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Improving Household and Community Disaster Recovery:

Evidence on the Role of Insurance

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Improving Household and Community Disaster Recovery: Evidence on the Role of Insurance

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Abstract

We study the role of insurance in improving household and community disaster recovery. Harnessing unique survey data of residents impacted by four land-falling hurricanes in the U.S., we find that insured households are less likely to experience high financial burdens in both the short and longer-run post-disaster and are less likely to have unmet funding needs. Insurance also provides spillover benefits for the local economy. Post-disaster visitation rates to many local businesses increase with flood insurance payouts. Despite this, motivating purchase of disaster insurance remains a challenge among low-income households who are less likely to report seeing insurance as useful.

Key Words

Natural disaster, recovery, insurance

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1 Introduction

As climate change and continued development in at-risk areas has advanced, the costs of natural disasters in the U.S. have grown dramatically. As measured by the National Oceanic and Atmospheric Administration (NOAA), between 2012 and 2021, weather-related disasters cost the U.S. at least $1 trillion in damages. These disasters impose substantial costs on households. Key to household recovery is access to sufficient funds to cover wide-ranging and often large post-disaster expenses. In this paper, we document how households facing hurricane damage finance their recovery, with a focus on the role of insurance—both for the household and the community.

While there is a growing body of work on household impacts from natural disasters, very few papers are able to provide a comprehensive examination of financial recovery, instead limiting analysis to particular sources of funds or impacts. This is due in large part to data limitations that prevent a comprehensive empirical investigation. Several papers, for instance, focus on post-disaster credit behaviors, leveraging either credit bureau or loan-level data (e.g., Gallagher and Hartley, 2017; Billings et al., 2022; Gallagher et al., 2022; del Valle et al., 2022; Kousky et al., 2020). Disaster-impacted households, however, can make use of a wide array of funding sources and financial coping strategies and little is known about how households manage these various approaches.

We overcome this challenge by developing and deploying a unique survey of households impacted by one of four major hurricanes to make landfall in the United States between 2017 to 2021. Our survey provides a detailed account of both the financial costs that households face after a hurricane and also the funding sources used to weather the negative shock to their finances. We find that households face a myriad of costs post disaster. While property damage to homes, contents, and cars can be severe, and is one of the most visible disaster costs, households also face an array of additional expenses, from evacuation costs to debris clean-up to lost income from disaster-related business interruption. Households turn to many funding sources to cover these costs, including insurance, their own savings, their friends or family, federal assistance, or taking on debt. Using cluster analysis, we observe that people sort into two unique groups according to the disaster financing strategies: one group is defined entirely by their use of insurance, and the other group is largely uninsured, instead turning to family and/or friends for financial support.

We use this survey data to undertake a deeper examination of insurance, contributing to a growing literature on the role of insurance in disaster recovery. A few economic, empirical studies provide suggestive evidence on this role, focused specifically on flood insurance, with inference based on the federal requirement that homeowners with a mortgage in the 100-year floodplain as mapped by the Federal Emergency Management Agency (FEMA) purchase insurance (Billings et al., 2022; Ouazad and Kahn, 2022). Other papers focus on just one avenue by which insurance can have an impact, such as on loan outcomes (Kousky et al., 2020). A few other papers look at a country level with a focus on total insured losses and the impact on macroeconomic outcomes (e.g., Von Peter et al., 2012). We add to this literature, reviewed more below, with household-level information on both homeowners and flood insurance, as well as all the other financing sources used, to isolate the impact of insurance on recovery.

We examine several post-disaster recovery outcomes. We find that among households experiencing property damage from a hurricane, those with insurance ex-ante report fewer financial burdens in both the short- and long-run post-hurricane and are less likely to report having unaddressed funding needs. Given the concern that insurance status could be correlated with other factors that would improve recovery, such as income and education, our preferred specifications use a propensity score model. From this model we specifically find that those with insurance at the time of the storm are 85% less likely to report high financial burdens three weeks after the hurricane, 82% less likely to report high financial burdens one year after the hurricane, and 58% less likely to have unmet funding needs. We also find that insured households, on average, use one more funding source than uninsured households, suggesting they are able to have various disaster costs covered more comprehensively.

With clear evidence on the financial protection insurance offers households, we next turn to examining whether insurance provides any broader spillover benefits to local communities, a relatively under-researched topic (French and Kousky, 2023). We do this by drawing on foot traffic data collected from cell phones for households in areas impacted by Hurricane Michael. We use this data to examine how visitation rates to local firms change post-hurricane according to the amount of flooding and the uptake of flood insurance within the community. Employing a triple difference-in-differences framework, we find that households from flooded neighborhoods, but with higher rates of flood insurance coverage among households, visited local businesses more often, suggesting economic benefits to local firms when residents are insured against disasters. Given a particular depth of flooding, we find that a 10 percentage point increase in the flood insurance take-up rate leads to 15% more visits to local businesses from flooded residents. We examine how this effect varies by type of firm, finding increases in visitations to both businesses providing necessities, such as groceries, as well as more discretionary purchases, such as clothing and general merchandise. By accounting for social networks in these communities, we are able to show that in areas with lower flood insurance purchase, higher social connectivity can increase firm visits, but only in the shorter term and only if those social networks include greater connections to others outside the impacted area and with higher incomes. Social networks that are geographically proximal, and so also hit by the storm, or who are lower income, do not provide this benefit. While past studies have examined the importance of social networks in community disaster recovery (Carpenter et al., 2013), we are among the first to study its role in comparison with the role of insurance.

Finally, in our survey we also assess perceptions on the usefulness of insurance. We find that those of lower income are less likely to report finding insurance useful and are less likely to purchase flood insurance after a hurricane if they were not insured previously. This points to the ongoing challenges with affordability of disaster insurance. Given the large economic benefits we find from insurance, both for the household and the community, policy proposals for providing means-tested assistance to lower-income households to afford insurance merit closer scrutiny.

The next section of our paper reviews the related literature. In Section 3, we discuss the results from our survey. We outline our methods, the data, and provide summary statistics and insights from a cluster analysis, before then discussing our regression strategy and empirical results. In Section 4 we present the analysis of the foot traffic data, explaining the data sources we combine for the analysis, our empirical approach, which relies on triple-interaction terms and a wide set of fixed effects, and then discuss our results. Section 5 presents analysis of the perceived usefulness of insurance. We conclude in Section 6.

2 Background and Related Literature

Disasters are negative economic shocks to a household. After a disaster, households must find funding to cover the necessary repairs, rebuilding, and other recovery costs. This could involve drawing down savings, taking on additional debt, receiving support from friends and family, potentially receiving government aid, or drawing on insurance proceeds. For many households, though, savings are limited, additional debt can be burdensome, and their friends and family may also be suffering and unable to provide sufficient funds. When a disaster is large enough to trigger a presidential disaster declaration that authorizes the Individual and Households Program (IHP) from FEMA, households may be eligible for grants, but funds are limited and awards are typically small; between 2017 and 2022, the average grant from FEMA's IHP for natural disasters was only $2,765 in 2022 dollars.[1]

As such, when households are insured against disasters, it can be an important source of needed funds. In the U.S., there is no hurricane insurance. To be covered against these storms, households need both homeowners insurance, which typically covers damage from hurricane winds, and flood insurance, which covers damage from hurricane-related flooding from either storm surge or heavy precipitation. The overwhelming majority of flood insurance policies are provided by the federal National Flood Insurance Program (NFIP). Many households at risk, however, lack complete insurance coverage for disasters (Kousky, 2022).

Only a small body of literature has examined the role of insurance in recovery. These studies generally find a positive relationship between being insured and post-disaster measures of recovery or financial health (Kousky, 2019). Few of these studies offer a direct, household-level analysis of the role of insurance. A couple of papers link greater insurance uptake at the level of the country with improved macroeconomic indicators post-disaster (Von Peter et al., 2012; Melecky and Raddatz, 2015). An analysis of the Canterbury Earthquake Sequence in New Zealand using nightlights as a proxy for economic recovery found greater insurance payouts were associated with greater economic recovery (Nguyen and Noy, 2020).

[1] According to the authors' calculation using FEMA's publicly available "OpenFEMA Dataset: Individuals and Households Program - Valid Registrations."

A couple of papers do undertake a household analysis, drawing on survey findings, as we do in this paper. One analysis after the 2005 hurricanes found that if a property was insured it was 37% more likely to have been rebuilt (Turnham et al., 2011). Among those who did not rebuild in their sample, approximately 36% said it was due to not being able to obtain or afford flood insurance. A survey of flood survivors in Germany found that those with insurance received higher total loss compensation from external sources and were more satisfied with their post-disaster funding (Thieken et al., 2006).

Finally, several studies indirectly examine insurance or make inferences about its role in recovery. Analysis of credit performance after Hurricane Harvey offered suggestive evidence that flood insurance helped mitigate negative financial impacts across the income distribution (Billings et al., 2022). Those in areas with a higher degree of insurance, but also potentially less vulnerable housing, have been found to borrow less post-flood (del Valle et al., 2022). A study of Hurricane Katrina found that flooded households had lower home loan debts after the storm, which the authors argue is likely driven by flood insurance payouts being used to pay off mortgages (Gallagher and Hartley, 2017). A study of mortgage performance after Harvey supports this inference, finding that prepayment was higher among those with flood insurance as flood-related damage increased (Kousky et al., 2020). That study also found that having flood insurance was protective against needing loan modifications and against delinquency and default. Flood insurance may also protect housing prices post-disaster (Box-Couillard and Xu, 2022). An earlier analysis of properties damaged by Hurricane Sandy found greater investments in damaged properties inside the FEMA-designated 100-year floodplain, which the authors attribute to greater flood insurance takeup (McCoy and Zhao, 2018). These studies suggest there are multiple channels by which insurance supports recovery and provides financial protection post-disaster.

We expand on this small but growing literature on the role of insurance in recovery at both a household and a community level. There is currently limited quantification of how much better those with insurance fare post-disaster and how their recovery compares to uninsured survivors. Drawing on a unique survey of households impacted by one of four landfalling hurricanes in the United States, we are able to relate reported measures of financial recovery to insurance status at the time of the storm. In addition, we use a database of visits to local firms to examine not just the role of insurance in household recovery, but in broader community recovery, as well. No research to date has focused on the level of the community and examined local economic spillovers from greater insurance penetration.

3 Survey Analysis

3.1 Survey Methods

Our first set of analyses uses data from a survey we administered to individuals who sustained damage from one of four U.S. land-falling hurricanes: Harvey (Category 4 at landfall in Texas, 2017), Florence (Category 1 at landfall in North Carolina, 2018), Michael (Category 5 at landfall in Florida, 2018), and Ida (Category 4 at landfall in Louisiana, 2021). The survey was designed to elicit information about household financial recovery from hurricanes that is unavailable in public datasets. The survey design process and question development followed best practices as described in Dillman et al. (2014). Questions were peer-reviewed by two disaster scholars, and the survey was piloted by four individuals who sustained damage from Hurricane Michael or Ida before being deployed to the larger sample.

We recruited survey respondents for Hurricanes Harvey, Florence, and Ida using the Qualtrics internet panel to obtain a random sample of impacted individuals. Qualtrics maintains a panel and provides incentive payments for survey responses. While limited by the need for a sufficient sample size, Qualtrics attempted to match demographic characteristics for income and race to the broader population in our target geographies. We collected survey responses for Hurricane Harvey in February and March 2022, responses from Hurricane Florence in April 2022, and responses from Hurricane Ida in May 2022. Qualtrics, compared with convenience sampling via Facebook or MTurk, has been found to generate more representative samples, although many respondents tend to have low levels of attentiveness (Boas et al., 2020). We address this concern by employing three accuracy screeners (Arndt et al., 2022), including a speed check, an attention check, and reviews of open-ended questions.[2] We remove respondents who fail these tests. In addition, there

[2]The speed check eliminates responses where the completion time is so fast as to suggest the respondent was simply clicking answers without reading the survey. These are responses that took less than one-half the median completion time of the first 10 percent of our target sample size. The attention check ensures that respondents were

are increasing concerns about possible bots corrupting online samples, as well as a range of types of responses that researchers might consider "low-quality data" (DeSimone and Harms, 2018; DeSimone et al., 2015). We thus used two selection screeners to ensure a valid sample, including a CAPtCHA verification to prevent bots from accessing the survey, and a cookie-based screening to prevent multiple responses from the same person.[3]

Recruitment for Hurricane Michael differed, athough we used the same accuracy and selection screeners. For the Hurricane Michael survey, respondents were recruited by a non-profit partner, Resilience Action Fund,[4] which utilized multiple channels, including a Facebook ad campaign, spots on local radio stations, and outreach to local communities. Recruitment was targeted in Mexico Beach and Panama City, the communities that sustained the greatest damage from the storm and was undertaken in July, 2021. One in ten respondents who completed the survey by July 18, 2021 was given a $30 gift card as an incentive to participate, and one in ten who completed it by July 24, 2021 was given a $20 gift card. Summary statistics from the Hurricane Michael responses have been presented in a stand-alone report (Sweeney et al., 2022). Survey questions across all four samples were identical.

Across all storms, to complete the full survey, respondents had to indicate that they experienced damage to their home, contents, or car from the target hurricane; were involved in the financial decisions of their household; and were over 18 years of age. These were our three screening questions, in addition to the methods above to remove low-quality data. In total, we had 493 complete responses. For this paper, we limit our focus to respondents who sustained building or contents damage and thus eliminate 32 respondents who experienced no damage to their home or contents, but did have their car damaged. Our final sample consists of a total of 461 survey responses: 135 from Harvey, 114 from Florence, 116 from Ida, and 96 from Michael. Given the difference

actually reading and correctly responding to questions and not randomly clicking answers. We do so by asking the same question, how long they had lived at their current homes, both at the beginning and the end of the survey. We omitted the responses if their answers were different. Finally, we reviewed open-text questions. If any were gibberish, the respondent's survey was removed from the sample.

[3]Qualtrics places a cookie on their browser when they submit a response and then prevents a respondent from taking the survey again, although if someone switched browsers or devices, they could circumnavigate this restriction.

[4]The Resilience Action Fund, headquartered in Miami, Florida, is a nonprofit organization that educates consumers and policymakers to create stronger, more resilient homes and communities.

in sampling from Hurricane Michael, the difference across all four samples in timing between the storm and when we collected data, and the difference in intensity for Hurricane Florence, we include storm fixed effects in all pooled models and also consider the data for the storms individually.[5]

3.2 Survey Data and Summary Statistics

Table 1 presents descriptive statistics from the survey related to the household, their home, and the disaster impacts they experienced. The table also divides the sample by whether the household had any insurance (homeowners/renters and/or flood insurance) at the time of the hurricane. We see some statistically significant differences in demographic characteristics between those who purchased some type of insurance and those who did not. Insured households are more likely to have savings and are more likely to have higher incomes. We also see that renters are less likely to have any insurance, those with a mortgage are more likely to have insurance, and those with any insurance tend to have lived in their homes slightly longer.

Our survey asked respondents about the costs they faced post-disaster and we find that hurricanes impose a broad array of financial costs on affected households. As shown in Panel A of Figure 1, among our sample, 88% report damage to their home (real property damage), 82% report damage to the contents of their home, and 55% also report damage to one or more vehicles. Beyond property damage, we find that 93% experienced service disruptions (for example, disruptions to electricity, water, internet, or access to food/groceries). Such disruptions impose another set of costs on households as they must adopt substitute measures to cope with the lack of services. In our sample, 54% evacuated from the storm; of these, the average cost of evacuation was $1,250. Beyond evacuation costs, 91% report other costs such as debris cleanup and landscaping expenses, fuel and miscellaneous supply expenses, or temporary housing. We also find that 47% lost income from the storm due to a reduction in working hours, job loss, or being furloughed. Among those

[5] In Appendix Figure A.1, we compare pre-disaster census variables in counties affected by the four events in our survey (i.e., Harvey, Michael, Florence, and Ida) and 14 other hurricane declarations from 2010 to 2021. For each hurricane, we calculate population-weighted averages of census variables across affected counties. We show that the four events appear quite representative of all declarations in pre-event attributes, as in most cases they fall within the interquartile range for median household income (inflation-adjusted), unemployment rate, poverty rate, and population share with a college education or above. Similarly, in Figure A.2, we look at changes in census variables from one-year pre- to one-year post-disaster. Due to data limitations, we compare Harvey/Michael/Florence with 8 other hurricane declarations from 2010 to 2020. Along most measures, Harvey (Category 4) and Michael (Category 5) tend to be more representative than Florence (Category 1), possibly a reflection of Florence's differing intensity.

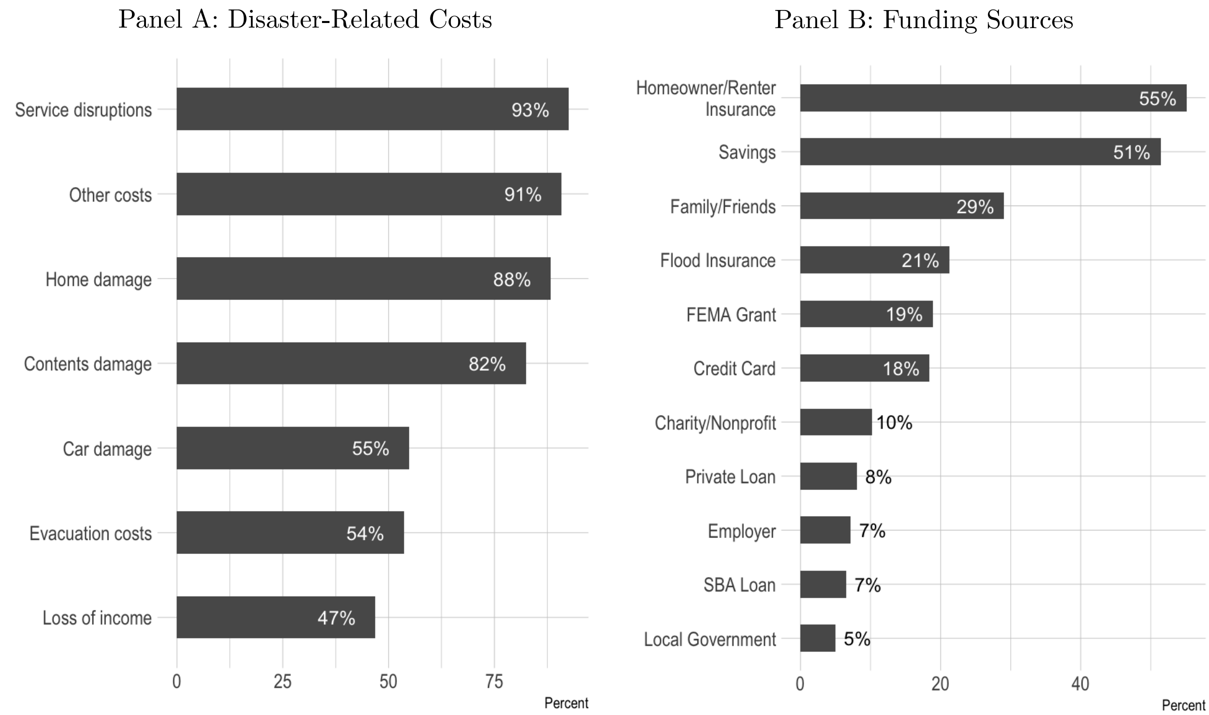
Table 1: Summary Statistics, Survey Sample

	All Survey Respondents			Mean by Insurance Status (Homewoners/Renters *or* Flood Ins)		
	Mean (1)	Median (2)	S.D. (3)	No Ins (4)	Any Ins (5)	*t*-stat (6)
Household Characteristics						
Savings	0.87	1.00	0.34	0.75	0.91	−3.86***
Income < \$34,999	0.29	0.00	0.45	0.52	0.20	6.35***
Income \$35,000 to \$74,999	0.36	0.00	0.48	0.35	0.36	−0.28
Income ≥ \$75,000	0.32	0.00	0.47	0.12	0.40	−6.89***
Employed full-time	0.61	1.00	0.49	0.55	0.63	−1.54
Part-time/self-employed	0.11	0.00	0.32	0.17	0.09	2.02**
Retired	0.15	0.00	0.36	0.06	0.19	−4.34***
Employed other	0.12	0.00	0.32	0.22	0.08	3.39***
Nonwhite	0.37	0.00	0.48	0.39	0.36	0.57
No. of residents	3.03	3.00	1.47	3.11	3.01	0.68
Children/seniors/disability/pets	0.82	1.00	0.38	0.85	0.82	0.74
Home Characteristics						
Renter	0.27	0.00	0.44	0.57	0.16	8.34***
Home mortgage	0.40	0.00	0.49	0.06	0.53	−13.68***
Home tenure (years)	9.38	5.00	10.23	7.12	10.21	−3.17***
Single-family home	0.72	1.00	0.45	0.52	0.79	−5.35***
Disaster-Related Variables						
High burden three weeks after	0.40	0.00	0.49	0.63	0.31	6.36***
High burden one year after	0.16	0.00	0.36	0.24	0.12	2.79***
Unaddressed funding needs	0.34	0.00	0.47	0.50	0.28	4.24***
Real property damage extent	2.79	3.00	1.39	2.76	2.80	−0.25
Home content damage extent	2.46	3.00	1.53	2.46	2.46	−0.04
Service disruption extent	2.93	3.00	1.42	3.20	2.83	2.30**
Evacuation costs (\$000)	1.25	0.00	3.21	0.85	1.39	−2.30**
Car damage	0.55	1.00	0.50	0.46	0.58	−2.22**
Loss of income	0.47	0.00	0.50	0.54	0.44	1.76*
Other costs	0.91	1.00	0.29	0.89	0.92	−0.96
Observations	461			123	338	

Note: Table presents summary statistics for our sample. Household and home characteristics capture information at the time of a disaster event. Columns (1)–(3) consist of survey respondents affected by one of four U.S. land-falling hurricanes: Harvey, Michael, Florence, and Ida. In Columns (4) and (5), we divide sample by a respondent's insurance status. Column (4), labeled as "No Ins", only includes those with neither homeowners/renters insurance nor flood insurance at the time of a disaster. Column (5), labeled as "Any Ins", includes those who had either homeowners/renters insurance or flood insurance. In Column (6), we conduct simple mean comparisons of each variable between the two subsamples and present the corresponding *t*-statistics. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

who report damage of various types, the median households describe their real property damage, home content damage, and service disruption costs as "moderate." The full range of experienced costs also appears persistent across events (see Appendix Table A.1).

Figure 1: Disaster Costs and Funding Choices



Note: Disaster-related costs (Panel A) and funding sources (Panel B) are reported for the 461 surveyed households affected by Hurricane Harvey, Michael, Florence, or Ida. Home damage only includes damage to real property (e.g., damage to roof, windows, garage, walls, floorboards, foundation, etc.). Contents damage only includes damage to personal property (e.g., personal possessions, furniture, carpets, appliances, etc.). Service disruptions include disruptions to electricity, water, internet, phone services, and access to food/groceries, banking, transportation, etc. Evacuation costs include any expenses as a result of evacuation (e.g., shelter, food, healthcare, transportation, healthcare, etc.). Other costs include other expenses excluding the aforementioned ones (e.g., debris cleanup and landscaping expenses, fuel and miscellaneous supply expenses, legal fees, temporary housing, etc.).

Given such a wide range of costs, one single funding source may be insufficient to cover all expenses. We also know that certain types of funding sources are limited in what they will cover. For example, flood insurance will only cover flood damages and FEMA's IHP grants are capped and limited to certain expenses. In addition, homeowners policies will have coverage caps, deductibles, and other possible exclusions. It is unsurprising, then, that we find over 66% of our survey respondents report using more than one funding source for recovery. The median respondent used two sources of funding, with homeowners/renters insurance and savings as the most common combination. Figure 1B shows the percent of respondents that reported using various funding sources.

Drawing on savings and using insurance payouts were the two most common sources used. Almost 30% report using support from family and friends and a bit less than 20% used FEMA grants or credit card debt.

We apply cluster analysis to identify whether there exist systematic patterns in funding strategies for disaster recovery among affected households. Cluster analysis is a machine learning technique that groups observations based on similarities without relying on specific hypotheses – that is, clusters are not predefined but emerge from the data. The respondents that are identified as belonging to a specific cluster from this analysis use a similar portfolio of funding sources compared to those outside the cluster. Specifically, we apply a k-means clustering algorithm and identify two distinct clusters that capture the most variation in our data, as shown in Table 2. Cluster 1 is dominated by respondents' use of insurance: all members of this group report using homeowners/renters insurance and 32% report using flood insurance for their recovery. By contrast, in Cluster 2, none of the members report using homeowners/renters insurance and only 8% used flood insurance. Cluster 2 is distinctive for its greater reliance on family or friends as a funding source. The average use of all other funding sources, however, does not appear significantly different according to our simple mean comparisons between Cluster 1 and Cluster 2 as indicated in the last column. We do find, though, that households in Cluster 2 used fewer funding sources: on average those in Cluster 2 used 2 funding sources, while those in Cluster 1 used 3 sources.

In Appendix Table A.2, we apply cluster analysis to the four hurricane events separately (all storms are pooled in Table 2). Across all storms, the use of insurance remains the major distinction regarding how households fund their recovery. Consistently across events, one cluster is always populated with respondents' dominant use of homeowners/renters insurance and flood insurance. The results suggest that insurance plays a unique role in financing household disaster recovery.

Our key outcome of interest in our regression models (discussed in the next section) is household economic recovery, which we measure in several ways. First, we elicited self-reports of financial burden from the disaster, in both the short- and longer-run.[6] We asked respondents to provide, on

[6]The exact questions being asked in the survey are: (1) "on a scale of 1 to 10, to what extent did you feel that you had enough money in the 3 weeks following the hurricane to pay all immediate disaster expenses (including finding a safe place to live);" and (2) "compared to just before the hurricane, how would you characterize your personal financial situation one year after the hurricane." For the second question, respondents could answer: "much worse," "worse," "slightly worse," "about the same," "slightly better," "better," "much better," or "I prefer not to answer."

Table 2: Cluster Analysis of Funding Sources for Disaster Recovery

	Mean by Clusters		
	Cluster 1 (N=254)	Cluster 2 (N=207)	Cluster 1 *vs.* Cluster 2 t-stat
Funding Source			
Homeowners/Renters Insurance	1.00	0.00	***
Flood Insurance	0.32	0.08	7.06***
Family or Friends	0.24	0.36	−2.84***
Savings	0.52	0.50	0.45
Credit Card	0.20	0.17	0.77
FEMA Grant	0.18	0.20	−0.70
SBA Loan	0.07	0.05	0.95
Private Loan from Bank or Other Lenders	0.09	0.07	0.56
Charity, Non-Profit, or Community Group	0.10	0.10	0.03
Employer	0.06	0.09	−1.13
Local Government	0.05	0.05	0.14
No. of Funding Sources	2.83	1.68	9.08***

Note: Table presents the average funding portfolio composition of the two clusters identified from cluster analysis. Sample includes survey respondents affected by one of four U.S. land-falling hurricanes: Harvey, Michael, Florence, and Ida. In the last column, we conduct simple t-tests for differences in the mean of each funding source by comparing cluster 1 and cluster 2. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

a scale from 1 to 10, the extent to which they felt their household had enough money three weeks following the hurricane to pay for all immediate expenses, with 1 indicating not enough money at all and 10 indicating plenty of funds. The median respondent across all storms reports a measure of 5. Accordingly, for our econometric analyses, we categorize anyone with a reported response below 5 as having "high financial burden" three weeks after the storm. Similarly, to measure longer-run recovery, we asked respondents to characterize their financial situation one year after the hurricane relative to just before the storm. For this question, we define a household as having a high financial burden if they describe their financial status as "worse" or "much worse" than prior to the storm. For robustness checks, we also use continuous measures (instead of high versus low) to capture the intensity of financial burdens in the short and long run.

As our second measure of economic recovery, we examine whether the household's existing funding sources post-hurricane (combining external sources and personal savings, if any) were sufficient to cover all disaster costs. We define a respondent as having unaddressed funding needs if they report either that funds received from all the external sources were not enough to have fully covered all financial costs or, if they report using savings, that the funds were still insufficient even after using savings. Across these measures, we find, on average, that 40% and 16% of disaster-affected households in our survey sample reported high financial burdens three months and a year after the disaster, respectively. Meanwhile, 34% reported still having unmet funding needs to resolve all financial costs at the time of the survey.

Across our sample, we find 73% (338 out of 461) of respondents had homeowners/renters insurance or/and flood insurance at the time of disaster. Among them, over half (190 out of 338) had both homeowners/renters insurance *and* flood insurance prior to the storm; 140 had homeowners/renters insurance only; and only 8 had flood insurance only. In Columns (4) and (5) of Table 1, we divide our sample by a household's ex-ante insurance status (whether they had any insurance or none). The naïve comparison of means between the two groups shows that households with any insurance in place at the time of the hurricane appear in a better financial position post-disaster. Compared to those without insurance, they have a lower likelihood of reporting high financial burdens both three months and one year after a disaster and are less likely to have unaddressed funding needs. There are, however, as discussed above, key differences between those with insurance and those without, such as their income level. We thus turn to econometric analyses to further examine the role of insurance in recovery.

3.3 Empirical Strategy

To identify the role of insurance in household disaster recovery, we begin with simple regressions of the following form:

$$y_i = \beta_0 + \beta_1 AnyIns_i + \beta_2 Savings_i + \Gamma \mathbf{Cost}_i + \Omega \mathbf{X}_i + \Phi \mathbf{Event}_i + \varepsilon_i \tag{1}$$

where y_i is recovery-related outcome for household i, $AnyIns_i$ is an indicator for whether a household i had either homeowners/renters insurance or flood insurance at the time of a disaster, $\mathbf{Cost}_i$ represents reported disaster-related financial costs, $\mathbf{X}_i$ represents a vector of home and household characteristics (including home tenure, home ownership, home mortgage status, home type, number of residents, income, race, employment status, and whether there are family members in need of care). We also include disaster event dummies, $\mathbf{Event}_i$, to account for systematic differences across hurricanes. Standard errors are clustered by hurricane.

Our coefficient of interest is β_1. Recall that all survey respondents in our sample suffered some type of property damage (i.e., damage to their home or contents). Having either homeowners/renters insurance or flood insurance in place would help cover property losses incurred as a result of the hurricane. Accordingly, β_1 can be interpreted as the difference in the mean recovery outcome for households with any insurance (treatment group) relative to those without insurance (control group).

A household's economic recovery is a function of both disaster-incurred financial costs and available funding tools. Therefore, we control for any reported disaster expenses ($\mathbf{Cost}_i$), including the extent of real property damages, the extent of damages to home contents, the extent of service disruptions, evacuation costs, whether the household reported lost income, whether they had car damage, and whether they experienced any additional costs (such as debris cleanup, fuel expenses, etc.).[7] We also include a dummy variable, $Savings_i$, indicating whether or not a household i had any savings in hand when a disaster struck. The summary statistics in Table 1 show that disaster-related physical damage is evenly spread across our treatment and control groups. This supports our assumption that hurricanes can be considered quasi-random shocks to households in our survey sample.

One identification concern regarding our approach in Eq. (1) is that a household's insurance status could be correlated with other factors that would have led to better recovery outcomes even in the absence of insurance. For instance, we find in the previous section that having insurance is significantly associated with a household's annual income, home tenure, and home ownership.

[7]The extent of real property damages and the extent of damages to home contents are both self-reported indexes ranging between 0 and 5, with a value of 0 indicating no damage, 1 indicating minimal damage, 2 indicating minor damage, 3 indicating moderate damage, 4 indicating severe damage, and 5 indicating completely destroyed. Similarly, the extent of service disruptions is a self-reported index ranging between 0 and 5, with a value of 0 indicating no service disruptions, 1 indicating having had service disruptions but with no costs, 2 indicating minor costs, 3 indicating moderate costs, 4 indicating major costs, and 5 indicating extreme costs.

While we do control for these factors in Eq. (1), individuals with the same characteristics may not be represented equally in control and treatment groups. That being the case, β_1 might also be capturing the uneven distributions of these observed covariates between the two groups.

To better address this concern, we re-estimate Eq. (1) using a propensity score weighting approach (Imbens and Wooldridge, 2009).[8] More specifically, we predict the probability (or propensity score) of a survey respondent being treated by running a logistic regression as follows:

$$AnyIns_i = \alpha_0 + \alpha_1 Savings_i + \Theta \mathbf{X}_i + \Psi \mathbf{Event}_i + \mu_i \tag{2}$$

where $\mathbf{X}_i$ consists of the same set of home- and household-level variables as in Eq. (1), including home tenure, home ownership (homeowner or renter), mortgage status, home type (whether a single-family home or not), number of residents, income, race (white or nonwhite), employment status (full-time, part-time/self-employed, retired, or other), and whether there are children/seniors/pets/people with disabilities in the home.

We then run weighted regression estimations of Eq. (1), where the treated units are assigned a weight equal to one and the control units are assigned the inverse probability weights of having insurance. That is,

$$w_i = \begin{cases} 1 & \text{if } AnyIns_i = 1 \\ PropensityScore_i/(1 - PropensitySocre_i) & \text{if } AnyIns_i = 0 \end{cases} \tag{3}$$

where $PropensityScore_i$ is the predicted probability of a household having any insurance from Eq. (2). The weighting process has the effect of up-weighting (down-weighting) observations in the control group that are the most (least) similar to treated observations when it comes to baseline covariates. This pushes our tests close to a hypothetical setting where individuals in control and treatment groups have the same characteristics (except insurance status) and are equally represented. Our findings on recovery outcomes, thus, can be more plausibly explained by a household's insurance status.

[8] We also attempted a propensity score matching method. However, we are unable to find suitable match per treated household (having any insurance), given the limited size of our survey data.

3.4 Survey Results: Role of Insurance

3.4.1 Disaster Recovery

In Table 3, we first examine whether having any insurance at the time of the hurricane improves a household's financial situation post-disaster. More specifically, as discussed in Section 3.2, our dependent variables are indicators for whether or not a household reported high financial burden three weeks (Columns 1 and 2) and one year (Columns 3 and 4) after the storm, respectively. Our baseline logit regression estimations of Eq. (1) are shown in Columns (1) and (3), while the propensity score weighted models are shown in Columns (2) and (4).

Our baseline results show that households with insurance in place are less likely to report high financial burden three weeks after a disaster (Column 1), suggesting that they were more financially capable of covering immediate expenses in the short run. In addition, in Column (3), their likelihood of having high financial burden in the long run is also significantly lower. Compared to those without insurance, households with insurance are less likely to report their financial situation one year post-disaster as becoming worse or much worse relative to just before the storm.

Columns (2) and (4) present our preferred estimation using propensity score weighting, as we are able to construct a weighted control group of households (who had no insurance) with similar compositions of baseline characteristics to the treatment group (who had insurance). Our results remain statistically significant. Specifically, we find that having insurance ex-ante decreases a household's likelihood of having a high financial burden by 85% ($|e^{-1.915}-1|$) and 82% ($|e^{-1.723}-1|$) three weeks and one year after a disaster, respectively. Robustness checks that use continuous measures of financial burdens in both the short and long run confirm the same pattern of results (see Appendix Table A.3).

We next ask *how* insurance affects household disaster recovery to further explore the potential mechanisms behind differential recovery outcomes. Recall that respondents report that a hurricane imposes a wide range of costs. To the extent that insurance is an ex-ante risk management tool that provides financial protection against physical damages, we expect that households with insurance would retain more resources at their disposal ex-post and thus have their broad funding needs covered more easily. In Columns (5) and (6), we re-estimate our equations with an additional

Table 3: Effects of Any Insurance, Survey Analysis

	High Burden Three Weeks After Disaster		High Burden One Year After Disaster		Unaddressed Funding Needs	
	(1) logit	(2) logit	(3) logit	(4) logit	(5) logit	(6) logit
AnyIns	−1.382***	−1.915***	−1.258***	−1.723***	−0.662*	−0.857**
	(0.524)	(0.559)	(0.475)	(0.660)	(0.373)	(0.397)
Savings	−0.609	−0.459	0.255	1.029***	−1.452***	−2.500***
	(0.611)	(0.847)	(0.569)	(0.083)	(0.380)	(0.465)
Real property damage extent	0.009	0.060	0.253	0.407	−0.164	−0.153
	(0.034)	(0.078)	(0.230)	(0.309)	(0.134)	(0.152)
Home content damage extent	0.021	0.108	0.295***	0.505***	0.345***	0.321***
	(0.097)	(0.105)	(0.094)	(0.176)	(0.089)	(0.076)
Service disruption extent	0.115	0.297***	0.236**	0.395*	0.192***	0.053
	(0.104)	(0.068)	(0.101)	(0.227)	(0.073)	(0.100)
Evacuation costs	0.002	−0.013	0.099**	0.092	0.016	0.029
	(0.042)	(0.040)	(0.040)	(0.059)	(0.025)	(0.023)
Car damage	0.277	−0.093	−0.566*	−1.051***	−0.284	0.140
	(0.259)	(0.147)	(0.309)	(0.357)	(0.464)	(0.401)
Loss of income	0.548**	0.469	0.533***	0.063	−0.130	0.234
	(0.264)	(0.377)	(0.185)	(0.198)	(0.372)	(0.462)
Other costs	1.681***	2.633***	1.315	1.442	0.226	0.451
	(0.322)	(0.774)	(1.438)	(1.787)	(0.840)	(0.894)
Propensity Score Weighted	No	Yes	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Event	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.167	0.284	0.297	0.554	0.170	0.245
N	451	451	455	455	456	456

Note: Table presents regression estimation results of Eq. (1). The key variable of interest is *AnyIns*, an indicator for whether or not a household had any insurance (either homeowners/renters insurance or flood insurance) at the time of a storm. The dependent variable in Columns (1)–(2) is a dummy variable equal to one if a household reported high financial burdens (i.e., below-median enough money to pay all immediate expenses) three weeks after a disaster, and zero otherwise. The dependent variable in Columns (3)–(4) is a dummy variable equal to one if a household reported high financial burdens (i.e., described their financial status as "worse" or "much worse") one year after a disaster, and zero otherwise. The dependent variable in Columns (5)–(6) is a dummy variable equal to one if a household had unaddressed funding needs to cover all disaster-related costs at the time of the survey and zero otherwise. All columns include home- and household-level controls. Standard errors are clustered by storm. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

dependent variable: whether the respondent reports unaddressed funding needs at the time of the survey. We find that affected households with insurance have a decreased likelihood of reporting unaddressed funding needs after controlling for all external and internal funding sources used (if any). The result remains consistent in the propensity score weighted model, as well. In Column

(6), those who held insurance at the time of the disaster event are 58% ($|e^{-0.857} - 1|$) less likely to have unmet funding needs. This finding helps explain observed better financial conditions following a disaster, both in the short and long run.

3.4.2 Substitutes and Complements for Insurance

Without funding from insurance, households with property damage and other costs must turn to alternative sources to meet their post-disaster financial needs. In this section, we explore how households with and without any insurance differ in their funding strategies to cover disaster-related expenses. In Table 4, we estimate our propensity score weighted model with the dependent variable being whether a specific funding source was used or not by the respondent from Columns (1) to (9) and the total number of reported funding sources in Column (10).

Table 4: Funding Sources for Recovery, Survey Analysis

	Type of Funding Source									
	Family/ Friends	FEMA Grant	SBA Loan	Savings	Employer	Charity/ Nonprofit	Credit Card	Bank Loan	Local Gov.	# of Sources
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	logit	logit	logit	logit	logit	logit	logit	logit	logit	OLS
AnyIns	-0.891^{**}	-1.102	0.467	0.291	0.441	0.826	0.756^{***}	0.882^{**}	2.471^{***}	0.696^{***}
	(0.447)	(0.898)	(0.625)	(0.537)	(0.431)	(0.538)	(0.199)	(0.431)	(0.462)	(0.195)
Propensity Weighted	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Event	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo/Adj. R^2	0.183	0.217	0.264	0.184	0.253	0.334	0.133	0.269	0.418	0.284
N	461	461	461	461	461	461	461	461	461	461

Note: Table presents propensity-score-weighted estimation results of Eq. (1). The dependent variables in Columns (1)–(9) represent different types of funding sources used by households for disaster recovery. The dependent variable in Column (10) is the total number of funding sources used for recovery. All columns include disaster-related costs, home- and household-level controls. Standard errors are clustered by storm. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

After controlling for the full set of disaster-related costs, as well as home- and household-level characteristics, we find that households with insurance are 59% ($|e^{-0.891} - 1|$) and 67% ($|e^{-1.102} - 1|$) less likely to draw on funding from family or friends (Column 1) and FEMA IHP grants (Column 2) to fund recovery, although the coefficient for FEMA IHP grants is not statistically significant.[9]

[9] We also examine the probability of applying for a FEMA grant as shown in Appendix Table A.4; we do not find significant effects of having any insurance on the probability of applying.

This suggests that family and friends act as a substitute for insurance in household disaster recovery. One's social network can provide funds faster: on average, 60% of survey respondents who used family/friends as a funding source indicate that they received those funds within two weeks after the storm, while only 16% (18%) received funds from homeowners/renters insurance (flood insurance) within two weeks after the storm. That said, support from one's social network is not a perfect or reliable substitute for insurance. Informal borrowing from family/friends likely has limits in scale. Data from FEMA's NFIP program reveals that the average flood insurance payment amount is $95,105, $49,428, $44,225, and $49,685 for Hurricane Harvey, Michael, Florence, and Ida, respectively. It is unlikely that friends and family can match such large amounts. Also, family/friends may be unavailable for support if they live nearby, given that disasters are systemic shocks that adversely affect those in the same region at the same time.

If insurance largely alleviates financial burdens for disaster-affected households, we would expect those with insurance to use fewer funding sources post-disaster compared to those who were uninsured. Surprisingly, we find that households with insurance, on average, used one more funding source for recovery (Column 10).[10] Specifically, across the complete set of financing options, those with insurance are more likely to combine funding from credit cards (Column 7), bank loans (Column 8), and local governments (Column 9). These sources are likely to complement insurance in terms of timing and flexibility. Dollars from these sources arrive relatively faster than insurance. There may also exist fewer restrictions on how to use the funds. Together, our findings suggest that households with insurance may be better able to manage their funding structure, often combining multiple sources of funding, which leads to faster reconstruction.

Overall, our results signify the important role of insurance in financing household disaster recovery. Households who held insurance at the time of a disaster are more financially resilient both in the short and long run post-disaster and are less likely to have unaddressed funding needs. They also tend to address their funding needs more comprehensively by combining insurance with other sources of funding. This may indicate that having insurance as a funding tool allows households to be more strategic about financial risk management and that insured households are better able

[10] Note that we consider insurance as one funding source, regardless of the type of insurance. For instance, if a respondent reports using both homeowners insurance and flood insurance, we do not count them as two funding sources but only one.

to navigate the challenges of dealing with a myriad of costs, perhaps indicating higher financial literacy. In the absence of insurance, households turn to family or friends instead to fund disaster losses, delaying the timing and the extent of recovery.

4 Foot Traffic Analysis

Our survey analysis highlights the important role of insurance in household financial recovery. We now turn to examining spillover benefits from more widespread insurance take-up to the local economy, using flood insurance and one of our sample hurricanes, Hurricane Michael, as a case analysis. We use unique foot traffic data, discussed in the next subsection, to examine how often residents visit local businesses. We are able to look at visitation rates before and after the hurricane and how those rates vary by both degrees of flooding and insurance penetration rates. Hurricane Michael was a Category 5 storm when it made landfall in the Florida Panhandle in early October 2018. The storm caused an estimated $25 billion in damages, of which only $7.4 billion was insured (Sassian, 2020). While the strong wind caused property damage, the hurricane also brought a storm surge of 9 to 14 feet along with heavy rainfall, with some locations registering near a foot of precipitation (Beven II et al., 2019)–both led to widespread flooding.

4.1 Data and Summary Statistics

We combine multiple sources of data for our community spillover analysis. We focus on the area impacted by Hurricane Michael, which we define as the 161 census tracts that comprise the counties where FEMA's IHP was authorized through a Presidential Disaster Declaration. First, to estimate an area's pre-disaster flood insurance coverage, we combine NFIP Redacted Policies data from FEMA (2022)[11] and data on total housing units from the U.S. Census Bureau (2022). FEMA does not provide finer geographic resolution for NFIP data beyond the census tract, hence we use tracts as our level of analysis. We calculate the take-up rate of flood insurance within a census tract by dividing the number of NFIP-insured units under an active policy at the end of 2017 by the 2017

[11]Note that while FEMA's NFIP does not account for the entire flood insurance market, over 95% of policies are purchased through the NFIP (versus the private market) (Kousky et al., 2018). Also, according to Florida Office of Insurance Regulation (2019), there were 169 paid claims from private flood policies as of October 2019 (approximately one year after Michael), equivalent to only 6% of NFIP paid claims during the same period.

Table 5: Summary Statistics, Foot Traffic Analysis

	Mean (1)	Median (2)	S.D. (3)	Mean by Flooding Treatment: No Flood (4)	Mean by Flooding Treatment: Flooded (5)
Visitor-Establishment-Level Variable, Sep. 2018					
No. of Visitors	13.24	6.00	22.93	13.28	13.17
Observations	8,151			5,511	2,640
Tract-Level Variables					
Flood Depth (ft.)	0.05	0.00	0.14	0.00	0.19
Flood Ins Take-up Rate	0.10	0.02	0.18	0.04	0.27
Floodplain Share of Developed Area	0.15	0.09	0.17	0.09	0.32
Median Income ($000)	48.98	42.93	21.05	48.94	49.07
Population (000)	4.37	4.21	1.98	4.51	4.03
Ptg. Owner-Occupied	0.61	0.67	0.24	0.61	0.63
Income Gini Index	0.43	0.42	0.05	0.43	0.43
Ptg. Mortgage	0.55	0.55	0.15	0.56	0.51
Ptg. White	0.69	0.73	0.22	0.65	0.81
Ptg. Bachelor's Degree	0.28	0.23	0.18	0.31	0.22
Ptg. Unemployed	0.08	0.07	0.05	0.09	0.06
Ptg. Savings	0.70	0.70	0.06	0.70	0.70
No. of Census Tracts	161			116	45
Establishment-Level Variables					
Location Flood Depth (ft.)	0.04	0.00	0.30	0.00	0.14
Brand	0.26	0.00	0.44	0.28	0.22
No. of Establishments	8,151			5,511	2,640

Note: Table presents summary statistics for foot traffic analysis. In Columns (4) and (5), we divide sample by whether or not a census tract was flooded from Hurricane Michael. Tract-level variables except flood depth are measured as of 2017. *Data Source:* Foot traffic data (e.g., number of visitors, whether an establishment belongs to a brand) is obtained from SafeGraph (2022). Flood depth information is aggregated using data from First Street Foundation (2020). Flood insurance policy information as of the end of 2017 comes from FEMA (2022). Tract-level socio-demographic variables are from the 2017 American Community Survey data (U.S. Census Bureau, 2022). Tract-level household savings status as of 2017 (i.e., share of households with a traditional savings account) is from the Claritas Financial CLOUT data set accessed via S&P Global.

estimate of the number of housing units. This measure can be interpreted as the probability of a household in that tract being covered by a flood insurance policy. Alternatively, we obtained information on NFIP flood insurance claims paid to Michael-affected victims from a FOIA request to FEMA. The data discloses the census tract of the flooded property, as well as the timing and amount of the claim payment. We then aggregate the data to the tract-month level by calculating both the cumulative number of claims and the total dollar amount of flood insurance claims paid to residents in a census tract by the end of a month.

Next, we use estimated flood depths developed by the First Street Foundation (2020) to capture flood intensity from Hurricane Michael. The flood depths are estimated from a combination of remote sensing, interpolations, hydrodynamic modeling, and peer-reviewed by an independent expert panel (Wing et al., 2021). We follow Billings et al. (2022) in calculating the weighted average flood depth (in feet) across developed land area within a census tract. We identify developable land area using land cover data from The Multi-Resolution Land Characteristics Consortium (2022).

To measure local economic activity, we use monthly foot traffic data from SafeGraph (2022).[12] The SafeGraph Patterns dataset aggregates data from approximately 10% of mobile devices in the U.S., identifying their visitation patterns to commercial establishments (e.g., restaurants, retail stores, etc.). The data includes information on the number of visitors to an establishment and where these visitors originated (i.e., the census block group in which their home is located). We limit attention to visitors living in the 161 census tracts in the disaster area of Hurricane Michael, examining their visitations to local commercial establishments. This allows us to investigate consumer behavior over time before and after the disaster.

Summary statistics for our tract-level variables are provided in Table 5. Among the 161 tracts impacted by Michael, 45 tracts had flooding, with an average flood depth of 0.19 feet. In Columns (4) and (5), we compare the socio-demographic characteristics between non-flooded and flooded tracts using the 2017 American Community Survey data from the U.S. Census Bureau (2022). Michael-related flooding hit neighborhoods with similar income, population, home ownership rates, and levels of income inequality, but flooded tracts had a slightly greater population share identifying as white and slightly lower levels of education and unemployment rates.

We construct our outcome variable of interest as the monthly number of visitors from a particular census tract to an establishment, a measure of the frequency of visits from residents living in a specific census tract to that establishment. We use these monthly visitation numbers as a proxy for the extent of economic activity generated by a given tract. In our main analysis, we limit attention to households who lived inside the area impacted by Hurricane Michael and examine their visitation patterns to commercial establishments located in the same census tract where their

[12] SafeGraph is a data company that aggregates anonymized location data from numerous applications in order to provide insights about physical places.

home was located. For example, if we look at all businesses in a census tract and their visitors in September 2018 (a month before Michael), on average, 13 visitors were local residents living in the same tract (see Table 5). We then investigate how those numbers change as a result of flooding and how insurance mediates that relationship. Our final sample consists of a balanced panel of 8,151 establishments located in 161 Michael-affected census tracts and the monthly sample period spans from April 2018 (6 months before Michael) to October 2019 (a year after Michael). As a robustness check, we also examine household visitation patterns to businesses that are located within 1 to 4 miles from an individual's residence.

4.2 Empirical Strategy

For this analysis, we first examine the impact of flooding on household visitations to local commercial establishments. Therefore, we start by estimating a visitor-establishment-level difference-in-difference regression as follows:

$$
\begin{aligned}
Y_{m,n,t} = \rho_0 &+ \rho_1(Post_t \times FloodDepth_m) + \Theta(Post_t \times \mathbf{X}_m) + \Lambda(Post_t \times \mathbf{X}_n) \\
&+ FE_{m,n} + FE_t + \varepsilon_{m,n,t}.
\end{aligned} \tag{4}
$$

In Eq. (4), the outcome variable, $Y_{m,n,t}$, is the logarithm of (one plus) the number of households from census tract m who visited establishment n (e.g., a specific restaurant or shop) in month t. $Post_t$ is an indicator for months, t, after Hurricane Michael. $FloodDepth_m$ is the weighted average flood depth in census tract m where households lived, which measures the intensity of our treatment. Our reference group is households who lived in non-flooded tracts inside the area impacted by Hurricane Michael. As such, the coefficient ρ_1 captures the effect of flooding on household visitation patterns to local businesses in the post-Michael periods, relative to visitation outcomes in non-flooded areas.

We interact a set of control variables with the post-event dummy to account for heterogeneity unrelated to the flood. These controls include demographic characteristics of the census tract where households lived as of 2017 ($\mathbf{X}_m$, a vector which includes the share of developed area in the floodplain, median household income, total population, share of homes that are owner occupied, Gini Index of income inequality, share of households with a home mortgage, population share identifying as white, share of population with a Bachelor's degree or above, unemployment rate, and share of households with a traditional savings account) and establishment-specific information ($\mathbf{X}_n$, a vector which includes the specific industry and whether it is a chain of a larger brand). In our analysis, we are interested in how Michael-related flooding affects consumer behaviors rather than business outcomes. Therefore, we add to $\mathbf{X}_n$ a control that captures the level of flooding at establishment n's location to absorb any business-induced effects on household visitation patterns. We also include visitor-establishment fixed effects ($FE_{m,n}$) and time fixed effects (FE_t). Standard errors are clustered at the census tract level.

Underlying our empirical approach in Eq. (4) are two assumptions. First, in order for us to identify the causal effect of flooding, the assignment of flooding must be quasi-random along our outcome of interest. While Florida is more prone to hurricanes than other states, the specific nature and extent of flooding from Hurricane Michael can be considered an exogenous shock. We also provide descriptive evidence in Table 5 that Michael-related flooding impacted areas of varying socio-economic demographics fairly evenly. Second, we assume that trends in household visitation patterns would have evolved in parallel for both the treatment and reference groups in the absence of the flooding. We gauge the plausibility of this assumption by comparing trends between treatment and control groups in the pre-Michael period. To do this, we estimate an event study version of Eq. (4) by replacing $Post_t$ with a series of time dummies $\sum_t EventMonth_t$.[13] The month before Michael, September 2018, is omitted and used as the reference period. The full sets of coefficients on $\sum_t EventMonth_t \times FloodDepth_m$ thus allow us to observe how the flooding effects evolve over time before and after Michael as flooding intensifies. We present the results in Appendix Figure A.3 and find no differential pre-trends between non-flooded and flooded groups, in support of our parallel trend assumption.

[13] The event study version of Eq. 4 is as follows: $Y_{m,n,t} = \rho_0 + \sum_t \rho_{1t}(EventMonth_t \times FloodDepth_m) + \Theta(\sum_t EventMonth_t \times \mathbf{X}_m) + \Lambda(\sum_t EventMonth_t \times \mathbf{X}_n) + FE_{m,n} + FE_t + \varepsilon_{m,n,t}$.

To then examine how flood insurance mediates the impact of flooding on commercial visitation rates, we add a triple interaction term in Eq. (4) and estimate the following regression:

$$\begin{aligned} Y_{m,n,t} = \gamma_0 &+ \gamma_1(Post_t \times FloodDepth_m \times FloodInsCoverage_{m,t}) \\ &+ \gamma_2(Post_t \times FloodDepth_m) + \Theta(Post_t \times \mathbf{X}_m) + \Lambda(Post_t \times \mathbf{X}_n) \\ &+ FE_{m,n} + FE_t + \varepsilon_{m,n,t}. \end{aligned} \tag{5}$$

Our key coefficient of interest, γ_1, is on the triple interaction term, $Post_t \times FloodDepth_m \times FloodInsCoverage_{m,t}$, which captures how the flooding effects vary by a census tract's flood insurance coverage for a particular flooding intensity. We expect that flooding would impose financial burdens on households forcing them to reduce their consumption and thus visitations to local businesses. Flood insurance, however, we hypothesize should mitigate negative impacts on general consumption, given our findings in the previous section. Thus, we expect residents who lived in flooded tracts with higher flood insurance coverage to recover faster and visit local businesses more frequently, compared to those who lived in flooded tracts with low flood insurance coverage. Accordingly, we expect that $\gamma_1 > 0$ and $\gamma_2 < 0$. We use three measures of flood insurance coverage for our estimation: a tract m's pre-event flood insurance take-up rate, the cumulative count number of actual flood insurance claims paid to tract m by the end of each post-disaster month t, and the cumulative dollar volume of claims paid to tract m by the end of month t.

4.3 Results: Role of Flood Insurance

4.3.1 Effect of Flood Insurance Coverage and Claim Payments

Table 6 reports the difference-in-difference estimation results of Eq. (4) and Eq. (5). Again, our dependent variable is how often residents from a census tract visited local businesses in a given month to examine how the visitation patterns change in the 12 months after Hurricane Michael relative to the 6 months before the hurricane. We hypothesize that losses caused by Michael-related flooding would place financial burdens on affected households that result in reduced consumer spending. This should lead to a decrease in post-disaster visitation frequency to local businesses from households living in flooded neighborhoods. For our baseline estimates, we consider a business as local if they are located in the same census tract as the visitors.

Table 6: Foot Traffic Analysis, Visits to Local Businesses

	(1)	(2)	(3)	(4)
$Post \times FloodDepth$	−0.050	−0.838**	−0.944**	−1.767***
	(0.181)	(0.366)	(0.362)	(0.519)
$Post \times FloodDepth \times FloodInsTakeup$		1.404***		
		(0.523)		
$Post \times FloodDepth \times \log(1{+}ClaimCount)$			0.175***	
			(0.053)	
$Post \times FloodDepth \times \log(1{+}ClaimAmount)$				0.117***
				(0.030)
Visitor-Establishment FEs	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Cluster by Tract	Yes	Yes	Yes	Yes
Adj. R^2	0.722	0.722	0.722	0.722
N	154,869	154,869	154,869	154,869

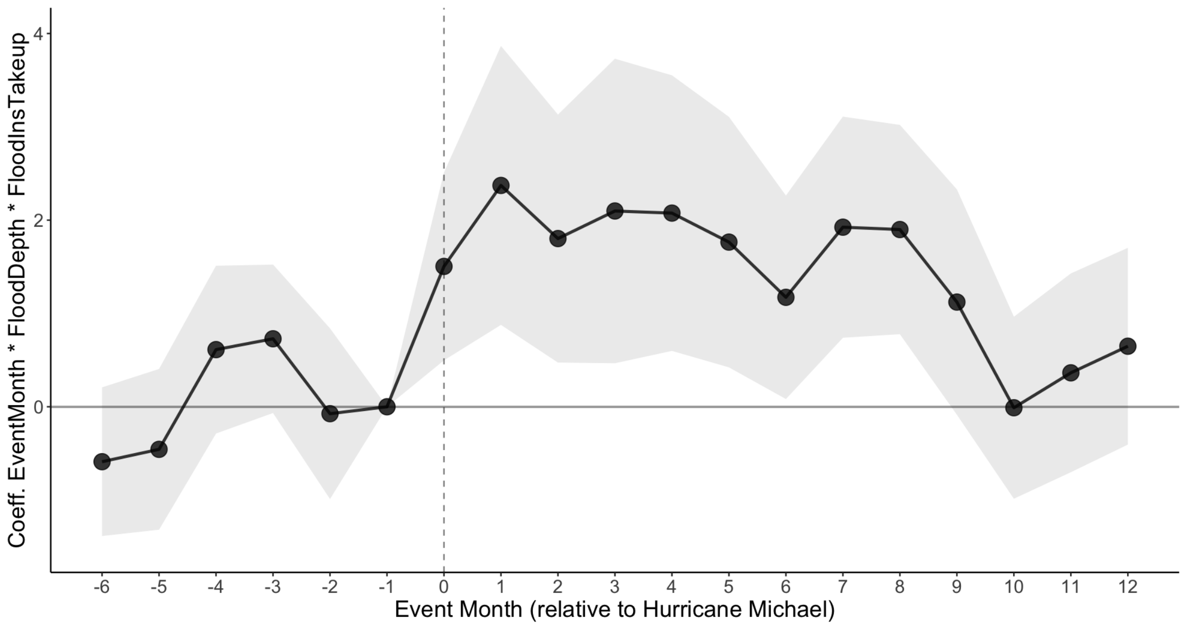
Note: Table presents estimation results of Eqs. (4) and (5). The dependent variable is the logarithm of (one plus) the number of residents who visited a local business in a month. The post-disaster indicator, *Post*, takes the value of one for the 12 months after Hurricane Michael from October 2018 to October 2019, and equals zero for the 6 months before Michael from April 2018 to September 2018. The variable *FloodDepth* captures our treatment intensity, calculated as the weighted average of flood depth within a census tract's developed area. All regressions include control variables, visitor-establishment fixed effects, time fixed effects, and report standard errors clustered at census tract level. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

In Column (1), we observe no noticeable change in residents' visitation frequency to local businesses in flooded neighborhoods relative to non-flooded neighborhoods. The coefficient on the interaction term between post-Michael periods and a tract's average flood depth is negative but not statistically significant. However, Columns (2) to (4) highlight that the overall effect is masked by heterogeneity depending on an area's flood insurance coverage – the negative effect of flooding on visitation rates increases significantly with flood intensity but decreases with flood insurance coverage. In Column (2), we use a tract's pre-event flood insurance take-up rate to measure flood insurance coverage, a proxy for the likelihood of a household being covered by a flood insurance policy. We find that, at a given level of flooding, a 10 percentage point increase in the flood insurance take-up rate leads to 15% ($e^{1.404\times0.1}-1$) more visits to local businesses from flooded residents.

We also run an event study version of the specification in Column (2) and present the coefficients on the triple interaction term of $EventMonth \times FloodDepth \times FloodInsTakeup$ along with their 95% confidence intervals in Figure 2. The estimated coefficients allow us to observe how the mediating effect of flood insurance coverage evolves over time in flooded neighborhoods. The reference period is September 2018, one month before Michael. We show in Figure 2 that there is no differential pre-trend for the months prior to Michael. During the post-Michael months, however, the visitation frequency to local businesses continued to increase with flood insurance penetration rates in flooded neighborhoods. Visitations remain elevated until approximately nine months after the disaster. This finding suggests that flood insurance may help relieve financial constraints for affected households, generating spillover benefits to the local economy. As flooding intensifies, the flood insurance effect also magnifies. This implies that flood insurance may be even more helpful in cases of severe flood damage.

In Columns (3) and (4) of Table 6, we directly estimate how receiving flood insurance payouts mitigates the adverse impact of flooding. During the 12 months following Michael, NFIP paid a total of \$0.18 billion to 2,710 households with flood damage. While over 50% of the claims (by count) were paid within three months, the timing of final payouts varied. We thus look at how many NFIP claims (Column 3) and what dollar volume (Column 4) had been paid by the end of each month in each flooded census tract, and examine to what extent these payouts alleviate household financial constraints as reflected in their visitation to local businesses. We show that households visited local businesses 1.75% more often in neighborhoods that received 10% more flood insurance payouts, at a particular degree of flooding. Similarly, a 10% greater dollar amount of claim payments is associated with 1.17% more visits to local businesses. In Appendix Table A.5, we extend our analysis to local businesses within 1-4 miles of affected residents' homes. Our results remain consistent.

Figure 2: Interaction Effect of Flooding and Flood Insurance Take-up Rate



Note: Figure plots coefficient estimates of γ_{1t} and their 95% confidence intervals from the following: $Y_{m,n,t} = \gamma_0 + \sum_t \gamma_{1t}(EventMonth_t \times FloodDepth_m \times FloodInsTakeup_m) + \sum_t \gamma_{2t}(EventMonth_t \times FloodDepth_m) + \Theta(\sum_t EventMonth_t \times \mathbf{X}_m) + \Lambda(\sum_t EventMonth_t \times \mathbf{X}_n) + FE_{m,n} + FE_t + \varepsilon_{m,n,t}$. This regression is equivalent to an event study version of Eq. (5) with the month before Michael ($t = -1$) as the reference period. The event month $t = 0$ represents October 2018, when Hurricane Michael occurred. The dependent variable is the logarithm of (one plus) the number of residents who visited a local commercial establishment in a month, which represents how often residents who lived in a census tract visited local businesses. The plotted coefficients capture the differential effects of flooding on household visitation frequency to local businesses as a tract's flood insurance take-up rate increases (i.e., flood insurance effects) for a particular flooding intensity. Standard errors are clustered at census tract level.

Together, these results suggest flood insurance facilitates post-disaster economic activities, providing community-level spillover benefits to the neighborhoods. The spillover benefits also extend to several miles away from Michael-flooded areas.

4.3.2 Effect of Flood Insurance by Local Business Type

What local economic activities receive the most spillover benefits from local residents' flood insurance payouts? In Table 7, we estimate Eq. (5) separately for household visitation rates to different types of local establishments. Based on an establishment's industry NAICS code, we divide our sample into 10 selected local business categories defined by Delgado et al. (2016). These business categories are classified according to similarities in activities reflected in aggregated U.S. industry categories.

Table 7: Flood Insurance Effect by Local Business Type

	(1) Vehicle Production & Services	(2) Food/Beverage Process & Distrib	(3) Retailing Clothing & Gen Merch	(4) Non-Medical Personal Services	(5) Hospitality
$Post \times FloodDepth$	−1.073**	−2.014**	−4.550***	−2.620***	−1.500**
	(0.505)	(1.014)	(0.899)	(0.984)	(0.659)
$Post \times FloodDepth \times \log(1{+}ClaimAmount)$	0.082***	0.129**	0.289***	0.178**	0.104***
	(0.030)	(0.060)	(0.056)	(0.074)	(0.038)
Adj. R^2	0.764	0.731	0.653	0.548	0.709
N	17,480	9,519	5,472	8,189	38,741
	(6) Health Care Services	(7) Financial Services	(8) Entertainment & Media	(9) Real Estate & Dev	(10) Household G&S
$Post \times FloodDepth$	−1.501***	−2.214*	−0.045	−2.265	−1.310
	(0.548)	(1.137)	(1.151)	(1.547)	(1.262)
$Post \times FloodDepth \times \log(1{+}ClaimAmount)$	0.087**	0.136**	0.034	0.099	0.095
	(0.035)	(0.065)	(0.066)	(0.099)	(0.083)
Adj. R^2	0.577	0.571	0.643	0.873	0.684
N	11,723	3,477	4,142	4,446	5,700

Note: Table presents triple difference-in-differences estimation results of Eq. (5) by local business type. The dependent variable is the logarithm of (one plus) the number of residents who visited a local business in a month. All regressions include control variables, visitor-establishment fixed effects, time fixed effects, and report standard errors clustered at census tract level. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

We find several business types that see statistically significant and positive increases in visitations as the amount of flood insurance payouts increases: motor vehicle production and services (e.g., gas stations and automotive accessories), flood and beverage processing and distribution (e.g., grocery stores), retail for clothing and general merchandise, non-medical personal services (e.g., child care services or hair salons), hospitality (e.g., restaurants), health care services (excluding pharmacies and drug stores), and financial services (e.g., banks and insurance agencies). This list includes both businesses providing necessities, such as groceries, as well as more discretionary consumption, but several do seem plausibly related to post-disaster needs. For instance, cars may be damaged and need repairs, contents of homes could have been damaged necessitating replacement, and with damaged homes, people may need to eat more in restaurants. The businesses without any positive association to increased insurance payouts include entertainment, which might not be in high demand by any household immediately after a disaster, real estate, which may be equally used by those with and without insurance, and household goods and services, many of which may be of lesser priority than larger home and car repairs.

4.3.3 Role of Family/Friends vs. Flood Insurance

In analysis of our survey results, we find that friends and family act as a substitute recovery funding source for affected households with no insurance. To understand the role of family/friends in the setting of our foot traffic analysis, we add to Eq. (5) another triple interaction term $Post_t \times FloodDepth_m \times SC_m$, where SC_m represents the degree of social connectedness to family/friends of residents living in tract m. We use the Social Connectedness Index (SCI) data created by Bailey et al. (2018) to measure SC_m. The index is obtained from Meta (formerly Facebook) (2022) and estimates the relative probability of social ties between locations by examining active Facebook users and their friendship networks. This allows us to gauge the relative importance of family/friends in disaster recovery, in comparison to using flood insurance.

We test the role of social interactions across several dimensions. We hypothesize that funding from family and friends may have limitations according to their geographic proximity and their socioeconomic status. If family and friends live nearby and were financially challenged by the same disaster, their likelihood of being able to provide to support may be low. Their income levels could also matter: we expect higher-income family/friends to be more capable of offering financial support. Accordingly, we create three new indexes: $SCI\_MichaelArea_m$ which captures tract m's social connectedness to Michael-affected areas (as defined previously); $SCI\_HighIncome_m$ which captures tract m's social connectedness to high-income areas across the U.S.; and $SCI\_LowIncome_m$ which captures tract m's social connectedness to low-income areas across U.S. To do so, we identify the lists of ZIP codes within the Michael-affected area, those with income above the state median (our definition of high-income), and those with income below the state median (our definition of low-income). We then calculate the population-weighted average of relative probability of social ties between tract m and the ZIP codes within each area of interest. For each of the three indexes, a higher value indicates a greater relative probability of social interactions. We provide further details regarding how we construct the three indexes in Appendix B.

Table 8: Foot Traffic Analysis, Role of Flood Insurance vs. Family/Friends

	(1)	(2)	(3)	(4)
$Post \times FloodDepth$	−61.470**	−63.960**	−60.281**	−51.557**
	(25.132)	(30.591)	(28.882)	(25.537)
$Post \times FloodDepth \times \log(1{+}ClaimAmount)$	0.067*	0.121***	0.130***	0.102***
	(0.035)	(0.026)	(0.027)	(0.028)
$Post \times FloodDepth \times \log(SCI\_MichaelArea)$	0.860	0.083	0.306	0.626
	(0.801)	(0.690)	(0.682)	(0.650)
$Post \times FloodDepth \times \log(SCI\_HighIncome)$	3.072**	3.217*	2.962*	2.551*
	(1.280)	(1.689)	(1.573)	(1.336)
$Post \times FloodDepth \times \log(SCI\_LowIncome)$	1.873	3.092*	2.612*	1.673
	(1.531)	(1.626)	(1.512)	(1.360)
Sample Periods (Months) relative to Michael	[−6, 0]	[−6, 3]	[−6, 6]	[−6, 12]
Percent of Claims Amount Paid	2.7%	51.9%	65.4%	76.2%
Visitor-Establishment FEs	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Cluster by Tract	Yes	Yes	Yes	Yes
Adj. R^2	0.725	0.714	0.720	0.722
N	57,057	81,510	105,963	154,869

Note: The dependent variable is the logarithm of (one plus) the number of residents who visited a local business in a month. All regressions include control variables, visitor-establishment fixed effects, time fixed effects, and report standard errors clustered at census tract level. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Regression results are presented in Table 8. The sample periods in Columns (1) to (4) differ. In Column (1), the post-event period is shortened to the month when Michael occurred. Columns (2) to (4) include observations up to 3, 6, and 12 months after the event, respectively. Consistent with our hypotheses, we show in Table 8 that the largest and the most significant effect among the three social connectedness indexes comes from high-income family/friends. That is, we observe more frequent visitations to local businesses among flooded residents with a higher likelihood of being connected with family or friends located in higher-income areas. However, the effect appears short-lived and is strongest in the month when Michael made landfall and when only 2.7% of NFIP flood insurance claims had been paid (see Column 1). As flood insurance payouts grow in the months following the hurricane (see Columns 2 to 4), the positive effect of social connectedness dissipates and becomes marginally significant. The estimates for social connectedness to family/friends living in Michael-affected areas are not statistically distinguishable from zero, regardless of the length of post-event periods. Together, these findings provide suggestive evidence that affected households rely more on their social networks when insurance is less available. Also, family and friends as funding sources appear the most useful when they are more affluent and not exposed to the same shock.

5 Perception of Insurance Usefulness

In the previous sections, we demonstrate that insurance provides financial protection for households against the negative financial shock of a disaster and that wide take-up of insurance improves post-disaster community economic activity. Despite these benefits, there is still typically a lack of demand for disaster insurance in the U.S. (see, e.g., Roth Sr and Kunreuther, 1998; Kousky, 2022). In this section, we return to our survey data to examine how respondents impacted by the hurricanes perceive insurance.

In our survey, we asked all respondents to rate the usefulness of insurance as a funding tool for disaster recovery. Respondents were asked to enter a score between 1 and 10, with a lower number indicating lower perceived utility.[14] To investigate what household characteristics are associated with perceptions of insurance usefulness, we run OLS regressions of Eq. (1) using the reported index as our dependent variable. Again, we control for any disaster-related costs and the same set of home- and household-level characteristics as described in Section 3.3. Standard errors are clustered by storm. Results are shown in Table 9. In Column (1), households with insurance in place at the time of the storm consider insurance more helpful than those with no insurance, suggesting that having direct experience with insurance in the event of an unexpected financial shock facilitates perceived usefulness of insurance. While this is not surprising, it raises questions as to how to motivate demand in advance of a disaster.

We also find variation in perceived usefulness of insurance by income level. We find that low-income households (with an annual income below $75,000) tend to consider insurance a less useful tool, compared to higher-income households with an income of $75,000 or above (the omitted group). The income effects appear the largest when the sample is limited to those who had no

[14] The exact question being asked in the survey is "on a scale of 1 to 10, how useful was insurance to your recovery? (1 as not as all useful, 10 as extremely useful)."

Table 9: Perception of Insurance Usefulness and New Flood Insurance Purchases

	Insurance Usefulness			New Flood Ins Purchase
	(1) OLS	(2) OLS	(3) OLS	(4) logit
AnyIns	2.686*** (0.451)			
Homeowners/Renters Ins				0.374 (0.285)
Income < $34,999	−1.264*** (0.333)	−1.006*** (0.234)	−2.420*** (0.884)	−2.089*** (0.354)
Income $35,000 to $74,999	−1.628*** (0.438)	−1.513*** (0.558)	−2.021*** (0.487)	−0.994*** (0.328)
Sample	All	AnyIns=1	AnyIns=0	FloodIns=0
Controls	Yes	Yes	Yes	Yes
Cluster by Event	Yes	Yes	Yes	Yes
Y-mean	6.217	7.060	3.810	0.240
Adj./Pseudo R^2	0.235	0.069	0.079	0.339
N	447	331	116	258

Note: Table presents regression estimation results of Eq. (1). The dependent variable in Columns (1)–(3) represents the extent to which a survey respondent considered insurance as a useful funding tool for disaster recovery. Column (1) includes all survey respondents (except the 14 respondents who did not answer this question). Column (2) only includes those who held either homeowners/renters insurance or flood insurance when a disaster occurred; Column (3) only includes those who had none. In Column (4), we limit the survey sample to those who had no flood insurance at the time of the disaster event and the dependent variable is whether or not they purchased new flood insurance post-disaster when they answered our survey. The omitted income group is survey respondents who had an annual income of $75,000 or above. All columns include disaster-related costs, home- and household-level controls. Standard errors are clustered by storm. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

insurance at the time of a disaster (Column 3). This could be related to challenges lower-income households face with finding affordable disaster insurance that meets their needs, as well as potential lack of trust in the market (Kousky and French, 2023).

In Column (4), we restrict our attention to new flood insurance purchases. In total, about 24% of survey respondents who had no flood insurance at the time of the hurricane had purchased a flood insurance policy by the time they answered our survey. We find that new flood insurance take-up rates decrease with income. In comparison to those with an income of $75,000 or more, those with an income below $35,000 are 88% ($|e^{-2.089}-1|$) less likely to start holding flood insurance post-disaster; the likelihood is also 63% ($|e^{-0.994}-1|$) lower among those with an income between

$35,000 and $75,000. This finding supports the longstanding policy suggestion that Congress adopt a means-tested program for the NFIP to provide premium assistance to low-income households (CRS, 2023; FEMA, 2018; National Academies of Sciences, 2016).

6 Conclusion

As weather-related disasters continue to increase in frequency and/or severity, the economic burden of these events is growing. Insurance is a tool to help spread the financial costs of disasters over time and protect the policyholder from a large, negative financial shock. In this paper, we provide empirical evidence of the role of insurance in improving household and community economic recovery. We find that insurance is indeed financially protective for households. Harnessing unique survey data of households impacted by four U.S. land-falling hurricanes, we find that those with insurance are less likely to experience high financial burdens in both the short and longer-run and are less likely to have unmet funding needs.

These household-level financial benefits also create spillover benefits for the local community. Utilizing a database of foot traffic before and after Hurricane Michael, we examine how greater insurance take-up rates influence post-disaster economic activity. As the uptake of flood insurance increases in a community, we find that visitation rates post-disaster to commercial establishments increase, mitigating against the decline in visitations experienced in flooded areas. There is very little empirical evidence on the role of widespread insurance coverage on community-level post-disaster recovery; we provide some of the first empirical support at this scale for the spillover benefits of insurance.

Despite these economic benefits, however, there is still a substantial disaster insurance gap, both in the U.S. and worldwide. In the United States, for example, on average less than half of households in FEMA-mapped 100-year floodplains have flood insurance and very few have coverage outside that area (see, e.g., Bradt et al., 2021). Two reasons for this gap that we identify are variations in the perceived usefulness of insurance and affordability constraints. Households find insurance more useful after having direct experience with it. Motivating purchase of disaster insurance in advance of any adverse impacts, however, remains difficult. We also find lower-income households are less likely to perceive insurance as useful. This could be because disaster insurance can be expensive and those with lower incomes are less able to afford a policy. Investments in insurance literacy programs and in public policies to help lower-income households afford coverage would improve disaster recoveries for both households and communities.

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Appendix A Other Tables and Figures

Table A.1: Summary Statistics by Events, Survey Sample

	Harvey (N=135)		Michael (N=96)		Florence (N=114)		Ida (N=116)	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Household Characteristics								
Savings	0.90	0.31	0.91	0.29	0.86	0.35	0.81	0.39
Income < \$34,999	0.30	0.46	0.20	0.40	0.23	0.42	0.41	0.49
Income \$35,000 to \$74,999	0.38	0.49	0.33	0.47	0.39	0.49	0.33	0.47
Income ≥ \$75,000	0.30	0.46	0.39	0.49	0.36	0.48	0.27	0.44
Employed full-time	0.67	0.47	0.49	0.50	0.61	0.49	0.64	0.48
Part-time/self-employed	0.10	0.31	0.07	0.26	0.14	0.35	0.14	0.35
Retired	0.10	0.30	0.38	0.49	0.13	0.34	0.05	0.22
Employed other	0.13	0.33	0.05	0.22	0.11	0.32	0.17	0.38
Nonwhite	0.64	0.48	0.07	0.26	0.31	0.46	0.36	0.48
No. of residents	3.26	1.60	2.31	1.19	3.08	1.31	3.33	1.48
Children/seniors/disability/pets	0.87	0.33	0.74	0.44	0.78	0.42	0.88	0.33
Home Characteristics								
Renter	0.36	0.48	0.03	0.17	0.26	0.44	0.37	0.49
Home mortgage	0.41	0.49	0.45	0.50	0.44	0.50	0.32	0.47
Home tenure (years)	8.59	9.84	14.65	12.23	8.31	9.47	7.01	7.95
Single-family home	0.70	0.46	0.79	0.41	0.81	0.40	0.59	0.49
Disaster-Related Variables								
High burden three weeks after	0.35	0.48	0.43	0.50	0.36	0.48	0.47	0.50
High burden one year after	0.11	0.32	0.35	0.48	0.11	0.31	0.09	0.29
Unaddressed funding needs	0.29	0.45	0.40	0.49	0.30	0.46	0.38	0.49
Real property damage extent	2.86	1.33	3.52	0.88	2.47	1.43	2.42	1.53
Home content damage extent	2.56	1.52	2.57	1.57	2.18	1.56	2.53	1.46
Service disruption extent	2.90	1.52	2.97	1.18	2.78	1.46	3.08	1.45
Evacuation costs (\$000)	1.74	4.60	0.65	1.38	1.09	2.80	1.32	2.61
Car damage	0.52	0.50	0.56	0.50	0.48	0.50	0.64	0.48
Loss of income	0.48	0.50	0.39	0.49	0.42	0.50	0.57	0.50
Other costs	0.88	0.32	0.98	0.14	0.89	0.32	0.91	0.29

Note: Table presents descriptive statistics of variables in our survey sample by disaster events.

Table A.2: Cluster Analysis of Funding Sources for Disaster Recovery by Events

	Hurricane Harvey			Hurricane Michael		
	Cluster 1 (N=55)	Cluster 2 (N=80)	*t*-stat	Cluster 1 (N=69)	Cluster 2 (N=27)	*t*-stat
Homeowners/Renters Insurance	1.00	0.00	***	1.00	0.00	***
Flood Insurance	0.64	0.02	9.02***	0.07	0.00	2.30**
Family or Friends	0.15	0.40	-3.48***	0.12	0.15	-0.40
Savings	0.27	0.59	-3.83***	0.67	0.67	0.00
Credit Card	0.22	0.16	0.80	0.20	0.15	0.64
FEMA Grant	0.40	0.15	3.21***	0.03	0.30	-2.91***
SBA Loan	0.07	0.04	0.85	0.10	0.19	-0.99
Private Loan from Bank or Other Lenders	0.09	0.10	-0.29	0.01	0.07	-1.12
Charity, Non-Profit, or Community Group	0.18	0.05	2.28**	0.04	0.15	-1.42
Employer	0.09	0.09	0.07	0.04	0.07	-0.54
Local Government	0.09	0.06	0.60	0.00	0.00	–
	Hurricane Florence			**Hurricane Ida**		
	Cluster 1 (N=67)	Cluster 2 (N=47)	*t*-stat	Cluster 1 (N=61)	Cluster 2 (N=55)	*t*-stat
Homeowners/Renters Insurance	0.84	0.17	9.28***	0.67	0.22	5.49***
Flood Insurance	0.37	0.11	3.56***	0.36	0.07	4.04***
Family or Friends	0.10	0.53	-5.17***	0.44	0.42	0.26
Savings	0.30	0.85	-7.18***	0.84	0.00	17.49***
Credit Card	0.06	0.36	-3.94***	0.18	0.24	-0.74
FEMA Grant	0.21	0.11	1.52	0.25	0.11	1.96*
SBA Loan	0.01	0.02	-0.24	0.10	0.05	0.89
Private Loan from Bank or Other Lenders	0.09	0.00	2.55**	0.16	0.09	1.18
Charity, Non-Profit, or Community Group	0.07	0.06	0.22	0.20	0.11	1.32
Employer	0.03	0.06	-0.82	0.07	0.13	-1.11
Local Government	0.03	0.04	-0.35	0.03	0.13	-1.86*

Note: Table presents the average funding source composition of the two clusters identified from cluster analysis. We run cluster analysis separately for survey respondents affected by Hurricane Harvey, Hurricane Michael, Hurricane Florence, and Hurricane Ida, respectively. *t*-statistics represent results of simple *t*-tests for differences in the mean of each funding source by comparing cluster 1 and cluster 2. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table A.3: Continuous Measures of Financial Burdens, Survey Analysis

	Financial Burden Three Weeks After		Financial Burden One Year After	
	(1) OLS	(2) OLS	(3) OLS	(4) OLS
AnyIns	−1.840***	−2.309***	−0.395**	−0.437*
	(0.490)	(0.588)	(0.156)	(0.261)
Savings	−0.601	−0.668	−0.142	−0.070***
	(0.702)	(0.921)	(0.296)	(0.023)
Propensity Score Weighted	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes
Cluster by Event	Yes	Yes	Yes	Yes
Adj. R^2	0.235	0.379	0.144	0.384
N	451	451	455	455

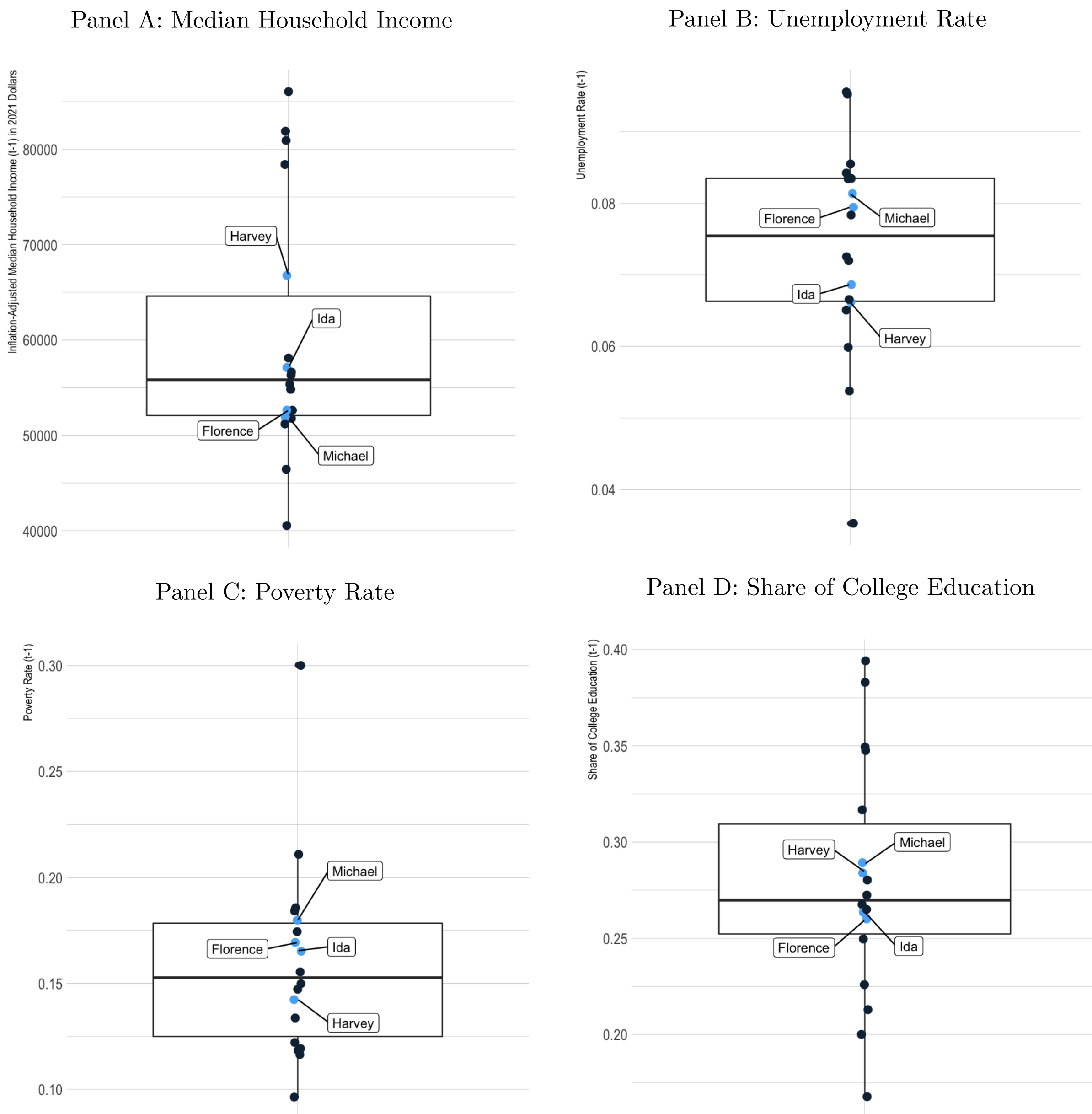
Note: Table presents regression estimation results of Eq. (1). The dependent variable in Columns (1)–(2) is an index ranging from 1 to 10, with a value of 1 indicating the survey respondent felt their household had plenty of money three weeks following the hurricane and a value of 10 indicating not enough money at all. 10 respondents did not answer this question. The dependent variable in Columns (3)–(4) is an index ranging from 1 to 7, with a value of 1 indicating respondents' financial situation one year after the hurricane as "much better" relative to just before the storm, 2 as "slightly better", 3 as "better", 4 as "almost the same", 5 as "slightly worse", 6 as "worse", and 7 as "much worse." 6 respondents did not answer this question. For both indexes, a higher value indicates a greater financial burden. All columns include home- and household-level controls. Standard errors are clustered by storm. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table A.4: Application for Federal Assistance, Survey Analysis

	Applied for FEMA Grant		Applied for SBA Disaster Loan	
	(1) logit	(2) logit	(3) logit	(4) logit
AnyIns	0.004	−0.095	0.678	0.538
	(0.226)	(0.470)	(0.435)	(0.551)
Savings	−0.314	−0.466	0.619	−0.351
	(0.308)	(0.926)	(0.511)	(0.635)
Propensity Score Weighted	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes
Cluster by Event	Yes	Yes	Yes	Yes
Pseudo R^2	0.228	0.278	0.193	0.240
N	457	457	460	460

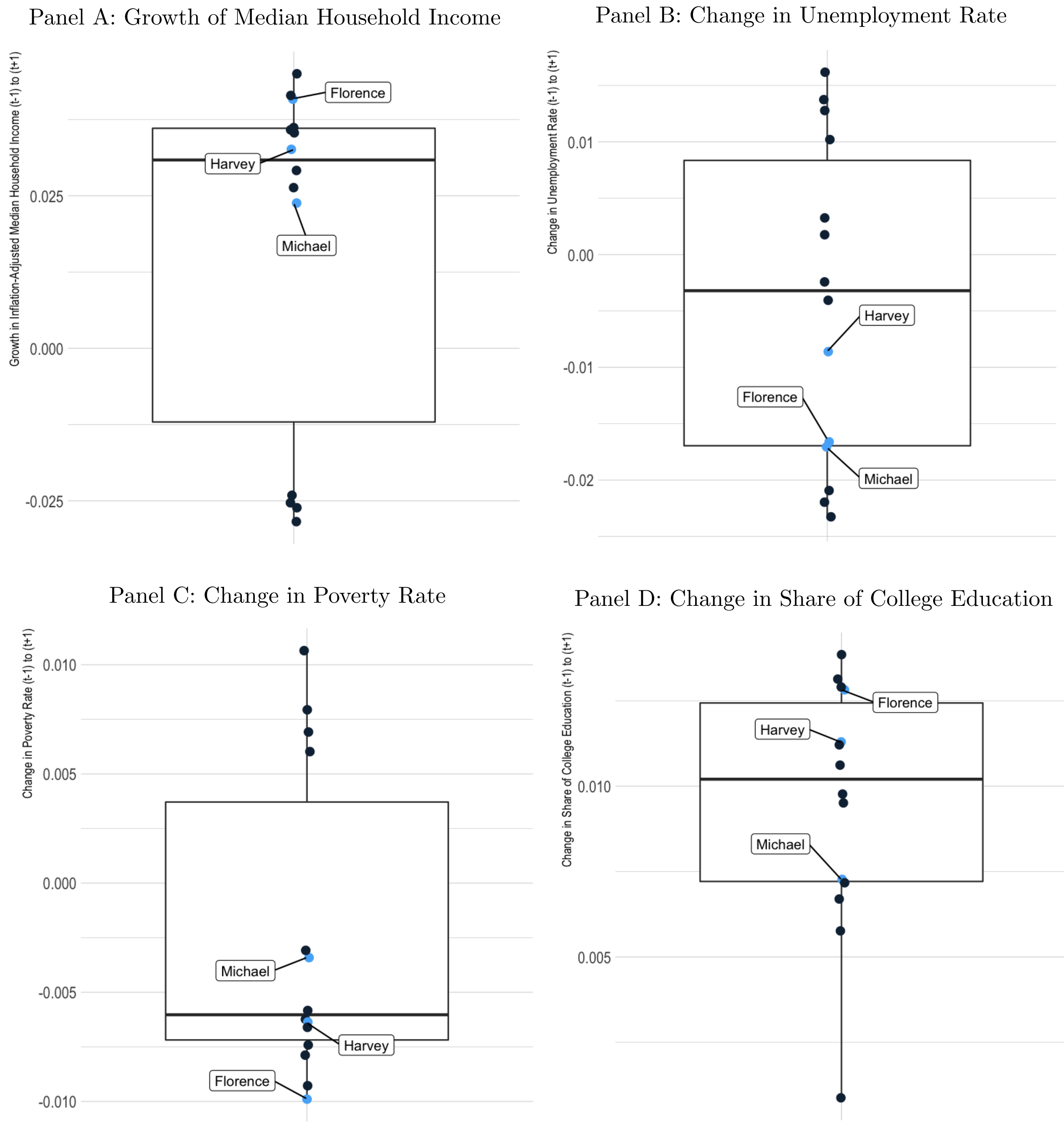
Note: Table presents regression estimation results of Eq. (1). The dependent variable in Columns (1)–(2) is a dummy variable equal to one if a survey respondent applied for a FEMA grant, and zero otherwise. The dependent variable in Columns (3)–(4) is a dummy variable equal to one if a survey respondent applied for an SBA disaster loan. All columns include home- and household-level controls. Standard errors are clustered by storm. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Figure A.1: Historic Hurricanes and Prior-Year Attributes: 2010 to 2021



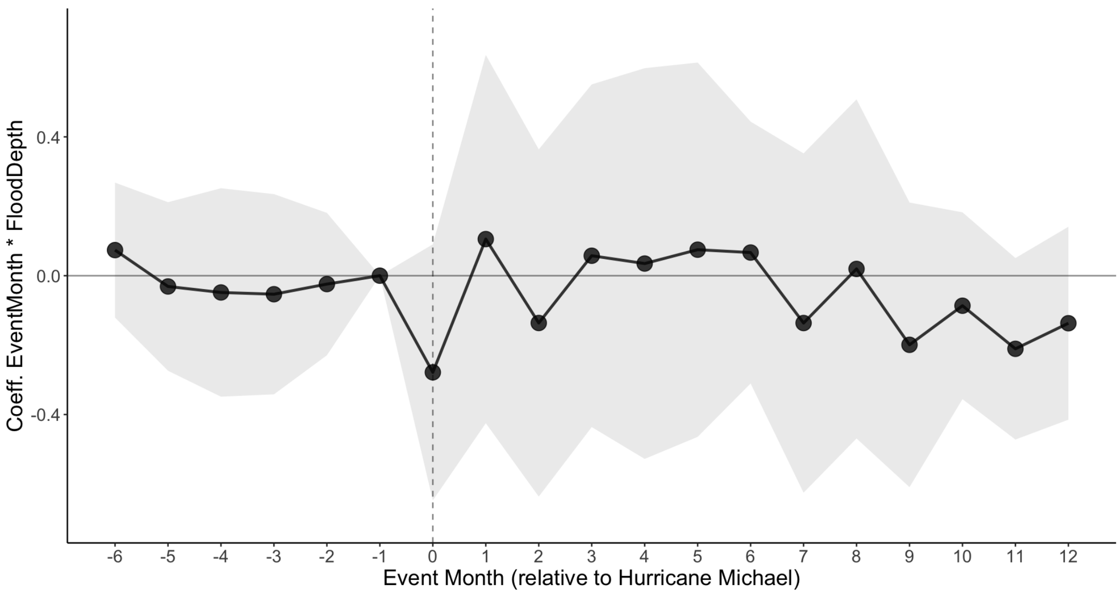
Note: Boxplots present the distribution of prior-year attributes for areas that experienced a hurricane event in year t. The attributes include the inflation-adjusted median household income in $t-1$ (Panel A), the unemployment rate in year $t-1$ (Panel B), the poverty rate in year $t-1$ (Panel B), and the share with a college education in year $t-1$ (Panel D). We first use OpenFEMA data and identify 18 major disaster declarations with the incident type as "hurricane" from 2010 to 2021. For each hurricane event, we only keep disaster-affected counties where both the Individuals and Households program (IHP) and the Public Assistance program (PA) were declared. We then merge in Census Bureau's 5-year ACS data at the county level and generate population-weighted averages of Census variables across counties for each hurricane event.

Figure A.2: Historic Hurricanes and Change in Attributes



Note: Boxplots present the distribution of changes in attributes from year $t-1$ to year $t+1$ for areas that experienced a hurricane event in year t. The attributes include the growth of inflation-adjusted median household income in year $t-1$ (Panel A), the change in unemployment rate in year $t-1$ (Panel B), the change in poverty rate in year $t-1$ (Panel B), and the change in population share with a college education in year $t-1$ (Panel D). We first use OpenFEMA data and identify 14 major disaster declarations with the incident type as "hurricane" from 2010 to 2020. For each hurricane event, we only keep disaster-affected counties where both the Individuals and Households Program (IHP) and the Public Assistance program (PA) were declared. We then merge in Census Bureau's 5-year ACS data at the county level and generate population-weighted averages of Census variables across counties for each hurricane event.

Figure A.3: Effect of Flooding, Visitations to Local Businesses



Note: Figure plots coefficient estimates of ρ_{1t}, along with their 95% confidence intervals, from the following: $Y_{m,n,t} = \rho_0 + \sum_t \rho_{1t}(EventMonth_t \times FloodDepth_m) + \Theta(\sum_t EventMonth_t \times \mathbf{X}_m) + \Lambda(\sum_t EventMonth_t \times \mathbf{X}_n) + FE_{m,n} + FE_t + \varepsilon_{m,n,t}$. This regression is equivalent to an event study version of Eq. (4) with the month before Michael ($t = -1$) as the reference period. The event month $t = 0$ represents October 2018, when Hurricane Michael occurred. The dependent variable is the logarithm of (one plus) the number of residents who visited a local commercial establishment in a month, which represents how often residents who lived in a census tract visited local businesses. The plotted coefficients capture the effects of flooding on household visitation frequency to local businesses as the level of flooding increases. Regression includes control variables, visitor-establishment fixed effects, time fixed effects, and reports standard errors clustered at census tract level.

Table A.5: Foot Traffic Analysis by Establishment Distance

	(1)	(2)	(3)	(4)
Post × *FloodDepth*	−0.572***	−0.484***	−0.417***	−0.368***
	(0.190)	(0.147)	(0.135)	(0.120)
Post × *FloodDepth* × *FloodInsTakeup*	0.927***	0.740**	0.640**	0.583**
	(0.349)	(0.321)	(0.317)	(0.282)
Business Distance from Affected Households	≤1 Mile	≤2 Miles	≤3 Miles	≤4 Miles
Visitor-Establishment FEs	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Cluster by Tract	Yes	Yes	Yes	Yes
Adjusted R^2	0.779	0.747	0.725	0.705
N	888,611	1,855,749	2,975,476	4,136,015
	(5)	(6)	(7)	(8)
Post × *FloodDepth*	−0.623***	−0.584***	−0.524***	−0.477***
	(0.209)	(0.166)	(0.149)	(0.136)
Post × *FloodDepth* × log(1+*ClaimCount*)	0.116***	0.116***	0.111***	0.107***
	(0.035)	(0.029)	(0.028)	(0.026)
Business Distance from Affected Households	≤1 Mile	≤2 Miles	≤3 Miles	≤4 Miles
Visitor-Establishment FEs	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Cluster by Tract	Yes	Yes	Yes	Yes
Adjusted R^2	0.779	0.747	0.725	0.705
N	888,611	1,855,749	2,975,476	4,136,015
	(9)	(10)	(11)	(12)
Post × *FloodDepth*	−1.244***	−1.053***	−0.938***	−0.862***
	(0.240)	(0.179)	(0.152)	(0.140)
Post × *FloodDepth* × log(1+*ClaimAmount*)	0.079***	0.067***	0.060***	0.057***
	(0.014)	(0.010)	(0.009)	(0.008)
Business Distance from Affected Households	≤1 Mile	≤2 Miles	≤3 Miles	≤4 Miles
Visitor-Establishment FEs	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Cluster by Tract	Yes	Yes	Yes	Yes
Adjusted R^2	0.779	0.747	0.725	0.705
N	888,611	1,855,749	2,975,476	4,136,015

Note: In this table, we look at households who lived inside the area impacted by Hurricane Michael and examine their visitation patterns to commercial establishments located within 1 mile (Columns 1, 5, 9), 2 miles (Columns 2, 6, 10), 3 miles (Columns 3, 7, 11), and 4 miles (Columns 4, 8, 12) from their home's census tract. Table presents triple difference-in-differences estimation results of Eq. (5). The dependent variable is the logarithm of (one plus) the number of residents who visited a local business in a month. All regressions include control variables, visitor-establishment fixed effects, time fixed effects, and report standard errors clustered at census tract level. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Appendix B Social Connectedness Indexes

To capture the degree of social interactions with family/friends of households living in areas affected by Hurricane Michael, we use the Social Connectedness Index (SCI) data created by Bailey et al. (2018). The SCI index measures the relative probability of friendship between locations by examining Facebook users and their friendship networks, with a higher value indicating a greater level of social connectedness. We obtain the ZIP-level SCI data, the finest geographic resolution available, from Meta (formerly Facebook) (2022). We then create three new SCI indexes at census tract level to measure (1) the degree of social connectedness to family/friends in Michael-affected areas; (2) the degree of social connectedness to family/friends in high-income areas; and (3) the degree of social connectedness to family/friends in low-income areas. We do so in three steps.

First, we identify a set of ZIP codes $\{x\}$ in Michael-affected areas declared for individual assistance, a set of ZIP codes $\{y\}$ with a 2017 median household income (MHI) above the state MHI across the U.S., and a set of zip codes $\{z\}$ with a 2017 MHI below the state MHI. Both the ZIP- and state-level MHI data are obtained from the American Community Survey (ACS) 5-Year data released by U.S. Census Bureau (2022).

Second, we calculate ZIP j's social connectedness to Michael-affected areas, $SCI\_MichaelArea_j$, as the population-weighted average of SCI between ZIP j and each ZIP $x \in \{x\}$:

$$SCI\_MichaelArea_j = \sum_{\{x\}} \frac{Population_x}{\sum_{\{x\}} Population_x} \times SCI_{j,x}, \tag{B1}$$

where $SCI_{j,x}$ represents the relative friendship probability between ZIP j and x; $Population_x$ represents the 2017 ACS population estimate in ZIP x.

Similarly, we calculate ZIP j's social connectedness to high-income (low-income) areas as the population-weighted average of SCI between ZIP j and each ZIP $y \in \{y\}$ (between ZIP j and each ZIP $z \in \{z\}$):

$$SCI\_HighIncome_j = \sum_{\{y\}} \frac{Population_y}{\sum_{\{y\}} Population_y} \times SCI_{j,y}; \quad \text{(B2)}$$

$$SCI\_LowIncome_j = \sum_{\{z\}} \frac{Population_z}{\sum_{\{z\}} Population_z} \times SCI_{j,z}, \quad \text{(B3)}$$

where $SCI_{j,y}$ and $SCI_{j,z}$ represent the relative friendship probability between ZIP j and y, and between ZIP j and z, respectively; $Population_y$ and $Population_z$ represent the 2017 ACS population estimate in ZIP y and z, respectively.

Third, to convert the three ZIP-level SCI indexes into census tract level, we use the tract-to-ZIP crosswalk file as of 2017-Q4 from HUD (2022). The crosswalk file identifies all ZIP codes $j \in \{j\}_m$ that residential addresses in tract m are located in and estimates the percentage of addresses that can be allocated to each ZIP j. We thus calculate tract-level indexes as the residential-address weighted average of ZIP-level indexes. More specifically,

$$SCI\_MichaelArea_m = \sum_{\{j\}_m} w_j \times SCI\_MichaelArea_j; \quad \text{(B4)}$$

$$SCI\_HighIncome_m = \sum_{\{j\}_m} w_j \times SCI\_HighIncome_j; \quad \text{(B5)}$$

$$SCI\_LowIncome_m = \sum_{\{j\}_m} w_j \times SCI\_LowIncome_j, \quad \text{(B6)}$$

where w_j represents the percentage of residential addresses in tract m that can be allocated to each ZIP $j \in \{j\}_m$ and $\sum_{\{j\}_m} w_j = 1$.

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