FEDERAL RESERVE BANK
PHILADELPHIA

Working Papers
RESEARCH DEPARTMENT

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WP 24-23

PUBLISHED
December 2024

FRB CFI PHILADELPHIA

ISSN: 1962-5361

DOI: https://doi.org/10.21799/frbp.wp.2024.23

Flood Underinsurance*†

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December 2024

Abstract

Using data on expected flood damage and National Flood Insurance Program policies, we estimate annual flood risk protection gaps and underinsurance among single-family residences in the contiguous United States. Annually, 70 percent ($17.1 billion) of total flood losses would be uninsured. Underinsurance, defined as protection gaps among properties with positive flood risk and incentives to purchase full flood insurance coverage, totals $15.7 billion annually. Eighty percent of at-risk households are underinsured, and average underinsurance is $7,208 per year. Underinsurance persists both inside and outside the Federal Emergency Management Agency's special flood hazard areas, suggesting frictions in the provision of risk information and regulatory compliance. Seventy percent of uninsured households would benefit from purchasing flood insurance, even as prevailing prices rise. Household beliefs about climate risks are strongly correlated with underinsurance.

Keywords: climate risk, physical risk, flood, underinsurance

JEL Codes: G22; G52; Q54

*We thank Isaac Hacamo and participants in the RADAR virtual climate seminar, CFPB Consumer Finance Round Robin, and AREUEA National Conference for valuable comments. We are also grateful to Jacob Dice and Paige Griggs for assistance with the First Street Foundation and CoreLogic datasets. This analysis was conducted using data from the Redistricting Data Hub. The Yale Program on Climate Change Communication (YPCCC) bears no responsibility for the analyses or interpretations of the data presented here. The authors declare that they have no relevant or material financial interests that relate to the research described in this paper. Corresponding author: Siddhartha Biswas, siddhartha.biswas@phil.frb.org.

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Physical climate risks have become more frequent and severe over time, and impact important economic outcomes such as local economic conditions, migration, home prices, and mortgage performance.[1] Homeowners insurance mitigates the financial risks from natural disasters collectively faced by homeowners, mortgage borrowers, lenders, and investors, but does not cover flooding. As a result, the National Flood Insurance Program (NFIP) is the primary financial protection against the $24.4 billion of expected annual flood-related property losses for single-family residences (SFRs).[2] Yet, if flood insurance does not adequately cover flood losses, agents in housing and mortgage markets become more exposed to physical climate risks than expected.

Trends in broader property insurance markets show a reduction in coverage against climate losses. Insurers are exiting markets with high physical climate risks, such as California and Florida, citing the rising costs of protecting against natural disasters (Boomhower et al., 2024; Sastry et al., 2023). Particularly for flooding, the NFIP faces financial stress, as large claims relative to premium revenue have left the program in more than $20 billion of debt to the U.S. Treasury (Horn and Webel, 2024). Understanding the magnitude of this insurance crisis is necessary to identify potential solutions for the mitigation of financial losses from physical climate risks.

This paper serves as the important first step of quantifying flood underinsurance to understand if current levels of flood insurance coverage would protect against expected flood losses and if the resulting protection gaps are economically inefficient. Related existing studies have considered complementary questions. Wing et al. (2022) and Wylie et al. (2024) document the magnitude of damage from floods and other physical climate risks, and show inequities in the distribution of damage faced by poorer communities. Weill (2023) identifies a mismatch between flood risks and FEMA flood maps, which provide information about flood

[1] For works on local economic conditions and migration, see Hsiang et al. (2017); Boustan et al. (2020); Bilal and Rossi-Hansberg (2023); Indaco and Ortega (2023). For the pricing of physical climate risks in housing, see Atreya et al. (2013); Ortega and Taşpinar (2018); Gibson and Mullins (2020); Gourevitch et al. (2023); Addoum et al. (2021); Bernstein et al. (2019); Baldauf et al. (2020); Keys and Mulder (2020); Atreya and Czajkowski (2019); Murfin and Spiegel (2020); Hino and Burke (2021). For analysis on the impact of natural disasters on mortgage performance, see Gallagher and Hartley (2017); Kousky et al. (2020); Ratcliffe et al. (2020); Du and Zhao (2020); Issler et al. (2023); Billings et al. (2022); Panjwani (2022); An et al. (2022, 2023); Biswas et al. (2023).

[2] Authors' calculation using First Street Foundation estimates of average annual flood losses. The next section details the steps to calculate this value.

risk and enforce insurance purchase requirements. Recent research on mortgage borrowers' homeowners insurance holdings, which does not cover flood damage, documents a sharp rise in premiums and decline in the share of rebuilding costs covered (Keys and Mulder, 2024; Sastry et al., 2024). Our paper fills the gap in the literature by measuring and describing the amount of underinsurance related to flooding faced by owners of SFRs.

First, we measure protection gaps by aggregating individual properties' expected flood damage that exceeds existing flood insurance coverage. Second, we estimate flood underinsurance by identifying protection gaps for properties that have suboptimal rates of full coverage as suggested by existing economic models of insurance demand. Third, we calculate the expected increase in underinsurance over the next thirty years for common climate scenarios. Fourth, we provide the distribution of underinsurance across locations, income, and race to understand which populations and areas face the largest insurance deficits. Last, we compare our measure of underinsurance and insurance premiums under counterfactual scenarios to calculate the expected benefit of purchasing flood insurance for uninsured homes.

Results

We measure flood protection gaps and underinsurance for SFRs in the contiguous U.S. by combining current estimates and 30-year projections of property-level flood damage in dollars from the First Street Foundation (FSF) with administrative data on flood insurance policies from the NFIP. Assuming adverse selection, we assign the highest observed coverage limits to the homes with the largest expected losses within a local area. This assumption ensures that we measure a lower bound on protection gaps and underinsurance because the riskiest properties in our merged data set have the most coverage.

We calculate the amount of flood losses that would not be covered by flood insurance. A property i with a coverage limit of C_i that is affected by a flood event j, which causes damage D_{ij}, would face a deficit δ_{ij} of

$$\delta_{ij} = \max\{0, D_{ij} - C_i\}.$$[3]

[3]This calculation abstracts away from policy deductibles. In a separate calculation, we add the deductible amount to each home's insurance coverage C_i, interpreting the policy deductible as the amount the homeowner is willing to pay out-of-pocket in the event of flood damage.

Events with damage lower than the coverage limit would result in a deficit of zero because insurance payouts are capped by damage. Therefore, properties that have more coverage than damage from all possible events have an expected deficit of zero. This definition allows us to correctly aggregate deficits to total protection gaps and underinsurance, as any excess insurance coverage cannot be transferred across properties.

We observe flood damage for a discrete number of J events covering a subset of return periods. The return period provides an interval and the inverse of this interval defines the exceedance probability P_j as the likelihood that damage would exceed a certain amount. For example, a property would experience annual damage of at least as much as a 100 year return period event (or 1 in 100 year event) with probability $P_j = \frac{1}{100}$. These events are ordered from most likely and least damaging to least likely and most damaging; that is, P_j is decreasing in j and δ_{ij} is increasing in j. We characterize any event that leads to no damage as $j = 0$, in which case $\delta_{i0} = 0$ and $P_0 = 1$.

For each property, the expected protection gap is $E(\delta_i)$ across the distribution of flood events. As we do not observe the full distribution, we estimate the protection gap as

$$G_i = \sum_{j=1}^{J} (P_{j-1} - P_j) \cdot \delta_{ij-1}.$$

The estimate G_i is a left Riemann sum that provides a lower bound for expected protection gaps $E(\delta_i)$. Specifically, we approximate the expected damage for the interval of unobserved events in between two observed events, $j-1$ and j, using damage from event j, the most likely and least damaging event in the interval. Figure A.3 illustrates that the discrete sum utilized in our estimation is a lower bound for the expected protection gap.

Protection gaps provide a descriptive measure, but the economic implications are unclear. Households may rationally purchase coverage that does not fully protect against expected damage as motivated by the price of insurance, expectations, and preferences. For example, households that expect low losses may have a willingness to pay that is lower than prevailing insurance premiums. Therefore, we provide a measure of economic underinsurance.

We define economic underinsurance as the expected protection gap faced by households for whom it is optimal to purchase full flood insurance coverage. Based on existing models of insurance demand, the annual premium, p_i, being less than or equal to expected losses in a year, $E(D_i)$, is a sufficient condition for full coverage to be optimal under the assumption of risk-aversion (Mossin, 1968; Einav et al., 2010).[4] Intuitively, households that face actuarially fair or favorable pricing should fully insure their property against flood damage. Any protection gap faced by these households would be economically inefficient.[5]

We estimate underinsurance as

$$U_i = \mathbb{1}(p_i \leq E(D_i)) \cdot G_i.$$

The estimate U_i is a lower bound for economic underinsurance for two reasons. First, similar to protection gaps, the discrete sum used to estimate U_i is lower than the underinsurance for households that have optimal demand for full insurance coverage for their property, $E(\delta_i | p_i \leq E(D_i))$. Second, we only include households that have optimal demand for full insurance coverage in our estimate. Our measure of underinsurance assumes that all protection gaps for households who optimally demand partial insurance coverage are efficient. Last, we aggregate across property-level underinsurance to total underinsurance. Appendix A provides additional details about the data and this approximation method.

Protection Gaps

Among the 92.3 million SFRs in the U.S., nearly 6 million face average annual losses (AALs) greater than zero. AAL measures the amount of flood-related losses, in dollars, a specific property expects to face in a year. Panel A of Table 1 shows that, for residences with positive AALs, the average protection gap is $2,865 (in 2023 US dollars), with 85 percent of at-risk SFRs having insurance coverage lower than their AALs.[6] In total, $17.1 billion of expected flood losses would be uninsured annually, representing 70 percent of the expected $24.4 billion of total flood damage faced by these properties.[7]

[4] This condition holds under the assumption of perfect credit markets and that households are not risk-loving.

[5] We do not decompose the mechanisms that may lead to inefficient levels of coverage. Examples of mechanisms include households' imperfect information about flood risks and institutional constraints such as the NFIP maximum allowed coverage limit of $250,000.

[6] We abstract away from deductibles, which are small relative to coverage limits. Over 70 percent of policies hold a $1,250 deductible. Accounting for deductibles does not change the results (see Tables A.1 and A.2).

[7] Wing et al. (2022) find that the AAL for all properties is $36.8 billion ($32.1 billion in 2021 USD), which makes our total SFR AAL appear too large because our sample does not include non-SFR properties. The

We decompose our results by federally designated flood zone status and SFRs' flood insurance status to understand the source of protection gaps. FEMA classifies Special Flood Hazard Areas (SFHAs) as floodplains that face at least a one percent annual probability of flooding. Borrowers of mortgages originated by federally regulated lenders in SFHAs must hold flood insurance. Therefore, SFHAs serve both as information about flood risk and as regulation for insurance purchase.

Comparing properties that are inside and outside of SFHAs, we see that 69 percent of the total protection gap falls outside of SFHAs, where 77 percent of SFRs do not hold flood insurance. Still, 76 percent of SFRs inside the SFHAs face protection gaps totaling $5.3 billion. These gaps imply that 52 percent of total expected flood losses inside SFHAs remain uninsured, suggesting that two important purposes of SFHAs, providing risk information and mandating coverage for mortgages in higher risk areas, function imperfectly.[8] The average protection gap of $3,012 inside the SFHAs is higher than the average of $2,804 outside of the SFHAs. This result is likely driven by higher expected flood losses inside the SFHAs than outside the SFHAs.

Panel A of Table 2 reports the distribution of the protection gaps across four mutually exclusive types of SFRs, defined by their insurance coverage. Uninsured SFRs, denoted by Types 1 and 3, account for 79 percent of our measured protection gap. "Type 1" SFRs, which are uninsured and located outside the SFHAs, face $10.8 billion, or 63 percent, of the protection gap. "Type 3" represents the 41 percent of SFRs in SFHAs that do not hold insurance and account for 19 percent ($3.2 billion) of the total protection gap. Last, two types of insured SFRs account for 16 percent of the deficit: "Type 2" hold less than the $250,000 maximum coverage, and "Type 4" hold the maximum coverage. The first group could increase their coverage, suggesting an information constraint on flood risks, but the

main driver of the discrepancy comes from the difference in data version. Our paper uses version 3 of the FSF data, while Wing et al. (2022) use version 1. Using version 1, we find that the AAL for all SFRs is $17.5 billion and the AAL for all properties is $34.6 billion, which is very close to the AAL estimate from Wing et al. (2022). The remaining discrepancy is likely driven by the difference in the data source for repair costs. We use repair costs directly provided by the FSF data, while Wing et al. (2022) use "a variety of sources" to compute structure valuation and repair costs.

[8] In a dynamic setting, Weill (2023) shows that changes to SFHAs over time have reduced insurance take-up rates even while flood risk has increased.

second group would require a policy change that increases the $250,000 maximum coverage in order to alleviate the insurance deficit.

Economic Underinsurance

To understand whether the protection gap is economically inefficient, we focus on households for whom purchasing full flood insurance coverage would be optimal. In total, 2,175,892 SFRs have positive expected flood damage and face annual premiums that are lower than or equal to AALs.[9] We refer to the protection gaps for this set of households who face actuarially favorable or fair prices as underinsurance.

As reported in Panel B of Table 1, underinsurance totals $15.7 billion of flood losses, and the average underinsurance of $7,208 is more than twice as large as the average protection gap. Moreover, 88 percent of at-risk households who face actuarially favorable or fair prices are underinsured. Underinsurance is concentrated among a smaller set of SFRs, as 36 percent of properties with a protection gap are underinsured but account for 91 percent of the total protection gap.[10]

Panel B of Table 2 shows that the dollar distribution of underinsurance across household types is identical to the dollar distribution of protection gaps, although the distribution of underinsured properties differs. Type 1 SFRs, who are uninsured and reside outside of SFHAs, represent 56 percent of underinsured SFRs. Type 4 SFRs, who face the NFIP constraint of a $250,000 coverage limit, represent 23 percent of all underinsured SFRs. The results suggest two types of frictions affecting a majority of households. First, Type 1 SFRs may face information frictions as they reside outside the SFHAs and may have inaccurate beliefs about their flood risks. Second, Type 4 SFRs may face institutional frictions as they are constrained by the NFIP maximum coverage limit. Conversely, both of these frictions

[9] We estimate counterfactual premiums for currently uninsured households using the average premium paid per dollar of coverage by insured households in the same census tract and SFHA.

[10] Our calculation does not account for federal disaster assistance grants and loans. Grants to restore property damage are small, as they totaled $349 million per year from 2014 to 2023, which is less than 1.5 percent of expected annual flood damage. While disaster loans comprise a larger share of aid, they should not crowd out the optimal insurance demand for our underinsurance estimation sample. Purchasing insurance coverage for property damage is cheaper than borrowing an equal amount of disaster loans – the insurance premium is lower than expected damage, while loan repayment is greater than or equal to expected damage and can require collateral for securitization (Collier et al., 2021). Furthermore, the regressive nature of disaster assistance allocation would further exacerbate the disparity in coverage by income, as we observe low income populations to be the most underinsured (Billings et al., 2022).

are less prevalent for Type 2 and Type 3 SFRs because they either hold insurance below the institutional limit or receive flood risk disclosures due to residing inside the SFHAs, respectively. Therefore, underinsurance for these households may be better explained by preference-based mechanisms.

For the remainder of the paper, we focus our analysis on the sample of households who are underinsured.

Severe Events and Future Climate Scenarios

Panel A of Table 3 shows underinsurance for events of varying severity with return periods from a 1 in 20 year flood (less severe) to a 1 in 500 year flood (more severe). Inside the SFHAs, depending on the flood severity, underinsured shares range from 38 to 80 percent, with average underinsurance of \$55,593 to \$150,613, while outside the SFHAs, underinsurance rates range from 37 to 93 percent, with average deficits of \$59,365 to \$223,953. A substantial share of residents who are underinsured against a 1 in 20 year event would face a certain and large financial expenditure of uninsured flood losses during their tenure, as 19 percent of households live in the same housing unit for longer than 20 years.[11]

Using 30-year projections under climate scenario Shared Socioeconomic Pathways 2-4.5 (SSP 2-4.5) and assuming insurance coverage and limits remain fixed, we show in Panel B of Table 3 that the underinsured share would increase modestly inside the SFHAs, by 3.2 percentage points. However, average underinsurance would increase by \$646 to \$1,350, depending on the location.

Geographic Distribution of Underinsurance

Figure 1 displays counties in the continental U.S. that face the highest underinsurance rates and deficits, and Table A.3 aggregates these statistics by census regions.[12] Unsurprisingly, the largest total insurance deficits occur in the coastal Middle Atlantic and South Atlantic regions, which are most likely to be affected by floods resulting from hurricanes and tropical storms. However, the inland East North Central, East South Central, and West North Central

[11]Source: American Community Survey 1-year estimates, 2022: Demographic Characteristics of Occupied Housing Units.

[12]For the maps, we restrict our sample to counties that have at least 20 properties with a positive AAL and optimal insurance demand of full coverage.

regions experience some of the highest underinsurance rates (95 to 98 percent) and amounts ($9,779 to $12,880). The prevalence of underinsurance in these central regions reflects damage from some of the highest rates of severe convective storms and inland flooding in the country (Wylie et al., 2024). This difference is visualized in Figure 1 by several inland counties in Appalachia and the Midwest being darker than tracts on the Atlantic and Gulf coasts. This geographic analysis further confirms that existing FEMA flood maps underestimate the need for insurance coverage in inland areas.

Income and Minority Composition

In addition to documenting aggregate underinsurance, we consider who the lack of coverage affects most using Census Bureau measures of tract-level income and racial composition. As shown in Figure 2, underinsurance shares and amounts are higher in tracts with lower median household income (Panels A and C). The lowest three income deciles face greater than 90 percent rates of underinsurance, with average underinsurance accounting for more than 20 percent of household income. The highest three income deciles face underinsurance that is less than 5 percent of household income.[13] Over the next 30 years, projected flood losses suggest that the disparity in underinsurance rates by income will flatten but will not reverse (Panel E). However, underinsurance amounts as a share of household income will increase more for low-income tracts than high-income tracts (Panel G).

We consider the demographic composition of tracts by defining the minority share as the share of Hispanic and Black individuals in the tract. Areas with the lowest minority shares have the highest underinsured rates (Panel B). However, the gradient remains relatively flat across the remainder of the minority share deciles. The pattern for underinsurance amounts as a share of income, however, is monotonic, as tracts with a lower share of minorities experience higher insurance deficits (Panel D). The latter finding is consistent with recent studies showing that areas experiencing the largest physical climate risk losses and the highest levels of unpriced climate risks tend to have a higher share of White residents (Gourevitch

[13]Underinsurance rates are not strictly decreasing in tract income. The underinsurance rates are higher for the top income decile than the eighth income decile. But the insurance deficit as a share of income is strictly decreasing in tract income. Figure A.1 shows that insurance rates increase by income, which suggests that higher income households are not more likely to self-insure. Instead, the uptick in underinsurance rates at the highest income deciles is potentially due to the $250,000 coverage limit not being sufficient for higher value properties.

et al., 2023; Wylie et al., 2024). Projections over the next 30 years suggest the underinsurance rate-minority share gradient will flatten, but underinsurance amounts will continue to be greater for the lowest minority share areas (Panels F and H).

Discussion

Our study has several notable limitations. First, the AALs from FSF are model-generated and, thus, contain a degree of uncertainty. Important sources of uncertainty include FSF's choice of model assumption, modeling method, and historical data. Our analyses take the point estimates as-is and do not reflect the aforementioned model uncertainty, which we cannot quantify. Second, our paper focuses on SFRs and, therefore, cannot quantify uninsured flood risk that other property types (e.g., multi-family residential properties, commercial properties, public infrastructure, and so on) face.[14] Third, analyses related to future climate scenarios, largely, do not account for adaptive behaviors (e.g., migration patterns and disaster-mitigating engineering changes). Last, our analysis on the value of flood insurance (discussed below) uses estimated local insurance premiums, which may differ from the NFIP's actual premium schedule.

Barring the limitations, this paper measures the amount by which expected flood damage exceeds existing NFIP flood insurance coverage. We find that $17.1 billion of expected flood losses would be uninsured annually for SFRs, representing 70 percent of total flood losses. Nearly the entire protection gap is economically inefficient, as we estimate $15.7 billion of flood underinsurance. Specifically, among homes with positive expected flood losses and an optimal demand for full flood insurance coverage, 88 percent are underinsured by an average of $7,208 (Table 1). Homes outside of SFHAs account for the majority of total underinsurance, suggesting that existing flood maps do not comprehensively capture flood risk. Our distributional analysis shows that inland areas, poorer tracts, and areas with a higher share of White residents face greater insurance deficits today and are expected to face higher underinsurance over the next 30 years (Figures 1 and 2).

Our results imply that existing NFIP insurance coverage leaves agents in housing and mortgage markets exposed to physical climate risks. As underinsurance is widespread both

[14]Particularly, our focus on SFRs measures the financial risks faced by the owners of these properties, which would understate the climate risks faced by minority populations who have lower home ownership rates.

inside and outside the SFHAs, the findings suggest frictions in both the risk information and regulatory compliance purposes of flood maps. Projections of flood damage under expected future climate scenarios show that this protection gap will increase if insurance coverage does not expand. As a result, the impact of future flood events will likely be higher than existing estimates of the detrimental impacts of flood damage on asset prices, mortgage performance, and post-disaster recovery.

Implications of Rising Premiums

Expanding insurance coverage is a complex policy solution, especially as premiums rise in response to increasing physical climate risks. If premiums increase, it is unclear whether flood insurance would continue to be financially beneficial for at-risk properties, as suggested by our underinsurance results assuming 2022 premiums. In order to understand whether the decision to purchase full insurance remains beneficial under different premiums, we conduct a simple cost-benefit analysis to derive the net gains of holding flood insurance for currently uninsured households facing positive AAL.

For each uninsured property, the net gain from flood insurance is the amount of insurable expected flood damage minus the cost of premiums. We calculate these net gains using two counterfactual scenarios for insurance premiums. First, we assume uninsured households pay relatively high prices in their local area, using the 99^{th} percentile of premiums for insured homes in their same tract and flood zone. Second, we assume our sample of uninsured homeowners faced the new pricing rules under Risk Rating 2.0, which transitioned towards more actuarially fair pricing and increased insurance premiums by 11 percent, on average, by 2023.[15]

In Table 4, we see that uninsured homes would have average net gains of \$7,146 to \$7,178, depending on their SFHA location, if they faced the 99^{th} percentile of local premiums for existing policies. Even if these uninsured households faced the highest prevailing insurance prices in their local areas, 70 to 92 percent would financially benefit from purchasing flood insurance. Alternatively, if these uninsured households faced the average premiums in their

[15] Our sample for this exercise includes uninsured SFRs with an optimal demand for full coverage. To classify these households, we use mean premiums of insured households in the local area as the counterfactual price uninsured households would pay when determining whether pricing is actuarially fair.

tract and flood zone under Risk Rating 2.0, their average net gains would be \$6,905 outside the SFHAs and \$8,590 inside the SFHAs, with 83 to 86 percent of these households benefiting financially. This result is consistent with existing findings that households' willingness to pay for flood insurance is lower than the benefits of flood insurance (Wagner, 2022). If a severe 1 in 100 year event does occur, the gains to uninsured households are very large, ranging from \$138,834 to \$162,388, depending on the pricing assumption and location within the SFHAs.

Figure A.2 shows that these net gains from purchasing insurance under Risk Rating 2.0 premiums are highest for areas with lower incomes and lower minority shares, exactly the areas facing the highest underinsurance. This finding suggests that subsidies for the purchase of NFIP policies would be both equitable and efficient, as the subsidies would simultaneously flow towards low income households and those who would gain the most from flood insurance.

Determinants of Underinsurance

Our results leave a puzzle – if holding flood insurance is financially beneficial, why are so many households underinsured? One potential explanation is that households' beliefs may underestimate future flood risks. Beliefs are likely most salient for households that do not face binding institutional constraints on their demand for flood insurance, such as FEMA's flood insurance limit of \$250,000. To assess the validity of this mechanism, we estimate the regression in Equation 1, which relates the average underinsurance amount, U_c, in census tract c to various measures of climate beliefs I_c. We restrict this regression to households that hold less than \$250,000 of flood insurance to avoid conflating information constraints (e.g., beliefs about climate risk) with institutional constraints (e.g., FEMA coverage limit) as determinants of underinsurance.

$$\log(1 + U_c) = \alpha + \beta I_c + \gamma X_c + \lambda_s + \epsilon_c \tag{1}$$

We use three different measures of I_c to proxy climate beliefs: county share of respondents in the Yale Climate Opinion Survey that believe global warming will harm them personally, tract share of voters registered as Republican, and tract share of residents with a bachelor's degree or higher. Each measure provides information on different dimensions of household climate beliefs, which may define the distribution of risks each household perceives in their decision to purchase insurance. The survey response regarding personal harm indicates to what extent households believe a climate event might lead to physical or financial damage. Political affiliation, measured by Republican voter share, measures divergence in beliefs about climate risks as well as beliefs about government support after disasters that might mitigate the need to purchase insurance. In addition, college education can indicate consumer sophistication and better knowledge of financial products such as property insurance. The coefficient of interest, β, measures the correlation between these measures of climate beliefs and underinsurance. We estimate Equation 1 using ordinary least squares (OLS) and state fixed effects, λ_s, while controlling for financial, demographic, and housing characteristics, X_c.[16]

In Table 5, columns (1) through (3) use the three different measures of climate beliefs individually, while column (4) includes all three measures simultaneously. Conditional on our extensive controls and state fixed effects, all three indicators of climate beliefs are strongly correlated with tract-level underinsurance. A 10 percent higher share of survey respondents perceiving personal harm from global warming is associated with 26.7 percent lower underinsurance.[17] A 10 percent higher share of Republican voters is associated with 14 percent higher underinsurance. Last, a 10 percent higher share of residents with college degrees is associated with 11.1 percent lower underinsurance. When including all three measures of climate beliefs in column (4), the associations between these belief measures and underinsurance remain economically and statistically significant. The association between perception of personal harm from global warming and underinsurance remains the strongest – a 10 percent higher share of respondents perceiving personal harm is associated with 14.2 percent lower underinsurance. Results suggest that factors that determine beliefs about future climate damage may be the most salient for households' insurance decisions, compared to factors such as financial sophistication and expectations of government responses.

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[16] The results are qualitatively and quantitatively similar when we instead use $\log(U_c)$ as the outcome variable, which eliminates the very few observations where $U_c = 0$. As such, the qualitative results discussed in the main text do not suffer from the problem described in Chen and Roth (2024).

[17] The estimate $\hat{\beta} = -3.108$ implies that a 10 percent change (or a 0.1 change in the share) is associated with a 0.3108 log point decrease in underinsurance, which is equivalent to a 26.7 percent decrease.

Together, our results imply that policies targeting uninsured homes, such as the expansion of flood maps and improving compliance with the mandatory purchase requirement, would yield large gains compared to policies that focus on expanding coverage for existing insured households, such as increasing coverage limits.[18] These policies would simultaneously benefit lower-income areas and direct insurance coverage most towards areas and populations with the highest financial benefits of holding insurance. Furthermore, policies that change the price of flood insurance may not substantially reduce underinsurance, as high rates of flood underinsurance persist even when policy premiums yield large financial benefits of purchasing insurance. Instead, our results suggest that household beliefs regarding future climate risks may be a larger determinant of underinsurance.

[18] This statement does not account for the possibility that flood risks are not properly priced into home values (Gourevitch et al., 2023), and the statement is based on the assumption that flood map expansions, which may trigger proper flood risk pricing through the information channel, do not trigger substantial repricing of homes that would offset the net gains presented here.

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A Methods

A.1 Data Sources

We combine several data sources to measure flood underinsurance for single-family residences (SFRs) in the contiguous U.S.

First Street Foundation (FSF) Data from FSF provide both current estimates and 30-year projections of property-level flood damage in dollars, which have been regarded as some of the best publicly available estimates of flood risk in the United States (Bates et al., 2010; Neal et al., 2012; de Almeida and Bates, 2013; Sampson et al., 2013, 2015; Weill, 2023). FSF's methodology can be summarized in three broad steps.

First, FSF simulates the physical flow of water through geography based on the open source hydrodynamic model, LISFLOOD-FP. This model accounts for features such as elevation, proximity to water, and adaptation measures, such as levees. Importantly, the model incorporates four types of flooding: fluvial (riverine flooding), pluvial (resulting from heavy rainfall), tidal, and storm surge. Model outputs perform well when validated against historic flood reports, government flood claims, and precise local flood hazard studies conducted by the United States Geological Survey (Wing et al., 2017; Armal et al., 2020; Bates et al., 2021).

Second, FSF combines their hydrodynamic model with climate projections to simulate the breadth and depth of flooding across different climate scenarios. These scenarios, from Coupled Model Intercomparison Project Phase 6 (CMIP6) simulations, project future environmental changes, such as carbon emissions, sea level rise, and precipitation patterns. The CMIP6 models are utilized by the United Nations' Intergovernmental Panel on Climate Change (IPCC) in their latest Assessment Report about the state of scientific, technical and socioeconomic knowledge on climate change. We use FSF's projections under CMIP6 Shared Socioeconomic Pathways 2-4.5 (SSP 2-4.5), which is considered to be most realistic future climate scenario.

Third, FSF uses a private engineering firm, Arup Corporation, to map flood depth to property damage. This step adds the inventory of buildings to the modeled flooding under different climate scenarios from the first two steps. Arup provides damage functions, which are derived from engineering principles, evidence of damage from past floods, and current building standards, to estimate the reconstruction costs after damage from flooding. These functions also account for the type and material of each building, including features such as a basement and first floor elevation.

The FSF methodology provides distinct advantages over existing measures of flood risk, such as FEMA's flood maps that are used to define federal policies on National Flood Insurance Program (NFIP) pricing and mandatory purchase requirements. The FSF model better captures floods from rainfall and ungauged streams and therefore improves coverage of inland flood risks. In addition to average annual losses (AALs) in dollars, the FSF data also include details about the loss distribution by providing expected damage for events of varying likelihoods.

National Flood Insurance Program (NFIP) We merge the flood damage data to administrative data on flood insurance policies from the NFIP. Under the assumption of complete adverse selection, we assign the highest observed coverage limits to the homes with the largest expected losses. This assumption ensures that we measure a lower bound on underinsurance because the riskiest properties in our merged data set have the most coverage.

Additional Data Sources We incorporate Census Bureau data on tract-level income and demographic characteristics to conduct our distributional analysis. For additional analysis in the paper, we gather publicly available data from (1) policy premiums under FEMA's Risk Rating 2.0 pricing proposal; (2) the Yale Climate Opinion Map, 2023, provided by the Yale Program on Climate Change Communication (YPCCC); and (3) L2 voter data.

A.2 Sample Construction

We merge FSF parcel-level data with its nearest neighbor, by Euclidean distance, in CoreLogic property data. We use CoreLogic to identify which properties are single-family residences (SFRs). We then map all these properties to census tracts, using 2010 map delineations. This results in a cross-section of virtually all SFR properties in the United States (FSF and CoreLogic coverage permitting) linked to FSF flood risk measures and damage estimates.

Second, we merge the above set of properties with the NFIP redacted policy data under an adverse selection assumption, described in more detail below. As our FSF data utilizes estimates for the year 2022, we want to identify all policies in effect at the start of 2022. To capture a snapshot of active policies in 2022, we keep policies with start dates from 2021Q2 through 2022Q1, which ensures that there is no more than one policy per home, as NFIP policies must be renewed every year. As with our set of FSF-CoreLogic matched properties, we only utilize NFIP policies taken out on SFRs.

As NFIP policy data does not contain addresses or detailed geocoding, we use an adverse selection assumption to match the policies to the properties in our FSF-CoreLogic data. We first classify all policies by census tract, flood zone designation (e.g., “A”, “V”, “X”), and the year the home was built. Within these cells defined by property characteristics, we rank policies by insurance coverage amount, from highest (a maximum of $250,000) to lowest. We also incorporate deductibles as a tie-breaker for a given amount of flood insurance. If two homes have the $250,000 maximum in flood insurance coverage, the home with the higher deductible receives the highest rank.

We perform an analogous ranking exercise with the FSF-CoreLogic data, assigning homes within each cell the highest ranking if they have the highest average annual loss (AAL), as estimated by FSF. For each property, FSF provides the 10^{th}, 50^{th}, and 90^{th} percentile of AAL. We use the 50^{th} percentile of AAL. We then merge NFIP policies to FSF-CoreLogic properties by census tract, flood zone, year built, and the above-described ranking. As not all policies merge in the first step, we iterate on this process, systematically relaxing the granularity of these policy and home characteristic cells, re-ranking the remaining policies and homes within each cell, and merging again, until virtually every NFIP policy is matched to a home. We perform this ranking and merge in the following six sequential steps:

1. Census tract-by-flood zone designation-by year built;
2. Census tract-by-SFHA-by year built;
3. Census tract-by-SFHA-by decade built;
4. Census tract-by-SFHA;
5. County-by-SFHA; and
6. County.

Flood zone designation refers to the alphabetic assignments A, B, C, D, X, and V. Therefore, in step (1), a property is matched to an NFIP policy if the alphabetic assignment matches exactly. In steps (2) through (5), SFHA signifies whether the property is located in an SFHA, defined as having a flood zone designation of A or V. Seventy-one percent of our matched policies merge in step (1), while 97 percent merge on or before step (4). In total, we match 3,418,656 NFIP policies to SFRs, excluding only 8,596 NFIP policies (0.25%) from our sample that we are unable to match through the above process.

The final property-level sample contains 92.3 million SFRs. The combination of adverse selection assumption and the imperfect coverage of FSF and CoreLogic implies that the underinsurance quantities presented in this paper can likely be interpreted as lower bounds.

For the tract-level analyses, we build the tract-level sample from the property-level sample using the 2010 census tract delineation. Tract characteristics such as median household income and minority share were collected from the 2015-2019 5-year American Community Survey (ACS). Minority share is defined as the share of Hispanic and Black individuals in the census tract. We use each year's January Consumer Price Index (CPI) from the U.S. Bureau of Labor Statistics to adjust for inflation on the median household income quantities. Additionally, we restrict our tract-level analyses to a total of 15,498 tracts that have at least 20 homes with positive AAL. This restriction reduces the geographic footprint from the 44,320 tracts used in our SFR-level analysis, but it does not substantially limit the set of properties used in the tract-level analysis, as 8.2 percent of SFRs are dropped.

A.3 Measures of Underinsurance

Our goal is to estimate expected protection gaps and underinsurance for flooding, conditional on expected flood losses and existing insurance coverage. Because protection gaps and underinsurance are non-linear functions of both AAL and coverage limits, the expectation of the deficit, $\delta_{ij} = \max\{0, D_{ij} - C_i\}$, does not equal the deficit between the expectation of losses, as measured by AAL, and insurance coverage:

$$E\left(\delta_{ij}\right) \neq \max\{0, E\left(D_{ij} - C_i\right)\}.$$

Instead, we rely on FSF's flood scenario loss estimates for the following return periods: 5 years, 20 years, 100 years, 200 years, and 500 years. For each property-scenario pair, FSF provides the 10^{th}, 50^{th}, and 90^{th} percentile of repair cost. We use the 50^{th} percentile number for all of our underinsurance calculations. For a specific return period r_j, the inverse of each return period defines the exceedance probability, P_j, which measures the likelihood with which annual damage will exceed or equal the loss estimate for the return period, D_j:

$$P_j \equiv P(D_i \geq D_{ij}) = \frac{1}{r_j} \text{ for } r_j \geq 1.$$

For example, annual flood damage for a property would exceed the 5-year return period loss estimate with a likelihood of $\frac{1}{5}$.

Since the exceedance probability is $1 - F_D$, where F_D is the cumulative loss distribution, the expected losses can be calculated as the area under the exceedance probability curve. We approximate the expected protection gaps, G_i, and underinsurance, U_i, using the discrete set of return periods available from FSF as following.

$$G_i = \sum_{j=1}^{J} (P_{j-1} - P_j) \cdot \delta_{ij-1}$$

$$U_i = \mathbb{1}(p_i \leq E(D_i)) \cdot G_i$$

Specifically, for each scenario and home, we subtract the home's insurance coverage from the estimated scenario loss amount to compute a dollar amount of deficit. We then perform step-wise integration over these five probabilistic underinsurance estimates for each home, such that the loss estimate remains flat across the density between flood return periods. For instance, we assign the 5-year flood underinsurance estimate for the density between a 5-year flood and a 20-year flood (the next likeliest return period in the data), and the 20-year estimate for the density between a 20-year flood and a 100-year flood. Similarly, since we have no estimate for return periods shorter than 5 years, underinsurance is equal to 0 for all shorter return periods.

As illustrated in Figure A.3, this method produces a lower-bound estimate of expected protection gaps and underinsurance for each home because we use the least severe loss estimate within the interval between two consecutive return periods. Visually, our approximation of the expected underinsurance aggregates the area of the white rectangles to the right of the coverage limit line C_i and under the exceedance probability curve. As a result, we underestimate the true expected underinsurance by the area of the gray regions.

A.4 Incorporating Policy Deductibles

To estimate the distribution of flood underinsurance with deductibles, we follow the same method as our main underinsurance calculation but simply adjust each home's insurance coverage by adding the deductible amount. We consider the insurance deductible as the amount the homeowner is willing to pay out-of-pocket in the event of flood damage. Accordingly, we match deductibles to homes in a similar fashion as we do for flood insurance coverage; that is, at a given amount of insurance coverage, the homes with the highest expected flood losses are assigned the highest deductibles. Therefore, we interpret underinsurance after accounting for deductibles as the amount a household needs to pay beyond their expected out-of-pocket expenses.

A.5 Valuation of Insurance

First, we compute the gain an uninsured home would receive from insurance as the expected flood damage in each flooding scenario capped at the NFIP coverage maximum of $250,000. Second, we estimate two counterfactual policy premiums for each policy. Third, we compute the net gain for each flooding scenario by subtracting the counterfactual premium from the expected insurance gain amount, including the scenario where no flooding occurs. As our sample focuses on households with optimal demand for full insurance, we assume that every exposed homeowner buys a policy with maximum coverage

The first counterfactual considers a costly policy, where we assign the local census tract-by-SFHA 99^{th} percentile premium for $250,000 worth of coverage. Premiums can be assigned in this manner for 3,967,580 homes, the vast majority of our sample of homes with positive AALs. There is no active NFIP policy in some census tracts from which to estimate local means; therefore, another 711,988 homes are assigned 99^{th} percentile premiums at the county-by-SFHA level. For 89,838 homes, premiums are assigned at the state-by-SFHA level. We are unable to assign premiums for 3 homes.

The second counterfactual considers FEMA's Risk Rating 2.0 pricing approach, which prices flood insurance policies in a more actuarially fair manner. Specifically, we gather publicly available data on policy premiums under FEMA's proposed pricing.[19] The data

[19]The data are available at https://www.fema.gov/flood-insurance/work-with-nfip/risk-rating/single-family-home.

provide zip code level average premium increases under Risk Rating 2.0 relative to premiums from September 2022. We scale existing policy premiums in our data by these zip code level premium increases to estimate the counterfactual for each policy under Risk Rating 2.0.

A.6 Climate Beliefs and Underinsurance

We estimate Equation 1 by aggregating the sample of homeowners who have an optimal demand for full insurance coverage (i.e., their annual premium is less than or equal to expected annual losses) to a census tract-level average underinsurance amount. We further focus on the sample of homeowners who hold less than the FEMA coverage limit of $250,000 of flood insurance. This restriction allows us to better identify the role of information constraints (e.g., beliefs about climate risk) in underinsurance, as these households should not be affected by other institutional constraints. We keep tracts with at least 20 homes in the sample.

We obtain three measures of climate beliefs, I_c, as follows. First, we calculate the share of residents in the county who believe "global warming will harm [them] personally" at least a moderate amount, as reported in the Yale Climate Opinion Maps from 2023.[20] Second, we obtain the share of voters in the census tract who are registered Republican from the 2021 census block aggregated L2 voter file (and aggregate to the census tract-level). Third, we measure the share of residents in the census tract who have obtained at least a bachelor's degree from the American Community Survey (2015-2019).

In addition to state fixed effects, Equation 1 includes the following census tract-level measures as control variables, X_c: the log of mean AAL and the share of homes in the SFHAs from FSF, the log of the number of housing units, the share of residents who identify as Black or Hispanic, the share of homeowners with a mortgage, the log of median income, and the log of median home value from the ACS adjusted to 2022 dollars by the FHFA house price index.[21]

[20] Data are provided by the Yale Program on Climate Change Communication (YPCCC); see Howe et al. (2015) and Marlon et al. (2022). The YPCCC bears no responsibility for the analyses or interpretations of the data presented here.

[21] The FHFA House Price Index is available at https://www.fhfa.gov/data/hpi.

B Tables

Table 1: Flood Protection Gaps and Underinsurance

Panel A: Protection Gaps, All Single Family Residences

	All SFRs	AAL > 0	SFHA	Non-SFHA
N	92,251,863	5,984,218	1,746,807	4,237,411
Share Insured	0.037	0.329	0.595	0.22
Share with Protection Gap	0.055	0.845	0.761	0.88
Mean Protection Gap ($)	186	2,865	3,012	2,804
SD Protection Gap ($)	3,411	13,103	17,280	10,925
Median Protection Gap ($)	0	350	313	362
Total Protection Gap ($)	17,143,444,903	17,143,444,841	5,260,774,784	11,882,670,057
% of Total Protection Gap	100	100	30.7	69.3
Total Estimated AAL ($)	24,392,317,257	24,392,317,257	10,193,731,941	14,198,585,315

Panel B: Underinsurance, Single Family Residences for which Full Coverage is Optimal

	AAL > 0	SFHA	Non-SFHA
N	2,175,892	742,043	1,433,849
Share Insured	0.4	0.687	0.252
Share Underinsured	0.884	0.798	0.928
Mean Underinsurance ($)	7,208	6,359	7,647
SD Underinsurance ($)	20,980	26,052	17,780
Median Underinsurance ($)	1,660	966	1,887
Total Underinsurance ($)	15,682,901,765	4,718,848,864	10,964,052,901
% of Total Underinsurance	100	30.1	69.9
Total Estimated AAL ($)	22,110,731,441	9,108,756,807	13,001,974,634

Notes: This table presents statistics on flood protection gaps and underinsurance. Panel A statistics are derived from the full sample of single-family residences (SFRs) in column one and separate subsamples in the last three columns: SFRs with positive flood risk, SFRs inside special flood hazard areas (SFHAs), and SFRs outside SFHAs. Dollar values are presented in 2023 USD. Panel B statistics are derived from the sample of positive flood risk SFRs for which purchasing full coverage of flood insurance is optimal. We assume full coverage is optimal for an SFR if the annual premium is less than or equal to average annual losses (AALs).

Table 2: Distribution of Protection Gaps and Underinsurance Across Household Type

Panel A: Single Family Residences with Protection Gap

	Type 1	Type 2	Type 3	Type 4
N	3,306,781	400,700	707,383	643,578
% of N	65.4	7.9	14	12.7
Mean Protection Gap ($)	3,283	3,658	4,546	2,495
Total Protection Gap ($)	10,856,510,405	1,465,931,517	3,215,506,576	1,605,493,943
% of Total Protection Gap	63.3	8.6	18.8	9.4
Total Estimated AAL ($)	10,856,510,405	2,950,137,517	3,215,506,576	5,844,149,530

Panel B: Underinsured Single Family Residences

	Type 1	Type 2	Type 3	Type 4
N	1,072,725	166,587	232,357	450,754
% of N	55.8	8.7	12.1	23.4
Mean Underinsurance ($)	9,332	7,844	12,360	3,313
Total Underinsurance ($)	10,011,161,960	1,306,627,122	2,871,850,493	1,493,259,790
% of Total Underinsurance	63.8	8.3	18.3	9.5
Total Estimated AAL ($)	10,011,161,960	2,578,114,418	2,871,850,493	5,411,407,790

Notes: This table presents the distribution of protection gaps (Panel A) and underinsurance (Panel B) across different types of single family residences (SFRs). Dollar values are presented in 2023 USD. SFHA stands for special flood hazard area. AAL stands for average annual loss. Type 1 covers SFRs located outside an SFHA that do not hold insurance. Type 2 covers SFRs that hold insurance policies with less than the $250,000 maximum coverage. Type 3 covers SFRs located inside an SFHA that do not hold insurance. Type 4 covers SFRs that hold insurance policies that have the maximum coverage. Panel B statistics are derived from the sample of positive flood risk SFRs for which purchasing full coverage of flood insurance is optimal. We assume full coverage is optimal for an SFR if the annual premium is less than or equal to average annual losses (AALs).

Table 3: Flood Underinsurance for Different Return Periods and Climate Scenarios

Panel A: Current Climate Scenario

Inside SFHAs	1/20	1/100	1/200	1/500
Share Underinsured	0.38	0.62	0.72	0.8
Mean Underinsurance ($)	55,593	103,485	124,939	150,613
Median Underinsurance	0	53,523	84,677	111,885
SD Underinsurance	237,109	268,986	285,745	324,173
Mean Flood Damage ($)	117,524	216,503	261,511	293,385
Median Flood Damage ($)	79,180	194,348	231,691	258,196
Outside SFHAs	1/20	1/100	1/200	1/500
Share Underinsured	0.37	0.72	0.88	0.93
Mean Underinsurance ($)	59,365	136,202	185,898	223,953
Median Underinsurance ($)	0	106,768	165,829	199,713
SD Underinsurance ($)	148,463	190,226	200,812	218,084
Mean Flood Damage ($)	70,545	166,067	237,186	278,167
Median Flood Damage ($)	0	138,654	208,168	245,700

Panel B: Future Climate Scenario SSP 2-4.5, 30-year Projections

Inside SFHAs	Baseline	1/20	1/100	1/200	1/500
Change in Share At Risk	0.032	0.053	0.061	0.046	0.032
Mean Change in Underinsurance ($)	1,350	16,177	16,165	16,623	20,789
Median Change in Underinsurance ($)	192	0	2,933	5,067	5,897
SD of Change in Underinsurance ($)	11,166	43,054	41,469	51,438	48,239
Change in Share Underinsured	0.038	0.11	0.09	0.056	0.038
Outside SFHAs	Baseline	1/20	1/100	1/200	1/500
Change in Share At Risk	0.0052	0.0011	0.0044	0.0047	0.0052
Mean Change in Underinsurance ($)	646	6,103	17,856	10,381	4,969
Median Change in Underinsurance ($)	45	0	144	1,293	660
SD of Change in Underinsurance ($)	4,007	34,990	57,924	33,674	20,704
Change in Share Underinsured	0.0047	0.039	0.077	0.03	0.0047

Notes: This table presents underinsurance statistics for different flood return periods under the current climate scenario (Panel A) and under 30-year projections using climate scenario Shared Socioeconomic Pathways 2-4.5 (SSP 2-4.5) and assuming insurance coverage and limits remain fixed (Panel B). For example, 1/20 refers to a 1 in 20 year flood event. SFHA refers to special flood hazard area. Statistics are derived from the sample of positive flood risk SFRs for which purchasing full coverage of flood insurance is optimal. We assume full coverage is optimal for an SFR if the annual premium is less than or equal to average annual losses (AALs).

Table 4: Net Gains from Purchasing Flood Insurance

Expected Flood Risk

99^{th} Percentile Premiums	Insurance Gain	Local Premiums	Net Gain	Share Net Gain
Non-SFHA+Uninsured (Mean)	8,004	858	7,146	0.92
Non-SFHA+Uninsured (Sum)	8,586,124,501	920,611,734	7,665,512,767	.
SFHA+Uninsured (Mean)	11,039	3,860	7,178	0.70
SFHA+Uninsured (Sum)	2,564,880,207	896,906,307	1,667,973,900	.
Risk Rating 2.0 Mean Premiums	Insurance Gain	Local Premiums	Net Gain	Share Net Gain
Non-SFHA+Uninsured (Mean)	8,004	1,099	6,905	0.86
Non-SFHA+Uninsured (Sum)	8,586,124,501	1,178,472,196	7,407,652,305	.
SFHA+Uninsured (Mean)	11,039	2,449	8,590	0.83
SFHA+Uninsured (Sum)	2,564,880,207	568,947,232	1,995,932,976	.

100-Year Flood

99^{th} Percentile Premiums	Insurance Gain	Local Premiums	Net Gain	Share Net Gain
Non-SFHA+Uninsured (Mean)	139,932	858	139,074	0.87
Non-SFHA+Uninsured (Sum)	150,108,875,157	920,611,734	149,188,263,421	.
SFHA+Uninsured (Mean)	164,837	3,860	160,977	0.98
SFHA+Uninsured (Sum)	38,301,037,874	896,906,307	37,404,131,565	.
Risk Rating 2.0 Mean Premiums	Insurance Gain	Local Premiums	Net Gain	Share Net Gain
Non-SFHA+Uninsured (Mean)	139,932	1,099	138,834	0.87
Non-SFHA+Uninsured (Sum)	150,108,875,157	1,178,472,196	148,930,402,840	.
SFHA+Uninsured (Mean)	164,837	2,449	162,388	0.98
SFHA+Uninsured (Sum)	38,301,037,874	568,947,232	37,732,090,610	.

Notes: This table presents statistics on insurance gains for uninsured homes that have non-zero exposure to flood risk. SFHA stands for special flood hazard area. The two panels separately present statistics for the expected flood risk and 1 in 100 year floods. Statistics are derived from the sample of positive flood risk SFRs for which purchasing full coverage of flood insurance is optimal. We assume full coverage is optimal for an SFR if the annual premium is less than or equal to average annual losses (AALs).

Table 5: Correlations of Climate Belief Indicators and Underinsurance

	(1)	(2)	(3)	(4)
Share Personal Harm	-3.108***			-1.533***
	(0.409)			(0.488)
Share Republican		1.310***		0.870***
		(0.163)		(0.176)
Share with College Degree			-1.176***	-0.628***
			(0.180)	(0.184)
Log(Mean AAL)	0.451***	0.458***	0.457***	0.452***
	(0.013)	(0.013)	(0.013)	(0.013)
Share in SFHAs	-2.318***	-2.300***	-2.331***	-2.303***
	(0.177)	(0.179)	(0.180)	(0.179)
Log(No. Housing Units)	0.282***	0.284***	0.311***	0.280***
	(0.027)	(0.026)	(0.027)	(0.027)
Minority Share	-0.425***	-0.292***	-0.932***	-0.292***
	(0.094)	(0.101)	(0.089)	(0.101)
Share Homes with Mortgage	-0.631***	-0.507***	-0.619***	-0.494***
	(0.120)	(0.122)	(0.119)	(0.124)
Log(Median Income)	-0.083	-0.968*	-0.597	-1.409**
	(0.504)	(0.545)	(0.556)	(0.606)
Log(Median Home Value)	-0.582	-1.326***	-1.048**	-1.654***
	(0.433)	(0.460)	(0.466)	(0.503)
Log(Home Value) $\times$ Log(Income)	0.044	0.105**	0.092**	0.148***
	(0.040)	(0.042)	(0.044)	(0.048)
State Fixed Effects	X	X	X	X
N	12,057	12,066	12,237	11,887

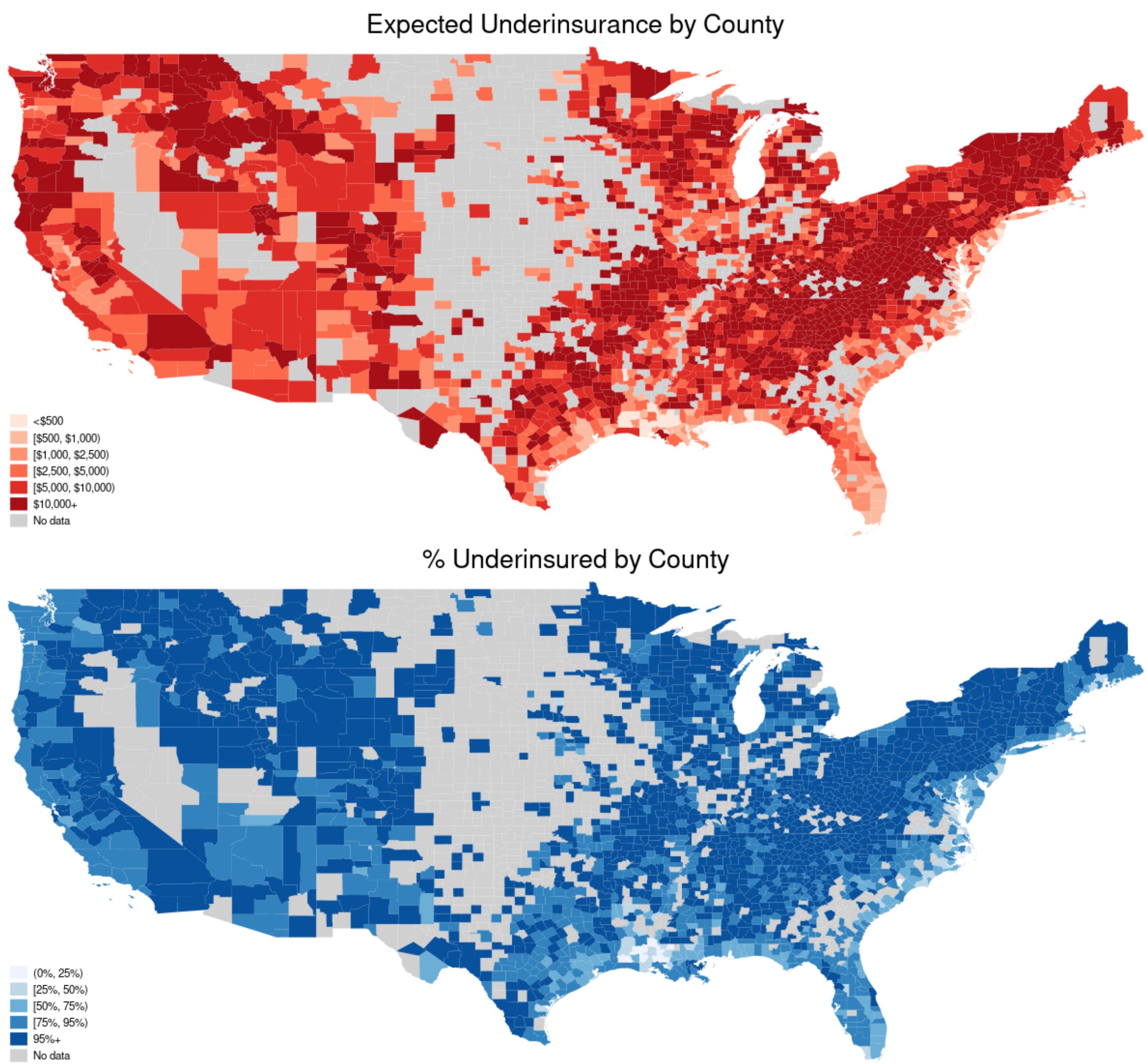
Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents coefficient estimates from four different specifications of Equation 1. The dependent variable is the log of average tract underinsurance. The indicators of climate beliefs for columns (1) through (3) are county-level share of Yale Climate Opinion survey respondents reporting that global warming will harm them personally, tract-level share of voters registered as Republican, and tract-level share of residents with a bachelor's degree or higher, respectively. Column (4) reports estimates from a multivariate regression with all three indicators included. The observations differ based on the data availability of each climate belief indicator. Underinsurance is derived from the sample of positive flood risk SFRs who hold below the FEMA limit of $250,000 in flood insurance and for whom purchasing full coverage of flood insurance is optimal. We assume full coverage is optimal for an SFR if the annual premium is less than or equal to average annual losses (AALs). The sample includes tracts that have at least 20 properties facing positive current AAL and optimal demand for full coverage.

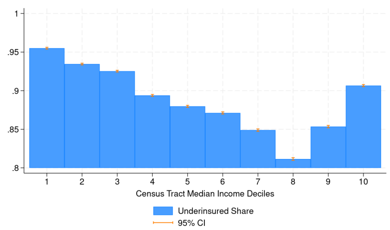
C Figures

Figure 1: Geographic Distribution of Flood Underinsurance

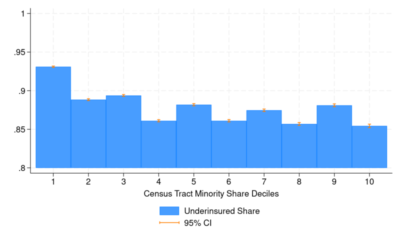


Notes: County-level average of expected underinsurance (top) and percentage of at-risk properties facing underinsurance (bottom). Negative values of underinsurance are set to zero. Statistics are derived from the sample of positive flood risk SFRs for which purchasing full coverage of flood insurance is optimal. We assume full coverage is optimal for an SFR if the annual premium is less than or equal to average annual losses (AALs). The map sample includes 2,222 counties that have at least 20 properties facing positive current AAL and optimal demand for full coverage. Counties with insufficient data are colored in gray.

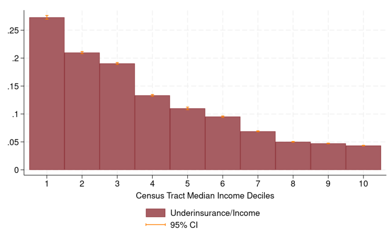
Figure 2: Underinsurance by Tract Income and Minority Composition



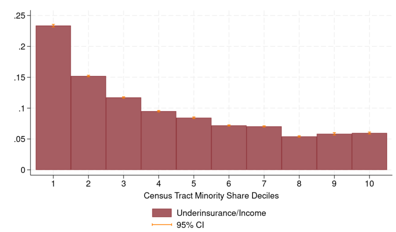
(a) Underinsured Share, By Income



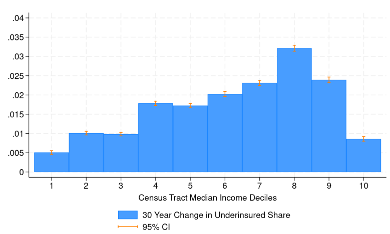
(b) Underinsured Share, By Minority Share



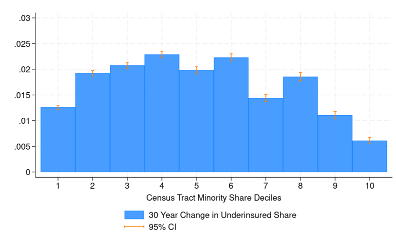
(c) Underinsurance, By Income



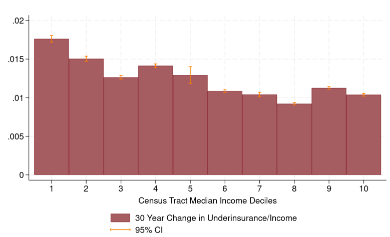
(d) Underinsurance, By Minority Share



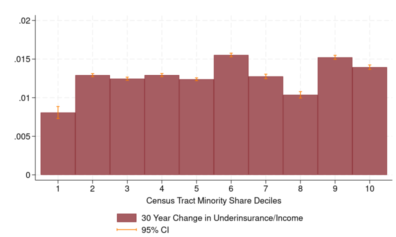
(e) ΔUnderinsured Share, By Income



(f) ΔUnderinsured Share, By Minority Share



(g) ΔUnderinsurance, By Income



(h) ΔUnderinsurance, By Minority Share

Notes: (a-d) Tract-level average underinsured share (percentage of properties with expected flood damage that exceeds insurance coverage) or tract-level average underinsurance as share of each tract's median household income, sorted by tract-level median household income or minority share decile. Minority share is defined as the share of Hispanic and Black individuals in the census tract. (e-h) The average change in underinsured share or underinsurance between the current climate condition and 30-year projections under Shared Socioeconomic Pathways 2-4.5 (SSP 2-4.5), sorted by tract-level median household income or minority share decile. Orange bars show the 95% confidence intervals. Statistics are derived from the sample of positive flood risk SFRs for which purchasing full coverage of flood insurance is optimal. We assume full coverage is optimal for an SFR if the annual premium is less than or equal to average annual losses (AALs). The sample includes 15,498 tracts that have at least 20 properties facing positive current AAL or positive 30-year projections of AAL and optimal demand for full coverage.

D Additional Figures and Tables

Table A.1: Flood Protection Gaps and Underinsurance with Deductibles

Panel A: Protection Gaps, All Single Family Residences

	All SFRs	AAL > 0	SFHA	Non-SFHA
N	92,251,863	5,984,218	1,746,807	4,237,411
Share Insured	0.037	0.329	0.595	0.22
Share with Protection Gap	0.055	0.843	0.756	0.879
Mean Protection Gap ($)	185	2,856	2,986	2,802
SD Protection Gap ($)	3,407	13,090	17,254	10,921
Median Protection Gap ($)	0	346	304	361
Total Protection Gap ($)	17,089,199,593	17,089,199,530	5,215,261,078	11,873,938,452
% of Total Protection Gap	100	100	30.5	69.5
Total Estimated AAL ($)	24,392,317,257	24,392,317,257	10,193,731,941	14,198,585,315

Panel B: Underinsurance, Single Family Residences for which Full Coverage is Optimal

	AAL > 0	SFHA	Non-SFHA
N	2,175,892	742,043	1,433,849
Share Insured	0.4	0.687	0.252
Share Underinsured	0.88	0.792	0.926
Mean Underinsurance ($)	7,186	6,306	7,641
SD Underinsurance ($)	20,962	26,017	17,774
Median Underinsurance ($)	1,651	933	1,886
Total Underinsurance ($)	15,635,325,980	4,679,058,697	10,956,267,283
% of Total Underinsurance	100	29.9	70.1
Total Estimated AAL ($)	22,110,731,441	9,108,756,807	13,001,974,634

Notes: This table presents statistics on flood protection gaps and underinsurance after accounting for deductibles. Panel A statistics are derived from the full sample of single-family residences (SFRs) in column one and separate subsamples in the last three columns: SFRs with positive flood risk, SFRs inside special flood hazard areas (SFHAs), and SFRs outside SFHAs. Dollar values are presented in 2023 USD. Panel B statistics are derived from the sample of positive flood risk SFRs for which purchasing full coverage of flood insurance is optimal. We assume full coverage is optimal for an SFR if the annual premium is less than or equal to average annual losses (AALs).

Table A.2: Distribution of Protection Gaps and Underinsurance Across Household Type with Deductibles

Panel A: Single Family Residences with Protection Gap

	Type 1	Type 2	Type 3	Type 4
N	3,306,781	395,267	707,383	635,670
% of N	65.5	7.8	14	12.6
Mean Protection Gap ($)	3,283	3,637	4,546	2,485
Total Protection Gap ($)	10,856,510,222	1,437,407,962	3,215,504,259	1,579,774,699
% of Total Protection Gap	63.5	8.4	18.8	9.4
Total Estimated AAL ($)	10,856,510,405	2,934,191,052	3,215,506,576	5,804,925,366

Panel B: Underinsured Single Family Residences

	Type 1	Type 2	Type 3	Type 4
N	1,072,725	164,811	232,357	445,854
% of N	56	8.6	12.1	23.3
Mean Underinsurance ($)	9,332	7,781	12,360	3,297
Total Underinsurance ($)	10,011,161,960	1,282,342,827	2,871,850,493	1,469,968,313
% of Total Underinsurance	64	8.2	18.4	9.4
Total Estimated AAL ($)	10,011,161,960	2,565,272,623	2,871,850,493	5,376,395,644

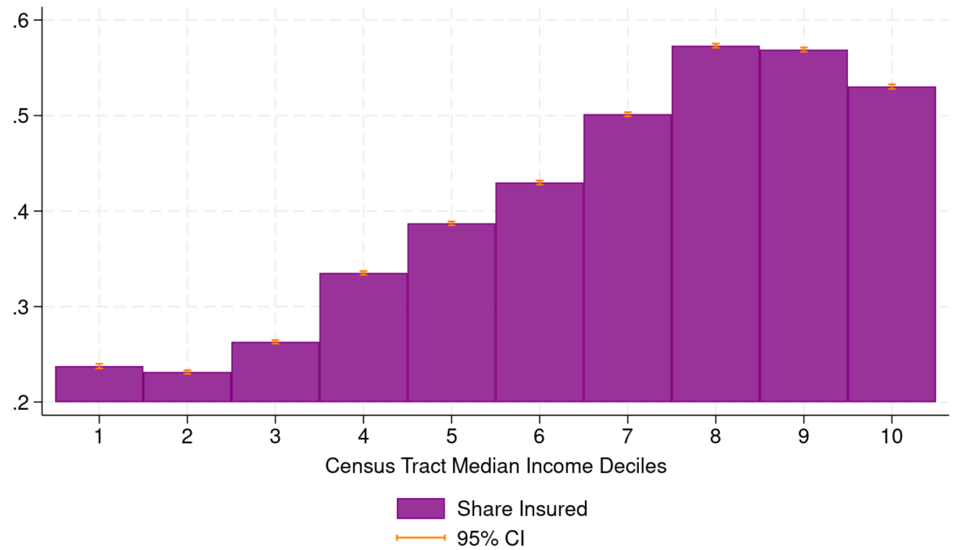
Notes: This table presents the distribution of protection gaps (Panel A) and underinsurance (Panel B) across different types of single family residences (SFRs) after accounting for deductibles. Dollar values are presented in 2023 USD. SFHA stands for special flood hazard area. AAL stands for average annual loss. Type 1 covers SFRs located outside an SFHA that do not hold insurance. Type 2 covers SFRs that hold insurance policies with less than the $250,000 maximum coverage. Type 3 covers SFRs located inside an SFHA that do not hold insurance. Type 4 covers SFRs that hold insurance policies that have the maximum coverage. Panel B statistics are derived from the sample of positive flood risk SFRs for which purchasing full coverage of flood insurance is optimal. We assume full coverage is optimal for an SFR if the annual premium is less than or equal to average annual losses (AALs).

Table A.3: Flood Underinsurance Rate and Deficit, By Census Region

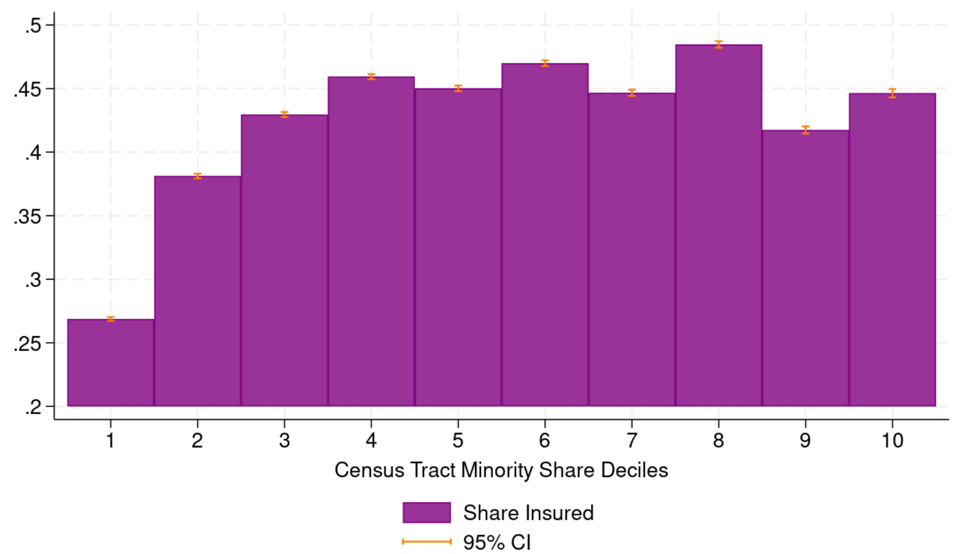
	East NC	East SC	Mid Atlantic	Mountain West	New England
N	14,243,400	6,708,765	9,376,788	7,329,108	3,303,304
Sample N	122,533	155,112	280,398	69,686	48,049
% Insured	11.9	17.7	26.2	13.1	26.5
% Underinsured	98.2	94.8	90.8	96	91.2
Mean Underinsurance ($)	10,824	12,880	10,012	9,820	10,158
Total Underinsurance ($)	1,326,247,782	1,997,847,556	2,807,271,229	684,348,251	488,073,451
Total AAL ($)	1,522,929,308	2,277,973,221	3,552,346,836	796,619,455	688,666,922
% from Type 1	64.8	75.5	64.8	80.5	74.1
% from Type 2, Non-SFHA	3.3	2.45	3.59	1.59	2.15
% from Type 2, SFHA	7.66	4.66	9.56	1.85	5.85
% from Type 3	21.1	14	16.7	10.2	8.27
% from Type 4, Non-SFHA	2.21	1.78	2.97	3.58	3.73
% from Type 4, SFHA	.923	1.61	2.4	2.25	5.92
	Pacific West	South Atlantic	West NC	West SC	
N	11,745,670	20,774,426	7,060,263	11,710,056	
Sample N	300,313	737,541	49,982	412,278	
% Insured	23	53.8	12.1	63.5	
% Underinsured	93.2	83.6	97.3	83.6	
Mean Underinsurance ($)	7,239	6,234	9,779	2,714	
Total Underinsurance ($)	2,173,865,443	4,597,488,019	488,781,906	1,118,978,126	
Total AAL ($)	2,922,707,565	7,600,959,233	559,460,160	2,189,068,742	
% from Type 1	70.3	54	71.4	49.3	
% from Type 2, Non-SFHA	1.11	1.51	2.63	3.08	
% from Type 2, SFHA	2.03	6.58	5.27	6.65	
% from Type 3	15.6	23.4	16.9	21.1	
% from Type 4, Non-SFHA	6.21	3.11	2.09	10.6	
% from Type 4, SFHA	4.72	11.4	1.68	9.27	

Notes: This table presents statistics on flood underinsurance rate and deficit by Census region. N represents all single family residences (SFRs) in each region, while "Sample N" represents the set of SFRs that have positive average annual losses (AALs) and for which purchasing full coverage is optimal. We assume full coverage is optimal for an SFR if the annual premium is less than or equal to average annual losses (AALs). Dollar values are presented in 2023 USD. SFHA stands for special flood hazard area. Type 1 covers SFRs located outside an SFHA that do not hold insurance. Type 2 covers SFRs that hold insurance policies with less than the $250,000 maximum coverage. Type 3 covers SFRs located inside an SFHA that do not hold insurance. Type 4 covers SFRs that hold insurance policies that have the maximum coverage.

Figure A.1: Insured Share by Tract Income and Minority Composition



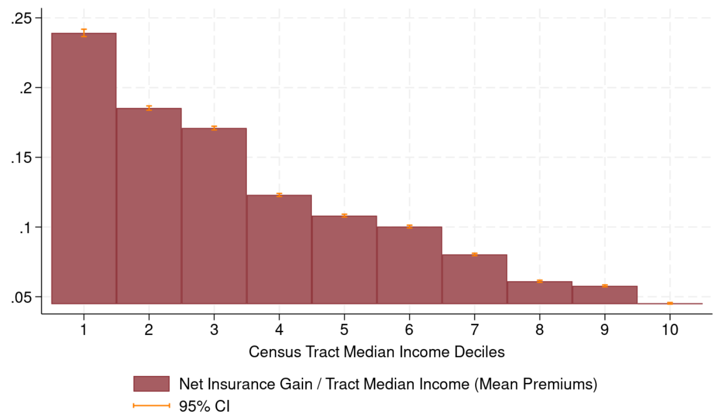
(a) Insured Share, By Income



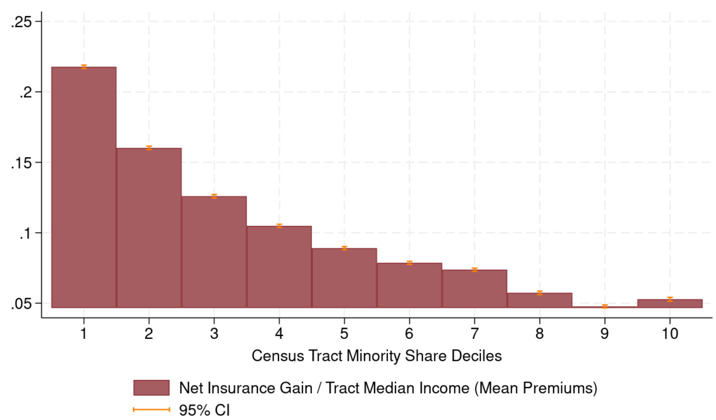
(b) Insured Share, By Minority Share

Notes: Tract-level average insured share sorted by (a) tract-level median household income decile or (b) tract-level minority share decile. Minority share is defined as the share of Hispanic and Black individuals in the census tract. Orange bars represent 95% confidence intervals. Statistics are derived from the sample of positive flood risk SFRs for which purchasing full coverage of flood insurance is optimal. We assume full coverage is optimal for an SFR if the annual premium is less than or equal to average annual losses (AALs). The sample includes 15,498 tracts that have at least 20 properties facing positive current AAL and optimal demand for full coverage.

Figure A.2: Net Gains from Purchasing Flood Insurance by Tract Income and Minority Composition



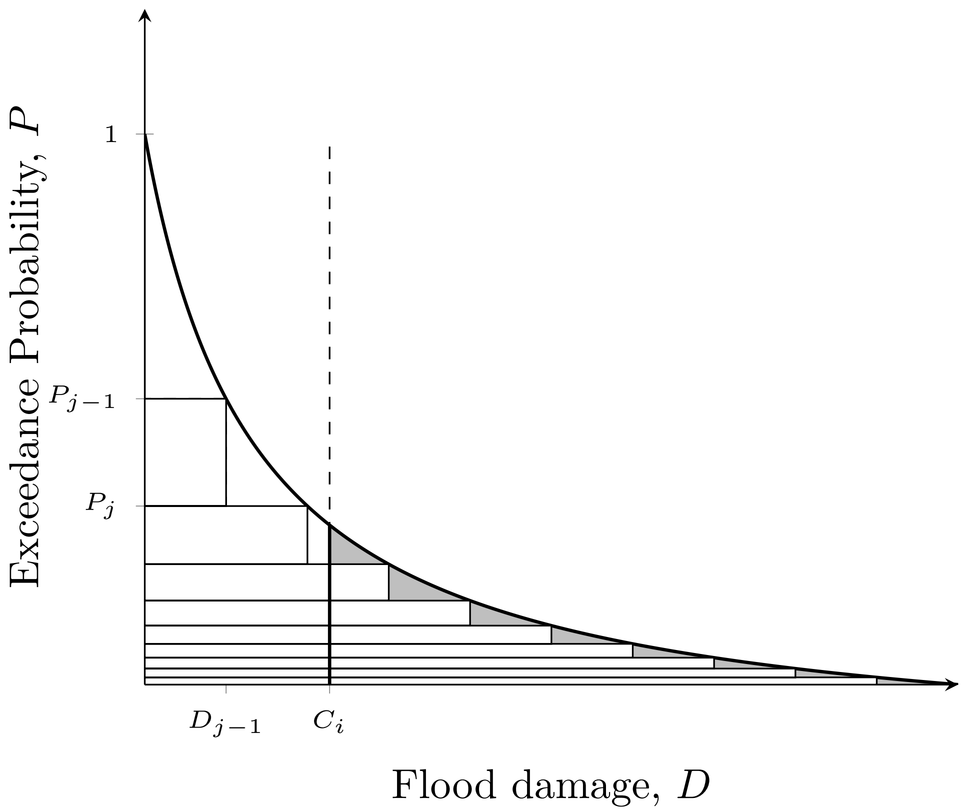
(a) Net Insurance Gain, By Income



(b) Net Insurance Gain, By Minority Share

Notes: Tract-level average net insurance gain as share of tract's median household income sorted by (a) tract-level median household income decile or (b) tract-level minority share decile. Minority share is defined as the share of Hispanic and Black individuals in the census tract. Net insurance gain is defined as the difference between insurance coverage of expected flood damage (capped at $250,000) and estimated premiums under Risk Rating 2.0. Net insurance gain is zero if estimated premium exceeds expected flood damage because the homeowner would not buy insurance in this scenario. Orange bars represent 95% confidence intervals. Statistics are derived from the sample of positive flood risk SFRs for which purchasing full coverage of flood insurance is optimal. We assume full coverage is optimal for an SFR if the annual premium is less than or equal to average annual losses (AALs). The sample includes 15,498 tracts that have at least 20 properties facing positive current AAL and optimal demand for full coverage.

Figure A.3: Example of Calculating Expected Insurance Deficit



Notes: Illustrative example of the exceedance probability curve. The area under the curve measures average annual losses (AALs). For damage below the policy coverage limit of C_i, the deficit is zero. For damage greater than C_i, we use the areas of the white rectangles as an approximation for the expected insurance deficit. Therefore, our method yields a lower bound, as we underestimate the expected insurance deficit by an amount equivalent to the area of the gray regions between the exceedance probability curve and the white rectangles.