The Effect of Flood Exposure on Insurance Adoption among US Households

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Abstract

Despite increasing exposure to flooding and associated financial damages, estimates suggest more than two-thirds of flood-exposed properties are currently uninsured. This low adoption rate could undermine the climate resilience of communities and weaken the financial solvency of the United States National Flood Insurance Program (NFIP). We study whether repeated exposure to flood events, especially disaster-scale floods expected to become more frequent in a warming climate, could spur insurance adoption. Using improved estimates of residential insurance take-up in locations where such insurance is voluntary, and exploiting variation in the frequency and severity of flood events over time, we quantify how flood events impact local insurance demand. We find that a flood disaster declaration in a given year increases the take-up rate of insurance by 7% in the following year, but the effect diminishes in subsequent years and is gone after five years. This effect is more short-lived in counties in inland states that do not border the Gulf and Atlantic coasts. The effect of a flood on takeup is substantially larger if there was also a flood in the previous year. We also find that recent disasters are more salient for homeowners whose primary residences are exposed to a disaster declaration compared to non-primary residences. Our results provide a more comprehensive understanding of the salience effect of flooding on insurance demand compared to previous studies. Overall, these findings suggest that relying on households to self-adapt to increasing flood risks in a changing climate is insufficient for closing the insurance protection gap.

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Key Points:

- Increasing flood risk is impacting areas where flood insurance is not currently mandated
- Consecutive disaster flood years increase insurance take-up but this effect diminishes over time
- Relying on the autonomous adaptation of households will be insufficient for closing the insurance protection gap

Abstract

Despite increasing exposure to flooding and associated financial damages, estimates suggest more than two-thirds of flood-exposed properties are currently uninsured. This low adoption rate could undermine the climate resilience of communities and weaken the financial solvency of the United States National Flood Insurance Program (NFIP). We study whether repeated exposure to flood events, especially disaster-scale floods expected to become more frequent in a warming climate, could spur insurance adoption. Using improved estimates of residential insurance take-up in locations where such insurance is voluntary, and exploiting variation in the frequency and severity of flood events over time, we quantify how flood events impact local insurance demand. We find that a flood disaster declaration in a given year increases the take-up rate of insurance by 7% in the following year, but the effect diminishes in subsequent years and is gone after five years. This effect is more short-lived in counties in inland states that do not border the Gulf and Atlantic coasts. The effect of a flood on takeup is substantially larger if there was also a flood in the previous year. We also find that recent disasters are more salient for homeowners whose primary residences are exposed to a disaster declaration compared to non-primary residences. Our results provide a more comprehensive understanding of the salience effect of flooding on insurance demand compared to previous studies. Overall, these findings suggest that relying on households to self-adapt to increasing flood risks in a changing climate is insufficient for closing the insurance protection gap.

1 Introduction

Roughly 90% of all natural disasters in the United States involve flooding (Wright, 2017). Just one inch of flooding can cause \$25,000 in damages to a home, causing long-term financial setbacks for both uninsured and underinsured households (FEMA, n.d.-e). Despite the increasing cost of flood-related damages (Davenport et al., 2021) and the increasing exposure outside Federal Emergency Management Agency (FEMA) designated 100-yr floodplains, only a third of 14.6 million flood-exposed properties currently at risk are insured (FEMA, n.d.-d; First Street Foundation, 2020). In addition, an estimated 41 million people are exposed to flooding, three times greater than the 13 million estimated by FEMA flood maps (Wing et al., 2018).

FEMA has traditionally relied on flood zone designations to mandate insurance adoption in areas facing substantial flood risk, which are defined as areas exposed to flood events that have a 1% or greater chance of occurrence each year. These areas are designated as "Special Flood Hazard Areas" (SFHA), where flood insurance has been mandatory for properties secured by government-insured mortgages since 1973. Areas outside the SFHA are called "non-Special Flood Hazard Areas" (nSFHA), where flood insurance is not mandated.

However, properties in nSFHA zones are increasingly at risk of flooding due to climate change, with predictions that overall flood risk will increase by 26% by 2050 in a moderate emissions scenario (Wing et al., 2018, 2022). An increasing share of flood damage claims have been made in nSFHA zones in recent years, with more than a third of total flood insurance claims filed by nSFHA residents in 2020 (FEMA, n.d.-d) (see Fig. S1b). Meanwhile, insured flood damages from both SFHA and nSFHA zones have covered only a small fraction of total damages historically (Fig. S1a). These trends point towards a clear and increasing insurance protection gap, especially when accounting for increasing flood risks in locations where insurance is not mandated. The low insurance coverage relative to overall flood risks, compounded by underpriced risk premia and damage claims following catastrophic hurricane events, has weakened the financial solvency of FEMA's National Flood Insurance Program (NFIP) (US GAO, 2023).

Given the increasing frequency and severity of extreme flood events (Davenport et al., 2021; A. B. Smith, 2020; Swain et al., 2020) (see Fig. S2) that are impacting more households in nSFHA zones, we ask whether households might autonomously adapt by purchasing insurance. Autonomous adaptation refers to adaptation that occurs "naturally" by the initiative of private actors in response to actual or anticipated climate change (Klein et al., 1999; Leary, 1999; Smit et al., 2000; J. B. Smith & Lenhart, 1996). This is distinguished from planned adaptation, which results from a deliberate policy decision (IPCC, 2007). Understanding autonomous adaptation is important to ensure that governance structures and other planned adaptation interventions are complementary (Mersha & van Laerhoven, 2018; Rahman & Hickey, 2019).

Previous literature found that insurance take-up spikes after disaster declarations (Browne & Hoyt, 2000; Gallagher, 2014; Kousky, 2017). However, because these studies do not distinguish between take-up rates in SFHA versus nSFHA zones, a significant portion of the identified take-up response may be due to the requirement that households in SFHA zones must purchase insurance if they request post-disaster financial assistance (Kousky, 2017).

New data released by NFIP in 2019 provides information about flood zones at the policy level, allowing researchers to isolate the take-up response in nSFHA zones (Dombrowski et al., 2020). One recent study estimating the voluntary response concludes that a major flood declaration increases insurance demand in nSFHA zones by less than 0.5 percentage points, and that the greatest increase in take-up rate occurs two years after a major disaster declaration (Bradt et al., 2021). The finding that demand for insurance spikes in the aftermath of disasters is in line with broader literature in behavioral science, where experiments have shown that people tend to neglect low-probability, high-impact events (Botzen & van den Bergh, 2012), but that emotional salience may inflate the risk perception of events (Keller et al., 2006; Slovic et al., 2004). While differences in risk perception owing to past flood experience can predict voluntary insurance take-up (Royal & Walls, 2019), this effect attenuates as catastrophic events fade from memory (Dumm et al., 2020). Salience effects have also been confirmed in studies investigating the impact of hurricane events on residential property sales (Bakkensen et al., 2019), cash holding behavior of firms (Dessaint & Matray, 2017), and the influence of social interactions with geographically-distant peers who have experienced floods (Hu, 2022).

Understanding how exposure to flood events drives insurance adoption in voluntary settings is essential for informing policies for improving community resilience to flood risk. In this study, we use an improved measure of voluntary take-up rates to investigate how households respond to large, disaster-scale flood events compared to non-disaster-scale events. We also investigate whether experiencing consecutive disaster events spurs additional insurance demand, and how these responses might be mediated by different baseline levels of risk perception and other household characteristics. The voluntary setting allows us to explicitly measure the autonomous adaptation behavior of households, which in turn can inform future estimates of uncovered flood risks in a changing climate and the design of complementary policies to reduce these risks.

2 Materials and Methods

In this study, we use insurance data from the U.S. NFIP, flood events data from the National Oceanic and Atmospheric Administration (NOAA), disaster declarations and flood maps from FEMA to quantify how exposure to flooding motivates insurance demand among households. We distinguish between the impact of experiencing non-disaster scale floods versus experiencing a flood that leads to a major disaster declaration, as well as the impact of experiencing disaster declarations in two consecutive years. In addition, we consider how a disaster declaration differentially impacts insurance take-up at the census tract level. To isolate the impact of flooding from other determinants of insurance take-up, we estimate panel regression models that exploit variation in the frequency and severity of flood events over time in specific locations.

2.1 **Constructing the Panel Data**

Combining data on insurance policies (FEMA, n.d.-d), population (U.S. Census Bureau, n.d.), floodplain maps (FEMA, n.d.-c), and household point coordinates (Corelogic), we estimate the annual residential insurance take-up rate in non-SFHA zones. First, we estimate the annual "policies-in-force", or the number of total policies that were newly purchased or renewed in a given year. We follow Kousky (2017) and Bradt et al (2021) in utilizing this metric as representing the coverage rate, or annual take-up rate, since NFIP policies are 1-year term policies that do not automatically renew, and new policies take 30 days to go into effect. The NFIP dataset provides data at the policy level, including the policy cost, coverage, and flood zone for each policy. As the publicly available NFIP dataset starts in 2009, we extend this to 2005 using additional NFIP data obtained through the Freedom Of Information Act (request 2022-FEFO-00527).

To estimate insurance take-up behavior when it is voluntary, we consider only policies in nSFHA zones. In SFHA zones, insurance is mandated for households with a government-backed mortgage. After a presidential disaster declaration, households in an SFHA zone that request financial assistance are automatically enrolled in a Group Flood Insurance Policy (GFIP) for three years. There is no such mandatory enrollment in place for households in non-SFHA areas.

For a more accurate measure of the voluntary insurance take-up rate, we calculate the number of policies-in-force (PIF) among households located in nSFHA zones at the tract level. The estimate of households located in nSFHA zones is derived in two steps. First, the point coordinates of unique residential property records from Corelogic are spatially joined to FEMA floodplain maps to calculate the percentage of properties that fall within nSFHA zones at the tract level. Given that 75% of FEMA flood maps were created before 2013 and do not update frequently (Eby, 2019; Frank, 2020), we take the floodplain boundaries in the latest available flood maps (downloaded from the FEMA Map Service Center, as of July 2022) to estimate the percentage of properties located in nSFHA zones. Here the assumption is that updates to flood maps do not significantly change the number of properties affected. Second, these percentages are applied to annual data on total household count provided by the five-year American Community Surveys (ACS5). This is because the residential property records provided by Corelogic do not account for whether properties are occupied, while the ACS5 data allows us to account for the increasing population over time. Here the assumption is that population increase is on average equally distributed across SFHA and nSFHA zones. Finally, we divide annual policies-in-force by the estimate of residential properties in nSFHA zones to construct the annual take-up rate. Based on these calculations, annual take-up rates are highest along the Gulf and Atlantic coast (Fig. 1a).

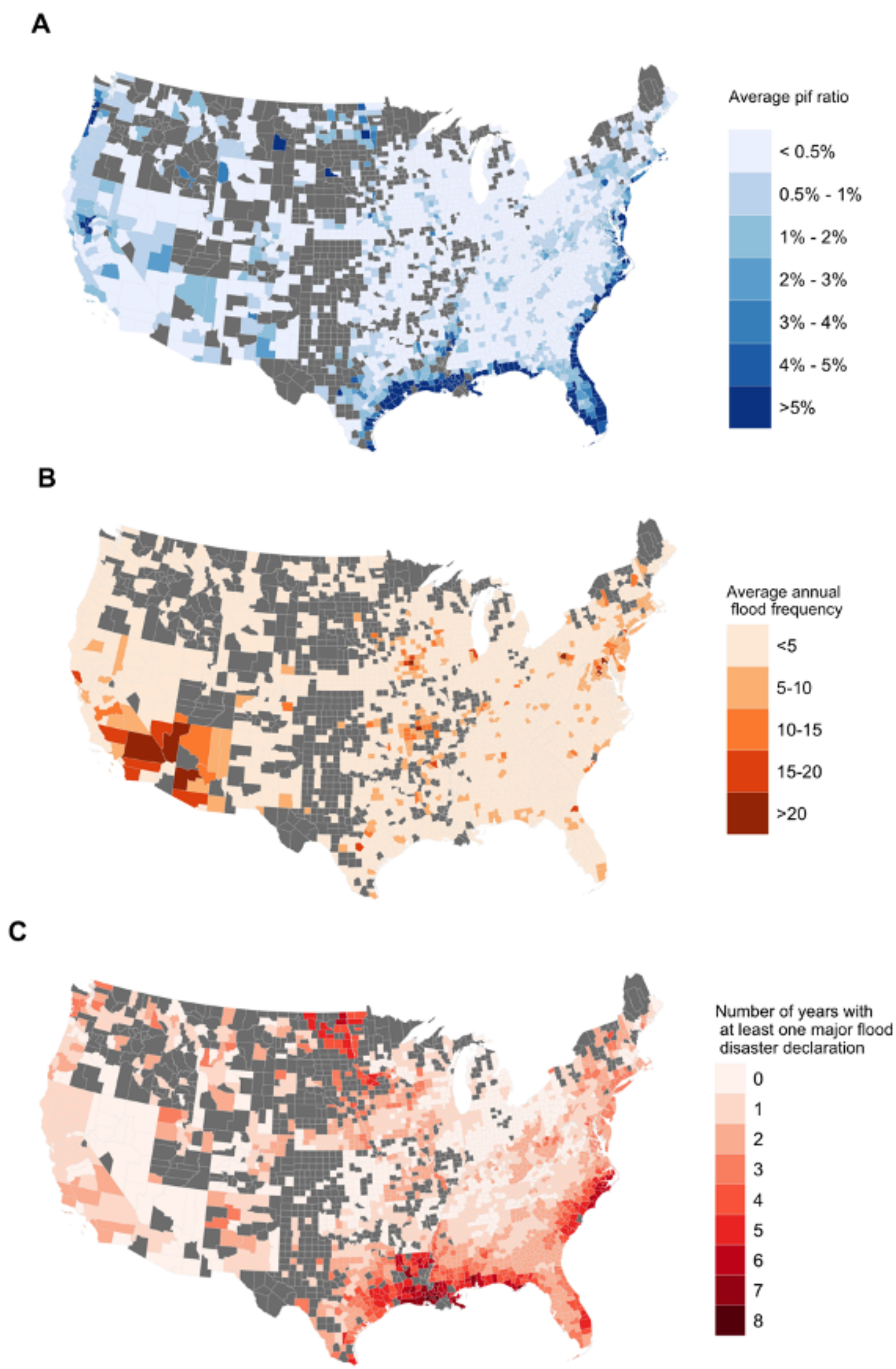

Figure 1. NFIP policies-in-force in non-SFHA zones and exposure to flood events at the county-level. a) average ratio of NFIP policies in force (2005 - 2020), in nSFHA zones. b) annual average of total flood events recorded (2005 - 2020). c) total number of years with at least one major flood disaster declaration in the county (2005 - 2020).

Not all US counties are covered by FEMA flood maps, as mapping efforts have focused primarily on counties with moderate population density (Association of State Floodplain Managers, n.d.). FEMA flood maps cover 57% of the territory of the 50 US states, but 93.6% of the population (Qiang, 2019). In our analysis, we additionally filter for counties in the contiguous US where more than 50% of residential properties are accounted for within flood mapped areas, leading to a final sample of 2,392 counties out of 3,108 total counties, accounting for 94% of the CONUS population (Fig. S3).

We use NOAA's Storm Events Database to estimate the total number of flood-related events for each county-year, and FEMA's Disaster Declaration dataset to count the number of floods that resulted in a major disaster declaration for each county-year (Fig. 1b, 1c). NOAA's Storm Events Database records the occurrence of storms and other significant weather phenomena across a variety of sources, including newspapers and broadcast media, law enforcement, park and forest service, trained spotters, Automated Surface Observing Systems (ASOS), and citizen science. From this dataset, we include: *"Flash Flood", "Flood", "Heavy Rain", "Coastal Flood", "Storm Surge/Tide", "Tropical Storm", "Lakeshore Flood", "Hurricane (Typhoon)".*

We distinguish between disaster-scale flood events that trigger a Presidential Disaster Declaration and all other non-disaster-scale flood events recorded in the NOAA dataset, to capture how different types of flood events may differentially affect insurance demand. There are two levels of presidential declarations: emergency declarations and major disaster declarations. While both authorize federal assistance, the total amount of assistance provided for any emergency event is capped at $5 million, whereas a major declaration provides significantly more funding once it is determined that the situation is beyond the State and local government's combined capacity to respond. Events may trigger both emergency declarations and major disaster declarations, but not all emergency declarations lead to a major disaster declaration. We capture only the major disaster declarations from the FEMA Presidential Declarations dataset, and the type of flood events include: *"Flood", "Hurricane", "Typhoon", "Coastal storm".*

2.2 **Panel Regression Model**

We employ a panel regression with two-way fixed effects to estimate the causal effect of flood experience on insurance demand. The county-level panel data that we construct allows us to estimate the salience effect of disaster-scale floods (i.e., those with a major disaster declaration) and frequent minor flooding on insurance take-up rates:

$$log(takeup\ rate)_{it} = \sum_{t=0}^{n} \left(\beta_{1,t-n}\, floodcount_{i,t-n} + \beta_{2,t-n} disaster_{i,t-n} \right) + \alpha_i + \delta_t + \epsilon_{it} \quad \text{(Eq. 1)}$$

where $takeup\ rate$ is the share of households that take-up flood insurance in county i and year t, $floodcount$ is the number of floods that occurred in year t, and $disaster$ is a dummy for whether there was a major flood event that triggered a presidential disaster declaration in that year. We introduce lags of up to 7 years to quantify how floods experienced $t - n$ years prior affect the outcome at year t. α and δ are county and year fixed effects, allowing us to plausibly isolate the impact of variation in flood exposure from other time-invariant and time-trending factors that may be correlated with both the flood exposure and the outcome that we are measuring. These panel estimators are commonly used in literature that measures human response to environmental change, and can deliver plausibly causal estimates of environmental impacts when within-location change in environmental risk over time (e.g. year to year variation in location-specific flooding) is uncorrelated with other drivers of the outcome in question. Standard errors are clustered at the county-level, to adjust for correlations in residuals within counties. After accounting for time trends and average differences across counties, remaining variation in flood frequency and severity is plausibly random, and thus we can infer that flood insurance adoption may be attributed to the flood experience.

The model above does not account for whether consecutive disaster years may be increasing the likelihood of insurance take-up. To isolate this potential consecutive effect, we employ the following interaction model to test whether the insurance take-up response to a disaster at time t is greater if there was also a disaster the previous year (t-1). If there is a positive consecutive effect, this would be captured in the interaction estimate β_3.

$$log(takeup\ rate)_{it} = \beta_{1,t} disaster_{i,t} + \beta_{2,t-1} disaster_{i,t-1} + \beta_3 disaster_{i,t} * disaster_{i,t-1} + \alpha_i + \delta_t + \epsilon_{it}$$
(Eq. 2a)

In addition, we test whether the occurrence of consecutive disaster events in the past further increases the insurance take-up response. To do this, we add a new variable to the dataset, where $disaster\_consecutive$ is a dummy for every year where there was also a disaster flood in the previous year.

$$\log(takeup\ rate)_{it} = \sum_{t=0}^{n} \left(\beta_{t-n} disaster\_consecutive_{i,t-n} \right) + \alpha_i + \delta_t + \epsilon_{it} \quad \text{(Eq. 2b)}$$

Finally, we consider insurance take-up rates at the census tract level to understand how the level of insurance take-up in response to disaster-scale flooding is different based on the type of exposure to homeowners and renters including whether the risk saliency of disaster floods is different among homeowners whose primary residence is within the same county where a disaster is declared. Since disaster floods are observed at the county-level, our model assigns flood exposure treatment to all census tracts within a county where a presidential disaster is declared. Here our panel data starts in 2010 to preserve a uniform set of census tracts, as census tract boundaries are updated every ten years. As in Equation 1, we introduce lags of up to 7 years to quantify how floods experienced $t-n$ years prior affect the outcome at year t (Eq. 3a). Additionally, we test whether the cost burden of insurance premiums mediates the take-up response. We calculate the cost burden of insurance within each census tract as the average insurance premium divided by household median income over the study period (based on NFIP data), and assign a dummy for tracts where the cost burden is greater than our calculated national median cost burden of 1% for homeowner policies and 0.3% for renter policies (Eq. 3b).

$$\log(takeup\ rate)_{it} = \sum_{t=0}^{n} \left(\beta_{t-n} disaster_{i,t-n} \right) + \alpha_i + \delta_t + \epsilon_{it} \quad (Eq. 3a)$$

$$log(takeup\ rate)_{it} = \beta_{1,t} disaster_{i,t-1} + \beta_{2,t}\, disaster_{i,t-1} * costburden\_dummy_i + \alpha_i + \delta_t + \epsilon_{it} \quad (Eq. 3b)$$

3 Results

The estimated relationship between flooding and insurance demand is shown in Figure 2. We estimate that a disaster declaration in the year prior (t-1) has the greatest impact on take-up, with an average 7% increase in the take-up rate (95% CI: 5.4% - 8.5%). Declarations occurring further back in time have a diminishing impact on take-up, and after five years (t-5) this impact is no longer significant. Meanwhile, experiencing any other flood event has a very small but consistently positive and significant impact on insurance demand. By way of comparison, the increase in take-up rate in a county in response to a major disaster declaration the previous year is equivalent to the response in a county that experiences forty non-disaster-scale flood events in the previous year (Fig. 2).

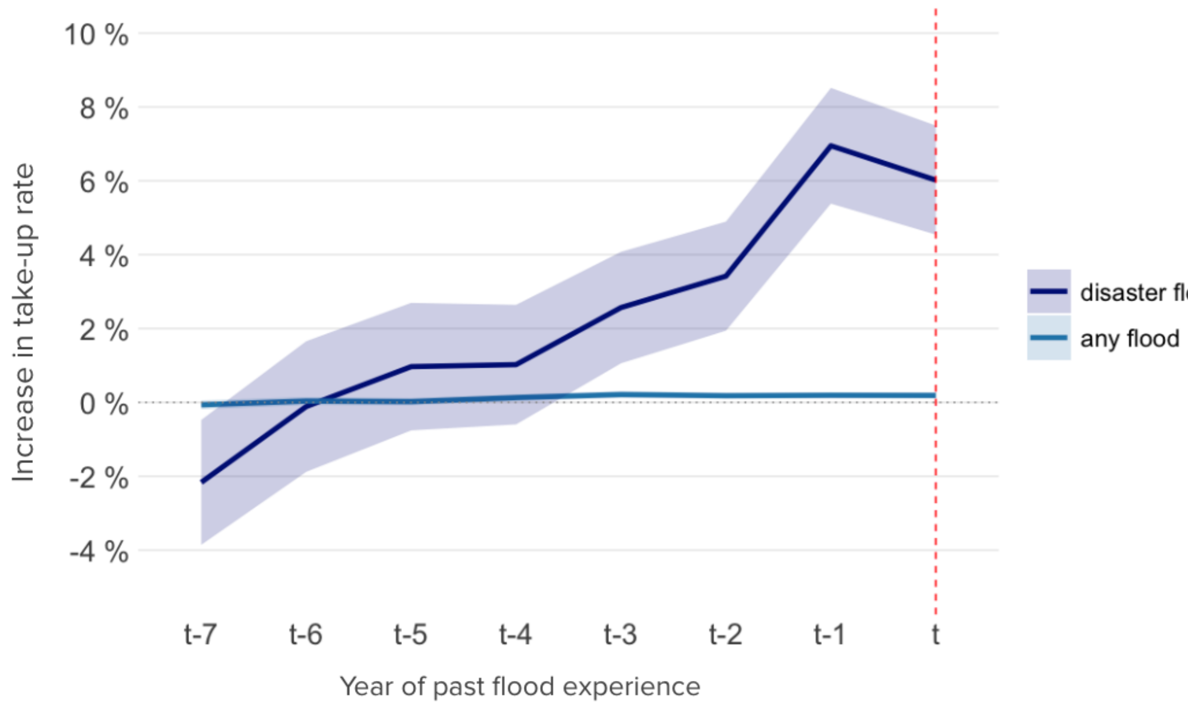

Figure 2. Estimated salience effect of flooding on insurance demand. The estimated relationship between a major flood disaster declaration versus any additional flood from previous years on insurance take-up in the current year (t) (Eq 1). Shaded regions represent the confidence intervals for each coefficient estimate.

Baseline take-up rates differ considerably depending on whether the county is located along the Gulf and Atlantic coasts (Table S1). To account for differing levels of baseline risk perception, we divide the sample into three main subsets: counties in non-hurricane exposed states (baseline take-up rate: 0.6%), coastal counties in hurricane-exposed states (7.8%), and inland counties in hurricane-exposed states (0.7%). We find that in non-hurricane states, the take-up rate increases by 9-12% in response to a disaster declaration in the concurrent year (95% CI: 9.1%-14.7%) or one year prior (95% CI: 6.1% - 11.4%) (Fig. 3a). In contrast, hurricane states have a smaller increase in the take-up rate (2.5% - 5.4%), but this response is driven by disaster declarations from up to five years prior (Fig. S4). However, given the low average baseline take-up rates in non-hurricane exposed states, these model estimates translate to overall fewer additional policies in non-hurricane exposed counties compared to coastal counties (Fig. S4). For instance, a disaster flood in one year prior would drive >10 additional policies in 8 counties in non-hurricane states, versus 59 counties in hurricane coastal counties.

Figure 3. Salience effect of experiencing consecutive disaster years. A) Estimated impact of two recent consecutive disaster flood years on insurance take-up (Eq 2a). B) Grey indicates policies attributed to a disaster declaration at time t, red indicates the predicted additional take-up in counties that also experienced a disaster declaration at time t-1. Coefficient estimates are detailed in S4. C) Comparison of the estimated impact of disaster declaration on insurance take-up for counties that never experienced consecutive disaster years during 1998-2020 (i.e., only were exposed to non-consecutive disasters), and the impact of a consecutive year of disaster among counties that experienced consecutive disaster years (Eq 2b).

We also test whether disaster declarations in two consecutive years may further increase the likelihood of insurance take-up, relative to our baseline model that assumes that the effect of a flood on take-up in one year is not influenced by whether there was a flood in the previous year (Eq. 2, Fig. 3a). We find that consecutive disaster declarations roughly double the take-up rate on average (i.e., the effect of a flood on take-up in a given year is twice as large if there was also a flood in the year prior). The take-up rate increases by 6% in response to a disaster declaration one year prior (95% CI: 4.6% - 7.5%), and further increases by 6% when there is another disaster declaration in the concurrent year (95% CI: 1.8% - 9.6%). While the consecutive effect is positive across all county subsets, the response is strongest in counties in non-hurricane states, where the take-up rate increases an additional 24% due to a consecutive disaster declaration, nearly tripling the take-up response. However, when we account for differing baseline take-up rates across the county subsets, the number of additional policies due to a consecutive disaster year is predicted to be greatest in hurricane coastal counties (Fig. 3b). For example, 13% of hurricane coastal counties are predicted to gain >100 policies due to two consecutive disaster years. Compared to counties that never experienced consecutive disaster years in the past, the estimated insurance take-up response can be up to two times greater in counties experiencing consecutive disaster years (Fig. 2c).

Finally, we test for heterogeneity in the take-up response across policy types at the census tract level. We find that among homeowners, the salience effect of a disaster flood in year t-1 in terms of insurance policy take-up is around 5.5 percentage points greater for primary residences compared to non-primary residences (Fig. 4A). A higher relative cost burden of insurance (calculated as tracts where the average insurance premium is greater than 1% of household median income) decreases the take-up response for primary residence policies by 3.8 percentage points, whereas the cost burden of insurance does not significantly impact the take-up response for non-primary residence policies (Fig. 4B). The salience effect of flooding on renter policies are visualized separately in Figure 4C as renters have significantly lower baseline adoption rates than among homeowners. Among renter policies, higher relative cost burden does not significantly decrease the take-up response (Fig. 4D). (The classification method for these policy types are detailed in Table S2, and a histogram of policy counts across each policy type is shown in Fig. S5.)

Figure 4. Estimated take-up response across policy types. A) The estimated impact of major flood disaster declarations (t-n) on insurance take-up at year t, comparing the response for policies that are purchased for primary residences and non-primary residences. B) Comparison of the estimated insurance take-up in response to a disaster declaration at year t-1 (shaded gray in panel A), for census tracts where the cost burden of insurance (calculated as the average policy cost divided by household median income) is above or below the national average (1%). C) As in panel A, for renter policies. D) As in panel B, for renter policies. Cost burden of insurance is adjusted to reflect the average cost of renter policies (0.3% of median income).

4 Discussion

We find that although households do respond to disaster-scale flood events by adopting insurance, this response is small, short-lived, and differential across baseline exposure to disaster-scale events. On average, county-level insurance take-up rates increase by 7% in response to a disaster-scale flood event in the previous year, but this increase is not sustained over time. Declarations occurring further back in time have a diminishing impact on take-up, consistent with previous studies (Bradt et al., 2021; Gallagher, 2014; Kousky, 2017).

One reason for the diminishing take-up response may be that NFIP policies are one-year term policies that do not renew automatically (FEMA, n.d.-a). As a result, households responding to a disaster-scale flood event by purchasing insurance in one year may decide not to renew the policy the following year once the flood event is less salient. This hypothesis is supported by evidence that individuals tend to overweight the probability of a catastrophic event immediately after it has occurred (Dumm et al., 2020), and that risk perception of future damages is a robust determinant of flood insurance take-up (Landry & Turner, 2020).

However, our results also show that the take-up rate response curve differs across counties with different baseline take-up rates. In counties in non-hurricane-exposed states where baseline take-up rates are low (0.58% compared to 10% in hurricane coastal counties), a disaster-scale flood may trigger a proportionally greater—but much more short-lived—demand response in comparison to coastal counties in hurricane-exposed states. A similar pattern is observed for consecutive disaster-scale floods, where the increase in insurance demand is proportionally greatest in counties in non-hurricane states. We also show that the type of exposure (e.g. whether the disaster declaration impacted a primary residence or a non-primary residence) plays a role in mediating the post-disaster demand response. Further work is needed to understand how baseline risk perception and household capacity to respond differentially impacts post-disaster risk perception and insurance demand.

Meanwhile, flood events that trigger a Presidential Disaster Declaration appear to have a much larger effect on insurance take-up response than floods that do not reach that threshold. For instance, the increase in take-up rate in a county in response to a disaster-scale flood is equivalent to the response in a county that experiences forty non-disaster-scale flood events in the previous year. The insurance take-up response can be five to nine times greater in counties that experienced consecutive disaster flood years compared to a county experiencing one independent disaster flood year (Fig. 3c). Given that climate change is driving the increasing frequency and severity of flood events associated with greater precipitation levels (Davenport et al., 2021; Kundzewicz et al., 2014; Markonis et al., 2019; Swain et al., 2020), it may be expected that insurance take-up responses will vary based on flood severity, and how frequently they experience disaster-scale floods.

Some other limitations should also be noted. First, our analysis assumes that a presidential disaster declaration equates "flood experience" for all households within a county, even though not all residents of a county will experience flooding directly. The result is that our estimates capture the insurance take-up response of households that may be experiencing the flood through indirect channels (such as from affected friends, family or other acquaintances, government communication to residents about the presidential disaster declaration, observing flooding while in transit or through media exposure, etc). It is plausible that the insurance response among households directly impacted by flood events may be greater than what we find in this study. Similarly, the NOAA dataset does not provide information on flood extents. Information on total flood event count is aggregated at the county level, and we use these data only in our first regression model (Eq. 1) to compare the insurance take-up response between the disaster-scale events and all other non-disaster-scale flood events.

Finally, this study is limited to measuring insurance demand in nSFHA zones where households may believe that they are not required to purchase insurance because they are not exposed to flood risk. This is largely the outcome of NFIP's reliance on FEMA-designated flood maps to communicate whether households should purchase insurance. While this policy setting provides a unique empirical opportunity in that it allows us to isolate insurance take-up when it is voluntary, it is possible that prior NFIP communication could be contributing to a downward bias in the risk perception of nSFHA households. One consequence is that the short-lived salience effect identified in this study may in part be due to the conflicting information with which households are presented about flood insurance requirements, even when their own experience may suggest otherwise.

Alternatively, it is possible that well-resourced communities are more likely to undertake investments that allow them to remain in nSFHA zones and further reduce insurance premiums. If this were happening at scale, this could mean that our estimates of the low take-up response is because households believe their communities are well protected from floods, and therefore less likely to respond to disaster floods by purchasing insurance. On the other hand, our results show that homeowners are more likely to respond to disaster floods by purchasing insurance if the cost burden of insurance is lower. Understanding the dynamics that drive the salience effect observed in this study requires deeper investigation of how different communities perceive flood risk, and how this perception in turn mediates the decision to purchase insurance in the face of changing flood risks.

The growing private flood insurance market raises the possibility that the entry of private players may help increase overall coverage or lower costs in the future. However, this market is currently small relative to the NFIP, representing only 3.5-4.5% of all primary residential flood policies in 2018, and it is unclear how many private flood insurance holders are newly insured or are switching from NFIP policies (Kousky et al., 2018). Private insurers will continue to be selective in the areas where they will underwrite risk, and will never be able to underwrite in some high-risk areas (Kousky et al., 2018), underscoring the importance of NFIP in closing the flood insurance protection gap. In the meantime, this gap is currently further exacerbated by a real estate market that continues to overvalue properties at flood risk (Gourevitch et al., 2023; Hino & Burke, 2021), encouraging development in risky areas.

The rollout of NFIP's new premium rating methodology, Risk Rating 2.0, is expected to tailor risk communication for each household, reducing the reliance on flood zone designation for pricing risks. Improved understanding of future flood risks may help reduce overoptimism and encourage households to sustain periodic insurance payments (Meyer & Kunreuther, 2017). Future studies may take this into account, to test how Risk Rating 2.0 might play a role in driving sustained insurance demand among households.

5 Conclusions

Our findings are relevant for understanding how changing flood risks will impact flood insurance demand, and for quantifying the magnitude of autonomous adaptation to climate change. By exploiting a setting where insurance take-up is voluntary, we investigate how differential exposures mediate the response of insurance demand to flood events. Our results indicate that the salience effect of flooding on insurance demand is insufficient to mitigate the increasing flood insurance protection gap. These findings have implications for designing policies that encourage households to maintain coverage at levels commensurate to their true flood risk, especially in nSFHA flood zones where flood risk is increasing but insurance is not currently mandated. More generally, our results suggest that in a warming climate where the frequency of multiple consecutive disaster years is likely to increase, households cannot be expected to autonomously adapt to increasing hazards by voluntarily purchasing and maintaining insurance coverage.

Acknowledgments

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Open Research

Data Availability Statement

NFIP data is available through OpenFEMA data (FEMA, n.d.-d), and FEMA flood maps are downloaded from the Map Service Center (FEMA, n.d.-c). Data for flood events is available at NOAA storm events database (NCEI, n.d.) and disaster declaration data is from FEMA (FEMA, n.d.-b). The original raw data on residential building point coordinates from Corelogic is not publicly available, however the processed data supporting this research is available at https://zenodo.org/record/8306902 (Choi, 2023). Figures were made using RStudio version 2023.06.0+421.

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The Effect of Flood Exposure on Insurance Adoption among US Households

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Key Points:

- Increasing flood risk is impacting areas where flood insurance is not currently mandated
- Consecutive disaster flood years increase insurance take-up but this effect diminishes over time
- Relying on the autonomous adaptation of households will be insufficient for closing the insurance protection gap

Abstract

Despite increasing exposure to flooding and associated financial damages, estimates suggest more than two-thirds of flood-exposed properties are currently uninsured. This low adoption rate could undermine the climate resilience of communities and weaken the financial solvency of the United States National Flood Insurance Program (NFIP). We study whether repeated exposure to flood events, especially disaster-scale floods expected to become more frequent in a warming climate, could spur insurance adoption. Using improved estimates of residential insurance take-up in locations where such insurance is voluntary, and exploiting variation in the frequency and severity of flood events over time, we quantify how flood events impact local insurance demand. We find that a flood disaster declaration in a given year increases the take-up rate of insurance by 7% in the following year, but the effect diminishes in subsequent years and is gone after five years. This effect is more short-lived in counties in inland states that do not border the Gulf and Atlantic coasts. The effect of a flood on takeup is substantially larger if there was also a flood in the previous year. We also find that recent disasters are more salient for homeowners whose primary residences are exposed to a disaster declaration compared to non-primary residences. Our results provide a more comprehensive understanding of the salience effect of flooding on insurance demand compared to previous studies. Overall, these findings suggest that relying on households to self-adapt to increasing flood risks in a changing climate is insufficient for closing the insurance protection gap.

1 Introduction

Roughly 90% of all natural disasters in the United States involve flooding (Wright, 2017). Just one inch of flooding can cause $25,000 in damages to a home, causing long-term financial setbacks for both uninsured and underinsured households (FEMA, n.d.-e). Despite the increasing cost of flood-related damages (Davenport et al., 2021) and the increasing exposure outside Federal Emergency Management Agency (FEMA) designated 100-yr floodplains, only a third of 14.6 million flood-exposed properties currently at risk are insured (FEMA, n.d.-d; First Street Foundation, 2020). In addition, an estimated 41 million people are exposed to flooding, three times greater than the 13 million estimated by FEMA flood maps (Wing et al., 2018).

FEMA has traditionally relied on flood zone designations to mandate insurance adoption in areas facing substantial flood risk, which are defined as areas exposed to flood events that have a 1% or greater chance of occurrence each year. These areas are designated as "Special Flood Hazard Areas" (SFHA), where flood insurance has been mandatory for properties secured by government-insured mortgages since 1973. Areas outside the SFHA are called "non-Special Flood Hazard Areas" (nSFHA), where flood insurance is not mandated.

However, properties in nSFHA zones are increasingly at risk of flooding due to climate change, with predictions that overall flood risk will increase by 26% by 2050 in a moderate emissions scenario (Wing et al., 2018, 2022). An increasing share of flood damage claims have been made in nSFHA zones in recent years, with more than a third of total flood insurance claims filed by nSFHA residents in 2020 (FEMA, n.d.-d) (see Fig. S1b). Meanwhile, insured flood damages from both SFHA and nSFHA zones have covered only a small fraction of total damages historically (Fig. S1a). These trends point towards a clear and increasing insurance protection gap, especially when accounting for increasing flood risks in locations where insurance is not mandated. The low insurance coverage relative to overall flood risks, compounded by underpriced risk premia and damage claims following catastrophic hurricane events, has weakened the financial solvency of FEMA's National Flood Insurance Program (NFIP) (US GAO, 2023).

Given the increasing frequency and severity of extreme flood events (Davenport et al., 2021; A. B. Smith, 2020; Swain et al., 2020) (see Fig. S2) that are impacting more households in nSFHA zones, we ask whether households might autonomously adapt by purchasing insurance. Autonomous adaptation refers to adaptation that occurs "naturally" by the initiative of private actors in response to actual or anticipated climate change (Klein et al., 1999; Leary, 1999; Smit et al., 2000; J. B. Smith & Lenhart, 1996). This is distinguished from planned adaptation, which results from a deliberate policy decision (IPCC, 2007). Understanding autonomous adaptation is important to ensure that governance structures and other planned adaptation interventions are complementary (Mersha & van Laerhoven, 2018; Rahman & Hickey, 2019).

Previous literature found that insurance take-up spikes after disaster declarations (Browne & Hoyt, 2000; Gallagher, 2014; Kousky, 2017). However, because these studies do not distinguish between take-up rates in SFHA versus nSFHA zones, a significant portion of the identified take-up response may be due to the requirement that households in SFHA zones must purchase insurance if they request post-disaster financial assistance (Kousky, 2017).

New data released by NFIP in 2019 provides information about flood zones at the policy level, allowing researchers to isolate the take-up response in nSFHA zones (Dombrowski et al., 2020). One recent study estimating the voluntary response concludes that a major flood declaration increases insurance demand in nSFHA zones by less than 0.5 percentage points, and that the greatest increase in take-up rate occurs two years after a major disaster declaration (Bradt et al., 2021). The finding that demand for insurance spikes in the aftermath of disasters is in line with broader literature in behavioral science, where experiments have shown that people tend to neglect low-probability, high-impact events (Botzen & van den Bergh, 2012), but that emotional salience may inflate the risk perception of events (Keller et al., 2006; Slovic et al., 2004). While differences in risk perception owing to past flood experience can predict voluntary insurance take-up (Royal & Walls, 2019), this effect attenuates as catastrophic events fade from memory (Dumm et al., 2020). Salience effects have also been confirmed in studies investigating the impact of hurricane events on residential property sales (Bakkensen et al., 2019), cash holding behavior of firms (Dessaint & Matray, 2017), and the influence of social interactions with geographically-distant peers who have experienced floods (Hu, 2022).

Understanding how exposure to flood events drives insurance adoption in voluntary settings is essential for informing policies for improving community resilience to flood risk. In this study, we use an improved measure of voluntary take-up rates to investigate how households respond to large, disaster-scale flood events compared to non-disaster-scale events. We also investigate whether experiencing consecutive disaster events spurs additional insurance demand, and how these responses might be mediated by different baseline levels of risk perception and other household characteristics. The voluntary setting allows us to explicitly measure the autonomous adaptation behavior of households, which in turn can inform future estimates of uncovered flood risks in a changing climate and the design of complementary policies to reduce these risks.

2 Materials and Methods

In this study, we use insurance data from the U.S. NFIP, flood events data from the National Oceanic and Atmospheric Administration (NOAA), disaster declarations and flood maps from FEMA to quantify how exposure to flooding motivates insurance demand among households. We distinguish between the impact of experiencing non-disaster scale floods versus experiencing a flood that leads to a major disaster declaration, as well as the impact of experiencing disaster declarations in two consecutive years. In addition, we consider how a disaster declaration differentially impacts insurance take-up at the census tract level. To isolate the impact of flooding from other determinants of insurance take-up, we estimate panel regression models that exploit variation in the frequency and severity of flood events over time in specific locations.

2.1 Constructing the Panel Data

Combining data on insurance policies (FEMA, n.d.-d), population (U.S. Census Bureau, n.d.), floodplain maps (FEMA, n.d.-c), and household point coordinates (Corelogic), we estimate the annual residential insurance take-up rate in non-SFHA zones. First, we estimate the annual "policies-in-force", or the number of total policies that were newly purchased or renewed in a given year. We follow Kousky (2017) and Bradt et al (2021) in utilizing this metric as representing the coverage rate, or annual take-up rate, since NFIP policies are 1-year term policies that do not automatically renew, and new policies take 30 days to go into effect. The NFIP dataset provides data at the policy level, including the policy cost, coverage, and flood zone for each policy. As the publicly available NFIP dataset starts in 2009, we extend this to 2005 using additional NFIP data obtained through the Freedom Of Information Act (request 2022-FEFO-00527).

To estimate insurance take-up behavior when it is voluntary, we consider only policies in nSFHA zones. In SFHA zones, insurance is mandated for households with a government-backed mortgage. After a presidential disaster declaration, households in an SFHA zone that request financial assistance are automatically enrolled in a Group Flood Insurance Policy (GFIP) for three years. There is no such mandatory enrollment in place for households in non-SFHA areas.

For a more accurate measure of the voluntary insurance take-up rate, we calculate the number of policies-in-force (PIF) among households located in nSFHA zones at the tract level. The estimate of households located in nSFHA zones is derived in two steps. First, the point coordinates of unique residential property records from Corelogic are spatially joined to FEMA floodplain maps to calculate the percentage of properties that fall within nSFHA zones at the tract level. Given that 75% of FEMA flood maps were created before 2013 and do not update frequently (Eby, 2019; Frank, 2020), we take the floodplain boundaries in the latest available flood maps (downloaded from the FEMA Map Service Center, as of July 2022) to estimate the percentage of properties located in nSFHA zones. Here the assumption is that updates to flood maps do not significantly change the number of properties affected. Second, these percentages are applied to annual data on total household count provided by the five-year American Community Surveys (ACS5). This is because the residential property records provided by Corelogic do not account for whether properties are occupied, while the ACS5 data allows us to account for the increasing population over time. Here the assumption is that population increase is on average equally distributed across SFHA and nSFHA zones. Finally, we divide annual policies-in-force by the estimate of residential properties in nSFHA zones to construct the annual take-up rate. Based on these calculations, annual take-up rates are highest along the Gulf and Atlantic coast (Fig. 1a).

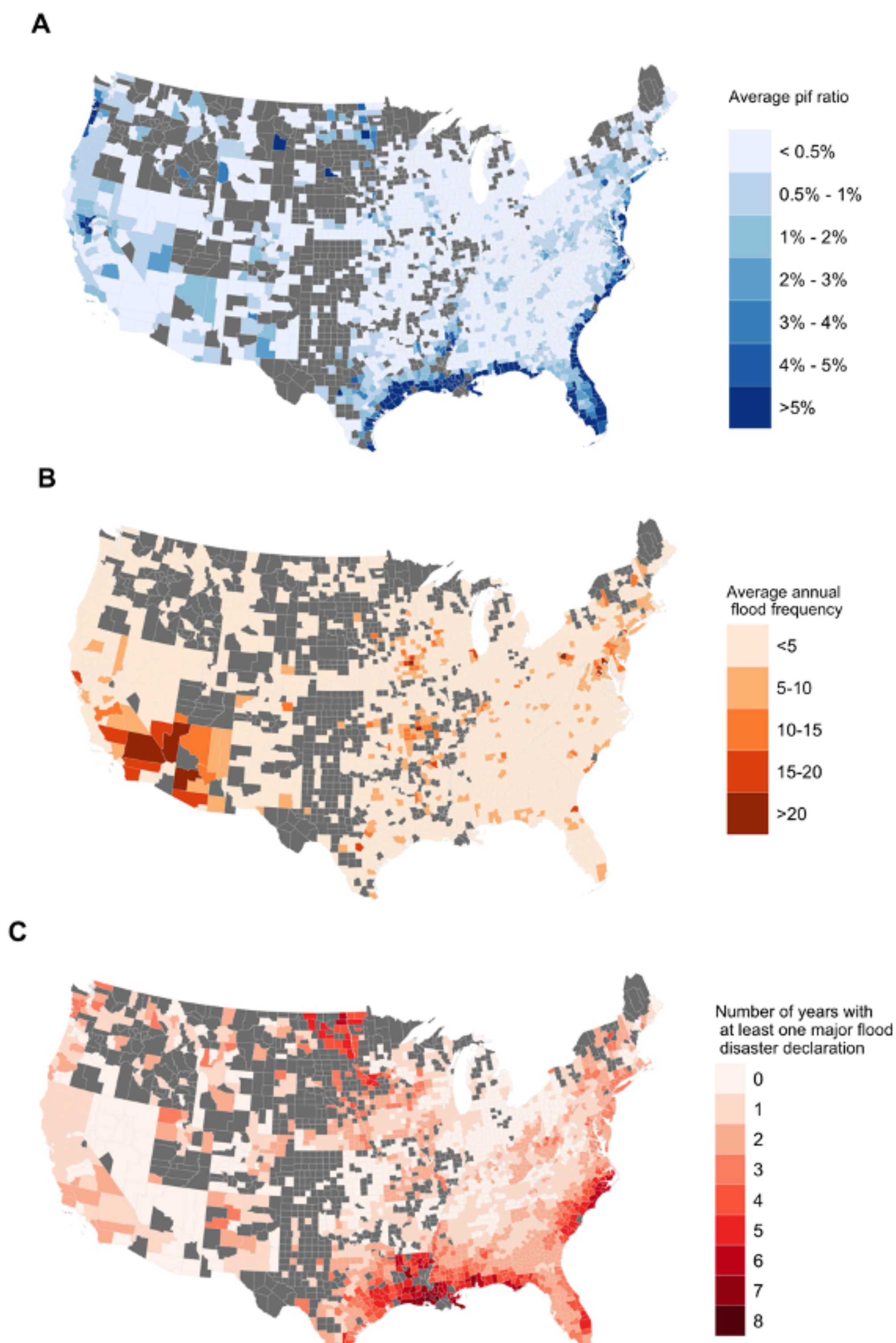

Figure 1. NFIP policies-in-force in non-SFHA zones and exposure to flood events at the county-level. a) average ratio of NFIP policies in force (2005 - 2020), in nSFHA zones. b) annual average of total flood events recorded (2005 - 2020). c) total number of years with at least one major flood disaster declaration in the county (2005 - 2020).

Not all US counties are covered by FEMA flood maps, as mapping efforts have focused primarily on counties with moderate population density (Association of State Floodplain Managers, n.d.). FEMA flood maps cover 57% of the territory of the 50 US states, but 93.6% of the population (Qiang, 2019). In our analysis, we additionally filter for counties in the contiguous US where more than 50% of residential properties are accounted for within flood mapped areas, leading to a final sample of 2,392 counties out of 3,108 total counties, accounting for 94% of the CONUS population (Fig. S3).

We use NOAA's Storm Events Database to estimate the total number of flood-related events for each county-year, and FEMA's Disaster Declaration dataset to count the number of floods that resulted in a major disaster declaration for each county-year (Fig. 1b, 1c). NOAA's Storm Events Database records the occurrence of storms and other significant weather phenomena across a variety of sources, including newspapers and broadcast media, law enforcement, park and forest service, trained spotters, Automated Surface Observing Systems (ASOS), and citizen science. From this dataset, we include: *"Flash Flood", "Flood", "Heavy Rain", "Coastal Flood", "Storm Surge/Tide", "Tropical Storm", "Lakeshore Flood", "Hurricane (Typhoon)".*

We distinguish between disaster-scale flood events that trigger a Presidential Disaster Declaration and all other non-disaster-scale flood events recorded in the NOAA dataset, to capture how different types of flood events may differentially affect insurance demand. There are two levels of presidential declarations: emergency declarations and major disaster declarations. While both authorize federal assistance, the total amount of assistance provided for any emergency event is capped at $5 million, whereas a major declaration provides significantly more funding once it is determined that the situation is beyond the State and local government's combined capacity to respond. Events may trigger both emergency declarations and major disaster declarations, but not all emergency declarations lead to a major disaster declaration. We capture only the major disaster declarations from the FEMA Presidential Declarations dataset, and the type of flood events include: *"Flood", "Hurricane", "Typhoon", "Coastal storm".*

2.2 **Panel Regression Model**

We employ a panel regression with two-way fixed effects to estimate the causal effect of flood experience on insurance demand. The county-level panel data that we construct allows us to estimate the salience effect of disaster-scale floods (i.e., those with a major disaster declaration) and frequent minor flooding on insurance take-up rates:

$$log(takeup\ rate)_{it} = \sum_{t=0}^{n} \left(\beta_{1,t-n}\, floodcount_{i,t-n} + \beta_{2,t-n} disaster_{i,t-n} \right) + \alpha_i + \delta_t + \epsilon_{it} \quad \text{(Eq. 1)}$$

where $takeup\ rate$ is the share of households that take-up flood insurance in county i and year t, $floodcount$ is the number of floods that occurred in year t, and $disaster$ is a dummy for whether there was a major flood event that triggered a presidential disaster declaration in that year. We introduce lags of up to 7 years to quantify how floods experienced $t-n$ years prior affect the outcome at year t. α and δ are county and year fixed effects, allowing us to plausibly isolate the impact of variation in flood exposure from other time-invariant and time-trending factors that may be correlated with both the flood exposure and the outcome that we are measuring. These panel estimators are commonly used in literature that measures human response to environmental change, and can deliver plausibly causal estimates of environmental impacts when within-location change in environmental risk over time (e.g. year to year variation in location-specific flooding) is uncorrelated with other drivers of the outcome in question. Standard errors are clustered at the county-level, to adjust for correlations in residuals within counties. After accounting for time trends and average differences across counties, remaining variation in flood frequency and severity is plausibly random, and thus we can infer that flood insurance adoption may be attributed to the flood experience.

The model above does not account for whether consecutive disaster years may be increasing the likelihood of insurance take-up. To isolate this potential consecutive effect, we employ the following interaction model to test whether the insurance take-up response to a disaster at time t is greater if there was also a disaster the previous year (t-1). If there is a positive consecutive effect, this would be captured in the interaction estimate β_3.

$$log(takeup\ rate)_{it} = \beta_{1,t} disaster_{i,t} + \beta_{2,t-1} disaster_{i,t-1} + \beta_3 disaster_{i,t} * disaster_{i,t-1} + \alpha_i + \delta_t + \epsilon_{it}$$
(Eq. 2a)

In addition, we test whether the occurrence of consecutive disaster events in the past further increases the insurance take-up response. To do this, we add a new variable to the dataset, where $disaster\_consecutive$ is a dummy for every year where there was also a disaster flood in the previous year.

$$\log(takeup\ rate)_{it} = \sum_{t=0}^{n} \left(\beta_{t-n} disaster\_consecutive_{i,t-n} \right) + \alpha_i + \delta_t + \epsilon_{it} \quad \text{(Eq. 2b)}$$

Finally, we consider insurance take-up rates at the census tract level to understand how the level of insurance take-up in response to disaster-scale flooding is different based on the type of exposure to homeowners and renters including whether the risk saliency of disaster floods is different among homeowners whose primary residence is within the same county where a disaster is declared. Since disaster floods are observed at the county-level, our model assigns flood exposure treatment to all census tracts within a county where a presidential disaster is declared. Here our panel data starts in 2010 to preserve a uniform set of census tracts, as census tract boundaries are updated every ten years. As in Equation 1, we introduce lags of up to 7 years to quantify how floods experienced $t - n$ years prior affect the outcome at year t (Eq. 3a). Additionally, we test whether the cost burden of insurance premiums mediates the take-up response. We calculate the cost burden of insurance within each census tract as the average insurance premium divided by household median income over the study period (based on NFIP data), and assign a dummy for tracts where the cost burden is greater than our calculated national median cost burden of 1% for homeowner policies and 0.3% for renter policies (Eq. 3b).

$$\log(takeup\ rate)_{it} = \sum_{t=0}^{n} \left(\beta_{t-n} disaster_{i,t-n} \right) + \alpha_i + \delta_t + \epsilon_{it} \quad (Eq. 3a)$$

$$log(takeup\ rate)_{it} = \beta_{1,t} disaster_{i,t-1} + \beta_{2,t}\ disaster_{i,t-1} * costburden\_dummy_i + \alpha_i + \delta_t + \epsilon_{it} \quad (Eq. 3b)$$

3 Results

The estimated relationship between flooding and insurance demand is shown in Figure 2. We estimate that a disaster declaration in the year prior (t-1) has the greatest impact on take-up, with an average 7% increase in the take-up rate (95% CI: 5.4% - 8.5%). Declarations occurring further back in time have a diminishing impact on take-up, and after five years (t-5) this impact is no longer significant. Meanwhile, experiencing any other flood event has a very small but consistently positive and significant impact on insurance demand. By way of comparison, the increase in take-up rate in a county in response to a major disaster declaration the previous year is equivalent to the response in a county that experiences forty non-disaster-scale flood events in the previous year (Fig. 2).

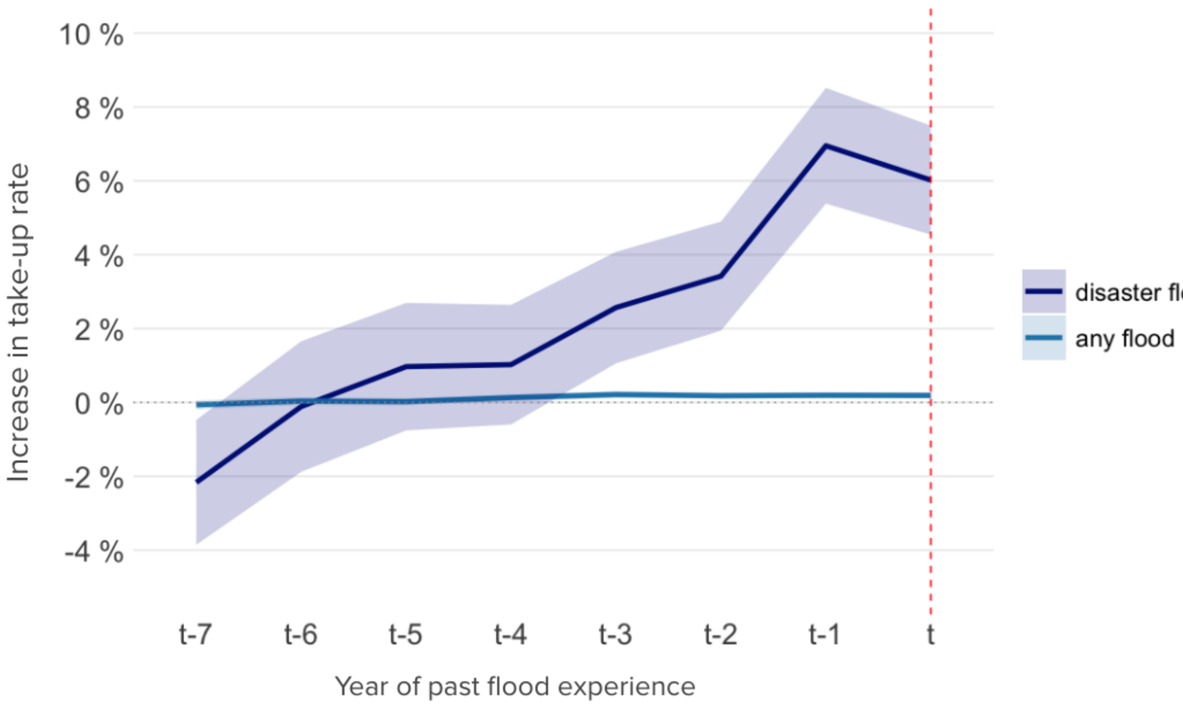

Figure 2. Estimated salience effect of flooding on insurance demand. The estimated relationship between a major flood disaster declaration versus any additional flood from previous years on insurance take-up in the current year (t) (Eq 1). Shaded regions represent the confidence intervals for each coefficient estimate.

Baseline take-up rates differ considerably depending on whether the county is located along the Gulf and Atlantic coasts (Table S1). To account for differing levels of baseline risk perception, we divide the sample into three main subsets: counties in non-hurricane exposed states (baseline take-up rate: 0.6%), coastal counties in hurricane-exposed states (7.8%), and inland counties in hurricane-exposed states (0.7%). We find that in non-hurricane states, the take-up rate increases by 9-12% in response to a disaster declaration in the concurrent year (95% CI: 9.1%-14.7%) or one year prior (95% CI: 6.1% - 11.4%) (Fig. 3a). In contrast, hurricane states have a smaller increase in the take-up rate (2.5% - 5.4%), but this response is driven by disaster declarations from up to five years prior (Fig. S4). However, given the low average baseline take-up rates in non-hurricane exposed states, these model estimates translate to overall fewer additional policies in non-hurricane exposed counties compared to coastal counties (Fig. S4). For instance, a disaster flood in one year prior would drive >10 additional policies in 8 counties in non-hurricane states, versus 59 counties in hurricane coastal counties.

Figure 3. Salience effect of experiencing consecutive disaster years. A) Estimated impact of two recent consecutive disaster flood years on insurance take-up (Eq 2a). B) Grey indicates policies attributed to a disaster declaration at time t, red indicates the predicted additional take-up in counties that also experienced a disaster declaration at time t-1. Coefficient estimates are detailed in S4. C) Comparison of the estimated impact of disaster declaration on insurance take-up for counties that never experienced consecutive disaster years during 1998-2020 (i.e., only were exposed to non-consecutive disasters), and the impact of a consecutive year of disaster among counties that experienced consecutive disaster years (Eq 2b).

We also test whether disaster declarations in two consecutive years may further increase the likelihood of insurance take-up, relative to our baseline model that assumes that the effect of a flood on take-up in one year is not influenced by whether there was a flood in the previous year (Eq. 2, Fig. 3a). We find that consecutive disaster declarations roughly double the take-up rate on average (i.e., the effect of a flood on take-up in a given year is twice as large if there was also a flood in the year prior). The take-up rate increases by 6% in response to a disaster declaration one year prior (95% CI: 4.6% - 7.5%), and further increases by 6% when there is another disaster declaration in the concurrent year (95% CI: 1.8% - 9.6%). While the consecutive effect is positive across all county subsets, the response is strongest in counties in non-hurricane states, where the take-up rate increases an additional 24% due to a consecutive disaster declaration, nearly tripling the take-up response. However, when we account for differing baseline take-up rates across the county subsets, the number of additional policies due to a consecutive disaster year is predicted to be greatest in hurricane coastal counties (Fig. 3b). For example, 13% of hurricane coastal counties are predicted to gain >100 policies due to two consecutive disaster years. Compared to counties that never experienced consecutive disaster years in the past, the estimated insurance take-up response can be up to two times greater in counties experiencing consecutive disaster years (Fig. 2c).

Finally, we test for heterogeneity in the take-up response across policy types at the census tract level. We find that among homeowners, the salience effect of a disaster flood in year t-1 in terms of insurance policy take-up is around 5.5 percentage points greater for primary residences compared to non-primary residences (Fig. 4A). A higher relative cost burden of insurance (calculated as tracts where the average insurance premium is greater than 1% of household median income) decreases the take-up response for primary residence policies by 3.8 percentage points, whereas the cost burden of insurance does not significantly impact the take-up response for non-primary residence policies (Fig. 4B). The salience effect of flooding on renter policies are visualized separately in Figure 4C as renters have significantly lower baseline adoption rates than among homeowners. Among renter policies, higher relative cost burden does not significantly decrease the take-up response (Fig. 4D). (The classification method for these policy types are detailed in Table S2, and a histogram of policy counts across each policy type is shown in Fig. S5.)

Figure 4. Estimated take-up response across policy types. A) The estimated impact of major flood disaster declarations (t-n) on insurance take-up at year t, comparing the response for policies that are purchased for primary residences and non-primary residences. B) Comparison of the estimated insurance take-up in response to a disaster declaration at year t-1 (shaded gray in panel A), for census tracts where the cost burden of insurance (calculated as the average policy cost divided by household median income) is above or below the national average (1%). C) As in panel A, for renter policies. D) As in panel B, for renter policies. Cost burden of insurance is adjusted to reflect the average cost of renter policies (0.3% of median income).

4 Discussion

We find that although households do respond to disaster-scale flood events by adopting insurance, this response is small, short-lived, and differential across baseline exposure to disaster-scale events. On average, county-level insurance take-up rates increase by 7% in response to a disaster-scale flood event in the previous year, but this increase is not sustained over time. Declarations occurring further back in time have a diminishing impact on take-up, consistent with previous studies (Bradt et al., 2021; Gallagher, 2014; Kousky, 2017).

One reason for the diminishing take-up response may be that NFIP policies are one-year term policies that do not renew automatically (FEMA, n.d.-a). As a result, households responding to a disaster-scale flood event by purchasing insurance in one year may decide not to renew the policy the following year once the flood event is less salient. This hypothesis is supported by evidence that individuals tend to overweight the probability of a catastrophic event immediately after it has occurred (Dumm et al., 2020), and that risk perception of future damages is a robust determinant of flood insurance take-up (Landry & Turner, 2020).

However, our results also show that the take-up rate response curve differs across counties with different baseline take-up rates. In counties in non-hurricane-exposed states where baseline take-up rates are low (0.58% compared to 10% in hurricane coastal counties), a disaster-scale flood may trigger a proportionally greater—but much more short-lived—demand response in comparison to coastal counties in hurricane-exposed states. A similar pattern is observed for consecutive disaster-scale floods, where the increase in insurance demand is proportionally greatest in counties in non-hurricane states. We also show that the type of exposure (e.g. whether the disaster declaration impacted a primary residence or a non-primary residence) plays a role in mediating the post-disaster demand response. Further work is needed to understand how baseline risk perception and household capacity to respond differentially impacts post-disaster risk perception and insurance demand.

Meanwhile, flood events that trigger a Presidential Disaster Declaration appear to have a much larger effect on insurance take-up response than floods that do not reach that threshold. For instance, the increase in take-up rate in a county in response to a disaster-scale flood is equivalent to the response in a county that experiences forty non-disaster-scale flood events in the previous year. The insurance take-up response can be five to nine times greater in counties that experienced consecutive disaster flood years compared to a county experiencing one independent disaster flood year (Fig. 3c). Given that climate change is driving the increasing frequency and severity of flood events associated with greater precipitation levels (Davenport et al., 2021; Kundzewicz et al., 2014; Markonis et al., 2019; Swain et al., 2020), it may be expected that insurance take-up responses will vary based on flood severity, and how frequently they experience disaster-scale floods.

Some other limitations should also be noted. First, our analysis assumes that a presidential disaster declaration equates "flood experience" for all households within a county, even though not all residents of a county will experience flooding directly. The result is that our estimates capture the insurance take-up response of households that may be experiencing the flood through indirect channels (such as from affected friends, family or other acquaintances, government communication to residents about the presidential disaster declaration, observing flooding while in transit or through media exposure, etc). It is plausible that the insurance response among households directly impacted by flood events may be greater than what we find in this study. Similarly, the NOAA dataset does not provide information on flood extents. Information on total flood event count is aggregated at the county level, and we use these data only in our first regression model (Eq. 1) to compare the insurance take-up response between the disaster-scale events and all other non-disaster-scale flood events.

Finally, this study is limited to measuring insurance demand in nSFHA zones where households may believe that they are not required to purchase insurance because they are not exposed to flood risk. This is largely the outcome of NFIP's reliance on FEMA-designated flood maps to communicate whether households should purchase insurance. While this policy setting provides a unique empirical opportunity in that it allows us to isolate insurance take-up when it is voluntary, it is possible that prior NFIP communication could be contributing to a downward bias in the risk perception of nSFHA households. One consequence is that the short-lived salience effect identified in this study may in part be due to the conflicting information with which households are presented about flood insurance requirements, even when their own experience may suggest otherwise.

Alternatively, it is possible that well-resourced communities are more likely to undertake investments that allow them to remain in nSFHA zones and further reduce insurance premiums. If this were happening at scale, this could mean that our estimates of the low take-up response is because households believe their communities are well protected from floods, and therefore less likely to respond to disaster floods by purchasing insurance. On the other hand, our results show that homeowners are more likely to respond to disaster floods by purchasing insurance if the cost burden of insurance is lower. Understanding the dynamics that drive the salience effect observed in this study requires deeper investigation of how different communities perceive flood risk, and how this perception in turn mediates the decision to purchase insurance in the face of changing flood risks.

The growing private flood insurance market raises the possibility that the entry of private players may help increase overall coverage or lower costs in the future. However, this market is currently small relative to the NFIP, representing only 3.5-4.5% of all primary residential flood policies in 2018, and it is unclear how many private flood insurance holders are newly insured or are switching from NFIP policies (Kousky et al., 2018). Private insurers will continue to be selective in the areas where they will underwrite risk, and will never be able to underwrite in some high-risk areas (Kousky et al., 2018), underscoring the importance of NFIP in closing the flood insurance protection gap. In the meantime, this gap is currently further exacerbated by a real estate market that continues to overvalue properties at flood risk (Gourevitch et al., 2023; Hino & Burke, 2021), encouraging development in risky areas.

The rollout of NFIP's new premium rating methodology, Risk Rating 2.0, is expected to tailor risk communication for each household, reducing the reliance on flood zone designation for pricing risks. Improved understanding of future flood risks may help reduce overoptimism and encourage households to sustain periodic insurance payments (Meyer & Kunreuther, 2017). Future studies may take this into account, to test how Risk Rating 2.0 might play a role in driving sustained insurance demand among households.

5 Conclusions

Our findings are relevant for understanding how changing flood risks will impact flood insurance demand, and for quantifying the magnitude of autonomous adaptation to climate change. By exploiting a setting where insurance take-up is voluntary, we investigate how differential exposures mediate the response of insurance demand to flood events. Our results indicate that the salience effect of flooding on insurance demand is insufficient to mitigate the increasing flood insurance protection gap. These findings have implications for designing policies that encourage households to maintain coverage at levels commensurate to their true flood risk, especially in nSFHA flood zones where flood risk is increasing but insurance is not currently mandated. More generally, our results suggest that in a warming climate where the frequency of multiple consecutive disaster years is likely to increase, households cannot be expected to autonomously adapt to increasing hazards by voluntarily purchasing and maintaining insurance coverage.

Acknowledgments

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Open Research

Data Availability Statement

NFIP data is available through OpenFEMA data (FEMA, n.d.-d), and FEMA flood maps are downloaded from the Map Service Center (FEMA, n.d.-c). Data for flood events is available at NOAA storm events database (NCEI, n.d.) and disaster declaration data is from FEMA (FEMA, n.d.-b). The original raw data on residential building point coordinates from Corelogic is not publicly available, however the processed data supporting this research is available at https://zenodo.org/record/8306902 (Choi, 2023). Figures were made using RStudio version 2023.06.0+421.

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Earth's Future

Supporting Information for

The Effect of Flood Exposure on Insurance Adoption among US Households

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[2] Center on Food Security and the Environment
[3] National Bureau of Economic Research

Contents of this file

Introduction

Following are supporting figures and tables describing the relevant data for the study and additional analyses.

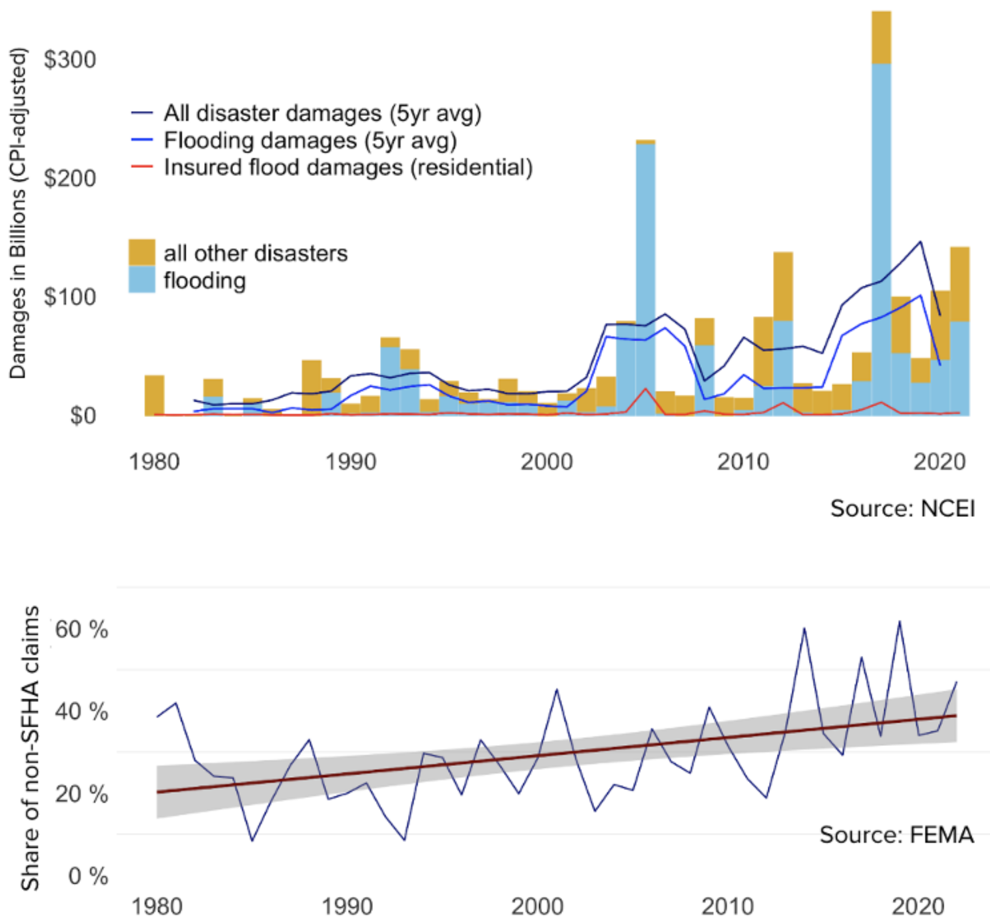


Figure S1. Flood-related damages and share of damage claims from non-SFHA zones. a) 5-year rolling average of flooding vs total disaster damages show that flooding has been a key driver of total damages over the time period 1980-2020. Flood damage claims from residential insurance policyholders continue to represent a small portion of total flood damages. b) The share of residential flood damage claims from non-SFHA zones have been increasing over the same time period.

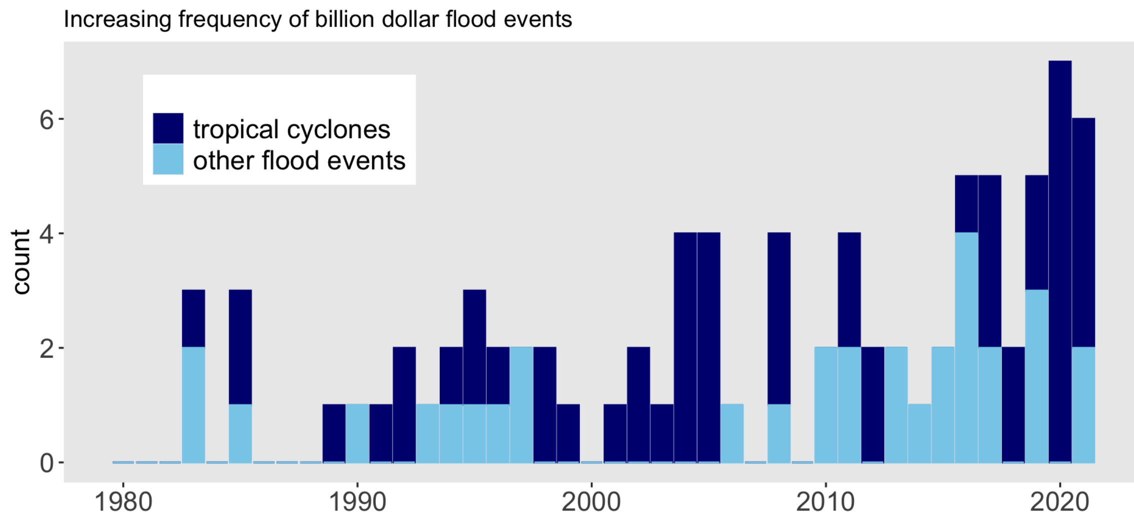


Figure S2. Frequency of billion-dollar flood events. The number of tropical cyclones and other flood events causing >billion in damages are increasing. (Source: NCEI)

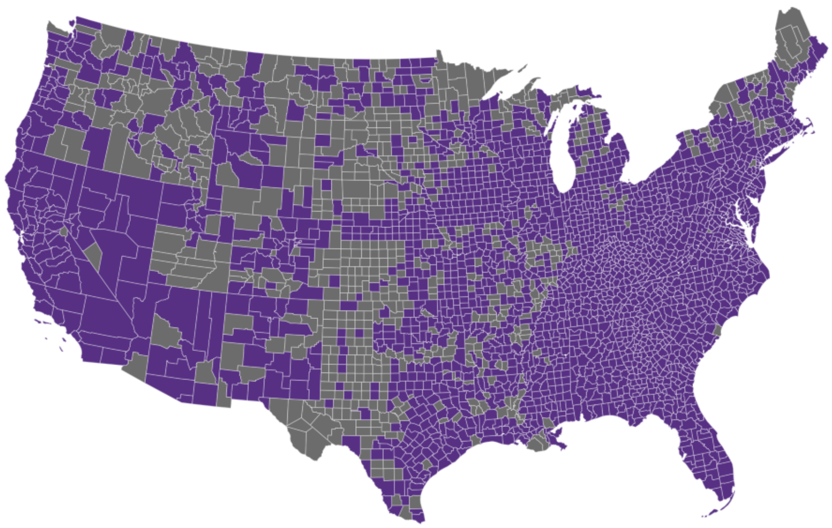
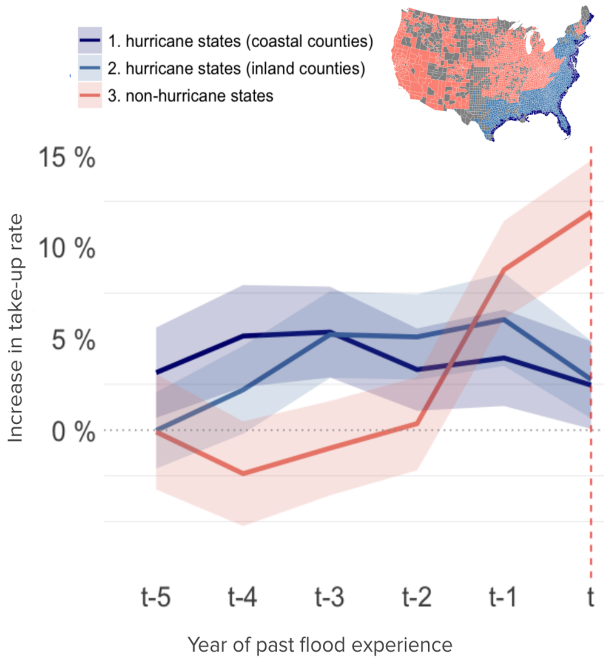


Figure S3. Counties with >50% properties covered by flood maps. Of the 2,408 counties where some level of flood map coverage exists, 2,392 counties are selected for this analysis, accounting for 94% of the population. These counties are selected based on the flood mapped areas accounting for at least 50% of residential properties in the county.



	Estimated take-up attributed to disaster at time t (95% CI)	Average predicted increase in policies per county
Hurricane states (coastal) n = 236	**2.5%** (0.06% - 4.9%)	**20**
Hurricane states (inland) n = 789	**2.8%** (0.64% - 4.9%)	**0.52**
Non-hurricane states n = 1367	**11.9%** (9.1% - 14.7%)	**0.58**

Figure S4. Estimated salience effect of flooding on insurance demand. The plot shows the estimated impact of disaster declarations on insurance take-up across counties with differing baseline take-up rates. Table shows the average predicted increase in insurance policies per county attributed to a major disaster declaration at time t (calculated as: increase in take-up rate x baseline take-up rate in 2020 x average policy count for each county). Predicted increase in policies are on average 35 times greater in hurricane coastal counties compared to counties in non-hurricane states.

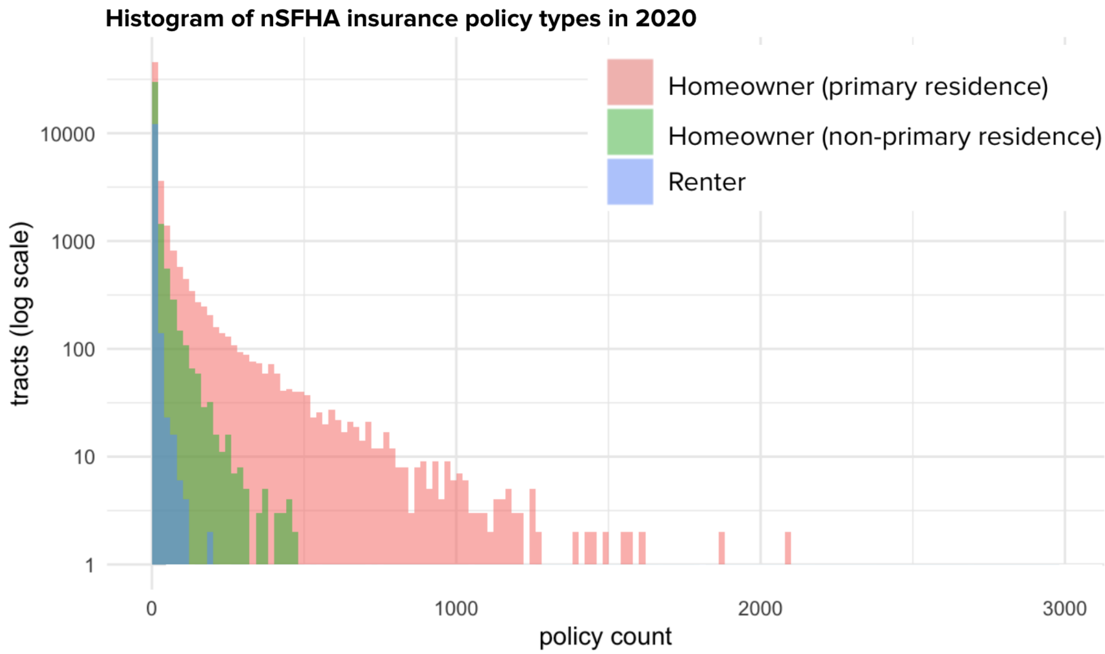


Figure S5. Histogram of nSFHA policies in 2020, comparison across policy types.

		2009		2020	
Subset	Number of Counties	**Average policies-in-force (PIF)**	**Average PIF ratio**	**Average policies-in-force (PIF)**	**Average PIF ratio**
All counties	2,392	777 (5774)	1.51% (5.6%)	903 (6985)	1.70% (5.7%)
Hurricane states - coastal	229	5316 (17036)	9.77% (14.9%)	6439 (20783)	10.5% (14.8%)
Hurricane states - inland	796	337 (1591)	0.80% (1.6%)	464 (2996)	0.96% (2.2%)
Non-hurricane states	1,367	236 (1555)	0.56% (1.3%)	208 (839)	0.58% (1.7%)

Table S1. Comparison of baseline flood insurance take-up rates across county subsets, in 2009 and 2020.

	Homeowners (Primary residence)		Homeowners (Non-primary residence)		Renters
Building coverage	Yes		Yes		No
Content coverage	Yes	No	Yes	No	Yes
Primary residence indicator	Yes		No		Yes/No
Number of census tracts with at least one policy in 2020	n=49,534		n=29,304		n=8,878

Table S2. Classification method for flood insurance policy types. Renter policies are distinguishable as they are only eligible to purchase content coverage. Policies purchased by homeowners versus landlords are distinguished by whether the policy is for a primary residence or not.