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**Key Points:**
- We evaluate how local and national-level social media activity correlates with insurance up-take patterns
- We propose a Cumulative Linked Mixed Models with random effects to account for geographical variability across counties
- Social media impact varies depending on timing relative to flood events

**Supporting Information:**

Supporting Information may be found in the online version of this article.

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# Temporal Dynamics of Social Media Impact on Flood Insurance Take-Up From a US County-Level Analysis

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**Abstract** This study investigates how social media posts correlate with flood insurance adoption patterns across the United States from 2014 to 2018. Despite increasing flood risks and the widespread availability of flood insurance, insurance adoption rates remains persistently low, prompting the need to understand factors affecting individuals' decisions. By integrating a panel data set combining flood occurrence data, insurance policy information, geo-located social media posts, and community flood reduction measures, we examine how local and national-level social media activity correlates with insurance uptake patterns. Our data-driven analysis includes cumulative linked mixed models with random effects to account for geographical variability across counties. Our findings reveal substantial geographic heterogeneity, captured through county-level random effects, suggesting that local context may filter the influence of social media. Further, while overall social media activity has a modest yet significant effect on insurance uptake, its impact varies depending on timing relative to flood events. Lower-than-average social media activity in a county during disasters correlates with a decreased probability of insurance uptake, while post-flood lower activity shows a positive association with policy adoption, an effect particularly evident following the 2015 Texas-Oklahoma floods. These insights depict a nuanced role of social media in shaping risk perceptions and preparedness, offering valuable implications for risk communication strategies.

**Plain Language Summary** In this research we looked at how social media posts relate to people buying flood insurance across the US (2014–2018). Even though flood risks are increasing, few people buy flood insurance. We combined data on floods, insurance policies, social media posts, and community flood protection efforts. We find that social media's impact on insurance purchases varies significantly by location, suggesting local factors play an important role. Interestingly, when social media activity in a county was lower than usual during a flood, fewer people bought insurance afterward. However, lower social media activity after a flood was linked to more people buying insurance—this was especially noticeable after the 2015 floods in Texas and Oklahoma. These findings show that social media influences how people perceive flood risks and prepare for them, but in heterogeneous ways that depend on timing and location.

## 1. Introduction

The increasing frequency and severity of flooding pose significant challenges requiring enhanced flood resilience in the United States (Wing et al., 2018; Wing et al., 2020). Flood insurance can provide financial means to the affected populations, boosting their recovery potential and therefore inducing a positive effect on resilience (Cremades et al., 2018). In addition to helping rebuild and recover, health impacts due to flooding, such as psychological distress, can be reduced by streamlining insurance processes and guidelines for quick recovery (Foudi et al., 2017; Sairam et al., 2024). In the US, flood insurance is regulated by the Federal Emergency Management Agency (FEMA) within the National Flood Insurance Program (NFIP). While the NFIP makes flood insurance available and aims at fostering its adoption, recent research identifies an insurance protection gap, underinsurance in at-risk populations, which is usually addressed by top-down measures, such as community policies, incentives or automatic renewals of policies, and affordability programs (Kousky et al., 2019).

The issue of closing the insurance protection gap can also be approached through bottom-up drivers, such as increasing risk perception and awareness (Robinson & Botzen, 2019). Identifying the drivers of flood insurance uptake which can be leveraged to expand insurance adoption has thus increasingly gained traction in the literature

(Atreya et al., 2015; Cannon et al., 2020; Huang & Xu, 2024; Xu & Huang, 2022). Experiencing a flood before taking action and purchasing an insurance policy emerges consistently as a primary factor influencing insurance uptake, indicating predominantly reactive adaptation behavioral patterns (Gallagher, 2014; Veigel et al., 2023). Since proactive insurance uptake is key to close the insurance protection gap, identifying drivers and factors that can turn insurance uptake into a preventive behavior independent of previous experience with flood events is essential to inform resilience measures. Agent-based modeling research, for instance, suggests that tailored, people-centered flood risk communication through social networks can be substantially more effective than traditional top-down government communication (Haer et al., 2016).

Social interactions play a crucial role in determining individuals' decisions, with evidence showing that households increase their flood insurance purchases by 1%–5% when their geographically distant friends experience flooding events (Hu, 2022). This social learning mechanism operates through information dissemination and attention triggering, suggesting that risk perception evolves through both direct experience and indirect experience via social networks. Media coverage, particularly related to climate change, has recently emerged as another significant factor in shaping adaptation decisions (Allaire, 2016; Feldman et al., 2016; Ogie et al., 2022; Xu & Huang, 2022). The impact of social media on human behavior was initially observed in consumer behavior studies and nowadays companies and brands rely on social media marketing to increase their visibility and sales (Pütter, 2017). Dellmuth and Shyrokykh (2023); Anderson (2017) show that social media platforms like Twitter (X), which is used as a data basis in this study, can influence public opinion formation about climate risks through sentiment and framing by key actors, which may subsequently affect citizens' and policymakers' perceptions of climate-related issues such as flood insurance needs. The mechanisms of norm diffusion and opinion leadership on social media could shape how flood insurance uptake is perceived and discussed, potentially influencing both individual decision-making and policy development through the spread of information, misinformation, and varying sentiments about climate adaptation measures (Dellmuth & Shyrokykh, 2023). Previous studies on traditional media coverage show, that spikes in news coverage can lead to increases in monthly growth rates of flood policies, with notably stronger effects in non-coastal counties (Xu & Huang, 2022). These responses exhibit significant socio-demographic heterogeneity, including variations tied to political affiliations, climate beliefs, flood risk exposure, education, and employment status (Xu & Huang, 2022), and thus demonstrating the broad reach of media coverage. While traditional media studies established principles about risk perception and adaptation, social media has enabled researchers to examine these same phenomena through real-time behavioral data. Nowadays, social media is the preferred source of information for many people, especially among younger groups (Feldman et al., 2016). Social media platforms can be effective enablers of substantial households flood loss reduction and preparedness (Anson et al., 2017; Ghosh et al., 2018), with one study finding an average 37% reduction in losses during the 2011 Bangkok flood for households using social media compared to similar households that did not follow flood information on social media (Allaire, 2016). Through their interactive characteristics, social media provide an information source as well as a digital social network for exchange. However, there is lacking evidence of their effectiveness in the recovery phase (Ogie et al., 2022). The content of flood-related long-term social media data reflects these characteristics with distinct patterns for different return periods. The information shared before heavier flood events is less than the one shared prior to floods with moderate return periods, but the impact-related during a more extreme event is higher, as well as the following discussion on responsibilities (Veigel et al., 2025).

Our research investigates the influence of flood-related social media post frequency on flood insurance uptake patterns. We examine how county-level social media activity influences households' flood insurance adoption decisions over a period of multiple years. We test the two hypotheses that (a) the volume of social media information sharing during the 2 quarters post-flood will increase insurance uptake in affected counties, and that (b) Higher volume of flood-related social media posts, will increase long-term risk awareness, thereby leading to sustained increases in policies in force over time.

To test the above hypotheses, we assimilate a panel data set combining historical records of flood occurrence from the National Centers for Environmental Information (NOAA) (National Centers for Environmental Information, 2023), insurance policy subscription over time from the FEMA (FEMA, 2023b), information on counties' participation in the Community Rating System (CRS) (FEMA, 2023a), and geo-located social media posts related to flooding (de Bruijn et al., 2017, 2019). Using a cumulative linked mixed model approach, we analyze how different types of social media engagement correlate with insurance uptake changes while controlling for top-down measures factors, geographical variability, and reactive insurance changes. This modeling approach

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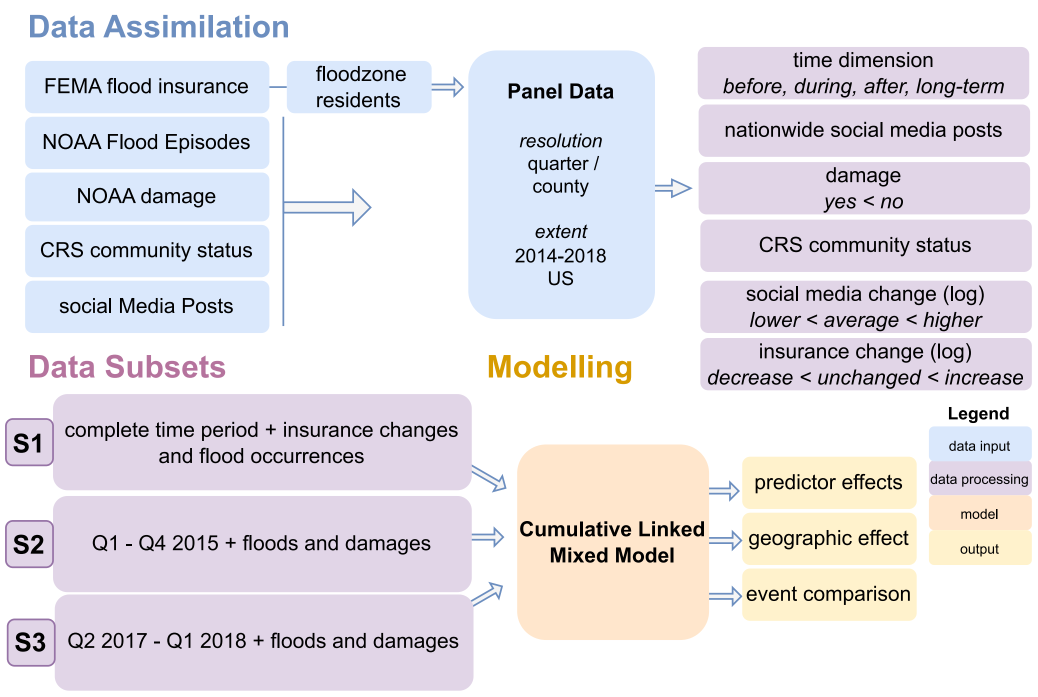


**Figure 1.** Methodological pipeline of the data assimilation, subsets, and modeling approach developed in this study. Figure headings are consistent with the subections in this section (Materials and Methods). We combine six data sources to compile a panel data set with quarterly timestep and a county geographical resolution (top left, blue boxes). We process the values into discrete bins (top right, purple boxes), then select three subsets based on flood occurrence, events and damages (bottom left, purple boxes). Using a Cumulative Linked Mixed Model approach we quantify predictor effects and geographic effects, which we compare for the different subsets (bottom right, yellow boxes).

allows accounting for both observed variables and unobserved county-specific characteristics that might influence insurance adoption decisions and disentangle the effects of different variables through interaction effects. Unobserved effects could be differences in dempgraphics of the different counties, which may influence insurance decisions and social media usage.

## 2. Materials and Methods

A complete overview of our methodological pipeline is provided in Figure 1, starting from the data sources and culminating with the model outputs. Our modeling pipeline is developed with the main goal of quantitatively describing the effect of 38,129 social media post counts in estimating household flood insurance uptake for the whole continental US, while including in the modeling formulation also other potential climatic and contextual predictors. To limit policy influences on the insurance market we evaluate the time period between 2014 and 2018, where no nationwide legislative changes were made. We provide a summary of the different components of our methodological pipeline below.

### 2.1. Data Assimilation

The top left, blue boxes in Figure 1 refer to the data assimilation we carry out in this study to combine data from different sources as follows. The primary variables we incorporate in our data set include: active policies per floodzone resident (*FEMA flood insurance* in Figure 1), NOAA flood records, NOAA flood damage values per county in each quarter, county-level Community Rating System (CRS) participation rates (*CRS community status*), and number of flood-related social media posts. We delimit the study period specifically to fall between two major legislative changes: the Homeowner Flood Insurance Affordability Act (2014) (Eastman, 2015) and the Disaster Recovery Reform Act (2018) (Schroeder, 2018). In 2015 flood insurance subsidies were partially eliminated (Eastman, 2015). Three years later multiple changes were made to the program in which the funding for FEMA was increased and individual assistance programs were made available (Schroeder, 2018). Our selected time period ensures that the flood insurance uptake cannot be attributed to major legislative changes. We

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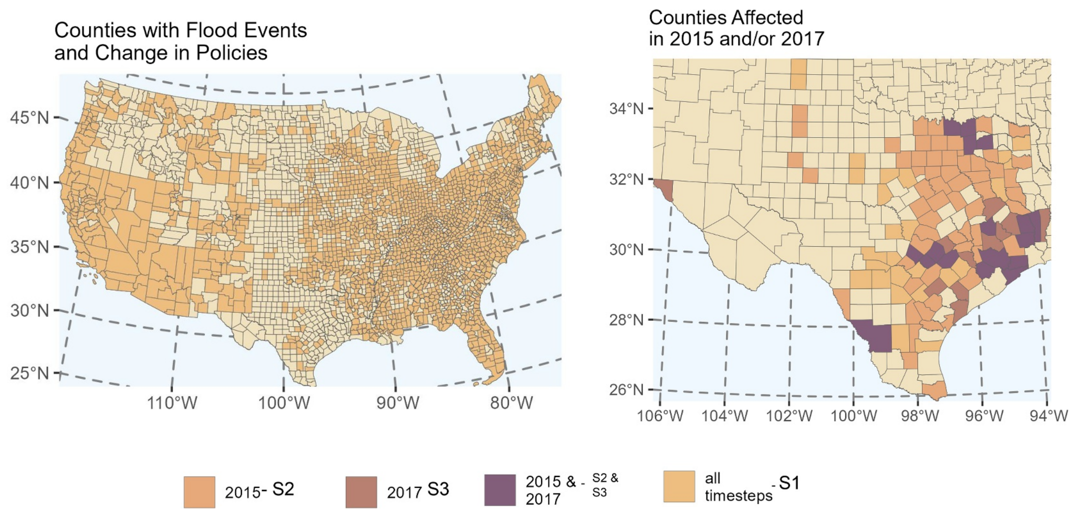


**Figure 2.** Geographical distribution of the three subsets considered in this study. The left map shows all counties with sufficient data, where at least one flood episode occurred between 2014 and 2018. The right map of Texas shows a fraction of the subsets S2 and S3, which consist of the counties that experienced flood damage during the 2015 Texas-Oklahoma flood and/or Hurricane Harvey in 2017.

process all data records first by aggregating them consistently on a county level with a quarterly time scale. We aggregate the data quarterly, since the insurance renewal period is 1 year, but we aim to capture seasonal variations in flood occurrence.

We removed counties without insurance policies or flood-related social media posts from our analysis. For the remaining counties we approximate missing values in the social media posts using linear interpolation. Second, we segment each variable and transform real-valued variables in ordered categorical variables. Figure 1 (top right, purple panel) summarizes the steps undertaken in such data processing. A more detailed description of variable transformation and threshold selection for the discretization of each variable retrieved in the data assimilation is reported in the next section.

### 2.2. Data Subsets

As shown in Figure 1 (bottom left, purple boxes), we split the complete data set into three different subsets, which we use to train different models for comparison. We train and analyze a cumulative linked mixed model (CLMM) for each subset. A comparison of the model outputs across the different subsets allows us to assess the stability of relationships between social media activity and insurance uptake while controlling for temporal variations and variations of flood characteristics. In detail, the three subsets are: S1: Complete time period 2014–2018, (National Centers for Environmental Information, 2023); S2: Q1–Q4 2015 (Texas-Oklahoma flood and tornado outbreak period, floods and damages) (National Centers for Environmental Information, 2015); S3: Q2 2017 through Q1 2018 (Hurricane Harvey period, floods and damages) (Brennan, 2017). In Figure 2 we show the geographical extent of S1 in the left map and a more detailed look at Texas, the state affected the most in both subsets S1 and S2 on the right. We can see that there is a geographical overlap of the two events around the Houston area (dark purple color) and the extent of floods and damages during the 2nd quarter of 2015 (S2) extends further inland.

### 2.3. Modeling

We develop a CLMM to estimate the probability of being assigned to a class of insurance change as a function of five potential predictors (event phase *-before*, *during*, *or after floods-*, CRS community status, amount of social media posts within a county, nationwide amount of social media posts, and county ID). The definition of each predictor is described in Section 2.1. This model class was developed to perform regression tasks on ordered factors, with the possibility to include random effects for entities with multiple observations, which is represented in our data set.

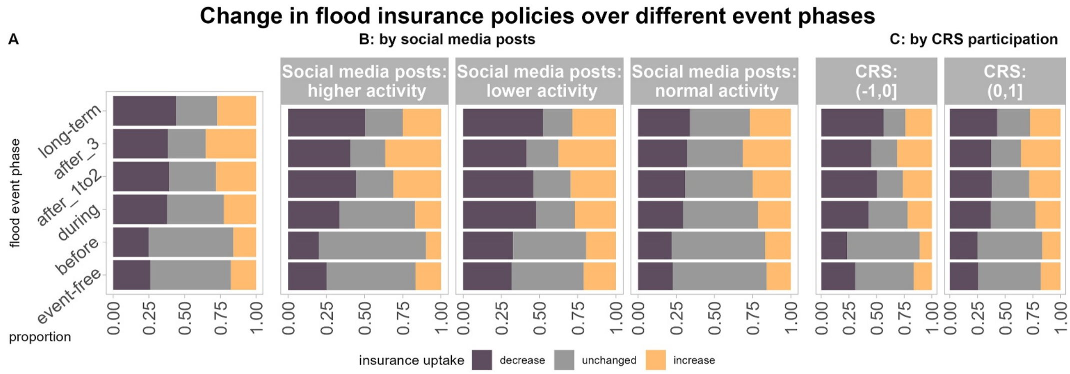


**Figure 3.** Distribution of change in insurance uptake (*decrease*, *unchanged*, *increase*) across the different flood phases for S1. The shared *y*-axis labels represent the time dimension categorized in the event phases and event-free times. The left panel aggregates all the analyzed data, showing that unchanged insurances (gray bars) are concentrated in the phase before the event and during event-free times. The middle three panels provide a disaggregated visualization of the insurance change for different levels of social media activity. Unchanged insurances are cumulated within the normal social media activity category and the orange and purple bars (decrease and increase) appear larger in the other panels. The distribution within the CRS categorization (right panels) is very similar for both classes.

## 2.4. Data Transformation and Definition of Model Variables

### 2.4.1. Time Dimension

We reduce the time dimension of our data into four categories. The top right panel in Figure 3 shows the divisions of the variables including the time dimension (simplified in Figure 1 as "*before*," "*during*," "*after,*" "long-term"). We further dissect the time dimension into the categories "*event-free*," "*before*," "*during*," "*after* 1–2," "*after* 3+," "*long-term*." A flood episode is defined as an accumulation of inundation events in different areas within a county that share the same meteorological or hydrological origin. This means that if two areas in a county report incidents of flooding a few days apart, but these floods are a result of the same meteorological condition, we group them into a single flood episode. This way we make sure that we are not over-estimating floods that proceeded slowly or were reported with a time lag. If a flood episode happens in a county in a specific quarter we label the observation as "*during*," and the two quarters following the episode are labeled as "*after*," with two subdivisions. We label the instances as "*after* 1–2" if there were one or two flood episodes related to the time-step and "*after* 3+" if there were three or more episodes. This allows us to distinguish between quarters in which multiple events occurred and those that were affected by only one event. We define a long-term phase, to understand effects of flooding, in the quarters not related to the immediate response to the flood, but where the social memory of a flood might still be present. Here, we considered the time period 3–5 quarters after an event as a "*long-term*" phase and the quarter before is labeled as "*before*" since in some cases there can be an increase in social media posts when warnings are available. We considered the time period 3–5 quarters after an event as a "long-term" phase based on prior literature showing that flood insurance uptake typically peaks 1–2 quarters post-event before slowly returning to baseline levels (Gallagher, 2014). When new floods occur during aftermath periods of previous events, this quarter is labeled as "during," then we reclassify quarters based on the most recent event's characteristics.

### 2.4.2. Social Media Data

The social media data was collected by de Bruijn et al. (2019). In this data set, posts from the Twitter API (now known as X) were collected in 11 languages. The posts were additionally geotagged as described in de Bruijn et al. (2017). A database of geographical locations and flood-related textual posts collected through the streaming API were processed using toponym recognition, location scoring, and BERT classification. For this specific study, we analyze posts written in English and located within the U.S. from 2014 to 2022, and containing flood-related keywords (flood, flooding, inundation). To calculate a variable that represents whether a time period is characterized by more or fewer flood-related social media posts than usual, we subtract the county mean over the whole time series from the number of social media posts. We use the county-specific standard deviation to determine whether the observation was higher/lower than usual or unchanged. With this approach we also generate a feature for which the changes in Twitter users over time is normalized compared to using the total count of tweets. The resulting categories are defined as "*normal activity*" if observations are within the county mean value $\pm 0.1*$ standard deviation, "*higher activity*" for larger positive deviations, and "*lower activity*" for larger negative deviations. The resulting proportions of the social media post change variable values for each event phase are shown in Figure 3 in the middle panels. The progression of social media posts over time is shown in the Figure S1 in Supporting Information S1.

#### 2.4.3. CRS and Flood Damage Data

For CRS participation, we calculate the relative community count extracting initial entry dates from the community status book (FEMA, 2024) and min-max-scaling these values for each county. The model input for the CRS variable is continuous, however, for ease of visualization, Figure 3 (right panel) shows the proportion of insurance change classes and flood phase for two distinct subsets of CRS participation. Here, we can see that the increase in insurance that is associated with the two quarters after 3+ flood episodes only occurs within the higher CRS category. However, the fraction of decreasing policies in the third and fourth quarters after the event is higher for the counties with high CRS participation. The flood damage reported by NOAA variable is used as to extract the subsets S2 and S3 but not included as a predictor variable in the models, since including it reduced the model performance. First the flood damage is summed up for each quarter and county. The flood damage data is divided into "*damage*" if the value was larger than 0 and "*no damage*" if it was reported as 0.

#### 2.4.4. Insurance Policy Data

We calculate the relative stock of policies by dividing the number of active NFIP policies in each county by the estimated number of residents living in FEMA-designated flood zones within that county. Flood zone residents are determined by intersecting census population data with FEMA flood zone boundaries and building footprint data (Titus, 2023). The change in active policies per flood zone resident $\Delta P_{i,t}$ serves as our model output variable, that is, the response variable, and is calculated as follows:

$$\Delta P_{i,t} = \frac{\text{Policies}_{i,t}}{\text{Residents}_{i,t}} - \frac{\text{Policies}_{i,(t-1)}}{\text{Residents}_{i,(t-1)}} \tag{1}$$

where $i$ refers to the county and $t$ represents the time step (quarter).

The categorical relative insurance change is calculated by subtracting two sequential time-steps (at time $t - 1$ and $t$), and applying a log transformation:

$$Y_{it} = \begin{cases} \text{if} \quad \log_{10}(\Delta P_{it} + 1) < -\alpha_1 & \text{'decreasing'} \\ \text{if} \quad \log_{10}(\Delta P_{it} + 1) > \alpha_2 & \text{'increasing'} \\ \text{else} & \text{'unchanged'} \end{cases} \tag{2}$$

where $\alpha$ represents the threshold for significant change resulting in a three-level ordinal scale. This scale is defined by the thresholds $[-0.0843, \ -5.98e - 05]$ for decreasing insurance policies, $(-5.98e - 05, 0]$ for unchanged policies, and (0,0.0897] for increasing policies. We selected the values of these thresholds so that an interval contains an approximately equal number of points possible. The resulting proportions of the insurance change variable values for each event phase are depicted in Figure 3.

### 2.5. Cumulative Linked Mixed Model

CLMMs are statistical models used for analyzing ordinal data that extend regular cumulative link models by incorporating random effects to account for hierarchical or grouped structures in the data. CLMMs are designed for ordinal outcome variables with natural ordering (decreasing < unchanged < increasing insurance uptake) by modeling cumulative probabilities across categories while avoiding the assumption of equal intervals between categories. We model the cumulative probabilities of ordinal responses (in our case insurance change category) using multiple thresholds while allowing for both fixed effects and random effects (to account for repeated observations in one entity), producing outputs in the form of log-odds ratios that indicate the likelihood of an

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observation falling into a higher versus lower category on the ordinal scale. The CLMM is based on the *ordinal* package in R (Christensen, 2023). Our implementation is based on Agresti and Natarajan (2001). This methodology is ideally suited for our application because we are comparing the effects of several independent variables on the probability of decreasing or increasing flood insurance. While we account for the effects of the CRS and the flood event itself by using the disaster phases as a predictor (model input), there may still be an effect of unobserved variables. We expect for them to be characterized by a geographical variability, since each county has a different flood history, risk perception, topology, and political inclinations (Atreya et al., 2015; Knighton et al., 2020). To account for this we included per county random effects term alongside the fixed effects of our variables. CLMMs assume the random effects to be distributed normally. In our study this means that we assume that the deviation of the insurance uptake in one county compared to the mean insurance uptake in all counties is normally distributed. The main potential limitation is residual spatial correlation not captured by county-level random effects. With this modeling approach we compute the following three output.

First, the *threshold parameters* $(\theta_j)$ for each variable $j$, which indicate the cut-points between ordinal categories of insurance change. Second, the *fixed effects* $(\beta_k)$ for each county $k$: these coefficients related to our predictors indicate the strength and direction of the relationship between each predictor and the likelihood of moving between insurance change categories. Positive coefficients suggest an increased probability of higher insurance uptake, while negative coefficients indicate the opposite. Finally, the *random effects variance*: this parameter quantifies the extent of county-level variation in insurance uptake patterns that is not explained by our fixed effects predictors. The CLMM is defined as described in Agresti and Natarajan (2001):

$$logit(P(Y_{i,t} \leq j)) = \theta_j - \left(\beta_1 X_{i,t}^{posts_c} + \beta_2 X_{i,t}^{floods} + \beta_3 X_{i,t}^{posts_n} + \beta_4 X_{i,t}^{CRS} + u_i\right) \tag{3}$$

$Y_{i,t}$ represents the ordinal insurance change category at time $t$ for county $i$, $\theta_j$ contains the threshold parameters for the cumulative probabilities of the random effects and the predictor effects for predictor $j$. These thresholds represent the boundaries between adjacent ordinal categories on a latent continuous scale. The model estimates these values by maximizing the likelihood function. $\beta_k$ are the regression coefficients, $X_{i,t}^k$ represent our predictor variables at time $t$ for county $i$, and $u_i$ accounts for random effects at the county level.

As the random effects are assumed to be normally distributed, we use the following logit link function on the simulated probabilities:

$$logit(p) = \log\left(\frac{p}{1-p}\right) \tag{4}$$

The CLMM is optimized using maximum likelihood with adaptive Gauss-Hermite quadrature for the random effects integration (Olver, 2010). We finally compute the model performance based on the Bayesian information criterion (BIC) and the Akaike information criterion (AIC), which is based on the number of model parameters and the information score (Akaike, 1976), with lower values indicating a better model.

Our results consist of three models, based on three different subsets (S1,S2, and S3), with each subset containing five predictor variable (event phase, CRS, county social media posts, nationwide social media posts, and county). S1 contains 38,129 observations from 48 states, S1 consists of 2546 observations from 46 states, and S2 contains 2386 observations from 43 states.

## 3. Results

The results of our data-driven analysis are based on the outputs obtained from the cumulative linked mixed models with logit links (see Figure 1) to identify drivers of flood insurance uptake across three different temporal scales and flood events with focus on social media activity. County social media posts are converted to categorical variables based on standardized deviations from county-specific means as described above. Nationwide social media posts are aggregated as the total count of flood-related posts across all US counties for each quarter, then log-transformed to address skewness. CRS participation is entered as a continuous variable representing the number of participating communities relative to the number of cities in a county. All model parameter estimates are summarized in Table 1 along with the levels of significance. The models show progressive improvements of

**Table 1**
*Estimated Parameters and Significance Levels of the Cumulative Linked Mixed Model for Three Subsets of Our Data Set*

| | S1 | S2 | S3 |
|---|---|---|---|
| phase: | | | |
| before | 0.00 (0.04) | | |
| during | −0.05 (0.03) | −0.05 (0.17) | −0.05 (0.22) |
| after 1–2 | −0.02 (0.03) | −0.18 (0.18) | 0.06 (0.23) |
| after 3 | 0.23 (0.06)*** | 0.58 (0.24)* | 0.20 (0.30) |
| long-term | −0.17 (0.03)*** | | |
| social media: | | | |
| lower activity | −0.15 (0.03)*** | −0.24 (0.12)* | −0.37 (0.12)** |
| higher activity | −0.01 (0.04) | −0.36 (0.15)* | 0.09 (0.17) |
| nationwide posts | −0.15 (0.01)*** | −0.24 (0.08)** | 0.09 (0.05) |
| CRS | −0.00 (0.05) | −0.26 (0.22) | 0.16 (0.22) |
| decrease \| unchanged | −0.71 (0.04)*** | −0.30 (0.20) | 0.06 (0.25) |
| unchanged \| increased | 1.22 (0.04)*** | 0.81 (0.21)*** | 0.78 (0.26)** |
| Log Likelihood | −39807.40 | −2473.95 | −2252.64 |
| AIC | 79638.79 | 4967.90 | 4525.28 |
| BIC | 79741.38 | 5026.19 | 4583.05 |
| Num. obs. | 38129 | 2512 | 2386 |
| Groups (GEOID) | 1907 | 732 | 677 |
| Variance: GEOID: (Intercept) | 0.41 | 1.46 | 1.46 |

*Note*. $***p < 0.001$; $**p < 0.01$; $*p < 0.05$.

AIC and BIC values, with Model 3 (S3, AIC: 4530.12) demonstrating the best overall fit. Model 1 (S1, AIC: 79604.41) is fitted on the complete time period with 38,129 observations across 1,907 counties. The temporal structure of flood impacts is captured through different phases (before, during, after 1–2 quarters, after 3+ flood episodes, and long-term). The estimated model effects ($\beta$) are with respect to the baseline category, which is the flood event free time for S1 and the values in the quarter before the event for S2 and S3. In the following sections we analyze the shift of probabilities in insurance uptake change class resulting from the different predictors. We focus on nationwide social media posts for the different event phases of S1 and S2. Considering the full data set we evaluate how the insurance uptake changes in the quarters after the flood and also long-term disentangling the results for below or above average social media activity. We find a significant geographical variability between the counties (see also Figure S2 in Supporting Information S1) indicating that unobserved, county-specific variables influence insurance decisions.

### 3.1. Effect of Flood Event Phases

The most pronounced effect, revealed consistently by all models, is an increased uptake of insurance policies after multiple flood episodes occurred in one quarter (S1: $\beta = 0.23$, $p < 0.001$; S2: $\beta = 0.58$, $p < 0.05$; S3: $\beta = 0.20$, not significant). This corresponds to a spike in insurance uptakes in the two quarters following a flood. This reactive behavior considering flood insurance uptake in the U.S has been reported consistently by previous studies (Gallagher, 2014; Veigel et al., 2023) and is further corroborated by out findings. A similar effect is not visible after quarters with 1–2 flood episodes, which is likely because fewer people are affected and thus less are motivated to take up flood insurance. The shift of probability from the "*unchanged*" insurance class to the "*increased*" insurance class attributed to the flood episodes ("*after_3*") is significant for S1, remains significant in S2 ($\beta = 0.58$, $p < 0.05$) but not in S3, for which the effect is also positive but non-significant. Given the enormous impact of Hurricane Harvey, displacing multiple thousands of people and resulting in over USD 128 billion of damages (Blake & Zelinsky, 2018), most likely the recovery period was longer and the insurance uptake did not increase as quickly in the quarters following the event.

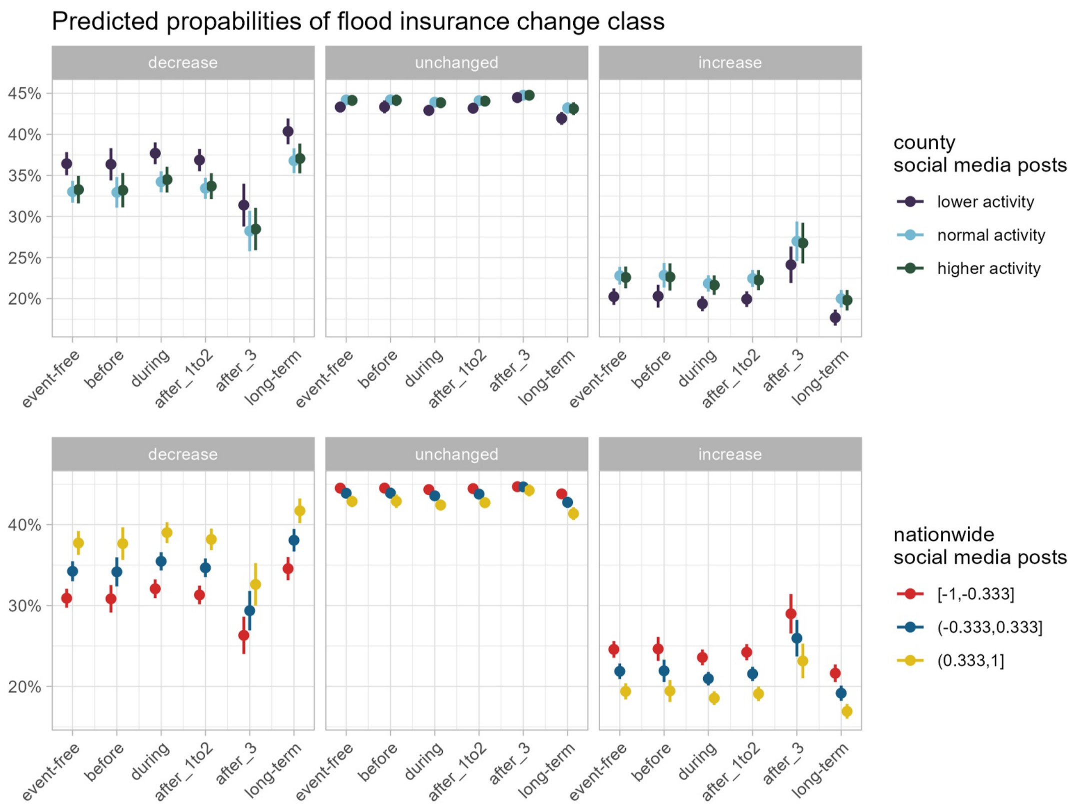


**Figure 4.** Modeling results presented in a set of dot-and-whisker plots representing predicted probabilities of changes in flood insurance behavior over time, stratified by social media activity. The top panel shows county-level social media activity and the bottom panel shows nationwide social media activity. Nationwide social media activity are represented as the scaled and normalized total tweet counts for the whole US. Each panel has three subplots for the possible flood insurance change classes: decrease, unchanged, and increase. For S1 the highest probabilities are overall in the unchanged class. The phase after an event is strongly associated with higher probabilities of increasing insurances.

The long-term effect shows a significant negative development in insurance uptake probability ($\beta = -0.17$, $p < 0.001$), potentially indicating a decay in risk perception over time. This is consistent with observation that fluctuations in insurance uptake are usually associated with major events (Gallagher, 2014). Figure 4 represents the changes in insurance uptake class related to each county social media activity class (top) and the nationwide social media posts class (bottom), showing the differences of insurance change for different flood phases overall and for each social media activity class. The highest probability changes overall are acquired for the "*unchanged*" insurance category across all flood phases, which shows that for S1 the model with the highest likelihood categorized most values in the "*unchanged*" insurance uptake category (see also Figure S3 in Supporting Information S1). This means that, if we include more observations, the likelihood of a data point being assigned in the "*unchanged*" insurance category is higher, compared to the subsets, where we observe the opposite. Figures 5S2 and 6S3 show the highest probabilities for the "*decrease*" in insurance category.

### 3.2. Social Media Influence

Models S2 and S3, focusing on specific events—the Texas-Oklahoma flooding and Hurricane Harvey, respectively—reveal distinct patterns from the general model. In S2, both lower and higher social media activity show significant negative associations with the insurance class probability (see coefficients in Table 1: $\beta = -0.24$ and $\beta = -0.36$, respectively, $p < 0.05$). This suggests that—during major events—social media posts might have different dynamics with larger variations between predictors and different relevant drivers for each event. To better understand the mixed effect of lower and/or higher county social media posts, we additionally ran a model that includes interaction terms for the predictors. The $\beta$ values and significance levels are

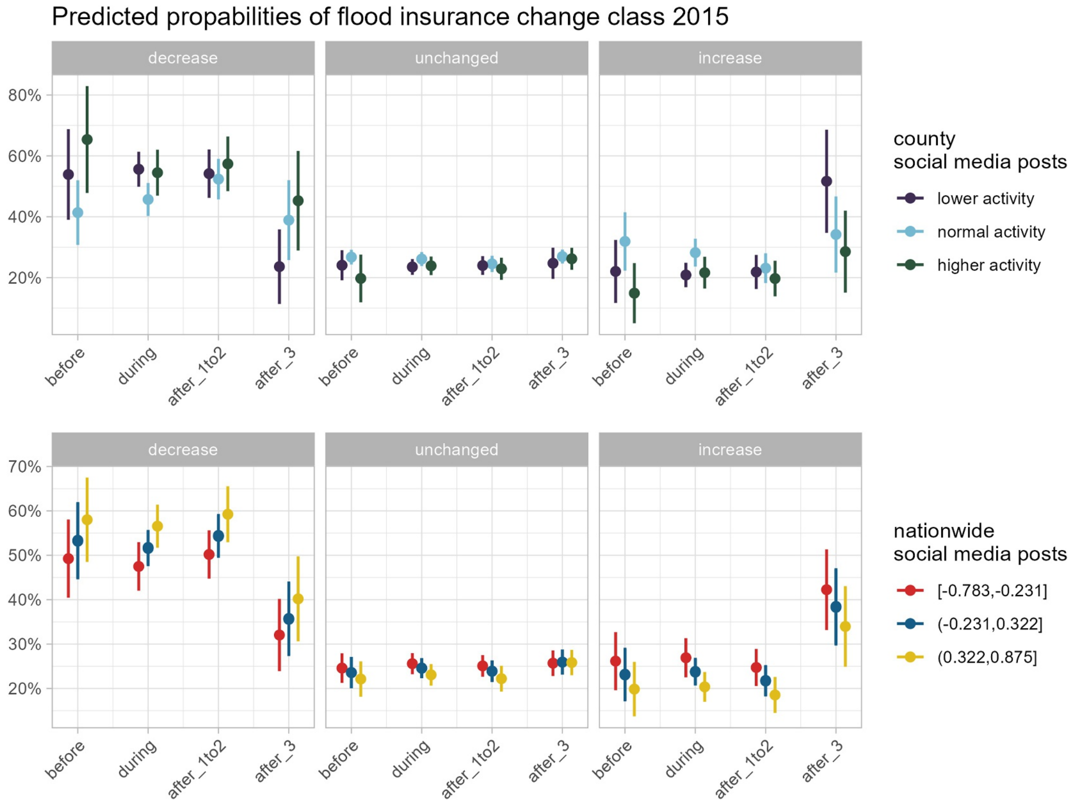


**Figure 5.** Modeling results for S2 presented in a set of dot-and-whisker plots representing predicted probabilities of changes in flood insurance behavior over time accounting for interaction effects, stratified by social media activity. The top panel shows county-level social media activity and the bottom panel shows nationwide social media activity. Nationwide social media activity are represented as the scaled and normalized total tweet counts for the whole US. Each panel has three subplots for the possible flood insurance change classes: decrease, unchanged, and increase. For S2 the highest probabilities are overall in the decreasing class. The phase after an event is strongly associated with higher probabilities of increasing insurances, and this is intensified by lower social media activity.

reported in Table S1 in Supporting Information S1. The model performance is comparable, but slightly lower (AIC, S1: 79604.41; S2: 4969.65; S3: 4530.12).

Figures 5 and 6 show the accounting for interaction effects. For S2 Figure 5 shows an increase in policies is mostly expected after 3+ flood episodes and the probability further intensifies if there is lower social media activity (see Table S1 in Supporting Information S1, $\beta = 1.23, p < 0.05$). We can observe inverse dynamics before the event where an average amount of social media posts results in a higher probability of insurance increase. The analysis of Figure 5 reveals complex relationships between social media activity and insurance uptake. In S1 and S2, lower social media activity is significantly associated with decreased insurance uptake probability ($\beta = -0.15$, $p < 0.001$), possibly suggesting mistrust in information that is not backed up quickly by observations. Figure 6 shows that, for S3, higher activity on social media before the event is associated with higher probabilities of decreasing policies, but after 3+ flood episodes more post result in a higher probability of increasing policies, however those effects are not significant (see Table S1 in Supporting Information S1).

National-level social media activity consistently shows a negative association for models S1 and S2 (S1: $\beta = -0.15$, $p < 0.001$; S2: $\beta = -0.24$, $p < 0.01$), suggesting that broader social media discourse might actually dampen local insurance adoption. The nationwide posts represent fluctuations of overall attention to the topics of floods, which for most users may not contain local or actionable information and therefore may not promote positive changes in insurance uptake. Higher values of nationwide post trough all event phases are associated with increasing insurances, which is distinct from the other models. Again, the phase after an event is strongly associated with higher probabilities of increasing insurance. This effect, however, is not significant and the difference is very small. Figure 6 shows that the effect is consistent for all phases of the event.

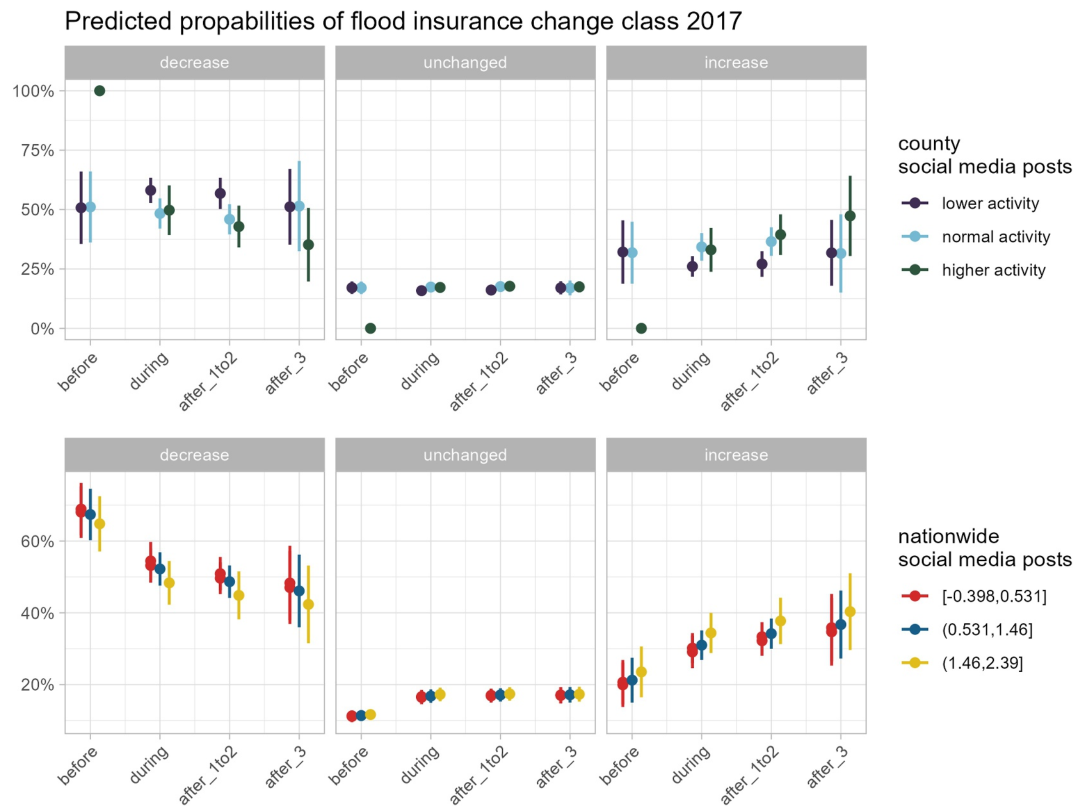


**Figure 6.** Modeling results for Hurricane Harvey presented in a set of dot-and-whisker plots representing predicted probabilities of changes in flood insurance behavior over time, stratified by social media activity. The top panel shows county-level social media activity and the bottom panel shows nationwide social media activity. Nationwide social media activity are represented as the scaled and normalized total tweet counts for the whole US. Each panel has three subplots for the possible flood insurance change classes: decrease, unchanged, and increase.

## 4. Discussion and Conclusion

The increasing frequency and severity of flood events globally highlight the importance of understanding what leads to the implementation of different top-down and bottom-up risk management measures. This includes knowing if information distributed via social media, can influence protective actions, particularly insurance uptake. Understanding the relationships between flood related social media posts and insurance uptake on a large scale is very complex, with local dynamics possibly having a major effect on individuals' decision-making. Our study examines if social media posts correlate with flood insurance uptake in the United States accounting for temporal variations during different phases of flood events. Overall the effects we observe are small but significant.

In our most general model (S1) we find that lower activity during flood events is significantly negatively correlated with insurance uptake, which could indicate that the overall positive effect on insurance uptake during this phase is related to better immediate response coordination through social media. Although we do not directly analyze it with this data set, this is consistent with studies evaluating the content of social media posts from the same source, which is most actionable at the time of the event or very shortly after (Han & Wang, 2019; Li et al., 2023; Veigel et al., 2025).

For S1, we observe that lower social media activity correlated with low probabilities of increasing insurance, which could indicate the beneficial impact of social media activity on insurance decisions. This is aligned with the findings of past studies, which showed that media activity increases risk perception of climate change (Xu & Huang, 2022) and that the use of social media can positively impact adaptation (Allaire, 2016).

Simultaneously, we show that the effect is more diverse than previously described (Allaire, 2016; Han & Wang, 2019; Li et al., 2023; Xu & Huang, 2022) and that higher social media activity after an event is also

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negatively associated with insurance change. Multiple factors could explain this, one reason for the increase and decrease in insurance attributed to social media posts may be the inequitable distribution of funds within FEMA. Deficiencies at the state level, such as a lack of knowledge about underserved communities, inadequate methods for locating and interacting with underserved communities, and a lack of local participation in policy discussions observed in some areas lead to reduced trust in FEMA (Vilá et al., 2022). Additionally, misinformation on social media may contribute to uninformed insurance decisions (Treen et al., 2020). Climate change misinformation may hinder adaptation efforts by creating doubt about climate risks, increasing political polarization, and stalling support for protective measures like flood insurance, while research methodologies from this climate misinformation study—including social network analysis to track opinion leaders, sentiment analysis to examine how flood risks are framed on social media, and investigation of echo chambers among different stakeholder groups—could be transferred to understand how misinformation about flooding spreads and influences public perceptions of flood preparedness measures (Treen et al., 2020). Most studies work with a tailored keyword extraction or questionnaires eliminating some of the information shared on the topic of floods (Allaire, 2016; Han & Wang, 2019; Li et al., 2023). In these cases the studies are more likely to observe consistent effects, that may only be the reality for a fraction of the population. More theoretical approaches assume that the information shared and received online or in social networks is free of misinformation (Haer et al., 2016; Houston et al., 2015). Although more research needs to be conducted on this topic a review by Daume (2024) found that there is substantial online misinformation connected to disasters. Also studies in other domains have shown the contribution of social media to misinformation, for example, belief in conspiracy theories (Enders et al., 2021).

Our findings show that lower social media activity during disasters correlates with a decreased probability of insurance uptake, while post-flood lower activity shows a positive association with policy adoption. Another factor to take into account for this observation is the age of people accessing social media platforms and the digital divide, meaning that risk information on social media reaches only certain demographic groups (Feldman et al., 2016).

Social media post content analysis might help disentangle different sentiments and attitudes beyond the amount of flood-related posts. Recent studies on the sentiment behind Twitter posts on the environment and climate change is far more likely to be negative than positive (Amangeldi et al., 2024). Bryan-Smith et al. (2023) proposed a method to extract sentiment from flood-related Tweets in real time, finding that there is a predominantly negative sentiment associated these posts as well. Considering, that both of these analysis were conducted on a large scale, posts discussed online nationwide may contain more negative sentiment compared to the county-level posts and thus may lead to frustrations hindering adaptation decisions. During the 2018 flood in Shouguang City in China, "*feeling sad about the disaster*" was the most prevalent topic shared in districts that had not been directly affected, while posts connected to the sentiment of being "*thankful for the rescue*" were shared only in the districts directly affected (Han & Wang, 2019). The same may be applicable to a more negative effect of county-level posts, that we observed for the long-term development of insurance uptake. A high occurrence of negative sentiment associated with social media posts following the event was observed for the flooding that occurred in 2021 in parts of Western Europe (Li et al., 2023). Wile information from official sources are still more reliable than social media posts, the experiences and resources shared on social media platforms present a complimentary source of information.

Recent research on the effect of social media posts focused on immediate protective actions. Our research extends this understanding to longer-term adaptive behaviors like insurance adoption. By integrating these perspectives with our empirical analysis of NFIP policy data, NOAA flood records, and social media activity, we provide new insights into how digital discourse influences long-term adaptive behaviors. Our findings suggest that while social media can significantly influence insurance uptake, its effectiveness based on timing and other factors, which could be content related, with particularly strong effects observed in the post-flood and long-term periods. The significant but varying effects we observed in social media influence on insurance uptake suggest that the role of such platforms in risk management extends beyond the immediate disaster response phase, yet they should focus on highlighting actionable and helpful information to users that could be tailored to their situation to avoid inverse effects, like the decrease of insurance policies.

## Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

## Availability Statement

Data is available under the cited links and sources. Historical records of flood occurrence are provided by the NOAA (National Centers for Environmental Information (2023), https://www.ncdc.noaa.gov/stormevents/), insurance policy subscription over time from the FEMA (FEMA (2023b), https://www.fema.gov/about/openfema/data-sets#nfip), information on counties' participation in the CRS from FEMA (FEMA (2023a), https://www.fema.gov/fact-sheet/community-rating-system-overview-and-participation). Twitter post location identification is based on an algorithm developed by de Bruijn et al. (2017). The data set of flood related Twitter posts from de Bruijn et al. (2019) is available at https://www.globalfloodmonitor.org/.

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