The Effect of Rising Insurance Premiums on Mortgage Delinquency and Household Relocation *

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Abstract

Homeowners' insurance premiums in the U.S. have risen dramatically. Using household-level microdata and a novel instrumental variable, we document three main findings. First, consistent with efforts to mitigate the impact of higher premiums, households experiencing larger premium increases are more likely to relocate, and move to areas with lower climate risk and lower insurance costs. Homes experiencing larger premium hikes are more likely to be acquired by investors, who obtain lower premium rates. Second, for households unable to mitigate effectively, higher premiums increase mortgage delinquencies. Third, the relocation effect is stronger among less financially constrained households, who can better afford the upfront costs of moving, while the delinquency effect is concentrated among more constrained households. Our findings reveal how rising insurance costs, increasingly driven by climate change, can threaten household financial resilience, while highlighting an adaptation mechanism through relocation.

JEL Classification: G21, G22, G5, G52, G53, R21, Q54, D14, R3

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1 Introduction

Rising insurance premiums have become a major financial concern for U.S. households in recent years, with 10% of households paying more than $5,000 as of 2024. As premiums continue to rise, they can push households toward costly adaptation strategies or trigger negative financial outcomes. Understanding these effects matters for assessing the broader impact of climate change, which is widely regarded as a main driver of the recent increases and is projected to drive further ones.

As premiums rise, homeowners can mitigate the financial pressure through various strategies that may be costly. They may shop more aggressively across insurers. They may also relocate to areas or properties with lower insurance costs. According to a Redfin survey, 10% of homeowners planning to move cite lowering insurance costs as a reason.[1]For marginal households, the present value of insurance savings can shift the cost-benefit calculation of whether to move or stay. Some buyers may have advantages in holding their vacated home, and thus they can pay above the departing owner's own valuation, further tipping the decision to move. Understanding this relocation response sheds light on a key adaptation mechanism to climate change.

For households unable to mitigate through these strategies, rising premiums threaten to erode financial resilience, which is a concern that has drawn mounting attention from policymakers and regulators.[2] The impact on mortgages warrants particular attention given their dominance on household balance sheets, accounting for 73% of total household debt.[3] Since mortgage payments typically take priority in household budgets, mortgage performance provides important insights into household financial health. Rising insurance premiums reduce the available liquidity for mortgage payments, potentially

[1]See `https://www.redfin.com/news/moving-reasons-safety-survey-2024/`.

[2]See, e.g., U.S. Department of the Treasury, Federal Insurance Office' Analyses of U.S. Homeowners Insurance Market, `https://home.treasury.gov/news/press-releases/jy2791` ; Financial Stability Oversight Council, 2025 Annual Report, `https://home.treasury.gov/system/files/261/FSOC2025AnnualReport.pdf`.

[3]See `https://www.newyorkfed.org/microeconomics/hhdc`. The number is as of 12/2/2025.

increasing delinquency rates and creating ripple effects across the financial sector, given the systemic importance of mortgages.

We study how homeowners' insurance costs trigger household adaptation, including through relocation, and how they affect household financial outcomes. These questions have important implications for understanding the effects of climate change, yet they remain largely unexplored. We study these questions using a newly available dataset that links detailed insurance policy information with household-level mortgage and credit report outcomes in the U.S. between 2015 and 2023.

To identify the causal effect of premium increases, we construct a novel instrumental variable for insurance premium increases, which exploits idiosyncratic differences in the timing and size of insurers' rate changes and which we describe in detail below.

We document three main findings. First, consistent with efforts to mitigate the impact of higher premiums, households facing larger premium increases are more likely to relocate, and go to areas with lower climate risk and lower insurance costs. Homes experiencing larger premium hikes are also more likely to be acquired by investors, who obtain lower premium rates. Second, higher premiums lead to increased mortgage delinquencies for households unable to mitigate their impact. Our estimates indicate that the average premium increase at 2022 renewals caused roughly 29,000 mortgages to be 60 days past due.[4] Third, the relocation effect is stronger among financially less constrained households, who can better afford the upfront costs of moving, while the delinquency effect is concentrated among more constrained households.

To establish causality, we employ an instrumental variables approach with two instruments. The first instrument is, for each household-policy-year, the average premium rate increase among policies renewing in the same month with the same insurer in other ZIP codes within the same state. The second instrument is constructed identically, except that

[4]We multiply the Column (5) estimate of 0.019 in Table 2 by the average premium rate increase at 2022 renewals, 0.030 percentage points of the coverage limit, which implies a $0.019 \times 0.030 \approx 0.057$ percentage point increase in the 60-day delinquency rate, and apply that increase to the 51 million first-lien mortgages outstanding in the U.S. (Federal Housing Finance Agency, National Mortgage Database).

it restricts to distant ZIP codes, those whose distance from the focal ZIP code exceeds the median pairwise ZIP code distance in the state.

The relevance of our instruments stems from two mechanisms. First, premium increases follow location-level trends driven by insurers' risk assessments of that location (Keys and Mulder, 2024) and state regulator approvals of insurers' rate change requests (Oh, Sen and Tenekedjieva, 2022). Therefore, a property's premium change should correlate strongly with the same insurer's premium changes implemented elsewhere in the state in the same month, making our instrument relevant.

Our instrument is also plausibly exogenous. Since our regressions include ZIP-by-renewal month fixed effects, we effectively compare borrowers within the same ZIP code who renew their insurance policies in the same month. The within-ZIP-by-renewal month variation in the instruments stems from differences across insurers based on their rate-setting models and the timing of their rate changes, which are subject to state regulatory approvals. Since households usually receive renewal notices with premium information before the actual renewal time, they could switch insurers before renewal.[5] To get around this endogenous response, we use the insurance policy expiration month and the insurer determined in the previous policy year; the instrument is unlikely to be subject to households' manipulation. Given these arguments, our instrument likely satisfies the exclusion restriction: it is unlikely to affect individual borrowers' mortgage performance or relocation outcomes through channels other than insurance costs.

Our instrument may itself reflect, in part, insurers' repricing of climate-related risk, since carriers incorporate updated risk assessments at different times. Indeed, the variation in the instrument at the ZIP-month level is larger in high-risk areas in recent years. We argue that the instrument is nonetheless valid: as we explain in Section 5, our location-by-time fixed effects absorb the direct effect of local risk on household outcomes, so the

[5]Indeed, households increase their probability of switching insurers in response to our instrument, both measured at the same policy renewal year; see Ge, Johnson, Tzur-Ilan and Wenning (2026) and Internet Appendix Table IA.3.

instrument moves household outcomes through the premium a household pays. Our analyses are thus a first step towards understanding the effect of climate risk through the insurance market. To the extent that it is difficult for households to distinguish the premium increases driven by our instrument from those driven by climate risk, the effect of premium increases attributable to climate risk may be similar.

Moreover, we control for each borrower's credit risk score from the month preceding their insurance policy renewal to further mitigate endogeneity concerns. We also control for house-level climate risk and climate risk bin-by-renewal month fixed effects to remove both fixed and time-varying effects of climate risk.

One may be concerned that sorting between insurers and households drives our results. For example, households that are more likely to become delinquent or to move are systematically matched with insurers that raise premiums more. We address this concern directly with robustness tests that include insurer-by-year fixed effects. The OLS estimates are essentially unchanged and the instrumental-variable estimates, while roughly halved, remain positive and statistically significant.

We begin with the delinquency results. We demonstrate that rising insurance premiums lead to higher probabilities of mortgage delinquency within 12 months after premium changes at policy renewals. When annual premiums increase by \$1,000, the probability of 60-day delinquency rises by 0.38 percentage points, representing a 22% increase relative to the mean probability (1.7%). This sensitivity is close to what Wong (2024) finds for property tax changes, and roughly two and a half times the payment sensitivity implied by Di Maggio, Kermani, Keys, Piskorski, Ramcharan, Seru and Yao (2017); we discuss the comparison in Section 6.

In addition, we find that the delinquency effects are stronger for borrowers with lower credit scores. The distress extends beyond missed payments: larger premium increases also raise rates of mortgage modification and foreclosure, imposing severe consequences on affected households. Additionally, higher premiums increase credit card utilization.

These results demonstrate that rising insurance premiums have broad negative effects across multiple dimensions of household finances, suggesting that the mortgage delinquency effects reflect genuine financial stress rather than a mechanical relationship between insurance and mortgage payments.

In the second part of the paper, we turn to how households mitigate the effects of rising premiums. One margin is to shop for a cheaper insurer: in a companion paper, Ge et al. (2026), we show that households facing larger premium increases are more likely to switch insurers, that switching lowers their premiums, and that this response is concentrated among households with higher credit scores. That margin, however, undoes only part of an increase. Here we focus on a more consequential form of adaptation (relocation) and on the households for whom no inexpensive mitigation is available.

We find that households are more likely to relocate in response to rising insurance premiums. Movers who experienced larger pre-move premium increases relocate to areas with lower climate risk and lower insurance premiums. We also find stronger relocation responses to premium increases among households with higher origination mortgage rates relative to contemporaneous market averages. Notably, mortgage rates have risen in recent years alongside drastic increases in insurance premiums, potentially limiting the relocation response to premium increases due to the mortgage "lock-in" effect. We expect the relocation effect to strengthen as mortgage rates fall, making it financially more favorable to purchase a new home with a mortgage.

In terms of magnitude, a $1,000 increase in annual premiums corresponds to a 0.82 percentage point increase in relocation probability (17% of the mean). This magnitude is comparable to the mortgage lock-in effect on household relocation documented by Fonseca and Liu (2024). The same premium increase leaves non-movers paying a further $260 per year, while movers end up $1,101 per year cheaper than those non-movers. Assuming a discount rate of 6% (Giglio, Maggiori, Rao, Stroebel and Weber, 2021), the present value of the movers' premium savings amounts to around $12,600 over 20 years.

Why relocate when switching insurers is far cheaper? Because the two actions address different parts of a premium increase: switching undoes the portion specific to a household's current carrier, whereas the portion reflecting the location's underlying (and increasingly climate-driven) risk is shared by the insurers serving the area and can be escaped only by moving. Consistent with switching being only a partial remedy, Ge et al. (2026) find that switchers recover only about forty cents of a one-dollar increase in the following year, whereas we show that movers shed close to the full increase. Because relocation is expensive, the present value of the insurance savings rarely triggers a move on its own; it stacks on a household's accumulated reasons to relocate (a job change, a growing family) and tips those already near the margin. Households too constrained to afford a move cannot shed the increase this way, and for a subset the added burden instead contributes to financial distress. We formalize this move-versus-switch choice in a simple model, presented in Internet Appendix IA.A.

Relocation has a further consequence for these neighborhoods. As movers vacate their previous homes, those houses that experienced larger premium increases are more likely to be purchased by investors subsequently. We find that investors pay 14% lower total premiums. This is a result of both lower insurance premium rates and lower coverage. Their lower premium rates likely reflect the competitive advantages that investors possess. They may have greater market power or lower search costs in negotiating or shopping for lower insurance premiums.

Investors also tend to choose higher deductibles and lower coverage amounts. This likely reflects lower effective risk aversion: investors with greater financial flexibility may be better positioned to self-insure against losses, and may hold operational advantages (such as established contractor relationships or economies of scale in repairs) that reduce the true cost of disaster damages. These deductible and coverage choices further compress their total premiums. Because the data come from mortgage servicers, the sample consists entirely of small investors who rely on traditional mortgage financing. Thus,

these results are not driven by large institutional investors.

Our mortgage delinquency results carry significant implications for household financial resilience and broader financial stability. While consistent with the literature on cash-flow shocks triggering mortgage defaults,[6] our findings reveal a distinct channel through which climate change can affect households and the financial system. As disasters become more severe and frequent, they push insurance rates higher, placing financial strain on even those who do not directly experience them. This mechanism poses an emerging threat to both the financial sector and the federal government, as we find delinquency effects in GSE and non-GSE mortgages alike. The magnitude is substantial: once premiums reach their projected 2055 levels, an additional 140,000 mortgages would become delinquent each year.[7] These results also speak directly to the heated policy debate over insurance affordability as policymakers consider interventions such as means-tested insurance subsidies.[8]

Our relocation findings have important implications for long-run demographic sorting and the distribution of climate risk exposure. We find that financially better-off households are more likely to relocate in response to premium increases, and to move to lower-risk areas, while constrained households remain in place despite higher costs. If premiums continue to rise in high-risk areas over the coming decades, this pattern may drive substantial demographic shifts, with wealthier households migrating away and lower-income households becoming increasingly concentrated in areas with elevated climate risk. Over time, this sorting mechanism could exacerbate existing inequalities, as financially constrained households face both higher disaster exposure and a reduced capacity to absorb climate-related shocks.

[6] See, for example, Gupta (2019); Ganong and Noel (2023); Indarte (2023).

[7] First Street Foundation projects premiums will rise 29.4% by 2055 on average in the U.S. (`https://www.realtor.com/news/trends/biggest-home-insurance-premium-hikes/`). Applied to the 0.49% average premium rate in our sample (Table 1), the Column (5) estimate of 0.019 in Table 2, and the 51 million first-lien mortgages outstanding in the U.S.: $0.49 \times 0.294 \times 0.019 \approx 0.27$ percentage points, or roughly 140,000 additional delinquencies per year. Mortgage count from the Federal Housing Finance Agency's National Mortgage Database, `https://www.fhfa.gov/data/dashboard/nmdb-aggregate-statistics`.

[8] For related policy proposals, see, `https://www.cbo.gov/publication/59918`.

The increased presence of investors in properties experiencing large premium increases also has significant long-term implications for housing markets in risky areas. Investors obtain substantially lower premiums and purchase less coverage than individual homeowners, giving them a competitive advantage in high-risk markets. As climate risks intensify and premiums continue to rise over the long term, this advantage may accelerate a shift away from individual homeownership toward investor ownership in vulnerable areas. Given extensive evidence that homeownership facilitates wealth accumulation and generates positive community externalities (Sodini, Van Nieuwerburgh, Vestman and von Lilienfeld-Toal, 2023; Artigue, Bayer, Ferreira and Ross, 2025; DiPasquale and Glaeser, 1999), such a transition could have profound implications for household wealth inequality and neighborhood amenities in climate-exposed regions over the coming decades.

We are among the first to identify the effect of property insurance premiums on households' financial distress and relocation decisions. Our work contributes to several related bodies of literature. First, we extend research on insurance and mortgage markets. Sastry, Sen, Tenekedjieva and Scharlemann (2024) find that financially less constrained households borrow more through purchase mortgages in response to increases in homeowners' insurance premiums. Sastry (2022) shows that lenders require higher down payments from borrowers who under-insure, potentially due to post-disaster default concerns. Sastry, Sen and Tenekedjieva (2023) find higher mortgage defaults in areas with greater insurer insolvency following disasters. We demonstrate that premium increases alone, independent of actual disasters, can also elevate default risk. This mechanism may explain the finding in Ge, Lam and Lewis (2024) that buyers of homes facing exogenous flood insurance premium increases are less likely to obtain mortgages, as lenders may anticipate higher default risks from elevated insurance costs. By highlighting the important effect of insurance premiums, we also contribute to a growing literature on insurance pricing and market dynamics.[9] Beyond insurance pricing, Kalda, Sharma, Soni and Wen-

[9]Cookson, Gallagher and Mulder (2024) uncover coverage neglect in the homeowners insurance market. Liao and Mulder (2021) study the effect of home equity on flood insurance demand. A few papers

ning (2025) and Jotikasthira, Kartasheva, Lundblad and Ramadorai (2025) uncover that insurers deny and delay claim payments as another response to losses. In concurrent work, Gruber and Solomon (2026) find that a recent reform to the National Flood Insurance Program, which directly conveyed property-level risk information and implemented a new pricing scheme, has an effect on net migration.

In addition, our study contributes to the growing body of literature examining the intersection of climate change, natural disasters, and mortgage markets. Prior papers explore the impact of disasters on mortgage delinquencies (Gallagher and Hartley, 2017; Kousky, Palim and Pan, 2020; Billings, Gallagher and Ricketts, 2022; Issler, Stanton, Vergara-Alert and Wallace, 2024; Biswas, Hossain and Zink, 2023) and the pricing of mortgage-related securities (Gete, Tsouderou and Wachter, 2024; Dice, Hossain and Rodziewicz, 2024). We highlight a different channel (insurance costs) through which disaster and climate risks can affect mortgage outcomes. In so doing, we also complement recent work on climate/environmental risk in housing markets (Bernstein, Gustafson and Lewis, 2019; Baldauf, Garlappi and Yannelis, 2020; Murfin and Spiegel, 2020; Keys and Mulder, 2020; Giglio et al., 2021; Lopez and Tzur-Ilan, 2023; Ge et al., 2024; An, Gabriel and Tzur-Ilan, 2024; Van Binsbergen, Cocco, Grotteria and Naaraayanan, 2025).

Our paper also contributes to the literature on how physical climate risk affects financial markets. Acharya, Berner, Engle, Jung, Stroebel, Zeng and Zhao (2023) summarize in their review of the literature that physical risks, such as rising sea levels, extreme weather events, and heat stress, can cause direct damage to assets and disrupt business operations, potentially leading to loan defaults and losses for banks. We highlight a new channel, i.e., insurance premiums, through which climate change can impose substantial risks on the

study the effect of insurance premiums on the housing market, including Ge et al. (2024), Georgic and Klaiber (2022), Gibson and Mullins (2020), and Bakkensen and Barrage (2021). Papers on home insurance pricing include Keys and Mulder (2024), Boomhower, Fowlie, Gellman and Plantinga (2024), Oh et al. (2022), Sastry et al. (2023), and Blonz, Hossain and Weill (2024). Papers on the National Flood Insurance Program pricing include Wagner (2022a), Weill (2022), Mulder and Kousky (2023), and Mulder (2021). Marcoux and Wagner (2023) and Wagner (2022b) study insurance market design. Jung, Engle, Ge and Zeng (2023) measure insurers' exposure to climate risk. See Sastry and Sen (2025) for a review.

financial market.

2 Institutional background

2.1 Background

Homeowners' insurance is a critical component of the U.S. housing market. According to the American Community Survey, around 86% of homeowners held such policies in 2023 and 2024. This high adoption rate is likely driven by mortgage lenders requiring insurance coverage as a precondition for loans. If insurance coverage lapses, the servicer may force-place a policy on the property at the borrower's expense. GSE guidelines require servicers to maintain adequate insurance coverage or risk mandatory loan repurchase upon default. Around 30% of homeowners reported being affected by weather events in the last five years, highlighting the importance of such coverage.[10]

Homeowners' insurance policies typically provide comprehensive coverage for the structure, contents, and temporary living expenses if the home becomes uninhabitable due to damage. These multi-peril policies typically have one-year terms with automatic renewal, subject to potential rate or term changes communicated through annual statements. Standard policies often exclude certain perils, such as floods and earthquakes. Specialized policies are available to cover these excluded risks.[11] In areas where private insurance is difficult to obtain, homeowners may resort to state-sponsored "insurers of last resort," such as Citizens Property Insurance in Florida or the California FAIR plan.

Homeowners' insurance policies typically include several key components that define the scope and extent of coverage. Homeowners can often adjust total insured value and deductibles to change their insurance premiums. The total insured value represents the maximum amount the insurer will pay in the event of a total loss, typically set to the

[10] See Homeowners Perception of Weather Risks 2023 Q2 Consumer Survey, https://www.iii.org/sites/default/files/docs/pdf/2023_q2_ho_perception_of_weather_risks.pdf.

[11] See https://content.naic.org/sites/default/files/publication-hoi-pp-consumer-homeowners.pdf.

estimated cost to rebuild the home. Lenders must maintain property insurance coverage equal to the lesser of 100% of the replacement cost value or the unpaid principal balance, so long as the latter is no less than 80% of the replacement cost value.[12] Deductibles are the amount the policyholder must pay out-of-pocket before insurance coverage kicks in. In our data, the average policyholder chooses a deductible of 0.5% of the total insured value.

2.2 Pricing

The cost of homeowners' insurance is primarily determined by location-specific risks, with states prone to natural disasters such as hurricanes, tornadoes, and wildfires typically having higher premiums. For instance, Florida and Louisiana have some of the highest average annual premiums, exceeding $5,700, while states like Hawaii and Vermont have much lower average costs, around $500 to $800 per year.[13] Other factors affecting pricing include the home's age, construction materials, proximity to fire stations, and the homeowner's claims history and credit score. Insurance companies use complex actuarial models to assess risk and set premiums, leading to variations in pricing among different insurers (Boomhower et al., 2024). Homeowners' insurance rates in the United States are subject to regulatory oversight and approval processes, which vary by state (Oh et al., 2022). Insurance companies typically must submit rate change requests to state insurance departments or commissions for review and approval before implementing new premiums.

[12] See https://selling-guide.fanniemae.com/sel/b7-3-02/property-insurance-requirements-one-four-unit-pr

[13] See https://www.bankrate.com/insurance/homeowners-insurance/home-insurance-statistics/.

3 Data

3.1 Residential Mortgage Servicing (ICE McDash Analytics)

The Residential Mortgage Servicing Database contains information from ICE McDash data. The data mainly comprise the servicing portfolios of the largest residential mortgage servicers in the US. It covers approximately two-thirds of installment-type loans in the residential mortgage servicing market. Loan-level attributes include borrower characteristics (credit scores, owner occupancy, documentation type, and loan purpose); collateral characteristics (LTV, property type, ZIP code); and loan characteristics (product type, loan balance, and loan status). We restrict our sample to loans secured by single-family homes with non-missing ZIP code, occupancy, origination date, LTV, DTI, and credit score. We also drop loans whose origination loan-to-value ratio exceeds 105 or debt-to-income ratio exceeds 65, which we treat as likely reporting errors. We obtain this data for 2013-2023. Because we residualize our instruments (constructed using the insurance data) against their values from the prior two years (described later), the years 2013–2014 do not enter the main regression analysis directly.

We rely on this data for the dependent variable of whether a mortgage is delinquent for at least 60 days. We drop loans that were transferred to a different servicer during our sample period or that were terminated for an unknown reason. Voluntary prepayment also includes refinancing.

To include a loan in our sample, we need to be able to compute the change in premium between policy renewals. As the insurance data are provided along with December loan performance data, a loan that was prepaid, for example, in June after a premium increase in March, would be dropped from the dataset because we do not have its latest insurance information before it was prepaid. Figure IA.3 plots the share of mortgages that are prepaid by the calendar month of the insurance policy expiration date. The share is approximately 15% for policies renewing in January, dropping down to around 3% for February

renewals, and then rises monotonically to 13% for December renewals. It is unlikely that these patterns are due to actual prepayment ratios changing with the insurance renewal month. Thus, we interpret the pattern in Figure IA.3 as being due to under-reporting of prepayment that is more severe between February and August. Because relocation is identified from mortgage prepayment, we therefore restrict the relocation analyses to borrowers whose policies renew between September and January, the window over which prepayment is most accurately reported.[14] Figure IA.2 plots the share of mortgages that are delinquent by the calendar month of the insurance policy expiration date. Note that delinquency reporting does not have this issue.

3.2 ICE McDash Property Insurance Module

We obtain data on insurance at the loan level from ICE McDash between 2015 and 2023. The property insurance module contains a loan identifier allowing insurance information to be matched with ICE McDash Residential Mortgage Servicing Data. Insurance data are obtained from a subset of mortgage servicers who agreed to participate and cover around three-quarters of mortgages in the servicing data.

If insurance coverage is not maintained in accordance with GSE requirements, the servicer may be required to repurchase the loan in the event of default. Because of these legal responsibilities and liability risks, servicers maintain detailed data on insurance coverage and enter these data into the servicing system. When a mortgage is closed, and every year thereafter, borrowers must submit proof of homeowners' insurance.

The ICE McDash Property Insurance data include the following variables: coverage amount per loan, deductible amount, the date when the policy expires, and "Replacement Cost Value" coverage flag, which indicates the primary insurance coverage type. We restrict our sample to loans with annual insurance policies[15] that also appeared in the ICE

[14] In a previous draft, we do not make this sample restriction.

[15] We classify a policy as annual when consecutive policy expiration dates are 351–379 days apart (i.e., one year $\pm$ 14 days).

McDash sample in the previous calendar year. We further require that the loan is current in the month before the insurance policy expires.

3.3 ICE McDash Credit Risk Insights Servicing Module (CRISM)

This dataset merges anonymized mortgage servicing records with borrower credit outcomes. Equifax matches the aforementioned ICE McDash mortgage servicing records to its credit bureau data. This merger adds other credit market outcomes for borrowers, such as their credit card utilization. Equifax also uses multiple data sources to determine whether a borrower has moved their residence. The data offer Risk Scores (different from credit scores), which are generated from Equifax's proprietary credit risk model that predicts the likelihood of a borrower becoming delinquent on credit obligations. Within the CRISM match, we keep borrowers with a single open first mortgage in the month before the policy expires, and we identify a borrower's post-renewal replacement loan from its origination timing and location, excluding candidate loans secured by the same property or Census block, and loans originated outside the window running from the policy start month to four months after the prior loan terminates. We treat reported credit-card utilization above 110% as missing.

3.4 CoreLogic Solutions Real Estate Data

We use CoreLogic's tax assessor and transaction data (Deeds and Tax Data). In addition, we also use CoreLogic Climate Risk Data, which contains structure-level data on measures of current and future climate risk for properties in the U.S. CoreLogic uses its proprietary climate model to generate measures of climate risk on nine perils. For each structure within a parcel or property, the data include a measure of Average Annual Loss (AAL) at various return periods. AAL is the expected annual loss to structure and contents generated by simulating many possible iterations of a given year and then calculating the average loss across all iterations. Thus, AALs account for the magnitude of

damage resulting from events of different severity as well as the likelihood of events of different severity occurring. CoreLogic reports AALs as a share of the coverage limit, which can be understood as the replacement cost of the structure (Wylie, Amornsiripanitch, Heilbron and Zhao, 2025).

3.5 Matching Loan-Level Data with CoreLogic

We merge our loan-level insurance data with CoreLogic's property-level data. This provides us with additional information about the property and its transaction history. We first identify a potential set of candidate properties by requiring an exact match on the 5-digit ZIP code, as well as a mortgage with the same month of origination and a loan amount rounded to the nearest thousand dollars. We exclude piggyback and subordinate-lien records (CoreLogic mortgage-purpose codes C, D, M, N, O, V, and Z) from the candidate set.

We then compute a measure of match quality based on the following criteria: the dollar loan amounts match exactly; origination dates match exactly; loans have the same purpose (i.e., purchase, refinance); the loan type matches (FHA, VA or conventional). We rank potential matches based on the number of these criteria that are satisfied. As a tiebreaker, we use a distance measure based on loan amount and origination date. For each loan, we use the property with the highest quality match. 85% of loans have a property match. 56% have an exact match on all the criteria. 80% of matches have at most one of the additional criteria not met.

We use the matched data to measure the climate risk exposure (proxied by AAL) at the household level. When property-level AAL is not available due to failed matching or missing information, we use the ZIP-level average AAL. We apply the same ZIP-level fallback (the ZIP-by-state median) to the other CoreLogic property characteristics we use as controls, namely the year the structure was built (house age), square footage, and property value, whenever the property-level value is missing or the CoreLogic match is am-

biguous (more than one candidate property maps to the loan). We sort households into three bins based on the AAL measure of their location prior to each insurance renewal. We then use climate risk bin-by-year fixed effects in our regression analyses.

Table 1 reports summary statistics for the main household, mortgage, insurance, and climate-risk variables used in our analysis.[16]

4 Climate Risk Associated with Larger Premium Increases

In Figure 1, we examine how premiums have evolved in recent years. We estimate the following regression at the ZIP-by-year level.

$$\Delta(\textit{Premium Rate})_{z,2014\ to\ t} = \gamma_z + \delta_{c,t} + \sum_{t=2015}^{2023} \beta_t \textit{ClimateRisk}_z + \alpha_t \textit{Controls}_z + \epsilon_{z,t},$$

where z denotes ZIP code, c denotes the county, and t the year. The dependent variable is the cumulative change since 2014 in the premium rate (total premiums relative to the coverage limit, in percentage points), averaged at the ZIP-year level; it is zero by construction in 2014. The main independent variable is CoreLogic's average annual loss (AAL) measure of climate risk at the ZIP level, expressed in percent of the coverage limit.[17] We control for ZIP and county-by-year fixed effects, as well as the ZIP's rural share and log population density from the 2010 census, each interacted with year, and we cluster standard errors by state $\times$ year. So that changes in coverage do not drive the results, we use only renewals at which the deductible (as a share of the coverage limit) and the coverage type are both unchanged from the previous renewal. Figure 1 plots the estimates of β_t and the corresponding 95% confidence interval. The figure suggests that insurance premiums have grown faster in areas with higher climate risk, consistent with Keys and

[16] To limit the influence of outliers, we winsorize or trim the tails of the continuous variables. The climate-risk (AAL) measure underlying our standardized climate-risk control is winsorized at the 98th percentile. Changes in premium rates and the mover-outcome variables (for example, pre-to-post changes in premium rates and in premiums relative to destination-ZIP averages) are winsorized at the 0.5th and 99.5th percentiles, and log premium changes and the mortgage rate gap are trimmed at their 0.1% tails.

[17] We take the average of the climate risk measure across the primary structures in a ZIP code.

Mulder (2024).

5 Instrumental Variables for Premium Increase

Before proceeding to the household-level analysis of the effect of premium increases, we describe our instrumental variable approach. One may be concerned that any observed OLS relationship between higher insurance premiums and household outcomes could be due to omitted variables. For instance, households experiencing financial distress may be more likely to have homes in disrepair and exhibit lower credit scores. These factors could potentially lead insurers to charge such households higher insurance premiums. At the same time, households' financial distress may also independently contribute to mortgage delinquency. We mitigate such endogeneity concerns in our OLS regressions by controlling for credit scores in the month preceding insurance policy renewal, as well as fixed effects, including ZIP-by-renewal month and origination LTV and DTI bin fixed effects.[18] To further address the identification challenge, we instrument for premium changes.

To construct our instruments, for each borrower we calculate the average premium rate increase at renewal across policies that renew in the same month by the same insurer in other ZIP codes within the same state. The first instrument uses all such ZIP codes; the second restricts to distant ZIP codes, those whose distance from the focal ZIP code exceeds the median pairwise ZIP code distance in the state. Rather than using the actual renewal month and insurer, both instruments are constructed using each policy's expiration month and insurer from the prior year to reduce concerns about endogenous renewal timing and insurer switching. These averages at the insurer-by-renewal-month level form our two instruments. The leave-out averages are computed over owner-occupied and investor policies (excluding second homes and policies with unknown occupancy) that

[18]The origination bins are constructed as follows: credit-score bins are 20 points wide and capped to the $[580, 800]$ range, DTI bins are 5 points wide with a floor at 10, and LTV bins are 5 points wide with values below 70 pooled into a single group.

renew with the same insurer and with unchanged deductible and coverage type, so that each contributing observation reflects a within-policy premium change. Policies whose carrier is recorded under certain non-standard insurer codes (such as lender-placed or master policies and unidentified carriers) are treated as having a missing insurer and are excluded both from the instrument and from the insurer-switching indicators.

Next, we residualize the instrument with respect to its 12- and 24-month lagged values, as well as month fixed effects. Table IA.1 presents the regression results. The coefficients on the lagged values are both positive and statistically significant. The magnitudes of the estimates indicate substantial serial correlation. By residualizing with respect to lagged values, we isolate the premium changes related to the instrument in the concurrent period.

Our instrument should satisfy the relevance restriction for the following reasons. Premium increases follow location-level trends driven by insurers' risk assessments (Keys and Mulder, 2024) and state regulatory approvals (Oh et al., 2022). Since premium changes only affect homeowners at renewal, a property's premium change should correlate with premium adjustments implemented by insurers in the same local area since the previous policy renewal.

Our instrument likely satisfies the exclusion restriction for two reasons. First, our main regressions include ZIP-by-renewal month fixed effects, effectively comparing borrowers within the same ZIP code who renew their insurance policies in the same month. The within-ZIP-by-renewal month variation in average premium changes stems from different insurers, including their timing of premium changes and regulatory approvals, rather than from factors related to individual borrowers' mortgage delinquency and other outcomes we examine. Second, we control for each borrower's credit risk score in the month preceding renewal, and for climate risk bin-by-renewal month fixed effects that remove the time-varying effect of climate risk on households' outcomes.

A natural question is whether the premium variation we exploit reflects differences

in risk rather than differences in price. It can: insurers incorporate updated assessments of a location's disaster risk at different times, so within a ZIP code and renewal month two carriers may quote different premiums for the same property simply because one has repriced the risk and the other has not yet done so. The variation our instrument isolates is therefore not necessarily orthogonal to risk: in part it reflects which insurer repriced. This does not threaten identification. Because we compare households in the same ZIP code and month, they face the same underlying risk; that risk, and any recent change in it, is common within the cell and absorbed by the fixed effects, and so cannot directly affect their outcomes. We argue that whatever its origin, the instrument moves delinquency or relocation only through the premium the household pays. If anything, the risk-related content of the variation is what makes our estimates informative about the climate-driven repricing of ultimate concern: we hold the direct effect of risk fixed and let the price of that risk vary.

Several pieces of descriptive evidence support this design. Figure 2 plots, separately for each of our two instruments and by renewal year, how within-ZIP-by-renewal-month dispersion across insurers relates to a ZIP code's climate risk. The relationship is positive in every year (higher-risk areas see insurers diverge more in how much they raise premiums, which is precisely the variation our instruments exploit), and it strengthens over the sample period, roughly tripling between 2016 and 2023. The two instruments track each other almost exactly. Internet Appendix Figure IA.4 further shows that, within a ZIP code, insurers raise premiums at different times but ultimately converge to similar cumulative increases, so the leave-out instrument isolates differences in the *timing* of otherwise-comparable repricing. Finally, Internet Appendix Figure IA.1 reports covariate-balance regressions of each instrument on predetermined household, house, and loan characteristics; the coefficients are uniformly small (on the order of a few thousandths of a standard deviation), indicating that our instruments are essentially orthogonal to these characteristics conditional on the fixed effects, as required by the exclusion restriction.

6 Effect of Premiums on Mortgage Delinquencies

We begin our analyses by examining the effect of premiums on mortgage delinquencies. Table 2 has five columns. Column (1) reports OLS estimates; Columns (2) and (3) report the first and second stages of the instrumental-variable specification using the Other-ZIP instrument, and Columns (4) and (5) repeat the two stages using the Far-ZIP instrument. The dependent variable is 60-day mortgage delinquency in the odd-numbered columns and *Premium Rate Increase* in the two first-stage columns. Column (1) estimates the following OLS regression, in which the mortgage outcome is measured over the 12 months following the insurance renewal.

$$Delinquency_{i,t \text{ to } t+12} = \beta \times Premium\ Rate\ Increase_{i,t} + Controls + FE_{ZIP,t} + OtherFEs + \epsilon_i,$$

where i indexes households, t indexes the insurance renewal month, and ZIP indexes the ZIP code. The dependent variable is an indicator of whether the household is delinquent on the mortgage for at least 60 days. The main independent variable, *Premium Rate Increase*, is defined as the change in the premium rate at policy renewal relative to the previous policy year, with a value of zero when the premium rate decreases. Decreases are rare in our sample and are often driven by households' choice of decreasing coverage and increasing deductibles.

Importantly, we control for the borrowers' credit scores in the month prior to the insurance renewal. In addition, we control for households' climate risk exposure at their residence. By controlling for ZIP-by-renewal month fixed effects, we effectively compare households within the same ZIP code who renewed their insurance policies in the same month. We also control for a battery of other fixed effects: climate risk bin-by-insurance renewal month, mortgage origination year, loan-to-value ratio bin, credit score at origination bin, and debt-to-income ratio bin. The estimated coefficient on the premium change is positive, suggesting that when premiums increase, households are more likely to be

delinquent on their mortgages.

One may be concerned that certain insurers are matched to households who are more likely to become delinquent on their mortgages. Such insurers may also increase premiums further. To mitigate such concerns about insurer-household endogenous matching, in Columns (1)–(3) of Table A.2, we repeat the OLS and both two-stage least-squares specifications, adding insurer-year fixed effects. The OLS estimate is essentially unchanged, while the two-stage least-squares estimates fall by roughly half but remain positive and statistically significant.

Figure 4 presents bin-scatter plots illustrating the relationship between the 60-day mortgage delinquency probability and changes in premium. The figure shows a positive relationship between delinquency probability and changes in premiums, supporting our regression results.

Columns (2) and (4) of Table 2 present the first-stage results, where the dependent variable is *Premium Rate Increase*, the same as the main independent variable in the OLS regression. Our instrument predicts premium increases, with positive, statistically significant coefficients, 0.885 and 0.674. The results indicate that households face larger premium increases when their insurers raise premiums more in other or distant ZIP codes within the same state. The large Kleibergen-Paap Wald F-statistic suggests that the instruments are sufficiently strong. Figure 3 illustrates this first stage with a bin-scatter of the premium rate increase against the Far-ZIP instrument, after partialling out the fixed effects and controls.

Columns (3) and (5) present the second-stage results. The dependent variable is an indicator for 60-day mortgage delinquency. The coefficients on the instrumented premium increases are positive and statistically significant, suggesting that premium increases cause higher mortgage delinquency rates. The estimate in Column (5) indicates that a \$1,000 increase in premium (or a 0.2 increase in premium rates) corresponds to a 0.38 percentage point increase in the 60-day delinquency rate, which corresponds to a

22% increase relative to the sample mean. The OLS coefficient is larger in absolute magnitude (Column 1) than both instrumental-variable estimates, consistent with endogeneity bias. For example, households experiencing financial difficulties are likely to face both larger premium increases (owing, for instance, to deferred maintenance) and elevated delinquency rates.

Our instrumental-variable estimate is similar to that in Wong (2024) who studies tax changes, using 30-day delinquencies (untabulated) to match what he reports. However, our sensitivity is roughly two and a half times that reported by Di Maggio et al. (2017), who find that when conforming five-year adjustable-rate mortgages automatically reset to lower rates, monthly payments fall by about $277 (23%) and the likelihood of 60+ day delinquency falls by 0.5 percentage points over the following year, roughly 0.15 percentage points per $1,000 of annual payment relief, compared with our 0.38 percentage point increase per $1,000 increase in annual premiums.[19] The difference in magnitudes likely stems from the asymmetric effects between payment increases and decreases. Di Maggio et al. (2017) studied borrowers who qualified for mortgages at higher interest rates, suggesting these households could already afford the higher payments absent adverse shocks. Consequently, substantial reductions in payments had a comparatively modest effect on their delinquency rates, even though their crisis-era sample, in which many borrowers were deeply underwater, is one where payment relief should be especially potent. In contrast, our study examines borrowers who initially qualified for mortgages with lower insurance payments. For these households, insurance payment increases could potentially push total monthly obligations beyond some borrowers' payment capacity. Supporting this interpretation, our analysis below shows that delinquency effects are more pronounced among borrowers with smaller financial buffers to absorb increased insurance payments. This asymmetry could explain the heightened sensitivity observed in

[19]Di Maggio et al. (2017) report that monthly payments on conforming five-year ARMs fell by $277 on average in the first year after reset (about $3,300 per year), and that the likelihood of 60+ day delinquency fell by 0.5 percentage points in the first year and 1.8 percentage points after two years. At the one-year horizon matching our outcome window, $0.5/3.3 \approx 0.15$ percentage points per $1,000 of annual payments.

our setting compared to Di Maggio et al. (2017).[20]

6.1 Delinquency Effect Across Investors

A natural question is whether the effect of insurance premiums on mortgage delinquencies is present for FHA and GSE loans, especially those without private mortgage insurance. This would imply a risk for the federal government, particularly if insurance premiums keep rising. We are also interested in whether the delinquency effect exists in private-label MBS and banks' portfolios, exposing investors and banks to associated risks. We investigate these questions in the following analysis.

In Table A.4, we repeat our instrumental variable analysis on mortgage delinquencies across different types of mortgages. We use mortgages guaranteed by Ginnie Mae in Column (1), by Fannie Mae in (2), by Freddie Mac in (3), private mortgages that are securitized in (4), and those that remain in banks' portfolios in (5). In Columns (6) and (7), we further split conventional mortgages by whether they have private mortgage insurance or not, i.e., whether the GSEs are ultimately exposed to credit risks. The results suggest that the effect of premiums on delinquency holds across subsamples, although it is not statistically significant for privately securitized mortgages, potentially due to a smaller sample size.

6.2 Delinquency Effect Not Driven by Disasters

A potential concern is that households in disaster-affected areas may experience larger insurance premium increases alongside higher delinquency rates, all as direct consequences of natural disasters. In our analyses so far, we effectively compare borrowers within the same ZIP codes who renew their insurance policies within the same month, who likely

[20]Similar to our paper, Mello (2024) also shows that even small unexpected fines can increase financial distress, especially among financially fragile Households, and find that receiving fines for traffic violations averaging $195 is associated with a $34 increase in unpaid bills in collections. Gallagher, Gopalan and Grinstein-Weiss (2019) find that receiving health insurance subsidies is associated with a roughly 25% decline in the delinquency rate. Their mechanism differs from ours, as it operates through reduced exposure to out-of-pocket medical expenditure risk rather than through direct insurance cost burdens.

share the same disaster experience, making disasters an unlikely explanation. Moreover, our instruments are constructed using insurers' pricing changes in other or distant ZIP codes, making them less related to the disasters that can affect delinquencies in the focal ZIP codes.

Regardless, we address this concern directly in Columns (1)–(3) of Table A.5, separately analyzing ZIP codes that experienced natural disasters within the current or preceding two calendar years (Column (1)) and those that did not (Column (2)), using First Street Foundation's Climate Data, and then pooling the two samples and adding an interaction between *Premium Rate Increase* and a recent-disaster indicator (Column (3)). The results provide reassuring evidence that disaster experiences do not drive our main findings, as the main results are closer to those using the non-disaster sample. The response is stronger in the disaster sample, consistent with the idea that households affected by disasters are more financially constrained and are more likely to fall behind on mortgages when insurance premiums increase.

6.3 The Delinquency Effect is Robust When Households Are Attentive to Premium Changes

One concern is that delinquency effects arise not from financial strain but from borrowers' inattention: households may fail to notice premium increases and consequently underfund their escrow accounts, leading to missed payments. To address this, Table A.3 restricts the sample to households that were likely attentive to premium changes (specifically, those that adjusted their deductible percentages or changed between Replacement Cost Value and Actual Cash Value coverage around the time of the premium increase) while excluding households that switched insurers, so that the premium increase we study is one they continued to bear. These active policy adjustments suggest awareness of the premium change.

The estimated coefficient on *Premium Rate Increase* remains positive and statistically

significant in all three columns: 0.019 in the OLS specification of Column (1), 0.017 in the Other-ZIP instrumental-variable specification of Column (2), and 0.020 in the Far-ZIP specification of Column (3). These estimates are qualitatively similar to their full-sample counterparts in Table 2. This result indicates that the delinquency effect is not driven by inattention to premium increases.

6.4 Mortgage Modification, Foreclosure, and Credit Card Usage

In Table 3, using the instrumental variable approach, we also find that increases in premiums also lead to an increase in mortgage modification and foreclosure probabilities, where foreclosure is measured over the 24 months following renewal to allow for the time it takes to complete. The estimate suggests that a $1,000 increase in premiums leads to a 0.04 and 0.06 percentage point increase in the probability of modification and foreclosure, respectively.

In Columns (3)-(4), we examine credit card outcomes. Column (3) suggests that a $1,000 increase in premiums leads to a 0.2 percentage point increase in credit card utilization. Column (4) replaces the endogenous variable with the dollar premium increases, while keeping the instrument the same. The estimate suggests that for a $1,000 increase in insurance premiums, credit card balances increase by $77.

These results demonstrate that rising insurance premiums have broad negative effects across multiple dimensions of household finances, and indicate that the mortgage delinquency effects reflect financial stress rather than mechanical relationships.

7 Effect of Premiums on Relocation

Why would a household bear the large fixed cost of relocation rather than shop for a cheaper insurer, a far less costly action? The key is that switching and moving neutralize different components of a premium increase. A household's premium has an insurer-specific component, reflecting the idiosyncrasies of its current carrier's rate-setting, and a

location-specific component, reflecting the underlying (and increasingly climate-driven) disaster risk of the location itself. Switching primarily addresses the former: a household can leave an unfavorable carrier, but insurers serving its location price broadly the same underlying risk, so shopping does little to undo the part of an increase that is common to the area. That component is difficult to escape without relocating, and a move tends to address it alongside the insurer-specific part, because a relocating household takes out a new policy on a different property and often re-shops carriers in the process; in our data, 38% of movers change insurer.

Recall that our main design identifies effects from within-area variation that is idiosyncratic to the insurer (Section 5); even so, it elicits both a strong switching response and a smaller but economically meaningful moving response. Two features help reconcile the moving response with the cost of moving. First, switching appears to recover only a fraction of a premium increase (Ge et al. (2026) estimate on the order of forty cents on the dollar in the year after switching, part of which reflects a transitory new-customer discount), whereas movers who experience larger pre-move increases subsequently shed an amount close to the full increase, so relocation can be the more effective response even to an insurer-specific shock.

Internet Appendix Figure IA.4 helps explain why switching yields so little durable relief. Within each ZIP code, we rank insurers by how early they implement their eventual premium increase and split them into an early- and a late-repricing half. The early half raises rates faster at first, so for much of the sample a household insured with one of them can find a cheaper carrier among the late half. That advantage does not last. The late half catches up and then overshoots, with the two paths crossing between 2020 and 2021 in the 2014–2023 window and in 2022 in the 2018–2023 window. By 2023 the late half has raised premium rates by roughly 19 and 14 percentage points of the coverage limit in the two windows, against roughly 11 and 10 percentage points for the early half. A household that switches away from an early repricer is therefore moving to a carrier that has not yet

repriced rather than to one that will ultimately charge less, so it captures the prevailing cross-carrier gap rather than a lasting saving. Relocation works differently: it changes the location-specific risk being priced, which no carrier serving the origin ZIP code can undo.

Second, households rarely move for insurance alone; the present value of the insurance savings stacks on top of a household's accumulated, idiosyncratic reasons to relocate, such as a job change or a growing family, and can tip those already near their moving threshold. Households far from that threshold tend to switch or to absorb the increase in place, whereas those too constrained to cover the upfront cost of moving are more exposed: when the increase cannot be shed cheaply, the added burden appears to contribute, for a subset of these households, to financial strain and, in some cases, missed mortgage payments.

If house prices fully capitalize on premium changes, relocating in response to premium increases may not have a positive present value. However, some market frictions can induce households to move in response to premium increases. For example, some buyers may have a larger advantage in owning properties that have experienced larger increases in premiums, as we discuss in Section 9.3. Table 4 tests the relocation hypothesis using the matched ICE McDash–Equifax Credit Risks Insight Servicing (CRISM) sample. Because we require movers to have prepaid their mortgage, we restrict the sample in this exercise to borrowers whose home insurance renews between September and January, as prepayment is more accurately identified for these borrowers.

Column (1) presents the OLS regression examining whether larger premium increases trigger more households to relocate. The dependent variable equals one if borrowers changed addresses within 12 months of insurance renewal, based on credit bureau data. The primary independent variable is the premium rate increase for each borrower, consistent with our main specification. The estimated coefficient on *Premium Rate Increase* is positive and statistically significant, indicating that households are significantly more likely to relocate when experiencing larger premium increases. Columns (2) and (4) present the

first-stage results of the instrumental variable regressions. Our instruments remain highly relevant in this smaller sample. Columns (3) and (5) present the second-stage results.

The estimated coefficients on *Premium Rate Increase* are highly similar between the OLS and the instrumental variable regressions. Based on Column (5), a $1,000 increase in premium corresponds to a 0.82 percentage point increase in relocation probability, equivalent to 17% of the mean. Figure 5 presents the corresponding bin-scatter plots, plotting the moving probability against the premium rate increase both unconditionally and in the instrumented second stage.

This magnitude is comparable to the mortgage lock-in effect on household relocation documented by Fonseca and Liu (2024). To compare effects in equivalent dollar terms, premium rate changes must be scaled by the ratio of loan amount to coverage amount (mean of 1/3.5 in our sample). A 1 percentage point increase in mortgage rates is thus comparable to a 0.3 percentage point increase in premium rates. Based on our 2SLS estimate in Column (5), a 0.3 percentage point premium rate increase raises moving probability by 1.2 percentage points. For a similar dollar amount change in moving incentives, Fonseca and Liu (2024) find that a 1 percentage point increase in mortgage rate deltas raises the moving rate by 0.7 percentage points.

Columns (4)–(6) of Table A.5 repeat the disaster split for relocation. The effect is not driven by households experiencing disasters: it is present in both subsamples, and it is in fact smaller in the disaster subsample (0.029 in Column (4)) than in the remaining ZIP codes (0.047 in Column (5)), with the interaction in Column (6) statistically insignificant. To mitigate concerns about insurer-household endogenous matching, in Columns (4)–(6) of Table A.2, we repeat the OLS and both two-stage least-squares specifications, adding insurer-year fixed effects. As with delinquency, the OLS estimate is essentially unchanged, while the two-stage least-squares estimates fall by roughly half but remain positive and statistically significant.

8 Heterogeneous Effects on Delinquency and Relocation

We now examine how the effects of premium increases on mortgage delinquency and relocation vary with household financial constraints, using credit scores as a proxy. Our predictions differ across outcomes. For mortgage delinquency, if premium increases represent negative liquidity shocks, the effect on delinquency should be concentrated among financially constrained households.

For relocation, competing forces are again at play. Although constrained households may benefit more from escaping high-premium areas, relocation entails substantial upfront costs that may be prohibitive for liquidity-constrained households. Moreover, less constrained households may find relocation easier to execute if they have greater flexibility to change jobs or work remotely.

To test these predictions, Table 5 sorts households into terciles by credit score (Columns 1–2) and, additionally, by loan-to-value ratio (Columns 3–4) and debt-to-income ratio (Columns 5–6), replicating our main OLS specification and adding interactions between *Premium Rate Increase* and indicators for the second and third terciles of each sort variable. We focus first on the credit-score columns, where the outcome variables are mortgage delinquency (60-day past due) in Column (1) and relocation in Column (2). Insurer switching, which we analyze in the companion paper Ge et al. (2026), is reported in Internet Appendix Table IA.2.

The coefficient on *Premium Rate Increase* remains positive and statistically significant across all columns, indicating that the baseline effects documented earlier are present among households in the omitted (lowest) tercile of each sort variable. For mortgage delinquency (Column 1), both interaction terms are negative and statistically significant, with magnitudes that largely offset the main effect. These results suggest that households in the second and third credit score terciles exhibit little delinquency response to premium increases, consistent with the view that financially flexible households can absorb these

shocks without falling behind on mortgage payments.

For relocation (Column 2), both interaction terms are again positive and statistically significant: they equal 76% and 133% of the main effect, so the implied relocation response is 76% and 133% larger for the second and third credit score terciles, respectively, than for the lowest tercile. This finding supports the hypothesis that less constrained households are better positioned to act on relocation incentives, whether due to greater liquidity to cover moving costs or greater flexibility in employment arrangements.

The loan-to-value and debt-to-income sorts in Columns (3)–(6) deliver the same message through two additional proxies for financial constraints. For delinquency, the interactions are positive and significant for both the middle and top terciles of LTV (0.010 and 0.053 in Column (3)) and of DTI (0.025 and 0.043 in Column (5)), so the delinquency response to premium increases is several times larger for the most levered and most debt-burdened households than for the least. For relocation, the pattern reverses: the top-tercile interactions are negative and significant for both LTV (-0.012 in Column (4)) and DTI (-0.013 in Column (6)), each roughly 30% of the corresponding main effect, so the households with the least equity and the highest debt burdens are the least likely to respond to premium increases by moving. Sorting on credit score, leverage, and debt burden therefore all point the same way: constrained households absorb premium increases by falling behind on their mortgages, while unconstrained households absorb them by relocating.

9 More Relocation Outcomes

9.1 Relocation Effect Depends on Mortgage Rate "Lock-In"

Table 6 repeats the analysis above with the addition of an interaction term between *the Premium Rate Increase* and the difference between mortgage rates at origination and the average mortgage rates in the month of insurance rate renewal. The interaction term is

positive and statistically significant in the OLS regression (Column 1) and in both the Other-ZIP (Column 2) and Far-ZIP (Column 3) instrumental-variable regressions, suggesting that households with higher origination mortgage rates relative to contemporaneous mortgage rates are more likely to relocate following premium increases.

This finding aligns with Fonseca and Liu (2024), who demonstrate that elevated mortgage rates reduce household mobility. Notably, mortgage rates have risen in recent years alongside drastic increases in insurance premiums, potentially limiting the relocation response to premium increases due to the mortgage "lock-in" effect. We expect the relocation effect to strengthen as mortgage rates fall, making it financially more favorable to purchase a new home with a mortgage.

9.2 Premium Increases Drive Relocation to Lower Premiums

If households move due to premium increases, they should achieve premium savings after moving. We next examine how premium rate increases affect households' subsequent premium changes and how this effect differs between movers and stayers. Table 7 presents second-stage results for a range of mover outcomes. In Column (1), the dependent variable is the change in premium rates from policy year t to $t+1$, with the initial *Premium Rate Increase* on the right-hand side measured from policy year $t-1$ to t; the remaining columns, discussed below, turn to where and with which insurer movers end up.

In this column we use the full sample and add an interaction term between the initial *Premium Rate Increase* and an indicator for moving within 12 months after renewal.[21] The positive coefficients on *Premium Rate Increase*, 0.280, indicate that for non-movers, larger premium increases from $t-1$ to t are associated with subsequent premium increases in policy year from t to $t+1$. This pattern can emerge despite our ZIP-by-renewal year fixed

[21] As a result, in the instrumental variable approach, we have two endogenous variables and two first stages. We also add an interaction term between our instrument and the indicator for moving as the second instrument in both first stages.

effects when households exhibit sticky insurer choice and certain insurers implement consecutive rate increases more often than others.

The results differ markedly for movers. Larger premium increases lead to larger subsequent premium reductions: the estimated coefficient on *Premium Rate Increase* $\times$ *Moved* is negative and statistically significant, -1.2; these interaction effects more than offset the positive main effect of *Premium Rate Increase*, resulting in a net negative relationship for movers.

Based on the interaction coefficient in Column (1), a \$1,000 increase in premium leads movers to reduce their subsequent premium rate by 0.24 (= 1.184 $\times$ 0.2) percentage points more than non-movers. Scaling by a coverage limit of \$465,000 in 2023, movers' premium savings translate to \$1,101 per year compared to non-movers. If this saving remains the same, assuming a discount rate of 6% (Giglio et al., 2021), the present value of the premium savings amounts to \$12,628 within 20 years.[22]

Table A.6 examines the effect of pre-move premium increases on other mover outcomes. Households experiencing larger pre-move premium increases relocate to newer homes at their destination (the change in house age is negative and statistically significant), while the destination homes are somewhat more expensive and carry slightly more coverage, though these latter two differences are not statistically significant. Their total premiums nonetheless decline significantly, reflecting the lower premium rates post move. Pre-move premium increases bear no statistically significant relationship to post-move principal, interest, and insurance payments combined, consistent with households offsetting their insurance savings with larger mortgage payments. This is consistent with the literature on household target expenditures.[23]

[22] In our data, the probability that a household moves in a year is 0.05 (Table 1), implying that the average borrower stays in a house for about 20 years.

[23] See Fuster and Willen (2017), Eberly and Krishnamurthy (2014), Di Maggio et al. (2017), Greenwald (2018), Ganong and Noel (2020), and Argyle, Nadauld and Palmer (2020).

9.2.1 Explaining Premium Savings for Movers With Larger Pre-move Premium Increases

How are movers with larger pre-move premium increases able to achieve such large premium savings? It is possible that they move to safer areas. Columns (2) and (3) of Table 7 examine whether larger insurance premium increases lead households to move to less risky locations, using the Far-ZIP instrument. In Column (2), the dependent variable is the change in climate risk, defined as the difference between the average risk level in the destination ZIP code and the original property-specific risk; in Column (3) it is the change from the mover's pre-move premium rate to the average premium rate in the new ZIP code. The specification restricts the sample to movers and, because the mover sample is much thinner, replaces the ZIP-by-renewal month fixed effects of our main specification with pre-move state-by-year and climate risk bin-by-year fixed effects, retaining our other controls.

Our measure of climate risk can be noisy. For example, it does not account for the age and condition of each property, while poorly maintained houses are more exposed to climate risk. An alternative proxy for movers' change in climate risk exposure is the change from their pre-move premium rate to the average in their new ZIP code, assuming that premium rates largely reflect insurers' assessments of local risks and average house quality. Using average premiums reduces the measure's sensitivity to factors such as lower teaser rates for new home buyers. This measure is the outcome variable in Column (3). We acknowledge that the new ZIP average premiums can also be correlated with factors unrelated to climate risk. However, our analysis below argues that our results are unlikely driven by state-wide factors such as regulation or state-wide construction costs.

In Column (3), the coefficient on *Premium Rate Increase* is negative and statistically significant. The magnitude suggests that for movers who experience a $1,000 larger increase in premiums before moving, the average premium rate in the new ZIP code is 0.24 percentage points lower than their old premium rate, which is 49% of the average premium

rate of 0.49.

Relocation typically bundles an insurer change: because movers take out a new policy on a different property, they tend to re-shop carriers in the process; indeed, over a third of movers in our sample switch insurers. Consistent with this, in Column (4) of Table 7 the coefficient on *Premium Rate Increase* is positive and statistically significant: movers facing larger pre-move increases are more likely to arrive at their new residence with a different insurer. The insurer-switching response to premium increases is analyzed in the companion paper Ge et al. (2026).

The remaining two columns ask whether movers with larger pre-moving premium increases switch to "cheaper" insurers or lower-cost states to save on insurance costs. Column (5) examines this by replacing the dependent variable with changes in insurers' average premium rates in other ZIP codes within the same state, with the state changing for across-state movers. For non-switchers, this change is driven by the same insurer's rate change year-over-year and sometimes across states. Note that among movers, the sample used here, the average switching probability is 38%. The coefficient on *Premium Rate Increase* is statistically insignificant.

Movers with larger pre-moving premium increases can also reduce insurance costs by moving to areas with a more competitive insurance market. In Column (6), we test this hypothesis by replacing the dependent variable with the change in insurers' Herfindahl index (HHI) from the old to the new ZIPs. The estimated coefficient on *Premium Rate Increase* is small and only marginally significant (at the 10 percent level), and if anything positive, providing no evidence that movers with larger pre-move premium increases relocate to less concentrated insurance markets.

What can explain the larger post-move premium savings for movers experiencing larger pre-move premium increases? We investigate this question in Internet Appendix Table IA.4. Using the full sample of movers and stayers, we regress the change in the premium rate from policy year t to $t+1$ on the mover's idiosyncratic pre-move *Premium Rate*

Increase (instrumented by the Far-ZIP instrument), an indicator for moving, and their interaction. The coefficient on *Premium Rate Increase* $\times$ *Moved* captures the additional post-move premium change experienced by movers, which is -1.184 absent any additional control (Column (1) of Table 7). In each column we add one candidate mechanism, entered on its own and, for Columns (2)–(5), also interacted with the moving indicator, to assess whether it absorbs this mover-specific premium saving.

In Column (1), we control for movers' pre-to-post change in their climate risk exposure. If it explains the premium savings for movers with larger pre-move premium increases, the coefficient on *Premium Rate Increase* $\times$ *Moved* should shrink in absolute magnitude. Instead it is essentially unchanged at -1.190, indicating that CoreLogic's noisy climate-risk measure accounts for little of the post-move premium savings.

In Column (2), we instead control for the alternative proxy for movers' change in climate exposure: the change from their pre-move premium rate to their post-move ZIP-average premium rate. The interaction coefficient shrinks substantially in absolute magnitude, from -1.184 to -0.695 (roughly 40%), indicating that much of the mover-specific premium saving is accounted for by movers relocating to ZIP codes with lower average premiums. Because ZIP-average premium rates plausibly reflect insurers' assessment of local risk, this is consistent with movers relocating to safer areas; the lower destination premiums could in principle also reflect factors unrelated to climate risk, such as regulation, though our results below argue against state(-time)-wide factors.

In Column (3), we control for an indicator of whether the mover also switched insurers, which can proxy for more active shopping. The interaction coefficient is essentially unchanged (-1.196), so switching does not explain the savings. In Column (4), we control for changes in insurers' average premium rates in other ZIP codes within the same state, which capture insurers' rate-setting driven by factors such as costs, markups, and regulation; here the interaction coefficient falls to -0.734 (roughly 38%), indicating that insurers' broader across-location rate-setting absorbs a meaningful share of the sav-

ing. In Column (5), we control for the change in insurer concentration, measured by the Herfindahl-Hirschman Index (HHI), from the mover's old to new ZIP codes; the coefficient is essentially unchanged (-1.187), providing no evidence that relocation to less concentrated insurance markets explains the savings.

In conclusion, Internet Appendix Table IA.4 suggests that movers with larger pre-move premium increases achieve larger post-move premium reductions largely because they relocate to ZIP codes with lower average premium rates (Column (2)), with insurers' broader across-location rate-setting accounting for a further share (Column (4)); switching insurers, destination-market concentration, and CoreLogic's noisy climate-risk measure explain little. The results are consistent with the idea that movers with larger pre-move premium increases are, on average, moving to safer, lower-premium ZIP codes.

9.3 Investors

As households move due to higher premiums, who are the buyers of those vacated homes? We hypothesize that buyers are more likely to be investors when the increase in the insurance premium is larger. Investors may have greater market power or lower search costs in negotiating or shopping for lower insurance premiums.

In Table 8, we examine whether the buyers of vacated homes are more likely to be investors when properties face larger premium increases. Column (1) presents OLS estimates using an indicator for whether the buyer is an investor, identified by CoreLogic's corporate-buyer flag[24], as the dependent variable and *Premium Rate Increase* as the independent variable. Columns (2) and (3) present the first- and second-stage results of our 2SLS analysis using the residualized Other-ZIP instrument. The second stage confirms the OLS findings: the coefficient on *Premium Rate Increase* is positive and statistically significant at the 1 percent level. The magnitude in Column (3) suggests that a \$1,000 increase in premiums raises the probability that the buyer is an investor by 0.78 percentage points,

[24]CoreLogic's corporate-buyer flag is based on the grantee's entity classification, which distinguishes non-individual buyers (e.g., corporations, LLCs, partnerships, and trusts) from individual buyers.

an 18% increase relative to the sample mean. Columns (4) and (5) repeat the instrumental variable regressions using the Far-ZIP instrument. The second-stage coefficient, 0.031, is larger than the OLS estimate and remains statistically significant at the 5 percent level, with a t-statistic of 2.12. Table IA.5 in the Internet Appendix reports a similar, somewhat larger effect using McDash's market-investor designation as an alternative definition of an investor buyer, with both second-stage estimates significant at the 1 percent level. We link a vacated home's sale to the borrower's premium change using CoreLogic transactions that occur within about two months of the loan's origination or termination and within twelve months after the policy start month; in constructing this buyer sample we set loan-to-value ratios above 1.5 to missing and assign a zero loan-to-value to all-cash purchases.

Table 9 examines whether investors hold advantages in lowering insurance costs and systematically make different insurance choices. The dependent variables are insurance outcomes described below, including insurance premiums. The main independent variables are an investor indicator and its interaction with the Census block-year average of premium rate increases relative to the prior year (standardized). Additional controls include climate risk, pre-renewal credit score, an indicator for properties under five years old, log square footage, and log appraisal value. Fixed effects include house age (10-year) bins, Census block-by-year, climate risk bin-by-year, origination year, credit score bin, LTV bin, and DTI bin.

Although investors do not select properties randomly, the controls we include partially absorb factors relevant to insurance outcomes. Census block-by-year fixed effects further mitigate endogeneity concerns by comparing homes within the same block in the same year.

Column (1), where the outcome is log premiums, yields a negative and significant coefficient on the investor indicator, suggesting that investors obtain lower total premiums. The negative and significant coefficient on the interaction term indicates that this advan-

tage grows when local premiums rise more sharply. The economic magnitude is meaningful: investors pay 14% lower total insurance premiums at the mean local premium rate increase. Column (2), where the outcome is the premium rate, corroborates this pattern: investors pay lower premium rates, around 9% relative to the sample average. Column (3), where the outcome is the premium rate increase from the prior renewal, similarly shows that investors experience slower premium growth relative to other homeowners in the same Census block by 21% relative to the mean rate increase of 0.029. In Columns (1)–(3) the interaction terms are all negative, and in each case they carry the same sign as the corresponding investor main effect, suggesting that investors' advantages are larger in blocks where premiums have increased more.

These premium advantages may reflect investors' choices of coverage and deductible. In Column (4), the dependent variable is log total insured value. Both the investor indicator and the interaction term carry negative, statistically significant coefficients, indicating that investors select lower coverage amounts by 7%, and do so more aggressively when local premiums are rising faster, which can reduce total premiums.

In Column (5), the dependent variable is the deductible relative to the total insured value. The investor indicator is positive and statistically significant, indicating that investors choose deductible ratios that are 21% higher than the sample mean; the interaction with local premium increases is positive but not statistically significant. Higher deductibles can contribute to lower premium rates and lower total premiums.

Investors may obtain lower premium rates through superior price shopping and greater bargaining power, potentially including scale discounts for insuring multiple properties. Their tendency to select lower coverage amounts and higher deductibles may reflect several factors. First, investors may have greater financial flexibility, reducing their effective risk aversion and making high-deductible plans more attractive. Second, smaller mortgage balances may lower lender-imposed insurance minimums. Third, investors may face lower disaster repair costs by maintaining contractor relationships, employing dedi-

cated repair staff, or handling repairs directly.

Taken together, the results in Table 9 indicate that investors hold advantages over owner-occupants in containing insurance costs, and that this advantage widens as local premium pressures intensify. These findings offer a partial explanation for why homeowners may be more likely to sell to investors when facing larger premium increases: investors' ability to contain insurance costs more effectively gives them comparative advantages in owning such properties.

10 Conclusion

This paper examines how rising homeowners' insurance premiums affect household financial outcomes. Using household-level microdata and a novel instrumental variable strategy, we document three main findings. First, households facing larger premium increases are more likely to relocate to areas with lower insurance costs. Homes experiencing larger hikes are more likely to be acquired by investors, who obtain lower premium rates and purchase less coverage. Second, households unable to mitigate the financial pressure experience higher rates of mortgage delinquency. Third, these responses vary systematically with financial constraints: relocation is concentrated among financially less constrained households who can afford moving costs, while delinquency effects are concentrated among more constrained households.

Our findings on mortgage delinquency reveal a distinct channel through which climate change can affect households and the broader financial system. As disasters become more severe and frequent, they push insurance rates higher, placing financial strain on even those who do not directly experience them. This mechanism poses an emerging threat to both the private financial sector and the federal government, as delinquency effects appear in GSE and non-GSE mortgages alike. These results speak directly to the heated policy debate over insurance affordability, as policymakers consider interventions such as means-tested insurance subsidies.

Our results on household relocation also carry important long-term implications. If premiums continue to rise in high-risk areas, the differential relocation response we document may drive substantial demographic shifts, with wealthier households migrating away while lower-income households become increasingly concentrated in climate-exposed regions. Meanwhile, investors' competitive advantage in high-risk markets, stemming from lower premiums, may accelerate a shift away from individual homeownership. Given evidence that homeownership facilitates wealth accumulation and generates positive community externalities, these dynamics could exacerbate inequality and erode community amenities in vulnerable areas over the coming decades.

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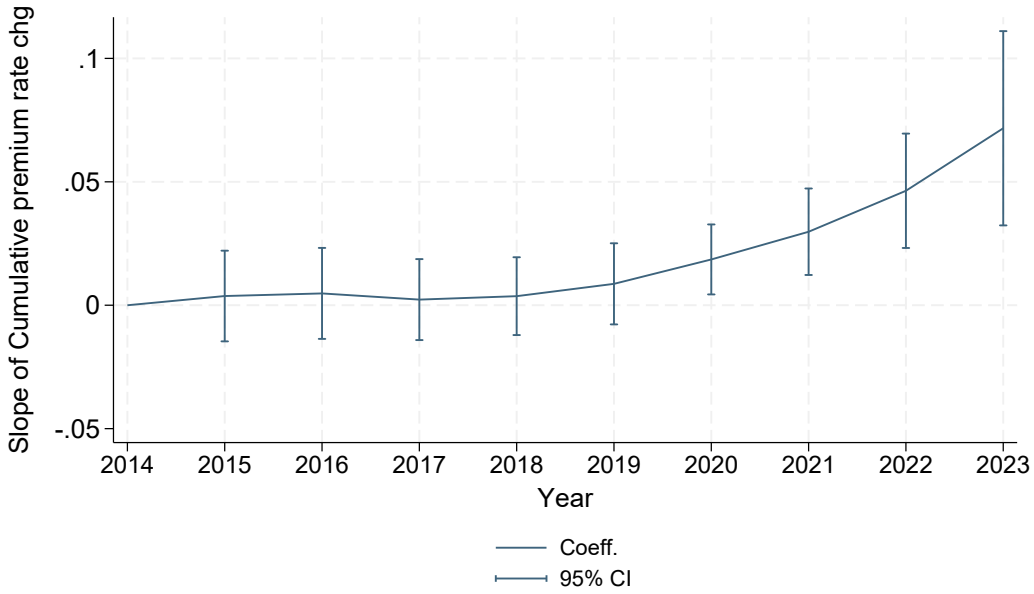
FIGURE 1

PREMIUMS HAVE INCREASED MORE IN HIGH-CLIMATE-RISK AREAS

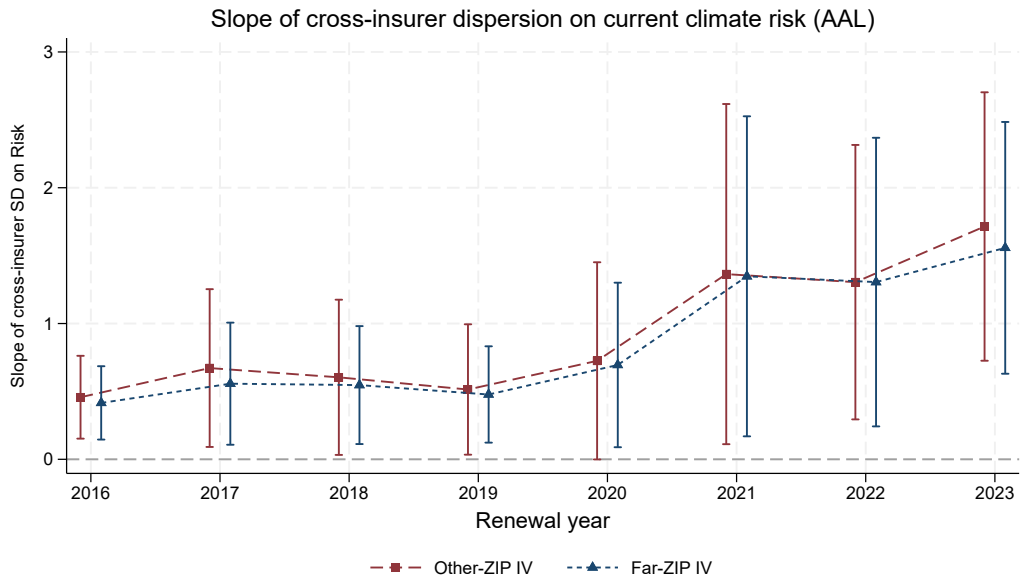


NOTES: Source: ICE McDash, decennial census (controls).

In Figure 1, we examine how premiums have evolved in recent years. We estimate the following regression at the ZIP-by-year level. $\Delta(Premium\ Rate)_{z,2014\ to\ t} = \gamma_z + \delta_{c,t} + \sum_{t=2015}^{2023} \beta_t ClimateRisk_z + \alpha_t Controls_z + \epsilon_{z,t}$, where z denotes ZIP code, c denotes the county, and t the year. The dependent variable is the cumulative change since 2014 in premiums relative to the coverage limit (in percentage points), averaged at the ZIP-year level; it is zero by construction in 2014. The main independent variable is CoreLogic's average annual loss (AAL) measure of climate risk at the ZIP level, expressed in percent of the coverage limit. γ_z are ZIP fixed effects and $\delta_{c,t}$ county-by-year fixed effects; $Controls_z$ are the ZIP's rural share and log population density from the 2010 census, each interacted with year. Standard errors are clustered by state $\times$ year. So that changes in coverage do not drive the results, we use only renewals at which the deductible (as a share of the coverage limit) and the coverage type (ACV or replacement cost) are both unchanged from the previous renewal, and we drop the top and bottom 0.5% of premium-rate changes. This measure is constructed using within-loan changes in premium only. The figure plots the estimates of β_t (the slope of the cumulative premium-rate change with respect to climate risk, in percentage points per percentage point of AAL) and the corresponding 95% confidence interval, anchored at zero in 2014.

FIGURE 2

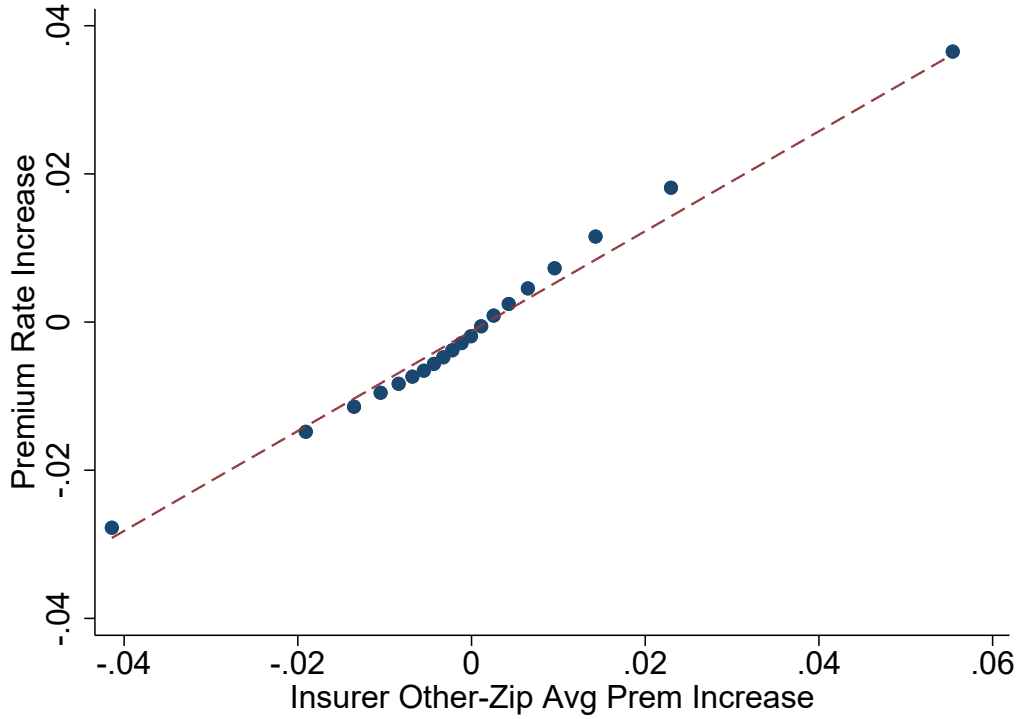
CROSS-INSURER DISPERSION OF PREMIUM INCREASES AND CLIMATE RISK, BY RENEWAL YEAR



NOTES: Source: ICE McDash and CoreLogic climate-risk data.
This figure plots, by insurance renewal year, the slope from regressing a within-ZIP-by-renewal-month measure of cross-insurer dispersion in the premium-increase instrument on ZIP-level climate risk, together with its 90% confidence interval. Climate risk is CoreLogic's current average annual loss (AAL) at the ZIP level. Dispersion is computed in two steps within each ZIP-by-renewal-month cell: we first average the instrument to one observation per insurer, then take the standard deviation across those insurers, keeping cells with at least three insurers. The two series use the two residualized leave-out instruments: the average premium-rate increase among policies of the same insurer renewing in the same month in other ZIP codes within the same state (Other-ZIP), and the same average restricted to distant ZIP codes (Far-ZIP). Both the premium rate and the instruments are expressed as a percentage of the coverage limit. The figure documents the cross-insurer variation in premium setting that the leave-out instruments exploit, and shows that this variation has widened as climate risk has risen. All specifications include renewal-year fixed effects, and standard errors are clustered by state $\times$ year. Each instrument is residualized on its own 12- and 24-month lags and so is defined only from 2016 onward; the series therefore span renewal years 2016–2023, and the sample ends in 2023.

FIGURE 3

PREMIUM RATE INCREASE VS. FAR-ZIP INSTRUMENT

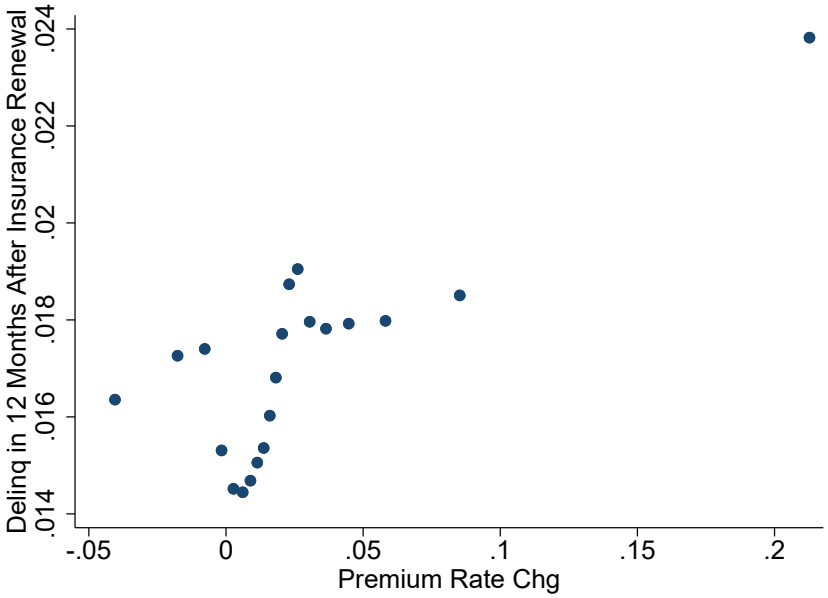


NOTES: Source: ICE McDash.
Bin-scatter plot of the household-level premium rate increase against the residualized average premium rate increase among policies renewing in the same month with the same insurer in distant ZIP codes within the same state. Both axes are demeaned by all controls and fixed effects in the main IV specification. The control variables include borrower's credit risk score in the month prior to the insurance renewal, the premium rate before the renewal and the standardized climate risk of the households' residence. The fixed effects (FE) include: 5-digit ZIP by insurance policy renewal month FE, climate risk bin by insurance policy renewal month FE, mortgage origination year FE, LTV bin FE, DTI bin FE, and credit score bin FE.

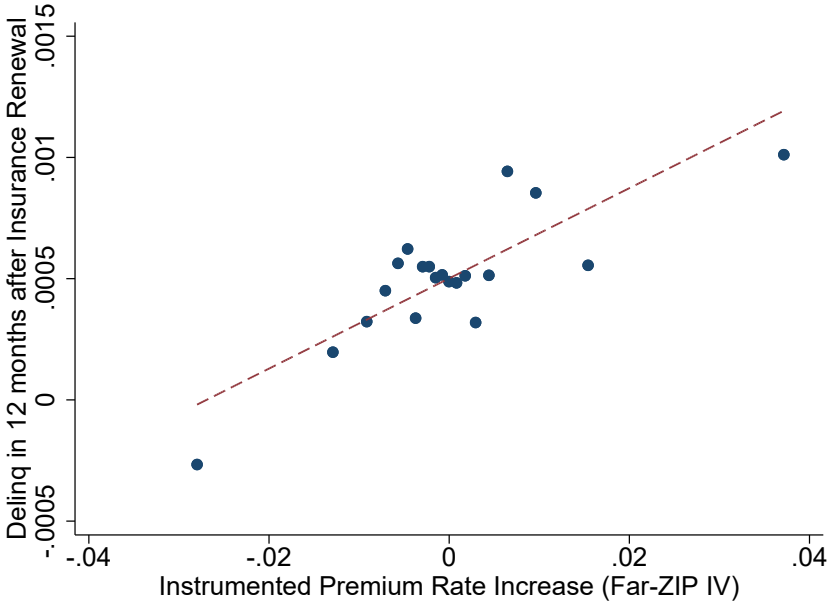
FIGURE 4

MORTGAGE DELINQUENCY AND PREMIUM RATE INCREASES

Panel A: OLS



Panel B: Instrumented Premium Rate Increase (Far-ZIP Instrument)



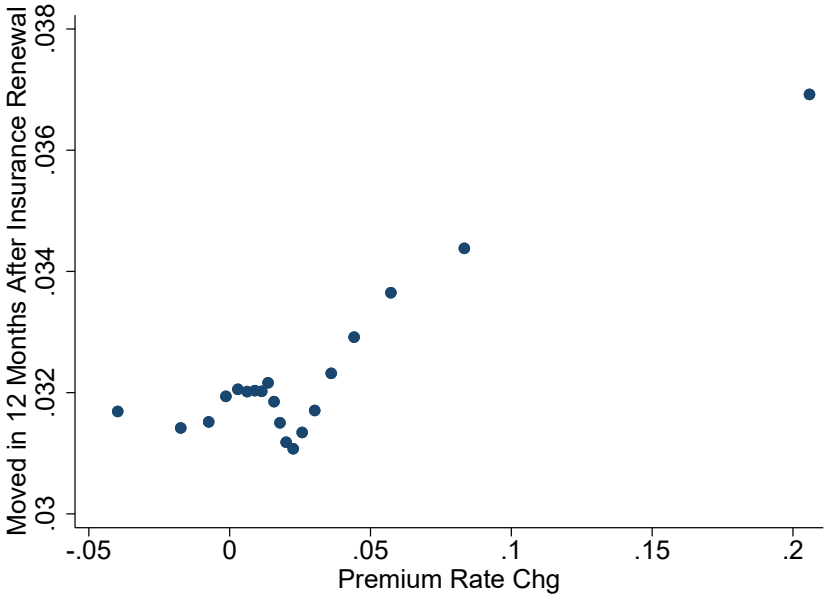
NOTES: Source: ICE McDash.

Panel A is a bin-scatter plot of 60-day mortgage delinquency against changes in annual insurance premium rate (insurance premiums as a percentage of the coverage limit). We control for credit score in the month preceding insurance renewal, and the following fixed effects (FE): insurance policy start month FE, mortgage origination year FE, LTV bin FE, DTI bin FE, credit score bin FE, 5-digit ZIP FE. We drop loans where the servicing is transferred within a year of policy reset and where the loan was not current as of the reset month.

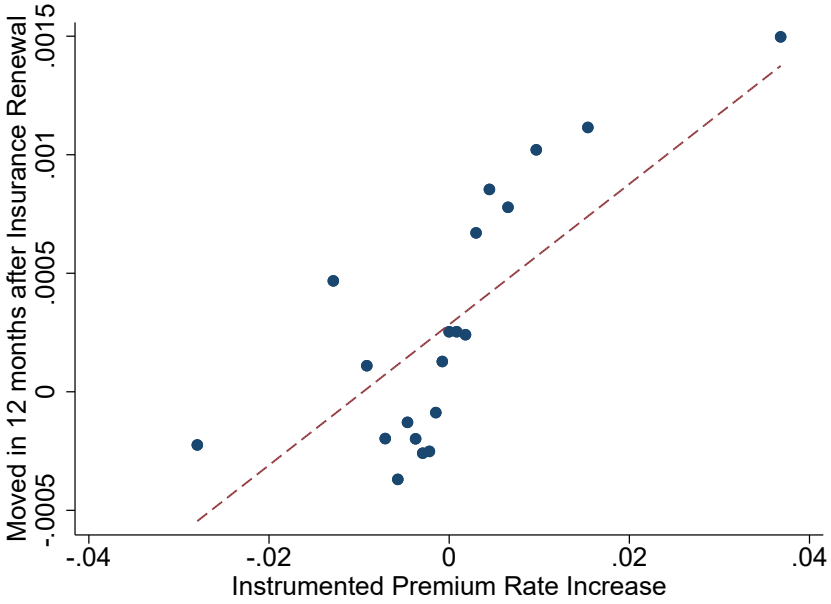
Panel B is a bin-scatter plot of 60-day mortgage delinquency against the increase in premium rate, i.e. change in premium as a percentage of the coverage limit, with residualized average premium rate increase among policies renewing in the same month with the same insurer in distant ZIP codes within the same state as the instrumental variable. Both axes are demeaned by all controls and fixed effects in the main IV specification. The control variables include borrower's credit risk score in the month prior to the insurance

FIGURE 5
MOVING AND PREMIUM RATE INCREASES

Panel A: OLS



Panel B: Instrumented Premium Rate Increase (Far-ZIP Instrument)



NOTES: Source: ICE McDash and CRISM.
Panel A is a bin-scatter plot of probability of household moving against changes in annual insurance premium rate (insurance premiums as a percentage of the coverage limit). We control for credit score in the month preceding insurance renewal, and the following fixed effects (FE): insurance policy start month FE, mortgage origination year FE, LTV bin FE, DTI bin FE, credit score bin FE, 5-digit ZIP FE. We drop loans where the servicing is transferred within a year of policy reset and where the loan was not current as of the reset month. We only keep loans with insurance renewals occurring between September and January.
Panel B is a bin-scatter plot of relocation probability against the increase in premium rate, i.e. change in premium as a percentage of the coverage limit, with residualized average premium rate increase among policies renewing in the same month with the same insurer in distant ZIP codes within the same state as the instrumental variable. Both axes are demeaned by all controls and fixed effects in the main IV specification. The control variables include borrower's credit risk score in the month prior to the insurance renewal, the

TABLE 1
SUMMARY STATISTICS

	Mean	SD	25 Pctl	Median	75 Pctl
30-Day Delinquent	0.05	0.21	0.00	0.00	0.00
60-Day Delinquent	0.02	0.12	0.00	0.00	0.00
90-Day Delinquent	0.01	0.10	0.00	0.00	0.00
Number of Insurers	232.00	0.00	232.00	232.00	232.00
Zip Had Recent Disaster	0.24	0.43	0.00	0.00	0.00
Premium Rate Increase (×100)	0.03	0.07	0.00	0.01	0.04
Premium Rate Change (×100)	1.32	9.71	-0.86	0.64	3.58
Insurer Other-Zip Avg Prem Increase (×100)	0.03	0.04	0.01	0.02	0.04
Premium Rate	0.49	0.32	0.28	0.40	0.58
Credit Score Before Renewal (McDash)	759.61	70.92	724.00	780.00	810.00
Climate Risk (×1M)	0.00	0.00	0.00	0.00	0.00
Climate Risk (Standardized)	-0.00	1.00	-0.59	-0.35	0.23
DTI	33.36	11.04	25.00	34.00	42.00
Credit Score at Origination	739.58	66.52	703.00	754.00	787.00
LTV	73.09	19.55	61.06	76.92	88.85
Premium *Changes*	126.35	578.51	12.00	72.00	192.00
Annual Premium	1,616.71	1,532.20	864.00	1,248.00	1,884.00
Coverage Limit	403,005.82	929,415.75	215,900.00	303,693.00	439,347.00
Deductible/TIV (%)	0.51	0.42	0.24	0.39	0.64
Insurer Premium Share	0.46	1.57	0.01	0.05	0.22
Insurer HHI	583.44	32.51	569.17	586.60	604.20
Insurer Premium Share (State)	1.49	3.41	0.01	0.22	1.10
Insurer HHI (State)	895.77	264.32	744.29	875.10	1,019.73
Credit Score before Renewal (CRISM)	768.15	67.91	738.00	791.00	820.00
Orig Mtg Rate - Current Avg	-0.22	1.64	-0.82	0.05	0.78
Premium as % of P&I Payment	14.24	10.81	7.21	11.19	17.63
Moved	0.05	0.21	0.00	0.00	0.00
Prepaid without Moving	0.02	0.14	0.00	0.00	0.00
Prepaid	0.11	0.31	0.00	0.00	0.00
Cash-Out Refinance	0.02	0.14	0.00	0.00	0.00
No-Cash-Out Refinance	0.03	0.16	0.00	0.00	0.00
Credit Utilization	11.13	16.31	1.21	6.17	15.81
Any Line Delinquent	0.12	0.32	0.00	0.00	0.00
Change in Credit Risk Score	-84.06	190.71	-51.00	-23.00	-10.00
Share of Lines Delinquent	0.03	0.12	0.00	0.00	0.00
Credit Card delinquent	0.06	0.23	0.00	0.00	0.00
Any First Mortgage Delinquent	0.02	0.14	0.00	0.00	0.00
Climate Risk Change (×100)	0.32	63.31	-12.11	0.00	17.26
Premium Rate Change (×100)	0.01	0.09	-0.01	0.00	0.03
New Zip Avg Premium Rate minus Old Own (×100)	0.02	0.20	-0.05	0.04	0.12
Moved to Lower Climate Risk	0.16	0.37	0.00	0.00	0.00
Moved to Higher Climate Risk	0.17	0.38	0.00	0.00	0.00
Change in Log Premium	0.06	0.16	0.01	0.06	0.12
Mortgage Rate Change	-0.02	0.31	0.00	0.00	0.00
Change in Log P&I Payments (×100)	0.29	8.97	0.00	0.00	0.00
Change in Log P&I Payments + Premium (×100)	0.96	7.27	0.06	0.51	1.38

NOTES: Source: ICE McDash, CRISM, CoreLogic, First Street, Census ACS.

TABLE 2
EFFECT OF PREMIUM INCREASES ON MORTGAGE DELINQUENCIES

	(1) 60-Day Delinquent	(2) Premium Rate Increase	(3) 60-Day Delinquent	(4) Premium Rate Increase	(5) 60-Day Delinquent
Premium Rate Increase	0.035***		0.017***		0.019***
	(14.01)		(3.84)		(3.86)
Insurer Other-ZIP Avg Prem Increase (residual)		0.885***			
		(88.24)			
Insurer Far-ZIP Avg Prem Increase (residual)				0.674***	
				(38.68)	
Lag Premium Rate	0.003***	0.022***	0.003***	0.022***	0.003***
	(4.55)	(10.85)	(3.77)	(10.61)	(3.78)
Credit Score/1k before Renewal	-0.371***	-0.041***	-0.362***	-0.041***	-0.362***
	(-40.20)	(-21.66)	(-34.91)	(-21.79)	(-35.61)
Climate Risk (standardized)/1k	0.109	0.429***	0.090	0.461***	0.077
	(1.30)	(3.42)	(0.89)	(3.52)	(0.77)
OLS/2SLS Stage	OLS	1st Stage	2nd Stage	1st Stage	2nd Stage
Sample	All	All	All	All	All
ZIP-by-Renewal Month FE	Y	Y	Y	Y	Y
Climate Risk Bin-by-Renewal Month FE	Y	Y	Y	Y	Y
Orig: Yr & Credit Score & LTV & DTI FE	Y	Y	Y	Y	Y
Y Mean	0.017	0.025	0.017	0.025	0.017
X Mean	0.028	-0.001	0.025	-0.001	0.025
X SD	0.060	0.023	0.055	0.024	0.055
N	54,154,105	35,904,523	35,904,523	35,619,020	35,619,020
Kleibergen-Paap Wald F stat			7,787		1,496

NOTES: Source: ICE McDash and CRISM.
This table presents the relationship between premium rate increases and mortgage delinquencies. The dependent variable is an indicator of whether the household is delinquent on the mortgage for at least 60 days in Columns (1), (3) and (5), and *Premium Rate Increase* in (2) and (4). Columns (1) presents OLS estimates, where the main independent variable is the change in the premium rate at policy renewal relative to the previous policy year, set to zero when the premium rate decreases. Column (2) and (4) present the first-stage result and (3) and (5) the second-stage of instrumental variable estimates. In Columns (2) and (3), we use the residualized average premium rate increase among policies renewing in the same month with the same insurer in other ZIP codes within the same state as the instrumental variable. In Columns (4) and (5), we repeat the instrumental variable analysis with residualized average premium rate increase among policies renewing in the same month with the same insurer in distant ZIP codes within the same state. The residualization is done by regressing it on its 12-month and 24-month lags, as well as on insurance renewal-month fixed effects. By using the residual from this regression, we essentially only use the component of the instrument that is orthogonal to its trend in the past two years. We control for the borrower's credit risk score in the month prior to the insurance renewal, the premium rate before the renewal, and the standardized climate risk of the households' residence. We also control for the following fixed effects (FE): 5-digit ZIP by insurance policy renewal month FE, climate risk bin by insurance policy renewal month FE, mortgage origination year FE, LTV bin FE, DTI bin FE, and credit score bin FE. Standard errors are corrected for clustering at the state-by-year level. ***p<0.01, **p<0.05, *p<0.1.

TABLE 3
EFFECTS OF PREMIUM INCREASES ON OTHER MORTGAGE AND CREDIT OUTCOMES

	(1) Mortgage Modification	(2) Mortgage Foreclosure (2yr)	(3) Credit Utilization (%)	(4) Credit Card Balance ($)
Premium Rate Increase	0.002***	0.003***	0.977***	
	(3.25)	(2.89)	(3.38)	
Premium Chg ($)				0.077**
				(2.16)
Lag Premium Rate	-0.000	0.002***	0.156***	313.752***
	(-1.43)	(10.96)	(6.28)	(27.06)
Credit Score/1k before Renewal	-0.013***	-0.064***	7.738***	12605.167***
	(-20.01)	(-24.31)	(51.99)	(163.13)
Climate Risk/1k	-0.065**	-0.029	27.554***	-5155.432*
	(-2.19)	(-1.23)	(4.26)	(-1.69)
OLS/2SLS Stage	2nd Stage	2nd Stage	2nd Stage	2nd Stage
Sample	All	All	All	All
Zip-by-Renewal Month FE	Y	Y	Y	Y
Climate Risk Bin-by-Renewal Month FE	Y	Y	Y	Y
Orig: Yr, Credit score, LTV, DTI FE	Y	Y	Y	Y
Y Mean	0.001	0.002	10.964	252.689
Y SD			16.043	6,853.008
X Mean	0.025	0.025	0.025	99.245
X SD	0.055	0.055	0.054	368.868
N	35,192,322	35,619,020	30,337,580	29,529,487
Kleibergen-Paap Wald F stat	1,481	1,496	2,508	1,107

NOTES: Source: ICE McDash and Equifax Credit Risks Insight Servicing (CRISM). This table presents results analyzing the effect of premium increases on mortgage and other credit outcomes, presenting the second stage of instrumental variable regressions. The dependent variables are: (1) an indicator for mortgage modification in the 12 months after insurance renewal; (2) an indicator for mortgage foreclosure in the 24 months after insurance renewal; (3) the change in credit card utilization, measured as peak utilization percentage in 12 months post-renewal minus pre-renewal utilization; (4) the change in credit card balance. The independent variable is *Premium Rate Increase* in Columns (1)-(3) and *Premium Chg ($)*, i.e. the change in insurance premium at policy renewal relative to the previous policy year, in Column (4). In every column the independent variable is instrumented with the residualized average premium rate increase among policies renewing in the same month with the same insurer in distant (Far-ZIP) ZIP codes within the same state, the same instrument used in Column (5) of Table 2 and Table 4. Columns (1) and (2) use the ICE McDash sample; Columns (3) and (4) use the smaller matched CRISM sample, which is why the sample sizes differ. We control for the borrower's credit risk score in the month prior to the insurance renewal, the premium rate before the renewal, and the standardized climate risk of the households' residences. We also control for the following fixed effects (FE): 5-digit ZIP by insurance policy renewal month FE, climate risk bin by insurance policy renewal month FE, mortgage origination year FE, LTV bin FE, DTI bin FE, and credit score bin FE. Standard errors are corrected for clustering at the state-by-year level. ***p<0.01, **p<0.05, *p<0.1.

TABLE 4
EFFECTS OF PREMIUM INCREASES ON MOVING PROBABILITIES

	(1)	(2)	(3)	(4)	(5)
	Moved	Prem Rate Increase	Moved	Prem Rate Increase	Moved
Premium Rate Increase	0.036***		0.035***		0.041***
	(24.79)		(6.56)		(6.46)
Insurer Other-ZIP Avg Prem Increase (residual)		0.913***			
		(77.68)			
Insurer Far-ZIP Avg Prem Increase (residual)				0.697***	
				(46.33)	
Lag Premium Rate	-0.006***	0.024***	-0.006***	0.025***	-0.006***
	(-16.61)	(22.04)	(-12.01)	(20.47)	(-12.08)
Credit Score/1k before Renewal	-0.014***	-0.039***	-0.016***	-0.039***	-0.015***
	(-10.26)	(-43.77)	(-9.15)	(-42.65)	(-8.95)
Climate Risk/1k	-1.071***	0.278***	-1.036***	0.306***	-1.032***
	(-7.62)	(4.49)	(-5.57)	(4.67)	(-5.51)
OLS/2SLS Stage	OLS	1st Stage	2nd Stage	1st Stage	2nd Stage
Sample	Sep-Jan	Sep-Jan	Sep-Jan	Sep-Jan	Sep-Jan
ZIP-by-Renewal Month FE	Y	Y	Y	Y	Y
Climate Risk Bin-by-Renewal Month FE	Y	Y	Y	Y	Y
Orig: Yr & Credit Score & LTV & DTI FE	Y	Y	Y	Y	Y
Y Mean	0.048	0.026	0.047	0.026	0.047
X Mean	0.027	-0.001	0.026	-0.001	0.026
X SD	0.059	0.023	0.055	0.025	0.055
N	16,349,433	10,475,160	10,475,160	10,385,294	10,385,294
Kleibergen-Paap Wald F stat			6,035		2,147

NOTES: Source: ICE McDash and Equifax Credit Risks Insight Servicing (CRISM).
This table presents the effect of premium rate increases on relocation probability. The dependent variable is an indicator for whether the household relocates in Columns (1), (3) and (5), and *premium rate increase* in (2) and (4). Columns (1) presents OLS estimates. The main independent variable is the increase in premium rate, i.e., change in premium as a percentage of the coverage limit. Column (2) and (4) present the first stage of instrumental variable regressions, while Column (3) and (5) present the corresponding second stage. In Columns (2) and (3), we use the residualized average premium rate increase among policies renewing in the same month with the same insurer in other ZIP codes within the same state as the instrumental variable. In Columns (4) and (5), we repeat the instrumental variable analysis with residualized average premium rate increase among policies renewing in the same month with the same insurer in distant ZIP codes within the same state. We control for the borrower's credit risk score in the month prior to the insurance renewal, the premium rate before the renewal, and the standardized climate risk of the households' residence. We also control for the following fixed effects (FE): 5-digit ZIP by insurance policy renewal month FE, climate risk bin by insurance policy renewal month FE, mortgage origination year FE, LTV bin FE, DTI bin FE, and credit score bin FE. We restrict the sample to borrowers whose home insurance renews between September and January. Standard errors are corrected for clustering at the state-by-year level. ***p<0.01, **p<0.05, *p<0.1.

TABLE 5
HETEROGENEOUS EFFECTS OF PREMIUM INCREASES

	(1) Delinq.	(2) Moved	(3) Delinq.	(4) Moved	(5) Delinq.	(6) Moved
Premium Rate Increase	0.085***	0.021***	0.012***	0.040***	0.015***	0.042***
	(12.03)	(10.23)	(11.61)	(22.30)	(8.63)	(21.24)
Premium Rate Increase × Mid CredScore	-0.060***	0.016***				
	(-10.83)	(6.26)				
Premium Rate Increase × High CredScore	-0.080***	0.028***				
	(-9.24)	(9.80)				
Premium Rate Increase × Mid LTV			0.010***	-0.000		
			(6.09)	(-0.12)		
Premium Rate Increase × High LTV			0.053***	-0.012***		
			(10.60)	(-4.69)		
Premium Rate Increase × Mid DTI					0.025***	-0.008***
					(6.92)	(-3.74)
Premium Rate Increase × High DTI					0.043***	-0.013***
					(6.04)	(-4.54)
Controls	Y	Y	Y	Y	Y	Y
Zip-by-Renewal Month FE	Y	Y	Y	Y	Y	Y
Climate Risk Bin-by-Renewal Month FE	Y	Y	Y	Y	Y	Y
Orig: Yr, Credit Score, LTV, DTI FE	Y	Y	Y	Y	Y	Y
Sample	All	Sep–Jan	All	Sep–Jan	All	Sep–Jan
Y Mean	0.017	0.048	0.017	0.048	0.017	0.048
N	54,154,105	16,349,433	54,154,105	16,349,433	54,154,105	16,349,433

NOTES: Source: ICE McDash and Equifax Credit Risks Insight Servicing (CRISM).
This table presents heterogeneity in the effects of premium rate increases on mortgage delinquency and residential mobility. Households are sorted into terciles of their credit score (Columns 1–2), loan-to-value (LTV) ratio (Columns 3–4), and debt-to-income (DTI) ratio (Columns 5–6); within each pair, the odd-numbered column reports an indicator for 60-day mortgage delinquency and the even-numbered column reports an indicator for moving. In each column we interact *Premium Rate Increase* with indicators for the second and third terciles of the sort variable; the tercile main effects are absorbed by the corresponding bin fixed effects and are not separately reported. The tercile cutoffs are fixed values applied to each household's origination characteristic: credit score at 680 and 780 (below 680; 680 to below 780; 780 and above), LTV at 75 and 85 (below 75; 75 to below 85; 85 and above), and DTI at 30 and 45 (below 30; 30 to below 45; 45 and above); the lowest group is the omitted base, and the "Mid" and "High" interactions correspond to the second and third terciles, respectively. We place the cutoffs at these values so that each tercile coincides with the boundaries of the corresponding fixed-effect bins (20-point credit score bins and 5-point LTV and DTI bins) and no tercile straddles more than one fixed-effect bin. The results are robust to instead using strict, equal-sized terciles. The delinquency columns use the full sample and the moving columns restrict to borrowers whose insurance renews between September and January. All columns report OLS estimates. We control for the borrower's credit risk score in the month prior to the insurance renewal, the premium rate before the renewal, and the standardized climate risk of the households' resi-

TABLE 6
EFFECT ON PREMIUM INCREASES ON MOVING DEPENDS ON MORTGAGE RATE LOCK-IN

	(1) Moved	(2) Moved	(3) Moved
Premium Rate Increase	0.037***	0.041***	0.050***
	(24.12)	(5.55)	(5.62)
Premium Rate Increase × (Orig Mtg Rate - Current Avg)/100	0.315***	0.450**	0.647**
	(5.40)	(2.04)	(2.49)
Instrument: Insurer Avg Prem Increase		Other-Zip	Far-Zip
OLS/2SLS Stage	OLS	2nd Stage	2nd Stage
Sample	Sep–Jan	Sep–Jan	Sep–Jan
ZIP-by-Renewal Month FE	Y	Y	Y
Climate Risk Bin-by-Renewal Month FE	Y	Y	Y
Orig: Yr & Credit Score & LTV & DTI FE	Y	Y	Y
Y Mean	0.048	0.047	0.047
X Mean	0.027	0.026	0.026
X SD	0.059	0.055	0.055
N	16,349,267	10,475,035	10,385,169
Kleibergen-Paap Wald F stat		2,679	612

NOTES: Source: ICE McDash, CRISM
This table presents analysis on how the effect of premium increases on moving depends on the degree of mortgage lock in. The independent variables are the change in premium as a percentage of the coverage limit and an additional interaction term between *Premium Rate Increase* and the difference between mortgage rates at origination and average mortgage rates in the month of insurance rate renewal. Columns (1) presents OLS estimates. Column (2) and (3) present the second stage of instrumental variable regressions. We use the residualized average premium rate increase among policies renewing in the same month with the same insurer in other ZIP codes within the same state as the instrumental variable in Column (2). In Columns (3), we repeat the instrumental variable analysis with residualized average premium rate increase among policies renewing in the same month with the same insurer in distant ZIP codes within the same state. We control for the borrower's credit risk score in the month prior to the insurance renewal, the premium rate before the renewal, and the standardized climate risk of the households' residence. We also control for the following fixed effects (FE): 5-digit ZIP by insurance policy renewal month FE, climate risk bin by insurance policy renewal month FE, mortgage origination year FE, LTV bin FE, DTI bin FE, and credit score bin FE. We restrict the sample to borrowers whose home insurance renews between September and January. Standard errors are corrected for clustering at the state-by-year level. ***p<0.01, **p<0.05, *p<0.1.

TABLE 7

THE EFFECT OF INSURANCE PREMIUM INCREASES ON MOVERS' PREMIUM CHANGES AND OTHER MOVER OUTCOMES

	(1) Δ Premium Rate (subsequent policy)	(2) Δ Climate Risk × 1k	(3) Δ Prem Rate to New ZIP Avg	(4) 1(Switch Insurer)	(5) Δ to Ins-Other-ZIP Avg	(6) Δ Insurer HHI/1k
Premium Rate Increase	0.280***	-2.301***	-1.202***	2.129***	0.009	0.100*
	(5.54)	(-2.98)	(-20.71)	(10.30)	(0.13)	(1.66)
Premium Rate Increase × Moved	-1.184***					
	(-13.95)					
Moved	-0.012***					
	(-5.29)					
Lag Premium Rate	-0.050***	0.737***	-0.652***	0.007	-0.028***	0.004
	(-25.01)	(12.03)	(-128.77)	(0.74)	(-9.36)	(0.87)
Credit Score/1k before Renewal	-0.051***	0.406***	-0.010*	0.487***	-0.017***	-0.066***
	(-21.28)	(4.18)	(-1.84)	(16.55)	(-2.73)	(-4.73)
Climate Risk/1k	0.689***	-2085.463***	19.113***	-5.334*	-0.310	-11.458***
	(6.53)	(-44.96)	(12.14)	(-1.91)	(-0.49)	(-7.11)
OLS/2SLS Stage	2nd Stage	2nd Stage	2nd Stage	2nd Stage	2nd Stage	2nd Stage
Sample	Sep-Jan	Sep-Jan	Sep-Jan	Sep-Jan	Sep-Jan	Sep-Jan
Subsample	Mover&Stayer	Mover	Mover	Mover	Mover	Mover
Old ZIP-by-Renewal Yr FE	Y					
Old State-by-Renewal Yr FE		Y	Y	Y	Y	Y
Climate Risk Bin-by-Renewal Yr FE	Y	Y	Y	Y	Y	Y
Orig: Yr & Credit Score & LTV & DTI FE	Y	Y	Y	Y	Y	Y
Y Mean	0.010	-0.056	0.012	0.381	0.004	0.012
Y SD	0.084	3.681	0.204	0.486	0.101	0.456
X Mean	0.023	0.028	0.028	0.025	0.025	0.028
X SD	0.050	0.058	0.057	0.051	0.051	0.058
N	7,799,676	442,098	349,257	98,489	99,370	468,432
Kleibergen-Paap Wald F stat	592	1,017	999	499	506	1,001

NOTES: Source: ICE McDash and Equifax Credit Risks Insight Servicing (CRISM).

This table presents second-stage 2SLS estimates of the effect of pre-move premium rate increases on movers' outcomes. In every column, *Premium Rate Increase* is instrumented with the residualized average premium rate increase among policies renewing in the same month with the same insurer in distant ZIP codes within the same state (the "Far-ZIP" instrument). Column (1) reports the change in premium rate from policy year t to $t+1$, using the full sample and adding an interaction between *Premium Rate Increase* and an indicator for moving within 12 months after renewal. Columns (2)–(6) restrict the sample to movers. The dependent variable is the change in climate risk, the destination ZIP-average risk minus the origin property-specific risk (×1,000), in Column (2); the change from the mover's pre-move premium rate to the average premium rate in the new ZIP code in Column (3); an indicator for whether the mover switched insurers in Column (4); the change in the mover's insurer's average premium rate in other ZIP codes within the same state, with the state changing for across-state movers, in Column (5); and the change in the insurer Herfindahl-Hirschman Index (HHI) from the old ZIP to the new ZIP in Column (6). We control for the borrower's credit risk score in the month prior to the insurance renewal, the premium rate before the renewal, and the standardized climate risk of the borrowers' old residence, along with climate risk bin by insurance policy renewal year FE, mortgage origination year FE, LTV bin FE, DTI bin FE, and credit score bin FE; Column (1) includes 5-digit old ZIP by insurance policy renewal year fixed effects, while Columns (2)–(6) include old state by insurance policy renewal year fixed effects. Stan-

TABLE 8
THE EFFECT OF INSURANCE PREMIUM INCREASES ON INVESTOR PURCHASE

	(1)	(2)	(3)	(4)	(5)
		Premium Rate		Premium Rate	
	Investor	Increase	Investor	Increase	Investor
Premium Rate Increase	0.027***		0.039***		0.031**
	(8.18)		(3.18)		(2.12)
Insurer Other-ZIP Avg Prem Increase (residual)		0.885***			
		(152.17)			
Insurer Far-ZIP Avg Prem Increase (residual)				0.708***	
				(114.83)	
Lag Premium Rate	0.027***	0.029***	0.027***	0.029***	0.027***
	(24.38)	(45.77)	(18.45)	(44.16)	(18.43)
CredScore/1k before Renewal	-0.178***	-0.072***	-0.157***	-0.073***	-0.158***
	(-45.35)	(-51.04)	(-34.18)	(-50.56)	(-34.02)
Climate Risk (Std)/1k	1.614***	0.463***	1.345***	0.529***	1.276***
	(4.38)	(3.01)	(2.97)	(3.35)	(2.81)
OLS/2SLS Stage	OLS	1st Stage	2nd Stage	1st Stage	2nd Stage
Sample	Transactions	Transactions	Transactions	Transactions	Transactions
Y Mean	0.044	0.033	0.044	0.033	0.044
X Mean	0.035	0.001	0.033	0.001	0.033
X SD	0.072	0.025	0.067	0.027	0.067
N	1,365,925	925,426	925,426	918,386	918,386
Kleibergen-Paap Wald F stat			23,155		13,187

NOTES: Source: ICE McDash, Equifax Credit Risks Insight Servicing (CRISM), and CoreLogic.
This table presents results analyzing the effect of premium increases on whether buyers of transacted homes are investors, identified by CoreLogic's corporate-buyer flag. The dependent variable is an indicator for whether the buyer is an investor (a corporate buyer). Column (1) presents OLS estimates. Columns (2) and (3) present the first and second stages of the instrumental variable regression using the residualized Other-ZIP instrument, and Columns (4) and (5) repeat the first and second stages using the residualized Far-ZIP instrument. We control for the previous owners' credit risk score in the month prior to the insurance renewal, the premium rate before the renewal, and the standardized climate risk of the borrowers' old residence. We also control for the following fixed effects (FE): 5-digit ZIP, climate risk bin by insurance policy renewal year FE, mortgage origination year FE, LTV bin FE, DTI bin FE, and credit score bin FE. Standard errors are corrected for clustering at the state-by-year level. ***p<0.01, **p<0.05, *p<0.1.

TABLE 9
THE EFFECT OF INVESTORS ON INSURANCE OUTCOMES

	(1) Log Premium	(2) Premium Rate	(3) Premium Rate Increase	(4) Log TIV	(5) Deductible $\times 100$/TIV
Investor	-0.148***	-0.041***	-0.006***	-0.074***	0.107***
	(-28.56)	(-13.94)	(-13.03)	(-26.67)	(22.37)
Investor $\times$ Block-Yr Avg Prem Increase (std)	-0.032***	-0.026***	-0.005***	-0.015***	0.009
	(-4.59)	(-7.40)	(-7.00)	(-3.48)	(1.48)
Climate Risk/1k	0.899***	3.172***	0.192***	-1.570***	2.963***
	(4.16)	(4.52)	(4.64)	(-4.56)	(10.58)
Credit Score before Renewal/1k	-0.488***	-0.335***	-0.051***	0.084***	-0.131***
	(-27.36)	(-24.65)	(-20.59)	(27.29)	(-23.61)
House Age ≤ 5	-0.193***	-0.069***	-0.007***	-0.008***	-0.017***
	(-56.67)	(-18.69)	(-8.96)	(-3.65)	(-8.27)
Log(Sqft)	0.445***	-0.062***	-0.002***	0.590***	-0.140***
	(22.49)	(-16.38)	(-7.69)	(24.23)	(-19.46)
Log(Appraisal$)	0.190***	-0.044***	-0.001**	0.260***	-0.038***
	(8.01)	(-5.82)	(-2.45)	(7.73)	(-2.93)
House Age Bin FE	Y	Y	Y	Y	Y
Block-by-Renewal Yr FE	Y	Y	Y	Y	Y
Climate Risk Bin-by-Renewal Yr FE	Y	Y	Y	Y	Y
Orig: Yr, Credit Score, LTV, DTI FE	Y	Y	Y	Y	Y
Y Mean	7.133	0.482	0.029	12.643	0.510
Y SD	0.582	0.331	0.060	0.558	0.412
Investor Mean	0.056	0.056	0.056	0.056	0.056
N	37,708,520	37,708,520	37,645,256	37,972,446	36,128,979

NOTES: Source: ICE McDash, Equifax Credit Risks Insight Servicing (CRISM), and CoreLogic.
This table examines whether real estate investors obtain different insurance outcomes than owner-occupants, and whether this difference grows when local insurance premiums rise more. The sample consists of mortgage loans in the McDash dataset matched to insurance records and credit scores. The unit of observation is a policy renewal. The main independent variables are an indicator for investor-owned properties, as designated by McDash, and its interaction with the block-year average of premium rate increases relative to the prior year. The dependent variables are: log total insurance premiums (Column 1), the premium rate (Column 2), the premium rate increase from the prior renewal (Column 3), log total insured value (Column 4), and the deductible as a share of total insured value multiplied by 100 (Column 5). Additional controls include climate risk, credit score prior to renewal (divided by 1,000), an indicator for properties under five years old, log square footage, and log appraisal value. All specifications include fixed effects for house age (10-year) bins, Census block-by-renewal year, climate risk bin-by-renewal year, and origination year, credit score bin, LTV bin, and DTI bin. Y Mean and Y SD report the mean and standard deviation of the dependent variable. Investor Mean reports the share of observations that are investor-owned. Standard errors are corrected for clustering at the state-by-year level. ***p$<$0.01, **p$<$0.05, *p$<$0.1.

Appendix

TABLE A.1
HOMEOWNERS' INSURANCE PREMIUMS BY STATE

	Annual Premium (Dollars) Level		Premium Increase (×100)		Cum. %	
State	Mean	SD	Mean	SD	2014–2023	N
AL	2,091	1,074	0.0547	0.0892	5.1	294,093
AR	2,018	1,012	0.0603	0.0915	2.6	202,507
AZ	1,457	938	0.0633	0.0884	3.1	458,820
CA	1,701	1,207	0.0227	0.0599	28.1	2,200,890
CO	2,942	1,464	0.0899	0.1021	27.0	397,331
CT	2,303	1,411	0.0319	0.0530	11.1	240,790
DC	1,805	1,237	0.0209	0.0483	-2.2	29,434
DE	1,328	850	0.0231	0.0451	9.2	79,696
FL	3,413	1,923	0.1319	0.1560	11.8	1,164,943
GA	1,995	1,064	0.0353	0.0609	17.4	680,891
IA	1,762	800	0.0607	0.0805	12.5	182,837
ID	1,359	870	0.0370	0.0575	5.9	99,177
IL	1,871	1,005	0.0505	0.0749	15.4	715,870
IN	1,617	832	0.0438	0.0689	-4.0	375,494
KS	2,387	1,095	0.0509	0.0848	-4.3	176,200
KY	1,732	901	0.0493	0.0756	3.7	202,567
LA	3,222	1,813	0.1506	0.1846	14.9	205,346
MA	2,181	1,206	0.0307	0.0468	9.2	344,204
MD	1,791	1,023	0.0375	0.0580	19.0	435,053
ME	1,301	825	0.0252	0.0537	20.7	73,239
MI	1,421	823	0.0313	0.0608	-23.4	648,548
MN	2,419	1,144	0.0605	0.0767	7.1	444,584
MO	2,075	1,040	0.0506	0.0841	7.5	420,516
MS	2,315	1,180	0.0566	0.1044	0.6	121,426
MT	2,068	1,117	0.0455	0.0770	11.9	67,448
NC	1,616	994	0.0426	0.0700	11.8	707,539
ND	2,027	942	0.0372	0.0623	-9.7	31,808
NE	2,557	1,114	0.0833	0.1013	28.1	156,419
NH	1,460	818	0.0248	0.0490	-3.4	77,906
NJ	1,786	1,065	0.0198	0.0416	-0.4	553,890
NM	1,662	1,028	0.0604	0.0904	8.7	125,454
NV	1,158	728	0.0198	0.0472	-1.0	179,988
NY	1,923	1,389	0.0249	0.0449	-5.3	800,621
OH	1,404	745	0.0398	0.0650	1.7	708,232
OK	2,755	1,375	0.1005	0.1322	-8.0	243,259

Continued on next page

Table A.1 (continued)

State	Mean	SD	Mean	SD	Cum. %	N
OR	1,302	832	0.0365	0.0559	10.4	280,130
PA	1,401	871	0.0248	0.0480	-3.8	739,311
RI	2,329	1,196	0.0424	0.0608	13.6	58,785
SC	1,928	1,280	0.0405	0.0780	-3.1	306,040
SD	2,233	1,118	0.0741	0.1005	21.7	49,357
TN	1,849	1,046	0.0440	0.0774	-9.4	397,722
TX	2,713	1,482	0.1136	0.1261	3.7	1,470,028
UT	1,305	828	0.0424	0.0605	9.6	218,396
VA	1,626	998	0.0377	0.0646	14.2	632,229
VT	1,410	912	0.0212	0.0500	-0.7	29,592
WA	1,467	846	0.0327	0.0639	0.8	516,735
WI	1,346	728	0.0305	0.0520	2.8	239,371
WV	1,309	750	0.0253	0.0575	2.3	80,195
WY	2,061	1,224	0.0726	0.1122	37.0	38,494

Notes: This table reports, for each continental U.S. state, the mean and standard deviation of the annual homeowners' insurance premium (in dollars) and of the premium-rate increase ($\times 100$), together with the cumulative percentage change in the state's average premium-to-value (premium-to-TIV) ratio over the sample period, computed as $(r_{\text{end}} - r_{\text{base}})/r_{\text{base}} \times 100$ where r is the mean premium-to-TIV ratio. Premium levels follow Keys and Mulder (2024). N is the number of policy observations in the final year. Source: ICE McDash; Keys and Mulder (2024).

TABLE A.2
CONTROLLING FOR INSURER-YEAR FIXED EFFECTS

	(1)	(2)	(3)	(4)	(5)	(6)
	60-Day Delinquent			Moved		
Premium Rate Increase	0.036***	0.008**	0.010**	0.034***	0.017***	0.022***
	(14.68)	(2.50)	(2.49)	(24.00)	(3.09)	(3.02)
Lag Premium Rate	0.002***	0.003***	0.003***	-0.006***	-0.006***	-0.006***
	(3.49)	(3.96)	(3.97)	(-18.98)	(-13.34)	(-13.28)
Credit Score/1k before Renewal	-0.369***	-0.361***	-0.361***	-0.014***	-0.017***	-0.017***
	(-40.23)	(-34.90)	(-35.58)	(-10.98)	(-10.23)	(-9.99)
Climate Risk (standardized)/1k	0.095	0.088	0.078	-1.059***	-1.006***	-1.001***
	(1.15)	(0.88)	(0.78)	(-7.54)	(-5.41)	(-5.36)
OLS/2SLS Stage	OLS	2nd Stage	2nd Stage	OLS	2nd Stage	2nd Stage
Instrument		Other-ZIP	Far-ZIP		Other-ZIP	Far-ZIP
Sample	All	All	All	Sep-Jan	Sep-Jan	Sep-Jan
Zip-by-Renewal Month FE	Y	Y	Y	Y	Y	Y
Climate Risk Bin-by-Renewal Month FE	Y	Y	Y	Y	Y	Y
Orig: Yr, Credit score, LTV, DTI FE	Y	Y	Y	Y	Y	Y
Insurer-Year FE	Y	Y	Y	Y	Y	Y
Y Mean	0.017	0.017	0.017	0.048	0.047	0.047
X Mean	0.028	0.025	0.025	0.027	0.026	0.026
X SD	0.060	0.055	0.055	0.059	0.055	0.055
N	54,149,927	35,904,506	35,619,003	16,349,369	10,475,146	10,385,274
Kleibergen-Paap Wald F stat		8,487	967		9,307	1,301

NOTES: Source: ICE McDash.
This table presents the effect of premium increases on mortgage delinquencies and relocation probability, adding insurer by insurance policy renewal year fixed effects to the baseline specification. The dependent variable is an indicator of whether the household is delinquent on the mortgage for at least 60 days within the 12 months after insurance policy renewal in Columns (1)–(3), and an indicator for whether the household relocates in Columns (4)–(6). The main independent variable is the increase in premium rate, i.e., change in premium as a percentage of the coverage limit. We use the full sample in Columns (1)–(3) and restrict the sample to borrowers whose home insurance renews between September and January in Columns (4)–(6). Columns (1) and (4) report OLS estimates, while the remaining columns report the second stage of two-stage least-squares regressions that instrument the premium rate increase with the residualized leave-out insurer premium increase in other ZIP codes (Columns (2) and (5)) or in distant ZIP codes (Columns (3) and (6)), both within the same state. We control for the borrower's credit risk score in the month prior to the insurance renewal, the premium rate before the renewal, and the standardized climate risk of the households' residence. We also control for the following fixed effects (FE): 5-digit zip by insurance policy renewal month FE, climate risk bin by insurance policy renewal month FE, mortgage

TABLE A.3
DELINQUENCY EFFECT WHEN HOUSEHOLDS ARE ATTENTIVE TO PREMIUM CHANGES

	(1) 60-Day Delinquent	(2) 60-Day Delinquent	(3) 60-Day Delinquent
Premium Rate Increase	0.019***	0.017***	0.020***
	(8.03)	(3.33)	(3.46)
Lag Premium Rate	0.003***	0.003***	0.003***
	(4.31)	(3.14)	(3.33)
Credit Score/1k before Renewal	-0.331***	-0.317***	-0.317***
	(-31.36)	(-27.12)	(-29.91)
Climate Risk (standardized)/1k	0.167	0.094	0.077
	(1.21)	(0.56)	(0.51)
OLS/2SLS Stage	OLS	2nd Stage	2nd Stage
Instrument		Other-ZIP	Far-ZIP
Sample	Attentive	Attentive	Attentive
Subsample	Non-Switcher	Non-Switcher	Non-Switcher
ZIP-by-Renewal Month FE	Y	Y	Y
Climate Risk Bin-by-Renewal Month FE	Y	Y	Y
Orig: Yr & Credit Score & LTV & DTI FE	Y	Y	Y
Y Mean	0.015	0.015	0.015
X Mean	0.029	0.026	0.026
X SD	0.066	0.059	0.059
N	5,080,629	3,460,308	3,430,460
Kleibergen-Paap Wald F stat		1,528	733

NOTES: Source: ICE McDash.
This table presents results testing whether the effect of premium increases on mortgage delinquency exists among households that were likely attentive to premium changes but that did not switch insurers, so that the instrumented premium increase is one they continued to bear. Attentive households are those that adjusted their deductible percentages or changed between Replacement Cost Value and Actual Cash Value coverage around the time of the premium increase. Column (1) reports OLS estimates. Columns (2) and (3) report the second stage of instrumental-variable specifications that instrument the premium rate increase with the residualized average premium rate increase among policies renewing in the same month with the same insurer in other ZIP codes within the same state (Other-ZIP; Column 2) and in distant ZIP codes within the same state (Far-ZIP; Column 3). We control for the borrower's credit risk score in the month prior to the insurance renewal, the premium rate before the renewal, and the standardized climate risk of the households' residences. We also control for the following fixed effects (FE): 5-digit zip by insurance policy renewal month FE, climate risk bin by insurance policy renewal month FE, mortgage origination year FE, LTV bin FE, DTI bin FE, credit score bin FE. Standard errors are corrected for clustering at the state-by-year level. ***p<0.01, **p<0.05, *p<0.1.

TABLE A.4
MORTGAGE DELINQUENCY EFFECT ACROSS INVESTOR TYPES

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				60-Day Mortgage Delinquent			
Premium Rate Increase	0.022***	0.016***	0.011***	0.029	0.019**	0.014***	0.019***
	(3.13)	(2.91)	(2.82)	(0.75)	(2.48)	(3.20)	(3.54)
Lag Premium Rate	0.006***	0.000	0.001	0.010***	0.006***	0.000	0.003***
	(4.53)	(0.54)	(1.18)	(3.83)	(6.25)	(0.54)	(4.09)
Credit Score/1k before Renewal	-0.526***	-0.246***	-0.231***	-0.364***	-0.327***	-0.265***	-0.297***
	(-54.56)	(-23.95)	(-26.73)	(-13.27)	(-19.41)	(-26.64)	(-28.62)
Climate Risk (standardized)/1k	0.202	0.026	0.057	1.332	-0.242	0.161	0.076
	(0.87)	(0.19)	(0.57)	(1.52)	(-1.36)	(1.31)	(0.69)
OLS/2SLS Stage	2nd Stage	2nd Stage	2nd Stage	2nd Stage	2nd Stage	2nd Stage	2nd Stage
Sample	GNMA	FNMA	FHLMC	Private Securitized	Portfolio	Cnvtnl w/ PMI	Cnvtnl w/o PMI
Zip-by-Renewal Month FE	Y	Y	Y	Y	Y	Y	Y
Climate Risk Bin-by-Renewal Month FE	Y	Y	Y	Y	Y	Y	Y
Orig: Yr, Credit score, LTV, DTI FE	Y	Y	Y	Y	Y	Y	Y
Y Mean	0.038	0.012	0.011	0.026	0.013	0.013	0.013
X Mean	0.032	0.024	0.024	0.022	0.023	0.026	0.023
X SD	0.063	0.053	0.052	0.054	0.053	0.056	0.051
N	5,861,946	13,432,394	10,794,285	382,855	3,613,964	10,551,959	18,044,323
Kleibergen-Paap Wald F stat	1,547	1,261	1,564	411	981	1,718	1,062

NOTES: Source: ICE McDash.
This table presents the effect premium increases on mortgage delinquency across investor types. The dependent variable is an indicator of whether the household is delinquent on the mortgage for at least 60 days within the 12 months after insurance policy renewal. The main independent variable is the change in premium as a percentage of the coverage limit. We use mortgages guaranteed by Ginnie Mae in Column (1), by Fannie Mae in (2), by Freddie Mac in (3), private mortgages that are securitized in (4), and those that remain in banks' portfolios in (5). The assignment of loans to these investor and guarantor types uses lagged loan information. In Columns (6) and (7), we further split conventional mortgages by whether they have private mortgage insurance or not, i.e., whether the GSEs are ultimately exposed to credit risks. We control for the borrower's credit risk score in the month prior to the insurance renewal, the premium rate before the renewal, and the standardized climate risk of the households' residence. We also control for the following fixed effects (FE): 5-digit zip by insurance policy renewal month FE, climate risk bin by insurance policy renewal month FE, mortgage origination year FE, LTV bin FE, DTI bin FE, credit score bin FE. Standard errors are corrected for clustering at the state-by-year level. ***p<0.01, **p<0.05, *p<0.1.

TABLE A.5
DELINQUENCY AND RELOCATION EFFECTS AND RECENT DISASTERS

	(1)	(2)	(3)	(4)	(5)	(6)
	60-Day Mortgage Delinquent			Moved		
Premium Rate Increase	0.024***	0.016***	0.016***	0.029***	0.047***	0.047***
	(3.01)	(3.01)	(3.03)	(2.88)	(6.18)	(6.22)
Premium Rate Increase × Disaster			0.010			-0.018
			(1.09)			(-1.51)
Lag Premium Rate	0.000	0.005***	0.003***	-0.006***	-0.006***	-0.006***
	(0.31)	(5.05)	(3.76)	(-7.84)	(-9.70)	(-12.05)
Credit Score/1k before Renewal	-0.382***	-0.354***	-0.362***	-0.012***	-0.016***	-0.015***
	(-24.29)	(-31.25)	(-35.60)	(-4.28)	(-8.18)	(-8.92)
Climate Risk (standardized)/1k	0.064	0.076	0.075	-0.674**	-1.170***	-1.030***
	(0.28)	(0.69)	(0.74)	(-2.34)	(-5.18)	(-5.50)
OLS/2SLS Stage	2nd Stage	2nd Stage	2nd Stage	2nd Stage	2nd Stage	2nd Stage
Sample	All	All	All	Sep-Jan	Sep-Jan	Sep-Jan
Subsample	Disaster	No Disaster	All	Disaster	No Disaster	All
ZIP-by-Renewal Month FE	Y	Y	Y	Y	Y	Y
Climate Risk Bin-by-Renewal Month FE	Y	Y	Y	Y	Y	Y
Orig: Yr, Credit Score, LTV, DTI FE	Y	Y	Y	Y	Y	Y
Y Mean	0.020	0.016	0.017	0.048	0.046	0.047
X Mean	0.029	0.024	0.025	0.030	0.024	0.026
X SD	0.063	0.052	0.055	0.063	0.052	0.055
N	9,101,343	26,513,949	35,615,293	2,563,867	7,820,266	10,384,134
Kleibergen-Paap Wald F stat	217	2,945	108	445	2,817	218

NOTES: Source: ICE McDash, Equifax Credit Risks Insight Servicing (CRISM), and First Street.
This table presents results testing whether the effects of premium increases on mortgage delinquency and on relocation are driven by borrowers who experience recent disasters. The dependent variable is an indicator of whether the household is delinquent on the mortgage for at least 60 days within the 12 months after insurance policy renewal in Columns (1)–(3), and an indicator for whether the household relocates in Columns (4)–(6). The main independent variable is the change in premium as a percentage of the coverage limit, instrumented with the residualized average premium rate increase among policies renewing in the same month with the same insurer in distant (Far-ZIP) ZIP codes within the same state; all columns report the second stage of the instrumental-variable specification. Within each outcome, the first column uses households in zip codes that experienced natural disasters within the current calendar year or the preceding two years according to First Street Foundation's Climate Data (Columns (1) and (4)); the second uses households in the remaining non-disaster-affected zip codes (Columns (2) and (5)); and the third uses the full sample, adding an indicator for recently disaster-affected zip codes and its interaction with *Premium Rate Increase* (Columns (3) and (6)). The delinquency columns use the full sample; the relocation columns restrict to borrowers whose home insurance renews between September and January. We control for the

TABLE A.6
EFFECT OF PREMIUMS ON OTHER MOVER OUTCOMES

	(1) Δ House Age	(2) Δ log Appraisal	(3) Δ log Cov Lmt	(4) Δ Log Prem	(5) Δ log (P&I+Prem)
Premium Rate Increase	-11.250**	0.106	0.022	-0.963***	0.050
	(-2.10)	(0.83)	(0.19)	(-7.42)	(0.37)
Lag Premium Rate	-12.356***	0.236***	0.231***	-0.275***	0.057***
	(-37.97)	(27.19)	(26.58)	(-27.94)	(7.80)
Credit Score/1k before Renewal	1.536*	-0.037	0.267***	-0.295***	0.034
	(1.90)	(-1.24)	(12.12)	(-13.24)	(1.47)
Climate Risk (Standardized)/1k	-825.106***	-10.761***	-7.920***	13.744***	-10.574***
	(-9.15)	(-4.52)	(-3.67)	(5.64)	(-5.08)
OLS/2SLS Stage	2nd Stage	2nd Stage	2nd Stage	2nd Stage	2nd Stage
Sample	Sep-Jan	Sep-Jan	Sep-Jan	Sep-Jan	Sep-Jan
Subsample	Mover	Mover	Mover	Mover	Mover
Old State-by-Renewal Yr FE	Y	Y	Y	Y	Y
Climate Risk Bin-by-Renewal Yr FE	Y	Y	Y	Y	Y
Orig: Yr & Credit Score & LTV & DTI FE	Y	Y	Y	Y	Y
Y Mean	-1.483	0.338	0.135	0.052	0.176
Y SD	27.372	0.457	0.399	0.380	0.397
X Mean	0.028	0.025	0.025	0.024	0.025
X SD	0.058	0.050	0.051	0.050	0.051
N	415,450	118,984	98,488	95,000	91,013
Kleibergen-Paap Wald F stat	972	457	499	494	515

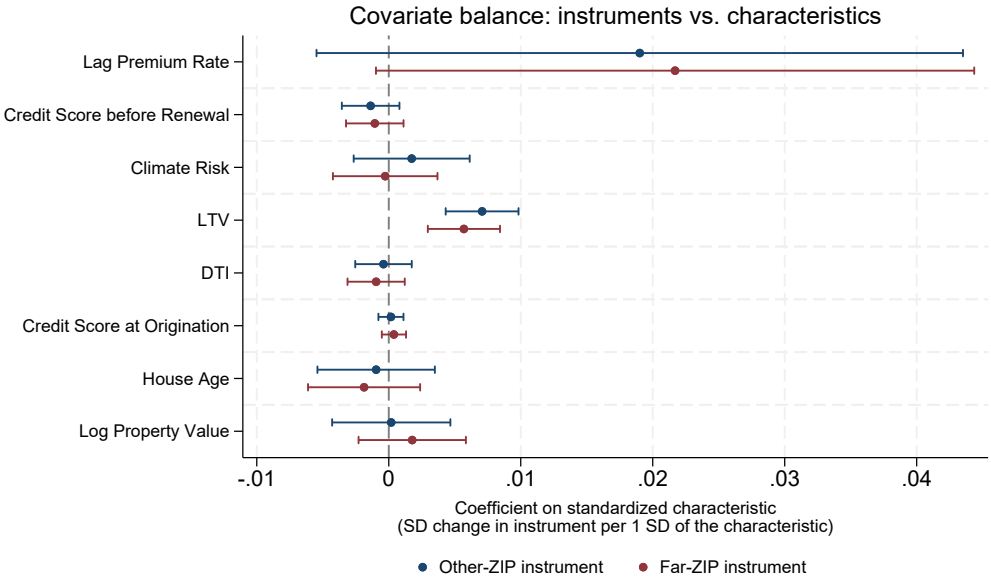
NOTES: Source: ICE McDash and Equifax Credit Risks Insight Servicing (CRISM).
This table examines the impact of premium increases on characteristics of new houses, mortgage and insurance choices. The dependent variable is the change in house age in Column (1), the change in logarithm of house appraisal value in Column (2), the change in logarithm of coverage limit in Column (3), the change in logarithm of insurance premium in Column (4), and the change in logarithm of the sum of insurance premium and Principal and interest payment in Column (5). In every column the change is defined as the difference between the variable value in the destination and in the original place. The movers' insurer-switching response is reported in Column (4) of Table 7. The main independent variable is the increase in premium rate, i.e., the change in premium as a percentage of the coverage limit, instrumented with the residualized far-ZIP instrument (the average premium rate increase among policies renewing in the same month with the same insurer in distant ZIP codes within the same state). All columns restrict the sample to movers (borrowers whose insurance renews between September and January) and use 5-digit old-state by renewal-year and climate-risk-bin by renewal-year fixed effects. We control for the borrower's credit risk score in the month prior to the insurance renewal, the premium rate before the renewal and the standardized climate risk of the households' old residence. We also control for mortgage origination year FE, LTV bin FE, DTI bin FE, and credit score bin FE in all columns. Standard errors are corrected for clustering at the state-by-year level. ***p<0.01, **p<0.05, *p<0.1.

Internet Appendix

For Online Publication

FIGURE IA.1

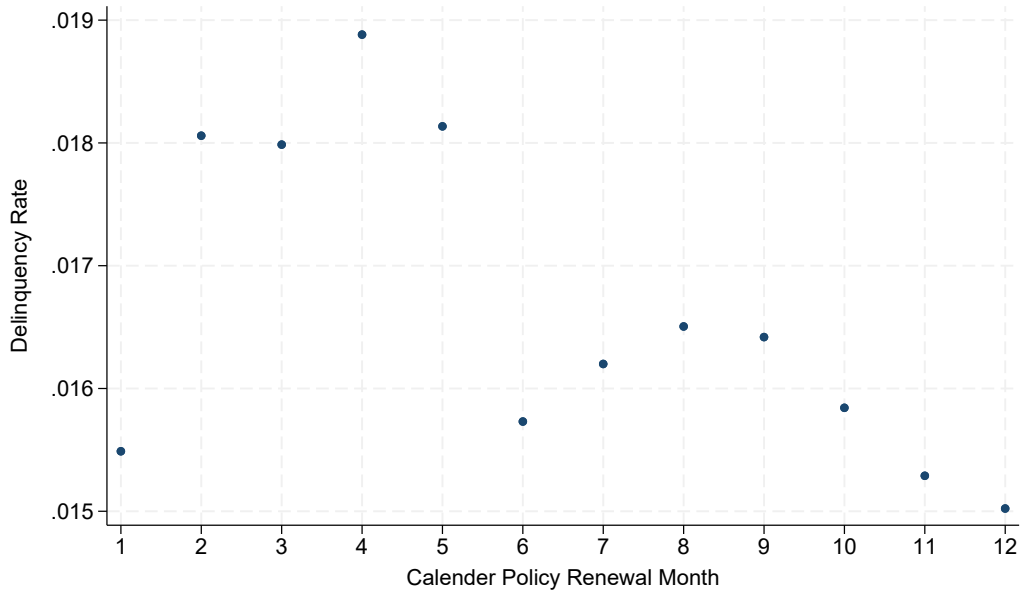
COVARIATE BALANCE: INSTRUMENTS AND PREDETERMINED CHARACTERISTICS



NOTES: Source: ICE McDash.
This figure reports covariate-balance regressions of our instruments on predetermined household, house, and loan characteristics, estimated on the full McDash sample (the mortgage-delinquency sample). Each row corresponds to one predetermined household, house, or loan characteristic. For each instrument, the marker is the coefficient from a regression of the standardized residualized leave-out instrument on all of the standardized characteristics jointly, and the horizontal cap spans its 95% confidence interval. Because every variable (the instrument and each characteristic) is standardized to mean zero and unit standard deviation within the estimation sample, each coefficient is the standard-deviation change in the instrument associated with a one-standard-deviation change in the characteristic; the dashed vertical line at zero marks perfect balance. Navy markers denote the Insurer Other-ZIP instrument and maroon markers the Insurer Far-ZIP instrument. The regressions include the same fixed effects as the corresponding main specifications (5-digit ZIP by insurance policy renewal month FE, climate risk bin by insurance policy renewal month FE, mortgage origination year FE, LTV bin FE, DTI bin FE, and credit score bin FE), and standard errors are clustered at the state-by-year level. The estimated coefficients are uniformly small (on the order of a few thousandths of a standard deviation), indicating that the instruments are essentially orthogonal to predetermined characteristics conditional on the fixed effects.

FIGURE IA.2

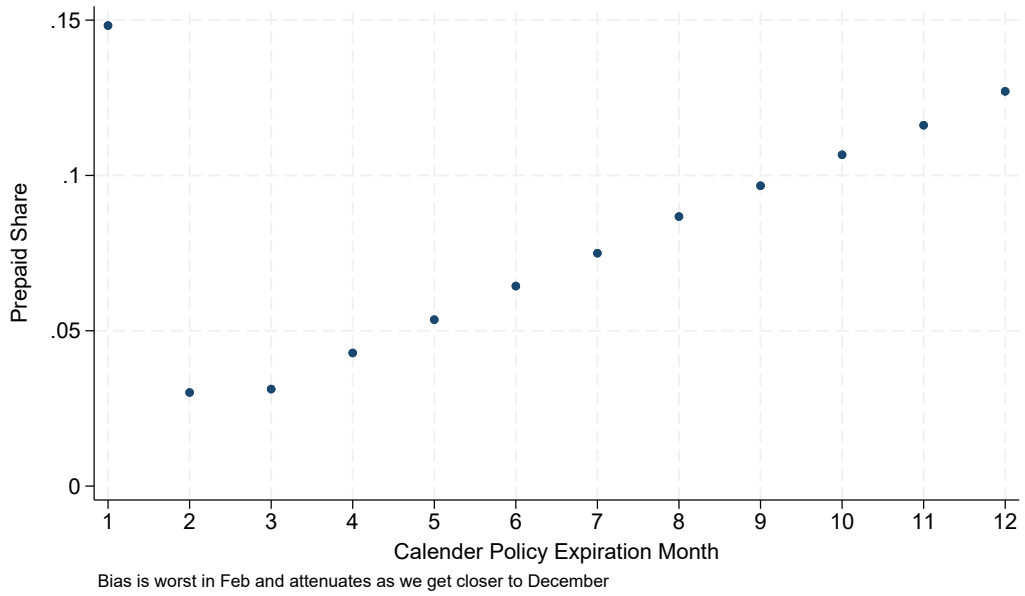
SHARE OF DELINQUENT MORTGAGES REPORTED BY INSURANCE RENEWAL MONTH



NOTES: Source: ICE McDash.
This figure plots the share of mortgages that are delinquent reported by the calendar month of the insurance policy expiration date.

FIGURE IA.3

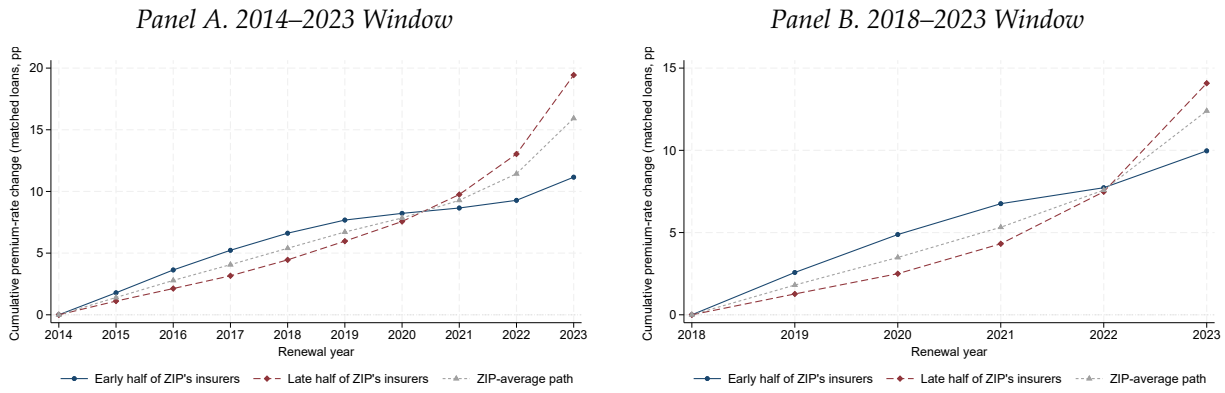
PROBABILITIES OF MORTGAGE PREPAYMENT REPORTED BY INSURANCE RENEWAL MONTH



NOTES: Source: ICE McDash and CRISM.
This figure plots the share of mortgages that are prepaid by the calendar month of the insurance policy expiration date.

FIGURE IA.4

STAGGERED INSURER REPRICING WITHIN A ZIP CODE



NOTES: Source: ICE McDash.

This figure documents that, within a ZIP code, insurers raise premiums at different times but end up raising premiums by similar cumulative amounts, the timing variation exploited by our leave-out insurer instrument. Cumulative change is measured as a matched loan-level long difference: for each loan we take its premium rate as a percentage of coverage limit (winsorized at the 0.5/99.5 percentiles) at its renewal in year y minus its rate at its renewal in the window's first year, keeping only loans whose insurer is unchanged between the two dates, and average these differences within insurer-ZIP-year cells. Because the cumulative change is a single level difference for a fixed set of loans rather than a sum of period-to-period changes, no chaining is involved; and no value is interpolated or carried forward for an insurer-ZIP-year with no matched loan, so the plotted series show a marker only at years with a genuine underlying observation. The sample is restricted to insurer-ZIP pairs with at least two matched loan-years per window-year, in ZIP codes with at least four such insurers, and to insurer-ZIP pairs whose cumulative change as of their last observed year is positive (net premium increases). Within each ZIP, we rank insurers by their *half-life year*, the first year by which the insurer has implemented half of its eventual cumulative increase, and split them into an early-moving and a late-moving half. Each panel plots the ZIP-year-average cumulative change together with the average for the early- and late-moving halves (each expressed as the ZIP-average path plus the within-ZIP deviation of that group), weighted by the number of matched loan-years per insurer-ZIP pair. Panel (a) uses a 2014–2023 window and Panel (b) a 2018–2023 window; the later window trades sample length for a larger set of loans that can be matched to the window's first year.

TABLE IA.1
RESIDUALIZING THE INSTRUMENTAL VARIABLE

	(1) Insurer Other-ZIP Avg Prem Rate Increase	(2) Insurer Far-ZIP Avg Prem Rate Increase
12-Month Lag Insurer Other-ZIP Avg Prem Rate Increase	0.596***	
	(1955.70)	
24-Month Lag Insurer Other-ZIP Avg Prem Rate Increase	0.223***	
	(625.48)	
12-Month Lag Insurer Far-ZIP Avg Prem Rate Increase		0.564***
		(0.000)
24-Month Lag Insurer Far-ZIP Avg Prem Rate Increase		0.234***
		(0.000)
Renewal Month FE	Yes	Yes
Y Mean	0.033	0.033
Y SD	0.040	0.040
N	15,833,086	15,833,133
R-squared	0.489	0.457

NOTES: Source: ICE McDash.
This table presents the regression used to residualize the initial values of the instrumental variable. The dependent variable is Δ *Insurer Other-ZIP Avg Prem Rate* in Column (1) and Δ *Insurer Far-ZIP Avg Prem Rate* in Column (2). The independent variables are its 12-month and 24-month lagged values. We also include month fixed effects. ***p<0.01, **p<0.05, *p<0.1.

TABLE IA.2
EFFECTS OF PREMIUM INCREASES ON INSURER SWITCHING

	(1)	(2)	(3)	(4)	(5)	(6)
			1(Switch Insurer)			
Premium Rate Increase	0.460***		0.888***		0.950***	0.424***
	(26.58)		(10.77)		(11.54)	(27.13)
Insurer Other-ZIP Avg Prem Increase (residual)		0.883***				
		(87.52)				
Insurer Far-ZIP Avg Prem Increase (residual)				0.676***		
				(38.50)		
Premium Rate Increase × Credit Score Tercile 2						0.040***
						(8.15)
Premium Rate Increase × Credit Score Tercile 3						0.063***
						(7.32)
Lag Premium Rate	0.009***	0.022***	0.004*	0.022***	0.002	0.009***
	(4.70)	(11.04)	(1.84)	(10.78)	(1.16)	(4.76)
Credit Score/1k before Renewal	-0.033***	-0.039***	-0.001	-0.039***	0.002	-0.033***
	(-9.44)	(-21.37)	(-0.15)	(-21.55)	(0.37)	(-9.57)
Climate Risk (standardized)/1k	-0.893***	0.385***	-1.155***	0.414***	-1.201***	-0.894***
	(-3.90)	(3.20)	(-4.46)	(3.30)	(-4.60)	(-3.90)
OLS/2SLS Stage	OLS	1st Stage	2nd Stage	1st Stage	2nd Stage	OLS
Sample	All	All	All	All	All	All
Credit Score Tercile Interactions						Y
ZIP-by-Renewal Month FE	Y	Y	Y	Y	Y	Y
Climate Risk Bin-by-Renewal Month FE	Y	Y	Y	Y	Y	Y
Orig: Yr & Credit Score & LTV & DTI FE	Y	Y	Y	Y	Y	Y
Y Mean	0.075	0.025	0.062	0.025	0.062	0.075
X Mean	0.027	-0.001	0.025	-0.001	0.025	0.027
X SD	0.059	0.023	0.054	0.024	0.054	0.059
N	45,072,018	29,889,519	29,889,519	29,651,554	29,651,554	45,072,018
Kleibergen-Paap Wald F stat			7,659		1,482	

NOTES: Source: ICE McDash and Equifax Credit Risks Insight Servicing (CRISM).
This table presents the effect of premium rate increases on insurer switching. The dependent variable in all columns is an indicator for switching insurers within 12 months of renewal. Columns (1)–(5) reproduce the switching specification: Column (1) is OLS; Columns (2) and (4) report the first stage (with *Premium Rate Increase* as the dependent variable) and Columns (3) and (5) the corresponding second stage, instrumented with the residualized average premium rate increase among policies renewing in the same month with the same insurer in other (Other-ZIP; Columns 2–3) and

TABLE IA.3
EFFECT OF PREMIUM INCREASES ON PROBABILITY OF CHANGING INSURER

	(1)	(2)
	1(Switch Insurer at Renewal)	
Insurer Other-ZIP Avg Prem Increase (residual)	0.659***	
	(14.15)	
Insurer Far-ZIP Avg Prem Increase (residual)		0.525***
		(14.55)
Lag Premium Rate	0.041***	0.041***
	(22.00)	(21.43)
Credit Score/1k before Renewal	0.005	0.004
	(1.31)	(1.27)
Climate Risk (standardized)/1k	-0.815***	-0.805***
	(-3.75)	(-3.78)
OLS/2SLS Stage	OLS	OLS
Sample	All	All
ZIP-by-Renewal Month FE	Y	Y
Climate Risk Bin-by-Renewal Month FE	Y	Y
Orig: Yr & Credit Score & LTV & DTI FE	Y	Y
Y Mean	0.053	0.053
X Mean	-0.001	-0.001
X SD	0.023	0.024
N	35,854,295	35,571,286
R-squared	0.047	0.046

NOTES: Source: ICE McDash.
This table presents results testing whether households are more likely to switch insurers when their previous insurers increase premiums. We use two instrumental variables as the independent variable separately. The dependent variable is an indicator of whether the switch-insurer occurs in policy year t, measured at the same time as the independent variable. The main independent variables are the instruments constructed in policy year t. Standard errors are corrected for clustering at the state-by-year level. ***p<0.01, **p<0.05, *p<0.1.

TABLE IA.4

EXPLAINING THE RELATIONSHIP BETWEEN IDIOSYNCRATIC PRE-MOVE PREMIUM INCREASE AND POST-MOVE PREMIUM REDUCTION

	(1)	(2)	(3)	(4)	(5)
	Δ Premium Rate (subsequent policy)				
Premium Rate Increase × Moved	-1.190***	-0.695***	-1.196***	-0.734***	-1.187***
	(-13.79)	(-8.70)	(-13.93)	(-10.73)	(-13.88)
Δ Climate Risk	3.328***				
	(8.93)				
Δ Premium Rate to New ZIP Avg		0.282***			
		(11.00)			
Δ Premium Rate to New ZIP Avg × Moved		0.222***			
		(25.45)			
1(Switch Insurer)			-0.087***		
			(-39.08)		
1(Switch Insurer) × Moved			0.055***		
			(22.74)		
Δ to Ins-Other-ZIP Avg				0.652***	
				(41.96)	
Δ to Ins-Other-ZIP Avg × Moved				0.078***	
				(5.18)	
Δ Insurer HHI/1k					0.001***
					(6.26)
Δ Insurer HHI/1k × Moved					0.020***
					(12.61)
Premium Rate Increase	0.280***	0.579***	0.366***	-0.002	0.280***
	(5.54)	(7.41)	(6.82)	(-0.04)	(5.53)
Moved	-0.013***	-0.032***	-0.006***	-0.027***	-0.013***
	(-5.33)	(-15.23)	(-2.94)	(-14.97)	(-5.41)
Controls	Y	Y	Y	Y	Y
OLS/2SLS Stage	2nd Stage	2nd Stage	2nd Stage	2nd Stage	2nd Stage
Sample	Sep-Jan	Sep-Jan	Sep-Jan	Sep-Jan	Sep-Jan
Subsample	Movers&Stayers	Movers&Stayers	Movers&Stayers	Movers&Stayers	Movers&Stayers
Old ZIP-by-Renewal Yr FE	Y	Y	Y	Y	Y
Climate Risk Bin-by-Renewal Yr FE	Y	Y	Y	Y	Y
Orig: Yr & Credit Score & LTV & DTI FE	Y	Y	Y	Y	Y
Y Mean	0.010	0.010	0.010	0.010	0.009
Y SD	0.084	0.083	0.084	0.084	0.084
X Mean	0.023	0.022	0.023	0.023	0.023
X SD	0.050	0.049	0.050	0.050	0.049
N	7,796,890	7,688,558	7,799,670	7,799,567	7,794,208
Kleibergen-Paap Wald F stat	591	411	589	585	591

NOTES: *Table IA.4.* Source: ICE McDash and Equifax Credit Risks Insight Servicing (CRISM). This table examines what explains the larger post-moving premium savings for movers experiencing larger pre-moving premium increases. The dependent variable is the change in premium rates from policy year t to $t+1$. The coefficient of interest is on the interaction of the mover's idiosyncratic pre-move premium rate increase (the change in premium as a percentage of the coverage limit, instrumented with the residualized average premium rate increase among policies renewing in the same month with the same insurer in distant (Far-ZIP) ZIP codes within the same state) with an indicator for moving; it captures the additional premium change experienced by movers. The sample includes both movers and stayers. Each column adds one candidate mechanism, entered on its own and, for Columns (2)–(5), also interacted with the moving indicator: the mover's pre-to-post change in their climate risk exposure in Column (1); the change from their pre-moving premium rate to their post-moving ZIP-average premium rate in Column (2); an indicator for whether the mover also switched insurers in Column (3); changes in insurers' average premium rates in other ZIP codes within the same state in Column (4); and the change in insurer concentration, measured by the Herfindahl-Hirschman Index (HHI), from the mover's old to new ZIP codes in Column (5). The change in climate risk in Column (1) is zero for stayers, so it enters without a moving interaction. The *Controls* row indicates that every column includes the same three control variables, whose coefficients we suppress to keep the table readable: the premium rate before the renewal (the lagged premium rate), the borrower's credit risk score in the month prior to the insurance renewal (divided by 1,000), and the standardized climate risk of the borrowers' old residence (divided by 1,000). We also control for the following fixed effects (FE): 5-digit old ZIP by insurance policy renewal year FE, climate risk bin by insurance policy renewal year FE, mortgage origination year FE, LTV bin FE, DTI bin FE, and credit score bin FE. Standard errors are corrected for clustering at the state-by-year level. ***p$<$0.01, **p$<$0.05, *p$<$0.1.

TABLE IA.5
THE EFFECT OF INSURANCE PREMIUM INCREASES ON INVESTOR PURCHASE: ALTERNATIVE INVESTOR DEFINITION

	(1)	(2)	(3)	(4)	(5)
		Premium Rate		Premium Rate	
	Investor	Increase	Investor	Increase	Investor
Premium Rate Increase	0.027***		0.052***		0.045***
	(8.27)		(4.24)		(3.16)
Insurer Other-ZIP Avg Prem Increase (residual)		0.885***			
		(152.17)			
Insurer Far-ZIP Avg Prem Increase (residual)				0.708***	
				(114.83)	
Lag Premium Rate	0.025***	0.029***	0.024***	0.029***	0.025***
	(23.26)	(45.77)	(17.31)	(44.16)	(17.31)
CredScore/1k before Renewal	-0.164***	-0.072***	-0.145***	-0.073***	-0.146***
	(-43.29)	(-51.04)	(-32.70)	(-50.56)	(-32.53)
Climate Risk (Std)/1k	0.779**	0.463***	0.607	0.529***	0.542
	(2.27)	(3.01)	(1.44)	(3.35)	(1.29)
OLS/2SLS Stage	OLS	1st Stage	2nd Stage	1st Stage	2nd Stage
Sample	Transactions	Transactions	Transactions	Transactions	Transactions
Y Mean	0.041	0.033	0.041	0.033	0.041
X Mean	0.035	0.001	0.033	0.001	0.033
X SD	0.072	0.025	0.067	0.027	0.067
N	1,365,925	925,426	925,426	918,386	918,386
Kleibergen-Paap Wald F stat			23,155		13,187

NOTES: Source: ICE McDash, Equifax Credit Risks Insight Servicing (CRISM), and CoreLogic.
This table repeats the main-text analysis of Table 8 using an alternative definition of an investor buyer: McDash's market-investor designation, rather than CoreLogic's corporate-buyer flag. The dependent variable is an indicator for whether the buyer is an investor. Column (1) presents OLS estimates. Columns (2) and (3) present the first and second stages of the instrumental variable regression using the residualized Other-ZIP instrument, and Columns (4) and (5) repeat the first and second stages using the residualized Far-ZIP instrument. We control for the previous owners' credit risk score in the month prior to the insurance renewal, the premium rate before the renewal, and the standardized climate risk of the borrowers' old residence. We also control for the following fixed effects (FE): 5-digit ZIP, climate risk bin by insurance policy renewal year FE, mortgage origination year FE, LTV bin FE, DTI bin FE, and credit score bin FE. Standard errors are corrected for clustering at the state-by-year level. ***p<0.01, **p<0.05, *p<0.1.

Internet Appendix IA.A A Model of the Move-versus-Switch Decision

A household facing a premium increase has two remedies. It can switch insurers, at a cost of a few hours of search, or it can relocate, at a cost of several percent of the value of the house. Because the inexpensive remedy is available to every household, an account of the relocation response documented in this paper must explain why a premium increase ever induces the costly action. This appendix presents a model that does so. The model has three components: insurers charge different premiums for the same property, and only the difference between a household's own premium and the best locally available alternative can be undone by switching; the price of insuring a location, which every insurer serving it comes to charge, can be escaped only by relocating; and households accumulate non-insurance reasons to move, so that an insurance shock need not be large enough to justify relocation on its own in order to induce it. Section IA.A.1 sets out the environment, Section IA.A.2 characterizes the household's decision, Section IA.A.3 derives comparative statics, Section IA.A.4 introduces financial constraints and heterogeneous search costs, and Section IA.A.5 collects the proofs.

IA.A.1 Environment

Premium levels, components, and pass-through

A household occupies a property, lives for $t = 0, 1, \ldots, T$, and discounts at $\beta \in (0, 1]$. The insurers j serving the property quote per-year premiums P_j that differ across insurers. Let P_c denote the current insurer's quote and $P^a \equiv \min_{j \neq c} P_j$ the best available alternative at the location, and define

$$W \equiv P_c - P^a, \qquad L \equiv \min\{P_c, P^a\}. \tag{1}$$

We refer to W as the *wedge*: the amount by which the household's insurer prices above the best local alternative, which switching removes. W is negative for a household whose current insurer is the cheapest available. We refer to L as the *location price level*: the lowest price at which the property can be insured, which is common to the location and is not removed by any change of insurer.

At date 0 the household's premium changes by Δp dollars per year, which decomposes into

$$\Delta p = \varepsilon_I + \varepsilon_L. \tag{2}$$

The *location component* ε_L is the repricing of the location's risk, arising from risk reassessment, disaster-driven repricing, or regulatory pass-through. It is charged by every insurer serving the location, though not simultaneously. The *insurer component* ε_I is the current insurer's movement relative to the local market, arising from its own loss experience, expense loadings, or pricing-model updates; it augments the wedge, so that $W = W_{-1} + \varepsilon_I$, where W_{-1} is the wedge inherited from previous periods. The two components persist at rates ρ_L and ρ_I respectively.

Insurers do not incorporate a common repricing at the same date.

Assumption 1 (Staggered pass-through)**.** Insurer j's premium increase at a location is

$$\lambda_j \, \varepsilon_L + \eta_j, \tag{3}$$

where $\lambda_j \in [0, 1]$ is the share of the common repricing ε_L that insurer j has passed through as of the renewal date and η_j is insurer-specific. The λ_j are dispersed across insurers at any date and converge to unity over time; the η_j are mean-zero and independent of ε_L.

Insurers update loss models, file rate requests, and obtain regulatory approvals on different schedules, so at a given renewal date insurers serving the same location differ in how much of a common repricing they have implemented. Figure IA.4 documents this pattern: within a ZIP code, insurers raise premiums at different times but converge to similar cumulative increases. Writing c for the current insurer and a for the best alternative, Assumption 1 implies that the date-0 innovations satisfy

$$\Delta p = \lambda_c \, \varepsilon_L + \eta_c, \qquad \Delta W = (\lambda_c - \lambda_a) \, \varepsilon_L + (\eta_c - \eta_a), \qquad \Delta L = \lambda_a \, \varepsilon_L + \eta_a. \tag{4}$$

The household's observed increase reflects its own insurer's pass-through and idiosyncrasy; the wedge increases by the pass-through differential; and the location price level increases by the amount the best alternative has so far passed through. Because pass-through is eventually complete, the portion of a common repricing that temporarily appears in the wedge is transient, which provides one foundation for the persistence ordering imposed below. Consequently the decomposition of an increase that is observable at a renewal date differs from its economic decomposition: part of a common repricing is, at that date, indistinguishable from an insurer-specific movement. This is the sense in which the variation used for identification may reflect which insurer has repriced, as discussed in Section 5.

The correlation of disaster risk within a state is what allows this component to be measured. An insurer's repricing in distant ZIP codes of the same state is informative about its pass-through of the focal location's risk, so the far-ZIP instrument is, in the terms of the model, predominantly a shifter of $\lambda_c \varepsilon_L$, together with whatever insurer-specific component is embedded in the statewide rate action.[25]

Present values

A gap of one dollar per year that persists at rate ρ_j has present value

$$A_j \;\equiv\; \sum_{t=0}^{T} (\beta \rho_j)^t, \qquad j \in \{I, L\}, \tag{5}$$

which converts a flow into a stock. A permanent gap evaluated at a six percent discount rate over a thirty-year horizon has $A \approx 13.6$, consistent with the calculation in the text that the \$1,101 annual premium saving realized by movers corresponds to approximately \$15,000 in present value.

[25]The empirical counterpart of the date-0 shock is the residualized premium-rate increase. Because the instruments are purged of their 12- and 24-month lagged values and of renewal-month effects, they isolate the innovation rather than the anticipated continuation of past repricing.

Assumption 2 (Persistence ordering)**.** $A_L \geq A_I$: location price gaps are at least as persistent as insurer wedges.

The price of a location's risk is durable, being driven by risk reassessment that persists or increases over time. An individual insurer's deviation from the local market is eroded by competitors' pricing, regulatory review, and the insurer's own mean reversion, and, under Assumption 1, by the completion of pass-through. Consistent with this ordering, Ge et al. (2026) find that the premium reduction obtained by switching insurers is partial and partly transitory. If the location component carries a trend g, then $A_L = \sum_t (\beta(1+g)\rho_L)^t$ exceeds its value in the absence of a trend.

Housing mismatch

Households accumulate a dollar-denominated mismatch $m_t \geq 0$ between the current house and the house they would choose conditional on moving:

$$m_t \;=\; \rho_m \, m_{t-1} + \eta_t^m, \qquad \eta_t^m = \begin{cases} \sim \Gamma(k,\theta) & \text{with probability } \pi, \\ 0 & \text{with probability } 1-\pi, \end{cases} \tag{6}$$

with $m = 0$ at the date of purchase and $\rho_m \leq 1$ permitting the relevance of past events to decay. Innovations are infrequent and highly dispersed: in most years no event occurs, and when one does (a change of employment, a change in family composition, a health event), its magnitude is drawn from a skewed distribution, so that occasional realizations are large enough to induce relocation irrespective of insurance costs. Moving realizes m; switching insurers does not affect it. Throughout, m denotes the date-0 stock. The shape of this distribution governs the magnitude of the relocation response, as Proposition 4 makes precise.

Actions, costs, and payoffs

At date 0 the household chooses among remaining with its current insurer and property, switching insurers, and relocating. Switching costs κ^s, which represents search and administrative effort. Relocation costs

$$c^m \;=\; \kappa^m - \delta L^{mtg}, \qquad \delta \;\equiv\; \text{origination rate} - \text{current market rate}, \tag{7}$$

where κ^m denotes transaction and relocation costs and L^{mtg} the mortgage balance. The second term is the mortgage consequence of relocation: a household that moves surrenders its existing loan and originates a new one at prevailing rates, which is advantageous when the origination rate exceeds the current rate ($\delta > 0$) and costly otherwise. The latter case is mortgage lock-in (Fonseca and Liu, 2024).[26] We maintain $c^m > \kappa^s \geq 0$.

Assumption 3 (Re-shopping accompanies relocation)**.** A household that relocates takes out a new policy on the new property and selects the best available insurer there; neither the incumbent insurer's wedge nor its household-specific advantages transfer to the new

[26] δL^{mtg} is to be interpreted as the present value of exchanging the existing loan for one at current rates rather than as a single year's interest differential; the results below use only $\partial c^m / \partial \delta = -L^{mtg} < 0$.

property. The incremental cost to a mover of selecting a non-incumbent insurer is $\kappa_M^s \in [0, \kappa^s)$, set to zero in the baseline.

A mortgage closing requires a new policy on the new property, priced as new business, and the search costs of obtaining it are shared with the other searches that a housing transaction entails. Relocation therefore accomplishes what switching accomplishes. Consistent with $\kappa_M^s < \kappa^s$, thirty-eight percent of movers in our sample change insurer at the move; the fact that the remainder do not indicates that some component of the incumbent's advantage (multi-policy discounts, underwriting classification, or claims history) transfers across properties, which corresponds to $\kappa_M^s > 0$.

Valuing relocation requires the destination's price level. Let L' denote the best available price at the destination and define the *location price gap*

$$G \equiv L - L', \tag{8}$$

the annual amount that relocation saves on the location itself. G varies for two reasons: a standing difference in price across locations, which predates any recent change, and the recent location component ε_L, which raises L while leaving L' unaffected. G is negative for a household that would relinquish an inexpensive location by moving.

Payoffs are measured net of remaining in place:

$$v(\varnothing) = 0, \qquad v(S) = A_I W - \kappa^s, \qquad v(M) = m + A_L G + A_I W - c^m. \tag{9}$$

Switching removes the wedge, at cost κ^s; it does not affect the location price level, since by construction every insurer serving the location charges L, and it does not affect the match between household and house. The relevant object is the level of the wedge, $W = W_{-1} + \varepsilon_I$, rather than the recent insurer component alone: a household insured at a persistently expensive insurer has a motive to switch in the absence of any increase. Relocation realizes the mismatch m, exchanges the origin's price level for the destination's, and, by Assumption 3, also removes the wedge, at cost c^m. Financial constraints are introduced in Section IA.A.4.

IA.A.2 The household's decision

Define

$$x \equiv A_I W, \qquad y \equiv m + A_L G. \tag{10}$$

The state x is the present value of the amount by which the household overpays relative to the best local alternative, whether inherited or newly arrived, and is removable by switching. The state y is the present value of the household's total non-insurer motive for relocating: the accumulated housing mismatch together with the price gap between the origin and the destination. Both components of y are removable only by moving, and they are perfect substitutes in the decision.

Proposition 1 (Decision rule)**.** *Let $c^m > \kappa^s \geq 0$. The optimal choice is*

$$\begin{aligned} \text{move} &\iff y > c^m - \min\{x, \kappa^s\}, \\ \text{switch} &\iff x > \kappa^s \text{ and } y \leq c^m - \kappa^s, \\ \text{stay} &\iff x \leq \kappa^s \text{ and } y \leq c^m - x. \end{aligned} \tag{11}$$

The relocation frontier $y^*(x) = c^m - \min\{x, \kappa^s\}$ is decreasing in x on $[0, \kappa^s)$, with slope -1, and constant at $c^m - \kappa^s$ for $x \geq \kappa^s$; it has a kink at $(\kappa^s,\ c^m - \kappa^s)$.

The household relocates when the value of doing so, comprising the relocation gap y and whatever wedge the move removes, exceeds the cost of relocation. The term $\min\{x, \kappa^s\}$ reduces the relocation threshold, but by at most κ^s: beyond that point the wedge can be removed by the inexpensive action, and it therefore ceases to constitute a reason to move. The household switches when the wedge alone justifies the search cost but the relocation gap does not justify the incremental cost of moving. Four properties of the solution merit emphasis.

First, where switching is optimal absent relocation considerations, that is, for $x > \kappa^s$, the comparison between the two remedies is

$$v(M) - v(S) \;=\; y - (c^m - \kappa^s) \;=\; m + A_L G - (c^m - \kappa^s), \tag{12}$$

which does not depend on W. Both remedies remove the wedge, so neither the inherited wedge nor the insurer component of a current increase can determine the choice between them. The household relocates rather than switches when its accumulated mismatch, together with the price gap between origin and destination, exceeds the incremental cost of relocating over switching.

Second, the availability of the inexpensive remedy caps the contribution of the wedge to the relocation decision at κ^s. For $x < \kappa^s$ a household that would not switch on its own account nonetheless removes its wedge without additional cost when it moves, so the wedge reduces the effective cost of relocation dollar for dollar. For $x > \kappa^s$ additional wedge induces switching rather than relocation. No corresponding bound applies to y.

Third, the rule admits an (s, S) interpretation. Insurance contributes $A_L G + \min\{A_I W, \kappa^s\}$ dollars to accumulated mismatch, and the household relocates when the total crosses c^m.

Fourth, the model contains two insurance analogues of mortgage lock-in. Neither x nor G is restricted in sign. A household whose current insurer prices below the local alternatives ($W < 0$) faces a relocation threshold $c^m - x > c^m$, because the favorable policy is not portable under Assumption 3. A household in a location priced below its alternatives ($G < 0$) relinquishes that advantage by moving. Both operate in the same direction as the mortgage term δL^{mtg} in c^m: a premium increase is a tax on remaining in place, and any below-market position the household holds is a subsidy to doing so.

IA.A.3 Comparative statics

Write $W = \mu_I + u_I$ and $G = \mu_L + u_L$, where μ_I and μ_L are location parameters and u_I and u_L are mean-zero disturbances. An increase in μ_I shifts the wedge, which an insurer-specific increase accomplishes and in which cross-household variation in the inherited

wedge also appears; an increase in μ_L shifts the location price gap, which a repricing of the origin accomplishes and in which standing differences in price across locations also appear. Assume (m, u_I, u_L) are mutually independent with continuous densities of full support, so that x and y are independent with densities f_x and f_y and distribution functions F_x and F_y. Proofs are in Section IA.A.6.

Proposition 2 (Assignment of components to remedies)**.**

(i) Switching responds positively to shifts in the wedge and negatively to shifts in the location price gap:

$$\frac{\partial \Pr(S)}{\partial \mu_I} > 0, \qquad \frac{\partial \Pr(S)}{\partial \mu_L} < 0. \tag{13}$$

(ii) Relocation responds positively to both, and, per dollar of present value, strictly more to the location price gap:

$$\frac{1}{A_L}\frac{\partial \Pr(M)}{\partial \mu_L} \;>\; \frac{1}{A_I}\frac{\partial \Pr(M)}{\partial \mu_I} \;\geq\; 0. \tag{14}$$

Measured in annual premium dollars the difference is larger still, since $A_L \geq A_I$ scales the left-hand side.

Each component of a household's premium is associated with the remedy that removes it. An increase in the wedge, whether inherited or newly arrived, induces switching. An increase in the location price gap does not make switching more attractive, and it induces some households that would otherwise have switched to relocate instead, which accounts for the negative cross-effect in part (i). Part (ii) reflects the bound established above: a marginal dollar of location price gap shifts households across the entire relocation frontier, whereas a marginal dollar of wedge shifts households across only its downward-sloping segment.

Under Assumption 1 a location-common repricing is not passed through by all insurers simultaneously, so at a given renewal date part of it is temporarily removable by switching to an insurer that has not yet repriced. That relief is transitory, since pass-through is eventually completed, and it does not affect the relocation margin, which responds to the full location component.

Proposition 3 (Mortgage lock-in and relocation)**.** *A reduction in the cost of relocation raises the probability of relocation:*

$$\frac{\partial \Pr(M)}{\partial \delta} > 0. \tag{15}$$

Since δ enters only through c^m, a relaxation of mortgage lock-in lowers the relocation frontier at every x, and relocation expands at the expense of both remaining in place and switching. This is the interaction estimated in Table 6.

Proposition 4 (The marginal relocating household)**.** *The relocation response to a shift in the location price gap is*

$$\frac{\partial \Pr(M)}{\partial \mu_L} \;=\; A_L\, \mathbb{E}_x\big[\, f_y\big(y^*(x)\big)\big], \tag{16}$$

the density of the relocation gap at the frontier, scaled by the present-value factor. Since the present value of a realistic premium shock is small relative to c^m, the households whose relocation decision is altered by a premium increase are those for which y already lies within $A_L\varepsilon_L$ of the frontier, either because recent events have raised m or because a standing price gap has raised $A_L G$.

Proposition 4 states that the relocation response to a premium increase is a statement about the density of households near the relocation frontier rather than about a preference parameter, and it has two implications.

The first concerns magnitude. A one-standard-deviation premium-rate shock, approximately \$220 per year, has a present value of roughly \$3,000, or about an eighth of a relocation cost of the order of \$24,000 for a property with \$400,000 of coverage. A premium increase of realistic size therefore cannot induce relocation on its own; it alters the decision of households already close to the frontier, and the magnitude of the response is governed by the mass of households in that region. Were mismatch to accumulate smoothly, so that its stationary distribution were approximately uniform on $[0, c^m]$, an increase of \$1,000 per year, with a present value of approximately \$14,000, would induce relocation by a large fraction of all households, exceeding the estimate in Table 4 by orders of magnitude. A process with infrequent and highly dispersed innovations does not have this property: most households have experienced no recent event, and realizations large enough to approach the frontier typically exceed it and induce relocation outright, leaving little mass immediately below it.

The second concerns the identity of the households whose behavior changes. The model implies that households induced to relocate by a premium increase resemble those that were already close to relocating for unrelated reasons, rather than households experiencing a contemporaneous shock to the property itself. This is consistent with the estimates in Table A.5, in which the relocation response is not attributable to households in areas experiencing disasters. It also implies that the estimated semi-elasticity is local: extrapolation to premium increases much larger than those observed requires the distribution of y rather than the estimated slope.

Proposition 5 (Insurer choice among movers)**.** *Suppose W_{-1}, ε_I, and ε_L are independent with log-concave densities, and consider households for which $m \geq c^m$, which relocate for every realization of the premium shock. Such a household changes insurer at the move if and only if $A_I W > \kappa_M^s$, with $W = W_{-1} + \varepsilon_I$, and*

$$d \;\longmapsto\; \Pr\big(A_I W > \kappa_M^s \;\big|\; \varepsilon_I + \varepsilon_L = d\big) \tag{17}$$

is nondecreasing: among movers, those that experienced a larger total premium increase before moving are more likely to change insurer.

Only the total increase $d = \varepsilon_I + \varepsilon_L$ is observed. A larger total is associated with a larger insurer component, by the monotonicity property of log-concave densities, and hence with a larger wedge carried into the move, which raises the probability that re-shopping at the destination yields an insurer preferable to the incumbent. Under Assumption 1 the conclusion is reinforced, since the wedge loads positively on both components of the observed increase.[27]

[27]For households whose relocation is itself induced by the premium increase there is an offsetting se-

Remark 1 (Partial and transitory recovery)**.** The baseline specification assumes that a switching household obtains the best available alternative and retains the resulting gain at persistence ρ_I. Ge et al. (2026) report that the realized reduction is partial and partly transitory: households that switch recover approximately forty cents of a one-dollar increase in the following year, part of which reflects a new-customer discount, whereas movers reduce their premiums by close to the full amount of the increase. Two mechanisms account for the difference. The first is imperfect search: a switching household obtains an insurer that is less expensive than the incumbent but not necessarily the least expensive available. The second follows from Assumption 1: the best alternative at the renewal date is inexpensive in part because it has not yet passed through the common repricing, and it converges upward thereafter, so that a recovery which is partial in the first year and declines subsequently is what the mechanism implies. Let $\phi \in (0, 1]$ denote the share of the wedge that switching recovers in present value, so that $v(S) = \phi A_I W - \kappa^s$ while $v(M)$ is unchanged, since a mover's premium is set anew at the destination. The household then switches if and only if $\phi x > \kappa^s$, and beyond the kink the relocation frontier declines with slope $-(1-\phi)$ rather than being constant,

$$y^*(x) = \begin{cases} c^m - x, & \phi x \le \kappa^s, \\ c^m - \kappa^s - (1-\phi)\, x, & \phi x > \kappa^s, \end{cases} \tag{18}$$

because the unrecovered share of the wedge remains a motive for relocation even for households that would otherwise switch. Equation (12) becomes $v(M) - v(S) = m + A_L G + (1-\phi) A_I W - (c^m - \kappa^s)$, and the bound established above applies only to the recovered share. All results below hold with the terms in W reweighted accordingly. The case $\phi = 1$ is the baseline; as $\phi \to 0$ switching ceases to be a remedy and the model reduces to one in which relocation is the only response.

IA.A.4 Financial constraints and search costs

The paper documents that the relocation response to premium increases is concentrated among households with higher credit scores, while the delinquency response is concentrated among households with lower credit scores. The model accommodates both, and implies that the two gradients identify distinct frictions.

Assumption 4 (Liquidity)**.** The household holds liquid wealth $w = \mu_w + u_w$ with distribution function G_w and density g_w, independent of (m, W, G). An action is feasible only if w covers its largest single outlay: relocation requires $w \ge c^m$ and switching requires $w \ge \kappa^s$. Since κ^s represents search effort rather than a payment, and is small relative to c^m, we set $\Pr(w \ge \kappa^s) = 1$. A household that would relocate but cannot finance the move optimizes over the remaining actions and therefore switches if and only if $x > \kappa^s$.

The binding requirement is the largest single outlay, namely the down payment and closing costs associated with a housing transaction, rather than the sum of the costs of

lection effect: conditional on the total increase and on relocating, such a household is more likely to have experienced a large location component and hence a small insurer component. This attenuates the relationship without necessarily reversing it.

all actions. Under Assumption 4, writing $G_c \equiv G_w(c^m - \mu_w) = \Pr(w < c^m)$ for the constrained share,

$$\Pr(M) = \big(1 - G_c\big)\,\Pr\big(y > y^*(x)\big), \tag{19}$$

$$\Pr(S) = \big(1 - G_c\big)\big[1 - F_x(\kappa^s)\big]F_y(c^m - \kappa^s) + G_c\big[1 - F_x(\kappa^s)\big]. \tag{20}$$

Relocation requires both that the household prefer it and that it be feasible. Switching comprises two groups: unconstrained households in the switching region, and constrained households, for which the relocation region is unavailable and which therefore switch whenever the wedge exceeds the search cost.

Proposition 6 (Financial capacity and relocation)**.**

(i) $\Pr(M)$ *is strictly increasing in* μ_w*.*

(ii) Wealth and the premium shock are complements in relocation:

$$\frac{\partial^2 \Pr(M)}{\partial \mu_L\, \partial \mu_w} \;=\; A_L\, \mathbb{E}_x\big[f_y(y^*(x))\big]\, g_w(c^m - \mu_w) \;>\; 0, \qquad \frac{\partial^2 \Pr(M)}{\partial \mu_I\, \partial \mu_w} \;\geq\; 0. \tag{21}$$

(iii) Conditional on $w < c^m$ *the relocation response is zero, and a shift in the location price gap has no available remedy.*

Part (i) follows from the feasibility requirement. Part (ii) states that a premium increase alters the behavior only of households that are able to respond, so its effect is scaled by the unconstrained share; this corresponds to Column 2 of Table 5, in which the relocation response is 76 and 133 percent larger in the second and third credit-score terciles than in the first. Part (iii) concerns the delinquency margin: for a constrained household a repricing of its location admits no behavioral response, and the increase is absorbed within the budget constraint. This corresponds to the estimates in Table 2 and to Column 1 of Table 5, in which the delinquency response is concentrated among households in the lowest credit-score tercile. The model therefore reproduces the paper's central distinction: the same premium increase induces relocation among unconstrained households and financial distress among constrained households.

Proposition 7 (Search costs and switching)**.** *Let households differ in* κ^s*, holding all else fixed.*

(i) $\Pr(S)$ *is strictly decreasing in* κ^s*.*

(ii) If the density of the wedge is nonincreasing at the threshold, $f'_x(\kappa^s) \leq 0$*, then* $\partial \Pr(S)/\partial \mu_I$ *is also decreasing in* κ^s*.*

Part (ii) requires that switching be a minority outcome, so that the threshold lies in the upper region of the wedge distribution. Interpreting κ^s as decreasing in financial sophistication, the proposition corresponds to the finding in Ge et al. (2026) that households with higher credit scores are more responsive to premium increases in their choice of insurer.

The two credit-score gradients identify distinct frictions. A binding constraint does not merely suppress relocation; because a household that would have relocated but cannot finance the move retains the inexpensive remedy, liquidity alone implies that switching is weakly *decreasing* in wealth,

$$\Pr(S \mid w < c^m) - \Pr(S \mid w \geq c^m) \;=\; \big[1 - F_x(\kappa^s)\big]\big[1 - F_y(c^m - \kappa^s)\big] \;>\; 0. \tag{22}$$

Since switching is observed to be increasing in credit score (Ge et al., 2026), that gradient cannot be attributed to liquidity, which would generate the opposite sign; it identifies heterogeneity in κ^s, through Proposition 7. The relocation gradient, by contrast, identifies liquidity, through Proposition 6.[28]

IA.A.5 Proofs

Throughout, $x = A_I W$ and $y = m + A_L G$ are independent with continuous densities of full support. A shift $d\mu_I$ displaces x by $A_I\, d\mu_I$ and a shift $d\mu_L$ displaces y by $A_L\, d\mu_L$.

Proof of Proposition 1. The household maximizes over the three payoffs $\{0,\ x-\kappa^s,\ y+x-c^m\}$. If $x \le \kappa^s$, switching is dominated by remaining in place, so the household relocates if and only if $y + x - c^m > 0$, that is, $y > c^m - x = c^m - \min\{x, \kappa^s\}$. If $x > \kappa^s$, switching dominates remaining in place, so the household relocates if and only if $y + x - c^m > x - \kappa^s$, that is, $y > c^m - \kappa^s = c^m - \min\{x, \kappa^s\}$; the term in x appears on both sides and cancels. On the relocation region with $x > \kappa^s$ we have $v(M) > v(S) > 0$, and on the segment with $x < \kappa^s$ we have $v(M) > 0 \ge v(S)$, which confirms the stated assignment.

Proof of Proposition 2. By independence,

$$\Pr(M) = \int \big[1 - F_y\big(c^m - \min\{x, \kappa^s\}\big)\big] f_x(x)\, dx, \qquad \Pr(S) = \big[1 - F_x(\kappa^s)\big]\, F_y\big(c^m - \kappa^s\big).$$

Differentiating the second expression,

$$\frac{\partial \Pr(S)}{\partial \mu_I} = A_I\, f_x(\kappa^s)\, F_y(c^m - \kappa^s) > 0, \qquad \frac{\partial \Pr(S)}{\partial \mu_L} = -A_L \big[1 - F_x(\kappa^s)\big] f_y(c^m - \kappa^s) < 0.$$

The first term counts households displaced across the switching threshold; the second counts households that would have switched and are displaced across the constant segment of the relocation frontier. For relocation, a shift in μ_L displaces y against the frontier at every x:

$$\frac{\partial \Pr(M)}{\partial \mu_L} = A_L \int f_y\big(c^m - \min\{x, \kappa^s\}\big) f_x(x)\, dx > 0.$$

For μ_I, write $x = A_I \mu_I + x_0$; the integrand depends on μ_I only through $\min\{x, \kappa^s\}$, which is locally increasing in x if and only if $x < \kappa^s$, so

$$\frac{\partial \Pr(M)}{\partial \mu_I} = A_I \int_{x<\kappa^s} f_y\big(c^m - x\big) f_x(x)\, dx \ \ge\ 0.$$

Subtracting the normalized derivatives,

$$\frac{1}{A_L}\frac{\partial \Pr(M)}{\partial \mu_L} - \frac{1}{A_I}\frac{\partial \Pr(M)}{\partial \mu_I} = f_y(c^m - \kappa^s)\big[1 - F_x(\kappa^s)\big] > 0$$

[28] With partial recovery, as in Remark 1, replace $x > \kappa^s$ by $\phi x > \kappa^s$ throughout; the statements are unchanged. All comparisons hold other heterogeneity fixed. Credit score is empirically associated with both wealth and search efficiency, which is why the argument above, which relies on the sign pattern rather than on magnitudes, is the relevant one.

under full support.

Proof of Proposition 3. Since $\partial c^m/\partial\delta = -L^{mtg}$,

$$\frac{\partial \Pr(M)}{\partial \delta} = L^{mtg} \int f_y\big(c^m - \min\{x, \kappa^s\}\big) f_x(x)\, dx > 0.$$

Proof of Proposition 4. The expression is the derivative with respect to μ_L computed in the proof of Proposition 2, written as $A_L \mathbb{E}_x[f_y(y^*(x))]$ with $y^*(x) = c^m - \min\{x, \kappa^s\}$. For a discrete shock of size ε_L, the affected mass is $\Pr\big(y \in (y^*(x) - A_L\varepsilon_L,\ y^*(x)]\big)$. Since the width of this interval is small relative to c^m, membership requires that y lie within $A_L\varepsilon_L$ of the frontier.

Proof of Proposition 5. For $m \geq c^m$ we have $y \geq c^m > c^m - \min\{x, \kappa^s\}$ for every realization, so relocation occurs irrespective of the premium shock and the relocation event is independent of $(W_{-1}, \varepsilon_I, \varepsilon_L)$. Conditional on relocating, the household changes insurer if and only if $A_I W > \kappa^s_M$ with $W = W_{-1} + \varepsilon_I$. By the monotonicity theorem for log-concave densities (Efron, 1965), the conditional law of ε_I given $\varepsilon_I + \varepsilon_L = d$ is stochastically increasing in d; adding the independent W_{-1} preserves the ordering, so the conditional law of W given d is stochastically increasing in d and the stated probability is nondecreasing.

For the remaining proofs, w is independent of (x, y) by Assumption 4 and $G_c \equiv G_w(c^m - \mu_w)$.

Proof of Proposition 6. Write $\Pr(M) = [1 - G_w(c^m - \mu_w)]P^M$ with $P^M \equiv \Pr(y > y^*(x))$, which does not depend on μ_w. Then $\partial \Pr(M)/\partial\mu_w = g_w(c^m - \mu_w)P^M > 0$, which is part (i). From the proof of Proposition 2, $\partial P^M/\partial\mu_L = A_L\mathbb{E}_x[f_y(y^*(x))]$, so $\partial \Pr(M)/\partial\mu_L = [1 - G_w(c^m - \mu_w)]A_L\mathbb{E}_x[f_y(y^*(x))]$; differentiating with respect to μ_w gives part (ii), the wealth parameter entering only the feasibility factor and the premium parameter only the preference factor. The statement for μ_I is identical with $A_I \int_{x<\kappa^s} f_y(c^m - x) f_x\, dx \geq 0$ in place of the integral in μ_L. For part (iii), conditional on $w < c^m$ the choice set is $\{\varnothing, S\}$, and neither payoff depends on y, μ_L, or m.

Proof of Proposition 7. For part (i),

$$\frac{\partial \Pr(S)}{\partial \kappa^s} = -(1 - G_c)\big\{f_x(\kappa^s)F_y(c^m - \kappa^s) + [1 - F_x(\kappa^s)]f_y(c^m - \kappa^s)\big\} - G_c\, f_x(\kappa^s) < 0,$$

every term reducing the switching region. For part (ii), the response is $\partial \Pr(S)/\partial\mu_I = A_I f_x(\kappa^s)[(1 - G_c)F_y(c^m - \kappa^s) + G_c]$; differentiating with respect to κ^s gives

$$A_I\Big(f'_x(\kappa^s)\big[(1 - G_c)F_y + G_c\big] - (1 - G_c)f_x f_y\Big) \ < \ 0 \quad \text{whenever } f'_x(\kappa^s) \leq 0.$$

For part (iii), $\Pr(M) = (1 - G_c)\int[1 - F_y(c^m - \min\{x, \kappa^s\})]f_x\, dx$, so $\partial \Pr(M)/\partial\kappa^s = (1 - G_c)f_y(c^m - \kappa^s)[1 - F_x(\kappa^s)] \geq 0$, the frontier declining only on its constant segment; and $\partial \Pr(M)/\partial\mu_I = (1 - G_c)A_I \int_{x<\kappa^s} f_y(c^m - x)f_x\, dx$ is increasing in κ^s because the domain of the positive integrand expands.

Equation (22) follows from $\Pr(S \mid w < c^m) = 1 - F_x(\kappa^s)$ and $\Pr(S \mid w \geq c^m) = [1 - F_x(\kappa^s)]F_y(c^m - \kappa^s)$.