Disaster Preparedness and Experience: Evidence from Purchases of Emergency Supplies Before and After Hurricanes

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November 7, 2024

Abstract

Hurricanes and tropical cyclones have been getting more severe over the past 40 years and are expected to intensify in the future due to climate change. Hurricanes not only cause economic damage and loss of human life but may also impact households' behaviors and risk preferences. In this paper, we seek to understand the impact of hurricanes on household expenditure patterns and how households learn from their past hurricane experience and modify their preparatory behaviors. These questions shed light on households' disaster preparedness and how policymakers can better support resiliency in the wake of climate change. We combine daily, household-level consumer goods purchase data from 2008-2018 with hurricane hit and warning data. Using propensity score trimming to obtain a sample of households with a similar probability of receiving a hurricane warning, we compare household purchases in areas experiencing hurricane warnings and hits to purchases of similar households elsewhere. We find that, in general, households prepare for forecast hurricanes by stocking up on non-perishable food and water. Responsiveness is greater towards storm systems that are forecast to be more severe. Households with recent hurricane experiences respond earlier and stronger.

Keywords: natural disaster, hurricane, experience, emergency supplies, NielsenIQ consumer panel

JEL classification codes: D12, H84, Q54, Q58

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1 Introduction

Hurricanes and tropical cyclones have been getting more severe over the past 40 years and are expected to intensify due to climate change (Knutson et al., 2020; Kossin et al., 2020). Since 1980, there has been a significant increase in the number of billion-dollar disasters each year in the United States, with more than ten per year from 2015 to 2020, according to the National Oceanic and Atmospheric Administration.[1] Hurricanes not only cause economic damage and loss of human life, but they may also affect the risk preferences and economic behaviors of households, from avoidance and adaptation to migration and housing decisions. In this paper, we seek to understand the impact of hurricanes on household expenditure patterns and whether households learn from their past hurricane experience and modify their behavioral response to subsequent events.

We attempt to answer two main research questions. (1) To what extent do households prepare for forecast hurricanes (e.g., by stocking up on essentials such as non-perishable food items and water)? (2) Does past hurricane exposure affect households' current preparedness behaviors? These questions can help us better understand households' behavioral response and preparedness, as well as how policymakers can better support resiliency.

We combine NielsenIQ Consumer Panel daily household-level consumer goods purchase data from 2008 to 2018 with the National Hurricane Center's Atlantic Hurricane Database and the National Weather Services' Watch, Warning, Advisory Database. The NielsenIQ data include information on a nationally representative sample of 40,000-60,000 panelists per year who use an in-home scanner to document all personal purchases. Data include products purchased, product characteristics, shopping trip characteristics, and demographic and geographic variables. The other two datasets detail the time and geographic areas of hurricane warnings and hits. Using propensity score trimming to obtain a sample of households with a similar probability of receiving a hurricane warning, we compare the purchases made by households in areas that were warned and/or hit by hurricanes to purchases made by similar households that were not. In particular, we employ a two-way fixed effects model to estimate households' purchase of emergency goods before, during, and after a hurricane.

[1] See https://www.ncdc.noaa.gov/billions.

We find that households stock up on bottled water and other drinks, non-perishable foods, flashlights, batteries, and first aid supplies up to two weeks before a hurricane but decrease purchases of these goods during and the week following the disaster; they stock up even more on these goods when expecting a more severe hurricane. This suggests that households indeed prepare for an oncoming storm. Furthermore, people are either unable or unwilling to venture out to purchase these items during and after the hurricane. This could be because of sufficient supplies purchased prior, infrastructure damage or road closures following a hurricane that prevent households from going out, increased risk aversion, or new liquidity constraints due to property damage. Notably, for an average hurricane, we find that households significantly decrease their net purchases of emergency supplies. That is, the pre-hurricane increase in purchases is outweighed by the subsequent decrease in purchases over our period of study. Moreover, households facing impending severe hurricanes (Category 3 or higher) stock up more, particularly during the hurricane warning period, which generally lasts a couple of days and occurs right before the storm.

Past hurricane exposure also impacts households' degree of preparation for an impending storm. Households that experienced a hurricane the prior year stock up on emergency goods earlier than "inexperienced" households, "hunkering down" in the days before a hurricane hits. Experienced households also decrease their purchases more the week following the storm because they either have more stockpiled or are more aware of lingering risks such as downed power lines. The effect of hurricane experience dissipates slightly over time but lasts for at least five years.

We also find heterogeneity in disaster preparedness and responsiveness across household incomes and locations. In particular, while households of all income levels prepare for hurricanes, low-income households appear under-prepared, possibly due to budget constraints. Neither is there a significant difference between experienced and inexperienced low-income households in hurricane preparation. Households residing in areas with a low risk of hurricanes are also less likely to respond to hurricane warnings; for such households, recent disaster exposure does not necessarily result in more attention to upcoming hurricanes.

Overall, our results suggest that households exhibit seemingly rational behavior, purchasing additional emergency supplies when expecting a hurricane and preparing more for more severe storms. Our results are consistent with a precautionary savings story. Households prepare and save emergency goods to smooth their consumption when a hurricane disrupts their lives. Recent experience seems to be a critical factor that bolsters preparation and may even drive safer behavior after a storm, making people less likely to go out in the wake of hurricane damage. Our results suggest policymakers and community leaders should continue encouraging preparedness purchases and even consider distributing emergency supplies in the wake of a storm to ensure all households have enough to eat and drink. These actions will likely be particularly useful in lower-risk areas and for households with limited resources or access to grocery stores.

Our paper is one of only a few to examine the impact of storms on pre- and post-disaster purchasing behavior. We execute our analysis at a finer level of detail and include a larger variety of goods than in the prior literature. Our main contribution, however, is to explore how past hurricane experience plays a role in disaster preparation purchases and to provide evidence on heterogeneous responses by storm severity and socio-demographics.

Our paper proceeds as follows. Section 2 reviews the related literature on hurricane impacts. Section 3 discusses our data sources, and Section 4 lays out our empirical methodology. Section 5 discusses the results, and Section 6 concludes.

2 Related Literature

There is growing literature on the human impacts of hurricanes. A number of studies investigate the economic impact of natural disasters, usually specific disasters like Hurricane Katrina. These include papers that estimate average total damage (e.g., Barthel and Neumayer, 2012; Kellenberg and Mobarak, 2008) and estimate long-run persistent impacts on economic growth, or GDP (e.g., Cavallo et al., 2013; Hsiang and Jina, 2014). A major limitation to this research area is the lack of precise data, particularly on damage (Kousky, 2014). Studies on Hurricane Katrina suggest that the financial impact on households was limited in scale and scope, perhaps due to disaster aid (Gallagher and Hartley, 2017; Deryugina, Kawano and Levitt, 2018; Groen, Kutzbach and Polivka, 2020).

Hurricanes and resulting flooding have been shown to impact housing prices and decisions. A large hedonic literature documents that house prices tend to fall and flood insurance take-up increases after a flood, but this effect tends to disappear after several years (Atreya and Ferreira, 2015; Atreya, Ferreira and Kriesel, 2013; Bin, Kruse and Landry, 2008; Bin and Landry, 2013; Gallagher, 2014; Bakkensen, Ding and Ma, 2019). Sheldon and Zhan (2019) show that migrants who move into areas recently hit by a hurricane or flood are more likely to rent than purchase a house. Bakkensen and Ma (2020) find that low-income households sort into higher flood risk areas. Several papers have found no net impact from hurricanes on domestic migration (Deryugina, 2017; Strobl, 2011; Sheldon and Zhan, 2022*a*,*b*), though there is heterogeneity across storm, severity, and households (Smith et al., 2006; Eyer et al., 2018; Sheldon and Zhan, 2022*a*,*b*).

There is also evidence that natural disasters make affected individuals more risk averse and revise their expectations of future disaster probabilities upward (Cameron and Shah, 2015; Chantarat et al., 2015), whereas households who experience a large loss may, at least in the near term, decrease risk aversion and accept risky gambles (Page, Savage and Torgler, 2014). For instance, Johar et al. (2022) find that households whose homes were damaged or destroyed by disasters in Australia do not, on average, experience a change in full-time employment or income but do become more likely to report a "major worsening in financial situation" and also become more risk averse; Hanaoka, Shigeoka and Watanabe (2018) show that men who experienced the greater intensity of an earthquake became more risk-tolerant.

Less work has been done on the impacts of natural disasters on consumer and producer behaviors. Jia, Ma and Xie (2022) find that high flood risk and actual flood events reduce firm output in the long and short run, respectively. However, Gagnon and López-Salido (2019) find that swings in demand due to shocks such as hurricanes have modest, if any, effects on retail prices.

The paper to which ours is the most closely related, Beatty, Shimshack and Volpe (2019), uses weekly supermarket scanner data combined with hurricane landfall data from 2002-2012 and finds that households stock up on bottled water, batteries, and flashlights prior to the storm. Pan et al. (2020) also use retail scanner data and extend the Beatty, Shimshack and Volpe (2019) analysis to a larger landfall radius. They, too, find evidence that consumers stockpile bottled water and that this stockpiling significantly impacts both near-term and longer-term in-store product availability. Our paper is differentiated in several important ways. First, we focus on longer-run impacts. In particular, we examine how households respond to a hurricane warning given their hurricane experience in the preceding years. Second, rather than supermarket scanner data, we use the NielsenIQ Consumer Panel data, which are both higher frequency and at the individual (rather than store) level. In addition to more precision on timing, we can better explore consumer heterogeneity, given individual rather than county characteristics. Third, we use propensity score matching to restrict the control observations to those with similar hurricane risk to account for sorting and unobserved characteristics, whereas Beatty, Shimshack and Volpe (2019) do not restrict the sample. Our findings are similar in that households appear to purchase more supplies in advance of a hurricane. However, Beatty, Shimshack and Volpe (2019) find that purchases also increase in the week following the hurricane. We find that purchases decrease during the hurricane and the week thereafter. This finding of ours is robust and consistent across various specifications and sub-samples. This may suggest that households cannot venture out to procure supplies they need in the wake of a storm, or that their prior procurement was sufficient and made further trips unnecessary.

3 Data

To analyze consumer responses to an approaching hurricane, we combine observations from several sources: (1) the Atlantic Hurricane Database (HURDAT2) from the National Hurricane Center (NHC), which tracks the location of each Atlantic hurricane over the course of its life cycle and identifies areas affected by it; (2) the Watch, Warning, Advisory (WWA) Database issued by the National Weather Service (NWS) that contains information on the time and location of each hurricane warning; and (3) the NielsenIQ Consumer Panel, a nationally representative home scan database that includes information on each shopping item that a participant purchases from a grocery store with its price, quantity, content, and location information from each shopping trip, as well as participant socio-demographics. We combine these three sources at the county-day level for the years 2008-2018.[2] Another restriction we put on our sample is to include only hurricane-prone states on the East Coast: those that were hit by a hurricane at least once during

[2]The WWA data include hurricane-related warnings beginning in 2008; hence our final sample includes observations from 2008-2018. Over this period, there were no hurricane landings on the Atlantic Coast of the U.S. in 2013 and 2015.

the analysis period to improve the comparability of treatment and control households.[3] Below, we provide more details for each of these three datasets.

3.1 Atlantic Hurricane Database (HURDAT2)

The NHC reports information on each storm's location in terms of the exact coordinates of its centroid updated every six hours. Detailed intensity measurements are also reported for each storm, including maximum sustained wind speed (in knots) and the system's status using the Saffir-Simpson Hurricane Wind Scale (i.e., category). We define a hurricane "hit" if a location experiences a hurricane (with maximum sustained wind speed greater than 64 knots) within a 100-mile radius from the storm system's centroid.[4] This allows us to identify the exact date and location of areas exposed to a hurricane at any point in time over our sample period. Appendix Table A.1 includes a list of hurricanes in our sample that made landfall on the U.S. Atlantic Coast as a hurricane of Category 1 or above.

3.2 National Weather Service: Watch, Warning, Advisory Database

We obtain weather watches, warnings, and advisories from the NWS's WWA. The NWS issues weather alerts if an extreme weather event is expected at a given location. These alerts are based on up-to-date forecasts and provide a general location where an extreme weather event is likely to occur. The NWS's main goal for issuing weather alerts is to inform and direct the public on hazardous weather events that may pose an imminent risk to life and property. Typically, these weather alerts are issued sufficiently early so residents can prepare and take necessary safety measures. A warning is the most urgent alert. The NWS issues a warning when "a hazardous weather or hydrologic event is occurring, imminent or likely. A warning

[3]These states include Alabama, Arkansas, Connecticut, Delaware, District of Columbia, Florida, Georgia, Kentucky, Louisiana, Maine, Maryland, Massachusetts, Mississippi, New Hampshire, New Jersey, New York, North Carolina, Ohio, Pennsylvania, Rhode Island, South Carolina, Texas, Vermont, Virginia, and West Virginia.

[4]Because we observe households at the county level in the NielsenIQ data, which we will describe in more detail, we define that a household is hit by a hurricane if their county of residence has a geographical border that falls within the 100-mile radius from the hurricane's centroid. Our results are robust to alternative definitions: 50 or 200 miles; or intersection criteria: any part of a county's border against all parts of borders; or the county's geographical or population centroid must fall inside the hurricane's span. Estimation results are available from the authors upon request.

means weather conditions pose a threat to life or property. People in the path of the storm need to take protective action."[5]

Weather alerts are typically issued 48-72 hours before a hazardous event is expected to take place. The average time between a hurricane-related warning and a hurricane hit in our sample is approximately two days. Given our focus on responses to hurricanes, we restrict the warnings to those issued specifically due to hurricane-related adverse conditions.

A hurricane that forms over the Atlantic with a direct path towards the U.S. coast could start generating interest in the national news, potentially weeks before the issuance of an NWS warning. To investigate when the public starts to form an interest in an approaching hurricane, we analyze the Google Search Trends of households across the Atlantic Coast. Appendix Figure A.1 displays the Google search trends for select hurricanes between 2008 and 2018. The graphs show that the number of online searches for an active hurricane starts to increase on average one to two weeks before a hurricane warning is issued. The searches peak close to the time when a hurricane warning is issued by the NWS. Given that hurricanes start to get the attention of households ahead of warnings, we construct our sample time frame to begin three weeks prior to a hurricane warning and analyze households' behavioral changes from two weeks before a warning till one week after a hurricane hit.

3.3 NielsenIQ Consumer Panel

NielsenIQ Consumer Panel is a nationally representative panel database provided by the NielsenIQ Company that records each participating household's grocery store purchases, including price, quantity, content, date of purchase, and location of purchase (at the three-digit zip-code level). There are 40,000 to 60,000 panelists per year. Household demographics are also reported, such as age, gender, race, and marital status. Purchase data is collected in one of three ways, depending on the respondent and his or her access to a smartphone and/or internet connection. The first method is a barcode scanner or smartphone app, which is used to scan each item a household purchases as they unpack their items, recording UPCs and price information. The second method is using a mobile app to take pictures of in-store or online receipts. In this case, the app extracts store and purchase information using image recognition. The third method is

[5] See https://www.weather.gov/sjt/WatchWarningAdvisoryExplained

referred to as the "dustbin" method. In this case, panelists keep both receipts and "consumed household, food and pantry items in a dustbin." Upon a pre-determined date, an auditor visits the household to manually record both the receipts as well as consumed and unconsumed items to avoid duplication.

To ensure data quality, the NielsenIQ Company performs various checks. On a quarterly basis, they compare the Consumer Panel data to another database they create using store-based scanning data, effectively ensuring sales match purchases. On a weekly basis, they track "historical static or usable sample counts on a weekly, monthly, quarterly, and annual bases." A "purchase static" filters out poor reporters, ensuring that all households who appear in the data set are considered "active" and "transmit the minimum spending dollars per four-week period." These measures help alleviate the concern that any changes we observe in the data result from a lower chance for households to scan their purchases during a crisis.

The NWS recommends that each household keeps an emergency supply kit with water, non-perishable food (such as canned food), flashlights and batteries, and first aid supplies (such as bandages and disinfectant wipes). If any of the items in the kit are missing, households are encouraged to purchase them before the extreme weather event. Therefore, our primary analysis focuses on the purchases of emergency supplies to identify household responses to hurricane threats. We restrict our sample to purchases made from June to November each year, months usually considered as the hurricane season for the Atlantic. Appendix Table A.2 shows a list of emergency items included in the analysis.

We consider two measures of purchases. The first is the total quantity of emergency items purchased, measured in the unit of an ounce, fluid ounce, or count. Only about 10% of the products accounted for in the analysis are measured in counts, and all the others are in ounces or fluid ounces. Because aggregating different units may make quantity difficult to interpret, we consider a second measure: the total expenditure on emergency goods (in 2008 U.S. dollars).[6] While prices may be endogenous to disasters, existing literature finds minimal impacts of hurricanes on retail prices (Gagnon and López-Salido, 2019; Beatty, Lade and Shimshack, 2021).

[6]We conduct robustness checks using quantity measured in a specific unit or the purchased quantity in a specific product category as the outcome, finding similar estimates. Appendix Table A.3 shows the estimates.

We combine the HURDAT2 and WWA data with the NielsenIQ Consumer Panel at the county level. Our final sample includes years 2008-2018 to match the consumer purchase observations with the hurricane-related HURDAT2 and WWA databases.

3.4 Sample Criteria

Natural disasters are spatially clustered, even though the actual location where a disaster strikes is somewhat random within higher-resolution geography. People may self-sort to different areas according to their risk preferences and climate awareness. For instance, people who are more risk-tolerant or care less about natural disasters may be more willing to reside in areas subject to high disaster risk to take advantage of benefits, such as lower housing costs (Bin and Landry, 2013; Atreya and Ferreira, 2015; Beltran, Maddison and Elliott, 2019) and coastal amenities. Also, households in locations that experience frequent natural disasters may become more disaster-resilient. Therefore, households' disaster preparedness may vary across regions with differential disaster risks because of the endogenous sorting and past disaster experiences.

To address this issue, we employ the method of propensity score trimming. First, we use a county's geographic and climatic attributes to estimate its probability of receiving a hurricane warning. In particular, we estimate the following equation:

$$Prob(warning_{iy} = 1) = F(\alpha_0 + \alpha_1 X_i + f_y) \tag{1}$$

where $warning_{iy}$ is a dummy variable indicating whether county i receives a hurricane warning in year y; X_i denotes the geographic and climatic features of the county, including the latitude and longitude of the county's centroid, the average elevation, a binary indicator for being on the coast, and the climate zone fixed effect.[7]

We use a Probit model to estimate Equation 1. The fitted value of the outcome, or the propensity score, reflects the probability that a county receives a hurricane warning in a specific year. Figure 1 displays the propensity score distribution for warned vs. non-warned locations.

[7] We derive the latitude and longitude at the centroid of counties based on the TIGER/Line Shapefiles from the Census Bureau and the average elevation of each county from the USA Topo Maps from ArcGIS. We designate counties as coastal or non-coastal based on the National Oceanic and Atmospheric Administration's categorization. The climate zone classification is from the International Energy Conservation Code (IECC) climate zone data from the US Department of Energy. The IECC has categorized each US county into one of eight climate zones based on average temperature and humidity.

A large density of control locations has a low propensity to get a hurricane warning; it is the opposite for the treated locations.

Second, we trim the sample to include only the county-year observations with a propensity score between 0.1 and 0.9. About 37% of the household-day observations in the dataset are dismissed. As we dismiss locations extremely likely or unlikely to be under hurricane threats, the sample contains household observations in regions facing somewhat similar disaster risks. Given the disaster risk, the realization of a hurricane is plausibly exogenous. The households in these counties may also share comparable unobserved risk attitudes and disaster awareness, conditional on their observed characteristics.[8]

Table 1 provides the summary statistics for the trimmed sample we use in the primary analyses. Columns 1-2 include observations from households never warned or hit by a hurricane, Columns 3-4 from households who received a warning at least once during the sample period, and Columns 5-6 from those hit by a hurricane one or more times. About 56% of households in the sample ever received a hurricane warning, and about 74% of the warned households were hit by hurricanes.[9] This confirms the NHC's conservative approach to issuing hurricane warnings and advisories. Given the uncertainty in predicting a hurricane's path, it is safer to issue warnings to all areas with the potential of being affected.[10]

We find very few significant differences in the household demographic characteristics across groups. The share of black households is slightly higher in the latter two groups. Also, households without experience with hurricanes purchase more emergency items and fewer perishable foods than the other two groups on average.

Figures 2a and 2b depict the purchase distribution of the control households (those never warned or hit by a hurricane) versus the treated households (who receive a hurricane warning) using the daily average purchase eight weeks before the warning as the baseline. The figures show that when a hurricane warning is issued, treated households purchase emergency goods more than the control group on average. The warning-induced change skews to the right, suggesting panic-buying of large amounts may exist. Nevertheless, panic-buying is not the sole driver for

[8] In an extended analysis in Section 5.4, we examine households by the range of the propensity scores (i.e., 0 to 0.25, 0.25 to 0.75, and 0.75 to 1).

[9] Among the households who were ever hit by a hurricane, about 9% did not receive a hurricane warning.

[10] To illustrate, Appendix Figure A.2 shows the variation in areas warned and hit in 2017.

the additional purchases. Most households reasonably increase their acquisition of emergency supplies to prepare for the upcoming hurricane.

4 Empirical Methodology

To inspect households' disaster preparedness over the course of a hurricane, we employ a two-way fixed effects model to estimate households' daily purchases of emergency supplies before, during, and after the period when a hurricane affects a location. The unit of observation in our analysis is household-day. The primary treatment for households is receiving a hurricane warning. Hurricane warnings usually last for two days and imply a high chance of a hurricane strike. While the NWS issues warnings to locations of varying sizes, we aggregate them to the county level. Moreover, households may start getting information about a hurricane before a warning is issued and could begin preparing for the upcoming disaster ahead of time. Therefore, we explore households' purchases during the two weeks before a hurricane warning and generate two binary indicators for the first and second weeks leading up to a hurricane warning. Because hurricane forecast errors increase with time, some locations on a hurricane's initial trajectory (e.g., areas inside the NHC's forecast cones) may not ultimately be warned. Therefore, we set the "two week" indicator to unity for locations within 100 miles of a warned county two weeks prior to the warning (and zero otherwise) and the "one week" indicator to unity for locations within 50 miles of a warned county one week prior to the warning (and zero otherwise).[11] The second treatment is a hurricane hit. Only a subset of warned areas is struck by a hurricane. The realization of a hurricane hit often causes life disturbances and destruction. Many households may suffer from property damage and, as a result, loss of income or wealth; some may even be displaced.[12] These impacts can linger even after a hurricane passes. Consequently, we also consider the purchases of emergency items the week after a hurricane hit and define a "post" indicator, which equals one for a location struck by a hurricane during the week following the event. The reference is the purchase made three weeks prior to a warning accordingly.

[11] The results are robust to alternative buffer zones we use to identify the potentially impacted households one or two weeks before a hurricane warning. Appendix Table A.4 and Table A.5 present the results.

[12] We cannot identify whether a NielsenIQ panelist was temporarily displaced in the data.

Specifically, we estimate the following function:

$$Purchase_{hct} = \Sigma_{\tau=-1}^{-2} \beta_\tau week_{\tau,ct} + \beta_1 warned_{ct} + \beta_2 hit_{ct} + \beta_3 week_{post,ct} \quad (2)$$
$$+\phi Z_{ht} + y_t + m_t + dow_t + \lambda_{(h)c} + \varepsilon_{hct}.$$

Here, the outcome is the amount of emergency supplies bought on day t by household h who resides in county c. $week_{\tau,ct}$ is a binary indicator for whether day t falls in one of the two weeks leading up to a hurricane warning issued in county c, where $\tau = -1$ or -2. Note that we regard a seven-day period as a week but do not use calendar weeks, as hurricane warnings or hits can occur on any day of the week. $warned_{ct}$ and hit_{ct} are treatment indicator variables, indicating whether county c receives a hurricane warning or is hit by a hurricane on day t. $week_{post,ct}$ is a dummy variable that takes the value of one if day t is within a week after a hurricane and zero otherwise. Therefore, the β coefficients capture the changes in the purchases of households facing hurricane threats and/or experiencing these disasters relative to those unaffected.

We control for the characteristics of a household and the household head that may affect the purchasing behaviors in Z_{ht}. These characteristics include household income, household size, whether children (under 18) are present, whether the household has internet access, and whether the household head is a college graduate, married, over 65, or black. To account for systematic temporal variation in shopping behaviors, we also control for a linear year trend, y_t, month fixed effect, m_t, and the day-of-week fixed effect, dow_t. Because the treatments, as well as the leads ($week_{-2,ct}$, $week_{-1,ct}$) and the lag ($week_{post,ct}$), are assigned at the county level, we include in the regression the county fixed effect, λ_c, to capture common regional variations. In an alternative specification, we test replacing county fixed effects with household fixed effects. Household fixed effects can more effectively absorb the unobserved time-invariant heterogeneity across households, but controlling for them may cause a problem of over-controlling and violate the assumption of conditional mean independence and bias the estimates (Wooldridge, 2005). ε_{hct} is an idiosyncratic error term. We estimate Equation 2 using the OLS and cluster the standard errors by county, the treatment level.

Next, we explore heterogeneity in treatment effects according to households' past disaster experiences. The experience of a hurricane, especially a catastrophic one, may alter the risk preferences of a household or their perception of risk (Page, Savage and Torgler, 2014; Cameron and Shah, 2015; Chantarat et al., 2015; Hanaoka, Shigeoka and Watanabe, 2018). It is also possible that prior hurricane exposure makes households more aware of natural disasters, more strategic in their purchases, and less likely to panic-buy. Accordingly, we estimate the following equation:

$$\begin{aligned} Purchase_{hct} \quad = \quad & \Sigma_{\tau=-1}^{-2}\beta_\tau week_{\tau,ct} + \beta_1 warned_{ct} + \beta_2 hit_{ct} + \beta_3 week_{post,ct} \\ & + \left(\Sigma_{\tau=-1}^{-2}\gamma_\tau week_{\tau,ct} + \gamma_1 warned_{ct} + \gamma_2 hit_{ct} + \gamma_3 week_{post,ct}\right) \times Experienced_{ht} \\ & + \phi Z_{ht} + y_t + m_t + dow_t + \lambda_{(h)c} + \varepsilon_{hct}, \end{aligned} \tag{3}$$

where $Experienced_{ht}$ reflects the past disaster experience of household h as of time t. Hence, the γ coefficients capture the difference between households with and without hurricane experience. In our primary analyses, we consider households' experience of hurricane hits one year prior. Then, we define experience in alternative ways, for example, based on the severity of the hurricane experienced or the time of exposure (i.e., one year versus two to three years ago).

5 Results

5.1 Effects on Purchases

We start by examining how household purchasing behaviors respond to hurricane warnings and hits. We present the estimation results in Table 2.[13] The outcome is the total daily purchase quantity in odd-numbered columns and the total daily expenditure in even-numbered columns. The first four columns inspect all hurricanes during the sample period, and the last two focus on *severe* hurricanes of category three or above. We control for household fixed effects in the first two columns and county fixed effects in the remaining columns.

We find evidence of households preparing for upcoming hurricanes by buying more emergency supplies. The estimated coefficients are comparable in magnitude controlling for household or county fixed effects. Specifically, households increase their purchases of disaster preparation

[13] We also estimate specifications with the inverse hyperbolic sine of the purchase quantity or expenditure as the outcome, controlling for county fixed effects. Columns 1 and 2 of Appendix Table A.6 display the results. The estimates show a similar pattern as those in Table 2.

items by about 6 units and the expenditures on these goods by $0.6 once a warning is issued. Since the average daily purchase quantity of these goods of the control households is approximately 40 units, with an average daily expenditure of $3.9 (see Table 1), these increases are economically meaningful. These results are consistent with the findings of Beatty, Shimshack and Volpe (2019), who use NielsenIQ's weekly store scanner data. Notably, we look at more purchase categories than in their study, which focuses only on the sales of bottled water, batteries, and flashlights.

In contrast to their findings,[14] we observe a large and statistically significant decrease in the purchase of emergency survival items during and after a hurricane's impact: households reduce the purchase of emergency items by almost 21 units or $2.1 on the day when a hurricane hits and by five units, or $0.4, per day the week afterward. Several explanations may be in order. First, warned households may need emergency supplies less during or after a hurricane simply because they have already stocked up. Second, infrastructure damage and road closures resulting from the disaster may prevent individuals from going out shopping. Third, households whose property is damaged by the hurricane may prioritize fixing their home rather than grocery shopping after it passes. Finally, those who bear disaster losses may have a tighter budget constraint and thus reduce non-essential consumption. Notably, while NielsenIQ takes measures to ensure households actively scan their purchases, we cannot perfectly rule out the possibility that the decreases are driven by households becoming less likely to scan their purchases during a crisis. The potential failure to scan purchases may partially explain why our results contradict those of Beatty, Shimshack and Volpe (2019), whose analyses are based on NielsenIQ's store scanner data. Nevertheless, if households start to scan purchases less than required before a hurricane hits, we would underestimate households' hurricane preparedness.

A back-of-the-envelope calculation using the estimates from Column 3, our preferred specification, and assuming the warned period lasts two days and the hit one day,[15] suggests that treated households increase their quantity of emergency supplies by 12 units prior to the hur-

[14] The difference in our findings is likely due to the weekly nature of the retail scanner data used in Beatty, Shimshack and Volpe (2019), who find that purchases increase in the week following the hurricane. With weekly data, they cannot pinpoint the date that a hurricane occurs- indeed, the hurricane could hit at the beginning, middle, or end of a week, meaning that the treatment week could capture some pre-hit and post-hit responses.

[15] We use only the statistically significant coefficients to perform the back-of-the-envelope calculations and use the same assumptions henceforth.

ricane hit and decrease their quantity by 58 units during and for the week after the hit, for a net decline in purchases of these goods. A similar calculation using the results from Column 4 shows that treated households spend \$1.3 more on emergency supplies prior to the hit and \$5 less during and after the hit. The net decline in the purchases is consistent with the summary statistics that households who were never warned nor hit buy more emergency goods than households warned or hit on average (as shown in Table 1). The decline, again, could stem from liquidity constraints and/or obstacles to shopping. In either case, it suggests that households may not be able to acquire as many of these goods as they would like in the wake of a storm.

Next, we explore how households respond to upcoming severe[16] hurricanes. About 17% of the treated location-day observations experienced a severe hurricane. Columns 5-6 of Table 2 repeat the regressions in Columns 3-4, restricting treatment to severe disasters.[17] We continue to find households purchase more emergency supplies when a hurricane warning is issued, but the increases are significantly larger than those estimated in Columns 3-4. In particular, households buy 10 units or \$1 (vs. 6 units or \$0.6 in Columns 3-4) more emergency items per day. These results could imply that a greater share of households prepares for upcoming severe disasters or that households buy a larger quantity on average. As in the first four columns, we find households buy fewer emergency items during and after a severe disaster, with effects of a similar magnitude.

5.2 Heterogeneous Effects by Hurricane Experience

5.2.1 Baseline

Next, we examine if and how household response to an upcoming hurricane differs based on past disaster experience. We estimate Equation 3, allowing the temporal effect of a current hurricane warning to differ by whether a household experienced a hurricane one year ago, and present the estimation results in Table 3. Columns 1-4 consider all impending hurricanes, and Columns 5-6 only those that are severe.[18] We control for household fixed effects in Columns 1-2 and county fixed effects in the remaining columns instead.

[16]We define a "severe" hurricane as one that is classified as Category 3 or higher on the Saffir-Simpson scale.

[17]In this specification, we exclude from the sample household-day observations that are impacted by a hurricane of category one or two.

[18]We rerun the regressions in Columns 3-4, restricting the treatment to severe disasters (of the current period) only.

We continue to find an increase in disaster-preparedness purchases when a hurricane warning is in effect but a decrease in such purchases during and after the hurricane among households with no hurricane exposure in the previous year ("inexperienced households").

Compared to inexperienced households, households hit by hurricanes one year prior ("experienced households") start preparation for hurricanes earlier. Indeed, these households buy significantly more emergency goods the week before the warning but fewer items when a warning is issued (which happens closer to the hurricane hit). These estimates are similar whether we control for household fixed effects or county fixed effects. Specifically, experienced households buy about 6 units, or \$0.5, more emergency goods each day the week before a hurricane warning. Unlike inexperienced households who make more purchases (by about 7 units, or \$0.8) under a warning, experienced households actually decrease such purchases by about 6 units, or \$0.6 per day.

A back-of-envelope calculation using the estimates in Columns 3-4 suggests that inexperienced households increase their purchase of emergency supplies by 14 units or \$1.5, whereas experienced ones increase the amount by 31 units or \$2.1 in total prior to the hurricane hit. Hurricane experience may make households either more aware of natural disasters or more risk-averse. They may be more likely to follow the news on approaching storms, start preparing for the disaster ahead of time, and buy more emergency supplies than households without such experience. That they buy less during the warning period (unlike inexperienced households) suggests they may be "hunkering down" a day or two preceding the storm. Note, however, that this hunkering down is likely not explained by evacuations, as purchases should still be logged regardless of the location of the stores.[19]

In addition, we find that emergency good purchases by experienced households decline by a smaller amount (by about 30% less) than inexperienced households when a hurricane hits; however, the difference is not significant in expenditure. One possible explanation is that experienced households tend to expect the risk of power and water outages to last longer such that they may continue to need emergency goods even after the hurricane passes. It is also

[19] We tried to identify evacuated households based on the store locations where they made purchases. We find less than 0.1% of the households in the sample purchased goods in zip code areas other than their regular ones during the warning period. The small number of potentially evacuated households should not impact our estimation results. Nevertheless, despite NielsenIQ's scanning requirements, it remains possible that some households stop scanning their purchases during an evacuation.

plausible that past exposure makes some households more comfortable going out shopping if necessary on the days of a hurricane, especially when the hurricane is not very severe, as we do not find any significant differences in purchases between experienced and inexperienced households on the day a severe hurricane hits (as shown in Columns 5-6).

Nevertheless, experienced households reduce their purchases two to three times more (in quantity and expenditure, respectively) than inexperienced households post-disaster. This could reflect less of a need to buy emergency goods, as they stocked up more prior to the hurricane hit. Also, experienced households may be better aware of lingering dangers after a hurricane (such as downed power lines) and thus be more reluctant to go shopping.

Lastly, we assess how an upcoming severe hurricane affects households with and without recent disaster experience differently. Columns 5-6 of Table 3 show the estimates and reveal a similar pattern: experienced households start disaster preparation one week earlier than inexperienced ones. The interaction effect of the one-week indicator is slightly smaller than those estimated in Columns 3-4. The interaction effect of the hurricane hit indicator is large, significant, and negative for households that experienced a severe hurricane (-18.5 versus 6.3 change in quantity for those who experienced any hurricane). In other words, households who experienced any hurricane the year prior tend to reduce their purchases less than inexperienced households during a hit, but those who experienced a severe hurricane reduce their purchases even more. Again, this could be either because they have sufficient stock from prior years, or because they are more aware of the hazards of venturing out.

5.2.2 Severity of Experienced Disasters

In this section, we assess whether the response of experienced households to a hurricane warning varies by the severity of the disaster to which they were exposed one year ago. We also consider a case in which households received a hurricane warning but were not hit (i.e., the least severe disaster experience). A more destructive disaster may raise a household's disaster awareness more substantially than a less destructive one. In contrast, households who experienced a relatively moderate disaster or were warned but not hit may underestimate the current disaster risk and thus be under-prepared. It is also possible that households do not use up their survival kit supplies when they experience a less severe disaster or are not hit by a hurricane, leaving items for the next hurricane season.

We classify disaster experience into three categories: severe disaster experience (experiencing a hurricane of category three or four[20], less severe disaster experience (experiencing a hurricane of category one or two), and minor disaster experience (being warned but not hit by a hurricane). We replicate the regressions from Columns 3-4 of Table 3, including the three experience indicators and their interactions with the time indicators, and display the estimation results in Table 4. Note that the estimates in Columns 1-4 are estimated from one regression, and those in Columns 5-8 are from another.

Table 4 reveal a similar pattern as Table 3. That is, households with previous exposure to hurricanes (or hurricane warnings) tend to prepare for an upcoming hurricane earlier and purchase more emergency supplies than households without such exposure. The more severe the hurricane experienced, the more purchases they make during the week prior to a hurricane warning. Specifically, compared to inexperienced households, those hit by a severe hurricane buy about 9 units or \$0.6 more items per day during the week prior to a warning; those hit by a less severe hurricane buy 4 units or \$0.3 more per day; households warned but not hit buy 2 more units per day. However, the difference in purchased quantity between experienced and inexperienced households is only marginally significant for the last group; the difference in expenditure is insignificant. It is also noticeable that households with severe disaster experience reduce the purchase of emergency goods by about 6 units or \$0.5 in the second week leading to the warning. One possibility is that these households understand the necessity of hurricane preparation, and they decrease such purchases on purpose so that they have the budget for more emergency goods when the storm system gets closer. Consequently, the overall increase in the purchase before a hurricane warning is similar for households with exposure to a severe disaster or a less severe one. Moreover, households struck by a hurricane or warned of one in the year prior buy fewer disaster-preparation items during the current warning period. The decline is of a similar magnitude regardless of the severity of the hurricane experienced.

[20]The only hurricane in our sample to make landfall as a Category 5 was Hurricane Michael in 2018, which occurred in the final year of our study. As a result, no households in our sample have experienced a Category 5 hurricane one year prior.

A back-of-the-envelope calculation implies that the pre-hurricane emergency item purchases increase by 9 units among households with severe disaster experience, 13 units among those with less severe experience, and 9.5 units among those warned but not hit. Meanwhile, expenditure changes by -\$0.06, \$0.5, and -\$0.7 for these three experienced groups, respectively. The smaller increase in the first group is driven by the purchase decrease two weeks before the warning. Therefore, both households with exposure to severe hurricanes and those who have been warned but not hit may not be as well prepared.

5.2.3 Long-run Effects

Traumatic experiences of natural disasters may have lasting impacts on households. Accordingly, this section investigates how hurricane exposure affects households' preparation for subsequent hurricanes.

We add two more experience indicators to the regressions in Columns 3-4 of Table 3, namely, whether a household experienced a hurricane two to three years ago and whether a household experienced a hurricane four to five years ago, as well as their interactions with the time indicators. We present the results in Table 5. Note that once again the estimates in Columns 1-4 are from one regression, and those in Columns 5-8 are from another.

Except for Column 3, the interaction effect of the one-week indicator is positive and significant in all specifications, suggesting that experienced households, no matter when they were exposed, start hurricane preparation earlier than households without such experience. The increase in purchases during the week leading to a hurricane warning is slightly smaller if a household was exposed to a hurricane a longer time ago. In particular, households hit by hurricanes two to three years ago spend \$0.3 more, and those hit four to five years ago buy 5 units or \$0.4 more than inexperienced households per day. In contrast, households with exposure in the previous year purchase 6 units or \$0.5 more each day. Nevertheless, the differences across groups are not statistically significant.

Another notable difference is that households hit in the prior year reduce their emergency goods purchases when warned, while those with earlier hurricane experience do not. The larger decrease in the first group may partially stem from the larger purchases they made in the previous week. As a result, the total pre-hurricane purchase increase is more significant for those exposed to hurricanes earlier (48 vs. 33 units or $4.1 vs. $2.3 for those hit four to five years ago compared to those hit one year ago).

These patterns suggest that hurricane experiences have lasting impacts on households. However, a fresh memory of the previous year's hurricane may make households choose to hunker down earlier before the hurricane hits. As time passes, experienced households are still likely to prepare for hurricanes ahead of time and make such purchases reasonably.

5.2.4 Categories of Purchases

To better understand what items households choose to stock up on, we inspect purchases of several individual categories and report the estimation results in Tables 6 and 7. In particular, we investigate baby foods, bottled water, batteries and flashlights, hardware and tools, non-water drinks, and snacks- six large categories included in emergency grocery-store items.[21]

We find households increase the purchases of bottled water, batteries, and flashlights the most pre-hurricane. These item categories are deemed the most essential in hurricane preparedness.[22] Experienced households appear to stock up on these goods earlier and in larger amounts than inexperienced ones when facing an upcoming hurricane. Indeed, the former group starts to acquire bottled water, batteries, and flashlights as early as two weeks before a hurricane warning. We also find that compared to their inexperienced counterparts, experienced households acquire snacks and drinks other than water not only earlier but also in larger quantities. Perhaps the experienced households have learned what they want and need during a hurricane from their experience while following governmental recommendations to build emergency survival kits. Finally, there is some evidence that households reduce their purchases of baby items and tools before a hurricane; there is no significant difference based on recent past disaster exposure. The reduction may reflect a reallocation of resources given a budget constraint. Households may consider these items less essential to survive a hurricane, especially if they already have them at home.

[21] Estimates for other categories are available upon requests. The results generally exhibit a similar pattern but are less significant for smaller categories, presumably due to the lack of variation.

[22] To investigate whether the significant changes found in Tables 2 and 3 are driven by the purchases of bottled water, batteries, and flashlights, we rerun the regressions in Columns 3-4 of the two tables excluding these items. We present the estimates in Appendix Table A.7 and find similar patterns, suggesting households also stock up on other emergency supplies.

In a similar vein, we inspect how hurricanes impact households' purchases of perishable foods, including dairy products, deli food, fresh produce, and fresh meat. We rerun the regressions from Columns 3-4 of both Table 2 and Table 3 using the daily purchased quantity of and expenditure on perishable foods as the outcomes and present the estimates in Appendix Table A.8. We find households increase their consumption of perishables two weeks prior to a hurricane warning, and decrease them thereafter, from the day they're warned through the week post hurricane hit. The decrease makes sense given that perishables are not part of the recommended emergency survival kit, as they may spoil or be unable to be cooked if power is lost.

5.3 Heterogeneous Effects by Income

This section explores the heterogeneous impacts of hurricanes on households with different incomes. Household purchasing behaviors are subject to budget constraints. Household income is also related to educational attainment, which may determine environmental awareness and access to disaster-related information. Moreover, households of different income levels reside in areas with varied infrastructure quality and public amenities. Hence, they may face different likelihoods of power and water outages if a hurricane strikes, and their grocery store access may be differentially impacted. Accordingly, we divide the sample into three groups based on their real annual income: the bottom tertile (low-income), the middle tertile (mid-income), and the top tertile (high-income). Notably, annual household income changes over the sample period. Some households may be categorized into different income groups in different years.

5.3.1 Main Effects

We first replicate the regressions from Columns 3-4 of Table 2 for each group. Table 8 shows the estimates. The three income groups all increase their purchases of emergency items when a hurricane warning is issued and decrease such purchases when the hurricane strikes and afterward. The increase during the warning is slightly larger for lower-income households, but the differences across groups are not statistically significant. Yet, notably, low-income households reduce the purchase amounts by almost two units per day during the week before a warning.

Our back-of-envelope calculation suggests that before a hurricane hit, low-, mid-, and high-income households purchase -1.4 units (\$0.9), 10 units (\$2.3), and 0 units (\$1.9) more emergency items in total. The stark differences across income levels may result from budget constraints. Given a much tighter budget, low-income households may wait until a warning is issued to start hurricane preparation because a warning indicates a high chance of a hurricane hit, and the emergency goods acquired are less likely to be wasted. Nevertheless, the decline in the total quantity of emergency goods acquired pre-hurricane indicates these households may be under-prepared despite they potentially face a higher chance of power and water outages than their higher-income counterparts.

Furthermore, the largest decrease in purchase amounts during a hurricane is among high-income households. High-income households avoid shopping more than the other two income groups perhaps because they already have abundant resources at home or are more aware of the disaster.

5.3.2 Heterogeneous Effects by Experience

Next, we examine the heterogeneous impacts of disaster experience on hurricane preparedness according to household income. We replicate the regressions from Columns 3-4 of Table 3 for each income group and report the estimates in Table 9. We do not find statistically significant differences between experienced and inexperienced households in the pre-disaster purchases in the low- and high-income groups. Low-income households may be too financially constrained to acquire more emergency supplies regardless of their past hurricane exposures. In contrast, high-income households may generally have a high disaster awareness, such that experienced and inexperienced households do not behave much differently when preparing for an upcoming hurricane. Nevertheless, in the mid-income sub-sample, experienced households appear to stock up on emergency goods significantly earlier and in larger quantities than inexperienced ones. During the week before a hurricane warning, the experienced group increases their purchase by 10 units, or \$1 per day, while the inexperienced group waits to act until a warning is issued.

Although the interaction effect of "warned" is not statistically significant for low-income households, such a pattern is concerning. Without enough climate awareness, some experienced households may underestimate the likelihood of a hurricane hit as they were already hit in the previous year. Also, the destruction caused by the prior hurricane might be costly and have lasting impacts on a household's financial well-being. Hence, the experienced low-income households may be worse off than their inexperienced peers and not have the resources for hurricane preparation.

Furthermore, experienced households of low incomes decrease purchases of emergency goods by 12 units or \$0.7 per day, while their inexperienced peers decrease purchases by 27 units or \$2.1 per day when a hurricane hits. Experienced households may know better than inexperienced ones that power and water outages can last even after the hurricane passes. So, the former group is more likely to get such items during a hurricane. The smaller reduction among experienced households may also stem from the fewer emergency items they acquired than inexperienced households pre-disaster.

5.3.3 Heterogeneous Effects by Other Demographic Characteristics

We assess the changes in the purchase of emergency items by other demographic characteristics, including householders' race, age, education, and metropolitan status. We present the estimates in Appendix Table A.9. All groups prepare for upcoming hurricanes. Besides Black households and those in non-metropolitan areas, households with past hurricane experience generally initiate the preparation earlier than households without such experience. However, the estimates vary in magnitude across groups. In particular, inexperienced Black households stockpile more when warned, but experienced ones do not appear to prepare. Among inexperienced households, households whose head is over 65 make the smallest increase in emergency goods purchases under a hurricane warning, and only the quantity increase is marginally significant. Such differences may stem from differential likelihood of water or power outage during a hurricane, risk tolerance, or store access.

5.4 Heterogeneous Effects by Disaster Risk

Finally, we evaluate how household disaster preparation varies according to the disaster risk of their location. In our primary analysis, we restrict the sample to include locations with a propensity score between 0.1 and 0.9 to alleviate the selection bias problem, as households residing in areas with a high disaster risk may inherently differ from those in low-risk areas.

Nevertheless, understanding the household response to a hurricane threat at locations with a low versus high probability of disasters is essential to researchers and policymakers. Therefore, in this section, we divide the untrimmed sample into three groups: those with propensity scores below 0.25, between 0.25 and 0.75, and above 0.75.

5.4.1 Main Effects

We re-run the regressions in Columns 3-4 from Tables 2 and 3 on each sub-sample and present the results in Tables 10 and 11, respectively. We find little evidence that households in low-risk locations prepare for impending hurricanes. In the medium-risk areas where the propensity score is between 0.25 and 0.75, we find a significant increase in both the purchase amount (8 units per day) and expenditure ($0.9 per day) when a warning is issued. In contrast, households in high-risk regions buy significantly more emergency items the week before a hurricane warning (3 units or $0.2 each day) but show no statistically significant change once the warning is in effect. Presumably, households residing in high-risk areas are more alert to upcoming hurricanes than households elsewhere. They may also expect a larger likelihood of being hit when their location is within the forecast trajectory of a hurricane. Therefore, these households are more likely to prepare for the hurricane early. When learning that a hurricane is coming their way, households in medium-risk areas would expect some chance of being hit. Many may wait for a hurricane warning to update the perceived risk and prepare for the hurricane. Lastly, households in low-risk areas may be less attuned to hurricane-related forecasts. Even if their location is in the hurricane trajectory, they may not take it seriously as they expect a low probability of being affected. As in Table 2, households in all areas appear to decrease their purchases when impacted by a hurricane and afterward, yet the decreases are not significant among households in low-risk areas. While households in low-risk areas are less experienced with hurricanes and may underestimate the danger of a hurricane, we cannot rule out the possibility that the behavioral differences result from the different disaster severity at different locations. Low-risk areas may be less likely to get hit by severe hurricanes, whereas high-risk regions experience not only more frequent but also more severe hurricanes. The fewer emergency goods acquired before the hurricane may be another explanation.

5.4.2 Heterogeneous Effects by Experience

Next, we distinguish the hurricane preparation of experienced and inexperienced households in areas subject to different levels of disaster risks. Table 11 displays the estimates. The interaction effect of the two-week prior indicator is positive and significant for medium-risk areas; the one-week interaction effect is positive and significant for medium- and high-risk areas. In particular, experienced households in medium-risk areas increase the purchase of emergency goods by 4 units or \$0.3 more per day two weeks before a hurricane warning and 11 units or \$1.2 more one week prior than inexperienced households. Experienced households in high-risk areas increase the purchase by 8 units or \$1 more than their inexperienced counterparts the week prior to the warning.

Recent exposures may significantly raise disaster awareness among the population in medium-risk regions, causing them to pay more attention to information on hurricane threats. On the contrary, since hurricanes are more frequent in high-risk areas, people in these regions may generally have high climate awareness, regardless of recent exposure. Indeed, households categorized as "inexperienced" in high-risk areas might have had disaster exposures in previous years going back further than one year. Therefore, we find more significant differences between experienced and inexperienced households in medium-risk than in high-risk areas.

We do not find significant differences in hurricane preparation between experienced and inexperienced households in low-risk areas. The only significant difference is that experienced households increase their purchase of emergency goods during a hurricane, while inexperienced households decrease such purchases. Past hurricane exposure may make households more comfortable going out during the event. Nevertheless, it is worth noting that very few locations in the low-risk region received hurricane warnings (or hits) for two consecutive years. Hence, the insignificant estimated interaction effects may result from the lack of variation.

6 Conclusion

This paper explores household preparedness for hurricanes. We use a two-way fixed effects model to estimate the changes in purchases of emergency goods for households impacted by a hurricane versus those who were not. We restrict our sample to households in counties with a similar probability of experiencing a hurricane to improve the comparability of the treatment and control groups.

In general, we find that households increase both the quantity of and expenditure on purchases of emergency goods, including bottled water, batteries and flashlights, non-perishable food, and other drinks when they receive a hurricane warning, stockpiling these goods in preparation for the storm. We also find that households decrease purchases of these goods during and after the storm. This could be because they have sufficiently stocked up prior to the hurricane or because they avoid going out due to obstacles such as infrastructure damage or road closures after the hurricane. We caveat that some households may respond to a hurricane threat by evacuating. If this is the case, their purchases can still be observed in the data. However, they are less likely to need to stockpile emergency goods. This would result in underestimating the effects on households facing hurricane threats but not evacuating.

We find differential impacts by past hurricane exposure. In general, households learn from past experiences of hurricanes and start hurricane preparation earlier while purchasing more emergency goods. However, a few sub-populations appear more likely to be under-prepared for hurricanes, including households previously warned but not hit by a hurricane, low-income households, and households in low-risk regions. Hence, raising climate awareness among these groups is critical, especially as global warming and climate change have brought more frequent and more severe disasters. For instance, the media and local leaders should remind residents of previous disasters in the weeks preceding a possible storm. Even locations historically facing a low risk of hurricanes may be hit in the near future. For households who fail to prepare for hurricanes due to budget constraints, governments may consider providing the essential items at a lower price or for free to income-eligible households.

Finally, given that households often appear hesitant or unable to venture out to grocery stores during and after hurricanes resulting in a net decrease in emergency goods purchases, it may be beneficial to establish a decentralized network of community centers stocked with emergency supplies. This proactive measure could help ensure that households with insufficient supplies receive the essentials they need, especially if combined with delivery services provided by trained professionals, such as the National Guard.

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7 Tables & Figures

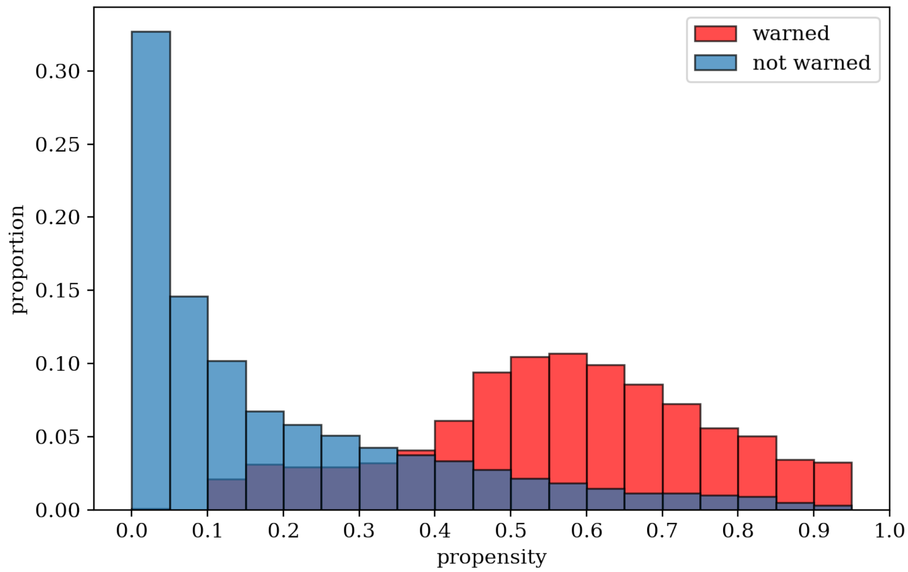
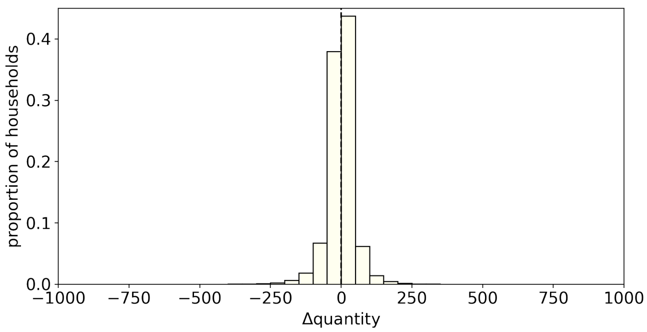


Figure 1: Propensity score distributions of counties that received and did not receive a hurricane-related warning within the past year across the sample years. The data is at the county-year level. We trim counties with propensity score less than 0.1 and higher than 0.9 for the primary analyses. We also present results for different propensity score ranges in Table 10 and Table 11.

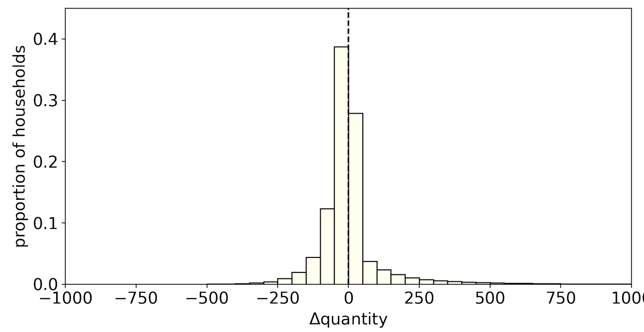
Table 1: Summary Statistics

	Non-Warned/Hit		Warned		Hit	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Demographics						
Household income, $	61,386.49	31,416.19	66,597.91	32,114.14	66,006.97	31,829.52
Household size	2.39	1.29	2.40	1.30	2.41	1.30
Married	0.63	0.48	0.61	0.49	0.61	0.49
Children present	0.23	0.42	0.23	0.42	0.23	0.42
Over-65	0.27	0.44	0.28	0.45	0.28	0.45
Black	0.14	0.35	0.16	0.36	0.17	0.37
No internet	0.11	0.32	0.08	0.27	0.08	0.27
College graduate	0.54	0.50	0.56	0.50	0.55	0.50
Purchases, All Emergency						
Quantity, oz or fl oz	39.66	155.39	37.23	148.42	37.64	150.68
Quantity, ct	2.21	29.86	2.21	31.54	2.22	31.49
Expenditure, $	3.86	12.66	3.81	12.84	3.81	12.86
Purchases, Perishable						
Quantity, oz or fl oz	12.81	53.59	12.28	51.39	13.04	53.03
Quantity, ct	0.16	1.94	0.15	1.91	0.21	2.15
Expenditure, $	1.63	6.60	1.58	6.44	1.77	7.06
Observations		3,433,513		5,214,055		4,221,419
Number of households		26,075		36,643		29,556
Number of counties		611		512		367

Notes: Data is arranged by household-day. The sample was trimmed using propensity score, and covers all hurricane-related hits or warnings between 2008 and 2018. Columns 1-2 restrict the sample to households who were never hit by a hurricane nor received any warning during the sample years; Columns 3-4 restrict to households who received a warning at least once; Columns 5-6 restrict to households who were hit by a hurricane at least for once. "Quantity" and "Expenditure" refer to purchases of bottled water and other drinks, non-perishable foods, flashlights, batteries, and first aid supplies, with a full list included in Table A.2. Perishable items include dairy products, milk, eggs, fresh meat, and fresh produce. Household income and expenditure are adjusted for inflation using 2008 as the base year.

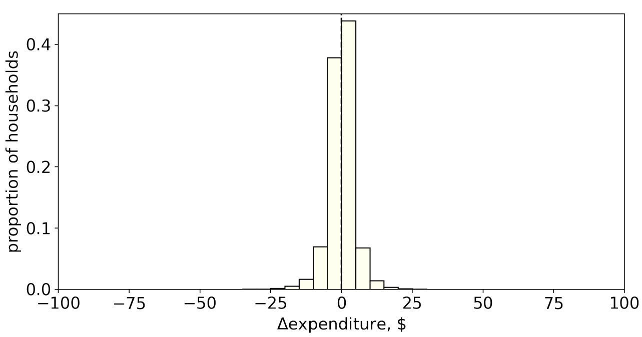


(a) control households
mean: -1.87, median: 0, skewness: 1.54

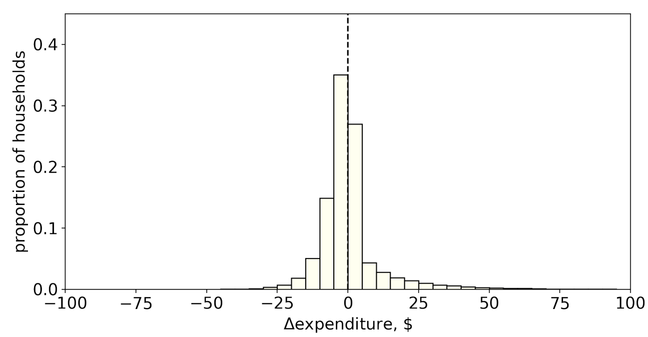


(b) warned households
mean: 1.31, median: -8.09, skewness: 5.14

Figure 2a: Distribution of Δquantity, defined as the difference between the daily average purchase quantity of emergency goods while a hurricane warning is in effect and eight weeks prior to being warned. Control households are those that never received a warning nor hit by a hurricane. The distributions are at the household-year level.



(a) control households
mean: -0.08, median: 0, skewness: -0.71



(b) warned households
mean: 0.32, median: -1.05, skewness: 4.50

Figure 2b: Distribution of Δexpenditure, defined as the difference between the daily average expenditure in USD on emergency goods while a hurricane warning is in effect and eight weeks prior to being warned. Control households are those that never received a warning nor hit by a hurricane. The distributions are at the household-year level.

Table 2: Main Results

	All Sample		All Sample		Severe Hurricane	
	(1)	(2)	(3)	(4)	(5)	(6)
	Quantity	Expenditure	Quantity	Expenditure	Quantity	Expenditure
Two weeks	-0.323	0.007	-0.525	0.016	-0.494	-0.006
	(0.321)	(0.024)	(0.368)	(0.028)	(0.444)	(0.032)
One week	-0.073	0.069	-0.143	0.085	-0.321	0.073
	(0.550)	(0.048)	(0.604)	(0.055)	(0.683)	(0.060)
Warned	6.258***	0.645***	5.907***	0.643***	10.192***	1.096***
	(1.347)	(0.105)	(1.287)	(0.101)	(1.954)	(0.157)
Hit	-20.792***	-2.111***	-20.674***	-2.100***	-18.415***	-2.233***
	(1.393)	(0.123)	(1.337)	(0.118)	(1.645)	(0.150)
Post	-5.189***	-0.425***	-5.275***	-0.402***	-6.779***	-0.495***
	(0.581)	(0.052)	(0.735)	(0.063)	(0.883)	(0.089)
Household FEs	X	X				
County FEs			X	X	X	X
Observations	8,941,166	8,941,166	8,941,166	8,941,166	8,240,215	8,240,215
AIC	115,113,082	70,510,289	115,369,510	70,777,355	106,280,133	65,125,934
BIC	115,113,292	70,510,499	115,369,706	70,777,551	106,280,342	65,126,143

Notes: Data is arranged by household-day. The outcome is purchase quantity in odd columns and expenditure in even columns. Columns 1-4 include all hurricane-related warnings; Columns 5-6 include only warnings issued for severe (Category 3 or above) hurricanes. "Two weeks" is a time indicator for being two weeks before a hurricane warning; "One week" indicates being one week before a warning; "Warned" indicates if a hurricane warning is in effect; "Hit" indicates the location is being hit by a hurricane; "Post" indicates the week after a hurricane hits. Standard errors clustered at the county level are in parentheses. Other controls include household income, household size, marital status, presence of children, whether college graduates, household head > 65, black, internet access, a year trend, month fixed effects, and day-of-week fixed effects.
* p<0.10, ** p<0.05, *** p<0.01

Table 3: Effect of Prior Experience

	All sample		All Sample		Severe Hurricane	
	(1)	(2)	(3)	(4)	(5)	(6)
	Quantity	Expenditure	Quantity	Expenditure	Quantity	Expenditure
Two weeks	-0.356	0.005	-0.495	0.020	-0.536	-0.011
	(0.337)	(0.025)	(0.384)	(0.029)	(0.469)	(0.033)
One week	-0.559	0.029	-0.592	0.049	-0.763	0.042
	(0.535)	(0.049)	(0.612)	(0.057)	(0.660)	(0.062)
Warned	7.501***	0.772***	7.153***	0.774***	11.953***	1.290***
	(1.428)	(0.111)	(1.361)	(0.106)	(2.299)	(0.179)
Hit	-21.582***	-2.143***	-21.388***	-2.124***	-14.139***	-1.791***
	(1.530)	(0.137)	(1.474)	(0.132)	(3.225)	(0.315)
Post	-4.719***	-0.370***	-4.735***	-0.338***	-6.145***	-0.413***
	(0.687)	(0.060)	(0.840)	(0.072)	(1.168)	(0.107)
Exp 1-year	-3.822***	-0.187***	-3.184***	-0.125**	-3.630***	-0.129**
	(0.625)	(0.053)	(0.638)	(0.054)	(0.643)	(0.053)
Two weeks × Exp 1-year	0.324	0.010	0.073	-0.054	1.260	0.077
	(1.067)	(0.083)	(1.057)	(0.084)	(1.252)	(0.096)
One week × Exp 1-year	6.134***	0.525***	6.212***	0.483***	5.572***	0.384**
	(1.319)	(0.109)	(1.428)	(0.119)	(1.946)	(0.156)
Warned × Exp 1-year	-13.763***	-1.370***	-13.256***	-1.389***	-15.344***	-1.598***
	(3.084)	(0.274)	(3.002)	(0.271)	(3.155)	(0.347)
Hit × Exp 1-year	6.386**	0.287	6.274**	0.264	-18.499***	-1.797***
	(3.054)	(0.317)	(3.155)	(0.325)	(3.930)	(0.412)
Post × Exp 1-year	-5.041***	-0.541***	-4.741***	-0.585***	-3.881	-0.683*
	(1.283)	(0.142)	(1.611)	(0.163)	(2.479)	(0.294)
Household FEs	X	X				
County FEs			X	X	X	X
Observations	8,941,166	8,941,166	8,941,166	8,941,166	8,240,215	8,240,215

Notes: Data is arranged by household-day. The outcome is purchase quantity in odd columns and expenditure in even columns. Columns 1-4 include all hurricane-related warnings; Columns 5-6 include only warnings issued for severe (Category 3 or above) hurricanes. "Two weeks" is a time indicator for being two weeks before a hurricane warning; "One week" indicates being one week before a warning; "Warned" indicates if a hurricane warning is in effect; "Hit" indicates the location is being hit by a hurricane; "Post" indicates the week after a hurricane hits. "Exp 1-year" indicates a household being hit by a hurricane one year prior. Standard errors clustered at the county level are in parentheses. Other controls include household income, household size, marital status, presence of children, whether college graduates, household head > 65, black, internet access, a year trend, month fixed effects, and day-of-week fixed effects. * p<0.10, ** p<0.05, *** p<0.01

Table 4: Heterogeneous Effects of Experience by Prior Hurricane Strength

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Quantity (one regression)				Expenditure (one regression)			
	All	Severe Exp	Less Severe	Warned Not Hit	All	Severe Exp	Less Severe	Warned Not Hit
Two weeks	-0.407				0.011			
	(0.407)				(0.031)			
One week	-0.984				0.030			
	(0.656)				(0.063)			
Warned	9.764***				1.037***			
	(1.780)				(0.129)			
Hit	-22.218***				-2.134***			
	(2.050)				(0.182)			
Post	-5.055***				-0.358***			
	(0.873)				(0.071)			
Exp		-1.408	-2.804***	-0.690		-0.018	-0.118**	0.061
		(1.122)	(0.697)	(0.754)		(0.105)	(0.059)	(0.063)
Two weeks × Exp		-5.605***	1.450	-0.246		-0.470***	0.107	-0.0000
		(1.325)	(1.404)	(1.061)		(0.101)	(0.107)	(0.097)
One week × Exp		8.541***	3.588**	2.290*		0.559***	0.307**	0.062
		(2.270)	(1.455)	(1.291)		(0.182)	(0.133)	(0.117)
Warned × Exp		-15.524***	-15.743***	-13.032***		-1.380***	-1.845***	-1.391***
		(2.118)	(4.831)	(3.158)		(0.222)	(0.390)	(0.247)
Hit × Exp		6.530**	20.778	3.309		0.111	2.064**	0.125
		(2.782)	(12.740)	(3.025)		(0.291)	(1.023)	(0.282)
Post × Exp		-8.278***	1.666	2.920		-0.790***	-0.003	0.091
		(1.643)	(2.249)	(2.199)		(0.196)	(0.223)	(0.197)
County FEs	X				X			
Observations	8,941,166				8,941,166			

Notes: This table presents the estimated coefficients for models distinguishing the severity of the household's past hurricane exposure. Columns 1-4 present estimated coefficients for a single regression with purchase quantity as the outcome variable; Columns 5-8 report the results for a single regression with expenditure as the outcome variable. Hurricane categories in our "Severe" definition include Category 3 or above, and in "Less Severe" are Category 1 or 2. Our "Warned, Not Hit" definition identifies households who received a hurricane warning one year prior but were not hit. * p<0.10, ** p<0.05, *** p<0.01.

Table 5: Long-run Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Quantity (one regression)				Expenditure (one regression)			
	All	1 Year	2-3 Years	4-5 Years	All	1 Year	2-3 Years	4-5 Years
Two weeks	-0.453				0.006			
	(0.396)				(0.030)			
One week	-0.743				0.013			
	(0.619)				(0.059)			
Warned	7.336***				0.736***			
	(1.451)				(0.110)			
Hit	-21.984***				-2.203***			
	(1.653)				(0.146)			
Post	-4.321***				-0.339***			
	(0.905)				(0.077)			
Exp		-2.952***	0.505	1.369**		-0.117**	-0.012	-0.051
		(0.658)	(0.509)	(0.554)		(0.055)	(0.040)	(0.050)
Two weeks × Exp		0.143	-0.782	1.724		-0.065	0.131	0.136
		(1.070)	(1.287)	(1.784)		(0.084)	(0.104)	(0.137)
One week × Exp		6.376***	0.227	4.691***		0.502***	0.299**	0.374**
		(1.461)	(1.575)	(1.769)		(0.118)	(0.127)	(0.180)
Warned × Exp		-13.320***	-8.903*	7.959		-1.366***	0.425	0.326
		(3.110)	(5.247)	(7.414)		(0.276)	(0.565)	(0.641)
Hit × Exp		6.921**	6.273	0.636		0.340	0.683*	-0.118
		(3.350)	(4.724)	(6.232)		(0.343)	(0.386)	(0.552)
Post × Exp		-5.109***	-3.346	-0.592		-0.597***	-0.119	0.094
		(1.629)	(2.305)	(2.479)		(0.162)	(0.190)	(0.161)
County FEs	X				X			
Observations	8,941,166				8,941,166			

Notes: This table examines the effects of household hurricane exposure of different years in the past. It presents two models, with the first model presented across columns 1-4 and the second model presented across columns 5-8. The table reports coefficients for households who experienced a hurricane 1 year prior, 2-3 years prior, and 4-5 years prior estimated in the same model. The outcome variable in 1-4 is quantity; in 5-8 is expenditure. Standard errors clustered at the county level are shown in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 6: Individual Emergency Items on Purchase Quantity

DV: Quantity	(1) Baby food	(2) Water	(3) Batteries & flashlight	(4) Tools	(5) Drinks	(6) Snacks
Two weeks	0.002	-0.091**	-0.002	0.002	-0.017	0.002
	(0.004)	(0.042)	(0.002)	(0.002)	(0.132)	(0.015)
One week	0.000	0.037	0.005*	0.006	-0.088	0.003
	(0.005)	(0.061)	(0.003)	(0.006)	(0.138)	(0.018)
Warned	-0.011*	0.799***	0.057***	-0.002	0.180	0.137**
	(0.006)	(0.232)	(0.014)	(0.002)	(0.394)	(0.054)
Hit	-0.020***	-0.823***	-0.020	-0.003***	-2.467***	-0.371***
	(0.005)	(0.114)	(0.017)	(0.001)	(0.416)	(0.055)
Post	-0.002	0.268	0.023***	-0.002**	-0.879***	-0.064***
	(0.007)	(0.190)	(0.005)	(0.001)	(0.200)	(0.023)
Exp 1-year	-0.003	-0.419***	-0.009***	-0.004	-1.422***	-0.213***
	(0.005)	(0.096)	(0.003)	(0.003)	(0.280)	(0.047)
Two weeks × Exp 1-year	0.012	0.524*	0.014*	-0.002	0.907	0.176**
	(0.017)	(0.271)	(0.007)	(0.003)	(0.609)	(0.074)
One week × Exp 1-year	0.018	0.489***	0.057***	-0.002	3.175***	0.476***
	(0.012)	(0.174)	(0.019)	(0.007)	(0.822)	(0.128)
Warned × Exp 1-year	0.025	-0.531*	0.016	-0.002	2.385*	0.363**
	(0.018)	(0.290)	(0.029)	(0.003)	(1.360)	(0.165)
Hit × Exp 1-year	0.021*	0.548***	-0.029	-0.005	-0.277	0.052
	(0.012)	(0.179)	(0.021)	(0.004)	(0.993)	(0.134)
Post × Exp 1-year	-0.015*	-0.075	0.011	0.003	2.293***	0.256***
	(0.009)	(0.251)	(0.015)	(0.004)	(0.640)	(0.071)
County FEs	X	X	X	X	X	X
Observations	8,941,166	8,941,166	8,941,166	8,941,166	8,941,166	8,941,166

Notes: This table replicates the regression in Column 3 of Table 3 for different individual product categories. Standard errors clustered at the county level are shown in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table 7: Individual Emergency Items on Expenditure

DV: Expenditure	(1)	(2)	(3)	(4)	(5)	(6)
	Baby food	Water	Batteries & flashlight	Tools	Drinks	Snacks
Two weeks	0.002	-0.001	-0.001	0.000	-0.002	-0.000
	(0.002)	(0.001)	(0.001)	(0.001)	(0.004)	(0.003)
One week	0.000	0.002	0.008***	0.001	0.005	0.004
	(0.003)	(0.002)	(0.003)	(0.002)	(0.006)	(0.004)
Warned	-0.005**	0.035***	0.055***	-0.005**	0.013	0.038***
	(0.003)	(0.007)	(0.012)	(0.002)	(0.012)	(0.013)
Hit	-0.009***	-0.024***	-0.034***	-0.010***	-0.110***	-0.092***
	(0.002)	(0.004)	(0.006)	(0.002)	(0.017)	(0.013)
Post	-0.003	0.006	0.027***	0.001	-0.032***	-0.012**
	(0.002)	(0.004)	(0.005)	(0.002)	(0.007)	(0.006)
Exp 1-year	-0.003	-0.013***	-0.006***	-0.002	-0.067***	-0.059***
	(0.002)	(0.003)	(0.002)	(0.003)	(0.016)	(0.013)
Two weeks × Exp 1-year	0.018	0.015*	0.007*	0.004	0.067**	0.058***
	(0.020)	(0.008)	(0.004)	(0.005)	(0.028)	(0.020)
One week × Exp 1-year	0.007	0.032***	0.034***	0.000	0.154***	0.106***
	(0.005)	(0.008)	(0.013)	(0.004)	(0.042)	(0.032)
Warned × Exp 1-year	0.011	0.000	0.002	0.002	0.064	0.095**
	(0.007)	(0.014)	(0.019)	(0.006)	(0.046)	(0.040)
Hit × Exp 1-year	0.007**	0.021*	-0.019*	0.006*	-0.011	0.005
	(0.003)	(0.013)	(0.011)	(0.003)	(0.039)	(0.040)
Post × Exp 1-year	-0.002	0.007	0.015	-0.003	0.100***	0.075***
	(0.003)	(0.007)	(0.011)	(0.005)	(0.026)	(0.020)
County FEs	X	X	X	X	X	X
Observations	8,941,166	8,941,166	8,941,166	8,941,166	8,941,166	8,941,166

Notes: This table replicates the regression in Column 4 of Table 3 for different individual product categories. Standard errors clustered at the county level are shown in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table 8: Effects by Income

	Low-income		Mid-income		High-income	
	(1)	(2)	(3)	(4)	(5)	(6)
	Quantity	Expenditure	Quantity	Expenditure	Quantity	Expenditure
Two weeks	-0.437	0.026	0.091	0.119**	2.105	0.154
	(0.697)	(0.061)	(0.821)	(0.056)	(1.308)	(0.111)
One week	-1.998**	-0.028	-0.288	0.023	1.584	0.141
	(0.863)	(0.076)	(1.112)	(0.089)	(1.574)	(0.138)
Warned	6.290*	0.424**	5.377*	0.706***	4.856	0.963**
	(3.300)	(0.208)	(2.919)	(0.224)	(3.677)	(0.426)
Hit	-25.560***	-2.037***	-24.416***	-2.368***	-28.474***	-3.100***
	(2.750)	(0.243)	(3.256)	(0.281)	(2.668)	(0.264)
Post	-6.473***	-0.417***	-2.311	-0.163	-5.667***	-0.596***
	(1.481)	(0.110)	(1.554)	(0.112)	(1.885)	(0.133)
County FEs	X	X	X	X	X	X
Observations	1,501,749	1,501,749	2,424,809	2,424,809	752,349	752,349

Note: This table replicates the regressions in Columns 3-4 of Table 2 on different income groups. Columns 1-2 restrict the sample to households with an inflation-adjusted income in the lower tertile, Columns 3-4 in the middle tertile, and Columns 5-6 in the upper tertile. * p<0.10, ** p<0.05, *** p<0.01

Table 9: Effects of Prior Experience by Income

	Low-income		Mid-income		High-income	
	(1)	(2)	(3)	(4)	(5)	(6)
	Quantity	Expenditure	Quantity	Expenditure	Quantity	Expenditure
Two weeks	-0.218	0.042	-0.134	0.105*	1.958	0.136
	(0.701)	(0.062)	(0.831)	(0.058)	(1.349)	(0.115)
One week	-2.118**	-0.033	-0.712	-0.023	1.501	0.116
	(0.858)	(0.079)	(1.147)	(0.088)	(1.635)	(0.143)
Warned	6.993**	0.465**	5.559*	0.718***	3.005	0.909**
	(3.516)	(0.225)	(3.104)	(0.240)	(3.907)	(0.437)
Hit	-26.731***	-2.122***	-24.382***	-2.305***	-27.579***	-3.023***
	(2.809)	(0.253)	(3.441)	(0.295)	(3.139)	(0.299)
Post	-6.506***	-0.386***	-2.195	-0.163	-5.746***	-0.621***
	(1.569)	(0.117)	(1.669)	(0.119)	(1.974)	(0.138)
Exp 1-year	-1.887	0.005	-4.047***	-0.229**	-1.232	-0.142
	(1.615)	(0.132)	(1.243)	(0.108)	(3.119)	(0.225)
Two weeks × Exp 1-year	-5.814*	-0.430	6.097*	0.365	4.629	0.540
	(3.236)	(0.268)	(3.637)	(0.257)	(6.854)	(0.615)
One week × Exp 1-year	2.695	0.100	9.950***	1.097**	2.597	0.744
	(4.456)	(0.384)	(3.626)	(0.451)	(6.873)	(0.610)
Warned × Exp 1-year	-15.640	-0.882	-3.891	-0.277	36.900	1.098
	(10.913)	(1.005)	(7.532)	(0.674)	(23.880)	(1.364)
Hit × Exp 1-year	14.652***	1.420***	0.170	-0.765	-10.708**	-1.201*
	(3.261)	(0.395)	(6.930)	(0.802)	(5.234)	(0.689)
Post × Exp 1-year	-0.722	-0.674**	-0.784	0.115	2.488	0.582
	(4.247)	(0.283)	(2.823)	(0.271)	(4.831)	(0.520)
County FEs	X	X	X	X	X	X
Observations	1,501,749	1,501,749	2,424,809	2,424,809	752,349	752,349

Notes: This table replicates the regressions in Columns 3-4 of Table 3 on different income groups. Columns 1-2 restrict the sample to households with an inflation-adjusted income in the lower tertile, Columns 3-4 in the middle tertile, and Columns 5-6 in the upper tertile. Standard errors clustered at the county level are shown in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 10: Effects by Disaster Propensity

	$Pr(Warning) \leq 0.25$		$0.25 < Pr(Warning) < 0.75$		$Pr(Warning) \geq 0.75$	
	(1)	(2)	(3)	(4)	(5)	(6)
	Quantity	Expenditure	Quantity	Expenditure	Quantity	Expenditure
Two weeks	-1.351	-0.013	-0.134	0.026	-1.519**	-0.149***
	(1.789)	(0.120)	(0.397)	(0.035)	(0.679)	(0.055)
One week	-2.885	-0.124	-0.339	0.077	2.551***	0.245***
	(2.192)	(0.149)	(0.780)	(0.079)	(0.859)	(0.078)
Warned	-1.773	-0.252	7.782***	0.854***	0.545	0.065
	(4.868)	(0.422)	(1.318)	(0.131)	(1.090)	(0.106)
Hit	-3.491	-0.160	-22.097***	-2.261***	-16.023***	-2.059***
	(20.053)	(1.636)	(1.230)	(0.118)	(1.364)	(0.146)
Post	-3.281	-0.244	-4.136***	-0.291***	-8.673***	-0.694***
	(2.351)	(0.158)	(0.715)	(0.064)	(1.315)	(0.127)
County FEs	X	X	X	X	X	X
Observations	8,074,844	8,074,844	5,058,859	5,058,859	1,058,448	1,058,448

Notes: This table replicates the regressions in Columns 3-4 of Table 2. Columns 1-2 are estimated on a sample with a propensity score of getting a hurricane warning no larger than 0.25, Columns 3-4 on a sample with a propensity score between 0.25 and 0.75, and Columns 5-6 on a sample with a propensity score equal to or larger than 0.75. Standard errors clustered at the county level are shown in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table 11: Effects of Prior Experience by Disaster Propensity

	$Pr(Warning) \leq 0.25$		$0.25 < Pr(Warning) < 0.75$		$Pr(Warning) \geq 0.75$	
	(1)	(2)	(3)	(4)	(5)	(6)
	Quantity	Expenditure	Quantity	Expenditure	Quantity	Expenditure
Two weeks	-0.297	0.059	-1.097**	-0.060	-0.924**	-0.088**
	(1.670)	(0.102)	(0.487)	(0.050)	(0.455)	(0.040)
One week	-1.605	-0.009	-1.593***	-0.043	1.669*	0.153*
	(2.318)	(0.145)	(0.500)	(0.049)	(0.927)	(0.084)
Warned	-0.938	-0.193	8.034***	0.881***	4.133***	0.366***
	(5.472)	(0.496)	(1.544)	(0.155)	(1.284)	(0.129)
Hit	-18.296	-3.531***	-22.913***	-2.326***	-18.461***	-2.288***
	(33.458)	(0.828)	(1.378)	(0.135)	(2.132)	(0.222)
Post	-0.291	0.009	-4.862***	-0.340***	-4.640***	-0.266*
	(2.492)	(0.169)	(0.486)	(0.042)	(1.315)	(0.142)
Exp 1-year	-0.360	-0.161***	-2.431***	-0.080	1.167	0.145**
	(0.772)	(0.062)	(0.528)	(0.051)	(0.910)	(0.071)
Two weeks × Exp 1-year	2.488	0.312	3.759**	0.300***	-1.510	-0.106
	(6.802)	(0.495)	(1.718)	(0.114)	(1.329)	(0.120)
One week × Exp 1-year	-1.029	0.039	11.107***	1.161***	8.391***	0.994***
	(3.815)	(0.358)	(1.826)	(0.198)	(1.892)	(0.152)
Warned × Exp 1-year	1.236	0.206	-9.059***	-0.925**	-15.534***	-1.189***
	(10.170)	(0.766)	(3.177)	(0.360)	(3.312)	(0.386)
Hit × Exp 1-year	25.009	5.805***	3.278	-0.013	6.481**	0.709***
	(36.594)	(1.535)	(2.006)	(0.230)	(2.703)	(0.249)
Post × Exp 1-year	-5.460	-0.287	0.555	-0.017	-6.011***	-0.686***
	(5.579)	(0.397)	(2.310)	(0.215)	(1.734)	(0.161)
County FEs	X	X	X	X	X	X
Observations	8,074,844	8,074,844	5,058,859	5,058,859	1,058,448	1,058,448

Note: This table replicates the regressions in Columns 3-4 of Table 3. Columns 1-2 are estimated on a sample with a propensity score of getting a hurricane warning no larger than 0.25, Columns 3-4 on a sample with a propensity score between 0.25 and 0.75, and Columns 5-6 on a sample with a propensity score equal to or larger than 0.75. The coefficients on the interaction of Hit and Exp 1-year cannot be identified in low-propensity areas. Standard errors clustered at the county level are shown in parentheses. * p<0.10, ** p<0.05, *** p<0.01

A Appendix

Table A.1: Hurricanes in the Sample

Hurricane	ID	Dates	Hit as HU	States Affected
Hurricane Dolly	AL042008	07/21-07/26/2008	✓	Texas
Hurricane Gustav	AL072008	08/29-09/05/2008	✓	Louisiana, Mississippi, Texas
Hurricane Ike	AL092008	09/07-09/15/2008	✓	Arkansas, Illinois, Indiana Louisiana, Missouri, New York Oklahoma, Texas
Hurricane Kyle*	AL112008	09/27-09/29/2008	✓	Maine
Hurricane Ida	AL112009	11/08-11/10/2009	✓	Alabama, Louisiana, Mississippi
Hurricane Earl*	AL072010	08/31-09/04/2010	✓	Massachusetts, North Carolina
Hurricane Irene	AL092011	08/23-08/29/2011	✓	Connecticut, Delaware, Maine Maryland, Massachusetts, New Hampshire New Jersey, New York, North Carolina Pennsylvania, Rhode Island, Vermont Virginia
Hurricane Isaac	AL092012	08/25-09/01/2012	✓	Arkansas, Louisiana, Mississippi Texas
Hurricane Sandy	AL182012	10/23-10/31/2012	✓	Delaware, District of Columbia, Maryland New Jersey, New York, Ohio Pennsylvania, Virginia, West Virginia
Hurricane Arthur	AL012014	06/28-07/05/2014	✓	Florida, Maine, Maryland Massachusetts, North Carolina, South Carolina Virginia
Hurricane Hermine	AL092016	08/28-09/08/2016	✓	Alabama, Florida, Georgia New Jersey, New York, North Carolina South Carolina, Virginia
Hurricane Matthew	AL142016	10/04-10/09/2016	✓	Florida, Georgia, North Carolina South Carolina
Hurricane Harvey	AL092017	08/23-09/02/2017	✓	Louisiana, Mississippi, Texas
Hurricane Irma	AL112017	09/07-09/13/2017	✓	Alabama, Florida, Georgia
Hurricane Nate	AL162017	10/06-10/10/2017	✓	Alabama, Florida, Louisiana Mississippi
Hurricane Florence	AL062018	09/11-09/18/2018	✓	Georgia, North Carolina, South Carolina
Hurricane Michael	AL142018	10/08-10/12/2018	✓	Alabama, Delaware, Florida Georgia, Maryland, North Carolina South Carolina, Virginia

*: Made landfall near Nova Scotia, Canada.
Notes: Column 1 includes each hurricane's name as named by the World Meteorological Organization. Column 2 includes the dates for each hurricane from their formation as a tropical system until their dissipation. Column 3 indicates if the listed hurricane was at least category 1 strength at the time of landfall. Column 4 includes a list of states that were impacted by the hurricane either through a warning and/or hit.

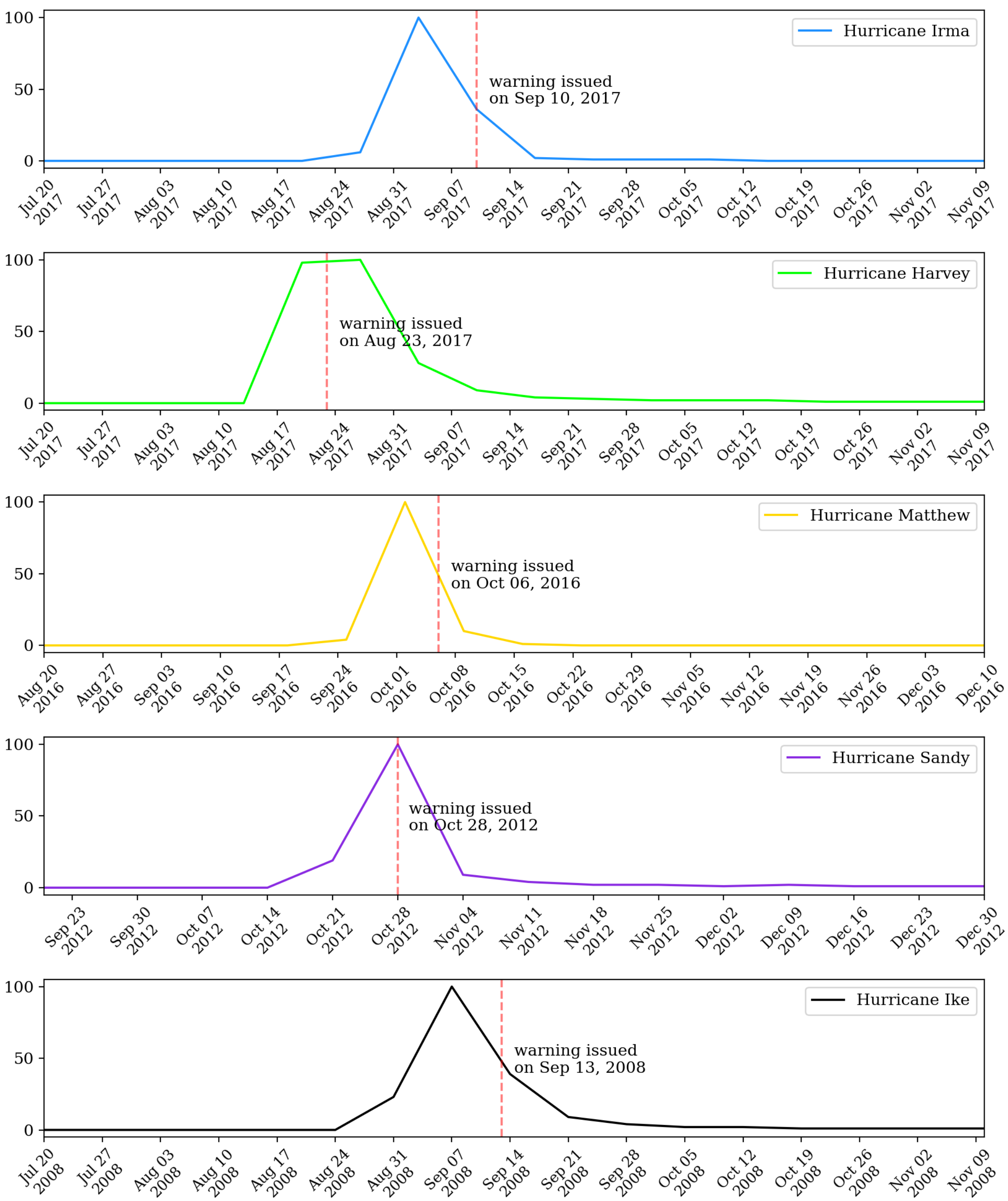


Figure A.1: Google Search Trends and the timings of the warnings issued by the National Hurricane Center for a sample of five hurricanes: Hurricane Irma, Hurricane Harvey, Hurricane Matthew, Hurricane Sandy, and Hurricane Ike.

Table A.2: Emergency Grocery-store Items Included in the Analyses

Product name
Baby Food
Baking Mixes
Baking Supplies
Batteries And Flashlights
Bottled Water
Bread And Baked Goods
Breakfast Food
Candy
Carbonated Beverages
Cereal
Coffee
Condiments, Gravies, And Sauces
Cookies
Crackers
Desserts, Gelatins, Syrup
First Aid
Flour
Fruit - Canned
Fruit - Dried
Gum
Hardware, Tools
Jams, Jellies, Spreads
Juice, Drinks - Canned, Bottled
Nuts
Packaged Milk And Modifiers
Pasta
Pet Food
Pickles, Olives, And Relish
Prepared Food: Dry Mixes
Prepared Food: Ready-to-serve
Salad Dressings, Mayo, Toppings
Seafood - Canned
Shortening, Oil
Snacks
Soft Drinks: Non-carbonated
Soup
Spices, Seasoning, Extracts
Sugar, Sweeteners
Table Syrups, Molasses
Tea
Vegetables - Canned
Vegetables And Grains - Dried

Table A.3: Different Quantity Definitions

	(1)	(2)	(3)	(4)	(5)	(6)
DV:	*count*	*count*	*oz*	*oz*	*count+oz*	*count+oz*
Two weeks	0.035	0.033	-0.358	-0.558	-0.323	-0.525
	(0.073)	(0.071)	(0.296)	(0.339)	(0.321)	(0.368)
One week	-0.030	-0.020	-0.043	-0.123	-0.073	-0.143
	(0.080)	(0.080)	(0.517)	(0.566)	(0.550)	(0.604)
Warned	0.150	0.125	6.108***	5.782***	6.258***	5.907***
	(0.202)	(0.204)	(1.312)	(1.252)	(1.347)	(1.287)
Hit	-1.187***	-1.193***	-19.605***	-19.481***	-20.792***	-20.674***
	(0.145)	(0.141)	(1.371)	(1.316)	(1.393)	(1.337)
Post	-0.351***	-0.354***	-4.838***	-4.921***	-5.189***	-5.275***
	(0.099)	(0.108)	(0.537)	(0.673)	(0.581)	(0.735)
Observations	8,941,166	8,941,166	8,941,166	8,941,166	8,941,166	8,941,166
Household FEs	X		X		X	
County FEs		X		X		X
Year FEs	X	X	X	X	X	X
Month FEs	X	X	X	X	X	X
Day-of-week FEs	X	X	X	X	X	X
Controls	X	X	X	X	X	X

Notes: This table replicates the regressions in Columns 1 and 3 of Table 2. The outcome is the purchase quantity measured in count in Columns 1-2 and the purchase quantity in ounce or flow ounce in Columns 3-4. Columns 5-6 are the same as Columns 1 and 3 in Table 2. Standard errors clustered at the county level are in parentheses. * p<0.10, ** p<0.05, *** p<0.01

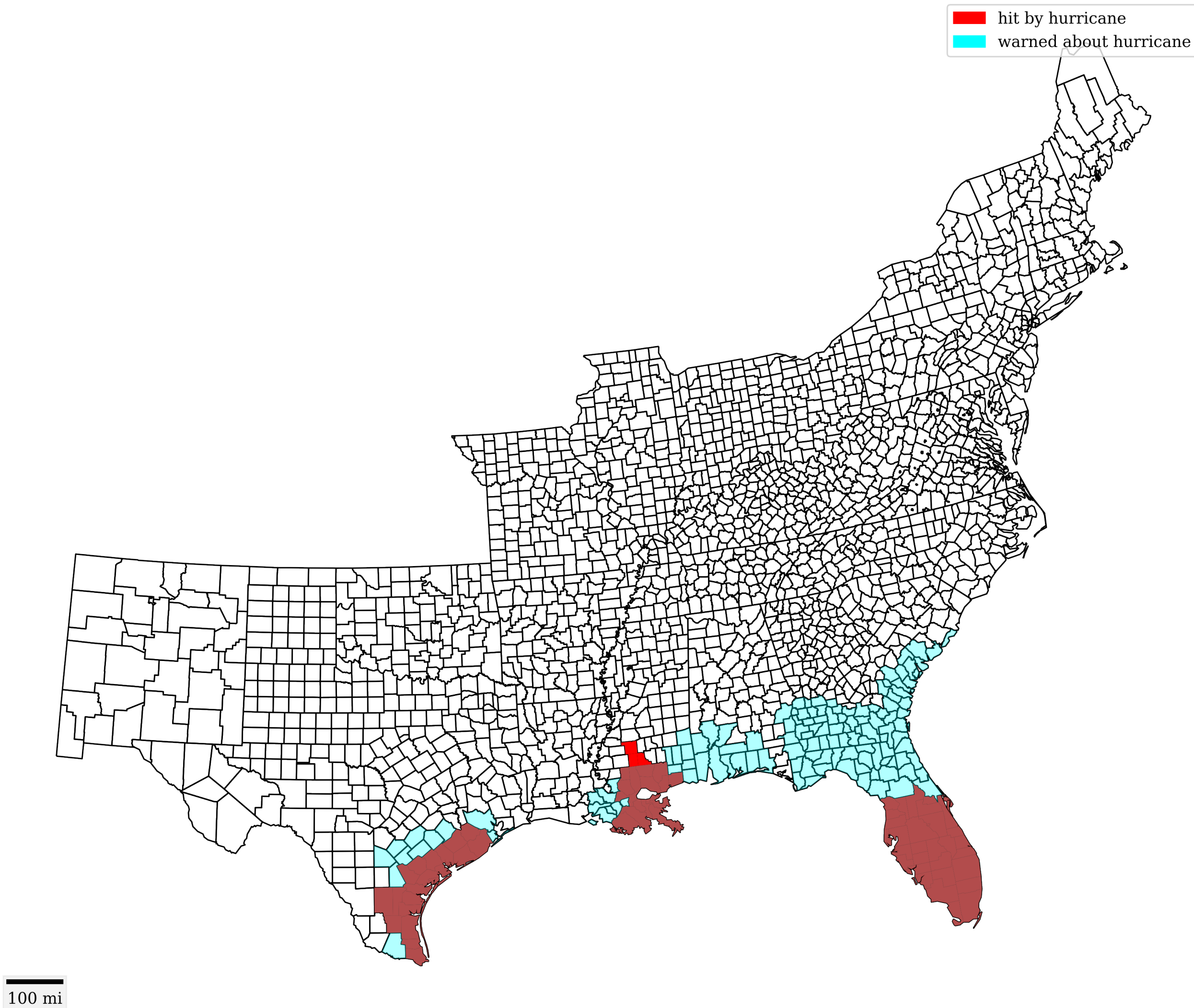


Figure A.2: Variation in counties that were hit and/or warned against a hurricane for the Atlantic Coast in 2017. For an interactive version of this graph, you can visit https://ernbilen.github.io/interactive_legend.

Table A.4: Alternative Warning Area Definitions Including a Buffer

	DV: Quantity				*DV: Expenditure*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	0-mile	10-mile	50-mile	100-mile	0-mile	10-mile	50-mile	100-mile
Two weeks	-0.525	-0.544	-0.502	-0.477	-0.495	-0.518	-0.458	-0.423
	(0.368)	(0.368)	(0.369)	(0.372)	(0.384)	(0.385)	(0.385)	(0.389)
One week	-0.143	-0.153	-0.141	-0.147	-0.592	-0.601	-0.578	-0.590
	(0.604)	(0.604)	(0.603)	(0.607)	(0.612)	(0.612)	(0.612)	(0.615)
Warned	5.907***	4.832***	3.954***	3.373***	7.153***	6.052***	5.259***	4.550***
	(1.287)	(1.216)	(0.890)	(0.693)	(1.361)	(1.266)	(0.904)	(0.739)
Hit	-20.674***	-20.726***	-20.851***	-21.014***	-21.388***	-21.508***	-21.691***	-21.876***
	(1.337)	(1.337)	(1.309)	(1.330)	(1.474)	(1.468)	(1.426)	(1.463)
Post	-5.275***	-5.309***	-5.407***	-5.475***	-4.735***	-4.754***	-4.867***	-4.952***
	(0.735)	(0.734)	(0.749)	(0.759)	(0.840)	(0.840)	(0.862)	(0.880)
County FEs	X	X	X	X	X	X	X	X
Observations	8,941,166	8,941,166	8,941,166	8,941,166	8,941,166	8,941,166	8,941,166	8,941,166

Notes: Data is arranged by household-day. Columns 1-4 use Quantity as the dependent variable; Columns 5-8 use Expenditure as the dependent variable. Columns 1 and 5 are replicate Table 2 and include no buffer-zone. Columns 2 and 6 include a 10-mile buffer-zone around each polygon-area that was issued a hurricane warning; Columns 3 and 7 include a 50-mile buffer-zone; Columns 4 and 8 include a 100-mile buffer-zone. Standard errors clustered at county level are in parentheses. Controls are household income, household size, marital status, presence of children at household, female head of household, head of household > 65 years of age, indicator for black, indicator for no internet at the household. * p<0.10, ** p<0.05, *** p<0.01

Table A.5: Alternative Warning Area Definitions Including a Buffer, Interactions

	DV: Quantity				*DV: Expenditure*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	0-mile	10-mile	50-mile	100-mile	0-mile	10-mile	50-mile	100-mile
Two weeks	-0.495	-0.518	-0.458	-0.423	0.020	0.018	0.025	0.030
	(0.384)	(0.385)	(0.385)	(0.389)	(0.029)	(0.029)	(0.029)	(0.029)
One week	-0.592	-0.601	-0.578	-0.590	0.049	0.049	0.052	0.051
	(0.612)	(0.612)	(0.612)	(0.615)	(0.057)	(0.057)	(0.057)	(0.057)
Warned	7.153***	6.052***	5.259***	4.550***	0.774***	0.699***	0.637***	0.571***
	(1.361)	(1.266)	(0.904)	(0.739)	(0.106)	(0.103)	(0.076)	(0.060)
Hit	-21.388***	-21.508***	-21.691***	-21.876***	-2.124***	-2.144***	-2.172***	-2.201***
	(1.474)	(1.468)	(1.426)	(1.463)	(0.132)	(0.131)	(0.128)	(0.134)
Post	-4.735***	-4.754***	-4.867***	-4.952***	-0.338***	-0.339***	-0.352***	-0.362***
	(0.840)	(0.840)	(0.862)	(0.880)	(0.072)	(0.072)	(0.074)	(0.077)
Exp 1-year	-3.184***	-3.177***	-3.004***	-2.865***	-0.125**	-0.122**	-0.104*	-0.090*
	(0.638)	(0.637)	(0.632)	(0.642)	(0.054)	(0.054)	(0.053)	(0.054)
Two weeks × Exp 1-year	0.073	0.073	-0.143	-0.293	-0.054	-0.056	-0.078	-0.093
	(1.057)	(1.056)	(1.068)	(1.069)	(0.084)	(0.083)	(0.084)	(0.084)
One week × Exp 1-year	6.212***	6.196***	6.009***	5.923***	0.483***	0.479***	0.460***	0.453***
	(1.428)	(1.427)	(1.431)	(1.430)	(0.119)	(0.119)	(0.119)	(0.119)
Warned × Exp 1-year	-13.256***	-12.763***	-14.390***	-13.903***	-1.389***	-1.440***	-1.587***	-1.508***
	(3.002)	(2.814)	(2.242)	(1.611)	(0.271)	(0.257)	(0.213)	(0.158)
Hit × Exp 1-year	6.274**	6.253**	7.357**	9.128***	0.264	0.272	0.395	0.577**
	(3.155)	(3.122)	(3.139)	(2.765)	(0.325)	(0.323)	(0.293)	(0.287)
Post × Exp 1-year	-4.741***	-4.581***	-4.176**	-3.792**	-0.585***	-0.571***	-0.527***	-0.487***
	(1.611)	(1.624)	(1.636)	(1.651)	(0.163)	(0.163)	(0.162)	(0.169)
County FEs	X	X	X	X	X	X	X	X
Observations	8,941,166	8,941,166	8,941,166	8,941,166	8,941,166	8,941,166	8,941,166	8,941,166

Notes: Data is arranged by household-day. Columns 1-4 use Quantity as the dependent variable; Columns 5-8 use Expenditure as the dependent variable. Columns 1 and 5 are replicate Table 3 and include no buffer-zone. Columns 2 and 6 include a 10-mile buffer-zone around each polygon-area that was issued a hurricane warning; Columns 3 and 7 include a 50-mile buffer-zone; Columns 4 and 8 include a 100-mile buffer-zone. Standard errors clustered at county level are in parentheses. Controls are household income, household size, marital status, presence of children at household, female head of household, head of household > 65 years of age, indicator for black, indicator for no internet at the household. * p<0.10, ** p<0.05, *** p<0.01

Table A.6: Inverse Hyperbolic Since of Outcomes

	(1) ln(Quantity)	(2) ln(Expenditure)	(3) ln(Quantity)	(4) ln(Expenditure)
Two weeks	-0.007	-0.002	-0.005	-0.001
	(0.005)	(0.003)	(0.005)	(0.003)
One week	-0.008	-0.003	-0.013	-0.005
	(0.008)	(0.005)	(0.008)	(0.005)
Warned	0.040**	0.033***	0.059***	0.047***
	(0.019)	(0.011)	(0.020)	(0.012)
Hit	-0.496***	-0.305***	-0.495***	-0.303***
	(0.023)	(0.014)	(0.028)	(0.017)
Post	-0.129***	-0.076***	-0.112***	-0.065***
	(0.012)	(0.007)	(0.014)	(0.009)
Exp 1-year			-0.019*	-0.005
			(0.011)	(0.007)
Two weeks × Exp 1-year			-0.027*	-0.022**
			(0.016)	(0.010)
One week × Exp 1-year			0.055**	0.031**
			(0.023)	(0.014)
Warned × Exp 1-year			-0.215***	-0.147***
			(0.059)	(0.036)
Hit × Exp 1-year			0.010	-0.001
			(0.065)	(0.041)
Post × Exp 1-year			-0.151***	-0.102***
			(0.040)	(0.025)
County FEs	X	X	X	X
Observations	8,941,166	8,941,166	8,941,166	8,941,166
AIC	23,521,920	18,316,835	23,521,711	18,316,612
BIC	23,522,096	18,317,011	23,521,968	18,316,869

Note: Columns 1-2 replicate the regressions in Columns 3-4 of Table 2, and Columns 3-4 replicate those in Columns 3-4 of Table 3, using the inverse hyperbolic sine of purchase quantity and expenditure as the outcomes. Standard errors clustered at the county level are shown in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table A.7: Purchases Excluding Bottled Water, Flashlight & Batteries

	(1) Quantity	(2) Expenditure	(1) Quantity	(2) Expenditure
Two weeks	-0.464	0.017	-0.402	0.022
	(0.369)	(0.029)	(0.384)	(0.029)
One week	-0.222	0.071	-0.635	0.040
	(0.594)	(0.054)	(0.603)	(0.056)
Warned	5.102***	0.554***	6.297***	0.684***
	(1.203)	(0.100)	(1.276)	(0.105)
Hit	-19.898***	-2.043***	-20.545***	-2.066***
	(1.319)	(0.117)	(1.455)	(0.131)
Post	-5.550***	-0.437***	-5.026***	-0.371***
	(0.680)	(0.061)	(0.779)	(0.070)
Exp 1-year			-2.755***	-0.107*
			(0.646)	(0.055)
Two weeks × Exp 1-year			-0.465	-0.076
			(1.025)	(0.084)
One week × Exp 1-year			5.666***	0.418***
			(1.378)	(0.113)
Warned × Exp 1-year			-12.741***	-1.392***
			(2.884)	(0.261)
Hit × Exp 1-year			5.755*	0.263
			(3.071)	(0.320)
Post × Exp 1-year			-4.677***	-0.606***
			(1.522)	(0.159)
Observations	8,941,166	8,941,166	8,941,166	8,941,166
County FEs	X	X	X	X

Notes: Columns 1-2 replicate the regressions in Columns 3-4 of Table 2, and Columns 3-4 replicate those in Columns 3-4 of Table 3. The outcome is the purchased quantity of emergency items except bottled water, batteries, and flashlights in Columns 1 and 3 and the expenditures on these items in Columns 2 and 4. Standard errors clustered at the county level are shown in parentheses.
* p<0.10, ** p<0.05, *** p<0.01

Table A.8: Purchase of Perishable Food

	(1) Quantity	(2) Expenditure	(3) Quantity	(4) Expenditure
Two weeks	0.485***	0.082***	0.598***	0.097***
	(0.175)	(0.021)	(0.169)	(0.020)
One week	-0.238	0.008	-0.110	0.033
	(0.270)	(0.033)	(0.266)	(0.032)
Warned	-1.466***	-0.206***	-1.023**	-0.129**
	(0.416)	(0.051)	(0.440)	(0.053)
Hit	-6.753***	-0.848***	-6.970***	-0.847***
	(0.474)	(0.060)	(0.551)	(0.071)
Post	-2.174***	-0.307***	-1.745***	-0.237***
	(0.338)	(0.047)	(0.382)	(0.055)
Exp 1-year			-0.314	-0.033
			(0.621)	(0.086)
Two weeks × Exp 1-year			-1.717***	-0.232**
			(0.619)	(0.102)
One week × Exp 1-year			-1.954**	-0.378***
			(0.804)	(0.131)
Warned × Exp 1-year			-5.018***	-0.884***
			(1.105)	(0.147)
Hit × Exp 1-year			2.743**	0.089
			(1.352)	(0.164)
Post × Exp 1-year			-4.324***	-0.687***
			(0.900)	(0.169)
County FEs	X	X	X	X
Observations	8,941,166	8,941,166	8,941,166	8,941,166

Note: Columns 1-2 replicate the regressions in Columns 3-4 of Table 2, and Columns 3-4 replicate those in Columns 3-4 of Table 3, using the purchase quantity of and expenditure on perishable food as the outcome. Perishable items include dairy products, milk, eggs, fresh meat, and fresh produce. Standard errors clustered at the county level are shown in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table A.9: Heterogeneous Effects by Demographics

	Full sample		*Black*		*Hispanic*		*Age <40*		*Age >65*		*Non-metro*		*Metro*		*College*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Quantity	Expenditure	Quantity	Expenditure	Quantity	Expenditure	Quantity	Expenditure	Quantity	Expenditure	Quantity	Expenditure	Quantity	Expenditure	Quantity	Expenditure
Two weeks	-0.477	0.024	-0.501	0.010	-2.378	-0.136	-0.655	-0.058	-0.374	-0.004	-1.204	-0.062	-0.460	0.025	0.044	0.027
	(0.391)	(0.029)	(0.879)	(0.060)	(1.521)	(0.102)	(0.821)	(0.071)	(0.608)	(0.043)	(1.003)	(0.080)	(0.414)	(0.031)	(0.533)	(0.041)
One week	-0.670	0.047	-1.948	-0.046	-3.613**	-0.192	-1.989*	-0.089	-0.401	0.047	-2.670**	-0.097	-0.496	0.057	0.430	0.099
	(0.624)	(0.058)	(1.230)	(0.103)	(1.455)	(0.125)	(1.143)	(0.100)	(0.764)	(0.064)	(1.220)	(0.093)	(0.686)	(0.065)	(0.820)	(0.076)
Warned	7.956***	0.840***	10.863***	1.122***	7.811**	0.935***	9.489***	0.940***	4.114*	0.319	6.136	0.647**	8.393***	0.877***	5.655***	0.814***
	(1.356)	(0.102)	(3.016)	(0.224)	(3.208)	(0.293)	(3.013)	(0.255)	(2.334)	(0.205)	(3.964)	(0.297)	(1.409)	(0.108)	(2.055)	(0.192)
Hit	-20.896***	-2.098***	-18.122***	-1.728***	-18.401***	-1.939***	-20.696***	-2.019***	-18.538***	-1.849***	-23.103***	-2.287***	-20.664***	-2.081***	-19.193***	-2.095***
	(1.513)	(0.135)	(2.894)	(0.253)	(3.625)	(0.336)	(2.467)	(0.200)	(1.772)	(0.159)	(4.687)	(0.237)	(1.602)	(0.148)	(1.788)	(0.178)
Post	-4.915***	-0.338***	-3.545*	0.043	-5.847**	-0.413**	-4.890***	-0.371***	-4.159***	-0.291***	-7.432***	-0.619***	-4.568***	-0.306***	-3.550***	-0.277***
	(0.846)	(0.074)	(2.127)	(0.219)	(2.397)	(0.193)	(1.363)	(0.137)	(1.043)	(0.080)	(2.283)	(0.142)	(0.923)	(0.083)	(1.120)	(0.090)
Exp 1-year	-3.347***	-0.138**	-3.218**	-0.186*	-2.970*	-0.037	-2.511*	-0.139	-3.745***	-0.240**	1.947	-0.008	-3.935***	-0.136**	-3.877***	-0.148**
	(0.658)	(0.057)	(1.382)	(0.108)	(1.688)	(0.111)	(1.427)	(0.134)	(1.300)	(0.110)	(2.090)	(0.167)	(0.742)	(0.064)	(0.757)	(0.067)
Two weeks × Exp 1-year	0.099	-0.050	1.753	0.211	-6.047**	-0.872***	-4.462**	-0.289	1.243	0.029	-1.361	0.143	0.319	-0.063	0.562	-0.023
	(1.062)	(0.085)	(3.020)	(0.268)	(2.355)	(0.164)	(2.019)	(0.215)	(1.741)	(0.136)	(4.744)	(0.344)	(1.061)	(0.087)	(1.244)	(0.108)
One week × Exp 1-year	6.330***	0.492***	-0.877	0.189	12.984***	0.664***	5.688**	0.432*	8.751***	0.733***	5.114	0.624*	6.326***	0.469***	8.644***	0.628***
	(1.426)	(0.119)	(2.881)	(0.304)	(3.389)	(0.255)	(2.892)	(0.232)	(2.560)	(0.257)	(3.792)	(0.346)	(1.500)	(0.127)	(1.875)	(0.159)
Warned × Exp 1-year	-14.027***	-1.450***	-11.114	-1.213***	-14.966***	-1.707***	-21.602***	-2.020***	-4.775	-0.573	-25.009***	-2.672***	-13.348***	-1.373***	-10.369***	-1.381***
	(2.928)	(0.264)	(6.778)	(0.411)	(4.529)	(0.475)	(7.280)	(0.668)	(4.836)	(0.443)	(8.520)	(0.755)	(2.989)	(0.271)	(3.588)	(0.317)
Hit × Exp 1-year	5.797*	0.238	-4.333	-0.994*	-0.515	0.023	13.318	0.417	4.138*	0.192	-2.652	0.813**	6.242*	0.205	5.603	0.173
	(3.125)	(0.325)	(5.836)	(0.562)	(4.439)	(0.423)	(9.572)	(0.568)	(2.378)	(0.285)	(7.568)	(0.383)	(3.266)	(0.327)	(5.289)	(0.397)
Post × Exp 1-year	-4.452***	-0.573***	-4.526	-0.478	-5.233	-0.816***	-12.450***	-1.069***	-0.176	-0.279	9.064	0.544	-5.825***	-0.689***	-5.983***	-0.673***
	(1.630)	(0.164)	(3.422)	(0.306)	(3.419)	(0.312)	(2.642)	(0.237)	(2.507)	(0.215)	(6.238)	(0.420)	(1.540)	(0.172)	(2.094)	(0.183)
County FEs	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Observations	8,608,473	8,608,473	1,289,411	1,289,411	514,613	514,613	1,375,186	1,375,186	2,375,730	2,375,730	1,463,760	1,463,760	7,144,713	7,144,713	4,750,528	4,750,528

Note: This table replicates the regressions in Columns 3-4 of Table 3 for different demographic groups. Standard errors clustered at the county level are shown in parentheses. * p<0.10, ** p<0.05, *** p<0.01