that proxy for credit constraints, play an important role in explaining the variation in coverage choices, a hypothesis we explore in great detail in the paper. We use this result to motivate our detailed look at the relation between borrower characteristics, mortgage contract, and insurance coverage choices.

In Figure C.4b we examine the drivers of variation in insurance prices. The most predictive

variable category is zip-year fixed effects, explaining close to 65% of the variation in prices. Adding housing, climate, mortgage, or insurance variables increases R^2 by less than 10%.

A.3.3. Coverage Ratio and Loan Age

We next examine how coverage ratios evolve as a loan ages over time. In Figure C.5 we plot a binned scatter plot of coverage ratios by loan age, after controlling for a loan fixed effect. We find limited evidence that a borrower significantly adjusts coverage ratios over the life of the loan. There are two reasons why this result is important. First, as coverage ratios are flat throughout the life of the loan implies that household under-insurance begins at origination and is persistent. Therefore, in our main analysis, we focus on insurance choices at mortgage origination. Second, a flat coverage ratio also points to limited borrower strategic behavior. A natural model of strategic behavior would suggest that households' incentives to insure *increases* as the loan ages, all else equal (Liao and Mulder, 2021), as households build up equity in the house over the life of the loan. Therefore, this pattern suggests that under-insurance is not likely to be driven by strategic behavior by indebted households having limited incentives to hedge.

A.4. Supplementary Data

FIO Data on Homeowners Insurance: The U.S. Treasury Department's Federal Insurance Office (FIO) in conjunction with the NAIC conducted a data call where they collect homeowners insurance data on premiums and claims from the largest 400 insurance companies, who represent over 80% of the property insurance market by premium volume. The data was collected at a ZIP code - year level, spanning 2018-2022. While the insurer submissions remain confidential, but the FIO released averages at the zip-level with information on claim probabilities, claim severity, loss ratios, and premiums. We use these estimates to validate the instrument in Section 3

B. Proofs

B.1. First Order Conditions

We can derive the first-order conditions (FOCs) with respect to c_t and k_t by differentiating the Bellman equation in Equation 6 subject to the constraints and the transversality condition.

FOC w.r.t. c_t:

$$\frac{\partial}{\partial c_t}\left[U(c_t) + \beta E_t V(w_{t+1})\right] = 0$$

$$U'(c_t) + \beta(E_t V'(w_{t+1})\frac{\partial w_{t+1}}{\partial c_t}) + \lambda_t(\frac{\partial S_t}{\partial c_t}) = 0$$

$$U'(c_t) - \beta(1+r)E_t V'(w_{t+1}) - \lambda_t = 0$$

This yields the FOC in Equation 8.

FOC w.r.t. k_t:

$$\frac{\partial}{\partial k_t}\left[U(c_t) + \beta E_t V(w_{t+1})\right] = 0$$

$$E_t\left[V'(w_{t+1})\frac{\partial w_{t+1}}{\partial k_t}\right] + \lambda_t(\frac{\partial S_t}{\partial k_t}) = 0$$

$$E_t\left[V'(w_{t+1})(-(1+r)p + y_{t+1}M)\right] - \lambda_t p = 0$$

This yields the FOC in Equation 9. We represent this optimality condition with the function $G(c_t, k_t)$.

B.2. Propositions

Lemma. $G(c_t, k_t)$ is decreasing in k_t.

Proof of Lemma. Differentiating $G(c_t, k_t)$ with respect to k_t we get:

$$\frac{\partial G}{\partial k_t} = E_t\left[V''(w_{t+1}) \cdot \frac{\partial w_{t+1}}{\partial k_t} \cdot (-(1+r)p + y_{t+1}M)\right]$$

Note that $\frac{\partial w_{t+1}}{\partial k_t} = (-(1+r)p + y_{t+1}M)$. Substituting this in we get:

$$\frac{\partial G}{\partial k_t} = E_t\left[V''(w_{t+1}) \cdot (-(1+r)p + y_{t+1}M) \cdot (-(1+r)p + y_{t+1}M)\right]$$

This derivative is negative because (i) $V''(w_{t+1})$ is negative due to the concavity of the value function (risk aversion). (ii) $(-(1+r)p+yM)^2$ is a squared term. Thus, $G(c_t, k_t)$ is indeed decreasing in k.

Proof of Proposition 1A. We first show that $k_t = 1$ is a solution to the optimality condition in Equation 9, and then show that it is the unique solution.

When there is no borrowing constraint ($s = -\infty$), we have the Lagrange multiplier on the borrowing constraint $\lambda_t = 0$. This implies that Equation 9 becomes

$$G(c_t, k_t) = E_t\left[V'(w_{t+1})(-(1+r)p + y_{t+1}M)\right] = 0. \tag{B.20}$$

Full insurance is a solution. Let's assume that $k_t = 1$ then

$$w_{t+1} = (1+r)(w_t - c_t - p) + M. \tag{B.21}$$

Note that Equation B.21 holds with probability 1. That is, wealth is period $t+1$ is invariant to the loss event y as the individual is fully insured.

Substituting Equation B.21 into Equation B.20 we get:

$$V'(w_{t+1})E_t\left[-(1+r)p + y_{t+1}M\right] = 0,$$

where $V'(w_{t+1})$ comes out of the expectation as there is no uncertainty.

For actuarially fair insurance, we have that $p = \phi M/(1+r)$, where ϕ is the probability of loss given by $E_t(y_{t+1}) = \phi$. Thus, we have:

$$V'(w_{t+1})\left[-(1+r)(\phi M/(1+r)) + \phi M\right] = 0,$$

$$V'(w_{t+1})\left[-\phi M + \phi M\right] = 0,$$

$$V'(w_{t+1}) \cdot 0 = 0.$$

This shows that FOC is satisfied when $k_t = 1$, showing that $k_t = 1$ is a solution.

Uniqueness. We next show that it is the only solution. From the Lemma, we know that $G(c_t, k_t)$ is decreasing in k_t. Given that $G(c_t, 1) = 0$, we can conclude that $k_t = 1$ is the unique solution. To see why note that when $k_t < 1$, then $G(c_t, k)$ would still be positive as it is decreasing in k_t and equal to zero when $k_t = 1$, violating the optimality condition $G(c_t, k_t) = 0$. Assuming $k_t > 1$ (over-insurance) is not feasible, $k_t = 1$ is the unique solution.

Proof of Proposition 1B. *Demand elasticities.* As long as insurance remains actuarially fair, the optimal insurance choice will be full insurance ($k_t = 1$). This implies that the demand for insurance is perfectly inelastic (price elasticity = 0) at the actuarially fair price.

Proof of Proposition 2A. When borrowing constraints are binding, we have $\lambda_t > 0$. We evaluate $G(c_t, k_t)$ at $k_t = 1$. When $k_t = 1$, w_{t+1} is given by Equation B.21.

$$G(c_t, 1) = V'(w_{t+1}) E_t \left[-(1+r)p + y_{t+1}M\right] - \lambda_t p.$$

Since we assume, actuarially fair insurance,

$$G(c_t, 1) = V'(w_{t+1}) \left[-(1+r)(\phi M/(1+r)) + \phi M\right] - \lambda_t p$$

$$G(c_t, 1) = V'(w_{t+1}) \cdot 0 - \lambda_t p$$

$$G(c_t, 1) = -\lambda_t p < 0$$

This holds because $\lambda_t > 0$ (binding constraint) and $p > 0$.

From the Lemma, we know that $G(c_t, k_t)$ is decreasing in k_t. Since $G(c_t, 1) < 0$ and $G(c_t, k_t)$ is decreasing in k_t, the optimal k_t that satisfies $G(c_t, k_t) = 0$ must be less than 1. Therefore, with a binding borrowing constraint and actuarially fair insurance, the optimal insurance coverage is less than full insurance ($k < 1$).

Proof of Proposition 2B. *Demand elasticities.* To derive the expression for demand elasticity, we differentiate $G(c_t, k_t)$ with respect to p and with respect to k and apply the implicit function

theorem, $\frac{\partial k}{\partial p} = -\frac{\partial G}{\partial p} \ / \ \frac{\partial G}{\partial k}$.

$$\frac{\partial G}{\partial p} = E_t\left[V''(w_{t+1})(-(1+r)p + y_{t+1}M)\frac{\partial w_{t+1}}{\partial p}\right] - E_t\left[V'(w_{t+1})(1+r)\right] - \lambda_t$$

$$\frac{\partial G}{\partial k} = E_t\left[V''(w_{t+1})(-(1+r)p + y_{t+1}M)\frac{\partial w_{t+1}}{\partial k}\right]$$

From the Lemma, we know that the denominator $\frac{\partial G}{\partial k}$ is negative due to the concavity of the value function. We need the numerator $\frac{\partial G}{\partial p}$ to be negative (ensuring a negative $\frac{\partial k}{\partial p}$).

The second and the third term are negative, as

$$E_t\left[V'(w_{t+1})(1+r)\right] > 0, \lambda_t > 0.$$

The first term has three parts. The first part $V''(w_{t+1}) < 0$, and the third part $\frac{\partial w_{t+1}}{\partial p} < 0$. The part in the middle will be negative when $y_{t+1} = 0$ and will be positive when $y_{t+1} = 1$. Therefore, when $y_{t+1} = 0$, we have the entire first term negative, implying $\frac{\partial G}{\partial p} < 0$. Instead, when $y_{t+1} = 1$, we may have the first term as positive. However, note that the expectation is likely to be dominated by the higher probability event of no loss $y_{t+1} = 0$, implying that the first term is likely negative and $\frac{\partial G}{\partial p} < 0$. Therefore, we can conclude that $\frac{\partial k}{\partial p}$ is negative, implying a negative demand elasticity for insurance coverage with respect to price, as long as the probability of loss is not very high.[50]

Proof of Proposition 2C. Let k_t^u and k_t^c be the optimal coverage levels for the unconstrained and constrained cases respectively. From the first-order conditions:

$$\text{Unconstrained} \quad E_t\left[V'(w_{t+1}^u)(-(1+r)p + y_{t+1}M)\right] = 0$$

$$\text{Constrained} \quad E_t\left[V'(w_{t+1}^c)(-(1+r)p + y_{t+1}M)\right] - \lambda_t p = 0$$

Since $V'(w)$ is decreasing in w (due to concavity of V), and $E_t\left[-(1+r)p + y_{t+1}M\right] < 0$ (assuming

[50] We require $\phi < \frac{V''(w_{t+1}^0)p(1+r)\frac{\partial w_{t+1}^0}{\partial p}}{V''(w_{t+1}^1)(M-p(1+r))\frac{\partial w_{t+1}^1}{\partial p} + V''(w_{t+1}^0)p(1+r)\frac{\partial w_{t+1}^0}{\partial p}}$, where w_{t+1}^y is the optimum wealth evaluated at $y = 0$. Note that ϕ is a value between 0 and 1, because it takes the form of $\frac{f_0}{f_1+f_0}$ where both f_0 and f_1 are positive due to (i) the concavity of V and (ii) $\partial w_{t+1}/\partial p < 0$, since wealth decreases in insurance prices.

$p > E_t[y_{t+1}]\, M/(1+r))$, we must have $w^u_{t+1} > w^c_{t+1}$ to satisfy these conditions. This implies $k^u_t > k^c_t$.

Proof of Proposition 3A. *Unconstrained borrowers.* Differentiating the budget constraint with respect to p_t we get

$$\frac{\partial S_t}{\partial p_t} = -\frac{\partial c_t}{\partial p_t} - k_t - p_t \frac{\partial k_t}{\partial p_t},$$

since, $\frac{\partial w_t}{\partial p_t} = 0$ as wealth w_t is given at t.

We next evaluate the signs of each of the three terms.

(i) $\frac{\partial k_t}{\partial p_t} < 0$, as shown above. This makes the last term positive.

(ii) $k_t > 0$ so the middle term is negative.

(iii) We show below that $\frac{\partial c_t}{\partial p_t} < 0$. So, the first term is positive.

Thus, the overall sign of $\frac{\partial S_t}{\partial p_t}$ depends on the relative magnitudes of these three terms. When an individual is relatively inelastic, such that coverage does not change by a large amount as insurance price changes, the third term will be small. This also implies that the first term will be relatively small, implying that the middle term will dominate. If so, $\frac{\partial S_t}{\partial p_t} < 0$. Thus, as insurance prices increase S_t would fall, i.e. borrowing would rise. In contrast, when an individual is highly elastic, changes in insurance prices would bring large changes in insurance demand, making the positive term dominate. If so, $\frac{\partial S_t}{\partial p_t} > 0$. Thus, as insurance prices increase S_t would rise, i.e. borrowing would fall.

Sign of $\frac{\partial c_t}{\partial p_t}$: We differentiate $G(c_t, k_t)$ with respect to p and with respect to c and apply the implicit function theorem, $\frac{\partial c}{\partial p}$ = - $\frac{\partial G}{\partial p}$ / $\frac{\partial G}{\partial c}$.

As shown above, $\frac{\partial G}{\partial p} = E_t\left[V''(w_{t+1})(-(1+r)p + y_{t+1}M)\frac{\partial w_{t+1}}{\partial p}\right] - E_t\left[V'(w_{t+1})(1+r)\right] - \lambda_t < 0$ (see Proposition 2).

$$\frac{\partial G}{\partial c} = E_t\left[V''(w_{t+1})(-(1+r)p + y_{t+1}M)\frac{\partial w_{t+1}}{\partial c}\right]$$

$$\frac{\partial G}{\partial c} = -(1+r)\cdot E_t\left[V''(w_{t+1})(-(1+r)p + y_{t+1}M)\right]$$

Note that the first part $V''(w_{t+1}) < 0$, and the third part $\frac{\partial w_{t+1}}{\partial c} < 0$. The part in the middle will

be negative when $y_{t+1} = 0$ and will be positive when $y_{t+1} = 1$. Therefore, when $y_{t+1} = 0$, we have the entire term as negative, implying $\frac{\partial G}{\partial c} < 0$. Instead, when $y_{t+1} = 1$, we have the term as positive. However, note that the expectation is likely to be dominated by the higher probability event of no loss $y_{t+1} = 0$, implying that as long as the probability of loss is not very high, $\frac{\partial G}{\partial c} < 0$.[51]

Proof of Proposition 3B. *Constrained borrowers.* In the constrained case, debt is pinned down by the borrowing constraint as $\lambda_t > 0$, implying $S_t = s$. An increase in insurance prices does not make the budget constraint slack ($\partial\lambda_t/\partial p_t > 0$), implying S remains at s. Thus, $\partial S_t/\partial p_t = 0$.

[51] We require $\phi < \frac{V''(w^0_{t+1})p(1+r)}{V''(w^1_{t+1})(M-p(1+r))+V''(w^0_{t+1})p(1+r)}$. Note that ϕ is a value between 0 and 1, because it takes the form of $\frac{f_0}{f_1+f_0}$ where both f_0 and f_1 are less than 0 due to the concavity of V.

C. Additional Tables and Figures

Figure C.1: Data Construction Procedure

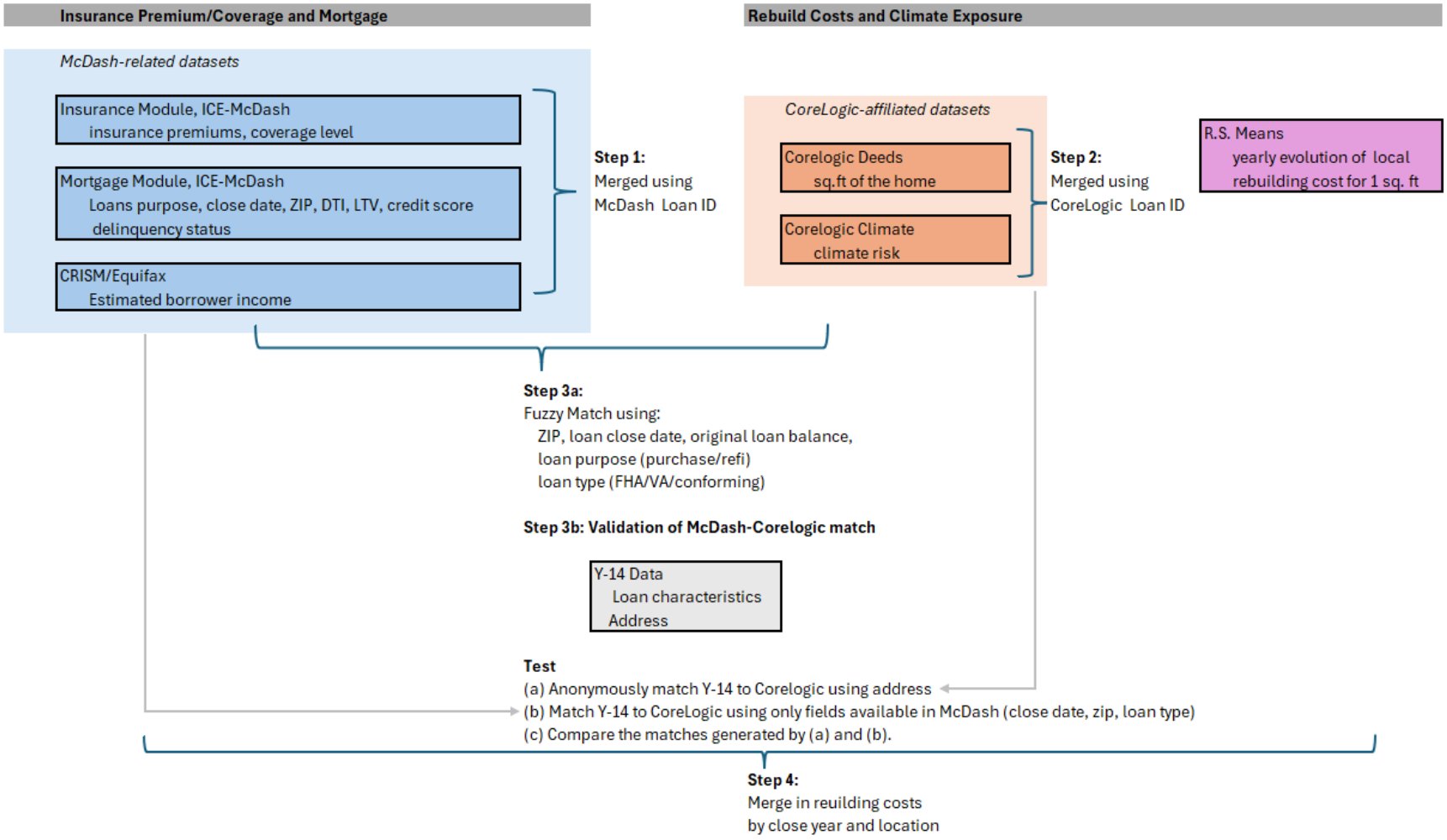
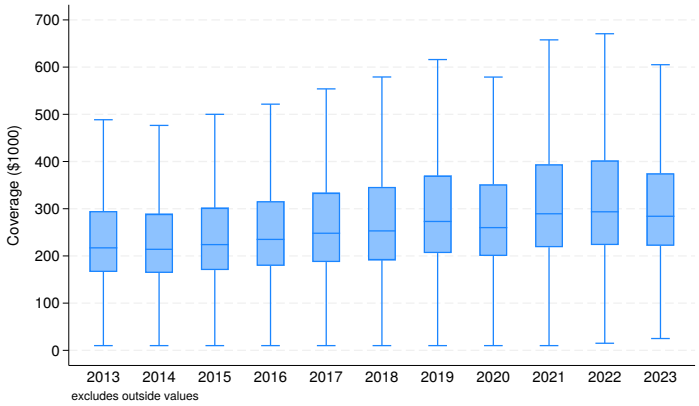


Figure C.2: Evolution of Insurance Coverage and Premiums Over Time

This figure shows a box plot time series of insurance coverage levels (nominal values reported in thousands) in panel a and annual insurance premiums in panel b. The shaded area indicates the inter-quartile range, with the median marked with a horizontal line. The whiskers indicate the upper and lower adjacent values. The data are from ICE-McDash. The figure is based on the main analysis sample, outlined in Section 1.2.

(a) Coverage Levels



(b) Insurance Premiums

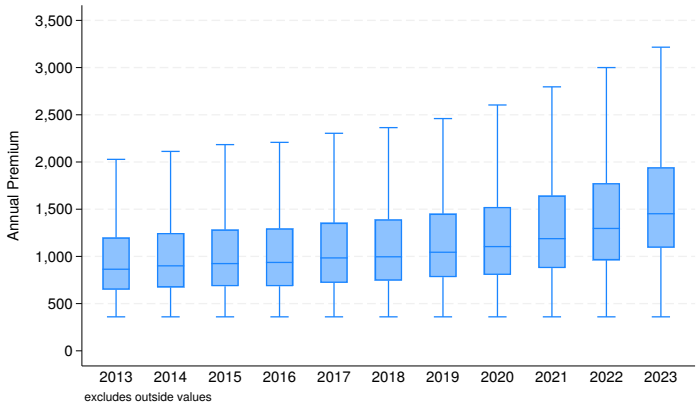


Figure C.3: Histogram of Coverage Ratio

This figure shows a histogram of coverage ratios, defined as insurance coverage amount divided by the estimated replacement cost, obtained by multiplying structure size and local construction costs from the R.S. Means Company. The insurance coverage data are from ICE-McDash. The figure is based on the main analysis sample, outlined in Section 1.2.

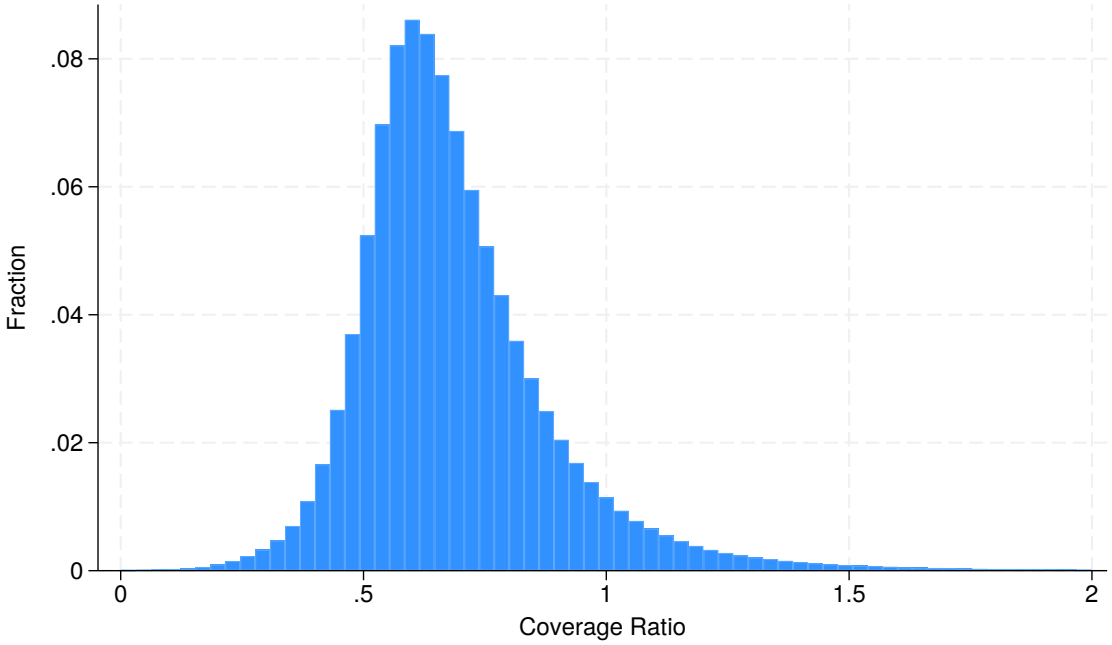
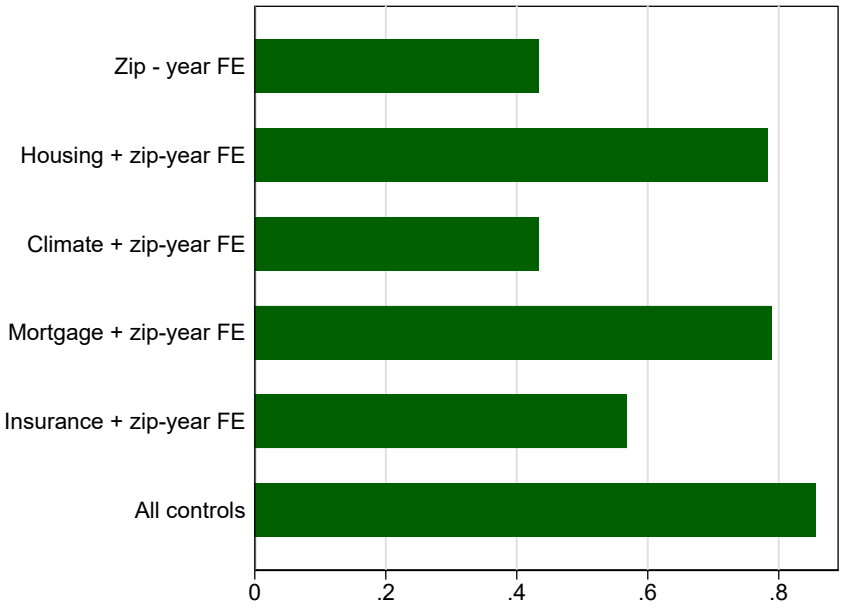


Figure C.4: Explaining the Heterogeneity in Insurance Coverage and Prices

The bar chart shows the R^2 from a series of regressions with thematic subsets of control variables explaining log insurance coverage levels (panel a) and log insurance prices (monthly premium per $100,000 of coverage) (panel b). The variables are (i) ZIP-year fixed effects; (ii) "Housing", includes rebuild cost; (iii) "Climate", includes indicators for properties in top decile of climate risk, and if the house is in a flood plain; (iv) "Mortgage", includes LTV, origination credit score, original principal balance, investor type (FHA, GSE, other) etc.; (v) "Insurance" includes log insurance price and deductible amount for panel (a) and includes log coverage and deductible amount for panel (b). The figure is based on the main analysis sample, outlined in Section 1.2.

(a) Insurance Coverage



(b) Insurance Price

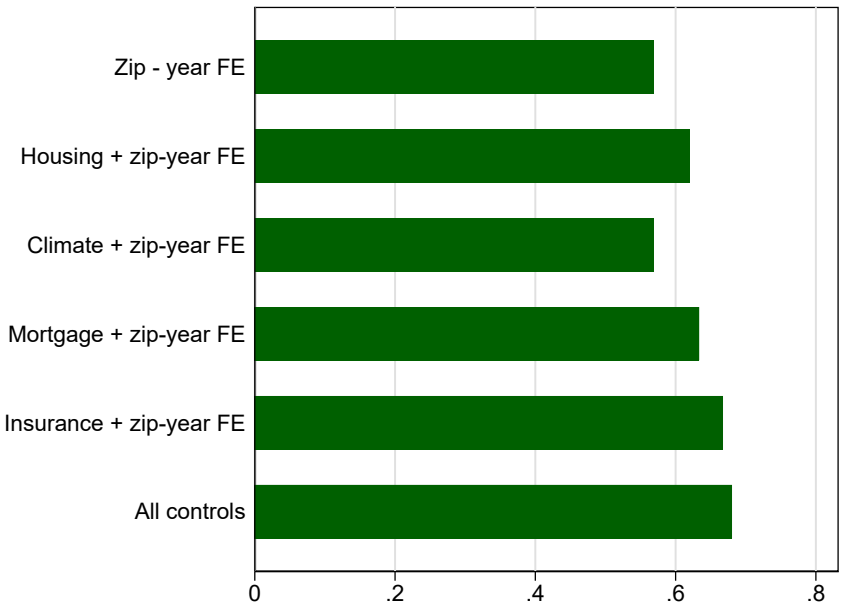


Figure C.5: Coverage Ratios by Loan Age

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 defined as insurance coverage amount divided by the estimated replacement cost, obtained by multiplying structure size and local construction costs from the R.S. Means Company. The sample of loans included are based on the main analysis sample, outlined in Section 1.2, which we observe through time to assess changes in coverage ratio.

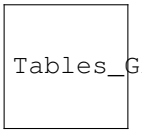
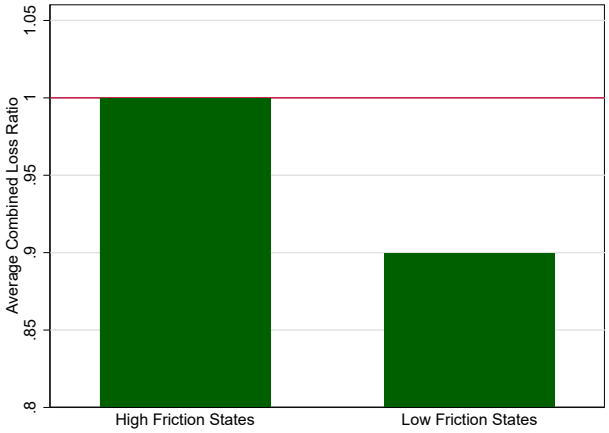


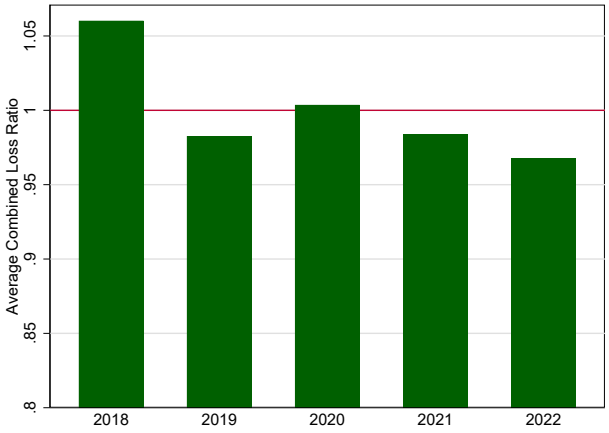
Figure C.6: Insurers' Underwriting Profitability Across State Types

This figure shows estimates of insurers' combined ratios by high and low friction states (panel a) and over time for high friction states (panel b). Combined ratio is a widely used metric to measure insurers' underwriting profitability. We compute the combined ratio as the sum of ZIP code level loss ratio (losses-to-premiums ratio) taken from Treasury's FIO data (see Appendix A), the average annual aggregate expense-to-premium ratio, and the annual loss-adjustment expense-to-premium ratio from the NAIC regulatory filings.

(a) Combined Ratios by State Type



(b) Combined Ratios over time for High Friction States



C.1. Appendix Tables

Table C.1: Comparison of McDash Insurance Module to Overall McDash Sample

This table compares summary statistics from a 10% random sample of the ICE McDash Mortgage modules, and from the subset with the Insurance module. Insurance variables are measured at the first observation in the ICE McDash loan performance data, as in our main analysis sample. The sample in this table does not include a property-level merge, so property-level data like climate risk and replacement cost are omitted. All variables are as defined in the table notes in Table 1.

	McDash Insurance Module		Overall McDash Sample	
	(1) Mean	(2) SD	(3) Mean	(4) SD
Coverage Amount	284085.6	153112.7		
Annual Insurance Premium	1109.3	606.3		
Insurance Price	37.1	21.0		
Annual Income	55.0	24.4	50.9	23.2
Loan Amount	243336.3	152177.6	257857.1	178836.7
DTI Ratio	35.8	9.46	35.1	10.0
LTV Ratio	86.3	13.4	84.9	14.4
Credit Score	735.1	51.3	736.9	52.2
Share with high DTI	0.69	0.46	0.65	0.48
Share with high LTV	0.64	0.48	0.59	0.49
N	538093		822914	

Table C.2: Sensitivity of Insurance Prices to Climate Risk by Regulatory Friction

This table presents the results of a property-level OLS regression to measure the sensitivity of insurance prices to climate risk depending on whether properties are in high vs. low friction states. The dependent variable is log insurance price (monthly premiums per $100,000 of coverage). High climate risk refers to properties in the top decile of climate risk by CoreLogic's AAL measure. AAL is a property-level measure of climate risk which refers to expected losses due to damages from climate disasters. We group states into two types: high and low friction, following the classification in Oh et al. (2021). High friction are states in the top tercile of regulatory friction and low friction are all the remaining states. Both specifications control for the property's replacement cost, which is obtained by multiplying structure size and local construction costs from the R.S. Means Company. Standard errors are clustered at the county level. Note: *p<0.1; **p<0.05; ***p<0.01.

	ln P_{izt}	
	(1)	(2)
High Climate Risk = 1	0.0860***	0.0859***
	(0.0112)	(0.0112)
High Climate Risk = 1 × High Friction = 1	-0.0765***	-0.0777***
	(0.0123)	(0.0124)
ZIP-Year FE	Y	Y
Rebuild Cost Controls	N	Y
Number of Observations	3238688	3238688
Adjusted R-squared	0.605	0.617

Table C.3: Sensitivity of Insurance Prices to Loss Ratios by Regulatory Friction

This table presents the results of a ZIP-level OLS regression to measure the sensitivity of insurance prices to loss ratio depending on whether properties are in high vs. low friction states. The dependent variable is the average annual insurance premium per policy in ZIP code z in year t. The variable of interest are the ZIP's lagged loss ratio – the average loss ratio from reporting insurers in the previous year – and a dummy for whether the ZIP is in a high-friction state. We group states into two types: high and low friction, following the classification in Oh et al. (2021). High friction are states in the top tercile of regulatory friction and low friction are all the remaining states. We include a fixed effect for a categorical variable that indicates market size where indicated. The data are from Treasury FIO. Standard errors are clustered at the ZIP level. Note: *p<0.1; **p<0.05; ***p<0.01.

	Premiums per policy$_{z,t}$	
	(1)	(2)
Loss Ratio$_{z,t-1}$	0.627***	0.608***
	(0.194)	(0.196)
High Friction=1 × Loss Ratio$_{z,t-1}$	-1.514***	-1.589***
	(0.447)	(0.406)
ZIP FE	Y	Y
Year FE	Y	Y
Market Size FE	N	Y
Number of Observations	89884	89884

Table C.4: OLS Results: Effect of Insurance Prices on Coverage (Low Friction States)

This table presents the results of the following OLS regression:

$$\ln \text{coverage}_{i,c,z,t} = \alpha + \beta \ln P_{i,c,z,t} + \gamma' W_{i,c,z,t} + \varepsilon_{i,c,z,t},$$

which is the simple OLS equivalent of the 2SLS in Equation 14. The dependent variable is log coverage amount. The independent variable is log insurance price (monthly premiums per $100,000 of coverage). The analysis uses the sample of low friction states. High and low friction states are as defined in Section 1.2. Specifications include ZIP-year fixed effects and controls for property and borrower characteristics, as indicated. The exact list of control variables is as outlined in Table 2. Standard errors are clustered at the county level. The sample is as outlined in Section 1.2. Note: *p<0.1; **p<0.05; ***p<0.01.

	ln coverage$_{izct}$	
	(1)	(2)
ln P$_{izct}$	-0.235***	-0.228***
	(0.00745)	(0.00744)
ZIP-Year FE	Y	Y
Property Controls	Y	Y
Borrower Controls	N	Y
Number of Observations	1791932	1791932

Table C.5: OLS Results: Effect of Insurance Prices on Coverage (High Friction States)

This table presents the results of the following OLS regression:

$$\ln \text{coverage}_{i,c,z,t} = \alpha + \beta \ln P_{i,c,z,t} + \gamma' W_{i,c,z,t} + \varepsilon_{i,c,z,t}.$$

The dependent variable is log coverage amount. The independent variable is log insurance price (monthly premiums per $100,000 of coverage). The analysis uses the sample of high friction states. High and low friction states are as defined in Section 1.2. Specifications include ZIP-year fixed effects and controls for property and borrower characteristics, as indicated. The exact list of control variables is as outlined in Table 2. Standard errors are clustered at the county level. The sample is as outlined in Section 1.2. Note: *p<0.1; **p<0.05; ***p<0.01.

	ln coverage$_{izct}$	
	(1)	(2)
ln P$_{izct}$	-0.258***	-0.252***
	(0.0131)	(0.0131)
ZIP-Year FE	Y	Y
Property Controls	Y	Y
Borrower Controls	N	Y
Number of Observations	1446756	1446756

Table C.6: OLS Results: Effect of Insurance Prices on Mortgage Debt (Low Friction States)

This table presents the results of the following OLS regression:

$$\ln Debt_{i,c,z,t} = \alpha + \beta \ln P_{i,c,z,t} + \gamma' W_{i,c,z,t} + \epsilon_{i,c,z,t}$$

which is the simple OLS equivalent of the 2SLS in Equation 15. The dependent variables in columns 1 and 2 are the log of the loan's DTI ratio and in columns 3 and 4 the log of the loan's LTV ratio, both taken as of origination. The independent variable is log insurance price (monthly premiums per $100,000 of coverage). The analysis uses the sample of low friction states. High and low friction states are as defined in Section 1.2. Specifications include ZIP-year fixed effects and controls for property and borrower characteristics, as indicated. The exact list of control variables is as outlined in Table 2. Standard errors are clustered at the county level. The sample is as outlined in Section 1.2. Note: *p<0.1; **p<0.05; ***p<0.01.

	ln DTI_{izct}		ln LTV_{izct}	
	(1)	(2)	(3)	(4)
ln P_{izct}	0.0445***	0.00828***	0.0288***	0.00803***
	(0.00318)	(0.00182)	(0.00168)	(0.00103)
ZIP-Year FE	Y	Y	Y	Y
Property Controls	Y	Y	Y	Y
Borrower Controls	N	Y	N	Y
Number of Observations	1791932	1791932	1791932	1791932

Table C.7: Robustness: 2SLS for Mortgage Debt with Interest Rate Controls

This table presents the second stage of the two-stage least squares regression shown in Equation 15, where we show that the results shown in Table 5 are robust to controlling for the interest rate of the mortgage. The analysis uses the sample of low friction states. The dependent variables in columns 1 and 2 are the log of the loan's DTI ratio and in columns 3 and 4 the log of the loan's LTV ratio, both taken as of origination. The independent variable is log insurance price (monthly premiums per $100,000 of coverage), instrumented using average prices in high friction states for each credit score group in each year. High and low friction states are as defined in Section 1.2. Specifications include ZIP-year fixed effects and controls for property and borrower characteristics, as indicated. The exact list of control variables is as outlined in Table 2. In addition, we control for the interest rate of the mortgage. Standard errors are clustered at the county level. The sample is as outlined in Section 1.2, but limited to the sample of loans in low friction states. Note: *p<0.1; **p<0.05; ***p<0.01.

	ln DTI_{izct}		ln LTV_{izct}	
	(1)	(2)	(3)	(4)
$\widehat{\ln P_{izct}}$	1.041***	1.217***	0.614***	0.695***
	(0.0411)	(0.0650)	(0.0232)	(0.0407)
ZIP-Year FE	Y	Y	Y	Y
Property Controls	Y	Y	Y	Y
Borrower Controls	N	Y	N	Y
Interest Rate Control	Y	Y	Y	Y
Number of Observations	1791932	1791932	1791932	1791932
First-stage F	744.4	462.3	744.4	462.3

Table C.8: First-Stage Results: Required Mortgage Insurance Discontinuity

This table presents the first stage of the two-stage least squares regression shown in Equation 16, whose second stage is shown in Table 7. The dependent variables of the first stages are log price (columns 3 and 4) and its interaction with a dummy for whether the loan's LTV ratio exceeds 80% (columns 1 and 2). Both ln price and its interaction with the dummy are instrumented using log of the average prices in high-friction states and the interaction of this variable with the LTV dummy. The sample and the control variables are as outlined in Table 7. Standard errors are clustered at the county level. Note: *p<0.1; **p<0.05; ***p<0.01.

	ln P_{izct} × I(LTV > 80%)		ln P_{izct}	
	(1)	(2)	(3)	(4)
	LTV 70-90%	LTV 75-85%	LTV 70-90%	LTV 75-85%
ln $P_{HF,ct}$× I(LTV>80%)	0.750***	0.766***	0.0341***	0.766***
	(0.0346)	(0.0345)	(0.00798)	(0.0345)
ln $P_{HF,ct}$	-0.206***	-0.0929***	0.114***	-0.0929***
	(0.0120)	(0.00582)	(0.00822)	(0.00582)
I(LTV>80%)	0.721***	0.671***	-0.121***	0.671***
	(0.131)	(0.132)	(0.0294)	(0.132)
ZIP-Year FE	Y	Y	Y	Y
Property Controls	Y	Y	Y	Y
Borrower Controls	Y	Y	Y	Y
N	585430	358570	585430	358570