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

13 **Abstract**

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

31 **1 Introduction**

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

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

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

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

66 Previous literature found that insurance take-up spikes after disaster declarations (Browne & Hoyt,
67 2000; Gallagher, 2014; Kousky, 2017). However, because these studies do not distinguish between
68 take-up rates in SFHA versus nSFHA zones, a significant portion of the identified take-up response
69 may be due to the requirement that households in SFHA zones must purchase insurance if they
70 request post-disaster financial assistance (Kousky, 2017).

71 New data released by NFIP in 2019 provides information about flood zones at the policy level,
72 allowing researchers to isolate the take-up response in nSFHA zones (Dombrowski et al., 2020).
73 One recent study estimating the voluntary response concludes that a major flood declaration
74 increases insurance demand in nSFHA zones by less than 0.5 percentage points, and that the
75 greatest increase in take-up rate occurs two years after a major disaster declaration (Bradt et al.,
76 2021). The finding that demand for insurance spikes in the aftermath of disasters is in line with
77 broader literature in behavioral science, where experiments have shown that people tend to neglect
78 low-probability, high-impact events (Botzen & van den Bergh, 2012), but that emotional salience
79 may inflate the risk perception of events (Keller et al., 2006; Slovic et al., 2004). While differences
80 in risk perception owing to past flood experience can predict voluntary insurance take-up (Royal
81 & Walls, 2019), this effect attenuates as catastrophic events fade from memory (Dumm et al.,
82 2020). Salience effects have also been confirmed in studies investigating the impact of hurricane
83 events on residential property sales (Bakkensen et al., 2019), cash holding behavior of firms
84 (Dessaint & Matray, 2017), and the influence of social interactions with geographically-distant
85 peers who have experienced floods (Hu, 2022).

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

95 **2 Materials and Methods**

96 In this study, we use insurance data from the U.S. NFIP, flood events data from the National
97 Oceanic and Atmospheric Administration (NOAA), disaster declarations and flood maps from
98 FEMA to quantify how exposure to flooding motivates insurance demand among households. We
99 distinguish between the impact of experiencing non-disaster scale floods versus experiencing a

100 flood that leads to a major disaster declaration, as well as the impact of experiencing disaster
101 declarations in two consecutive years. In addition, we consider how a disaster declaration
102 differentially impacts insurance take-up at the census tract level. To isolate the impact of flooding
103 from other determinants of insurance take-up, we estimate panel regression models that exploit
104 variation in the frequency and severity of flood events over time in specific locations.

105 ### 2.1 Constructing the Panel Data

106 Combining data on insurance policies (FEMA, n.d.-d), population (U.S. Census Bureau, n.d.),
107 floodplain maps (FEMA, n.d.-c), and household point coordinates (Corelogic), we estimate the
108 annual residential insurance take-up rate in non-SFHA zones. First, we estimate the annual
109 "policies-in-force", or the number of total policies that were newly purchased or renewed in a
110 given year. We follow Kousky (2017) and Bradt et al (2021) in utilizing this metric as representing
111 the coverage rate, or annual take-up rate, since NFIP policies are 1-year term policies that do not
112 automatically renew, and new policies take 30 days to go into effect. The NFIP dataset provides
113 data at the policy level, including the policy cost, coverage, and flood zone for each policy. As the
114 publicly available NFIP dataset starts in 2009, we extend this to 2005 using additional NFIP data
115 obtained through the Freedom Of Information Act (request 2022-FEFO-00527).
116
117 To estimate insurance take-up behavior when it is voluntary, we consider only policies in nSFHA
118 zones. In SFHA zones, insurance is mandated for households with a government-backed mortgage.
119 After a presidential disaster declaration, households in an SFHA zone that request financial
120 assistance are automatically enrolled in a Group Flood Insurance Policy (GFIP) for three years.
121 There is no such mandatory enrollment in place for households in non-SFHA areas.
122
123 For a more accurate measure of the voluntary insurance take-up rate, we calculate the number of
124 policies-in-force (PIF) among households located in nSFHA zones at the tract level. The estimate
125 of households located in nSFHA zones is derived in two steps. First, the point coordinates of
126 unique residential property records from Corelogic are spatially joined to FEMA floodplain maps
127 to calculate the percentage of properties that fall within nSFHA zones at the tract level. Given that
128 75% of FEMA flood maps were created before 2013 and do not update frequently (Eby, 2019;
129 Frank, 2020), we take the floodplain boundaries in the latest available flood maps (downloaded
130 from the FEMA Map Service Center, as of July 2022) to estimate the percentage of properties
131 located in nSFHA zones. Here the assumption is that updates to flood maps do not significantly
132 change the number of properties affected. Second, these percentages are applied to annual data on
133 total household count provided by the five-year American Community Surveys (ACS5). This is
134 because the residential property records provided by Corelogic do not account for whether
135 properties are occupied, while the ACS5 data allows us to account for the increasing population
136 over time. Here the assumption is that population increase is on average equally distributed across
137 SFHA and nSFHA zones. Finally, we divide annual policies-in-force by the estimate of residential
138 properties in nSFHA zones to construct the annual take-up rate. Based on these calculations,
139 annual take-up rates are highest along the Gulf and Atlantic coast (Fig. 1a).
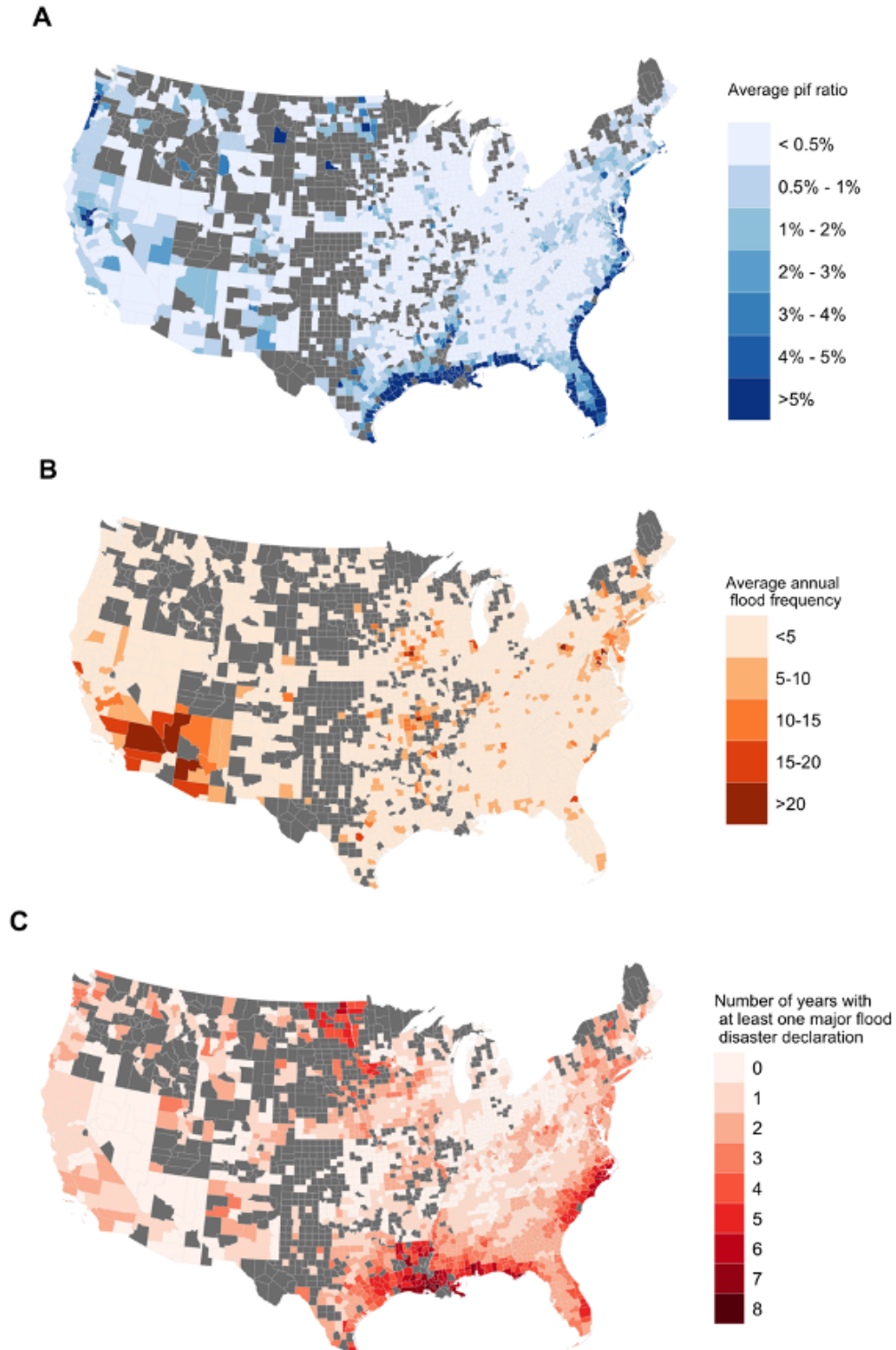140
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Figure 1. NFIP policies-in-force in non-SFHA zones and exposure to flood events at the county-level. a) average ratio of NFIP policies in force (2005 - 2020), in nSFHA zones. b) annual average of total flood events recorded (2005 - 2020). c) total number of years with at least one major flood disaster declaration in the county (2005 - 2020).

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

155

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

164

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

176

177   ## 2.2 **Panel Regression Model**

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

182

183
$$log(takeup\ rate)_{it} = \sum_{t=0}^{n} \left(\beta_{1,t-n}\ floodcount_{i,t-n} + \beta_{2,t-n} disaster_{i,t-n} \right) + \alpha_i + \delta_t + \epsilon_{it} \quad \text{(Eq. 1)}$$

184

185   where $takeup\ rate$ is the share of households that take-up flood insurance in county i and year t,
186   $floodcount$ is the number of floods that occurred in year t, and $disaster$ is a dummy for whether
187   there was a major flood event that triggered a presidential disaster declaration in that year. We
188   introduce lags of up to 7 years to quantify how floods experienced $t - n$ years prior affect the
189   outcome at year t. α and δ are county and year fixed effects, allowing us to plausibly isolate the
190   impact of variation in flood exposure from other time-invariant and time-trending factors that may
191   be correlated with both the flood exposure and the outcome that we are measuring. These panel

192   estimators are commonly used in literature that measures human response to environmental
193   change, and can deliver plausibly causal estimates of environmental impacts when within-location
194   change in environmental risk over time (e.g. year to year variation in location-specific flooding) is
195   uncorrelated with other drivers of the outcome in question. Standard errors are clustered at the
196   county-level, to adjust for correlations in residuals within counties. After accounting for time
197   trends and average differences across counties, remaining variation in flood frequency and severity
198   is plausibly random, and thus we can infer that flood insurance adoption may be attributed to the
199   flood experience.

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

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

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

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

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

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

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

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).
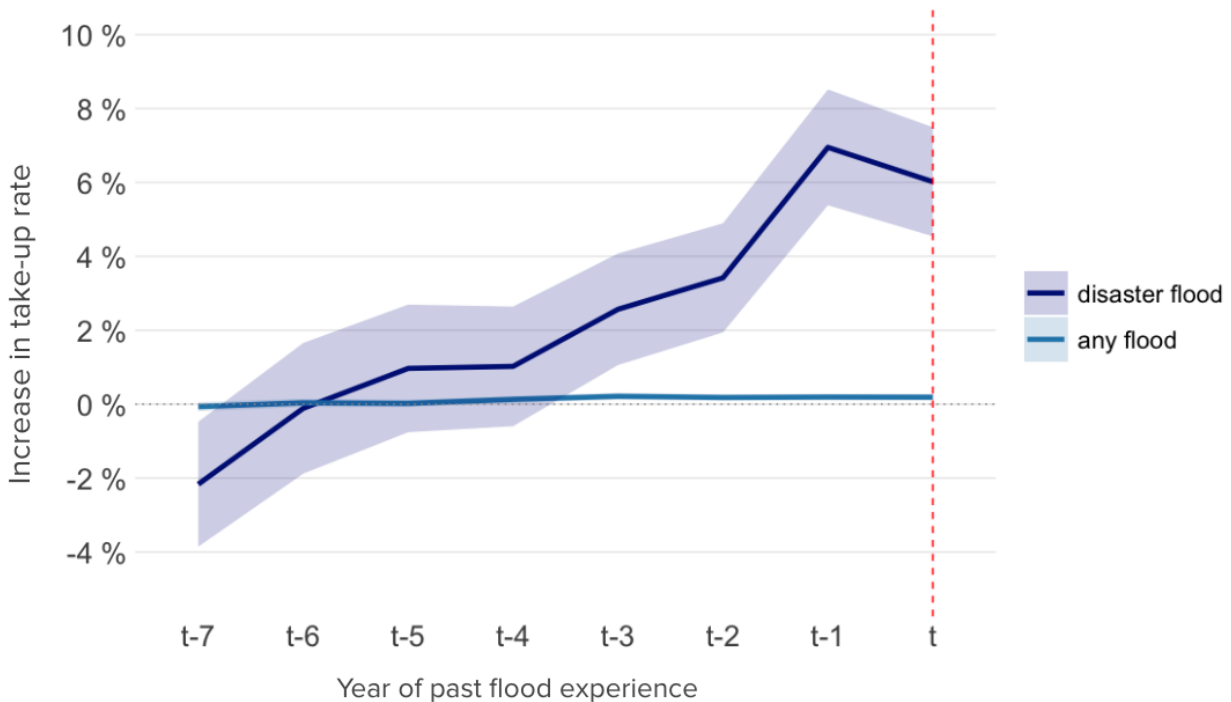

Figure 2. Estimated salience effect of flooding on insurance demand. The estimated relationship between a major flood disaster declaration versus any additional flood from previous years on insurance take-up in the current year (t) (Eq 1). Shaded regions represent the confidence intervals for each coefficient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

273   We also test whether disaster declarations in two consecutive years may further increase the
274   likelihood of insurance take-up, relative to our baseline model that assumes that the effect of a
275   flood on take-up in one year is not influenced by whether there was a flood in the previous year
276   (Eq. 2, Fig. 3a). We find that consecutive disaster declarations roughly double the take-up rate on
277   average (i.e., the effect of a flood on take-up in a given year is twice as large if there was also a
278   flood in the year prior). The take-up rate increases by 6% in response to a disaster declaration one
279   year prior (95% CI: 4.6% - 7.5%), and further increases by 6% when there is another disaster
280   declaration in the concurrent year (95% CI: 1.8% - 9.6%). While the consecutive effect is positive
281   across all county subsets, the response is strongest in counties in non-hurricane states, where the
282   take-up rate increases an additional 24% due to a consecutive disaster declaration, nearly tripling
283   the take-up response. However, when we account for differing baseline take-up rates across the
284   county subsets, the number of additional policies due to a consecutive disaster year is predicted to
285   be greatest in hurricane coastal counties (Fig. 3b). For example, 13% of hurricane coastal counties
286   are predicted to gain >100 policies due to two consecutive disaster years. Compared to counties
287   that never experienced consecutive disaster years in the past, the estimated insurance take-up
288   response can be up to two times greater in counties experiencing consecutive disaster years (Fig.
289   2c).
290
291   Finally, we test for heterogeneity in the take-up response across policy types at the census tract
292   level. We find that among homeowners, the salience effect of a disaster flood in year t-1 in terms
293   of insurance policy take-up is around 5.5 percentage points greater for primary residences
294   compared to non-primary residences (Fig. 4A). A higher relative cost burden of insurance
295   (calculated as tracts where the average insurance premium is greater than 1% of household median
296   income) decreases the take-up response for primary residence policies by 3.8 percentage points,
297   whereas the cost burden of insurance does not significantly impact the take-up response for non-
298   primary residence policies (Fig. 4B). The salience effect of flooding on renter policies are
299   visualized separately in Figure 4C as renters have significantly lower baseline adoption rates than
300   among homeowners. Among renter policies, higher relative cost burden does not significantly
301   decrease the take-up response (Fig. 4D). (The classification method for these policy types are
302   detailed in Table S2, and a histogram of policy counts across each policy type is shown in Fig.
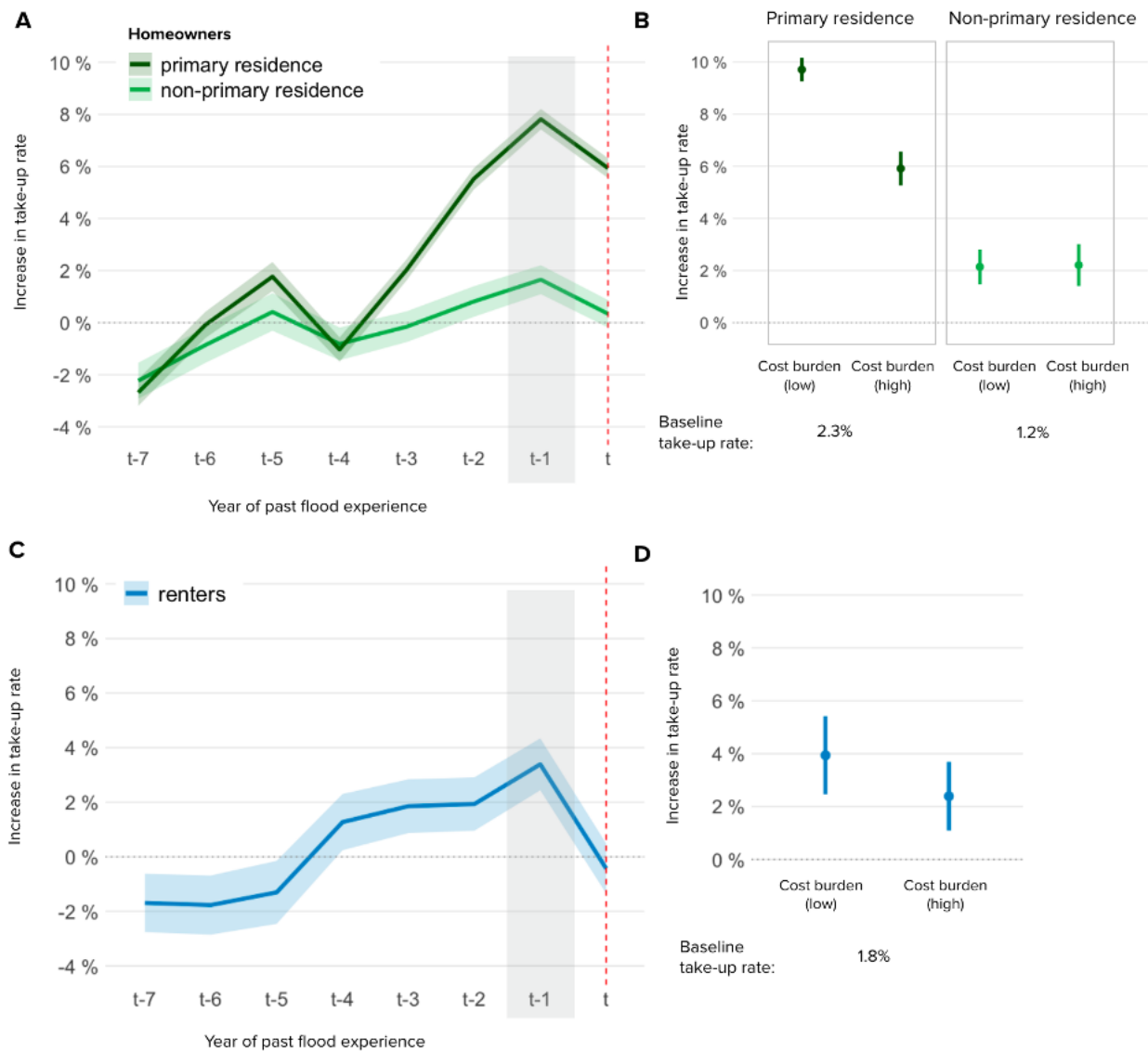303   S5.)
304

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).

321

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

329

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

341

342 Meanwhile, flood events that trigger a Presidential Disaster Declaration appear to have a much
343 larger effect on insurance take-up response than floods that do not reach that threshold. For
344 instance, the increase in take-up rate in a county in response to a disaster-scale flood is equivalent
345 to the response in a county that experiences forty non-disaster-scale flood events in the previous
346 year. The insurance take-up response can be five to nine times greater in counties that experienced
347 consecutive disaster flood years compared to a county experiencing one independent disaster flood
348 year (Fig. 3c). Given that climate change is driving the increasing frequency and severity of flood
349 events associated with greater precipitation levels (Davenport et al., 2021; Kundzewicz et al.,
350 2014; Markonis et al., 2019; Swain et al., 2020), it may be expected that insurance take-up
351 responses will vary based on flood severity, and how frequently they experience disaster-scale
352 floods.

353

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

366

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

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

388 The growing private flood insurance market raises the possibility that the entry of private players
389 may help increase overall coverage or lower costs in the future. However, this market is currently
390 small relative to the NFIP, representing only 3.5-4.5% of all primary residential flood policies in
391 2018, and it is unclear how many private flood insurance holders are newly insured or are
392 switching from NFIP policies (Kousky et al., 2018). Private insurers will continue to be selective
393 in the areas where they will underwrite risk, and will never be able to underwrite in some high-
394 risk areas (Kousky et al., 2018), underscoring the importance of NFIP in closing the flood
395 insurance protection gap. In the meantime, this gap is currently further exacerbated by a real estate
396 market that continues to overvalue properties at flood risk (Gourevitch et al., 2023; Hino & Burke,
397 2021), encouraging development in risky areas.

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

5 Conclusions

406 Our findings are relevant for understanding how changing flood risks will impact flood insurance
407 demand, and for quantifying the magnitude of autonomous adaptation to climate change. By
408 exploiting a setting where insurance take-up is voluntary, we investigate how differential
409 exposures mediate the response of insurance demand to flood events. Our results indicate that the
410 salience effect of flooding on insurance demand is insufficient to mitigate the increasing flood
411 insurance protection gap. These findings have implications for designing policies that encourage

412 households to maintain coverage at levels commensurate to their true flood risk, especially in
413 nSFHA flood zones where flood risk is increasing but insurance is not currently mandated. More
414 generally, our results suggest that in a warming climate where the frequency of multiple
415 consecutive disaster years is likely to increase, households cannot be expected to autonomously
416 adapt to increasing hazards by voluntarily purchasing and maintaining insurance coverage.

Acknowledgments

422

Open Research

Data Availability Statement

425 NFIP data is available through OpenFEMA data (FEMA, n.d.-d), and FEMA flood maps are
426 downloaded from the Map Service Center (FEMA, n.d.-c). Data for flood events is available at
427 NOAA storm events database (NCEI, n.d.) and disaster declaration data is from FEMA (FEMA,
428 n.d.-b). The original raw data on residential building point coordinates from Corelogic is not
429 publicly available, however the processed data supporting this research is available at
430 https://zenodo.org/record/8306902 (Choi, 2023). Figures were made using RStudio version
431 2023.06.0+421.

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