Social Learning about Climate Risks

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Abstract

This paper examines whether social learning facilitates climate risk perception updates. We estimate a network difference-in-differences (NDID) model with a social network adjacency matrix constructed from the Facebook Social Connectedness Index (SCI). We find that regional flooding brought by Hurricanes Harvey and Irma increased flood insurance policies in all US counties to the extent of their social network proximity to the flooded areas. Such social learning induced 250,000 more policies in flooded counties and 81,000 more policies in unflooded counties in three years. We find evidence of the salience effect but no support for adverse selection or over-insurance.

Keywords: social learning, flood insurance, Hurricane Harvey, social network, SCI

JEL codes: D12, Q54, G22, R2

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Introduction

Formulating up-to-date climate risk perceptions is important for climate change adaptation and mitigation. Studies have shown that people learn from personal disaster experiences to update their climate risk perception, as reflected in adaptation behavior such as flood insurance take-up (Gallagher, 2014; Kousky, 2010) and discounted housing price (Atreya, Ferreira, & Kriesel, 2013; Beltrán, Maddison, & Elliott, 2019). However, relying on personal experiences of rare disaster events to learn about climate risks leads to a slow updating process. Instead, if decision-makers can account for peer experiences in their climate risk perception updates, i.e., social learning, they will gain many more opportunities to learn and thus adapt much faster. This study tests this hypothesis by investigating whether major regional floods caused by Hurricanes Harvey and Irma in 2017 increased county-level flood insurance take-up nationwide through a social learning process.

A growing social finance literature has shown that information shared through social networks influences financial behaviors (Hirshleifer, 2020; Kuchler & Stroebel, 2020). For instance, peers' financial experience can affect individuals' bankruptcy decisions (Kleiner, Stoffman, & Yonker, 2020) and debt use (Kalda, 2020). Friendship networks on social media such as Facebook can help facilitate international trade relationships (Bailey, Gupta, Hillenbrand, & Kuchler, 2021), share housing price information (Bailey, Cao, Kuchler, & Stroebel, 2018b), influence housing and mortgage choice (Bailey, Dávila, & Kuchler, 2019), claims for the Earned Income Tax Credit (R. Wilson, 2019), and choice of cell phones (Bailey et al., 2022). During disasters, social media networks can help provide instant information (Dong, Li, Zhang, & Cai, 2018) that may help people outside the disaster areas update their risk perception. For instance, during the

COVID-19 pandemic, regions with strong Facebook friendship connections with countries that suffered large outbreaks (Ben Charoenwong, Kwan, & Pursiainen, 2020) and individuals with greater friend exposure to local COVID-19 cases (Bailey et al., 2020) were more aware of the risk and complied more closely with mobility restrictions. Likewise, the Facebook friendship network may facilitate social learning about climate risks.

In this study, we convert the county-to-county Facebook Social Connectedness Index (SCI) (Bailey, Cao, Kuchler, & Stroebel, 2018a) to a social network adjacency matrix, which is then used as the network for social learning. We use two major hurricanes as a case study: Hurricane Harvey which made landfall in Houston, Texas on August 24, 2017, followed by Hurricane Irma which made landfall in Cudjoe Key, Florida on September 10, 2017. To measure changes in climate risk perception as reflected in climate adaptation behavior, we investigate National Flood Insurance Program (NFIP) take-up. Social learning in the context of climate risk is of particular interest for two reasons. First, most people underestimate climate risks and do not adapt. For instance, 40% of people in high-risk flood zones are "not at all" worried about flooding (Bakkensen & Barrage, 2017), and only 20% of those flooded during Hurricanes Sandy and Harvey had flood insurance (City of New York, 2013; Yu, 2017). Social learning may have a better chance than scientific communication in helping correct risk perception bias because peer experiences of climate disasters are affective and associative (Weber, 2010). Second, flood insurance take-up as an adaptation triggered by social learning has an ambiguous social welfare effect because of potential adverse selection and over-insurance that result in inefficiency. Our study investigates these unique concerns about flood insurance.

With the social network adjacency matrix constructed from the Facebook SCI, we estimate a Network difference-in-differences (NDID) model, which is an extension of the Spatial Difference-in-differences (SDID) model (Delgado & Florax, 2015). Flooding increased the salience of local flood risk for both flooded and unflooded areas, with the flooded areas randomly assigned by nature. The salience of the risk signal varies because homeowners nationwide resonated with their flooded peers to the extent of their social connection with the flooded region. The NDID framework allows for the exploration of a complete social network and thus our results have a social learning interpretation per the social learning literature (Mobius & Rosenblat, 2014). Decision-makers in flooded areas potentially learn from both personal experience (direct effect in the NDID) and peer experience (indirect effect), whereas those in unflooded areas only learn from peer experience (indirect effects). To our knowledge, we are the first to convert the Facebook SCI to a social network adjacency matrix to study social learning behavior. We formalize the information externality of climate disasters (Gallagher, 2014; Muller & Hopkins, 2019) in a social network structure and add to the insight that social connectedness mediates the reaction to a distant disaster (Hu, 2021; Ratnadiwakara, 2021), which focuses on a bilateral relationship without a social context.

Our identification strategy departs from the technology adoption studies that conclude social learning from peer effects of adoption (Gillingham & Bollinger, 2021; Oster & Thornton, 2012; Sorensen, 2006). The biggest challenge in this line of research is to separate similar peer behaviors from exogenous peer effects and from mimicking behavior without learning. In our case, decision-makers do not learn from observing peers' flood insurance uptake because insurance is not conspicuous consumption necessarily observable to peers. Rather, peers' flood experiences generate a salience shock to one's local flood risk to the extent of their social connection with the flooded, triggering them to update their climate risk perception and adapt accordingly. The randomness in locations hit by hurricanes generates exogenous variation in each county's relative social proximity to the disaster, which identifies the social learning effects. In this sense, our work is closer to Kremer & Miguel (2007), which explores random peer treatments in an endogenous social network.

We find evidence of social learning in that Hurricanes Harvey and Irma increased flood insurance policies in force (PIF), renewed policies, and new policies nationwide according to the relative social network proximity to flooded areas. For instance, the social learning coefficient for flood insurance PIF is 0.43, implying that in the counterfactual scenario that all peer counties experience a flood, PIF would increase by 43% in the focal county due to social learning. Weighted by the social proximity to the flooded areas, the average social learning effect is 19.8% in flooded counties and 1.8% in unflooded counties. The average increase in PIF in flooded counties, accounting for both the direct effect of the hurricanes and the social learning effect, is 16%, which is statistically indistinguishable from the social learning effect of 19.8%, suggesting no direct effects of floods. A back-of-the-envelope calculation suggests that Hurricanes Harvey and Irma brought in 250,000 more PIF in flooded areas and 81,000 more PIF in unflooded areas in the three years following the event.

We run several tests to bolster our confidence in the social learning mechanism. We first show that the increase in flood insurance take-up nationwide is accompanied by an increase in the belief that global warming is happening. Meanwhile, we do not find health insurance rate increases in a similar fashion as flood insurance, suggesting that peers' hurricane experiences did not change overall risk preferences. According to salience theory, it is expected that adaptation takes place to the extent of the salience of the climate risk signal brought by the regional floods. We show more prominent increases among policies for properties outside of the Special Flood Hazard Areas (i.e., non-SFHA policies) than for SFHA policies, which reflects different levels of salience because SFHAs homeowners are presumably more aware of their local flood risk. We further address potential exogenous peer effects, i.e., the possibility that the differential flood insurance take-up reaction to regional floods is because of similar demographics (i.e., homophily) or geographic proximity rather than social connection. We show no heterogeneity in the reaction among the unflooded across the medians of the above demographics or larger reactions from unflooded coastal counties, adjacent counties in the same states as the flooded, counties in the same media market as the flooded, and counties within median geographic distance to the flooded.

The economically significant social learning-induced flood insurance uptake that we find seems encouraging, given that the flood insurance take-up rate is 48.3% in Special Flood Hazard Areas (SFHAs) and 2.2% outside of SFHAs as of 2019 (Bradt, Kousky, & Wing, 2021). However, there could be potential concerns about adverse selection and over-insurance. For instance, homeowners with greater hidden risks are more likely to buy insurance, and more so with higher education (Bradt, Kousky, & Wing, 2021). Flood insurance take-up would increase in unhit communities within flood disaster-declared counties regardless of the damage size of the floods, suggesting over-insurance (Gallagher, 2014). We find that, in non-SFHAs, the social learning effect is no larger for homeowners in zip codes with higher hidden flood risk as measured by the

First Street Flood Factor. This may alleviate the concern about adverse selection but may point to over-insurance for non-SFHA properties in low-risk zones. We use flood risks captured by ex post flood insurance claims to measure if the insurance protects against real flood damage. We show no decrease in insurance claim rates for new policies originated after the two hurricanes compared to those originated before, suggesting utilization of the insurance to cover actual losses rather than underutilization resulting from over-insurance.

Our evidence of social learning suggests that a short episode of a regional climate disaster can stimulate adaptation behavior in the entire social network. The social network structure can thus be leveraged to design educational programs and science communication and to inform the timing and location of marketing campaigns to promote disaster adaptation and loss mitigation (Duflo, Banerjee, Glennerster, & Kinnan, 2013). Interventions such as nudging for adaptation can be seeded among the key influencers in the social network to trigger adaptation in a wider population. Communication strategies can be designed to enhance information dissemination to the less socially connected communities so that they can be better informed about climate risk and be engaged in climate risk management.

Our work contributes to the flood insurance literature. The social learning mechanism we find suggests that regional disasters can raise the overall awareness of climate risk in the general population and stimulate insurance take-up in distant regions and low-risk regions. Our findings also alleviate the concerns that regional floods triggered only limited voluntary insurance in the flooded areas (Kousky, 2017). We show that flooding increased local flood insurance take-up mainly through social learning rather than through a direct effect. In contrast, a result driven mostly through a direct effect may have reflected the mandatory insurance requirement to receive Federal Emergency Management Agency (FEMA) financial assistance. More importantly, we show no evidence of adverse selection or over-insurance in social learning-induced flood insurance take-up. As flood insurance take-up rates increase nationwide through social learning, disaster risks can be diversified across broader geographic areas and policies could be made more affordable.

Our analytical framework shifts the paradigm of natural disaster impact evaluation from an atomic to a social network scope. Evidence exists that a major US hurricane can have spillover effects on geographic neighbors' population (Petkov, 2018), labor market (Tran & Wilson, 2020), housing market (Daepp & Bunten, 2020), and school system (Özek, 2021), but less attention has been paid to the spillover effect through social networks. Our work fills the gap by incorporating the friendship network between US counties as a potential channel for social learning so that regional floods can have spillovers on flood insurance take-up nationwide. We extend the regional science literature that quantifies spatial spillovers using a spatial difference-in-differences (SDID) method (Chagas, Azzoni, & Almeida, 2016; de Andrade Lima & Barbosa, 2019; Kosfeld, Mitze, Rode, & Wälde, 2021; Triaca, Ribeiro, & Tejada, 2021). Future disaster impact evaluation will need to account for various forms of social connections between regions such as social media, trade, migration, and mobility.

Empirical Method

Data

We use the two major hurricanes of 2017, Hurricanes Harvey and Irma, which made landfall in the US nine days apart, as our case study. Hurricane Harvey made its first landfall in the contiguous US as a category 4 hurricane on August 25, 2017 in Texas and set the historical record for the most rainfall from a US tropical cyclone. As a result, nearly 80,000 homes found themselves in at least 18 inches of floodwater (FEMA, 2017). Hurricane Irma emerged as the strongest Atlantic hurricane in history and made landfall on September 10, 2017, in Florida. Hurricane Irma also caused extensive flooding. In this paper, the flooded areas are defined as counties that had a presidential disaster declaration because of Hurricane Harvey or Hurricane Irma. In Texas for instance (Figure D1), the presidential disaster declaration is a good proxy for flooded areas. A total of 97 counties in Texas, Florida, and Georgia are defined as flooded regions, and 2694 counties are defined as unflooded regions. Our full sample of counties is slightly smaller than the sample of all US counties because some counties do not have the SCI or have no flood insurance policies over the duration of our sample.

The main variable of interest is flood insurance take-up at the county-month level. We examine the county-month number of flood insurance policies for one year before and three years after Hurricane Harvey's landfall, i.e., from September 2016 to August 2020. The period starting in September 2017 is defined as the treatment period. Our sample of National Flood Insurance Program (NFIP) policies only includes flood insurance for single-family homes, excluding those for homes under construction, houses of worship, businesses, and multi-unit structures. We also further divide policies in force into new and renewed policies. Consistent with the literature (Gallagher, 2014), we use a log transformation in order for the results to be interpretable as a percentage change.

We use the percentage of Americans who believe global warming is happening as another variable of interest. This variable comes from the Yale Climate Opinions Maps (Howe, Mildenberger, Marlon, & Leiserowitz, 2015). These maps show how Americans' climate change beliefs vary at the county level and are based on a nationally representative sample of over 28,000 Americans. We construct a panel using the 2014, 2016, 2018, and 2020 survey waves. To verify that our results are not simply driven by a general change in risk preferences we gather health insurance coverage rate information from the ACS and use the county-level coverage rate as a dependent variable instead of PIF. Finally, to address the over-insurance concern, we examine the utilization of flood insurance after hurricanes by collecting data from FEMA on NFIP insurance claims, aggregated to the county-month level by damage date.

To construct the social network of all US counties, we use the 2018 Facebook SCI, which is a snapshot taken in September 2018, approximately one year after Hurricanes Harvey and Irma. We believe it is still a good proxy for the social network connection during the hurricane time because the two hurricanes caused little migration effects (Billings et al., 2019). For a county pair, the SCI is a measure of intensity of friendship between two counties, constructed as the number of friendship connections between the two counties divided by the product of the total number of users in each county.

For the homophily analysis, we examine factors that could be correlated with SCI as well as demand for flood insurance. Previous studies have shown that demand for flood insurance is stronger among consumers facing higher flood hazard (Bradt et al., 2021), having higher property value at stake (Liao & Mulder, 2021), and obtaining higher education (Atreya, Ferreira, & Michel-Kerjan, 2015). In addition, climate change attitudes and climate adaptations are politicized (Botzen, Michel-Kerjan, Kunreuther, Moel, & Aerts, 2016). We obtain county-level education and housing value from the ACS, county-level vote shares in the 2016 presidential election from the MIT election lab (MIT Election Data and Science Lab, 2018) and flood risk scores from Columbia University's National Center for Disaster Preparedness (Columbia Climate School National Center for Disaster Preparedness, 2020). This score classifies counties according to their flood risk from 1-3, we define level 1 as low flood risk, and levels 2 and 3 as high flood risk in our analysis. In our analyses involving beliefs, we include demographics for each wave to control for change in demographics in each county that may contribute to changes in county-level climate belief. These controls include the median household income, percentage of the population aged between 20-24, 25-34, 35-44 and over 65, percentage of the population with a bachelor's degree, percentage of white and black from the American Community Survey (ACS) for each wave of the belief data.

Table D1 reports the summary statistics for flooded and unflooded areas pre and post Harvey. There are 97 flooded counties and 2,847 unflooded counties. The mean number of active policies is twenty times higher in flooded areas than in unflooded areas. Flood risk is also much higher in flooded areas at 2.38 instead of just 1.61 in unflooded areas. In any given month, most active policies are renewals. In flooded areas, the average number of active policies in the post-Harvey and Irma period increase by around 11%, driven by an increase in both new policies and renewals, whereas they remain stable in unflooded counties.

Network difference-in-differences model

We estimate an NDID model as follows:

$$y_{it} = \alpha d_{it} + \beta \sum_{j \neq i} w_{ij} d_{jt} + X_{it} + \kappa_i + \lambda_t + \eta_m + \nu_{it} \qquad (1)$$

Where y_{it} is the outcome variable in log terms for county *i* in month *t*. The dummy variable d_{it} indicates post-treatment status for county *i* at time *t.* It takes the value of one for Hurricane Harvey or Irma flooded counties after the landfall of Hurricane Harvey; and it takes the value of zero for flooded counties before the landfall and for unflooded counties in all periods. d_{jt} is a dummy indicating the post-treatment status for peer county *j* at time *t*, w_{ij} is the normalized SCI between counties *i* and *j* such that $\sum_{j \neq i} w_{ij} = 1$, with $w_{ij} = 0$ for *i* = *j*. To demonstrate the difference between unnormalized and normalized social connection, we plot each county's average SCI to all flood counties and the average SCI to flooded normalized by their total SCI to all counties (i.e., weighted SCI) in Figure D2. Compared to inter-person binary friendship networks where $w_{ij} = 1$ if *i* and *j* are friends, 0 otherwise (Xu and Fan, 2017)*,* our SCI network is a denser network in the sense that w_{ij} is never zero. The vector of control variables, X_{it}, controls for Presidential Declaration of Disasters and precipitation in county *i* in month *t.* County fixed effects κ_i control for time-invariant county-specific factors such flood risk, income, and education that contribute to flood insurance decisions. Month fixed effects λ_t control for time-varying factors at the national level. Calendar month fixed effects η_m control for seasonality in flood insurance decisions.

Without the term of $\beta \sum_{j \neq i} w_{ij} d_{jt}$, equation 1 boils down to a standard DID estimation that takes the counties flooded by Hurricane Harvey as the treatment group and the remaining counties in the US as the control group. In this case, α measures the average treatment effect (ATE) of the hurricanes on flooded counties' outcomes, which is effectively the difference between the average outcome variables for the flooded and unflooded counties in the periods after Hurricane Harvey. The DID estimation assumes stable unit treatment value (SUTVA), i.e., the potential outcome of one unit should not be dependent on the treatment status of another unit (Angrist, Imbens, & Rubin, 1996). In the context of disaster impact, this assumption is violated, and the unflooded counties are no longer a valid control group for the flooded areas.

Note that $\sum_{j \neq i} w_{ij} d_{jt}$ corresponds to the SCI-weighted portion of peer counties receiving the flood treatment. As such, the extent to which peer county j's hurricane experience will indirectly impact county i's outcome depends on the importance of the connection with county j relative to i's total social connections. This is different from using the average SCI to flooded areas as the mediator of flood event on flood insurance take-up in unflooded area (Hu, 2021; Ratnadiwakara, 2021) for two reasons. First, the mediator approach does not put the social connection to flooded areas in relation to all social connections. It focuses on a bilateral relationship between two counties without a social context. Second, it does not allow flooded areas to experience the indirect treatment effect arising from their peers' flooding experience. In contrast, according to equation 1, a county in the flooded area will experience both the average direct treatment effect (ADTE), as measured by α, and the average indirect treatment effect (AITE), measured by $\beta \sum_{j \neq i} w_{ij} d_{jt}$. The average treatment effect on the treated (ATT) = ADTE + AITE= α+$\beta E(WD_t|D_t = 1)$, where W is row-standardized spatial weight matrix where each element is w_{ij} and D_t is a vector of the treatment indicator. An unflooded county will only experience AITE, i.e., the spillover effect. The average AITE on unflooded counties is $\beta E(WD_t|D_t = 0)$.

Results

Baseline Effects on NFIP Take-up and Climate Belief

Table 1 reports the estimated coefficients from the NDID estimations, the estimated Average Treatment Effects on the Treated (ATT), and the Average Indirect Treated Effects (AITEs) on the treated and on the untreated, respectively. The dependent variables are the number of flood insurance policies in force (PIF), the number of renewed policies, the number of new policies, and belief in global warming, respectively. The coefficients for peer flood experience are positive and statistically significant at the one percent level across the board, which suggests a social learning effect from peer experiences. The estimate of 0.43 in Column 1, for instance, can be interpreted as the percentage increase (43%) in PIF in the counterfactual scenario where a county is not flooded but all its social peers are flooded. When we split the PIF into renewals (Column 2) and new policy purchases (Column 3), the coefficient for peer flood experience is almost six times as large for new purchases (=1.528) than for policy renewals (=0.259), suggesting a larger extensive margin than intensive margin. Finally, the coefficient is 0.073 in Column 4, indicating that the increase in flood insurance take-up is consistent with a 7% increase in the share of individuals believing global warming is happening. This is a key piece of evidence that distinguishes social learning from mimicking behavior without a belief update. When the estimates are weighted by the average social connection to flooded counties, the AITE on the flooded is 19.8% (0.198) for PIF, 12% (0.120) for renewals, 71% (0.705) for new policies, and 3.4% (0.034) for climate belief. The AITE for the unflooded is about one-tenth of the magnitude given the different levels of social connection to the flooded.

It is worth noting that the hurricanes did not have a statistically significant direct impact on flooded counties' PIF, renewals, and new policies. The ATTs are thus not statistically different from the AITEs for the flooded. This finding implies that the observed increase in insurance take-up in the flooded counties stemmed from the social learning from social peers who were also flooded rather than the direct experience of the hurricane. With a traditional DID model, the social learning effects would have all been attributed to the direct treatment effects. Separating the learning effect from the direct effect is important. Social learning implies voluntary insurance take-up, whereas the direct effect could have been driven by the flood insurance requirement to receive Individual Assistance (IA) from FEMA. Comparing increases in counties on hurricane paths with and without receiving IA, Kousky (2017) concluded that IA requirement increases PIF by 5% whereas voluntary insurance take-up increases by 1.5%. Our findings are more optimistic about voluntary insurance.

In our NDID model, the indirect effect is identified out of the variations in social connections to the flooded from both the flooded and unflooded counties. As robustness checks, we first restrict our sample to only the flooded areas to see how much the peer experience as opposed to direct experience can explain the increase in insurance take-up. We also restrict our sample to only unflooded areas to see if the social learning effect can still be identified without the stronger social connections among flooded counties. The estimation results (Columns 1-2 in Table D2) show that social learning effects are almost identical whether we consider the full sample, only flooded or only unflooded areas. The results are also robust to excluding Hurricane Irma-affected areas from the sample or treating them as unflooded counties (Columns 3-4 in Table D2). When we separate the untreated countries into rural and urban counties (Columns 5-6 in Table D2), we find that social learning takes place only in urban counties, which may reflect different demands for flood insurance.

Understanding the Magnitudes

Our NDID estimates an ATT of 16% for Hurricanes Harvey and Irma on flood insurance take-up. The point estimate is larger than the DID estimates documented in the literature. Using a sample of floods between 1990-2007 with presidential disaster declarations (PDD), Gallagher (2014) finds a PDD flood increases local flood insurance policies by 9% up to nine years, and by 3% in media neighbors up to five years. Using a sample of Atlantic and Gulf hurricanes between 20001 and 2010, Kousky (2017) finds that a PDD flood increases insurance take-up rates by 6.7% in the next year. Atreya et al. (2015) find that the county-level flood insurance take-up rate increases with flood damage per capita up to the past three years, with a semi-elasticity of less than 2%. One potential reason that our estimates are larger than in the literature is the severity of the unexpected floods in the Houston areas after Hurricane Harvey's landfall. Hurricane Harvey flooded more than 50,000 homes in Houston areas alone, cost $125 billion and caused more than 100 deaths. Given the economic significance of Houston, the floods may receive more media and social media attention than an ordinary PDD flood.

We provide spatial visualizations of the marginal effects of hurricanes on PIF, renewals, new policies, and climate change beliefs at the county level to help understand the spatial distribution of the effect (Figure 1). The marginal effects are computed from the NDID model; thus, the marginal effect for a county depends on whether the county experienced the hurricane and its social connectedness to flooded counties. Unsurprisingly, the flooded areas had the largest marginal effects. Texas counties immediately outside of the flooded areas, counties in northeast, Appalachia, great lakes, gulf, and southwest also had larger marginal effects due to their stronger social connections with flooded regions. Social learning-induced new take-ups are greater and more geographically prevailing than social learning-induced renewals. The climate belief update has smaller marginal effects than the take-up behaviors, but the geographic pattern is similar. A back-of-the-envelope calculation suggests that Hurricane Harvey brought in 250,000 more PIF in flooded areas and 81,000 more PIF in unflooded areas in the three years following the event (see Appendix C for details).

Potential threats to identification

The social network constructed from the SCI is endogenous to sociodemographic characteristics (Bailey et al., 2018). The county fixed effects in our NDID model control for the level differences in flood insurance take-up related to related sociodemographic characteristics in the absence of regional floods. One remaining threat to the identification is that the differential reactions to the hurricanes reflect similarities in these factors. We thus estimate an NDID model that allows heterogeneous social learning effects among the untreated across demographics (Chagas et al., 2016), i.e., heterogeneous network difference-in-differences (HNDID, see Appendix B for the estimation equation). If demographics drive the differential reactions to hurricanes, we should expect differential social learning effects above and below the sample medians of these demographics. Estimates plotted in the upper panel of Figure D3 show no statistically different social learning effects along demographic characteristics.

Meanwhile, counties that are geographically proximate to the flooded counties naturally have closer relative social proximity to the flooded, but they could also be subject to similar flood risks, similar post-hurricane excess rainfall, or more intense media coverage of the floods, which could drive up flood insurance take-up. To test this alternative explanation, we estimate an NDID model where the AITE for the unflooded counties can be different for those adjacent to flooded, counties in the same states as the flooded, counties in the same DMAs as the flooded, coastal counties, counties within median distance to the flooded and counties on the hurricane path. If it is geographic factors that drive the results, we should expect to see a larger AITE for these subsamples. Estimates plotted in the bottom panel of Figure D3 show no statistically different social learning effects along geographic dimensions. In sum, our HNDID results suggest that demographic homophily and geographic proximity are unlikely to drive the social learning effects estimated in the baseline model.

Learning mechanism? Salience

Our interpretation of the social learning effect is that the hurricanes increased the salience of flood risk to not just the flooded population but the population somewhere else to the extent of pre-existing social connections that help convey disaster information. The increased salience triggered adaptation behavior. We show two pieces of indirect evidence. First, we show that adaptation does not work through changes in risk preference. If direct and peer hurricane experiences change risk preference, we would expect to see similar AITEs on other insurance purchase decisions. To test this hypothesis, we use the county-year level health insurance coverage rate as the dependent variable and estimate the baseline NDID model. We find a different pattern in the estimation results (Column 3 of Table D2). The hurricanes decreased the health insurance coverage rate by 0.8% in flooded counties but didn't change the coverage rate in unflooded counties.

Although we cannot directly test to what extent the SCI reflects salience, we show that adaptation does respond to salience using the difference between SFHAs and non-SFHAs. The NFIP mandates that mortgaged properties within the SFHAs must be insured in the program. Thus, the local flood risk should already be salient to homeowners inside SFHAs compared to those outside, and the former would learn less from peer flood experience, especially when they are already insured. We estimate the social learning effects separately for SFHAs and non-SFHAs policies (Table 2). For PIF in SFHAs, the ATT of 4.6% in the flooded areas is totally attributable to direct experience but not social learning, there is also no social learning for unflooded SFHA homeowners. For non-SFHA PIF, social learning takes place both in flooded and unflooded areas. When we investigate the renewed policies and new policies separately, we find social learning-induced new SFHA and non-SFHA policies but not social learning-induced renewals. This suggests that homeowners without pre-existing flood insurance indeed learned from the hurricanes whereas insured homeowners did not learn, consistent with the salience effect. The social learning induced increase in new policies is larger in non-SFHAs than in SFHAs, which again suggests that adaptation depends on the salience of the flood risk signal.

Adverse selection or over-insurance?

Having established that social learning effects are larger in non-SFHAs, a natural question to ask is whether this is efficient and rational. On one hand, adverse selection happens if only homeowners in non-SFHAs with better information about their hidden flood risk opt-in to buy insurance when receiving a salient flood risk signal (Bradt et al., 2021). On the other hand, if homeowners in non-SFHAs with low flood risks overreact to the salient flood risk signal, they are irrationally over-insured. We address the adverse selection concern by investigating the social learning effects in non-SFHAs by the hidden flood risk. Using the Flood Factor (FF) measure from the First Street Foundation, we separate the non-SFHA policies into two groups by hidden flood risk proxied by the zip code-level average FF for all non-SFHA properties in the zip code and estimate the social leaning effects. Figure 2 plots the ATT, AITE on flooded, and AITE on unflooded for non-SFHA policies in zip codes above and below the median non-SFHA FF for all zip codes (FF=1.96), respectively. The estimates are similar regardless of hidden risks. The absence of a stronger social learning effects in non-SFHAs with higher hidden risk may alleviate concerns about adverse selection.

Next, we address the over-insurance concern by examining insurance claims on new policies originated before and after hurricanes. Specifically, for each month-county, we compute the number of new policies originated in the month and county, then we compute the one-year claim rate as the percentage of insurance policies having claims within one year. We drop any duplicate claims in the computation. If social learning-induced flood insurance take-up resulted from an overreaction to peer flood experience and is not justified by local flood risk, one would expect the claim rate for the new policies originated after Hurricanes Harvey and Irma to have a lower claim rate than policies originated before the hurricanes. Figure 3 plots the time effects on the claim rates by origination date. There is no decrease in the claim rate after the hurricanes, suggesting there is little evidence for over-insurance. The claim rate increases in October 2018, reflecting the impact of Hurricane Michael for which the claims were concentrated in Florida.

Conclusion

This study investigates the social learning-induced nationwide changes in flood insurance take-up in the three years after the floods brought by Hurricanes Harvey and Irma. The county-to-county Facebook Social Connectedness Index (SCI) is used to construct a social network through which flood insurance decisions nationwide could be affected by regional floods. We find that short but severe episodes of floods brought by the two hurricanes triggered a nationwide increase in flood insurance take-up according to relative social proximity to the flooded counties, accompanied by a climate belief update. We find social learning in non-SFHAs but not in SFHAs, consistent with salience theory. Social learning is more pronounced in non-SFHAs with low hidden flood risk than in those with high hidden risks, suggesting no evidence of adverse selection. Moreover, we find higher utilization of flood insurance claims after the hurricanes, which alleviates concerns about over-insurance. Our study sheds light on how social networks can be leveraged to promote timely updates on risk perceptions and helps correct the underestimation of climate risks.

Our study points to several directions for future work. As discussed earlier, Hurricane Harvey brought about a large and unexpected flood in the Houston metropolitan area, a major city in the US with a population of 7.15 million. The disaster event could attract higher press attention because of its severity and more social media attention because of its larger population presence in the social media network. To generalize the social learning effects of climate risks, an investigation with a panel of floods hitting different areas would be helpful. With the variabilities in the disaster locations and therefore their social network positions, future studies can investigate to what extent the network position and other attributes of the disaster affect the intensity of social learning. Another area of promising research is to investigate whether social learning can take place across different categories of climate risks. For instance, do extreme weather events unrelated to floods such as tornadoes also send a salience signal about climate change and affect consumers' flood insurance decisions?

It remains to be explored to what extent the Facebook social network coincides with the conversation network that conveys the information for social learning. An experiment with college students shows that conversation networks are more geographically concentrated and that conversation does not necessarily take place between direct or indirect Facebook friends (Mobius, Phan, & Szeidl, 2015). Facebook is a static friendship network that serves as a proxy for the information exchange between two localities in our study. By construct, it is a symmetric network. The conversation network, however, can be directional. During a natural disaster event, the conversation network is also dynamic. A study shows that a hurricane can change the intensity of information exchange on Facebook (Phan & Airoldi, 2015). Furthermore, Facebook users can customize post-viewing privilege for their friends, which could create information frictions on social media and make the information diffusion structure differ from the friendship structure. It could be fruitful for future studies to exploit the actual information flows on social media to construct directed, weighted, and dynamic information networks for social learning.

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Table 1: Baseline results

	(1)	(2)	(3)	(4)
	PIF	renewals	new policies	happening
Own flood	-0.038	-0.034	-0.024	-0.024***
	(0.061)	(0.057)	(0.201)	(0.008)
Peer flood	0.430***	0.259***	1.528***	0.073***
	(0.151)	(0.147)	(0.488)	(0.016)
Constant	4.460***	4.286***	1.803***	4.247***
	(0.005)	(0.005)	(0.016)	(0.033)
Observations	142,560	142,560	142,560	11,884
R-squared	0.979	0.981	0.908	0.918
ATT	0.160***	0.086***	0.681***	0.009***
	(0.021)	(0.021)	(0.062)	(0.004)
AITE on treated	0.198***	0.120***	0.705***	0.034***
	(0.070)	(0.068)	(0.225)	(0.008)
AITE on Untreated	0.018***	0.011***	0.064***	0.003***
	(0.006)	(0.006)	(0.020)	(0.001)

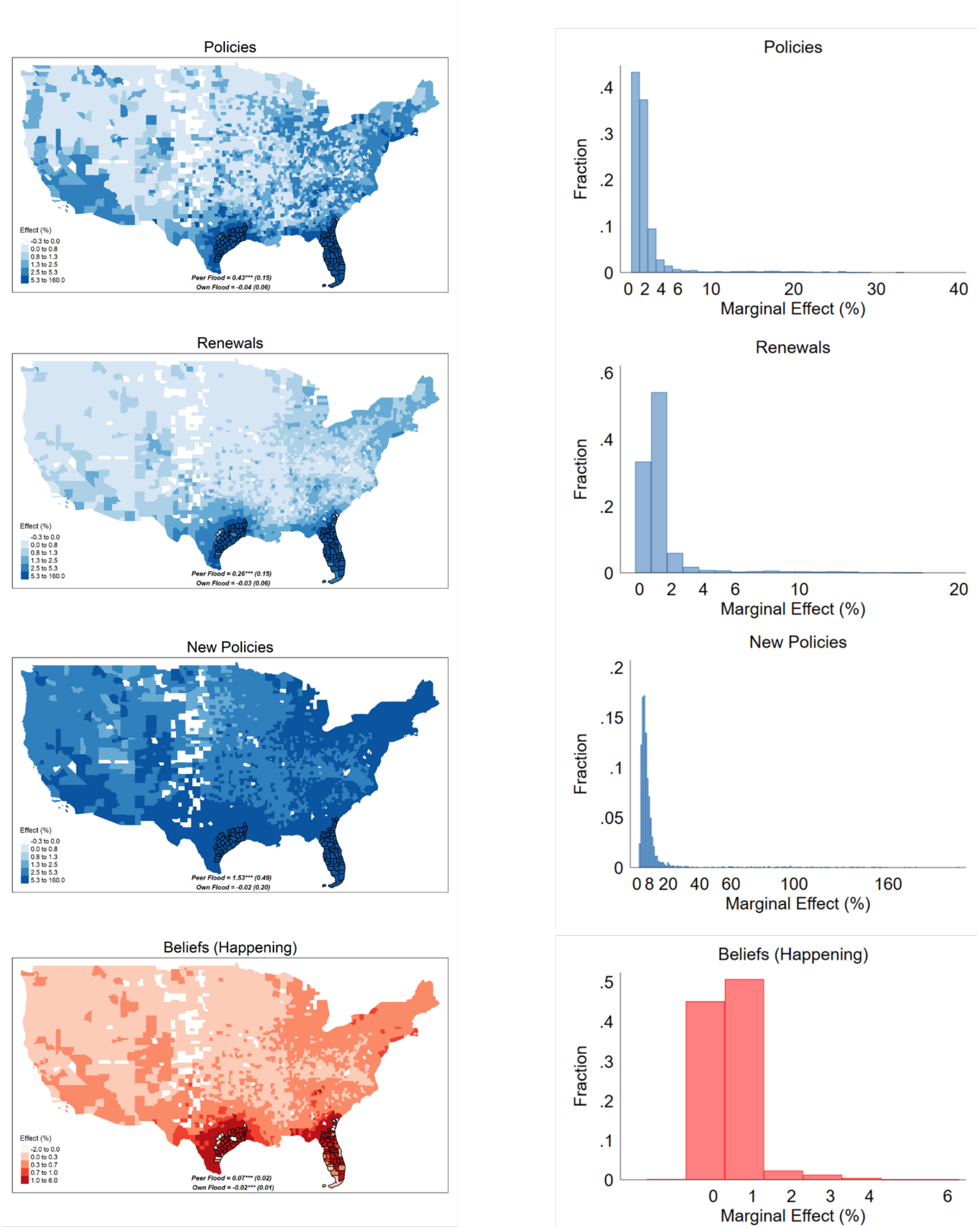
Notes: Table presents estimation results for our baseline NDID model as shown in equation 1. We regress each outcome variable in log terms on treatment and peer-treatment indicators. *Own flood* is a dummy that takes the value of one for flooded counties after the hurricanes and zero otherwise. *Peer flood* is the SCI-weighted portion of social peers flooded. In columns 1-3, calendar month, month-year and county fixed effects are controlled. In columns 1-3, monthly precipitation and the number of presidential flood disaster declarations are controlled for. In columns 4, county-wave socio-demographic controls from the ACS, year and county fixed effects are controlled for. Standard errors are clustered at the county level. ***p<0.01, **p<0.05, *p<0.1

Table 2: SFHA and Non-SFHA policies

	(1) SFHA policies	(2) non-SFHAs policies
Panel A: PIF		
ATT	0.046**	0.231***
	(0.028)	(0.029)
AITE on flooded	0.003	0.301*
	(0.223)	(0.175)
AITE on unflooded	0.000	0.027*
	(0.020)	(0.016)
Panel A: Renewed policies		
ATT	0.012	0.146*
	(0.028)	(0.057)
AITE on flooded	-0.058	0.107
	(0.204)	(0.104)
AITE on unflooded	-0.005	0.010
	(0.018)	(0.304)
Panel A: New policies		
ATT	0.446***	1.056***
	(0.092)	(0.084)
AITE on flooded	0.724***	1.732***
	(0.257)	(0.315)
AITE on unflooded	0.066***	0.158***
	(0.023)	(0.029)

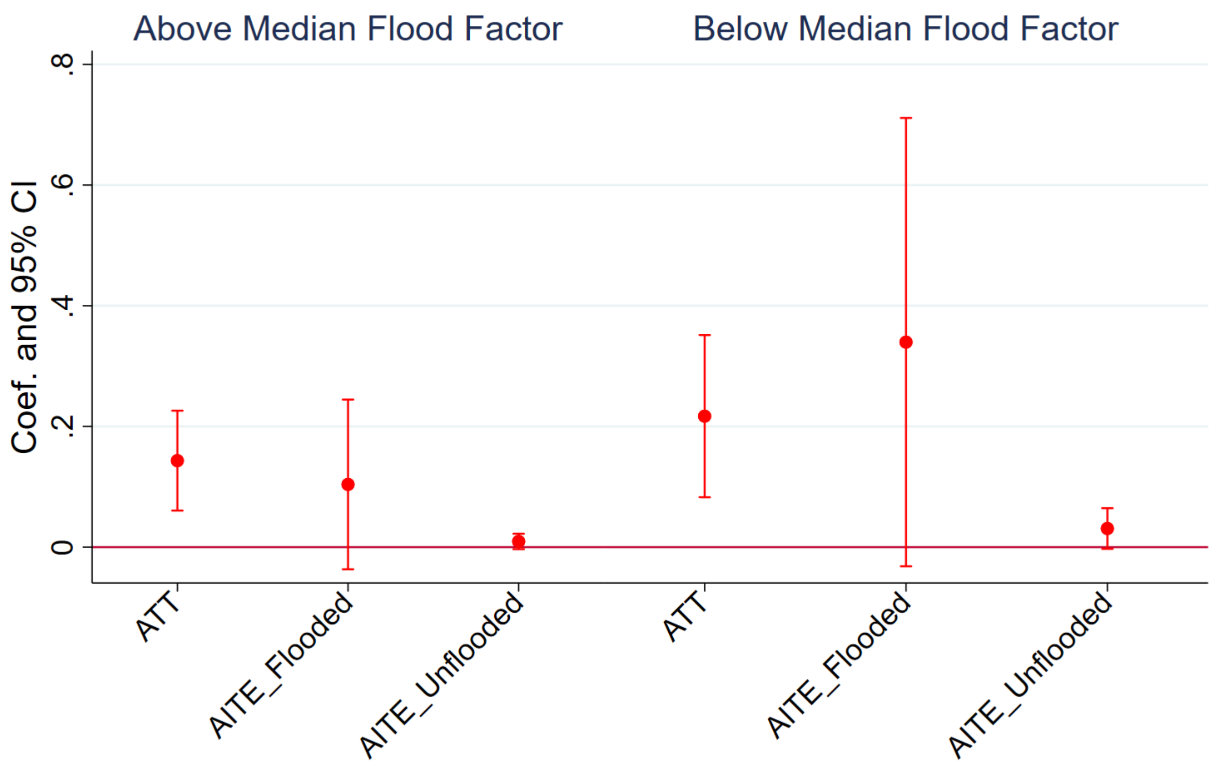
Notes: Column 1 presents results from regressing the log of monthly flood insurance policies in SFHA areas (i.e. 100-year flood zones) aggregated at the county-level on a post treat indicator, the SCI-weighted portion of social peers receiving the flood treatment, monthly precipitation, the number of presidential flood disaster declarations, calendar month, month-year and county fixed effects as outlined in equation 1. Column 2 presents the same results, but for policies in non-SFHA areas. Standard errors are clustered at the county level. ***p<0.01, **p<0.05, *p<0.1

Figure 1: geographic distribution of marginal effects



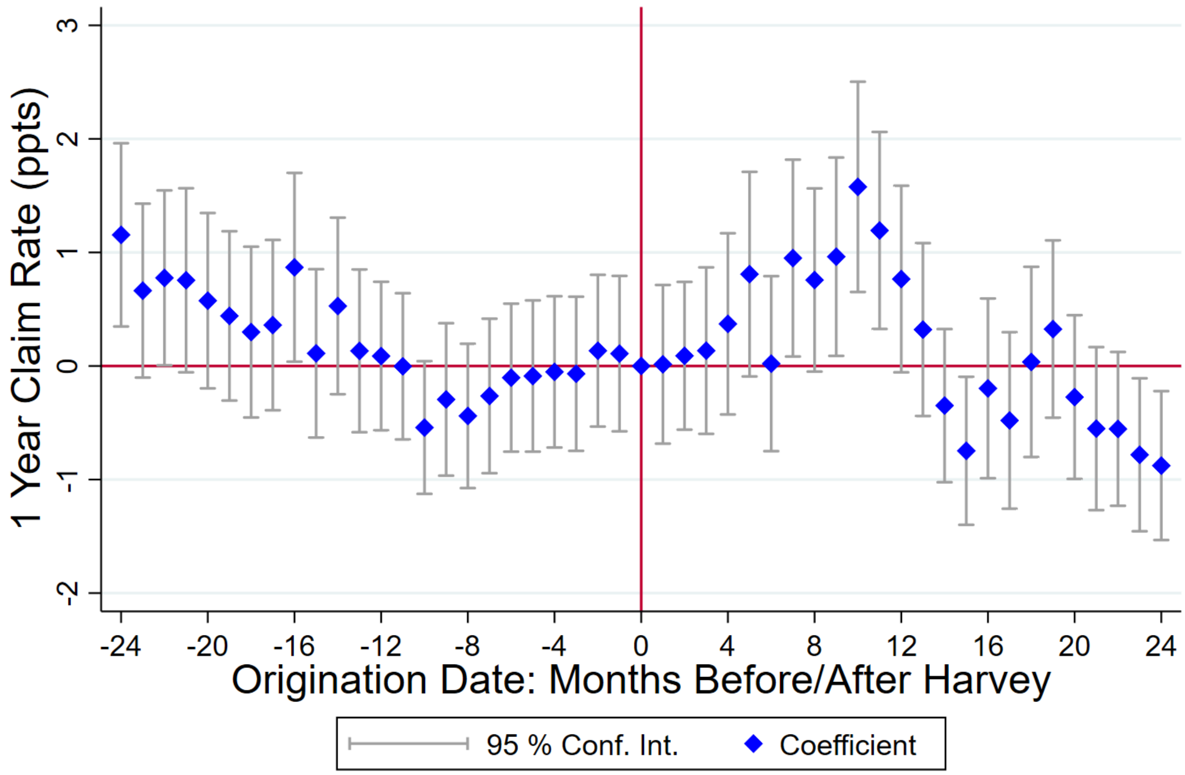
Notes: Figure 1 plots the geographic distribution and density of the marginal effects estimated using equation 1 for each county in our sample. Marginal effects correspond to the multiplication of the coefficients on the Own Flood and Peer Flood coefficients in table 1 multiplied by the post-treatment status and WD_t value in each county. Affected counties are outlined in black. Bins in the first three maps are determined according to quintiles of the joint distribution of PIF, renewals and new policies Bins in the beliefs figure are determined by quartiles. Zero and negative effects are shown in white.

Figure 2: Estimates for Non-SFHA policies by Flood Factor



Notes: Figure 2 plots the average treatment effect on the treated (ATT), average indirect treatment effect estimates for flooded (AITE_Flooded) and unflooded (AITE_Unflooded) counties for policies outside SFHAs. The left panel presents results for policies located in with above-median flood risk as measured by first street's Flood Factor measure while the right panel presents estimates for areas with below-median flood risk. All regressions include monthly precipitation and the number of presidential flood disaster declarations as controls as well as calendar month, month-year and county fixed effects. Standard errors are clustered at the county level.

Figure 3: One-year Claim Rate by Origination Date



Notes: Figure plots the results from a regression of the one-year claim rate for newly originated policies (i.e. the number of claims within 1 year of policy origination divided by the total number of new policies in each county-month-year period) on origination month-year dummies and county fixed effects. The omitted period is September 2017. Standard errors are clustered at the county level.

Appendix A: Variable construction

The NFIP data contains variables identifying the effective date when a policy comes into force and the original date at which the policy was first purchased. For example, a homeowner could have bought her first policy on October 1st 2000 and renewed her policy yearly since then. Thus, the original date of her policy would be October 1st 2000, but there would be an entry in the data every year since then with a different effective date each time. Thus, new policies are identified as those whose effective date is identical to the original date of purchase. Renewed policies are those for which the effective date is later than the original policy date. We construct all our dependent variables as $Y_{it} = \ln(y_{it} + 0.01)$, where y_{it} is the outcome variable for county i in month t. We add 0.01 to deal with county-month observations with zero policies. This is necessary due to the high frequency of zeros among the policy measure. While 1.4% of the observations for total policies and 2% of observations for renewals are equal to zero, 16% of the observations for new policies are equal to zero.

Claims data are constructed by aggregating building and contents claims for all claims made for single-family dwellings in a given county-month-year. We drop claims with a negative or zero claim amount. We also drop duplicate claims where duplicate claims are defined as claims in the same census tract, with the same date of loss, policy origination date and flood-zone status. Similar to our policy data, we log-transform the claim amounts to interpret our coefficients as percentage changes. The average claim in our sample is $55, 963.10. 92% of county-month-year observations have $0 in claims.

Appendix B: Heterogenous network difference-in-differences estimation.

Equation 1 can be written in matrix notation as follows:

$$Y_t = \alpha D_t + \beta W D_t + K \quad + \Lambda_t + M_m + N_t$$

In matrix notation, W is a row-standardized spatial weight matrix where each element is w_{ij}. The above NDID model assumes the spillover effect of Hurricane Harvey on a county is uniform regardless of whether this county experienced the hurricane or whether the county has flood risks. The spillover effect could in fact vary because flood insurance decision-makers resonate with the flood in Huston area to various degrees depending on their experience of the flood and their flood hazard. Following (Chagas et al., 2016), we estimate an NDID model that allows heterogeneous spillover effects as the following equation in matrix notation:

$$Y_t = \hat{\alpha} D_t + \beta_T W_T D_t + \beta_{NT}^H W_{NT}^H D_t + \beta_{NT}^L W_{NT}^L D_t + \kappa_i + \lambda_t + \eta_m + \nu_t$$

Where W is partitioned into W_T, W_{NT}^H, W_{NT}^L, i.e., $W = W_T + W_{NT}^H + W_{NT}^L$. $W_T = \mathcal{D}_t \times W \times \mathcal{D}_t, W_{NT}^H = R^H \times D_t^C \times W \times \mathcal{D}_t$, $W_{NT}^L = R^L \times D_t^C \times W \times \mathcal{D}_t$, where $\mathcal{D}_t = diag(D_t)$ is an $n \times n$ matrix with D_{it} in the diagonal and zeros elsewhere, $D_t^C = diag(\iota_n - D_t)$, with ι_n a $1 \times n$ vector of 1's, and R^H is a $1 \times n$ vector indicating areas with high flood risk, and R^L is a vector indicating areas with low flood risk. Thus, β_T measures the spillover effects on treated areas, β_{NT}^H measures the spillover effect on untreated areas with high flood risk, β_{NT}^L measures the spillover effect on untreated areas with low flood risk. The direct treatment effect on the treated is $\hat{\alpha}$. The average treatment effect on the treated (Bardaka et al., 2018) is thus $\hat{\alpha} + \beta_T E(W_T D_t | D_t = 1)$. The average spillover effect on untreated with high risk is $\beta_{NT}^H E(W_{NT}^H D_t | D_t = 0)$, and the average spillover effect on untreated with low risk is $\beta_{NT}^L E(W_{NT}^L D_t | D_t = 0)$. Table D1 reports the conditional means of W_T, W_{NT}^H, W_{NT}^L.

Appendix C: Back-of-the-envelope calculation

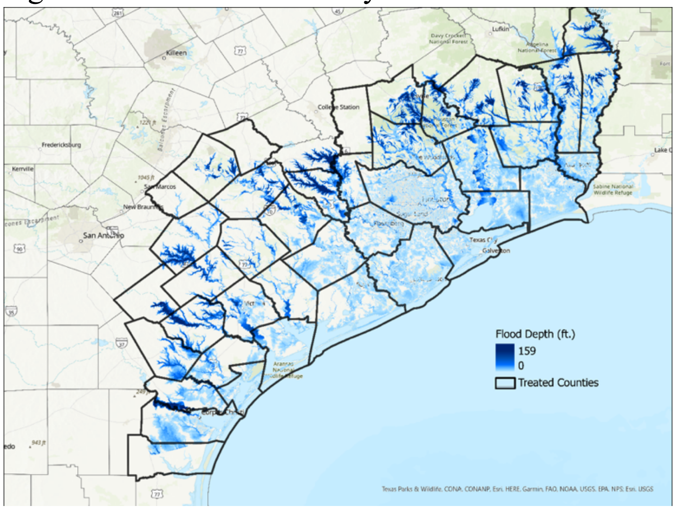
To generate the number of additional policies caused by the social learning effect after Hurricanes Harvey and Irma, we generate the counterfactual predicted number of policies if no counties were affected and if the SCI was 0 between each county pair. To do so we estimate equation 1:

$$y_{it} = \alpha d_{it} + \beta \sum_{j \neq i} w_{ij} d_{jt} + \kappa_i + \lambda_t + \eta_m + \nu_{it} \quad (1)$$

We then force $d_{it} = 0$ and $\sum_{j \neq i} w_{ij} d_{jt} = 0$ for all observations in our data and obtain the predicted values $\widehat{y_{it}}$. Since $\widehat{y_{it}}$ is logged, we generate $\tilde{y}_{it} = \exp(\widehat{y_{it}})$ (. Thus, $\tilde{y}_{it}$ is the predicted number of policies after Hurricanes Harvey and Irma for each county-month-year in the absence of both the direct and indirect treatments caused by these events. We then obtain the total number of policies additional policies by subtracting the sum of all counterfactual policies from the sum of all policies $\Delta Y = \sum y_{it} - \sum \tilde{y}_{it}$. Similarly, to determine the number of new policies caused by social learning, we keep d_{it} as its true value and only force $\sum_{j \neq i} w_{ij} d_{jt} = 0$. This produces the counterfactual in the absence of social learning.

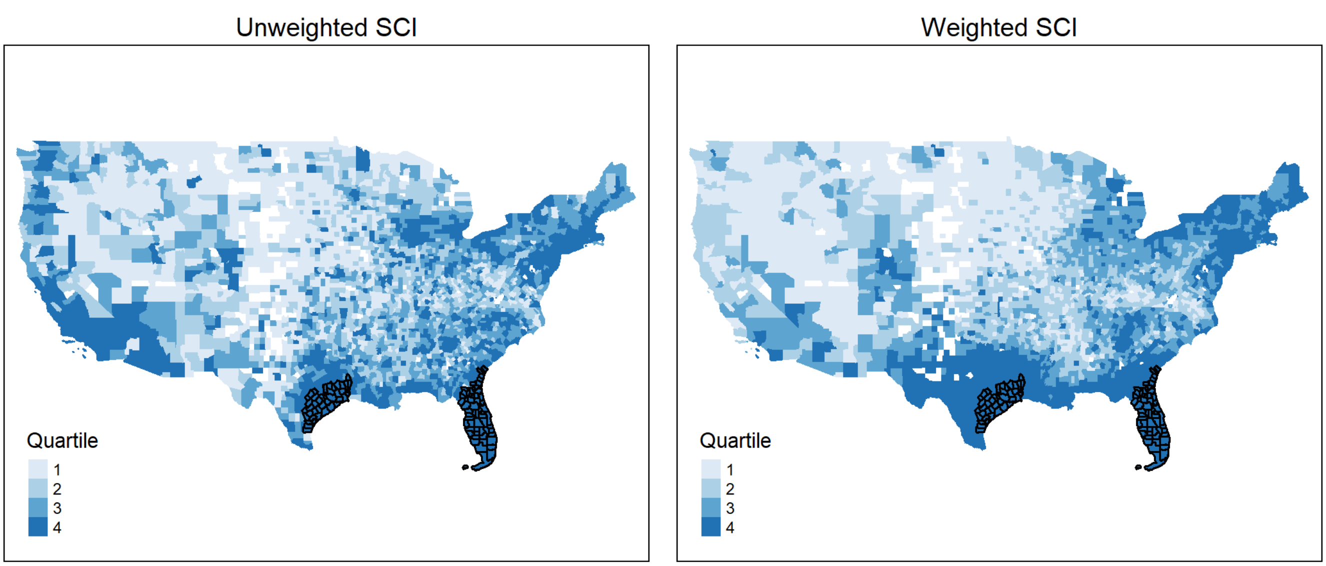
Appendix D: Additional Figures and Tables

Figure D1: Hurricane Harvey-flooded counties and flooded regions



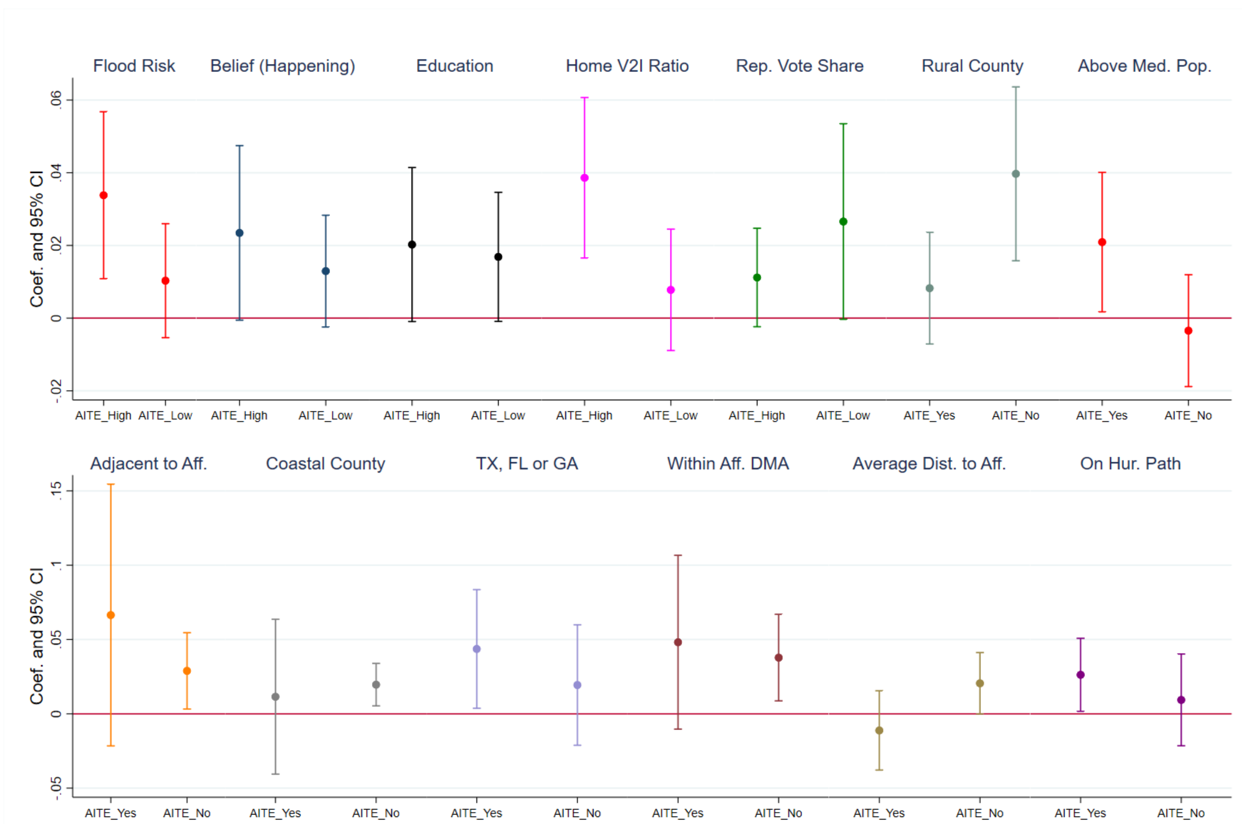
Notes: Figure D1 overlays counties with a presidential disaster declaration onto flood depth obtained from FEMA and the USGS for Hurricane Harvey.

Figure D2: Average SCI to flooded counties.



Notes: Figure D2 plots the average SCI from any given county to counties affected by Hurricanes Harvey or Irma (black outline). The unweighted SCI refers to the raw connection before row-normalization and weighted SCI refers to row-normalized SCI.

Figure D3: No evidence of heterogeneity



Notes: Figure D3 plots the average indirect treatment effect (AITE) estimates from HNDID models that split the sample based on demographic (top row) and geographic (bottom row) characteristics (see appendix B for estimating equation). All regressions include monthly precipitation and the number of presidential flood disaster declarations as controls as well as calendar month, month-year and county fixed effects. Standard errors are clustered at the county level.

Table D1: summary statistics

	Affected		Unaffected	
	Pre	Post	Pre	Post
Mean Active Policies per Month	15,091	16,744	749	741
Mean New Policies per Month	2,487	3,140	125	94
Mean Renewals per Month	12,604	13,550	624	651
Mean Flood Risk	2.38		1.61	
Mean Number of Single-family Households	66,809	69,036	25,527	25,971
Number of Counties	97	97	2,873	2,873
Mean W	0.461		0.042	

Table D2: Robustness checks

VARIABLES	(1) Treated Only	(2) Untreated Only	(3) Urban Only	(4) Rural Only	(5) No Irma Areas	(6) Irma as Untreated	(7) Health insurance
Own Flood			-0.102*	-0.003	0.009	-0.038	-0.008**
			(0.053)	(0.097)	(0.079)	(0.061)	(0.004)
Peer Flood	0.429***	0.429**	0.594***	0.314	0.492***	0.430***	0.007
	(0.127)	(0.200)	(0.135)	(0.212)	(0.181)	(0.151)	(0.009)
Constant	7.558***	4.354***	5.860***	3.578***	4.387***	4.460***	4.459***
	(0.044)	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)	(0.000)
Observations	4,656	137,904	55,104	87,456	139,872	142,560	8,913
R-squared	0.998	0.977	0.996	0.959	0.978	0.979	0.984
AITE on Treated	0.198***		0.257***	0.159	0.231***	0.202***	0.003
	(0.059)		(0.058)	(0.107)	(0.085)	(0.071)	(0.004)
AITE on Untreated		0.018**	0.028***	0.012	0.021***	0.018***	0.000
		(0.008)	(0.006)	(0.008)	(0.008)	(0.006)	(0.000)

Notes: Table presents NDID estimates for a split sample of only treated (Column 1), only untreated (Column 2), only urban (Column 3), only rural (Column 4), without Irma affected (Column 5) and treating Irma counties as untreated (Column 6) counties. In Column 7, the log of the pct of individuals with health insurance is the dependent variable. Precipitation, disaster declarations, calendar month, month-year and county fixed effects are controlled. Month-year FEs absorb the post-treat indicator. Sample in Column 7 covers the years 2016-2019, 2016 is the pre-treat year, 2017 is dropped and 2018-2019 are the post-treat years. The mean insured percentage is 86.6% in our sample. For all columns, robust standard errors are reported in parentheses, and standard errors are clustered at the county level.