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

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Abstract

Hurricanes and tropical cyclones have been getting more severe over the past 40 years and are expected to intensify in the future as a result of climate change. Hurricanes not only cause economic damage and loss of human life, but they may also impact households' behaviors and risk preferences. In this paper, we seek to understand the impact of hurricanes on household expenditure patterns, which can help us understand the behavioral response, preparedness, and how policymakers can better support resiliency. 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 by households in areas experiencing hurricane warnings and hits to purchases made by 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 storms that are forecast to be more severe. Households with recent hurricane experience respond earlier and stronger. We also find differential impacts by several socio-demographic characteristics.

Keywords: natural disaster, hurricane, experience, emergency supplies, Nielsen 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 in the future as a result of 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 10 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 impact households' risk preferences and economic behaviors, from avoidance and adaptation to migration and housing decisions. In this paper, we seek to understand the impact of hurricanes on household expenditure patterns, which can help us understand households' behavioral response, preparedness, and how policymakers can better support resiliency.

We combine Nielsen 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 Nielsen 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 experiencing a hurricane warning, we compare household purchases by households in areas warned and hit by hurricanes to purchases made by similar households who were not.

Using this approach, we attempt to answer several questions. To what extent do households prepare for forecast hurricanes (e.g., by stocking up on essentials such as non-perishable food items and water)? Is there evidence of heterogeneity across households in preparedness behavior? We also explore longer-run impacts- in particular, we investigate how household preparation for a forecast hurricane differs for those who experienced a hurricane in the previous years.

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 prior to a hurricane but decrease

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

purchases of these goods during and the week following the disaster. This suggests that households do indeed prepare for an oncoming storm. We find evidence that households stock up even more on these goods when expecting a more severe hurricane. Furthermore, people are either unable or unwilling to venture out to purchase these items during and after the hurricane (or, perhaps, they have sufficient stockpiles). In general, the post-event decrease in purchases exceeds the pre-event increase, leading to a net decrease in purchases of these goods over the time period of study. However, for households facing a more severe impending hurricane, there is a significant net increase in their purchases.

Moreover, past experience matters substantially. Effects are larger on households with recent hurricane experience, especially if they recently experienced a more severe hurricane. These households stock up earlier when expecting more severe hurricanes and appear to "hunker down" in the couple of days preceding the storm. However, the effect of experience dissipates completely after four or five years.

We also find some heterogeneity in disaster preparedness and responsiveness across socio-demographics. Notably, we do not find substantial differences across income groups. We do, however, find that households located in non-metropolitan areas and those with more education tend to stockpile more emergency goods when anticipating a hurricane. Lastly, we find that the higher the hurricane risk in which households reside, the more responsive they are to upcoming storms. The heterogeneity in disaster preparedness may stem from differential risk tolerance and liquidity constraints of households.

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 the effect of experience on disaster preparation purchases, as well as 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). Nevertheless, Hanaoka, Shigeoka and Watanabe (2018) show that men who experienced greater intensity of the earthquake became more risk-tolerant.

Little work has been done on the impacts of natural disasters on the 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 modesty if any effect 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 to find 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 Nielsen Consumer Panel data, which are both higher frequency and at the individual (rather than store) level. In addition to more precision on timing, we are better able to 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. While our findings are similar in that households appear to purchase more supplies in advance of a hurricane, Beatty, Shimshack and Volpe (2019) find that purchases also increase in the week following the hurricane. We, however, find that purchases decrease during the hurricane and for the week thereafter. This finding of ours is robust-consistent across various specifications and sub-samples. This may suggest that households are unable to venture out to procure supplies that they need in the wake of a storm.

3 Data

To analyze consumers' 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 Nielsen 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] We also restrict the sample to include only hurricane-prone states (those that were hit by a hurricane at least once in our sample) to improve the comparability of treatment and control households.[3] Below, we provide more details for each of these three data sources.

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. In addition, detailed intensity measurements are 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 tropical storm or hurricane (with maximum sustained wind speed greater than 64 knots) within a 100-mile radius from the storm system's centroid. 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 with their dates of being active and the states they affected.

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 in 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,

[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 2009, 2013, 2014, or 2015.

[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.

these weather alerts are issued sufficiently in advance such that residents can prepare and take necessary safety measures. A warning is the most urgent and a watch is the least urgent. The NWS issues a warning when "a hazardous weather or hydrologic event is occurring, imminent or likely. A warning means weather conditions pose a threat to life or property. People in the path of the storm need to take protective action."[4]

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 2017. 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 the households' interest could start ahead of warnings, we construct our sample time frame to begin two weeks before a hurricane warning.

3.3 Nielsen Consumer Panel

Nielsen Consumer Panel is a nationally representative panel database provided by the Nielsen 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, marital status, etc. Each participating household uses a barcode scanner to scan each item purchased from grocery stores, recording the UPC codes and price information. We restrict the sample to include only emergency supplies. A list of these items is shown in Appendix Table A.2. Moreover, we restrict our sample to purchases made from June to

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

November each year, months usually considered as part of the hurricane season for the Atlantic. Our final sample includes the years 2008-2018 to match the consumer purchase observations with the hurricane-related HURDAT2 and WWA databases.

For safety measures, the NWS recommends that each household keeps an emergency supply kit with water, non-perishable food (such as canned food), flashlight 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. We restrict the items purchased by Nielsen respondents to such emergency supplies to identify any potential changes in consumers' shopping behavior in response to hurricane threats. We consider two measures of purchases: the first is the quantity of emergency items purchased, and the second is the expenditure on these goods. The quantity is measured in the unit of an ounce, fluid ounce, or count. The expenditures are expressed in U.S. dollars of 2008.

3.4 Sample Criteria

Natural disasters are spatially clustered, even though the actual location that 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 other benefits, including lower housing costs (Bin and Landry, 2013; Atreya and Ferreira, 2015; Beltran, Maddison and Elliott, 2019) and coastal amenities, and vice versa. Also, households at locations that experience frequent natural disasters may become more disaster-resilient. Therefore, household preparedness for natural disasters may vary across regions with differential disaster risks because of the endogenous sorting of households and their past disaster experiences.

To address this issue, we employ propensity score trimming. First, we estimate how the probability of a county that receives a hurricane warning is related to the geographic and climatic attributes of the county, as well as its demographics and measures of the labor and housing markets. In particular, we estimate the following equation:

$$Prob(warning_{iy} = 1) = F(\alpha_0 + \alpha_1 X_{1i} + \alpha_2 X_{2iy} + f_y) \quad (1)$$

where $warning_{iy}$ is a dummy variable indicating whether county i receives a hurricane warning in year y; X_{1i} 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;[5] X_{2iy} contains measures of the demographics and economic conditions of county i in year y. The demographic controls include total population, the share of the urban population, age structure (share of population over age of 65 and the share below 18 years of age), the share of blacks, average adult educational attainment, the share enrolled in schools, and average household income. The labor and housing market measures include the labor force participation rate, unemployment rate, median rental price, median property tax (as an indicator for house values), and median property insurance.[6] Lastly, f_y denotes year fixed effects.

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, conditional on its demographic and economic characteristics. Figure 1 displays the propensity score distribution for warned vs. unwarned locations. 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 17% of the household-day observations in the dataset are dismissed. As we dismiss locations that are extremely likely or unlikely to be under hurricane threats, the sample contains household observations in regions facing similar disaster risks. Given the disaster risk, the realization of a hurricane may be plausibly exogenous. The households in these counties may also share comparable unobserved risk attitudes and disaster awareness, conditional on their observed characteristics.

Table 1 provides the summary statistics for the trimmed sample we use in the primary analyses. Columns 1 and 2 include observations from households that were never warned or

[5] 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 county in the US into one of eight climate zones based on average temperature and humidity.

[6] The demographic and economic characteristics of counties are derived from the US Census Bureau's American Community Survey 2008-2018.

hit by a hurricane, Columns 3 and 4 from households who received a warning at least once during the sample period, and Columns 5 and 6 from those hit by a hurricane for one or more times. About 28% of households in the sample ever experienced a hurricane warning, and 23% were hit by a hurricane. 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.[7]

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 with no experience of hurricanes seem to purchase more emergency items and perishable foods than the other two groups.

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 to households is receiving a hurricane warning. Hurricane warnings usually last for two days and imply a high chance of a hurricane strike. While the warnings are issued at locations of varying sizes, we aggregate them to the county level. However, since households may start getting information about a hurricane before a warning is issued and could begin preparing for the upcoming disaster ahead of time, we explore households' purchases during the two weeks before a hurricane warning. The second treatment is a hurricane hit, as only a subset of warned areas is actually struck by hurricanes. 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.[8] These impacts can linger even after a hurricane passes. Consequently, we also consider the purchases of emergency items in the week after a hurricane hit.

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

[8]We cannot identify whether a Nielsen panelist was temporarily displaced in the data.

In particular, 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 reside in county c. $week_{\tau,ct}$ is a binary indicator for whether day t falls in one of the two weeks leading 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 a week. Admittedly, locations on a hurricane trajectory (e.g., areas inside the National Hurricane Center's forecast cones) may end up not warned. Under our current definitions, households in such areas belong to the control group even though the hurricane also threatens them. The misclassification may thus lead to an underestimated effect of hurricane threats on disaster preparedness. $warned_{ct}$ and hit_{ct} are treatment dummy 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 passes 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 the households not affected by the disasters.

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, whether the household head is male, married, over 65 years of age, or black. To account for systematic temporal variation in shopping behaviors, we also control for year fixed effect, y_t, month fix 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 also test replacing county fixed effects using household fixed effects. Admittedly, household fixed effects can better 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 families with prior hurricane exposure become more experienced - perhaps making them more strategic in their purchases or perhaps 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 in purchases between households with and without hurricane experience. We use an indicator variable and identify whether a household was hit by a hurricane one year prior in our primary analyses. Then we consider defining the experience in alternative ways, for example, based on the severity of the hurricane experienced or the time of exposure (e.g., one year ago v.s. two to three years ago).

5 Results

5.1 Baseline Results

We start by looking at how household purchasing behaviors respond to hurricane warnings. We focus on emergency survival supplies to prepare for upcoming hurricanes, including bottled water and other drinks, non-perishable foods, flashlights, batteries, and first aid supplies. We measure the amount of purchase in two ways- total quantity and total expenditure, and consider the purchases two weeks prior to a hurricane warning, one week prior, when the hurricane warning is in effect, the day the hurricane hits a location, and one week post-hurricane. We present the results in Table 2.[9] The outcome is total daily purchase quantity in Columns 1 and 3 and total daily expenditure in Columns 2 and 4. 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 in terms of buying more emergency supplies. Specifically, households increase their purchases of disaster preparation items by one to two units and increase their expenditures on these goods by \$0.2 to \$0.3 per day in the week prior to a hurricane warning; the increase is more significant (about three units and \$0.3 to \$0.5 per day) once a warning is issued. Since the average daily purchase quantity of these goods over the sample is approximately 35, with an average daily expenditure of \$3.5 (see Table 1), these increases are economically meaningful. When controlling for household fixed effects in the first two columns, we find that households start to stock up for hurricanes as early as two weeks before a warning is issued (the increase in purchases is about one unit and \$0.1 per day). However, we do not observe such a pattern when controlling for county fixed effects instead of household fixed effects. These results are, in general, consistent with the findings of Beatty, Shimshack and Volpe (2019), who use Nielsen's weekly store scanner data. Notably, we look at more purchase categories than their paper, which focuses only on the sales of bottled water, batteries, and flashlights.

In contrast to their findings,[10] 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 18 units or \$2 each day when a hurricane hits and by two to three units, or 0.2 to \$0.3, per day the week after a disaster. 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

[9]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.3 display the results. The estimates show a similar pattern as those in Table 2 but are less statistically significant.

[10]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 are unable to 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.

than grocery shopping after it passes. Lastly, those who bear disaster losses may have a tighter budget constraint and reduce non-essential consumption as a result.

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,[11] suggests that treated households increase their quantity of emergency supplies by 13 units prior to the hurricane hit and decrease their quantity by 37 units during and 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 increase spending on emergency supplies by $2 prior to the hit and decrease it by $4 during/after the hit. The net decline in the purchases, 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 if household purchases of emergency items respond differently to upcoming *severe* hurricanes. We consider category two or above hurricanes as severe and those of category one and tropical storms as less severe. Columns 5 and 6 of Table 2 repeat the regressions from Columns 3 and 4, but restricting treatment to severe disasters. We continue to find households purchase more emergency supplies when a severe hurricane approaches them; the increase starts two weeks before a hurricane warning. The increases are significantly larger for households facing more severe disasters. Specifically, when a severe hurricane approaches, households buy two units or a $0.25 (vs. one unit or $0.2 in Columns 3 and 4) and 22 units or $2.4 (vs. three units or $0.3) more emergency items per day one week prior to a hurricane warning and when the warning is in effect, respectively. These results could imply either that a greater share of households prepares for upcoming severe disasters or that each household buys a larger quantity. As in the first four columns in Table 2, we find households buy fewer emergency items when a severe disaster hits; the decrease is slightly larger in magnitude for a more severe disaster (20 units or $2 for a severe hurricane vs. 18 units or $2 for an average one). However, the reduction in purchases is smaller following a severe more hurricane. Because households are more likely to experience property destruction and face other obstacles to shopping after a more severe disaster, the pre-disaster acquisition of additional supplies is a more plausible explanation for the post-disaster decrease in purchases.

[11] We use the same assumptions for back-of-the-envelope calculations henceforth.

In contrast to an average hurricane, a severe one leads to an increase in the net purchase of emergency supplies during the examined window. In particular, household purchases rise by 67 units or $7 in total prior to the hit, and drop by 29 units or $3 during/after the hit. These results suggest that households do receive external information that enables them to distinguish warnings for more severe hurricanes from those that are less severe and respond accordingly by stockpiling more for a more intense hurricane.

5.2 Heterogeneous Effects by Hurricane Experience

Next, we examine how households respond to an upcoming hurricane differently according to their 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. We present the estimation results in Table 3. Among households that were not affected by a hurricane in the previous year ("inexperienced households"), we continue to find an increase in the disaster-preparedness purchases before and when a hurricane warning is in effect but a decrease in such purchases during and after the hurricane.

Compared to those without recent hurricane experience, the households hit by a hurricane one year prior ("experienced households") buy almost twice as many emergency items one week before the hurricane warning but significantly 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 four units, or $0.4, more emergency goods for hurricane preparation per day than inexperienced households in the week before a hurricane warning. Unlike inexperienced households who make more purchases (by four to five units, or $0.5 to $0.6) under a hurricane warning, experienced households actually decrease such purchases by about three to four units, or $0.3 each day. Based on the estimates in Columns 3 and 4, inexperienced households increase their purchase of emergency supplies by nine units or $1.4, while experienced households increase the amount by 28 units or $3 in total prior to the hurricane hit. Experience may make households either more aware of natural disasters or more risk averse. They appear more likely to follow the news on approaching storms, start preparing for the disaster earlier, 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" in the day or two preceding the storm. The larger increase in the purchase before a hurricane may partially lead to a larger decrease in the purchase afterward.

It is also notable that experienced households reduce their purchase significantly more than inexperienced households after a hurricane. The decrease is more than threefold in the former group relative to the latter. According to the estimates from Columns 3 and 4, inexperienced households decrease the purchase by 32 units or $3, whereas experienced households decrease the amount by 57 units or $7 during and after a hurricane. 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; they may also have been more conservative in their consumption of emergency goods. The decrease may also partially stem from the greater increase (relative to inexperienced households) in purchases prior to the storm.

We inspect purchases of several individual categories or goods and report the estimation results in Appendix Table A.4 and Table A.5. We find the most significant pre-hurricane increases in the purchase of bottled water, batteries, and flashlights. These two categories may be deemed the most essential in hurricane preparedness.[12] We do not, however, find inexperienced and experienced households act much differently in stocking up on these products. Nevertheless, we find experienced households tend to acquire snacks and drinks other than water earlier than inexperienced households, as the former may have learned about what they want and need during a hurricane from their past experience. We also find some evidence that households reduce their purchases of baby items and tools when facing an upcoming 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 important for them to survive a hurricane.

Next, we assess how an upcoming severe hurricane deferentially affects households with and without recent disaster experience. Again, we consider hurricanes of category two or above as severe and rerun the regressions in Columns 3 and 4, restricting the treatment to severe

[12] To investigate whether the significant changes found in Table 2 and Table 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.6 and find very similar patterns, suggesting households also stock up on other emergency supplies, such as non-perishable foods, when preparing for a hurricane.

disasters (of the current period) only. The results are shown in the last two columns of Table 3. We find that experienced households appear to start disaster preparation one week earlier than inexperienced ones when expecting a severe hurricane. The difference in the purchase amount one-week pre-warning is more pronounced when the upcoming hurricane is severe (seven units or $1 for a severe disaster vs. four units or $0.4 for an average disaster).

A back-of-the-envelope calculation suggests that inexperienced and experienced households buy 69 units or $14 vs. 56 units or $16 more emergency items before a severe hurricane hit; the two groups decrease purchases by 26 units or $3 and 49 units or $4, respectively, during and after the hit. Therefore, we may conclude that the experienced households do not necessarily stock up more in than inexperienced ones when expecting a major hurricane. Indeed, the net change in purchases of emergency supplies of experienced households is not significant. Possibly, compared to their counterparts, experienced households have a better idea of the essential items and the appropriate amount to include in their emergency survival kit so that these households are less likely to overbuy.

5.3 Severity of Experienced Disasters

In this section, we inspect 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, as well as a third case in which households received a hurricane warning but were not actually hit (i.e., the least severe disaster experience). A more destructive disaster may raise household disaster awareness more substantially than a less destructive one. Meanwhile, households may not use up their survival kit supplies when they experience a less severe disaster, leaving items for the next hurricane season. Also, households that were warned but not hit may underestimate the current disaster risk, expecting the hurricane will miss their location again.

Therefore, we classify disaster experience into three categories: severe disaster experience (experiencing a hurricane of categories two to four[13]), less severe disaster experience (experiencing a tropical storm or a category one hurricane), and minor disaster experience (being warned but not hit by a hurricane). We replicate the regressions from Columns 3 and 4 of Table 3 by the degree of prior disaster experience and report the estimates in Table 4. Note that the intensity

[13] There are no category five hurricanes in our sample period.

of a hurricane changes over time. The severity of a hurricane a household experiences depends on their location on the path of the disaster. Also, when we assess how a disaster experience of a certain severity affects households' later disaster preparedness, we exclude households exposed to hurricanes of the other severity categories from the sample so that the comparison group contains only households not impacted by a hurricane in the prior year.

As in Table 3, in Table 4 we find households with previous hurricane experience start to prepare for an upcoming hurricane earlier than households without such experience. Households struck by severe hurricanes in the past year increase their purchase of emergency goods more than those struck by less severe hurricanes one week before a hurricane warning in the current year. Specifically, those who experienced a category two to four hurricane buy about ten units or $1 more items per day during that week than those with no experience of hurricanes in the past year; those who experienced a tropical storm or a category one hurricane purchase six units or $0.6 more per day than those without hurricane experience. Indeed, households with severe disaster experience are estimated to increase their purchase amount by 44 units or $5 prior to a hurricane hit, while those with less severe experience increase the amount by 17 units or $3. There is little evidence, however, that households that were warned but not hit make a greater amount of purchases than inexperienced households when a hurricane is approaching but the warning is not yet issued.

We also find that households struck by a hurricane or warned of one in the year prior buy significantly fewer disaster-preparation items during the current hurricane warning period than inexperienced households. In particular, households who experienced a severe hurricane, a less severe one, or received a hurricane warning but were not actually hit decrease their disaster-related purchase by 12 units ($1.3), 18 units ($2), or 0.1 units ($0.1) every day, respectively, under a hurricane warning. The decreases may represent "hunkering down" and/or stem from the increase in previous purchases or remaining stockpiles from the prior year.

Notably, for treated households who experienced a severe hurricane the year prior, a back-of-the-envelope calculation shows that the increase in quantity purchased and spending prior to the storm exceeds the decrease during/following the storm, for a net quantity increase of 3 units and a net spending increase of $1. Yet, the net quantity of purchases decreases for the other two inexperienced households groups (by 39 and 21 units, respectively). The heightened disaster awareness and the unconsumed items from the previous year's hurricane preparation may be explanations.

5.4 Long-run Effects

Traumatic experiences of natural disasters can have lasting impacts on households, including their risk preferences and climate awareness. Therefore, in this section, we inspect how past hurricane exposure affects household preparation for an impending hurricane in the longer run.

Table 5 presents the regression results. Columns 1 and 2 are identical to Columns 3 and 4 of Table 3, where we consider the effect of experiencing a hurricane one year prior. In Columns 3 and 4, we assess the experience of a hurricane that occurred two to three years ago, and in Columns 5 and 6 the experience of a hurricane that occurred four to five years ago.

While households who experienced a hurricane in the past year appear stock up on emergency supplies more and sooner, we do not find such an effect for those who experienced a hurricane two or three years prior. However, those who experienced a hurricane two or three years prior do buy a significantly greater amount of emergency items (by eight units per day) under a hurricane warning relative to inexperienced ones, presumably because the former group has more awareness of or fear for hurricanes given their experience. Moreover, when a hurricane hits, the experienced households decrease their purchase amount (by seven units per day) and total expenditure (by \$0.8 per day) more than households without exposure to hurricanes two to three years prior. This decrease may result from previously stockpiled goods or reflect these households' reluctance to go out during the storm. Therefore, we may argue that while households with a disaster experience two to three years prior do not necessarily start disaster preparation as early as households struck by a hurricane more recently, they do purchase more survival supplies than their inexperienced counterparts.

We do not, however, find households that experienced a hurricane four to five years ago behave any differently from those without such experience when a new hurricane approaches. The result is consistent with the literature suggesting that households tend to forget about their past disaster experience over time (e.g., Atreya, Ferreira and Kriesel, 2013; Beltran, Maddison and Elliott, 2019).

5.5 Heterogeneous Effects by Income

In this section, we explore the heterogeneous impacts of hurricanes on households with different incomes. The purchasing behaviors of households are subject to their budget constraints. Household income is also correlated with educational attainment, which may partially determine environmental awareness and access to disaster-related information. Accordingly, we divide the sample into three groups of similar size based on their real annual income: the bottom tertile (low-income), the middle tertile (mid-income), and the top tertile (high-income). It is worth noting that the annual household income can change over the period of analysis. Hence, one household can be categorized into different income groups in different years.

We first replicate the regressions from Columns 3 and 4 of Table 2 for each group but do not find significant differences across income levels. Indeed, we do not find significant increases in household pre-hit purchases of emergency supplies; the coefficients are generally smaller, and the standard errors are larger, presumably due to the lack of variation. But we continue to find households of all incomes decrease their purchases when a hurricane strikes and afterward, whereas the decrease is the greatest in the low-income group post-hurricane. The budget constraint may be an explanation. Appendix **??** shows the estimates.

Next, we examine the heterogeneous impacts of disaster experience on hurricane preparedness according to household income. We replicate the regressions from Columns 3 and 4 of Table 3 for each income group and report the estimates in Table 6. We find weakly significant evidence that experienced low-income households stockpile more (by seven units or $0.4 one week prior) before a hurricane than their inexperienced counterparts. As in Table 3, we continue to find that inexperienced households reduce their emergency supply purchase when warned, decrease such purchase less during a hurricane but more after a hurricane than inexperienced households. These changes are of similar magnitude across household income levels.

We also assess the changes in the purchase of emergency items by demographic characteristics, including householders' race, age, education, and metropolitan status. We present the estimates in Appendix Table A.8. We find all groups prepare for upcoming hurricanes, and households with past hurricane experience tend to initiate the preparation earlier than households without such experience. However, the estimates vary in magnitude across groups, presumably due to differential risk tolerance or access to stores. Notable differences include the following. Black and Hispanic households stockpile more when warned. Households in which the head of household is over the age of 65 purchase more emergency goods one week ahead and when warned. We also see a greater degree of stockpiling in non-metropolitan areas. Finally, disaster preparation is more pronounced by college-educated households, particularly those with recent hurricane experience.

5.6 Purchase of Perishable Goods

Extreme weather conditions can restrict household access to grocery stores even without water or power outages. Thus, some households may stockpile perishable foods in addition to emergency survival supplies before a hurricane. Accordingly, we analyze household purchases of dairy products, deli food, fresh produce, and fresh meat in this section. We re-run the regressions from Columns 3 and 4 of both Table 2 and Table 3 using the daily purchased quantity of and expenditure on perishable foods as the outcomes. Table 7 presents the estimates.

In contrast to Table 2, we find that households buy one unit or \$0.1 less perishable foods each day when receiving a hurricane warning. This reduction may reflect a reallocation of resources since these households buy more emergency items during this period. As in Table 2, households reduce their purchases of perishable foods during a hurricane and afterward. Specifically, households decrease the purchase amount by 6.5 units or \$0.9 per day during a hurricane (v.s. 18 units or \$2 in emergency supplies) and one unit or \$0.2 per day after a hurricane (v.s. three units or \$0.3 in emergency supplies), perhaps because the disaster prevents people from going out.

When distinguishing households with and without exposure to hurricanes in the previous year in Columns 3 and 4, we find experienced households buy significantly more perishable foods than inexperienced households one week before a hurricane warning relative to a control household. Indeed, experienced households increase their purchase by 0.7 units or \$0.1 each day during the week pre-warning. At the same time, experienced households decrease the purchase more than inexperienced households when warned and after a hurricane but reduce it less than inexperienced households during a hurricane. Therefore, while the total reduction in the pre-hit purchase of perishable foods is significantly higher among inexperienced than experienced households (six units or \$0.4 vs. one unit or -\$0.3), the total decline during the whole window studied is very similar in the two groups (around 19 units or \$2 to \$3).

These patterns resemble those found in Table 3 when we assess emergency supplies. They suggest that households with recent hurricane exposure tend to also stock up on perishable foods to prepare for a hurricane. However, emergency goods are still of higher priority in preparation for disasters.

5.7 Heterogeneous Effects by Disaster Risk

Finally, we inspect 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 be inherently different from those in low-risk areas. Nevertheless, it is also important to understand the household response to a hurricane threat at locations with a low versus high probability of disasters. Therefore, 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. We re-run the regressions in Columns 3 and 4 from Table 2 and Table 3 on each sub-sample and present the results in Table 8 and Table 9, respectively.

We find little evidence in Table 8 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 marginally significant increase in household expenditure on emergency supplies one week before a hurricane warning (by over \$0.1 per day) but a larger and more significant increase in both the purchase amount (three units per day) and spending (\$0.4 per day) when a warning is issued. On the other hand, households in high-risk regions buy significantly more emergency items during the week before a hurricane warning (two units or \$0.3 each day) but show no change once the warning is in effect. Notably, households that reside in areas subject to a high risk of hurricanes may be more alert to upcoming hurricanes than households elsewhere. They may also expect a large likelihood of being hit if their location is on the forecast trajectory of a hurricane. Therefore, when they learn about a hurricane threat, these households are more likely to prepare for it early on. In contrast, learning about an upcoming hurricane, households in medium-risk areas may expect some chance of being hit. Hence, while some more risk-averse people begin shopping for emergency supplies early, many others choose to wait till a hurricane warning is issued, and they update the perceived risk. Lastly, households in low-risk areas may be less-attuned to hurricane-related forecasts. Even if they learn that a hurricane is coming their way, 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 amount of purchases when being impacted by a hurricane and afterward. The size of the decrease is generally negatively related to the propensity score. Possibly, households in low-risk regions have the least past hurricane experience and are thus most discouraged from going outside when a hurricane hits or has passed. It is also possible that the most risk-averse households self-select to areas associated with low hurricane risk. Hence, compared to households elsewhere, they are least likely to go shopping during this period.

When distinguishing the heterogeneous effects of hurricane warnings by recent disaster exposure, we find in Table 9 a similar pattern among inexperienced households. In particular, those living in higher-risk areas are more responsive to hurricane threats: they tend to stock up on more emergency supplies and to do so earlier. Meanwhile, households in lower-risk locations reduce their purchases more during or after a hurricane.

Compared to their inexperienced counterparts, experienced households in all areas appear to start preparing for upcoming hurricanes earlier. The interaction effect of the one-week prior indicator is statistically significant for all the sub-samples, and the difference between inexperienced households and inexperienced households is the largest in low-risk regions. Specifically, experienced households buy 15 units or \$1 more emergency goods per day during the week before a hurricane warning than inexperienced households in low-risk areas, three units or \$0.5 more in medium-risk areas, and three units or \$0.3 more in high-risk areas. Recent disaster exposure may significantly raise disaster awareness in the population in low-risk regions so that they pay more attention to the information on hurricane threats. They also understand that a hurricane can hit them even if the chance is low. Therefore, we find the greatest difference between the inexperienced households and inexperienced households in low-risk areas.

Similar to Table 9, we find that experienced households do not necessarily increase the purchase amount of emergency items when warned while inexperienced households generally do. The difference between the two groups is similar in size (ten units or \$1 to \$2 per day) in low- and high-risk areas but is insignificant in medium-risk areas. Unlike Table 9, we find no difference between inexperienced households and inexperienced households when a hurricane hits in medium- or high-risk locations. Unfortunately, the coefficient on the interaction between hit and experience cannot be identified for the low-risk locations since no such locations were hit by a hurricane in two consecutive years in our sample.

Lastly, we find experienced households reduce the purchase amount of and spending on emergency supplies significantly more than their inexperienced peers after a hurricane in medium- and high-risk regions. Indeed, the post-disaster decrease among experienced households is of comparable size across locations with different propensities of hurricanes. Experienced households may be better aware of the lingering danger of a hurricane and are thus less likely to go out. A tighter budget constraint due to previous disaster damage may be another explanation. Both possible reasons presumably do not depend on the risk level of a hurricane, so we do not expect the experienced households to act differently after a hurricane across locations.

6 Conclusion

We explore household preparedness for hurricanes in this paper. 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 are not. We restrict our sample to households in counties with a similar probability of experiencing a hurricane to improve comparability of the treatment and control group. In general, we find that treated households increase both the quantity of and spending on purchases of emergency goods, including bottled water, batteries and flashlights, non-perishable food, and other drinks in the week or two prior to a hurricane, stockpiling these goods in preparation for the storm. We also find that treated households decrease purchases of these goods during and after the storm. This could be because they do not need more yet or because they avoid going out due to obstacles such as infrastructure damage or road closures following the hurricane. Alternatively, if facing significant property damage from the storm, a household may face new liquidity constraints.

We find that, for the average hurricane, 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.

Households facing impending severe hurricanes (Category 2 or higher) stock up more, particularly during the hurricane warning period, which generally lasts a couple of days and occurs right before the storm. Though they also decrease purchases during and after the event, we do find a substantial and large net increase in purchases over the pre- and post- hurricane period studied.

Past experience also impacts households degree of preparation for an impending storm. Households who 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, either because they have more stockpiled or are more aware of lingering risks such as downed power lines. This behavior is particularly salient for households who experienced a severe disaster the prior year. The effect of experience dissipates over time, with no differential response by households who experienced a hurricane four to five years prior.

While we find some differential hurricane preparedness response by socio-demographics, we do not find a significant differential response by income. Notably, we find that households in non-metropolitan areas stockpile more, as do higher educated households- particularly those with recent hurricane experience.

Households who reside in higher risk areas tend to increase purchases of emergency supplies earlier than those who reside in medium-risk areas, who wait until a warning is issued before stocking up. Households who reside in low-risk areas do not appear to stock up on emergency supplies when expecting a hurricane. On the other hand, for households with recent hurricane experience, those in low risk areas stockpile significantly more than those in higher risk areas.

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. This behavior is consistent across incomes and many socio-demographic variables. Only college education and living in a non metropolitan area are associated with differential increases in pre-disaster purchases, out of the covariates we examine. Recent experience seems to be the biggest factor that bolsters preparation and may even drive safer behavior following a storm, making people less likely to go out in the wake of hurricane damage. However, the effect of experience dissipates quickly over time, with only a small effect two to three years out and no effect four to five years out.

The existing hurricane warning system appears to be effective at inducing households to prepare. One area where these efforts could be improved is in lower risk areas, where households appear to not react to forecast hurricanes. In the weeks preceding a possible storm, the media and local leaders should also remind residents of previous disasters in an attempt to activate the responsiveness to experience that appears to fade with time. Finally, since households in many cases appear reluctant or unable to venture out to grocery stores during and in the wake of hurricanes, resulting in a net decrease in purchases of emergency goods, it may be useful to stockpile a decentralized network of community centers with emergency supplies and/or provide delivery services by trained professionals (such as the National Guard) to provide essentials to households with insufficient supplies.

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7 Tables & Figures

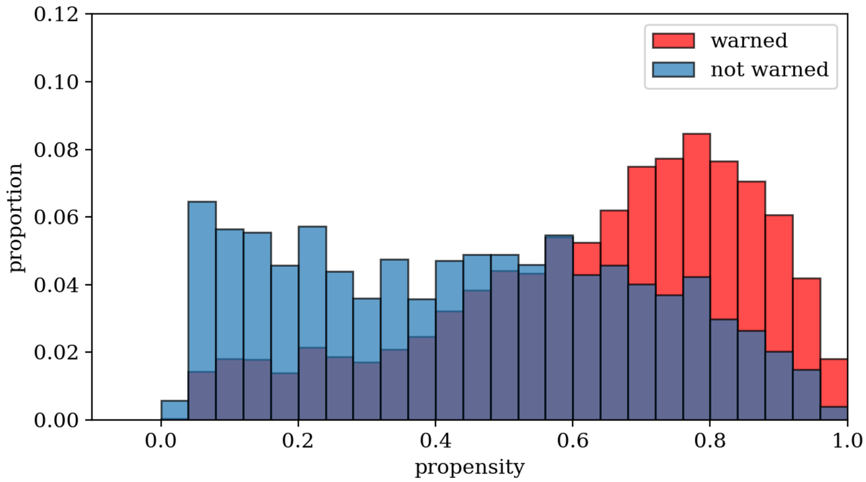

Figure 1: Propensity score distributions of counties that received and did not receive a hurricane-related warning within the past year across the sample years

Table 1: Summary Statistics

	Non-Warned/Hit		Warned		Hit	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Demographics						
Household income, $	62,329	31,665	62,396	31,446	63,528	30,716
Household size	2.39	1.28	2.40	1.27	2.38	1.28
Married	0.64	0.48	0.65	0.48	0.62	0.49
Children present	0.23	0.42	0.23	0.42	0.23	0.42
Over-65	0.29	0.45	0.30	0.46	0.27	0.45
Black	0.11	0.32	0.15	0.36	0.17	0.37
No internet	0.09	0.29	0.09	0.28	0.10	0.30
College graduate	0.52	0.50	0.53	0.50	0.55	0.50
Purchases, All Emergency						
Quantity, oz or ct	38.27	159.06	34.25	144.75	35.81	149.54
Expenditure, $	3.92	12.88	3.52	12.26	3.70	12.81
Purchases, Perishable						
Quantity, oz or ct	15.49	60.11	12.68	52.49	12.80	52.43
Expenditure, $	1.97	7.24	1.75	6.96	1.58	6.21
Observations		7,360,700		1,075,574		923,203
Number of households		68,541		26,508		21,596
Number of counties		1,451		1,362		1,266

Notes: Data is arranged by household-day. Our sample covers all hurricane-related warnings hits or warnings between the years 2008-2018. Columns 1-2 restrict the sample to households who were never hit by a hurricane nor received any warning during our sample years; Columns 3-4 restrict to households who received a warning at least once during our sample years; Columns 5-6 restrict to households who were hit by a hurricane at least for once during our sample years. “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, with 2008 as the base year.

Table 2: Main Results

	All Sample		All Sample		Severe Hurricane	
	(1)	(2)	(3)	(4)	(5)	(6)
	Quantity	Spending	Quantity	Spending	Quantity	Spending
Two weeks	1.178***	0.141***	-0.046	0.006	0.849	0.049
	(0.423)	(0.044)	(0.380)	(0.036)	(0.687)	(0.052)
One week	2.099***	0.284***	1.145**	0.175***	2.300**	0.247***
	(0.564)	(0.055)	(0.514)	(0.050)	(0.904)	(0.078)
Warned	3.493***	0.431***	2.540***	0.318***	22.401***	2.408***
	(0.964)	(0.090)	(0.842)	(0.076)	(2.549)	(0.238)
Hit	-17.910***	-1.865***	-17.958***	-1.860***	-19.880***	-2.044***
	(1.908)	(0.182)	(1.861)	(0.180)	(2.164)	(0.210)
Post	-2.318***	-0.210***	-2.809***	-0.272***	-1.344**	-0.161***
	(0.502)	(0.049)	(0.476)	(0.043)	(0.599)	(0.053)
Household FEs	X	X				
County FEs			X	X	X	X
Observations	8,992,946	8,992,946	8,993,529	8,993,529	8,331,810	8,331,810
AIC	116145740	71075180	116402358	71346624	107884701	66095613
BIC	116145936	71075376	116402540	71346806	107884883	66095794

Note: 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 hurricanes, which we define as Category 2 or above. “Two weeks” is a time indicator for being two weeks prior to a hurricane warning; “One week” indicates being one week prior to 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, female household head, household head > 65, black, internet access, year fixed effects, 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	Spending	Quantity	Spending	Quantity	Spending
Two weeks	1.167**	0.128***	-0.149	-0.016	0.935	0.031
	(0.474)	(0.049)	(0.432)	(0.042)	(0.725)	(0.055)
One week	1.436**	0.208***	0.374	0.088*	1.441	0.135*
	(0.650)	(0.062)	(0.560)	(0.053)	(0.938)	(0.078)
Warned	4.992***	0.578***	3.923***	0.452***	26.382***	2.764***
	(1.046)	(0.101)	(0.955)	(0.090)	(2.613)	(0.246)
Hit	-18.489***	-1.900***	-18.500***	-1.892***	-19.822***	-2.005***
	(1.998)	(0.190)	(1.953)	(0.188)	(2.319)	(0.225)
Post	-1.271**	-0.105**	-1.888***	-0.179***	-0.889	-0.152***
	(0.545)	(0.050)	(0.505)	(0.042)	(0.684)	(0.056)
Exp 1-year	-0.326	0.065	-0.307	0.063*	-0.003	0.069*
	(0.495)	(0.050)	(0.407)	(0.037)	(0.471)	(0.041)
Two weeks × Exp 1-year	0.203	0.025	0.681	0.067	-0.845	0.127
	(0.916)	(0.096)	(0.832)	(0.080)	(1.427)	(0.115)
One week × Exp 1-year	3.514***	0.349***	4.074***	0.400***	6.950***	0.907***
	(1.306)	(0.130)	(1.187)	(0.111)	(2.156)	(0.169)
Warned × Exp 1-year	-8.186***	-0.839***	-7.542***	-0.776***	-28.152***	-2.452***
	(2.357)	(0.231)	(2.169)	(0.209)	(3.065)	(0.319)
Hit × Exp 1-year	4.861*	0.112	4.984*	0.092	1.967	-0.589*
	(2.917)	(0.280)	(2.847)	(0.276)	(2.760)	(0.332)
Post × Exp 1-year	-5.019***	-0.551***	-4.385***	-0.497***	-3.548***	-0.089
	(1.335)	(0.146)	(1.169)	(0.125)	(1.358)	(0.144)
Household FEs	X	X				
County FEs			X	X	X	X
Observations	8,992,946	8,992,946	8,993,529	8,993,529	8,329,004	8,329,004

Note: 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 hurricanes, which we define as Category 2 or above. “Two weeks” is a time indicator for being two weeks prior to a hurricane warning; “One week” indicates being one week prior to 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, female household head, household head > 65, black, internet access, year fixed effects, 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

	Severe		Less Severe		Warned, Not Hit	
	(1)	(2)	(3)	(4)	(5)	(6)
	Quantity	Spending	Quantity	Spending	Quantity	Spending
Two weeks	-0.072	0.007	-0.055	0.007	-0.420	-0.024
	(0.395)	(0.040)	(0.391)	(0.039)	(0.496)	(0.048)
One week	0.526	0.119**	0.547	0.121**	0.039	0.066
	(0.510)	(0.047)	(0.511)	(0.048)	(0.599)	(0.054)
Warned	3.811***	0.461***	3.836***	0.462***	4.528***	0.540***
	(0.912)	(0.083)	(0.911)	(0.083)	(1.078)	(0.099)
Hit	-18.330***	-1.870***	-18.324***	-1.871***	-18.916***	-1.912***
	(1.970)	(0.191)	(1.972)	(0.191)	(2.322)	(0.224)
Post	-2.715***	-0.264***	-2.688***	-0.262***	-1.637***	-0.144***
	(0.513)	(0.046)	(0.513)	(0.046)	(0.535)	(0.045)
Exp 1-year	0.138	0.121	-0.461	0.048	-0.204	0.043
	(0.811)	(0.089)	(0.569)	(0.050)	(0.406)	(0.037)
Two weeks × Exp 1-year	-1.439	-0.130	0.161	0.138	1.375	0.020
	(1.187)	(0.117)	(1.633)	(0.163)	(1.061)	(0.087)
One week × Exp 1-year	9.777***	0.989***	5.616***	0.607***	2.208	0.166
	(2.168)	(0.154)	(1.478)	(0.161)	(1.363)	(0.116)
Warned × Exp 1-year	-12.472***	-1.292***	-17.505***	-1.967***	-4.747*	-0.624***
	(2.171)	(0.211)	(3.631)	(0.351)	(2.449)	(0.216)
Hit × Exp 1-year	5.016*	-0.030	2.424	2.154	2.710	0.128
	(2.944)	(0.290)	(5.387)	(1.484)	(2.777)	(0.268)
Post × Exp 1-year	-1.265	-0.061	-2.990*	-0.173	-2.235	-0.244**
	(1.411)	(0.204)	(1.719)	(0.144)	(1.544)	(0.121)
County Fixed Effects	X	X	X	X	X	X
Observations	8,792,118	8,792,118	8,880,048	8,880,048	8,571,563	8,571,563

Note: This table replicates the regressions in Columns 3-4 of Table 3, distinguishing the severity of household past hurricane exposure. Hurricane categories in Columns 1-2 are Category 2 or above, in Columns 3-4 Tropical Storm (less severe than a hurricane), and in Columns 5-6 the household's are received a hurricane warning one year prior but did not get hit. Standard errors clustered at the county level are in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table 5: Long-run Effects

	1 Year		2-3 Years		4-5 Years	
	(1)	(2)	(3)	(4)	(5)	(6)
	Quantity	Spending	Quantity	Spending	Quantity	Spending
Two weeks	-0.149	-0.016	-0.009	0.014	-0.118	0.001
	(0.432)	(0.042)	(0.403)	(0.038)	(0.390)	(0.037)
One week	0.374	0.088*	1.098**	0.180***	1.144**	0.171***
	(0.560)	(0.053)	(0.518)	(0.051)	(0.523)	(0.050)
Warned	3.923***	0.452***	2.132**	0.295***	2.528***	0.316***
	(0.955)	(0.090)	(0.845)	(0.077)	(0.856)	(0.077)
Hit	-18.500***	-1.892***	-17.536***	-1.821***	-17.965***	-1.868***
	(1.953)	(0.188)	(1.932)	(0.187)	(1.940)	(0.187)
Post	-1.888***	-0.179***	-2.741***	-0.269***	-2.945***	-0.285***
	(0.505)	(0.042)	(0.502)	(0.045)	(0.477)	(0.045)
Exp	-0.307	0.063*	0.825	0.015	-0.821**	-0.103***
	(0.407)	(0.037)	(0.889)	(0.057)	(0.350)	(0.031)
Two weeks × Exp	0.681	0.067	-0.884	-0.141	0.982	-0.041
	(0.832)	(0.080)	(1.442)	(0.108)	(1.901)	(0.184)
One week × Exp	4.074***	0.400***	0.451	-0.081	-1.737	-0.061
	(1.187)	(0.111)	(1.697)	(0.114)	(2.054)	(0.190)
Warned × Exp	-7.542***	-0.776***	8.418**	0.437	-1.778	-0.157
	(2.169)	(0.209)	(3.344)	(0.285)	(3.769)	(0.378)
Hit × Exp	4.984*	0.092	-7.226**	-0.815***	-1.859	0.034
	(2.847)	(0.276)	(2.833)	(0.247)	(3.599)	(0.374)
Post × Exp	-4.385***	-0.497***	-0.976	0.001	3.661	0.280*
	(1.169)	(0.125)	(1.695)	(0.128)	(3.873)	(0.153)
County Fixed Effects	X	X	X	X	X	X
Observations	8,993,529	8,993,529	8,993,529	8,993,529	8,993,529	8,993,529

Note: This table replicates the regressions in Columns 3-4 of Table 3, examining the effects of household hurricane exposure of different years in the past. The outcome is purchase quantity in Columns 1-3 and expenditure in Columns 4-6. Columns 1-2 report coefficients for households who experienced a hurricane 1 year prior, Columns 3-4 for 2 or 3 years prior, and Columns 5-6 for 4 or 5 years prior. Standard errors clustered at the county level are shown in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 6: Effects of Prior Experience by Income

	Low-income		Mid-income		High-income	
	(1)	(2)	(3)	(4)	(5)	(6)
	Quantity	Spending	Quantity	Spending	Quantity	Spending
Two weeks	-0.411	-0.042	-1.136	-0.030	0.889	0.057
	(1.085)	(0.066)	(1.019)	(0.072)	(1.251)	(0.138)
One week	0.453	0.033	-0.969	0.037	-0.133	-0.030
	(1.209)	(0.085)	(1.053)	(0.080)	(1.277)	(0.128)
Warned	2.028	0.245	2.795	0.240	3.432*	0.410**
	(1.831)	(0.163)	(2.033)	(0.157)	(1.967)	(0.207)
Hit	-22.293***	-1.892***	-21.684***	-2.054***	-22.331***	-2.382***
	(2.237)	(0.206)	(3.441)	(0.296)	(4.222)	(0.463)
Post	-3.924***	-0.255***	-0.301	-0.126	-1.498	-0.165
	(1.237)	(0.083)	(1.063)	(0.092)	(0.997)	(0.104)
Exp 1-year	-1.334	-0.061	-0.111	0.081	-0.232	0.036
	(1.002)	(0.079)	(0.963)	(0.082)	(0.946)	(0.075)
Two weeks × Exp 1-year	1.950	0.223	1.698	0.100	-1.377	-0.041
	(2.179)	(0.187)	(2.437)	(0.211)	(2.079)	(0.219)
One week × Exp 1-year	7.729*	0.388*	2.832	0.189	2.136	0.321
	(4.021)	(0.216)	(2.064)	(0.186)	(2.380)	(0.230)
Warned × Exp 1-year	-8.611**	-1.034***	-6.120	-0.835**	-8.496*	-0.977*
	(3.507)	(0.320)	(5.440)	(0.395)	(4.811)	(0.511)
Hit × Exp 1-year	12.428***	0.561	10.317**	0.527	10.294**	0.394
	(4.088)	(0.375)	(5.103)	(0.395)	(5.154)	(0.597)
Post × Exp 1-year	-4.703*	-0.374*	-5.780**	-0.482**	-8.472***	-0.781***
	(2.402)	(0.199)	(2.378)	(0.206)	(2.049)	(0.229)
County Fixed Effects	X	X	X	X	X	X
Observations	1,758,415	1,758,415	1,630,575	1,630,575	1,663,333	1,663,333

Note: 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 that falls within the lower tertile; Columns 3-4 the middle tertile; Columns 5-6 the upper tertile. Standard errors clustered at the county level are shown in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table 7: Effects of Prior Experience for Perishable Food

	(1) Quantity	(2) Spending	(3) Quantity	(4) Spending
Two weeks	-0.243*	-0.012	-0.297*	-0.031*
	(0.139)	(0.017)	(0.155)	(0.018)
One week	-0.134	0.028	-0.321*	-0.001
	(0.162)	(0.022)	(0.178)	(0.024)
Warned	-1.140***	-0.136***	-0.737	-0.076
	(0.419)	(0.045)	(0.507)	(0.055)
Hit	-6.577***	-0.902***	-6.913***	-0.935***
	(0.594)	(0.067)	(0.606)	(0.069)
Post	-1.249***	-0.165***	-0.983***	-0.119***
	(0.216)	(0.029)	(0.236)	(0.031)
Exp1-year			-0.090	0.034
			0.145	0.026
Two weeks × Exp 1-year			0.318	0.073
			(0.300)	(0.047)
One week × Exp 1-year			0.997***	0.125**
			(0.367)	(0.051)
Warned × Exp 1-year			-2.338***	-0.364***
			(0.812)	(0.117)
Hit × Exp 1-year			5.398***	0.437***
			(0.989)	(0.129)
Post × Exp 1-year			-1.272***	-0.253***
			(0.482)	(0.075)
County Fixed Effects	X	X	X	X
Observations	8,457,206	8,419,711	8,457,206	8,419,711

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 spending 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 8: 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	Spending	Quantity	Spending	Quantity	Spending
Two weeks	-0.663	-0.137	-0.426	-0.010	0.101	-0.003
	(1.317)	(0.099)	(0.602)	(0.062)	(0.346)	(0.032)
One week	-0.955	-0.018	0.517	0.138*	2.236***	0.279***
	(1.278)	(0.136)	(0.865)	(0.077)	(0.483)	(0.053)
Warned	2.619	0.239	3.346**	0.434***	0.910	0.127
	(4.436)	(0.428)	(1.341)	(0.117)	(0.887)	(0.091)
Hit	-20.171***	-1.810***	-18.030***	-1.931***	-13.882***	-1.564***
	(2.837)	(0.267)	(2.928)	(0.276)	(2.261)	(0.250)
Post	-6.319***	-0.417***	-2.663***	-0.210***	-3.846***	-0.429***
	(1.438)	(0.116)	(0.704)	(0.064)	(0.665)	(0.066)
County Fixed Effects	X	X	X	X	X	X
Observations	1,045,644	1,045,644	5,161,533	5,161,533	4,630,170	4,630,170

Note: This table replicates the regressions in Columns 3-4 of Table 2. Columns 1-2 are estimated on a sample with the propensity score of getting hit by a hurricane no larger than 0.25, Columns 3-4 on a sample with the propensity score between 0.25 and 0.75, and Columns 5-6 on a sample with the 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 9: 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	Spending	Quantity	Spending	Quantity	Spending
Two weeks	-0.801	-0.123	-0.721	-0.038	0.136	-0.045
	(1.366)	(0.099)	(0.674)	(0.070)	(0.458)	(0.040)
One week	-1.310	-0.030	0.217	0.083	1.104**	0.129**
	(1.239)	(0.126)	(0.930)	(0.082)	(0.475)	(0.054)
Warned	2.851	0.313	3.231**	0.450***	4.932***	0.516***
	(4.499)	(0.429)	(1.380)	(0.124)	(1.192)	(0.122)
Hit	-20.180***	-1.815***	-18.124***	-1.945***	-14.348***	-1.505***
	(2.837)	(0.267)	(2.925)	(0.276)	(2.764)	(0.284)
Post	-6.384***	-0.411***	-2.257***	-0.163**	-1.280**	-0.192***
	(1.465)	(0.117)	(0.739)	(0.067)	(0.626)	(0.056)
Exp 1-year	-1.741	0.289*	-0.190	0.054	0.269	0.105**
	(2.252)	(0.175)	(0.686)	(0.071)	(0.384)	(0.041)
Two weeks × Exp 1-year	5.490	-0.093	2.736*	0.221	-0.188	0.037
	(4.395)	(0.222)	(1.514)	(0.138)	(0.795)	(0.072)
One week × Exp 1-year	14.977***	0.983*	2.814*	0.479***	2.668***	0.306***
	(4.704)	(0.579)	(1.602)	(0.160)	(0.990)	(0.099)
Warned × Exp 1-year	-10.362	-2.569***	1.629	-0.225	-10.232***	-1.021***
	(7.854)	(0.509)	(5.517)	(0.453)	(1.569)	(0.167)
Hit × Exp 1-year	-	-	-1.807	-0.072	-0.008	-0.422
			(7.788)	(0.614)	(3.142)	(0.324)
Post × Exp 1-year	2.676	0.265	-3.802**	-0.471**	-6.247***	-0.635***
	(2.417)	(0.284)	(1.916)	(0.211)	(1.155)	(0.120)
County Fixed Effects	X	X	X	X	X	X
Observations	1,045,644	1,045,644	5,161,533	5,161,533	4,630,170	4,630,170

Note: This table replicates the regressions in Columns 3-4 of Table 3. Columns 1-2 are estimated on a sample with the propensity score of getting hit by a hurricane no larger than 0.25, Columns 3-4 on a sample with the propensity score between 0.25 and 0.75, and Columns 5-6 on a sample with the 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

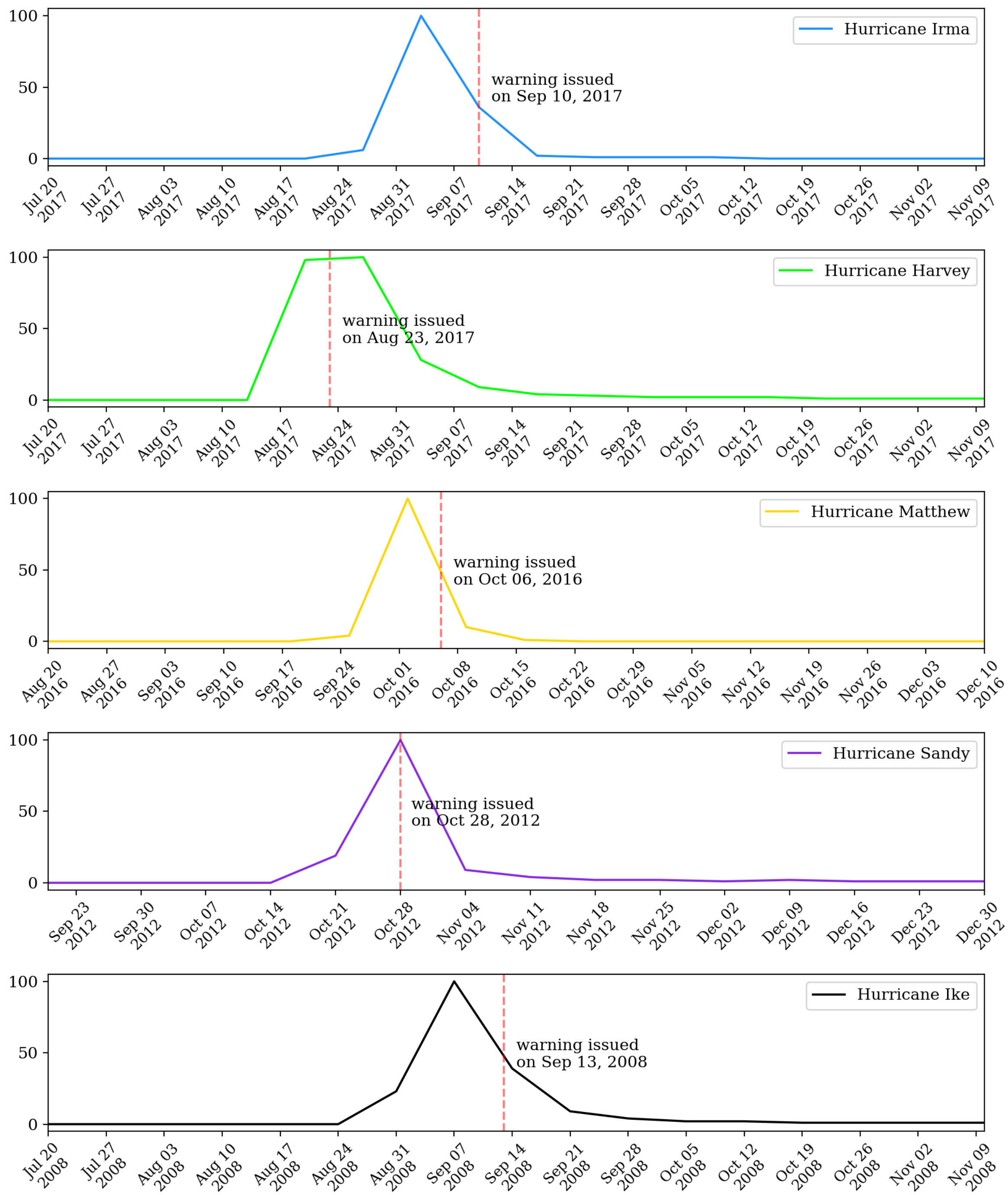

Figure A.1: Google Search Trends and the timings of the warnings issued by the National Hurricane Center for a sample of five hurricanes: Hurricane Irma, Hurricane Harvey, Hurricane Matthew, Hurricane Sandy, and Hurricane Ike

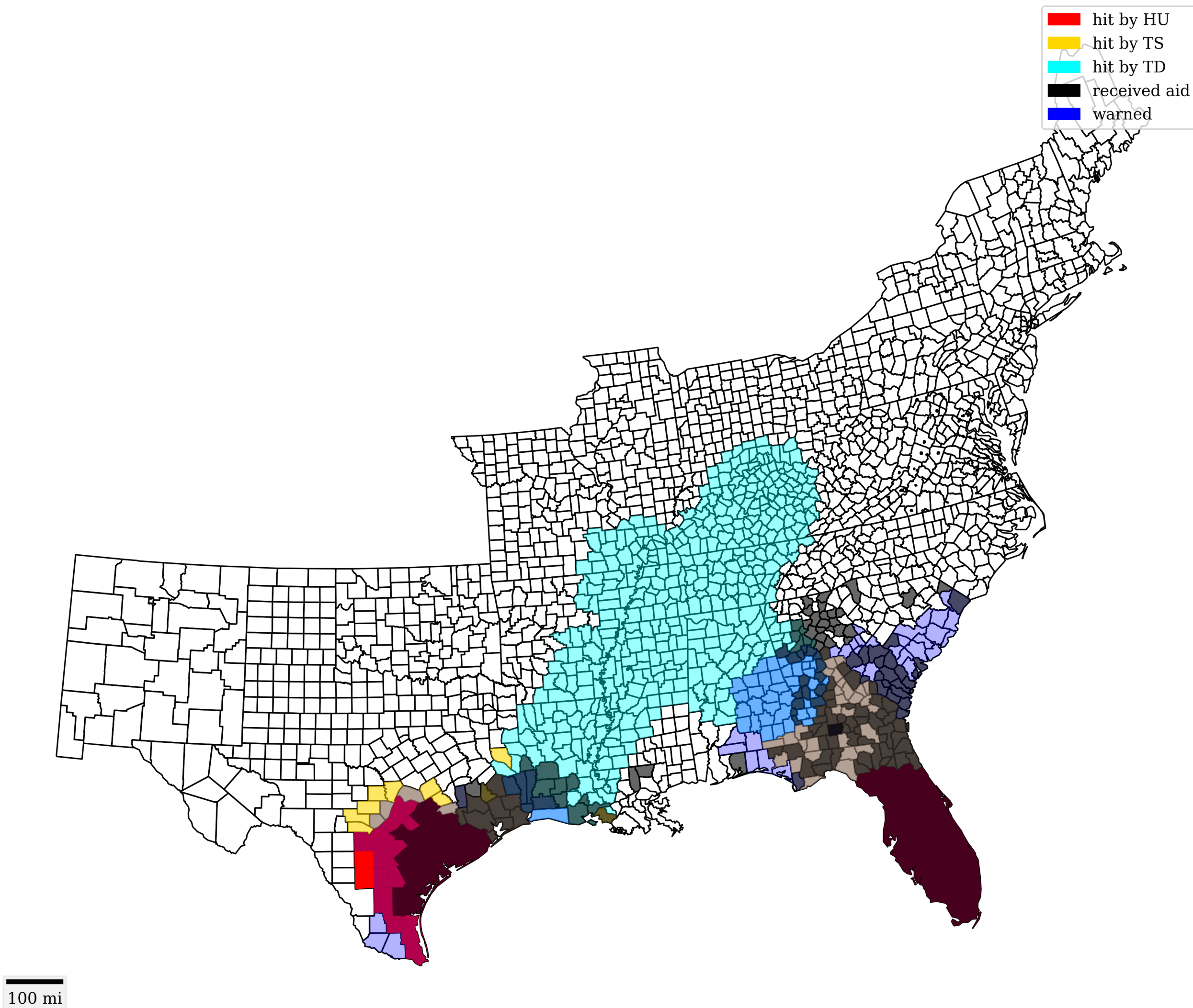

Figure A.2: Variation in counties hit/warned against a hurricane, tropical storm, tropical depression for the Atlantic Coast in 2017. For an interactive version of this graph, visit https://ernbilen.github.io/interactive_legend

Table A.1: Hurricanes in Sample

Hurricane	Dates	States Affected
Hurricane Gustav	08/31-09/18/2008	Louisiana, Mississippi
Hurricane Ike	09/01-09/15/2008	Arkansas, Illinois, Indiana, Louisiana, Missouri, New York, Oklahoma, Texas
Hurricane Earl	08/25-09/05/2010	Massachusetts, North Carolina
Hurricane Irene	08/21-08/28/2011	Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, North Carolina, Pennsylvania, Rhode Island, Vermont, Virginia
Hurricane Isaac	08/21-09/03/2012	Arkansas, Louisiana, Mississippi, Texas
Hurricane Sandy	10/22-11/02/2012	Delaware, Maryland, New Jersey, New York, Pennsylvania, Virginia
Hurricane Matthew	09/28-10/10/2016	Florida, Georgia, North Carolina, South Carolina
Hurricane Harvey	08/17-09/03/2017	Louisiana, Texas
Hurricane Irma	08/30-09/13/2017	Alabama, Florida, Georgia
Hurricane Florence	08/31-09/18/2018	North Carolina, South Carolina, Tennessee Virginia, West Virginia

Notes: Column 1 includes names of each hurricane as named by the World Meteorological Organization. Column 2 includes the official dates for each hurricane from their formation as a tropical system until their dissipation. Column 3 includes a list of states that were hit by the hurricane when its status was tropical storm or $\geq$ category 1 hurricane. Each hurricane in the list was at least category 1 strength at the time of landfall.

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

Product code	Product name
0501	Baby Food
1001	Baking Mixes
1002	Baking Supplies
5502	Batteries And Flashlights
0001	Bottled Water
1501	Bread And Baked Goods
1004	Breakfast Food
0503	Candy
1503	Carbonated Beverages
1005	Cereal
1006	Coffee
1007	Condiments, Gravies, And Sauces
1505	Cookies
1506	Crackers
1008	Desserts, Gelatins, Syrup
6008	First Aid
1009	Flour
0504	Fruit - Canned
1010	Fruit - Dried
0505	Gum
5511	Hardware, Tools
0506	Jams, Jellies, Spreads
0507	Juice, Drinks - Canned, Bottled
1011	Nuts
1012	Packaged Milk And Modifiers
1013	Pasta
0508	Pet Food
1014	Pickles, Olives, And Relish
0511	Prepared Food: Dry Mixes
0510	Prepared Food: Ready-to-serve
1015	Salad Dressings, Mayo, Toppings
0512	Seafood - Canned
1016	Shortening, Oil
1507	Snacks
1508	Soft Drinks: Non-carbonated
0513	Soup
1017	Spices, Seasoning, Extracts
1018	Sugar, Sweeteners
1019	Table Syrups, Molasses
1020	Tea
0514	Vegetables - Canned
1021	Vegetables And Grains - Dried

Table A.3: Log Outcomes

	(1) ln(Quantity)	(2) ln(Spending)	(3) ln(Quantity)	(4) ln(Spending)
Two weeks	0.001	-0.000	-0.002	-0.002
	(0.005)	(0.003)	(0.006)	(0.004)
One week	0.012	0.010**	-0.000	0.002
	(0.008)	(0.005)	(0.008)	(0.005)
Warned	-0.012	0.002	0.009	0.016
	(0.018)	(0.011)	(0.022)	(0.013)
Hit	-0.482***	-0.303***	-0.483***	-0.304***
	(0.033)	(0.021)	(0.034)	(0.022)
Post	-0.081***	-0.048***	-0.064***	-0.037***
	(0.013)	(0.008)	(0.015)	(0.008)
Exp 1-year			0.005	0.005
			(0.007)	(0.004)
Two Week × Exp 1-year			0.009	0.008
			(0.013)	(0.009)
One Week × Exp 1-year			0.062***	0.042***
			(0.017)	(0.011)
Warned × Exp 1-year			-0.112***	-0.079***
			(0.042)	(0.025)
Hit × Exp 1-year			-0.091*	-0.060*
			(0.053)	(0.034)
Post × Exp 1-year			-0.088***	-0.058***
			(0.028)	(0.018)
County Fixed Effects	X	X	X	X
Observations	8,993,529	8,993,529	8,993,529	8,993,529
AIC	39047347	30684651	39047245	30684530
BIC	39047529	30684834	39047511	30684796

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.4: Effects of Experience by Individual Items on Purchase Quantity

Dependent variable: Quantity	(1)	(2)	(3)	(4)	(5)	(6)
	Baby food	Water	Batteries & flashlight	Tools	Drinks	Snacks
Two weeks	-0.007**	0.118	-0.002***	-0.004**	-0.205	-0.012
	(0.003)	(0.074)	(0.001)	(0.002)	(0.125)	(0.020)
One week	-0.009***	0.195**	0.001	0.006	-0.299*	0.023
	(0.003)	(0.078)	(0.001)	(0.006)	(0.162)	(0.022)
Warned	-0.012**	0.628***	0.010***	-0.004***	-0.327	0.063*
	(0.005)	(0.158)	(0.003)	(0.002)	(0.283)	(0.036)
Hit	-0.017***	-0.617***	-0.003***	-0.005***	-2.391***	-0.528***
	(0.005)	(0.122)	(0.001)	(0.001)	(0.498)	(0.050)
Post	-0.008**	0.007	0.001	-0.003	-0.393**	-0.073***
	(0.004)	(0.068)	(0.001)	(0.002)	(0.199)	(0.020)
Exp 1-year	-0.005*	-0.086	-0.001	0.004	0.057	-0.028*
	(0.003)	(0.058)	(0.001)	(0.004)	(0.113)	(0.016)
Two weeks × Exp 1-year	0.010	-0.188	-0.002	0.006	-0.228	0.020
	(0.008)	(0.163)	(0.002)	(0.007)	(0.251)	(0.040)
One week × Exp 1-year	-0.001	0.210	-0.003	-0.010	0.587*	0.192***
	(0.005)	(0.165)	(0.002)	(0.009)	(0.352)	(0.049)
Warned × Exp 1-year	0.005	0.085	-0.007	-0.005	-1.138**	0.022
	(0.010)	(0.338)	(0.005)	(0.004)	(0.478)	(0.096)
Hit × Exp 1-year	0.007	-0.384	0.004	-0.002	-0.062	-0.126
	(0.008)	(0.264)	(0.003)	(0.005)	(0.630)	(0.104)
Post × Exp 1-year	0.002	0.002	-0.000	-0.002	-0.726**	-0.079*
	(0.007)	(0.128)	(0.003)	(0.005)	(0.330)	(0.045)
County FEs	X	X	X	X	X	X
Observations	8,993,529	8,993,529	8,993,529	8,993,529	8,993,529	8,993,529

Note: 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 A.5: Effects of Experience By Individual Items on Expenditure

Dependent variable: Spending	(1)	(2)	(3)	(4)	(5)	(6)
	Baby food	Water	Batteries & flashlight	Tools	Drinks	Snacks
Two weeks	-0.004***	-0.001	-0.000	0.001	0.003	-0.006
	(0.001)	(0.002)	(0.003)	(0.002)	(0.005)	(0.004)
One week	-0.006***	0.006***	0.013***	0.001	-0.009	0.006
	(0.001)	(0.002)	(0.003)	(0.002)	(0.006)	(0.006)
Warned	-0.004	0.028***	0.068***	-0.003	-0.020*	0.011
	(0.003)	(0.004)	(0.008)	(0.003)	(0.011)	(0.008)
Hit	-0.004	-0.020***	-0.025***	-0.007	-0.130***	-0.123***
	(0.005)	(0.005)	(0.007)	(0.005)	(0.016)	(0.012)
Post	-0.006***	-0.003	0.018***	-0.004**	-0.015**	-0.021***
	(0.002)	(0.002)	(0.004)	(0.002)	(0.006)	(0.005)
Exp 1-year	-0.000	0.001	0.003*	-0.000	0.008	-0.008**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.004)
Two weeks × Exp 1-year	0.004	-0.004	-0.003	-0.001	-0.006	0.014
	(0.006)	(0.004)	(0.005)	(0.004)	(0.012)	(0.010)
One week × Exp 1-year	-0.002	0.004	0.015*	-0.005	0.037***	0.045***
	(0.003)	(0.005)	(0.008)	(0.004)	(0.013)	(0.012)
Warned × Exp 1-year	-0.004	-0.005	-0.024*	0.001	-0.046**	0.002
	(0.006)	(0.008)	(0.014)	(0.006)	(0.020)	(0.022)
Hit × Exp 1-year	-0.005	-0.012	-0.033***	-0.005	0.001	-0.051**
	(0.005)	(0.010)	(0.012)	(0.006)	(0.026)	(0.026)
Post × Exp 1-year	0.000	-0.005	-0.009	-0.000	-0.025**	-0.014
	(0.003)	(0.003)	(0.007)	(0.004)	(0.013)	(0.012)
County FEs	X	X	X	X	X	X
Observations	8,993,529	8,993,529	8,993,529	8,993,529	8,993,529	8,993,529

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

Table A.6: Purchases Excluding Bottled Water, Flashlight & Batteries

	(1) Quantity	(2) Spending	(1) Quantity	(2) Spending
Two weeks	-0.120	0.009	-0.271	-0.014
	(0.358)	(0.034)	(0.403)	(0.039)
One week	0.912*	0.153***	0.171	0.070
	(0.493)	(0.048)	(0.534)	(0.051)
Warned	1.890**	0.228***	3.276***	0.357***
	(0.803)	(0.072)	(0.926)	(0.086)
Hit	-17.330***	-1.814***	-17.883***	-1.847***
	(1.796)	(0.173)	(1.884)	(0.181)
Post	-2.814***	-0.284***	-1.901***	-0.194***
	(0.461)	(0.043)	(0.488)	(0.042)
Exp 1-year			-0.226	0.059
			(0.402)	(0.037)
Two weeks × Exp 1-year			0.869	0.075
			(0.817)	(0.078)
One week × Exp 1-year			3.865***	0.382***
			(1.154)	(0.108)
Warned × Exp 1-year			-7.622***	-0.747***
			(2.079)	(0.204)
Hit × Exp 1-year			5.360*	0.138
			(2.743)	(0.268)
Post × Exp 1-year			-4.390***	-0.482***
			(1.135)	(0.124)
Observations	8,993,529	8,993,529	8,993,529	8,993,529
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, using the inverse hyperbolic sine of purchase quantity and expenditure as the outcomes. The outcome is the purchase 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.7: Effects by Income

	Low-income		Mid-income		High-income	
	(1)	(2)	(3)	(4)	(5)	(6)
	Quantity	Spending	Quantity	Spending	Quantity	Spending
Two weeks	-0.275	-0.019	-0.909	-0.008	0.594	0.052
	(0.973)	(0.060)	(0.910)	(0.067)	(1.092)	(0.118)
One week	1.286	0.075	-0.590	0.070	0.144	0.023
	(1.193)	(0.082)	(0.965)	(0.076)	(1.150)	(0.116)
Warned	0.992	0.125	2.045	0.146	2.267	0.284
	(1.681)	(0.145)	(1.866)	(0.142)	(1.908)	(0.202)
Hit	-21.606***	-1.848***	-21.168***	-2.019***	-21.720***	-2.338***
	(2.188)	(0.198)	(3.366)	(0.289)	(4.132)	(0.451)
Post	-4.621***	-0.308***	-1.148	-0.189**	-2.944***	-0.292***
	(1.101)	(0.077)	(0.956)	(0.080)	(0.921)	(0.101)
County Fixed Effects	X	X	X	X	X	X
Observations	1,758,415	1,758,415	1,630,575	1,630,575	1,663,333	1,663,333

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 that falls within the lower tertile; Columns 3-4 the middle tertiles; Columns 5-6 the upper tertile. * p<0.10, ** p<0.05, *** p<0.01

Table A.8: 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	Spending	Quantity	Spending	Quantity	Spending	Quantity	Spending	Quantity	Spending	Quantity	Spending	Quantity	Spending	Quantity	Spending
Two weeks	-0.155	-0.015	-0.504	-0.045	-1.502	-0.116	-0.463	-0.022	-0.857	-0.067	-2.235**	-0.143*	0.550	0.046	-0.093	-0.003
	(0.432)	(0.042)	(0.978)	(0.074)	(1.836)	(0.126)	(0.957)	(0.081)	(0.646)	(0.054)	(0.883)	(0.080)	(0.671)	(0.067)	(0.748)	(0.079)
One week	0.368	0.088*	-0.844	-0.100	-2.511*	-0.225	-0.955	-0.013	0.901	0.145**	-1.048	-0.069	-0.036	0.077	1.549*	0.169**
	(0.561)	(0.052)	(1.141)	(0.067)	(1.511)	(0.139)	(1.289)	(0.116)	(0.708)	(0.065)	(1.116)	(0.083)	(0.962)	(0.093)	(0.819)	(0.074)
Warned	3.914***	0.453***	8.033***	0.718***	6.616*	0.749**	0.831	0.158	2.820*	0.291*	5.368**	0.570***	2.873*	0.340**	6.127***	0.610***
	(0.956)	(0.090)	(2.144)	(0.157)	(3.670)	(0.324)	(2.016)	(0.168)	(1.442)	(0.149)	(2.210)	(0.185)	(1.477)	(0.135)	(1.282)	(0.129)
Hit	-18.504***	-1.892***	-14.752***	-1.156***	-14.403***	-1.739***	-17.024***	-1.737***	-15.062***	-1.631***	-17.935***	-1.809***	-20.745***	-2.103***	-19.644***	-2.074***
	(1.953)	(0.188)	(3.648)	(0.300)	(4.528)	(0.454)	(3.245)	(0.315)	(1.699)	(0.135)	(2.487)	(0.203)	(2.761)	(0.260)	(2.562)	(0.276)
Post	-1.893***	-0.179***	-3.235***	-0.314***	-5.435***	-0.383**	-4.744***	-0.367***	-1.330*	-0.130*	-1.156	-0.103	-2.110***	-0.154**	-1.855**	-0.089
	(0.505)	(0.042)	(1.140)	(0.070)	(1.645)	(0.155)	(1.171)	(0.102)	(0.723)	(0.073)	(1.173)	(0.081)	(0.795)	(0.066)	(0.828)	(0.078)
Exp 1-year	-0.313	0.063*	0.359	0.126	1.718	0.218*	-1.865*	-0.082	0.179	0.060	0.929	0.106	-0.114	0.069	-0.645	0.004
	(0.406)	(0.037)	(0.930)	(0.080)	(1.838)	(0.120)	(1.071)	(0.088)	(0.659)	(0.056)	(1.042)	(0.071)	(0.628)	(0.057)	(0.722)	(0.054)
Two weeks × Exp 1-year	0.680	0.068	-0.583	-0.197	7.166	0.234	-0.003	-0.175	0.120	-0.039	1.826	0.090	-0.273	0.011	0.294	0.038
	(0.831)	(0.080)	(1.948)	(0.180)	(4.815)	(0.307)	(1.980)	(0.181)	(1.188)	(0.114)	(2.274)	(0.163)	(1.756)	(0.173)	(1.425)	(0.135)
One week × Exp 1-year	4.073***	0.401***	-0.829	-0.107	15.308**	0.962***	6.709***	0.550**	3.837***	0.407***	1.757	0.392*	3.410*	0.234	2.909*	0.358**
	(1.187)	(0.111)	(2.054)	(0.158)	(6.895)	(0.366)	(2.562)	(0.238)	(1.470)	(0.135)	(3.004)	(0.237)	(1.953)	(0.212)	(1.588)	(0.164)
Warned × Exp 1-year	-7.543***	-0.776***	-8.423*	-0.758**	-21.048***	-1.963***	-6.862*	-0.378	-3.346	-0.478*	-0.972	-0.189	-9.109***	-0.927***	-10.366***	-0.879***
	(2.170)	(0.209)	(4.544)	(0.312)	(5.402)	(0.505)	(4.083)	(0.439)	(2.666)	(0.268)	(5.475)	(0.600)	(3.403)	(0.340)	(3.114)	(0.305)
Hit × Exp 1-year	4.980*	0.093	-0.917	-0.826**	-0.362	-0.157	-2.884	-0.800	1.442	-0.242	-10.398	0.534	12.608***	0.655	5.914*	0.155
	(2.848)	(0.276)	(5.805)	(0.416)	(5.780)	(0.546)	(4.737)	(0.489)	(2.284)	(0.230)	(9.046)	(1.925)	(4.161)	(0.436)	(3.378)	(0.398)
Post × Exp 1-year	-4.388***	-0.496***	-3.406*	-0.246	-4.599	-0.639**	-1.665	-0.346*	-3.589**	-0.310**	-8.828***	-0.977***	-4.605***	-0.580***	-4.241**	-0.597***
	(1.169)	(0.125)	(2.035)	(0.164)	(3.606)	(0.317)	(2.031)	(0.183)	(1.411)	(0.144)	(2.523)	(0.248)	(1.659)	(0.155)	(1.905)	(0.200)
Observations	8993529	8993529	1095454	1095454	459322	459322	1401384	1401384	2579968	2579968	1943782	1943782	5182217	5182217	2723123	2723123
Household FEs	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Month FEs	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Day-of-week FEs	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Controls	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X

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