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

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Abstract

It is widely believed that U.S. households are under-insured, but limited granular data on insurance has made this difficult to measure. This project develops a new methodology to construct the first U.S.-wide, long term dataset on homeowners insurance premiums and coverage at the individual level. We combine mortgage servicing, deeds, and property tax data, and then employ a novel algorithm to back out insurance payments from recurring mortgage payments made through escrow accounts. We then estimate coverage amounts from payments using data on insurance pricing functions. We validate our estimates using newly available data on insurance information for a subset of mortgage borrowers. We find that under-insurance is a significant problem, particularly for vulnerable borrowers in high climate risk states and with the lowest credit scores. We show under-insurance is driven both by responsive borrowers reacting to rising premiums, as well as by behavioral inertia that limits updating coverage as inflation and construction costs change. We finally study the broader implications of under-insurance for mortgage and real estate markets.

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

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1 Introduction

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

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

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

To help fill this gap, we design a new methodology combining state-of-the-art mortgage, climate, tax, and insurance databases to provide the most comprehensive

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

picture of climate risk exposures, values at risk, insurance payments, take-up (extensive margin), and coverage amounts (intensive margin) at the property level. Our methodology makes it possible to shed light on the ongoing unraveling of property insurance markets and the implications it has for households, and for the financial system more broadly through the connections in the mortgage market.

We do so by backing out insurance payments from individual mortgage payments that are recorded by mortgage servicers. Importantly, for most states, household mortgage payments include the debt payment, the insurance premium, as well as property tax payments. We are able to observe property tax payments from deeds data, and can merge this with the servicer data to estimate insurance premiums. We then use our premiums estimates to infer coverage amounts by extrapolating from premiums paid, using local prices (which are quoted as premiums per dollar of coverage). Our new dataset covers nearly 8 million loans in 2020, representing over 30% of all mortgages in the servicer data. Our data covers 2011-2023 across the United States. We are also able to validate our methodology against McDash, which released a new dataset with verified information on homeowners insurance for loans in 2023 that comes directly from mortgage servicers. For this sub-sample, we find a 95% correlation between our premiums estimates and reported premiums in the data.

This novel data allows us to then connect insurance premiums and coverage with other loan-level borrower characteristics, including credit scores, debt-to-income ratios, loan-to-value ratios, the maturity of the loan, and zip code. To our knowledge, this is the first dataset to connect individual and mortgage characteristics to homeowners insurance contracts at the loan level.

Using this novel data, we uncover three striking facts about under-insurance in homeowners insurance markets. First, we show that under-insurance is not an issue at the extensive margin on average. Most mortgage borrowers seem to have insurance. We estimate insurance take-up rates are close to 80%. However, there states where contracts which cover fewer perils than the standard HO-3 contract are predominant. For example, in Texas, fewer than 60% of owner-occupied homes seem to have a comprehensive HO-3 homeowners insurance policy.

Second, underinsurance is a significant issue on the intensive margin. We show that coverage amounts are far lower than estimated replacement costs. In 2023, the average loan on a single-family property only had about $390,000 in coverage, even though average replacement cost was close to $590,000. We show that coverage tends to deteriorate over time. Most households have adequate coverage at the beginning of the mortgage, but this amount is highly persistent, and does not seem to change with construction costs or inflation.

Third, we show there are wide disparities across states and borrower types. In Louisiana, coverage amounts represented less than 50% of building values; by contrast, in Rhode Island, this number was closer to 75%.

These stylized facts raise the question of what drives such high levels of underinsurance on the intensive margin. We consider two explanations. In the first explanation, responsive households react to rising insurance premiums by dropping coverage levels. To estimate household demand elasticities, we subset to high friction states where insurers face more regulatory hurdles to changing premiums (Oh et al., 2021). This means that, for these states, insurers cannot easily change premiums in response to changing demand conditions, making the classic simultaneity problem less challenging. We find that households are surprisingly responsive to insurance prices. A 1% increase in price is associated with a 0.35% decline in coverage. In the second explanation, households choose coverage amounts at origination, and do not update these amounts as construction costs and inflation change over time due to inertia. Consistent with this explanation, we find that coverage ratios are declining with loan age, even after controlling for property-level climate risk, the borrower's credit score, and state fixed effects.

Our findings suggest that under-insurance is a significant issue, particularly for the poorest states and poorest borrowers. This coverage gap implies that households may have less financial resiliency towards natural disasters, and the the costs of under-insurance may be passed onto banks, mortgage owners, and taxpayers through enhanced mortgage default and fiscal transfers. Our under-insurance estimates are a first-step to mapping out the full distribution of climate risk throughout the financial system.

Related Literature: This paper contributes to two strands of the literature. First, we add to the literature on the industrial organization of insurance markets. Froot and O'Connell (1999) and Jaffee and Russell (1997) study the role of frictions from capital markets; Oh et al. (2023) study the role of insurer pricing regulation across states, Boomhower et al. (2023) study the effect of asymmetric information and use of catastrophe models.[2] Our paper also relates to the broader insurance literature on supply side frictions and their effects on insurance products and asset holdings (Koijen and Yogo, 2015, 2016, 2022; Ellul et al., 2015, 2022; Ge, 2022; Sen and Humphry, 2018; Sen, 2021; Sen and Sharma, 2020; Barbu, 2021; Tang, 2023; Tenekedjieva, 2021; Oh, 2020; Gennaioli et al., 2021; Egan et al., 2021). We contribute this literature by providing some of the first nationwide estimates of insurance take-up on both the intensive and extensive margin.

In contemporaneous work, Mulder and Keys (2024) use a similar algorithm to estimate insurance premiums from mortgage escrow payments. Their paper focuses on quantifying the drivers of rising premiums, in particular the role of rising disaster risk and reinsurance premiums. In contrast to their paper, our paper focuses on the measurement and drivers of insurance coverage rather insurer pricing.

Second, this paper contributes to the growing literature on the relationship between

[2] A separate but related literature also studies federal provision of flood insurance (e.g., Wagner (2022)).

property insurance, climate risk, and real-estate outcomes. A first set considers how flood insurance market affects mortgage lending (Sastry, 2022) and real estate prices (Ge et al., 2023), and the effects of mis-pricing in homeowners insurance (Boomhower et al., 2023). Another literature shows that climate events create financial losses for lenders, and that flood insurance payments helps to reduce delinquencies after disasters (Gallagher and Hartley, 2017; Kousky et al., 2020; Billings et al., 2019; Issler et al., 2019; An et al., 2023; Biswas et al., 2023). We contribute to this literature by studying the effect of under-insurance on the intensive margin, rather than the extensive margin, which has more often been the focus of the literature.

Third, our findings speak to the literature on the implications of climate risk for households' finances. Households bear climate risk directly through mortgage markets (Issler et al., 2020), real estate prices (Baldauf et al., 2020; Murfin and Spiegel, 2020; Bernstein et al., 2019), and equity prices (Engle et al., 2020), and indirectly through labor markets (Kruttli et al., 2019) and discounts in municipal bond prices (Goldsmith-Pinkham et al., 2020). The degree to which households are protected from physical climate damage depends on how much of the losses get absorbed from the P&C insurers. Sastry et al. (2024) show that financially fragile insurers contribute to the shift of risk away from the insurance sector and to GSEs and households. This problem is further exacerbated however, if even households relying on high quality insurers are underinsured, as we show in this paper.[3]

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

2 Institutional Details

2.1 Homeowners' Insurance

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

The standard homeowners contract is annual and covers damages from most natural disasters.[4] The insurance contract has three key characteristics: the coverage taken, the deductible choice, and the premium paid. Those purchasing insurance are entitled to claim payouts up to a pre-specified coverage amount if an insured loss event materializes. Coverage amounts are usually dictated by the mortgage lender. For example, any mortgage purchased or securitized by the government-sponsored enterprise require that coverage represents the full the estimated replacement cost of the house.[5] Deductibles is a clause in the insurance contract that requires insurance companies to only pay for losses that exceeds the pre-specified deductible amount. Lastly, the premium is the annual amount that the insured party must pay to the insurer. It is a function of the risk of the house, the other contract features including the coverage and deductible choices of the insured.

[4]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.

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

2.2 Mortgage Servicers and Escrow Accounts

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

To simplify payments and enforce requirements, most mortgage payments are handled through escrow accounts. Mortgage escrow accounts are separate legal arrangements that are used to collect monthly mortgage payments, homeowners insurance premiums, and property tax payments. The mortgage servicer will send payment requirements to household, and then ensure that payments are made from the borrower's escrow account to the insurance company and tax authorities. Escrow accounts may also include flood insurance and mortgage insurance payments. The majority of of mortgages feature escrow deposit accounts (Anderson and Dokko, 2008), and are required by FHA, Fannie Mae, and Freddie Mac in most circumstances.[6].

To the extent that households pay for insurance through escrow accounts, this means that mortgage payments will include both insurance and property tax information. If mortgage payments and property tax is observed, this implies that insurance premiums can be inferred. This will be the idea behind our estimation approach, described in the next section.

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

3 Data

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

3.1 Mortgage and Climate Datasets

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

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

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

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

3.2 Insurance Datasets

Quadrant Data: We obtain ZIP code level insurance pricing data from Quadrant Information Services from 2011-2020. The data cover over 34,000 ZIP codes across all 51 states in the US. The data is compiled from the rate filings made by the largest insurers operating in a state by market share.[7] The data includes information on premiums, coverage amounts, age of the property, insurance scores, insurer, and ZIP code of the property. The pricing data assumes a $1,000 deductible amount, which is the most common deductible chosen by households.

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

McDash Property Insurance: Starting from 2023, we have insurance data made available by BlackKnight McDash to the Federal Reserve system. A subset of mortgage servicers provided information about homeowners insurance to McDash; this includes data on monthly insurance premiums, coverage amounts, deductibles, and information about other insurance policies such as flood insurance. This insurance module can be linked to McDash's mortgage data using loan-level identifiers. One limitation of this data is that as of this time, it is only available for one year. Thus, we cannot rely on this dataset to do any time series analysis on how coverage amounts evolve as risk of the property or loan age change over time. Nevertheless, it allows us to validate our insurance payment and coverage estimates, giving confidence that the underlying methodology to extract payments and infer coverage amounts is accurate.

NAIC aggregate insurance payment data: We also obtain state-level aggregate data from the NAIC of the average insurance payment per policy. This data is compiled from insurers' regulatory filings on the total premiums underwritten, number of policies, and coverage amounts for each state and business line that insurers operate in. The advantage of these data is that it provides another way to validate that our insurance payment and coverage estimates are accurate. Relative to the McDash Property Insurance data described above, the NAIC data is available for a number of years, allowing us to check if our estimation methodology works year by year.

4 Estimation Methodology

Most households pay their mortgage payments, property tax, and insurance premiums through escrow accounts. For such households in the McDash data, we observe their mortgage payments and property tax information, allowing us to infer insurance premiums. We can then combine our premiums estimates with other granular information on insurers' pricing functions that relates premiums to coverage, climate risk, and other policyholder and house characteristics to estimate coverage amounts. We then validate our estimates using the recent McDash property insurance module, for the subset of borrowers where this information is observed, and using NAIC aggregate data for the full sample. This is the core idea behind our methodology, but we will describe our approach in more detail below.

4.1 Methodology to Estimate Premiums

Our baseline dataset is the merged McDash-Deeds-Tax dataset. For the final merged sample, we start with the mortgage payment reported by the servicer in McDash. We then subtract tax payments as reported in Deeds records matched to the mortgage loan. This yields us an estimate of insurance payments.

$$\begin{aligned} \text{Insurance payment} = &\ \text{Total amount in Escrow} \\ &- \text{Mortgage payment} \\ &- \text{Property taxes.} \end{aligned} \tag{1}$$

We now discuss a number of steps taken to ensure our estimation provide a realistic picture of insurance payments. We omit borrowers with private mortgage insurance (PMI), because these costs vary along similar dimensions as homeowners' insurance. In our final data, nearly 3/4 of loans originated without PMI escrow homeowners insurance. We then exclude the state of Texas, because escrowing seems less common there. For FHA borrowers, we estimate their mortgage insurance payment based on their origination date.

There are a number of other details about our procedure. We use the escrow payment in May for our insurance payment calculations – usually, by this point in the calendar year, new property assessments and insurance payments generally appear to have been recalculated, and average monthly escrow adjustments shrink. We cannot tell when escrow payments are recalculated for borrowers due to changes in property taxes, so this assumption may create some potential timing issues. We also cannot observe any ad-hoc adjustments to borrowers' escrow payments for past-due amounts.

4.1.1 Data representativeness and selection issues

Our methodology allows us to estimate payments for 19000 ZIPs out of 30000 US ZIPs.[8] We validate this measure using NAIC data, which is administrative data provided by insurance companies to the state on total premiums, coverage, and policies underwritten. To understand potential issues with selection and representativeness, we look at the correlation between our measure and the NAIC provided estimates. We obtain for each state-year observation our estimated average insurance payment per policy, and compare this to average insurance payment per policy in the NAIC data (Figure 1). The two measures are strongly correlated, with the line-of-best-fit nearly lining up with the 45-degree line. This suggests that our data is broadly representative with less selection issues.

Nevertheless, we go into detail to understand possible selection issues due to our data construction and methodological assumptions. The first issue comes from the fuzzy merge between Deeds-McDash. The match rate can vary by state and county, but seems to largely reflect local record keeping. The second issue comes from potential selection into escrowing premiums. Table 1 shows average mortgage characteristics in the unfiltered McDash data (Column 1), the McDash data merged with CoreLogic Deeds (Column 2), and our filtered dataset (Column 3). At the loan-level, we find that escrowing homeowners insurance appears largely uncorrelated with credit quality (measured using credit scores, loan-to-value ratios, etc.).

[8] Table 1 shows, for an example year, how our sample relates to the universe of loans in CRISM.

4.2 Methodology to Estimate Coverage from Premiums

To estimate coverage amounts, we have to go a step further. Insurance payments can vary because of many reasons, e.g., individual's risks, property's risks, coverage amount, deductibles etc. We use data from Quadrant on insurance pricing by various coverage amounts, deductibles, age of the property, ZIP (to capture property's risks) and insurance score (to capture individual's risks). Using this data we obtain a relation between insurance pricing and the various available characteristics described above. ZIP and insurance score explain a large part of the variation in insurance pricing. We therefore look within a ZIP and insurance score band to estimate the premiums being paid for a dollar of coverage. Given that we have estimates of insurance payments, as obtained in the previous step, we can use this relationship to infer the level of coverage for a given property within a ZIP and insurance score band.

To assess how insured a given property is, in addition to coverage, we also need estimates on total rebuilding values (also known as replacement costs, i.e. what it will cost to rebuild the property to its current state in case it suffers damages). We obtain property-level data on replacement costs from CoreLogic as of 2021. To obtain a time series, we take this estimate and then deflate it by measures of construction inflation.

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

$$\text{Coverage Ratio}_{pt} = \frac{\text{Estimated coverage}_{pt}}{\text{Estimated replacement cost}_{pt}}. \tag{2}$$

4.3 Validating Premiums and Coverage Measures

Starting in 2023, we have detailed data on insurance premiums and coverage through the McDash Property Insurance module. We can therefore validate the accuracy of our estimation procedure for the subset of loans where we have servicer-provided information on premiums and coverage information. Figure 2 shows the binscatter of our measures (y-axis) against the true amounts (x-axis) for both premiums and coverage. These estimates are strongly correlated.

Furthermore, we find other qualitative and quantitative similarities between our estimates and the official Property Insurance Module. Per our estimates, the average coverage to replacement cost ratio is 0.60 nationwide. In the McDash property insurance module, it is 0.67. Additionally, states that are low coverage in our data are also low coverage in the McDash Property Insurance module data. Given this validation exercise, we are sufficiently confident in our estimates of insurance premiums, coverage, and replacement costs.

5 Results

With this novel dataset on loan-level estimates of borrower characteristics, mortgage characteristics, and homeowners insurance, we provide a number of novel stylized facts regarding insurance take-up and coverage. We also explore the key economic drivers of insurance demand and under-insurance.

5.1 Insurance Take-up

When looking at the extensive margin, we find that most households have insurance coverage. Estimates from the NAIC suggests that nearly 80% of owner-occupied housing units had a homeowners insurance policy. We construct this number by using NAIC state-wide estimates of the number of house-year policy exposures for either dwelling (DW) or homeowners (HO-1 through HO-8) as an estimate of the number of annual homeowners insurance policies. We then scale this by the number of owner-occupied housing units, reported in the Census' American Community Survey.[9]

[9] We use the 5-year ACS estimates from 2018-2022.

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

5.2 Insurance Coverage Ratio

While these aggregate trends can be observed from existing data, they mask whether households have enough insurance. In our sample, Figure 4 shows severe underinsurance on the intensive margin. This figure plots the median coverage amount across zip codes for each year, and compares that to the median of total inflation-adjusted rebuilding costs. We find that over time, average coverage amounts stays constant, around $210,000 across all categories. However, total rebuilding costs are nearly $300,000 - $410,000, implying that even those households that may have an insurance policy do not take out enough. In 2011 we find an insurance coverage ratio of 70%; this number decreases to 50%.

Table 2 shows that there is significant heterogeneity across states. On average, the top five states–Massachusetts, Connecticut, Wyoming, Washington D.C., and Rhode Island–have coverage ratios that exceed 80% in 2020. However, the bottom five states–Mississippi, Arkansas, Texas, Alabama, and Louisiana –have coverage ratios below 55%.[10] In these states, even the 90th percentile of borrowers less than 75% of their building values covered by insurance. This is likely to pose challenges for the households themselves, as well as the lender of mortgage owner exposed to these

[10]Note that this state-level data uses the official McDash HO Module, not our imputed coverage estimates.

borrowers.

5.3 Drivers of Under-insurance

These results raise the question of what drives such severe under-insurance. We posit two potential explanations that we test using our data on imputed coverage.

Elastic Borrowers: The first concerns rising perceptions of risks. In this channel, insurers seek to raise premiums because of rising probabilities of insured loss events; this then reduces coverage quantities because household are very elastic. To test this explanation, we consider the following empirical specification:

$$log(Q_{zft}) = \beta log(P_{zft-1}) + \alpha_{zf} + \alpha_{zt} + X_{zft} + e_{zft} \quad (3)$$

where the subscript z denotes ZIP, f denotes credit score category, and t denotes year. The variable Q is our measure of insurance coverage, and the variable P is insurance price (premiums per \$1 of coverage) taken from the Quadrant database. We include ZIP-credit-score fixed effects (α_{zf}) and zip-year fixed effects (α_{zt}). X_{zft} refers to borrower-level controls that could also affect borrower insurance demand: LTV, age of the house, principal balance, and credit score.

Instrument. A standard concern with this regression is that prices and quantities are simultaneously determined, leading to biased estimates of the demand elasticities. To address this issue, we consider the subset of states that have high pricing frictions. Oh et al. (2021) show that in these states, insurers cannot change prices in response to demand shocks because of stringent rate regulation. As a result, for these states, β is less likely to be biased and identify the elasticity of demand.

Table 3 shows the results from estimating Equation (3). We find that households react strongly to changes in pricing. Our estimate in Column (3) includes the full set of fixed effects and controls. The elasticity of -0.35 implies that a 1 percent increase in insurance prices is associated with a 0.35 percent decrease in quantity demanded (coverage), on average. To contextualize this number, the average increase in insurance premium every year is about 4 percent. This suggests that the observed increase in insurance prices every year reduces coverage by 1.4 percent per year. For the typical mortgage (loan age 6 years), this means that coverage declines by roughly 8 percentage points over the course of the loan.

It may be surprising to see that household coverage demand reacts to premiums at all– it is widely thought that coverage levels are driven by replacement costs because that is what most mortgage lenders require.[11] Our results, in contrast, suggest that there seems to be borrower discretion on the intensive margin for how much they seek to insure.

Inertia: The second potential explanation for the under-insurance gap relates to borrower inertia. Under this hypothesis, coverage amounts are set at mortgage origination, but do not update over time sufficiently with inflation or changing construction costs. We test this channel by showing how coverage ratios vary with several drivers of risks, and in particular with the age of the loan:

$$\text{Coverage Ratio}_{lt} = \gamma_1 \text{Year} + \gamma_2 \text{Credit score}_{lt} + \gamma_3 \text{Climate Risk}_l + \text{Fixed effects} + \epsilon_{lt} \tag{4}$$

where the subscript l denotes loan and t denotes calendar year. The variable Coverage Ratio is the ratio of estimated coverage to rebuilding cost for loan l at time t, Year is calendar year, credit score is the credit score of the borrower of loan l in year t and Climate Risk is the property's annual expected loss as provided by CoreLogic. Climate Risk is only available as of year 2023. We also include state and year fixed effects. The most stringent specification also includes loan fixed effect.

[11] Indeed, the GSEs Fannie Mae and Freddie Mac require household to obtain the minimum of the unpaid principle balance and the total replacement cost as coverage for the loans they purchase.

Table 4 shows the main results. We find that coverage ratios are increasing with property-level loss exposures, suggesting that more exposed households have higher coverage. Coverage ratios are also increasing with credit scores, suggesting that less credit worthy households have lower coverage. Moreover, coverage ratio also significantly declines with the age of the loan. This holds even after including other control variables, and including state-level and year fixed effects.

In columns (2) and (3) we add loan fixed effects to understand whether this result holds over the life of a given loan. For ease of interpretation, we add the calendar year to the regression. A negative coefficient quantifies the decay in coverage ratio from year to year. Column (2) shows the results for the unadjusted coverage ratio. Column (2) asks if it cost the same nominal amount to rebuild over time, would we observe a decay in coverage ratio, and if so by how much? $\gamma_1 = -0.006$ and statistically significant implying that coverage ratio declines even in the absence of inflation and growth of construction costs. This is potentially due to increases in insurance premia over time, as discussed in the previous section. However, the issue of coverage decay is significantly exacerbated when we allow for the fact that it costs more to rebuild over time because of inflation and growth in construction costs. Column (4) shows the results for inflation adjusted coverage ratio. We estimate $\gamma_1 = -0.0174$, i.e. coverage ratio declines by 1.74 percentage points each year that the loan ages.

6 Conclusion

This paper provides some of the first loan-level estimates on household under-insurance by connecting state-of-the-art mortgage, climate, tax, and insurance databases at a property level. We show that most households have insurance policies, but that few households have *enough* coverage. In other words, under-insurance is a problem at the intensive margin, not the extensive margin. Coverage ratios are the lowest in high climate risk states, and for the poorest borrowers. We test two explanations for these challenges and find evidence of both channels. The first channels is that borrowers are reacting to rising insurance premiums by reducing coverage because they are relatively elastic. We find evidence of this channel because coverage amounts do vary with premius in high friction states. The second channel is that borrowers are behavioral and do not adequately update their coverage levels as inflation and construction costs and inflation change over time. We also find evidence of this inertia channel, with older loans having lower coverage ratio. These results suggest that there is a significant coverage gap, with households, lenders, and taxpayers likely facing far more uninsured risk than is realized.

7 Tables and Figures

7.1 Tables

Table 1: Average mortgage and borrower characteristics

We compare characteristics of mortgages and borrowers for full original mortgage sample (column 1), for the sample of mortgages matched to deeds (column 2), and for the final sample in which we can estimate insurance payments through escrow (column 3). For each sample, we estimate average of credit score, principal balance, loan to value at a given time and at origination, the share of loans which are purchased and not refinanced, and loan age.

	Mortgage data	Mortgage + deeds match	In sample
Credit score	744	741	734
Principal Balance	$ 183,946	$ 184,207	$ 171,115
Loan to value ratio (current)	57	57	56
Loan to value ratio (original)	80	82	83
Share purchase (vs refinance)	46%	50%	49%
Loan age (years)	6.2	5.6	5.8

Table 2: Insurance Coverage Ratio by State in 2023

For merged loans in the 2023 McDash insurance module, we estimate the average ratio of insurance coverage to the average rebuilding value of the properties. Rebuilding costs are from First Street Foundation. In Panel A we show the distribution in 2023 for the five states that are the most protected by insurance. In Panel B we show the distribution in 2023 for the five states that are the least protected by insurance. The columns show the insurance coverage ratio's average value, standard deviation, quantiles (10th, 25th, 50th, 75th and 90th), and number of loans we estimate the distribution from.

State	Mean	SD	Q10	Q25	Median	Q75	Q90	N
Panel A: Top Five States by Coverage Ratio								
DC	105.5	46.7	63.1	75.4	95.3	123.9	159.9	9,055
HI	88.9	33.3	62.1	71.5	83.5	99.1	119.2	8,424
MN	88.3	28.5	60.1	72.0	85.9	102.0	118.2	110,464
RI	86.8	26.0	63.9	73.9	84.1	96.6	111.6	10,265
MA	85.7	33.7	50.7	60.5	71.6	82.0	94.2	312
UT	85.5	32.7	58.0	68.3	81.4	97.3	115.8	58,992
Panel B: Bottom Five States by Coverage Ratio								
MS	44.9	11.8	34.0	39.0	44.0	49.4	56.1	14,557
AR	46.2	15.7	28.2	36.7	45.2	53.8	63.1	974
TX	49.1	14.7	35.3	42.6	48.3	54.9	63.0	40,6324
AL	53.0	34.0	35.7	42.0	49.2	58.2	70.5	54,787
LA	54.0	22.3	35.0	42.8	50.9	60.6	73.6	52,199

Table 3: Estimating Elasticities of Demand for Insurance

This table shows the results of estimating Equation 3 in the text. The sample is limited to states with high pricing friction, where insurers cannot change prices in response to demand shocks because of stringent rate regulation. The dependent variable is average insurance coverage in a given zip code, credit score group and year. The independent variable is the average price charged by insurers per dollar coverage in for the prior year in the same location and credit score group. Column (1) includes no controls or fixed effects. Column (2) includes ZIP-year and ZIP-credit score fixed effects. Column (3) includes the same fixed effects as column (2), as well as controls (zip-by-year loan to value, structure age and principal balance amount) Standard errors are clustered at the ZIP level and reported in parentheses.
Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	Dependent variable:		
	log(Average Coverage$_{zft}$)		
	(1)	(2)	(3)
log(Average Price per \$1000$_{zft-1}$)	-0.750^{***}	-0.346^{***}	-0.336^{***}
	(0.005)	(0.009)	(0.010)
Controls	N	N	Y
Zip-FICO FE	N	Y	Y
Zip-Year FE	N	Y	Y
Observations	135,538	135,538	126,791
Adjusted R^2	0.693	0.954	0.956

Table 4: Drivers of Coverage Ratios over Time

This table shows the result of estimating the imputed coverage ratio on variables of interest. The sample includes the universe of matched loans from 2010-2020. Column 1 shows the relationship between the insurance coverage rate and variables of interest, including climate risk (measured using CoreLogic's measure of average annual loss from all climate causes), current credit score, and loan age. Each of these three independent variables is de-meaned and divided by its standard deviation. The insurance coverage ratio is measured as the imputed coverage amount divided by the cost to rebuild, as estimated by First Street Foundation. Because the cost to rebuild is estimated in 2020, we convert the rebuild cost to nominal dollars using the CPI in columns 1 and 3. Columns 2 and 3 add loan-level fixed effects and replace the loan age and year fixed effects with a continuous time variable. Column 4 replicates the estimate in column 1 on the sample of coverage data available from McDash in 2023.

	Dependent variable:			
	Coverage rate (Coverage/Rebuild cost)			
	(1)	(2)	(3)	(4)
Climate risk (std)	0.0395***			0.0021***
	(0.00872)			(0.0001)
Credit score (std)	0.0504***	0.0647***	0.0683***	0.020 ***
	(0.0128)	(0.0102)	(0.0108)	(0.0001)
Loan age (std)	-0.0295**			-0.0084 ***
	(0.00875)			(0.0001)
Year		-0.00604***	-0.0174***	
		(0.00147)	(0.00219)	
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No
Inflation-adjusted	Yes	No	Yes	No
Loan FE	No	Yes	Yes	No
N	73685527	73209723	67626620	4,421,573
R^2	0.0453	0.743	0.747	0.14

Standard errors in parentheses, clustered at the state level

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

7.2 Figures

Figure 1: Insurance payments: average escrow amounts and NAIC aggregates.

This figure compares year-state average insurance price as reported by NAIC on the x-axis and estimated through the escrow accounts on the y-axis. The source for the NAIC aggregates is *Dwelling Fire, Homeowners Owner-Occupied, and Homeowners Tenant and Condominium/Cooperative Unit Owner's Insurance Report Data*, hand collected for 2011 to 2020.

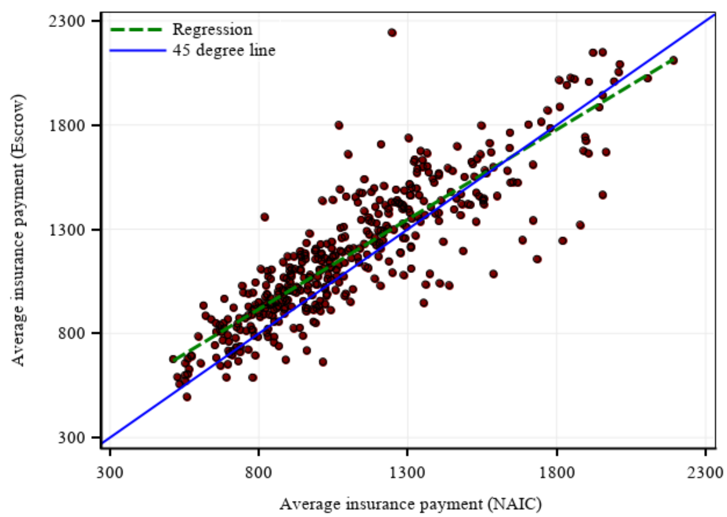
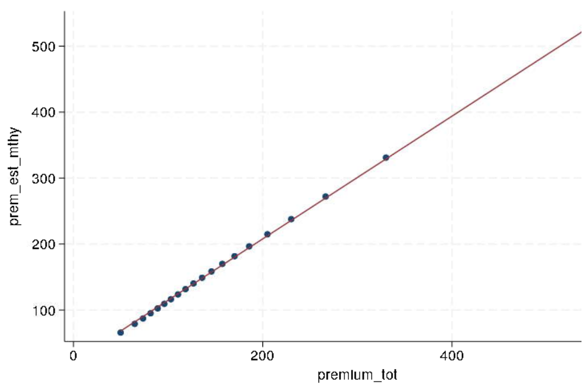


Figure 2: Insurance payments in Escrow vs. McDash Insurance Module

This figure compares the estimates obtained through the escrow method for 2020 to the 2023 McDash insurance estimates. In panel A we show a bin scatter of the loan-level insurance premiums from McDash (x-axis) and our estimates with the escrow method (y-axis). In panel B we show a bin scatter of the loan-level insurance coverage from McDash (x-axis) and our estimates with the escrow method (y-axis).

(a) Premiums



(b) Coverage

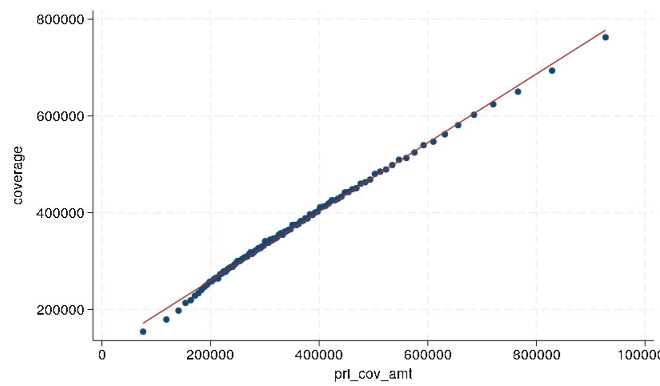


Figure 3: Share of HO-3 Homeowners Insurance Policies by State in 2021

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

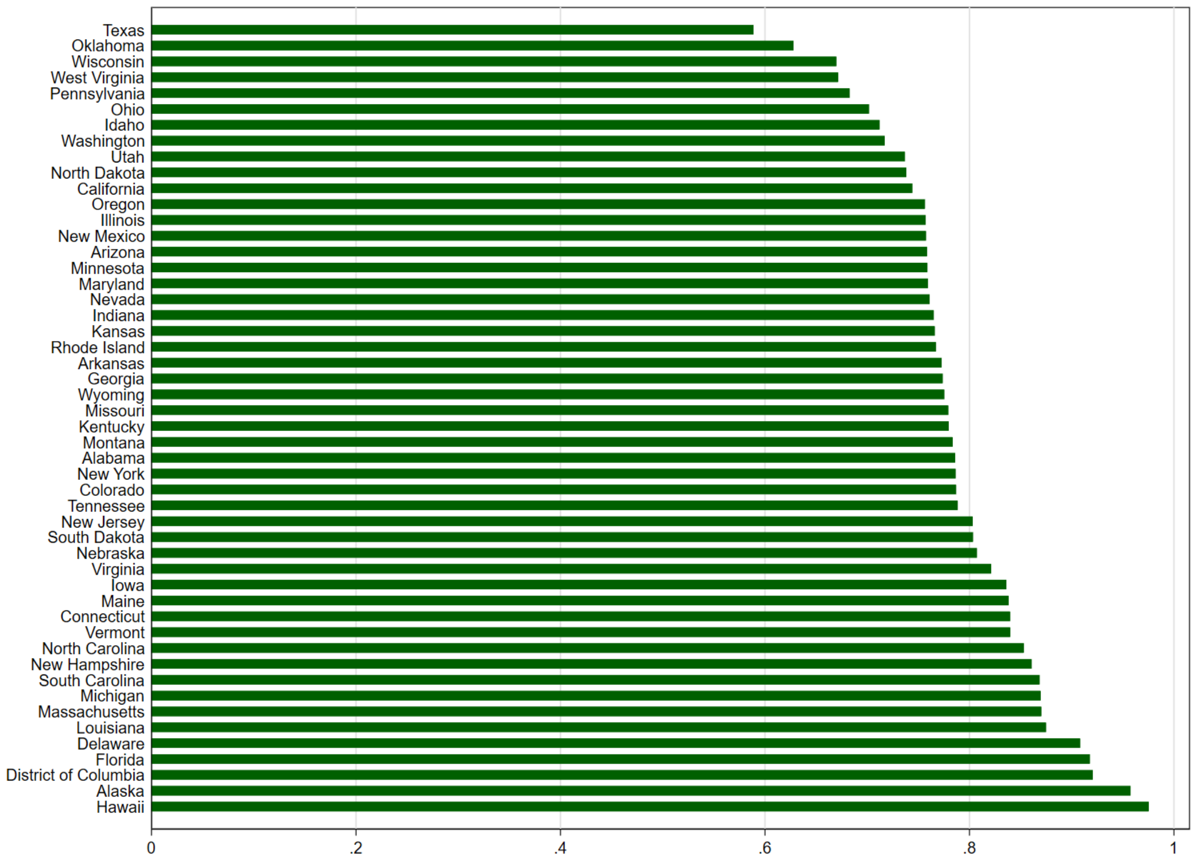
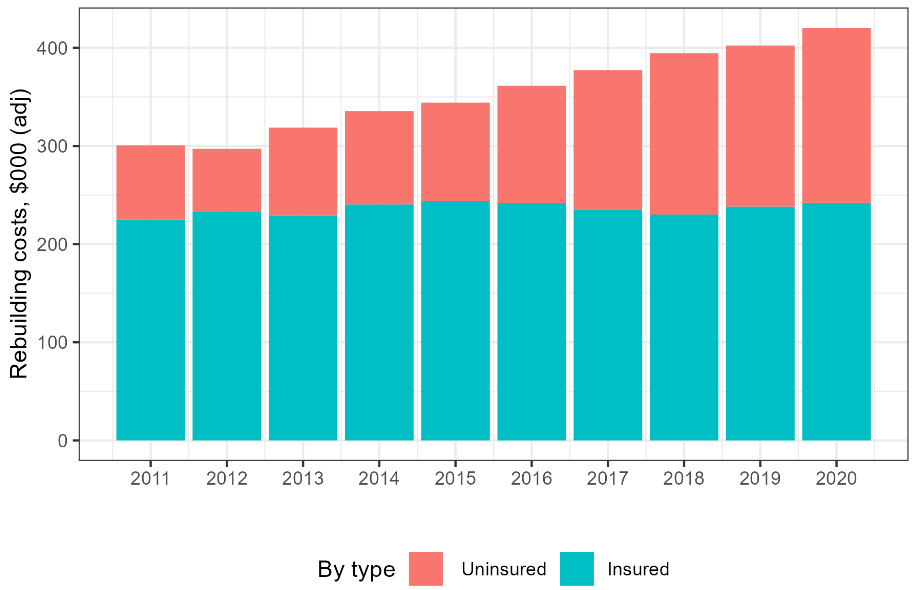


Figure 4: Intensive margin of Insurance: Coverage Ratios

This figure shows how much of the average rebuilding costs in a given year are insured. We estimate inflation-adjusted rebuilding costs from CoreLogic and compare against the escrow method estimates for rebuilding costs.



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