A Decade of U.S. Natural Disasters and Household Food-at-Home Expenditures and Quality: A Quasi-Experimental Study *

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Abstract

We exploit spatial and temporal variation in natural disasters in the United States via a generalized differences-in-differences approach to identify the impact of natural disasters on households' food-at-home (FAH) spending and quality from 2005 to 2016. Using the Storm Events Database and the Nielsen Consumer Panel Data, we find that floods (hurricanes) have a persistent (immediate) effect on FAH spending. On average, highly damaging floods (hurricanes) decrease 15-day FAH spending by about \$1-\$2 (\$7) in 90 days (30 days) after the events. The FAH spending effect of natural disasters works through both income and price channels. We also find that the natural disasters have an inconsequential or no impact on FAH quality. Our results are robust to the inclusion of county-specific linear trends. Our findings could be of interest to post-disaster relief organizations and their programs.

Keywords: expenditures, food-at-home, food quality, natural disasters

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Introduction

Since 1980, the U.S. has faced 241 "billion-dollar" natural disaster events defined such that each one's damage cost is greater than or equal to $1 billion (NCEI, 2019).[1] On an annual average basis, there were about six billion-dollar events in the U.S. for the period 1980-2018, however this spikes to about 13 events for the period 2014-2018 (NCEI, 2019).[2] This suggests a high frequency of billion-dollar natural disasters in the U.S. in recent years. High impact disasters can affect local economies through multiple channels, for instance, migration, unemployment, health outbreaks, agricultural losses, and food shortages. Often times, multiple types of natural disasters can pose a threat to a local economy. For instance, the main culprits of agricultural and livestock losses across the U.S. are wildfires, flooding, drought, and severe freezing (Smith, 2018). At the household-level, natural disasters can directly affect income through unemployment or indirectly through property damages (Vigdor, 2008; Smith and Katz, 2013).

Our objective in this study is to exploit spatial-temporal variation in county-level natural disasters across the U.S. and estimate their causal effect on household-level food-at-home (FAH) expenditures (interchangeably, spending). Subsequently, we identify a natural disaster's impact on FAH quality, which we measure through the "Grocery Purchase Quality Index" (GPQI). We study the four highest ranking natural disasters in terms of damage cost during 2005-2016 years, i.e., droughts, floods, hurricanes, and tornadoes. Although natural disasters affect gross domestic product (GDP) and productivity at a macro-level, their micro-level implications for household spending variables are subtle due to the complex and economically vulnerable environment in which households need to make economic decisions for survival and recovery. Natural disasters can potentially affect FAH spending through a loss in household income or a change in food prices. When a natural disaster disrupts food availability and supply, it can affect food prices.

We study FAH quality through the GPQI score because studying FAH spending might not be enough to assess the overall impact of natural disasters on the FAH basket. For instance, a household's FAH spending might stay the same after a disaster but a decrease in its GPQI score means that the household's food environment degrades in quality, hence jeopardizing

[1] CPI adjusted as of 2018.

[2] The loss estimates are based on revised and refined factor approach methodology (Smith and Katz, 2013).

the healthfulness of the FAH basket. The GPQI scoring method, which assesses grocery food purchase quality, is based on expenditure shares for food categories in the U.S. Department of Agriculture's (USDA) Food Plans.

We extend our study by investigating the effects of the four disasters on water and non-alcoholic beverages at home (WBAH) spending, total grocery spending, and alcohol-at-home spending. Both hurricanes and floods can affect water quality through a contamination of local water sources, so it is important to check whether WBAH spending changes after the two disasters. Studying total grocery spending provides an understanding of the impact of natural disasters on all groceries intended for personal, in-home use. And considering that alcohol is a harmful substance for human health, studying alcohol spending provides another measure of the healthfulness of grocery spending after disasters.

We enrich our overall study in five specific directions: (i) we study the impact of flood and hurricane events by their respective damage cost quartiles and check if the disaster severity affects outcome variables differently; (ii) we study the joint impact of flood and hurricane events from the fourth damage cost quartile on FAH spending and GPQI in coastal states that are highly exposed to these events; (iii) we check whether floods and hurricanes have an anticipation effect on food, water, or total grocery spending; (iv) we indirectly test whether natural disasters affect FAH spending through the income channel, i.e., we test whether low-income households (including poor) have a decrease in FAH spending after natural disasters, and compare the results against households that are above low income; and (v) we indirectly test whether natural disasters affect FAH spending through the price channel (supply-driven shock), i.e., we check if after flood and hurricane events there is an increase in fresh fruit price and a decrease in fresh fruit spending among households in coastal states.

We make use of two datasets in our study. First, using the Storm Events Database we assign counties to the treatment group whenever counties undergo economic damage of at least $9.1 million after natural disaster event(s) during the 2005-2016 period. Second, we merge the treatment counties and their control counties to the Nielsen Consumer Panel (NCP) survey, which has data on household grocery trips and product level details. The NCP survey randomly selects households from 52 metropolitan areas in the U.S. Our final dataset for empirical estimation comprises two dependent variables of primary interest, i.e., FAH spending and the

FAH quality index, and three dependent variables of secondary interest, i.e., WBAH spending, total grocery spending, and alcohol-at-home spending. All of our spending variables are in 2017 constant dollars, and each observation represents a 15-day period before or after the natural disaster event start date. Our pre-disaster window is always 180 days, and the post-disaster window varies between 30 days, 90 days, and 180 days.

Our empirical strategy is to exploit spatial and temporal variation in natural disasters in the U.S. counties via a generalized differences-in-differences (GDD) approach. We then identify the impact of each different natural disaster on FAH expenditures and FAH quality by comparing households' data in the treatment counties against those in the control counties. A crucial aspect of our empirical strategy is designing a spatial-temporal algorithm to identify treatment and control counties using the disaster's time, location, and damage cost information, which is available through the Storm Events database for 2005-2016.

We find that floods have a persistent and prolonged effect on FAH spending, and hurricanes have an immediate effect on FAH spending. The average 15-day decrease in FAH spending is about $1 in the 180 days after a flood and about $3 in the 30 days after a hurricane. However, the average 15-day decrease in FAH spending is about $1-$2 in the 90 days after a flood from the third damage quartile and about $7 in the 30 days after a hurricane from the fourth damage quartile. The joint effect of flood and hurricane events on the average 15-day FAH spending in highly exposed coastal states is about $4. Both droughts and tornadoes have no effect on FAH spending. We also find that together the four natural disasters only affect poor and low-income households' FAH spending, i.e., the disasters reduce average 15-day FAH spending by about $2 in the 30 days after the disasters, hence providing indirect evidence that the natural disasters affect FAH spending through the income channel. Regarding the indirect evidence that the food price channel (supply-driven shock) leads to a decrease in FAH spending, we find that flood and hurricane events jointly increase the average 15-day fresh fruit per unit price by about 4.5% and decrease fresh fruit spending by about 3.5% in the 30 days after the events. Except for tornadoes and hurricanes that have a very small effect on GPQI (0.4% of max GPQI score), the other natural disasters have no effect on GPQI, so the four natural disasters do not really affect a household's food quality.

Furthermore, we find that hurricanes have a persistent effect on WBAH spending in the

180 days after hurricane events — the effect size ranges between \$0.4 and \$1. Just as in the case of FAH spending, floods (hurricanes) have a persistent (immediate) effect on total grocery spending and alcohol-at-home spending. After flooding, the average 15-day household total grocery spending decreases by about \$4 in 90 days, and alcohol-at-home spending decreases by \$0.2 in 180 days. We find evidence that hurricanes have an anticipation effect on total grocery spending, so when we move back a hurricane event's start date by 15 days, the average 15-day effect of a hurricane on total grocery spending is about a \$14 decrease in spending in the 30 days after the hurricane. We do not find an anticipation effect of hurricanes or flooding on FAH and WBAH spending variables. Finally, in the 30 days after a hurricane the average 15-day alcohol-at-home spending decreases by about \$1. The decrease in alcohol spending after flood and hurricane events could partially counterbalance the negative effect of these events on FAH spending.

We make three contributions to the literature on the effect of natural disasters on household economic variables. First, our study causally identifies the impact of natural disasters on household FAH expenditures and quality, hence extending the literature on the impact of natural disasters on household income and financial decisions (Gallagher and Hartley, 2017; Deryugina et al., 2018). The effect of natural disasters on FAH spending and other spending variables could be working through the income and/or price channels. We show that different natural disasters affect household FAH spending and other spending variables with varying intensity and for different lengths of time. Second, we add to the GDD regression method by introducing a spatial-temporal algorithm to identify disaster-affected counties and their controls across space and time (Belasen and Polachek, 2008). Our algorithm could facilitate the study of other economic variables when natural disaster events are staggered over time and space. Third, we extend the literature on food grocery quality by studying FAH quality after disaster events using the GPQI, which is specifically designed for large datasets with food grocery transactions (Brewster et al., 2017).

Since public offices — like the Federal Emergency Management Agency (FEMA) — and non-profit organizations provide pecuniary and non-pecuniary support to households after natural disasters, our findings could be useful to their relief programs. The sizeable impact of highly damaging flood and hurricane events on FAH spending — especially in coastal states — should be a concern in the face of climate change, which can increase the severity and frequency of these disasters. The results from our research can help organizations to plan for customized solutions when it comes to protecting households' basic food and water needs. An efficient distribution of disaster aid could help households' economic recovery. Finally, in the discussion of post-disaster support to households, we should never forget to remind ourselves to prioritize support for poor and low-income households, who are easily affected by natural disasters and lose a larger share of their assets compared to wealthy households.

Literature Review

As natural disasters have a broad range of economic and social effects, the accompanying literature is also broad and rich. Here we provide a brief review of studies that look at the effect of disasters on the macro economy, economic sectors, and individuals. When possible, we restrict the geographic focus to the U.S.

Natural disasters can be upsetting in regard to performance of an economy, i.e., they affect GDP or slow down GDP growth. Since 1900, the costliest disaster in the U.S. has been hurricane Katrina, which fell on the Gulf Coast in 2005, resulting in an estimated cost of $125 billion, equivalent of about 0.8% of U.S. GDP in 2005 (NHC, 2018).[3] Hurricane Katrina severely affected the Gulf Coast in terms of resident displacement, human lives, property damage, and economic loss (Gallagher and Hartley, 2017). Hurricane Harvey comes as the second costliest event in the U.S. with a total cost of $125 billion, equivalent of about 0.6% of U.S. GDP in 2017 (NHC, 2018).[4] Beside hurricanes, the U.S. economy has undergone severe losses due to droughts, for instance, the drought and heat wave of 1988 in central and eastern U.S. brought losses in agriculture and its related industries. The 1988 drought and heat wave event caused a total loss of $40 billion which is about 0.8% of the U.S. GDP in 1988 (Ross and Lott, 2003).[5]

Studying natural disasters in the Latin American and Caribbean region (1970 – 1999), Charvériat (2000) finds that GDP declines during the year of the disaster, however it gains momentum and grows in the two years following the disaster. Regarding the long-run GDP effects of large tropical cyclones across countries, Hsiang and Jina (2014) estimate the effect

[3] Cost amounts are from the time of event and in 2005 dollars. For cost share of GDP, we use the World Bank data for GDP (https://data.worldbank.org/indicator/NY.GDP.MKTP.CD?locations=US).

[4] Cost amounts are from the time of event and in 2017 dollars. GDP data is from the World Bank.

[5] Cost amounts are from the time of event and in 1988 dollars. GDP data is from the World Bank.

to be as large as a banking crisis with per capita income to be persistently lower (-7.4%) even 20 years after the cyclones. In a similar vein, Dell et al. (2012) find a 1-degree Celsius rise in temperature in poor countries reduces economic growth by about 1.3 percentage points on average. Natural disasters can vary in economic costs but when they are on par with rare disasters like economic depression and wars, the negative implications for national consumption and output cannot be ignored (see Rietz, 1988; Barro, 2006).

Natural disasters can bring economic change to various sectors in the economy, affecting various facets of households' well-being, for instance, income, health, and nutrition.[6] In the U.S., a rise in temperature has been shown to affect agricultural yields (Schlenker and Roberts, 2009), birth weight as a health outcome (Deschnes et al., 2009), and time allocated for labor work (Graff Zivin and Neidell, 2014). Bin and Polasky (2004) find that due to Hurricane Floyd's damage in North Carolina, house property values fell by 4 – 12%, a cost that was greater than the insured value. Gallagher and Hartley (2017) find that Hurricane Katrina victims used flood insurance payouts to improve their finances by repaying mortgages; and that the victims carried credit card debt to smooth consumption but it was temporary and limited to $500. Meanwhile, Deryugina et al. (2018) find that after Hurricane Katrina in New Orleans, average labor income was lower by about $2,300 compared to control group cities. Hsiang et al. (2017) compute the potential economic costs of climate events for the U.S. for the late 21st century and report, (i) on average, a GDP loss of 1.2% for a 1-degree Celsius increase, (ii) a decrease in agricultural yields and labor supplied; increase in mortality, energy demand, crime rate, and coastal damage, and (iii) an increase in economic inequality between southern and northern U.S. regions.

When the cost of a natural disaster is substantial, it can easily put a strain on a government and local institutions. The National Flood Insurance Program (NFIP), a U.S. government led program, had to borrow $18.6 billion from the federal government to settle insurance claims after Hurricane Katrina (Michel-Kerjan, 2010). And in cases where local people are not consulted regarding relief work after a disaster, institutions can easily undermine local social capital (Ostrom, 1990, p. 184). Depending how social capital is affected after a disaster, and how much locals rely on social capital for recovery, the implications are not to be discounted for poverty traps (Barrett et al., 2016).

[6]Various measures of household well-being include, for instance, income, health, education, and nutrition (Barrett et al., 2016).

Finally, understanding individual behavior before and after a disaster is very important for knowing whether individuals are doing enough to protect themselves. Studies in behavioral economics have shown that individuals tend to be loss averse (Rabin, 1998). One potential reason is that individuals perceive the cost of a protection policy more heavily than its benefits. Meanwhile, individuals' perception of risk probabilities also seems to be inaccurate. In a national survey of risk beliefs in the U.S., most respondents assessed their fatality risk from natural disasters to be less than average (Viscusi and Zeckhauser, 2006). Surveying coastal residents in the U.S. before hurricane Isaac and Sandy revealed that participants misperceived the destructive effect of hurricane winds vs. flooding, and their preparation was only good enough for a mild wind or flood disaster (Meyer et al., 2014). Beatty et al. (2019) find that despite government advice to stockpile emergency kits before a hurricane, poor and minority populations do not follow the advice.

As facing the brunt of a natural disaster is an inevitable reality for a local economy and its population, we seek to answer what happens to household food-at-home expenditures and its quality after going through a costly disaster at the county level. Our study is alike in spirit to Gallagher and Hartley (2017) and Deryugina et al. (2018) as both studies exploit the exogenous shock from a natural disaster (Hurricane Katrina) to provide household-level estimates of a disaster's effect on finances and income (food expenditures and food quality in our case).

Conceptual Framework

We consider a demand function for n goods, $C_i = C_i(P; Y; E)$, where household consumption of good i is a function of a vector of market prices P, household income Y, and other household covariates E, such as socio-demographics. In this article, we study food-at-home (FAH) demand, i.e., FAH grocery expenditures, which is the aggregate measure of C_i, food goods consumed at home. We present a discussion of the potential variables (channels) in the demand function through which natural disasters can affect household FAH expenditures, and subsequently FAH quality. In regard to the effect of natural disasters on FAH expenditures and FAH quality, we hypothesize: (H_1) household FAH expenditures decline in counties that experience costly natural disasters compared to the counties that do not experience such disasters, and (H_2) household FAH quality declines in counties that experience costly natural disasters compared to the counties that do not experience such disasters.

The two most obvious channels through which natural disasters can affect household FAH expenditures are income and food prices, where a food supply shock may increase the price of food items in the short run. First, empirical studies find a positive income elasticity of food demand, i.e., food expenditures decrease if income decreases (Gruber, 1997; Lusk, 2017). So we expect a household to decrease its FAH expenditures after losing income due to a natural disaster. Post-Katrina in New Orleans, average labor income was lower by about $2,300 compared to control group cities (Deryugina et al., 2018).[7] Although we do not observe household incomes before and after the natural disasters in our study, we believe it is mainly the income channel after the natural disasters that affect FAH expenditures.

Second, regarding availability of food goods after a disaster, two scenarios can emerge in case of food shortage. First, household FAH expenditures could increase (decrease) if a household buys alternative grocery items that are more expensive (less expensive) than the regular items the household might have bought without a shortage. Second, household FAH expenditures can decrease after a disaster because the household buys large quantities of food before the disaster in anticipation of a food shortage due to the impending natural disaster.

Natural disasters can affect household FAH quality through two potential channels, i.e., household income and food prices. When household income decreases after a disaster, the income effect can lead to a decrease in the expenditures of more nutritious foods — particularly among families with teenage kids (Blanciforti et al., 1981).

Natural disasters can unsettle the partial equilibrium of food markets in local economies through a lower supply of food items (Ding et al., 2011). This will lead to an increase in food prices which can push a household to substitute for alternative food items (the substitution effect), which may substantially vary in nutritional quality (Zhen et al., 2014). When natural disasters affect the availability of specialty produce (fruits and vegetables) and their price levels, the resulting effects can include less spending on specialty produce and a decline in FAH quality. The above scenario can best be portrayed by considering a rural supermarket grocery store that sources some of its products from local markets. When the supply of local products is cut, the supermarket chain may maintain its supply through goods available outside the local

[7] On average, the drop in labor income is about 7% of adjusted gross income for a New Orleans household.

economy. This can translate into higher prices due to transportation costs (a source of cost increase).[8] After a disaster, the distorted food market equilibrium may transition back to its original position, however the length of this transition may depend on the context of each local economy. So, we expect a short-term impact of the natural disasters on household FAH quality.

Data

We make use of two datasets. First, the Storm Events Database from the the National Oceanic and Atmospheric Administration (NOAA) provides county-specific and day-specific information on natural disasters in the U.S.[9] Out of all standard disaster types (events) during our study period, 2005-2016, we select hurricane, flood, tornado, and drought because these are the top four damaging events in terms of total damage cost in the 2005-2016 period. Second, we use the Nielsen Consumer Panel (NCP) survey, which has data on household grocery trips, product purchases meant for in-home use, product-level details and prices, and household socio-demographics.[10] The NCP survey randomly selects households from 52 metropolitan areas in the U.S. When a household in the NCP survey buys products during a grocery trip, it scans product barcodes or manually enters the product information in a Nielsen-supplied electronic device, and the product information becomes part of the panel data. We select the years 2005-2016 for our study period because the Nielsen Consumer data was only available up to 2016 at the time of our analysis.

Our final dataset for empirical estimation is comprised of five dependent variables and various independent variables. The primary dependent variables are the FAH spending and FAH quality index. Other dependent variables include water and non-alcoholic beverages at home (WBAH) spending, alcohol-at-home spending, and total grocery trip spending.[11] The independent variables are household socio-demographics, county and month indicator variables, and an indicator variable to identify treatment households' observations after county disaster

[8] In the United States, supermarket chains have advanced logistical systems with disaster management capabilities, which enable them to exploit logistic networks and meet consumer food demand in times of a disaster (Palin, 2017).

[9] Data are available at: https://www.ncdc.noaa.gov/stormevents/

[10] Various Nielsen datasets are available through the Kilts Center at the University of Chicago Booth School of Business: https://www.chicagobooth.edu/research/kilts/datasets/nielsen

[11] Total grocery trip spending could include items from any of the following ten departments: dry grocery, frozen foods, dairy, deli, packaged meat, fresh produce, nonfood grocery, alcohol, general merchandise, and health and beauty aids.

events. We arrive at our final dataset through a series of steps that involve cleaning of the Storm Events data, designing an algorithm to identify treatment counties (treatment group) and matching them to potential counterfactuals (control group), and merging counties to the Nielsen data (please refer to Appendix A for complete details of our data and algorithm steps).

First, the cleaning of the Storm Events data requires multiple steps that primarily include (i) cleaning and verifying county names, (ii) assigning National Weather Service zones to associated counties, and (iii) cleaning the damage cost values associated with the disaster events.

Second, an important aspect of our empirical strategy is to identify treatment and control counties; hence we design a spatial-temporal algorithm. The algorithm identifies a county as treated when it meets the following criteria: (i) the county undergoes a "treatment event," i.e., the damage cost value of the disaster is greater than or equal to the 95^{th} percentile value (\$9,100,000) in the damage cost distribution, and (ii) the county has no other treatment event for 180 days before and after the treatment event date. The algorithm identifies a county as control for a treatment county if (i) the control county is outside the 40-miles radius, but within the state, of the treatment event county, and (ii) the control county has no treatment event for 180 days before and after the treatment county's event start date. As an output of the algorithm, we get 1,113 counties for each treatment and control groups (see Table 1). The regional distribution of 1,113 treatment counties shows that the majority (932) of them are located in the Midwest and Southern regions. Table 2 illustrates that among treatment events, (i) hurricanes have the highest average cost per county across the U.S. (\$403.18 million), (ii) droughts have the highest average cost per county in the West (\$175.94 million), floods in the South (\$129.85 million), hurricanes in the Northeast (\$516.17 million), and tornadoes in the South (\$86.42 million). Temporally, droughts had the highest average cost per county in 2014, floods in 2016, hurricanes in 2012, and tornadoes in 2013 (see Table 3).

Third, having the list of treatment and control counties, we merge them to the Nielsen Consumer Panel data to get information on treatment and control households' socio-demographics and grocery trip details. The Nielsen data has information on products' department, group, and module codes, which help us in creating the five dependent variables: FAH spending, FAH quality index, WBAH spending, total grocery trip spending, and alcohol-at-home spending. All our spending variables are in 2017 constant dollars, and each observation represents a 15-day period in the 180 days before or after the event start date, hence our analysis is at the 15-day level. We restrict our data to households that consistently report at least one shopping trip in each 15-day period for 90 days before and after a disaster event, to avoid bias that could arise due to potential migrant households, or households that do not comply with consistent scanning of products, or households that voluntarily drop.

Regarding our FAH quality variable, we follow Brewster et al. (2017) to create the Grocery Purchase Quality Index (GPQI)-2016. The GPQI-2016 is a scoring method, based on the US Department of Agriculture's (USDA) Food Plan model and the Healthy Eating Index (HEI)-2010 food components, to evaluate the quality of households' food purchases for in-home use (Brewster et al., 2017). The total GPQI-2016 score is a sum of the individual scores of 11 food components. The score for a food component is the product of a ratio term and the maximum score allowed for the food component, where the ratio term of a food component is equal to its observed food expenditure share over its "standardized" food expenditure share (Brewster et al., 2017). In Table 4 we show the percentage share of food expenditures by 11 food components for all households for up to 180 days before the disaster events. The highest expenditure shares are for Sweet and Sodas (22.07%), Refined Grains (14.9%), and Total Protein Foods (8.49%), whereas the lowest expenditure share is for Greens and Beans (0.82%).

Table 5 presents the summary statistics of households' socio-demographics and their distributional balances. We use the normalized difference and variance ratio scores to evaluate distributional balance. The sample households are characterized by an average household size of two members and an average age of 57 for the household head. The majority of households (i) live in a house as the residence type, (ii) earn between $30,000 - $99,999, (iii) have a household head with a college degree or below that, (iv) have a household head that is married, and (v) are white.

Since our empirical model is essentially a linear regression, we need a distributional balance (overlap) of socio-demographic variables between treatment and control groups to avoid bias. As a rule of thumb, a normalized difference score close to zero and below 0.25, and a variance ratio close to one and between 0.5 and 1.5 signifies a good balance (Rubin, 2007; Imbens and Rubin, 2015, p. 311), such that any remaining differences can be accounted for linearly via the regression. The majority of normalized difference scores and variance ratios in Table 5 are close to zero and one, respectively. The average normalized difference score (variance ratio) across the independent variables is 0.05 (1.08), indicating a good balance.

There are 34,571 distinct households in our treatment and control groups altogether. Ideally, a balanced panel dataset of these households would imply 829,704 observations, i.e., 34,571 households multiplied by twenty-four 15-day periods in the 180 days each before and after the disaster events. However, our panel data is not balanced due to these reasons: (i) a household might not have a grocery trip in each 15-day period outside the 90-day windows before or after the disaster event, or the 15-day period immediately after the disaster event, (ii) a household could be a treatment unit in different years during the study period, hence adding more observations to the panel. There are a total of 1,022,559 observations for the total grocery trip spending variable. Each of the 1,022,559 observations represents at least one grocery trip. If there are any 15-day periods without a grocery trip, we consider them to be true missing. We expect the other four dependent variables to have 1,022,559 observations. Each of the FAH spending and FAH quality (GPQI) variables has 1,004,545 (98.24%) observations, and we consider the missing observations to be true missing. Water and non-alcoholic beverages at home (WBAH) spending and alcohol-at-home spending variables have 787,050 (77.96%) and 215,368 (21.06%) observations, respectively. If a household never made a WBAH purchase (alcohol-at-home purchase) during the 180-day windows around a disaster event, then we consider the respective spending variable's observations as true missing. If a household ever made a WBAH purchase (alcohol-at-home purchase) during the 180-day windows around a disaster event, then we replace the missing 15-day observations for WBAH spending variable (alcohol-at-home spending variable) with zero whenever the household has non-missing FAH spending for the 15-day observations. After replacing missing values with zero for the WBAH spending and alcohol-at-home spending variables, their observations increase to 1,002,846 (98.07%) and 725,079 (70.9%), respectively.

Empirical Model

We exploit spatial and temporal variation in natural disasters in the United States via a generalized differences-in-differences (GDD) approach to identify the impact of natural disasters on households' FAH expenditures and FAH quality. As in Belasen and Polachek (2008), we use the GDD approach because the natural disasters in our study affect counties (treatment vs. control groups) at different points in time. Following the differences-in-differences discussion of Angrist and Pischke (2009, p. 227-238), the following equation represents our GDD regression model,

$$Y_{i,c,t} = \beta D_{c,t} + \boldsymbol{\gamma}_t + \boldsymbol{\lambda}_c + \mathbf{X'}_{i,c,t}\boldsymbol{\delta} + \varepsilon_{i,c,t}, \tag{1}$$

where i is an index for household, c for county, and t for 15-day periods that belong to a specific month-year. $Y_{i,c,t}$ is the outcome variable. The two outcome variables of primary interest are household FAH expenditures and FAH quality.[12] The three outcome variables of secondary interest are household water and non-alcoholic beverages at home (WBAH) expenditures, total grocery trip expenditures, and alcohol-at-home expenditures.[13] The indicator variable $D_{c,t}$ takes a value of one for the post-disaster period for each treatment county c, otherwise it takes a value of zero. Parameter β is of particular interest to us because it is the Average Treatment Effect on Treated (ATET). We also control for month-year fixed-effects $\boldsymbol{\gamma}_t$, county fixed-effects $\boldsymbol{\lambda}_c$, and time-varying household socio-demographics $\mathbf{X}_{i,c,t}$ such as household size, income, residence type, household head age, education, marital status, presence of children below the age of 18, presence of kitchen appliances, and internet.[14] Standard errors are clustered at the household level.[15]

Identification of the GDD treatment estimates (β) in equation (1) requires fulfillment of the parallel trends assumption. Since the counties in our study receive treatment at different points in time, it is a complex exercise to assemble the data for parallel trends graphs. In order to check that the treatment estimates (β) are identified, the econometric literature alternatively suggests an inclusion of county-specific parametric trends in equation (1) as a robustness exercise (Angrist and Pischke, 2009, p. 238). Our robust specification of equation (1) includes county-specific linear trends, i.e., $\boldsymbol{\lambda}_c * t$, which we obtain by interacting county dummies with a continuous linear month-year variable.

[12]FAH expenditures include expenditures for water and non-alocholic beverages.

[13]Total grocery expenditures include spending on items beyond food, water, and beverages, i.e., non-food grocery, cosmetics, and general merchandise.

[14]We control for time-varying household socio-demographic variables ($X_{i,c,t}$) as it helps in reducing the standard errors of the treatment effect β.

[15]Both autocorrelation and heteroscedasticity can bias the standard errors of the treatment effect in differences-in-differences studies, and this concern has been discussed in Bertrand et al. (2004), who suggest clustering of standard errors at the panel unit level (household in our case) as a possible remedy to the bias problem. Clustering of standard errors at the panel unit level is sensible because there can be correlation between repeated observations of a unit.

We use equation (1) and its robust specification to generate our main results and their robust versions, respectively. In the results section, we will discuss only those statistically significant treatment effects that are robust to county-specific linear trends. In all specifications, we use the data sample as described in the Data section which is a match of counties between the Storm Events Database and Nielsen Consumer Panel data.

Choosing Generalized Differences-in-Differences (GDD) over Classic Differences-in-Differences (DD)

Here we argue that GDD can potentially provide unbiased estimates of the ATET in our study, i.e., to identify the impact of natural disaster events (the treatment) on household FAH expenditures and FAH quality. Both GDD and DD are inherently fixed effects estimation methods. The main difference is that in DD there are only two treatment groups ($G = 2$) and two periods ($T = 2$), and in GDD there are multiple treatment groups ($G \geq 2$) and multiple periods ($T \geq 2$). In our GDD setting, treatment and control groups are assigned at the county-level, and periods refer to month-year combinations.

For any study design to be valid, none of the covariates should predict the allocation of treatment to a group (county). And if there are such covariates, then they should be controlled for and not omitted. In our study, although the disasters affect U.S. counties through natural processes which can be random, there can be certain qualities of counties that may predict the probability of their exposure to the disasters. For instance, the location of a county could possibly predict disaster treatment. Coastal counties in Louisiana usually get affected more by hurricanes and floods (e.g., Hurricanes Katrina, Gustav, and Harvey). From a temporal dimension, some months in each year might have a higher incidence of natural disasters. Additionally, there can be some other unknown county-level and month-year-level effects that could affect the assignment of treatment. It is due to the potential impact of county- and month-year-level fixed effects on treatment county selection that we find the GDD to be a complete specification compared to the DD one, and the GDD treatment estimate to be unbiased. This is true because we control for county and month-year fixed effects in GDD.

Why is it that we could possibly get a slightly biased estimate of the ATET in the classic DD model? To understand this, we realize that our data is panel form at the household-level, and the treatment counties are from across the U.S. which are exposed to disasters during the 2005-2016 period. This is a very rich data setting. To prepare this data for classic DD analysis we need to normalize the start dates of all the disaster events and align their pre- and post-disaster periods. So, there will be only two fixed-effects parameters, i.e., one for post-disaster and another for pre-disaster. We are essentially making all disasters to happen at the same. Similarly, we will need to reduce county-specific fixed-effects parameters to two parameters, i.e., one for treatment counties and another for control counties. This implies that if any temporal and spatial effects predict the assignment of a disaster to a county, we will not be able to adjust for them in the classic DD setting which could lead to a bias in the treatment estimate.

Whether we employ the DD or GDD method, we also need a good distributional balance for each socio-demographic variable between treatment and control households to ensure that our estimate of ATET is robust under linear regression methods. Our treatment samples are well-balanced in the socio-demographic variables, given the normalized difference and variance ratio scores in Table 5 in the Data section. We also argue that our study's design fulfills the strict exogeneity requirement of differences-in-differences which can be a concern when treatment assignments are made due to changes in the outcome variable. For instance, strict exogeneity can be violated if counties start passing a new road safety regulation (policy treatment) in the event of high rates of traffic incidents. In our study, it is the natural processes that assign disasters. Pre-existing levels of the outcome variables (FAH expenditures or FAH quality) cannot affect the assignment of disasters.

Results

We estimate equation (1) for each of the five outcome variables, i.e., food-at-home (FAH) spending, grocery purchase quality index (GPQI), water and non-alcoholic beverages at home (WBAH) spending, total grocery spending, and alcohol-at-home spending. We also estimate the robust version of equation (1) which includes county-specific linear trends. If we find that our statistically significant ATET estimates from estimating equation (1) are no different than zero under the robust specification, then we conclude that our differences-in-differences design cannot identify the causal effect of natural disasters on the outcome variable because the disaster events are potentially correlated with other county-level trends in the outcome variable. In other words, there are potential unobserved confounders at the county-level, for instance, unobserved tastes or spending behaviors that also affect the outcome variable. Whenever we present the ATET estimates from equation (1) (see Subsection 2 of Tables), we also present the accompanying ATET estimates from the robust specification (see Subsection 6 of Tables). In this section, we only discuss those estimates that are significant both in the main specification and in the robust specification with county-specific linear trends.

First, we present estimation results for each of the five variables under 15 different data settings, i.e., for each disaster type = {all disasters, drought, flood, hurricane, tornado} under each post-disaster period = {30 days, 90 days, 180 days}. The pre-disaster period always spans 180 days, so we can identify the treatment effect by exploiting the pre-disaster trends of the dependent variable. Second, we present results for the anticipation effect of hurricanes and floods on FAH spending, WBAH spending, and total grocery spending. Third, we show whether the natural disasters are potentially affecting FAH spending through the income and price channels.

As we describe in the Data section, households' spending data is in panel form but unbalanced. In all of the estimations, we only include those households that have at least one shopping trip in each 15-day period in the 90 days before and after a disaster. When a household does not have a shopping trip in the 15-day period, immediately after a disaster, we make an exception and include the household. We believe a 15-day period is enough time for a household to have at least one shopping trip. And by restricting the analysis to households that consistently report for 90-day windows before and after a disaster, we try to avoid bias in our estimates due to misreporting. A lack of consistent reporting could be due to potential migrant households, or households that do not comply with regular scanning of products, or households than voluntarily drop. Finally, in all of our estimations, the time unit of analysis is a 15-day period. For instance, each observation of FAH spending variable represents an aggregate of 15 days of FAH spending.

A. Effect of Natural Disasters on FAH Expenditures and GPQI

In this subsection, we present the estimation results of equation (1) for our hypotheses variables, i.e., households' FAH spending and GPQI. We find that after the four natural disaster events altogether, the average 15-day FAH spending of households in treatment counties decreases by \$0.868 in 90 days and \$0.96 in 180 days, in comparison to households in control counties

(Column 1 in Table 6). This means that the average effect of all disasters on FAH spending persists from 90 days up to 180 days and remains at about \$1. When we look at the effect of all disasters on the food grocery quality index, the average 15-day household GPQI decreases by 0.096 in 30 days, 0.069 in 90 days, and 0.078 in 180 days (Column 1 in Table 9). Since the maximum GPQI score can be 75, the above GPQI score changes translate into an approximate 0.1% decrease in GPQI in relation to the maximum score. We can say that the effect of the four natural disasters on household GPQI is negligible.

Moving to the results by each disaster type, we find that droughts have no impact on FAH spending and GPQI score (Column 2 in Tables 6 and 9). Floods do have a negative impact on FAH spending, albeit not within the first 30 days after the flooding (Column 3 in Table 6). After flooding, average 15-day FAH spending decreases by \$1.314 in 90 days, and \$1.403 in 180 days (Column 3 in Table 6). Although floods affect FAH spending in 90-180 days, they have no impact on GPQI in any post-flooding window (Column 3 in Table 9).

Hurricanes have the greatest impact on FAH spending among the four disasters, however surprisingly, they do not affect GPQI. After hurricanes, average 15-day FAH spending decreases by \$2.548 in the first 30 days (Column 4 in Table 6). Hurricanes' impact on FAH spending is only immediate and does not show up in the 90-day and 180-day windows (Column 4 in Table 6). Finally, tornadoes have no effect on FAH spending in any post-tornado window (Column 5 in Table 6). Since tornadoes affect relatively small geographic areas compared to hurricanes and floods, it could be a potential explanation for why tornadoes have no impact on FAH spending. However, tornadoes do affect GPQI within the first 30 days after tornado events, i.e., average 15-day GPQI decreases by 0.289 ($\sim$ 0.4% of max GPQI score), which is a rather very small effect (Column 5 in Table 9).

We further evaluate the impact of flood and hurricane events by their respective damage cost quartiles, to check if the severity of these disasters affects each FAH spending and GPQI heterogeneously. In case of floods, only the ones from the third quartile decrease average 15-day FAH spending by \$1.801 and \$1.149 in the 30 days and 90 days after the events, respectively (Column 3 in Table 7). Floods from the fourth quartile also decrease average 15-day FAH spending by about \$1 but this effect is not robust to county-specific linear trends, hence we ignore this result (Column 4 in Table 7). The main difference in the FAH spending effect under pooled flood events and the third quartile flood events is that in the former (latter) case the effect shows up in 90-180 days (30-90 days) after the events, however the magnitude of the effect is always between \$1 and \$2. Once again, we find that floods have a persistent and prolonged effect on FAH spending. In case of hurricanes, only the ones in the fourth quartile decrease average 15-day FAH spending by \$6.621 in the immediate 30 days after the events (Column 8 in Table 7). The effect of hurricanes from the fourth quartile on average 15-day FAH spending is about three times the size of the effect of pooled hurricane events — this shows that highly damaging hurricanes do leave a mark on FAH spending. The above results reveal that it is only the flood and hurricane events from the third and fourth quartiles that matter for FAH spending. Finally, only the hurricane events from the fourth quartile decrease average 15-day FAH quality (GPQI) by about 0.278 ($\sim 0.4\%$ of max GPQI score) in the 90 days after the events (Column 8 in Table 10), which is a very small effect just as in the case of tornadoes.

We also look at the joint impact of floods and hurricanes from the fourth quartile on FAH spending and GPQI in eight coastal states out of the ten states with the highest flood and hurricane damage costs from 2005-2016, i.e., Texas, Florida, North Carolina, Louisiana, Tennessee, Mississippi, New York, and New Jersey. These southern and eastern coastal states are highly exposed to the threat of hurricanes and flooding, which can increase in intensity and frequency with climate change, hence negatively affecting state-level gross domestic product (GDP) (Hsiang et al., 2017). Here we find that flood and hurricane events are already affecting FAH spending in high-exposure coastal states, i.e., the disaster events decrease average 15-day FAH spending by \$4.243 in 30 days after the events (Column 1 in Table 8), and the effect on average 15-day GPQI is rather very small ($\sim 0.4\%$ of max GPQI score) in the 90 days after the events (Column 2 in Table 11).

Putting all the results for FAH spending and GPQI into perspective, we can say that floods have a persistent and prolonged impact on FAH spending (180 days). Hurricanes have the largest and most immediate impact on FAH spending (30 days). Since the coastal states in the south and east of the U.S. are most likely to be hit by major hurricanes, we also find that hurricanes negatively affect FAH spending in these states. Droughts and tornadoes have no impact on FAH spending. Therefore, we find evidence (no evidence) in support of hypothesis H_1 when the natural disasters are floods and hurricanes (droughts and tornadoes). Meanwhile, hurricanes and tornadoes have a very small and almost negligible impact on GPQI in 30 days and 90 days after the events, respectively. Therefore, we find evidence (no evidence) in support of hypothesis H_2 when the natural disasters are hurricanes and tornadoes (droughts and floods).

The heterogeneity in ATET estimates, in terms of estimate size and post-disaster impact window, possibly has to do with the impact intensity of each disaster. Hurricanes have the highest average damage cost per treatment county ($403.18 million, see Table 2), and we find its impact on FAH spending to be the highest among the four disasters, especially among hurricanes in the fourth quartile of damage cost. Let us suppose that the impact of each disaster on FAH spending works through a decrease in household income due to home repairs. Since hurricanes wreak havoc upon landing and would require immediate home repairs, their impact on FAH spending can also be immediate. Floods can also have an immediate negative impact on residential homes, however, it is damages like disturbed home foundation, soaked insulation and swollen wood frames with potential mold, and damaged electrical systems that can take a while to identify and repair. Alternatively, if a decrease in household income is due to damaged crops, then floods are one major source of agricultural losses. Since farm income is seasonal, it will not be surprising that the effect of floods on income appear late after the floods.

B. Effect of Natural Disasters on Water and Non-Alcoholic Beverages at Home (WBAH) Spending, Total Grocery Spending, and Alcohol-at-Home Spending

In this subsection, we provide estimation results of equation (1) for three spending variables that are of general interest. For instance, hurricane or flooding can contaminate local water resources which makes it interesting to look at disasters' impact on WBAH spending. Studying disasters' impact on total grocery spending can help us understand the true effect of each disaster on aggregate grocery spending, beyond food. Considering that alcohol consumption is harmful for health, it is relevant from a health perspective to understand whether or not natural disasters lead to harmful spending behavior.

In the case of disasters' impact on WBAH spending, we find that each drought, flood, and tornado has no impact on the average 15-day WBAH spending in any of the post-disaster windows (Columns 2, 3, and 5 in Table 12). Hurricanes do have a negative and persistent impact on WBAH spending. After hurricanes, average 15-day WBAH spending decreases by

$0.829 in 30 days, $0.578 in 90 days, and $0.41 in 180 days (Column 4 in Table 12). Although in the previous section we find that hurricanes only have an immediate effect on FAH spending, here we find that their effect on WBAH spending is persistent. A decrease in WBAH spending is possibly due to a negative income effect of hurricanes, however provision of water supplies by state and federal authorities can also explain a decrease in household spending on bottled water and non-alcoholic beverages in the immediate aftermath of hurricanes.

Moving to total grocery spending, we find that each drought and tornado has no impact on the average 15-day total grocery spending in any of the post-disaster windows (Columns 2 and 5 in Table 13). Just as in the case of FAH spending, flooding has a persistent and prolonged impact on households' total grocery spending. After flooding, average 15-day total grocery spending decreases by $3.866 in 90 days (Column 3 in Table 13). In case of hurricanes, we do not find an immediate impact on total grocery spending in the 30 days (Column 4 in Table 13). However, when we account for the anticipation effect of hurricanes on total grocery spending, we find that average 15-day total grocery spending decreases by $14.339 in 30 days after hurricanes (we discuss the anticipation effect in the next subsection).

Moving to alcohol-at-home spending, we notice that except floods and hurricanes, droughts and tornadoes have no impact on average 15-day alcohol-at-home spending (Columns 2 and 5 in Table 14). After flooding, the average 15-day alcohol spending decreases by $0.234 in 180 days (Column 3 in Table 14). Just as in the case of FAH spending, flooding leads to a persistent impact on alcohol spending. Hurricanes do have an immediate impact on alcohol-at-home spending, i.e., hurricanes decrease average 15-day alcohol spending by $0.676 in 30 days after the event (Column 4 in Table 14). An interesting finding about floods and hurricanes is that they have a negative and positive aspect to them regarding spending behavior. If floods and hurricanes negatively affect "good" spending behavior, i.e., FAH spending, it also negatively affects "bad" spending behavior, i.e., alcohol spending, but the negative impact of floods and hurricanes on FAH spending is about six and four times greater than the alcohol spending impact, respectively.[16]

[16] We look into the effect of flood and hurricane events by damage cost quartiles on WBAH spending, total grocery spending, and alcohol-at-home spending, however, the results are not much different than what we already find under the pooled quartiles for each floods and hurricanes.

C. Anticipation Effect of Floods and Hurricanes on FAH Spending, WBAH Spending, and Total Grocery Spending

Both drought and tornado are natural events that are difficult to predict, however floods and hurricanes are relatively predictable events. The arrival of tornadoes can be abrupt, while droughts are rather unnoticeable in the early periods. Due to advancements in meteorology, it is possible to predict floods and hurricanes several days in advance. And with access to weather news, internet, and social media, it is reasonable to assume that the public can anticipate the arrival of a flood or hurricane event. Therefore, we check whether there is an anticipation effect of flood or hurricane event, 15 days before the event date, on household spending behavior for food, water, and total grocery.

When estimating equation (1) to identify the anticipation effect, we move back the post-disaster period by 15 days which leaves the pre-disaster period to be 165 days out of 180 days. We then keep the post-disaster window to be the 15 days before the original disaster date. We find that there is an anticipation effect of hurricanes on total grocery spending. In the 15 days before the original hurricane event date, the average 15-day total grocery spending decreases by \$7.579 (Column 6 in Table 15). Therefore, we adjust (move back by 15 days) the post-disaster period when estimating equation (1) for total grocery spending under hurricane events. The true impact of hurricanes on total grocery spending translates into an average 15-day spending decrease of \$14.339 (rather than the statistically insignificant decrease of \$10.533) in the 30 days of the post-disaster window, respectively (Columns 3 and 6 in Table 16). We do not find an anticipation effect of flooding or hurricane on FAH spending or WBAH spending (Columns 1-4 in Table 15). Meanwhile, flooding does not have an anticipation effect on total grocery spending (Column 5 in Table 15).

D. Do Natural Disasters Affect FAH Spending through the Income Channel?

The short answer is: yes. In this subsection, we indirectly test whether natural disasters are affecting FAH spending through the income channel, i.e., we test whether low-income households (including poor) have a decrease in FAH spending after natural disasters, and compare the results against households that are above low income. We expect that low-income households should have a decrease in FAH spending after natural disasters because (i) poor and low-income households are prone to losing income after a disaster due to their vulnerability to natural disasters and not having enough assets to recover from the disasters (Hallegatte et al., 2017; Boustan et al., 2020), and (ii) a decline in income will lead to a decline in food expenditure due to the positive income elasticity of food demand (Lusk, 2017).

We define a household as low-income if the upper bound of its income category is less than two times the poverty threshold. We use the weighted poverty thresholds for each family size for the years 2005-2017. Poverty thresholds are accessible through the U.S. Census Bureau website.[17] Our low-income household definition includes poor households.

We find that after natural disasters, the average 15-day FAH spending of low-income households decreases by \$1.613 in 30 days, and that there is no impact of natural disasters on the FAH spending of households that are not in the low-income class (Columns 1-2 in Table 17). This provides evidence that the income channel is one potential channel through which natural disasters affect FAH spending.

E. Do Natural Disasters Affect FAH Spending through the Price Channel?

The short answer is: yes. Natural disasters can negatively affect the short-term supply of food items in a local economy (Ding et al., 2011), hence increasing the price of food items. We indirectly test whether natural disasters activate the price channel for food items, i.e., food prices increase after natural disasters and lead to a decrease in FAH spending. In order to carry out this exercise, we look into fresh fruit price (per unit) and spending in household transactions after flood and hurricane events, which can have an immediate impact on fresh fruit production. We restrict analysis to the seven coastal states out of top ten fruit producing states per the 2017 Census of Agriculture, i.e., Texas, Florida, Georgia, California, Washington, Oregon, and New York. We pick the seven major fruit producing coastal states because they also get exposed to flood and hurricane events. Finally, we only look into flood and hurricane events that happen in June to December months because the active harvesting period for majority of fruits falls during June to December months (U.S. Department of Agriculture, 2006).

We find that flooding and hurricanes do lead to an increase in fresh fruit price and a decrease

[17] Poverty thresholds are available at: https://www.census.gov/data/tables/time-series/demo/income-poverty/historical-poverty-thresholds.html

in fresh fruit spending during the 30 days after the events. Precisely, flood and hurricane events increase (decrease) the average 15-day fresh fruit price (spending) by about 12 cents per unit (about 14 cents) in the 30 days after the events (Column 1 in Table 18).[18] The 12 cents increase in per unit price is equivalent to a 4.5% increase compared to the per unit price paid by households in treatment counties before the disaster. The 14 cents decrease in fresh fruit spending is equivalent to a 3.5% reduction compared to the fresh fruit spending of households in treatment counties before the disaster.

The above results point to the fact the whenever the short-term supply of food items is negatively affected, it can affect food prices and spending. The reader should also note that an increase in the price of food items can also be demand-driven in certain cases. For instance, the COVID-19 pandemic of 2020 led to an increase in meat prices which was mainly driven by a supply shock due to closures of meatpacking facilities, however, meat shortage led to a higher demand for alternative protein (eggs) which increased egg prices during the pandemic (Johansson, 2020).

Conclusion

We exploit spatial and temporal variation in natural disasters in the United States via a generalized difference-in-differences (GDD) approach to identify the impact of four different natural disasters on households' FAH expenditures and FAH quality. We measure FAH quality through the Grocery Purchase Quality Index (GPQI). The four disasters are droughts, floods, hurricanes, and tornadoes. As part of our empirical strategy, we design a spatial-temporal algorithm to identify treatment and control counties using disasters' time, location, and damage cost information, which is available through the Storm Events database for 2005 - 2016. We find that floods have a persistent and prolonged effect on FAH spending for 180 days after flooding. Hurricanes only have an immediate impact on FAH spending in the 30 days after the hurricane events. The average 15-day decrease in FAH spending after a disaster is about $1 for floods and $3 for hurricanes which further increases in magnitude for floods from the third damage cost quartile ($1-$2) and for hurricanes from the fourth damage cost quartile ($7). Flood and hurricane events from the fourth damage cost quartile reduce FAH spending by about $4 in

[18]Fresh fruit unit is either pound or count.

those coastal states that are highly exposed to floods and hurricanes. Climate change and rising temperatures could increase the severity and frequency of storm events in coastal states which can further worsen the impact on FAH spending. Both droughts and tornadoes have no effect on FAH spending. Hurricanes and tornadoes affect GPQI in the 30 days and 90 days after the events, respectively, however, the GPQI effect of hurricanes and tornadoes is almost negligible in magnitude — it is about 0.4% of the max GPQI score. Both droughts and floods have no effect on GPQI. So, the quality of food purchase after the four disasters does not really suffer by a noticeable magnitude.

We show that the FAH spending effect of natural disasters is potentially operating through the income and price channels. Jointly, the four natural disasters only affect poor and low-income households' FAH spending, hence providing the indirect evidence that the natural disasters affect FAH spending through the income channel because it is mainly the low-income households who lose income after natural disasters. We also find that flood and hurricane events jointly increase the per unit price of fresh fruit and decrease household spending on fresh fruit, hence providing the indirect evidence that the price channel is also at play after natural disasters.

We also explore the impact of natural disasters on WBAH (water/non-alcoholic beverages) spending, total grocery spending, and alcohol-at-home spending. We find that hurricanes consistently decrease WBAH spending by about \$0.4 - \$1 in the 180 days after the disasters. We also find that the effect of hurricanes on average 15-day total grocery spending translates into a decrease of about \$14, after adjusting for the anticipation effect of hurricanes. In case of alcohol-at-home spending, we find that the average 15-day spending decreases by \$0.234 in 180 days after a flood, and by \$0.676 in 30 days after a hurricane. This is a relatively small decrease in spending when compared to FAH spending decrease after flood and hurricane events. So, there is both a negative and positive aspect to floods and hurricanes. The negative aspect is the decrease in FAH spending, and the positive aspect is the decrease in alcohol spending.

There are two specific shortcomings in our study that are related to data quality and identifying drought events. First, the household grocery trip spending data probably suffers from missing transactions because of a couple of reasons: (i) households not being able to scan purchased items within the first 15 days after a disaster due to a lack of electricity or a lack of time to scan, (ii) some households completely dropping out of Nielsen panel after a disaster event, and (iii) some households being inconsistent in scanning and reporting purchased items. We try to overcome the data quality issue by restricting our analysis to households that consistently report at least one shopping trip in each 15-day period for 90 days before and after a disaster event, to avoid bias that could arise due to potential migrant households, or households that do not comply with consistent scanning of products, or households that voluntarily drop. Second, the start dates of our drought events are probably not completely accurate. Droughts usually span multiple months or years. We might not be capturing the exact starting date of droughts, although we try to circumvent this issue by focusing on the first drought event during a year in a county, to capture a drought's start date. The study of droughts and how they affect food and water consumption is an important research topic, which can benefit from alternative methods of drought measurement over time.

Our study extends the literature on the impact of natural disasters on household income and financial decisions and investigates the impact of natural disasters on household FAH expenditures and quality, which is closely associated with household income (Gallagher and Hartley, 2017; Deryugina et al., 2018). We show that different natural disasters affect household FAH expenditures and quality with varying intensity and for different time lengths. Since the share of food-away-from-home (FAFH) in food budget is as important as the share of FAH, our research can be extended to FAFH expenditures upon data availability. And we believe that the impact of flood and hurricane events on total FAH and FAFH spending would be more substantial than that of FAH spending alone. We contribute to the GDD regression approach by introducing a spatial-temporal algorithm to systematically identify disaster-affected and control counties (Belasen and Polachek, 2008). The algorithm makes it feasible to identify staggered natural events across the U.S. counties and to study various economic variables using the GDD approach. We also extend the literature on food grocery quality by studying FAH quality after disaster events using the GPQI, which is specifically designed for large datasets of food grocery transactions (Brewster et al., 2017).

We believe our findings can partially guide post-disaster relief organizations and their household recovery programs. Given that there is heterogeneity in the impact of different natural disasters on FAH expenditures, relief organizations can plan for a customized distribution of food items and non-alcoholic beverages after each disaster type, hence making post-disaster aid allocation more efficient. Knowing when a natural disaster starts affecting FAH expenditures and how long the impact lasts can help with the time sensitivity of aid distribution. Finally, we find it is mainly the poor and low-income households who suffer from natural disasters in terms of FAH expenditures, hence relief organizations should pay specific attention to this demographic in the population.

Tables

Subsection 1: Statistics on Disaster Events and Sample Household Socio-Demographics

Table 1: Regions and States of Treatment (T) and Control (C) Counties

Region	States	T/C Counties
Midwest	Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, Wisconsin	409 / 285
Northeast	Connecticut, Maine, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont	115 / 115
West	Arizona, California, Colorado, Montana, Nevada, New Mexico, Oregon, Utah, Washington, Wyoming	66 / 66
South	Alabama, Arkansas, Delaware, District of Columbia, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia, West Virginia	523 / 647
Total Counties		1,113 / 1,113
Distinct Counties		763 / 857
Distinct County-Year		1,108 / 1,074

Notes: Only those states are presented for which we have treatment and control counties. For treatment and control county definitions please see the Data and Appendix A sections. This data is based on 2005-2016 period, using NOAA's Storm Event Database.

Table 2: Spatial Profile of U.S. Natural Disasters and Mean Damage per County

Region	Drought ($M)	Flood ($M)	Hurricane ($M)	Tornado ($M)
Midwest	30.79	55.25	N/A	56.2
Northeast	N/A	64.81	516.17	54.99
West	175.94	46.54	68.69	57.18
South	76.46	129.85	399.44	86.42
All	47.75	80.51	403.18	75

Notes: Authors' calculations. Damage costs are for infrastructure and agriculture losses presented in millions ($M). This data is based on treatment counties' damages in 2005-2016 period, using NOAA's Storm Event Database.

Table 3: Temporal Profile of U.S. Natural Disasters and Mean Damage per County

Year	Drought ($M)	Flood ($M)	Hurricane ($M)	Tornado ($M)
2005	19.12	36.61	629.67	38.76
2006	193.54	60.14	11.95	29.09
2007	70.28	46.6	21.72	51.78
2008	N/A	58.49	340.13	42.15
2009	15.35	25.91	42.33	40.7
2010	N/A	45.63	15.09	51.32
2011	48.57	138.13	38.96	109.64
2012	38.78	45.22	641.56	90.23
2013	20.85	46.79	N/A	234.67
2014	300	121.36	40	37.38
2015	N/A	85.46	N/A	27.22
2016	N/A	256.97	198.55	40.21
All	47.75	80.51	403.18	74

Notes: Authors' calculations. Damage costs are for infrastructure and agriculture losses presented in millions ($M). This data is based on treatment counties' damages in 2005-2016 period, using NOAA's Storm Event Database.

Table 4: Percentage Share of Food Expenditures by Food Components (All Households)

Food Components of GPQI-2016	Mean	p25	p50	p75
Total Fruit	7.21	0	4.77	10.44
Whole Fruit	5.01	0	2.42	7.21
Total Vegetables	7.19	1.43	5.55	10.36
Greens and Beans	0.82	0	0	0.83
Whole Grains	1.22	0	0	1.28
Dairy	5.35	1.04	3.47	7.21
Total Protein Foods	8.49	0	4.76	12.73
Seafood and Nuts	2.94	0	0	3.43
Refined Grains	14.90	7.24	13.15	20.12
Processed Meats	7.44	0	4.43	10.28
Sweets and Sodas	22.07	11.06	19.30	29.52

Notes: Statistics are based on the Nielsen Consumer Panel data for years 2005-2016. Among statistics, p25, p50, and p75 represent 25th, 50th, and 75th percentiles, respectively. The total count of observations is 502,175. Household food expenditures are recorded for 15-day periods covering a 180-day length before disasters.

Table 5: Household Demographics by Treatment and Control Households

	Treatment	Control	Balance Test	Balance Test
	Mean (St. Deviation)	Mean (St. Deviation)	Normalized Diff	Variance Ratio
Household Size	2.29 (1.24)	2.32 (1.23)	0.02	1.01
Household Head Age	56.71 (12.87)	56.6 (12.85)	0.01	1.00
	Frequency (Percent)	Frequency (Percent)	Normalized Diff	Variance Ratio
Residence Type				
House	28,228 (88.9)	11,164 (89.6)	0.02	1.06
Condo/Coop	2,445 (7.7)	677 (5.4)	0.09	1.38
Mobile/Trailer	1,067 (3.4)	614 (4.9)	0.08	0.69
Household Income				
< $5K	291 (0.9)	132 (1.1)	0.01	0.87
$5K-14999	1,582 (5.0)	764 (6.1)	0.05	0.82
$15K-29999	4,723 (14.9)	2,193 (17.6)	0.07	0.87
$30K-59999	11,425 (36.0)	4,530 (36.4)	0.01	1.00
$60K-99999	8,966 (28.2)	3,284 (26.4)	0.04	1.04
>= $100K	4,753 (15.0)	1,554 (12.5)	0.07	1.17
Education				
HighSchool(grad or below)	8,575 (27.0)	3,642 (29.2)	0.05	0.95
College(grad or below)	19,245 (60.6)	7,358 (59.1)	0.03	0.99
PostCollege Grad	3,920 (12.4)	1,457 (11.7)	0.02	1.05
Marital Status				
Single	5,005 (15.8)	1,709 (13.7)	0.06	1.12
Married	19,121 (60.2)	7,805 (62.7)	0.05	1.02
Widow/Separate	7,614 (24.0)	2,943 (23.6)	0.01	1.01
Child Below 18Yrs				
No Child < 18 yrs	25,585 (80.6)	9,951 (79.9)	0.02	0.97
Child < 18 yrs	6,155 (19.4)	2,506 (20.1)		
Race				
White	25,608 (80.7)	10,573 (84.9)	0.11	1.21
Black	3,804 (12.0)	987 (7.9)	0.14	1.45
Asian	1,002 (3.2)	273 (2.2)	0.06	1.43
Other	1,326 (4.2)	624 (5.0)	0.04	0.84
Kitchen Appliances				
No Kitchen Apps	327 (1.0)	162 (1.3)	0.03	0.79
Have Kitchen Apps	31,413 (99.0)	12,295 (98.7)		
Presence of Internet				
No Internet	4,599 (14.5)	1,927 (15.5)	0.03	0.95
Have Internet	27,141 (85.5)	10,530 (84.5)		
Distinct Households	23,707	10,864		
Mean Scores			0.05	1.08

Notes: Statistics are based on total households in the Nielsen Consumer Panel data for years 2005-2016. Age and Education variables represent the household head, who is primarily the female household head, whom we replace with male household head when female head is missing. Normalized difference scores are calculated based on Imbens and Rubin (2015) methods. Variance ratio score is equal to the variance of treatment observations over the variance of control observations.

Subsection 2: Natural Disasters' Impact on FAH Spending and GPQI

Table 6: Natural Disasters' Impact on Food Spending

	(1) All	(2) Drought	(3) Flood	(4) Hurricane	(5) Tornado
			(Post-Disaster=30 Days)		
Treated × Post-Disaster=1	-0.689	0.659	-0.501	-2.548*	-0.850
	(0.446)	(1.456)	(0.456)	(1.315)	(1.032)
R^2	0.170	0.199	0.169	0.170	0.189
N	587,335	45,314	300,246	140,220	101,555
Unique Households	34,562	3,130	18,700	9,184	7,084
			(Post-Disaster=90 Days)		
Treated × Post-Disaster=1	-0.868**	0.187	-1.314***	-0.908	-0.714
	(0.376)	(0.989)	(0.395)	(0.902)	(0.765)
R^2	0.168	0.197	0.167	0.167	0.185
N	760,901	58,510	389,241	180,944	132,206
Unique Households	34,563	3,130	18,701	9,184	7,084
			(Post-Disaster=180 Days)		
Treated × Post-Disaster=1	-0.960**	0.984	-1.403***	-0.353	-0.653
	(0.384)	(0.972)	(0.419)	(0.807)	(0.755)
R^2	0.166	0.194	0.165	0.165	0.183
N	1,004,545	76,985	514,713	236,474	176,373
Unique Households	34,565	3,130	18,701	9,185	7,085

Notes: Dependent variable is food spending in 2017 constant dollars. Food spending includes water and non-alcoholic beverages spending. Pre-disaster (post-disaster) period is 180 days (30 days, 90 days, or 180 days); each observation represents a 15-day period. Household spending data is based on the Nielsen Consumer Panel data for 2005-2016. Specifications include year-month and county fixed effects and time-varying household demographics. Standard errors (SE) are in parentheses. SEs are cluster-robust at the county level. * p<0.1, ** p<0.05, *** p<0.01

Table 7: Floods' and Hurricanes' Impact on Food Spending by Damage Quartiles

	(1) F-q1	(2) F-q2	(3) F-q3	(4) F-q4	(5) H-q1	(6) H-q2	(7) H-q3	(8) H-q4
				(Post-Disaster=30 Days)				
Treated × Post-Disaster=1	1.319	-0.042	-1.801*	-1.333*	0.300	-1.143	-1.791	-6.621***
	(1.060)	(1.440)	(0.998)	(0.697)	(1.854)	(1.449)	(1.749)	(2.254)
R^2	0.169	0.173	0.174	0.172	0.184	0.172	0.179	0.180
N	119,127	120,354	119,202	146,202	63,728	80,734	70,451	75,091
Unique Households	8,456	8,787	8,476	9,677	4,587	5,849	5,022	5,413
				(Post-Disaster=90 Days)				
Treated × Post-Disaster=1	-0.010	-0.147	-1.149*	-1.182**	-0.836	-1.747	-0.257	-0.349
	(0.703)	(0.961)	(0.675)	(0.530)	(1.287)	(1.159)	(1.497)	(1.421)
R^2	0.167	0.170	0.172	0.169	0.182	0.168	0.177	0.178
N	154,055	156,578	154,219	189,178	82,190	104,192	90,843	96,850
Unique Households	8,457	8,788	8,477	9,678	4,587	5,849	5,022	5,413
				(Post-Disaster=180 Days)				
Treated × Post-Disaster=1	-1.028	-0.919	-0.055	-0.764	0.667	-1.113	0.749	-0.071
	(0.765)	(0.734)	(0.759)	(0.521)	(1.244)	(1.180)	(1.360)	(1.163)
R^2	0.166	0.168	0.170	0.167	0.179	0.166	0.174	0.175
N	203,019	207,690	203,506	249,416	107,342	136,171	118,384	126,466
Unique Households	8,457	8,789	8,477	9,678	4,588	5,850	5,023	5,414

Notes: Dependent variable is food spending in 2017 constant dollars. Food spending includes water and non-alcoholic beverages spending. "F" and "H" stand for Flood and Hurricane, respectively. Flood and hurricane events are split into their respective quartiles (q1-q4) using damage cost data. Pre-disaster (post-disaster) period is 180 days (30 days, 90 days, or 180 days); each observation represents a 15-day period. Household spending data is based on the Nielsen Consumer Panel data for 2005-2016. Specifications include year-month and county fixed effects and time-varying household demographics. Standard errors (SE) are in parentheses. SEs are cluster-robust at the county level. * p<0.1, ** p<0.05, *** p<0.01

Table 8: Floods' and Hurricanes' Impact on Food Spending in High-Exposure Coastal States

	(1) 30-Day	(2) 90-Day	(3) 180-Day
Treated × Post-Disaster=1	-4.243***	-1.125	-1.049
	(1.622)	(0.935)	(0.857)
R^2	0.172	0.170	0.168
N	109,087	141,021	185,156
Unique Households	7,199	7,200	7,200

Notes: Dependent variable is food spending in 2017 constant dollars. Food spending includes water and non-alcoholic beverages spending. High-exposure coastal states are eight out of ten states with the highest flood and hurricane damage costs from 2005-2016: Texas, Florida, North Carolina, Louisiana, Tennessee, Mississippi, New York, New Jersey. We restrict analysis to flood and hurricane events that are in the fourth quartile using damage cost data, respectively. Pre-disaster (post-disaster) period is 180 days (30 days, 90 days, or 180 days); each observation represents a 15-day period. Household spending data is based on the Nielsen Consumer Panel data for 2005-2016. Specifications include year-month and county fixed effects and time-varying household demographics. Standard errors (SE) are in parentheses. SEs are cluster-robust at the county level. * p<0.1, ** p<0.05, *** p<0.01

Table 9: Natural Disasters' Impact on GPQI

	(1) All	(2) Drought	(3) Flood	(4) Hurricane	(5) Tornado
			(Post-Disaster=30 Days)		
Treated × Post-Disaster=1	-0.096**	-0.045	-0.063	-0.060	-0.289***
	(0.047)	(0.155)	(0.055)	(0.092)	(0.096)
R^2	0.070	0.107	0.062	0.088	0.076
N	587,335	45,314	300,246	140,220	101,555
Unique Households	34,562	3,130	18,700	9,184	7,084
			(Post-Disaster=90 Days)		
Treated × Post-Disaster=1	-0.069*	0.021	-0.046	0.014	-0.114
	(0.037)	(0.118)	(0.043)	(0.101)	(0.077)
R^2	0.069	0.107	0.061	0.086	0.074
N	760,901	58,510	389,241	180,944	132,206
Unique Households	34,563	3,130	18,701	9,184	7,084
			(Post-Disaster=180 Days)		
Treated × Post-Disaster=1	-0.078**	0.004	-0.072**	0.069	-0.064
	(0.035)	(0.103)	(0.036)	(0.109)	(0.074)
R^2	0.068	0.107	0.061	0.084	0.073
N	1,004,545	76,985	514,713	236,474	176,373
Unique Households	34,565	3,130	18,701	9,185	7,085

Notes: Dependent variable is Grocery Purchase Quality Index (GPQI). Pre-disaster (post-disaster) period is 180 days (30 days, 90 days, or 180 days); each observation represents a 15-day period. Household spending data is based on the Nielsen Consumer Panel data for 2005-2016. Specifications include year-month and county fixed effects and time-varying household demographics. Standard errors (SE) are in parentheses. SEs are cluster-robust at the county level. * p<0.1, ** p<0.05, *** p<0.01

Table 10: Floods' and Hurricanes' Impact on GPQI by Damage Quartiles

	(1) F-q1	(2) F-q2	(3) F-q3	(4) F-q4	(5) H-q1	(6) H-q2	(7) H-q3	(8) H-q4
				(Post-Disaster=30 Days)				
Treated × Post-Disaster=1	-0.256**	-0.206	-0.052	0.041	-0.255	-0.011	-0.153	-0.260*
	(0.107)	(0.128)	(0.112)	(0.114)	(0.178)	(0.133)	(0.206)	(0.146)
R^2	0.071	0.073	0.083	0.068	0.104	0.091	0.098	0.095
N	119,127	120,354	119,202	146,202	63,728	80,734	70,451	75,091
Unique Households	8,456	8,787	8,476	9,677	4,587	5,849	5,022	5,413
				(Post-Disaster=90 Days)				
Treated × Post-Disaster=1	-0.207**	-0.203**	-0.055	0.028	0.089	0.055	-0.035	-0.278**
	(0.082)	(0.091)	(0.082)	(0.085)	(0.154)	(0.096)	(0.177)	(0.121)
R^2	0.069	0.072	0.082	0.067	0.102	0.089	0.095	0.093
N	154,055	156,578	154,219	189,178	82,190	104,192	90,843	96,850
Unique Households	8,457	8,788	8,477	9,678	4,587	5,849	5,022	5,413
				(Post-Disaster=180 Days)				
Treated × Post-Disaster=1	-0.129*	-0.090	0.005	0.016	0.178	0.100	0.024	-0.196
	(0.073)	(0.085)	(0.080)	(0.095)	(0.161)	(0.108)	(0.150)	(0.122)
R^2	0.068	0.071	0.082	0.067	0.099	0.086	0.091	0.090
N	203,019	207,690	203,506	249,416	107,342	136,171	118,384	126,466
Unique Households	8,457	8,789	8,477	9,678	4,588	5,850	5,023	5,414

Notes: Dependent variable is Grocery Purchase Quality Index (GPQI)."F" and "H" stand for Flood and Hurricane, respectively. Flood and hurricane events are split into their respective quartiles (q1-q4) using damage cost data. Pre-disaster (post-disaster) period is 180 days (30 days, 90 days, or 180 days); each observation represents a 15-day period. Household spending data is based on the Nielsen Consumer Panel data for 2005-2016. Specifications include year-month and county fixed effects and time-varying household demographics. Standard errors (SE) are in parentheses. SEs are cluster-robust at the county level. * p<0.1, ** p<0.05, *** p<0.01

Table 11: Floods' and Hurricanes' Impact on GPQI in High-Exposure Coastal States

	(1) 30-Day	(2) 90-Day	(3) 180-Day
Treated × Post-Disaster=1	-0.120	-0.212*	-0.124
	(0.121)	(0.110)	(0.118)
R^2	0.081	0.079	0.077
N	109,087	141,021	185,156
Unique Households	7,199	7,200	7,200

Notes: Dependent variable is Grocery Purchase Quality Index (GPQI). High-exposure coastal states are eight out of ten states with the highest flood and hurricane damage costs from 2005-2016: Texas, Florida, North Carolina, Louisiana, Tennessee, Mississippi, New York, New Jersey. We restrict analysis to flood and hurricane events that are in the fourth quartile using damage cost data, respectively. Pre-disaster (post-disaster) period is 180 days (30 days, 90 days, or 180 days); each observation represents a 15-day period. Household spending data is based on the Nielsen Consumer Panel data for 2005-2016. Specifications include year-month and county fixed effects and time-varying household demographics. Standard errors (SE) are in parentheses. SEs are cluster-robust at the county level. * p<0.1, ** p<0.05, *** p<0.01

Subsection 3: Natural Disasters' Impact on WBAH Spending, Total Grocery Spending, and Alcohol Spending

Table 12: Natural Disasters' Impact on WBAH Spending

	(1) All	(2) Drought	(3) Flood	(4) Hurricane	(5) Tornado
			(Post-Disaster=30 Days)		
Treated × Post-Disaster=1	-0.158**	0.191	-0.086	-0.829***	-0.247
	(0.065)	(0.320)	(0.088)	(0.246)	(0.158)
R^2	0.080	0.105	0.080	0.083	0.084
N	586,324	45,254	299,739	139,956	101,375
Unique Households	34,467	3,124	18,651	9,162	7,065
			(Post-Disaster=90 Days)		
Treated × Post-Disaster=1	-0.062	0.344	-0.039	-0.578***	-0.146
	(0.060)	(0.225)	(0.081)	(0.186)	(0.132)
R^2	0.079	0.104	0.079	0.083	0.083
N	759,603	58,434	388,590	180,607	131,972
Unique Households	34,467	3,124	18,651	9,162	7,065
			(Post-Disaster=180 Days)		
Treated × Post-Disaster=1	-0.063	0.323	-0.013	-0.410**	-0.198
	(0.056)	(0.197)	(0.062)	(0.178)	(0.138)
R^2	0.078	0.104	0.078	0.081	0.081
N	1,002,846	76,889	513,866	236,033	176,058
Unique Households	34,468	3,124	18,651	9,162	7,066

Notes: Dependent variable is water and non-alcoholic beverages spending in 2017 constant dollars. Pre-disaster (post-disaster) period is 180 days (30 days, 90 days, or 180 days); each observation represents a 15-day period. Household spending data is based on the Nielsen Consumer Panel data for 2005-2016. Specifications include year-month and county fixed effects and time-varying household demographics. Standard errors (SE) are in parentheses. SEs are cluster-robust at the county level. * p<0.1, ** p<0.05, *** p<0.01

Table 13: Natural Disasters' Impact on Total Grocery Spending

	(1) All	(2) Drought	(3) Flood	(4) Hurricane	(5) Tornado
			(Post-Disaster=30 Days)		
Treated × Post-Disaster=1	-3.131*	-1.470	-3.019*	-10.533	-1.230
	(1.688)	(6.645)	(1.799)	(6.626)	(3.533)
R^2	0.106	0.129	0.104	0.102	0.135
N	597,527	46,083	305,341	142,889	103,214
Unique Households	34,570	3,131	18,702	9,189	7,085
			(Post-Disaster=90 Days)		
Treated × Post-Disaster=1	-1.891	4.482	-3.866**	2.571	0.858
	(1.485)	(4.401)	(1.945)	(3.407)	(2.882)
R^2	0.105	0.127	0.102	0.102	0.131
N	774,307	59,527	395,921	184,409	134,450
Unique Households	34,570	3,131	18,702	9,189	7,085
			(Post-Disaster=180 Days)		
Treated × Post-Disaster=1	-0.514	3.877	-2.192	4.815	0.214
	(1.491)	(3.819)	(2.086)	(2.980)	(2.794)
R^2	0.106	0.129	0.103	0.103	0.129
N	1,022,559	78,315	523,752	241,007	179,485
Unique Households	34,570	3,131	18,702	9,189	7,085

Notes: Dependent variable is total grocery spending in 2017 constant dollars. Pre-disaster (post-disaster) period is 180 days (30 days, 90 days, or 180 days); each observation represents a 15-day period. Household spending data is based on the Nielsen Consumer Panel data for 2005-2016. Specifications include year-month and county fixed effects and time-varying household demographics. Standard errors (SE) are in parentheses. SEs are cluster-robust at the county level. * p<0.1, ** p<0.05, *** p<0.01

Table 14: Natural Disasters' Impact on Alcohol Spending

	(1) All	(2) Drought	(3) Flood	(4) Hurricane	(5) Tornado
	(Post-Disaster=30 Days)				
Treated × Post-Disaster=1	0.091	0.825	0.132	-0.676**	-0.069
	(0.109)	(0.525)	(0.155)	(0.298)	(0.298)
R^2	0.042	0.114	0.037	0.041	0.060
N	423,437	30,748	220,945	101,519	70,225
Unique Households	23,941	2,102	13,261	6,513	4,808
	(Post-Disaster=90 Days)				
Treated × Post-Disaster=1	-0.083	0.098	-0.287**	-0.344	0.260
	(0.095)	(0.328)	(0.123)	(0.271)	(0.229)
R^2	0.041	0.112	0.036	0.041	0.058
N	548,556	39,711	286,415	130,976	91,454
Unique Households	23,941	2,102	13,262	6,513	4,808
	(Post-Disaster=180 Days)				
Treated × Post-Disaster=1	-0.009	0.056	-0.234**	0.032	0.155
	(0.104)	(0.323)	(0.116)	(0.272)	(0.193)
R^2	0.041	0.109	0.036	0.040	0.058
N	725,079	52,317	379,209	171,472	122,081
Unique Households	23,941	2,102	13,262	6,513	4,808

Notes: Dependent variable is alcohol spending in 2017 constant dollars. Pre-disaster (post-disaster) period is 180 days (30 days, 90 days, or 180 days); each observation represents a 15-day period. Household spending data is based on the Nielsen Consumer Panel data for 2005-2016. Specifications include year-month and county fixed effects and time-varying household demographics. Standard errors (SE) are in parentheses. SEs are cluster-robust at the county level. * p<0.1, ** p<0.05, *** p<0.01

Subsection 4: Flood and Hurricane Anticipation Results for Food, Water, and Total Grocery Spending Variables

Table 15: Natural Disasters' Impact on Spending Variables (15 Days Anticipation)

	(1) Food-F	(2) Food-H	(3) Water-F	(4) Water-H	(5) Grocery-F	(6) Grocery-H
Treated × Post-Disaster=1	0.208	0.003	-0.145	0.310	-0.523	-7.579*
	(0.792)	(1.349)	(0.139)	(0.224)	(2.307)	(3.997)
R^2	0.171	0.171	0.081	0.084	0.105	0.103
N	256,206	120,238	255,767	120,012	260,548	122,501
Unique Households	18,699	9,184	18,651	9,162	18,702	9,189

Notes: Dependent variables are spending variables, i.e., food spending, water and non-alcoholic beverages spending, and total grocery spending. All spending variables are in 2017 constant dollars. (F) and (H) stand for floods and hurricanes. We check whether households anticipate the disaster events. The post-disaster period is the 15-day period before the disaster event date, and the pre-disaster period is the 165 days before the post-disaster period. Specifications include year-month and county fixed effects, and time-varying household demographics. Standard errors (SE) are in parentheses. SEs are cluster-robust at the county level. * p<0.1, ** p<0.05, *** p<0.01

Table 16: Hurricanes' Impact on Total Grocery Spending - Original vs. Anticipation Results

	(1) 180-Day Ori.	(2) 90-Day Ori.	(3) 30-Day Ori.	(4) 180-Day Ant.	(5) 90-Day Ant.	(6) 30-Day Ant.
Treated × Post-Disaster=1	4.815	2.571	-10.533	5.258**	1.600	-14.339***
	(2.980)	(3.407)	(6.626)	(2.669)	(2.819)	(3.935)
R^2	0.103	0.102	0.102	0.104	0.101	0.102
N	241,007	184,409	142,889	231,969	174,029	132,509
Unique Households	9,189	9,189	9,189	9,189	9,189	9,189

Notes: Dependent variable is total grocery spending in 2017 constant dollars. In first three specifications, the pre-disaster period is 180 days and the post-disaster period is 180 (90) (30) days, which starts after the event date. In the last three (anticipation) specifications, the pre-disaster period is 165 days and the post-disaster period is 180 (90) (30) days, which starts 15 days before the event date. Each observation represents a 15-day period. Specifications include year-month and county fixed effects, and time-varying household demographics. Standard errors (SE) are in parentheses. SEs are cluster-robust at the county level. * p<0.1, ** p<0.05, *** p<0.01

Subsection 5: Natural Disasters' Impact on Food-at-Home Spending by Household Income Class

Table 17: Disasters' Impact on Food Spending by Household Income Class (Post-Disaster=30 Days)

	(1) Above Low-Income Households	(2) Low-Income Households
Treated × Post-Disaster=1	-0.481	-1.613*
	(0.457)	(0.948)
R^2	0.168	0.231
N	482,550	104,785
Unique Households	28,536	6,713

Notes: Dependent variable is food spending in 2017 constant dollars. Pre-disaster (post-disaster) period is 180 days (30 days); each observation represents a 15-day period. Household spending data is based on the Nielsen Consumer Panel data for 2005-2016. Specifications include year-month and county fixed effects and time-varying household demographics. Standard errors (SE) are in parentheses. SEs are cluster-robust at the county level. * p<0.1, ** p<0.05, *** p<0.01

Subsection 6: Floods' and Hurricanes' Impact on Fresh Fruit Price and Spending

Table 18: Floods' and Hurricanes' Impact on Fresh Fruit Price and Spending

	(1) 30-Day	(2) 90-Day	(3) 180-Day
		(Fresh Fruit Price Per Unit)	
Treated × Post-Disaster=1	0.118**	0.049	0.035
	(0.047)	(0.034)	(0.032)
R^2	0.055	0.053	0.055
N	72,284	90,135	117,569
Unique Households	9,663	9,865	10,083
		(Fresh Fruit Spending)	
Treated × Post-Disaster=1	-0.141**	-0.066	-0.027
	(0.064)	(0.057)	(0.055)
R^2	0.105	0.103	0.101
N	169,789	219,099	286,978
Unique Households	11,038	11,039	11,039

Notes: Dependent variable in top (bottom) panel is fresh fruit price per unit (fresh fruit spending) in 2017 constant dollars. We restrict analysis to the seven coastal states out of top ten fruit producing states per the 2017 Census of Agriculture: Texas, Florida, Georgia, California, Washington, Oregon, and New York. Pre-disaster (post-disaster) period is 180 days (30 days, 90 days, or 180 days); each observation represents a 15-day period. Household spending and price data is based on the Nielsen Consumer Panel data for 2005-2016. If a household has purchase transactions for food grocery but no transaction for fresh fruit purchase, then fresh fruit spending is considered zero and fresh fruit price is considered missing. Specifications include year-month and county fixed effects and time-varying household demographics. Standard errors (SE) are in parentheses. SEs are cluster-robust at the county level. * p<0.1, ** p<0.05, *** p<0.01

Subsection 7: ATET Estimates after Including County-Specific Linear Trends

Table 19: Natural Disasters' Impact on Food Spending with County Trends

	(1) All	(2) Drought	(3) Flood	(4) Hurricane	(5) Tornado
	(Post-Disaster=30 Days)				
Treated × Post-Disaster=1	-0.736*	1.394	-0.750	-4.363***	-2.339**
	(0.429)	(1.961)	(0.492)	(1.490)	(1.186)
R^2	0.174	0.205	0.172	0.173	0.192
N	587,335	45,314	300,246	140,220	101,555
Unique Households	34,562	3,130	18,700	9,184	7,084
	(Post-Disaster=90 Days)				
Treated × Post-Disaster=1	-0.871**	-0.455	-1.303***	-2.399**	-1.920**
	(0.364)	(1.148)	(0.449)	(1.183)	(0.940)
R^2	0.172	0.201	0.169	0.170	0.188
N	760,901	58,510	389,241	180,944	132,206
Unique Households	34,563	3,130	18,701	9,184	7,084
	(Post-Disaster=180 Days)				
Treated × Post-Disaster=1	-1.020***	-0.862	-1.554***	-1.609	-0.908
	(0.364)	(1.195)	(0.447)	(1.105)	(0.784)
R^2	0.170	0.199	0.167	0.168	0.185
N	1,004,545	76,985	514,713	236,474	176,373
Unique Households	34,565	3,130	18,701	9,185	7,085

Notes: Dependent variable is food spending in 2017 constant dollars. Food spending includes water and non-alcoholic beverages spending. Pre-disaster (post-disaster) period is 180 days (30 days, 90 days, or 180 days); each observation represents a 15-day period. Household spending data is based on the Nielsen Consumer Panel data for 2005-2016. Specifications include year-month and county fixed effects, time-varying household demographics, and county-specific linear trends. In the above specifications, we check if our original results are robust to the inclusion of county-specific linear trends. Standard errors (SE) are in parentheses. SEs are cluster-robust at the county level. * p<0.1, ** p<0.05, *** p<0.01

Table 20: Floods' and Hurricanes' Impact on Food Spending by Damage Quartiles with County Trends

	(1) F-q1	(2) F-q2	(3) F-q3	(4) F-q4	(5) H-q1	(6) H-q2	(7) H-q3	(8) H-q4
				(Post-Disaster=30 Days)				
Treated × Post-Disaster=1	1.549	0.635	-3.369***	-1.048	0.489	-2.433	-2.978	-8.022***
	(1.486)	(1.688)	(1.125)	(0.743)	(2.247)	(1.820)	(2.423)	(2.829)
R^2	0.172	0.175	0.176	0.174	0.186	0.174	0.181	0.182
N	119,127	120,354	119,202	146,202	63,728	80,734	70,451	75,091
Unique Households	8,456	8,787	8,476	9,677	4,587	5,849	5,022	5,413
				(Post-Disaster=90 Days)				
Treated × Post-Disaster=1	0.433	0.027	-2.568***	-1.024	-0.425	-2.972*	-0.996	-2.979
	(1.116)	(1.244)	(0.889)	(0.790)	(2.021)	(1.592)	(2.098)	(2.130)
R^2	0.170	0.173	0.174	0.171	0.184	0.170	0.179	0.181
N	154,055	156,578	154,219	189,178	82,190	104,192	90,843	96,850
Unique Households	8,457	8,788	8,477	9,678	4,587	5,849	5,022	5,413
				(Post-Disaster=180 Days)				
Treated × Post-Disaster=1	0.369	-0.786	-1.722*	-0.829	0.303	-2.373	-1.818	-2.251
	(0.894)	(1.196)	(0.879)	(0.584)	(2.167)	(1.497)	(1.830)	(2.081)
R^2	0.169	0.170	0.172	0.169	0.181	0.168	0.177	0.177
N	203,019	207,690	203,506	249,416	107,342	136,171	118,384	126,466
Unique Households	8,457	8,789	8,477	9,678	4,588	5,850	5,023	5,414

Notes: Dependent variable is food spending in 2017 constant dollars. Food spending includes water and non-alcoholic beverages spending. "F" and "H" stand for Flood and Hurricane, respectively. Flood and hurricane events are split into their respective quartiles (q1-q4) using damage cost data. Pre-disaster (post-disaster) period is 180 days (30 days, 90 days, or 180 days); each observation represents a 15-day period. Household spending data is based on the Nielsen Consumer Panel data for 2005-2016. Specifications include year-month and county fixed effects, time-varying household demographics, and county-specific linear trends. In the above specifications, we check if our original results are robust to the inclusion of county-specific linear trends. Standard errors (SE) are in parentheses. SEs are cluster-robust at the county level. * p<0.1, ** p<0.05, *** p<0.01

Table 21: Floods' and Hurricanes' Impact on Food Spending in High-Exposure Coastal States with County Trends

	(1) 30-Day	(2) 90-Day	(3) 180-Day
Treated × Post-Disaster=1	-5.589***	-2.782**	-1.425
	(1.895)	(1.274)	(1.162)
R^2	0.175	0.173	0.170
N	109,087	141,021	185,156
Unique Households	7,199	7,200	7,200

Notes: Dependent variable is food spending in 2017 constant dollars. Food spending includes water and non-alcoholic beverages spending. High-exposure coastal states are eight out of ten states with the highest flood and hurricane damage costs from 2005-2016: Texas, Florida, North Carolina, Louisiana, Tennessee, Mississippi, New York, New Jersey. We restrict analysis to flood and hurricane events that are in the fourth quartile using damage cost data, respectively. Pre-disaster (post-disaster) period is 180 days (30 days, 90 days, or 180 days); each observation represents a 15-day period. Household spending data is based on the Nielsen Consumer Panel data for 2005-2016. Specifications include year-month and county fixed effects, time-varying household demographics, and county-specific linear trends. In the above specifications, we check if our original results are robust to the inclusion of county-specific linear trends.. Standard errors (SE) are in parentheses. SEs are cluster-robust at the county level. * p<0.1, ** p<0.05, *** p<0.01

Table 22: Natural Disasters' Impact on GPQI with County Trends

	(1) All	(2) Drought	(3) Flood	(4) Hurricane	(5) Tornado
	(Post-Disaster=30 Days)				
Treated × Post-Disaster=1	-0.103**	0.211	-0.060	-0.115	-0.355***
	(0.042)	(0.201)	(0.054)	(0.093)	(0.103)
R^2	0.075	0.114	0.066	0.091	0.079
N	587,335	45,314	300,246	140,220	101,555
Unique Households	34,562	3,130	18,700	9,184	7,084
	(Post-Disaster=90 Days)				
Treated × Post-Disaster=1	-0.080**	0.173	-0.051	-0.068	-0.236**
	(0.035)	(0.138)	(0.041)	(0.096)	(0.096)
R^2	0.074	0.113	0.065	0.089	0.078
N	760,901	58,510	389,241	180,944	132,206
Unique Households	34,563	3,130	18,701	9,184	7,084
	(Post-Disaster=180 Days)				
Treated × Post-Disaster=1	-0.069**	0.170	-0.066	0.045	-0.147
	(0.034)	(0.159)	(0.041)	(0.093)	(0.093)
R^2	0.072	0.112	0.064	0.086	0.076
N	1,004,545	76,985	514,713	236,474	176,373
Unique Households	34,565	3,130	18,701	9,185	7,085

Notes: Dependent variable is Grocery Purchase Quality Index (GPQI). Pre-disaster (post-disaster) period is 180 days (30 days, 90 days, or 180 days); each observation represents a 15-day period. Household spending data is based on the Nielsen Consumer Panel data for 2005-2016. Specifications include year-month and county fixed effects, time-varying household demographics, and county-specific linear trends. In the above specifications, we check if our original results are robust to the inclusion of county-specific linear trends. Standard errors (SE) are in parentheses. SEs are cluster-robust at the county level. * p<0.1, ** p<0.05, *** p<0.01

Table 23: Floods' and Hurricanes' Impact on GPQI by Damage Quartiles with County Trends

	(1) F-q1	(2) F-q2	(3) F-q3	(4) F-q4	(5) H-q1	(6) H-q2	(7) H-q3	(8) H-q4
				(Post-Disaster=30 Days)				
Treated × Post-Disaster=1	-0.151	-0.024	-0.025	-0.032	-0.544***	-0.181	-0.073	-0.294
	(0.124)	(0.132)	(0.123)	(0.121)	(0.194)	(0.171)	(0.233)	(0.184)
R^2	0.074	0.077	0.087	0.072	0.107	0.093	0.101	0.097
N	119,127	120,354	119,202	146,202	63,728	80,734	70,451	75,091
Unique Households	8,456	8,787	8,476	9,677	4,587	5,849	5,022	5,413
				(Post-Disaster=90 Days)				
Treated × Post-Disaster=1	-0.087	-0.057	-0.051	-0.090	-0.386**	-0.127	0.003	-0.304*
	(0.096)	(0.093)	(0.095)	(0.092)	(0.163)	(0.153)	(0.180)	(0.169)
R^2	0.072	0.076	0.085	0.070	0.105	0.091	0.098	0.095
N	154,055	156,578	154,219	189,178	82,190	104,192	90,843	96,850
Unique Households	8,457	8,788	8,477	9,678	4,587	5,849	5,022	5,413
				(Post-Disaster=180 Days)				
Treated × Post-Disaster=1	-0.044	-0.152*	0.046	-0.081	-0.169	0.055	0.053	-0.208
	(0.089)	(0.087)	(0.114)	(0.067)	(0.216)	(0.143)	(0.167)	(0.175)
R^2	0.071	0.074	0.085	0.070	0.102	0.088	0.093	0.092
N	203,019	207,690	203,506	249,416	107,342	136,171	118,384	126,466
Unique Households	8,457	8,789	8,477	9,678	4,588	5,850	5,023	5,414

Notes: Dependent variable is Grocery Purchase Quality Index (GPQI)."F" and "H" stand for Flood and Hurricane, respectively. Flood and hurricane events are split into their respective quartiles (q1-q4) using damage cost data. Pre-disaster (post-disaster) period is 180 days (30 days, 90 days, or 180 days); each observation represents a 15-day period. Household spending data is based on the Nielsen Consumer Panel data for 2005-2016. Specifications include year-month and county fixed effects, time-varying household demographics, and county-specific linear trends. In the above specifications, we check if our original results are robust to the inclusion of county-specific linear trends. Standard errors (SE) are in parentheses. SEs are cluster-robust at the county level. * p<0.1, ** p<0.05, *** p<0.01

Table 24: Floods' and Hurricanes' Impact on GPQI in High-Exposure Coastal States with County Trends

	(1) 30-Day	(2) 90-Day	(3) 180-Day
Treated × Post-Disaster=1	-0.077	-0.198*	-0.168*
	(0.140)	(0.109)	(0.093)
R^2	0.085	0.083	0.080
N	109,087	141,021	185,156
Unique Households	7,199	7,200	7,200

Notes: Dependent variable is Grocery Purchase Quality Index (GPQI). High-exposure coastal states are eight out of ten states with the highest flood and hurricane damage costs from 2005-2016: Texas, Florida, North Carolina, Louisiana, Tennessee, Mississippi, New York, New Jersey. We restrict analysis to flood and hurricane events that are in the fourth quartile using damage cost data, respectively. Pre-disaster (post-disaster) period is 180 days (30 days, 90 days, or 180 days); each observation represents a 15-day period. Household spending data is based on the Nielsen Consumer Panel data for 2005-2016. Specifications include year-month and county fixed effects, time-varying household demographics, and county-specific linear trends. In the above specifications, we check if our original results are robust to the inclusion of county-specific linear trends. Standard errors (SE) are in parentheses. SEs are cluster-robust at the county level. * p<0.1, ** p<0.05, *** p<0.01

Table 25: Natural Disasters' Impact on WBAH Spending with County Trends

	(1) All	(2) Drought	(3) Flood	(4) Hurricane	(5) Tornado
	(Post-Disaster=30 Days)				
Treated × Post-Disaster=1	-0.213***	-0.095	-0.129	-1.217***	-0.303*
	(0.064)	(0.345)	(0.086)	(0.283)	(0.177)
R^2	0.084	0.111	0.083	0.087	0.088
N	586,324	45,254	299,739	139,956	101,375
Unique Households	34,467	3,124	18,651	9,162	7,065
	(Post-Disaster=90 Days)				
Treated × Post-Disaster=1	-0.141***	0.031	-0.130*	-0.947***	-0.160
	(0.052)	(0.258)	(0.072)	(0.235)	(0.140)
R^2	0.083	0.109	0.082	0.086	0.087
N	759,603	58,434	388,590	180,607	131,972
Unique Households	34,467	3,124	18,651	9,162	7,065
	(Post-Disaster=180 Days)				
Treated × Post-Disaster=1	-0.130***	-0.002	-0.098**	-0.780***	-0.136
	(0.045)	(0.203)	(0.049)	(0.205)	(0.125)
R^2	0.082	0.109	0.080	0.085	0.085
N	1,002,846	76,889	513,866	236,033	176,058
Unique Households	34,468	3,124	18,651	9,162	7,066

Notes: Dependent variable is water and non-alcoholic beverages spending in 2017 constant dollars. Pre-disaster (post-disaster) period is 180 days (30 days, 90 days, or 180 days); each observation represents a 15-day period. Household spending data is based on the Nielsen Consumer Panel data for 2005-2016. Specifications include year-month and county fixed effects, time-varying household demographics, and county-specific linear trends. In the above specifications, we check if our original results are robust to the inclusion of county-specific linear trends. Standard errors (SE) are in parentheses. SEs are cluster-robust at the county level. * p<0.1, ** p<0.05, *** p<0.01

Table 26: Natural Disasters' Impact on Total Grocery Spending with County Trends

	(1) All	(2) Drought	(3) Flood	(4) Hurricane	(5) Tornado
			(Post-Disaster=30 Days)		
Treated × Post-Disaster=1	-4.105**	-8.487	-2.554	-16.553**	-3.665
	(1.783)	(7.452)	(2.080)	(7.962)	(3.585)
R^2	0.111	0.135	0.107	0.106	0.139
N	597,527	46,083	305,341	142,889	103,214
Unique Households	34,570	3,131	18,702	9,189	7,085
			(Post-Disaster=90 Days)		
Treated × Post-Disaster=1	-3.209**	2.305	-4.617**	-5.831	-1.220
	(1.488)	(4.996)	(2.173)	(5.389)	(2.984)
R^2	0.109	0.133	0.105	0.105	0.134
N	774,307	59,527	395,921	184,409	134,450
Unique Households	34,570	3,131	18,702	9,189	7,085
			(Post-Disaster=180 Days)		
Treated × Post-Disaster=1	-2.151	0.321	-3.411	-2.025	0.754
	(1.439)	(4.552)	(2.223)	(4.396)	(2.817)
R^2	0.110	0.133	0.105	0.107	0.132
N	1,022,559	78,315	523,752	241,007	179,485
Unique Households	34,570	3,131	18,702	9,189	7,085

Notes: Dependent variable is total grocery spending in 2017 constant dollars. Pre-disaster (post-disaster) period is 180 days (30 days, 90 days, or 180 days); each observation represents a 15-day period. Household spending data is based on the Nielsen Consumer Panel data for 2005-2016. Specifications include year-month and county fixed effects, time-varying household demographics, and county-specific linear trends. In the above specifications, we check if our original results are robust to the inclusion of county-specific linear trends. Standard errors (SE) are in parentheses. SEs are cluster-robust at the county level. * p<0.1, ** p<0.05, *** p<0.01

Table 27: Natural Disasters' Impact on Alcohol Spending with County Trends

	(1) All	(2) Drought	(3) Flood	(4) Hurricane	(5) Tornado
	(Post-Disaster=30 Days)				
Treated × Post-Disaster=1	0.053	0.692	0.206	-0.736**	-0.480
	(0.104)	(0.597)	(0.137)	(0.341)	(0.349)
R^2	0.047	0.119	0.040	0.045	0.064
N	423,437	30,748	220,945	101,519	70,225
Unique Households	23,941	2,102	13,261	6,513	4,808
	(Post-Disaster=90 Days)				
Treated × Post-Disaster=1	-0.164*	0.338	-0.197	-0.548*	-0.149
	(0.091)	(0.418)	(0.122)	(0.321)	(0.293)
R^2	0.046	0.116	0.039	0.044	0.061
N	548,556	39,711	286,415	130,976	91,454
Unique Households	23,941	2,102	13,262	6,513	4,808
	(Post-Disaster=180 Days)				
Treated × Post-Disaster=1	-0.143	-0.074	-0.179*	-0.500*	-0.176
	(0.090)	(0.355)	(0.097)	(0.297)	(0.251)
R^2	0.045	0.113	0.039	0.044	0.060
N	725,079	52,317	379,209	171,472	122,081
Unique Households	23,941	2,102	13,262	6,513	4,808

Notes: Dependent variable is alcohol spending in 2017 constant dollars. Pre-disaster (post-disaster) period is 180 days (30 days, 90 days, or 180 days); each observation represents a 15-day period. Household spending data is based on the Nielsen Consumer Panel data for 2005-2016. Specifications include year-month and county fixed effects, time-varying household demographics, and county-specific linear trends. In the above specifications, we check if our original results are robust to the inclusion of county-specific linear trends. Standard errors (SE) are in parentheses. SEs are cluster-robust at the county level. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 28: Natural Disasters' Impact on Spending Variables with County Trends (15 Days Anticipation)

	(1) Food-F	(2) Food-H	(3) Water-F	(4) Water-H	(5) Grocery-F	(6) Grocery-H
Treated × Post-Disaster=1	0.250	-0.886	-0.174	0.141	0.868	-10.037**
	(0.789)	(1.411)	(0.149)	(0.230)	(2.147)	(4.230)
R^2	0.173	0.174	0.084	0.088	0.108	0.107
N	256,206	120,238	255,767	120,012	260,548	122,501
Unique Households	18,699	9,184	18,651	9,162	18,702	9,189

Notes: Dependent variables are spending variables, i.e., food spending, water and non-alcoholic beverages spending, and total grocery spending. All spending variables are in 2017 constant dollars. (F) and (H) stand for floods and hurricanes. We check whether households anticipate the disaster events. The post-disaster period is the 15-day period before the disaster event date, and the pre-disaster period is the 165 days before the post-disaster period. Specifications include year-month and county fixed effects, time-varying household demographics, and county-specific linear trends. In the above specifications, we check if our original results are robust to the inclusion of county-specific linear trends. Standard errors (SE) are in parentheses. SEs are cluster-robust at the county level. * p<0.1, ** p<0.05, *** p<0.01

Table 29: Hurricanes' Impact on Total Grocery Spending with County Trends - Original vs. Anticipation Results

	(1) 180-Day Ori.	(2) 90-Day Ori.	(3) 30-Day Ori.	(4) 180-Day Ant.	(5) 90-Day Ant.	(6) 30-Day Ant.
Treated × Post-Disaster=1	-2.025	-5.831	-16.553**	-2.019	-4.116	-16.774***
	(4.396)	(5.389)	(7.962)	(3.240)	(3.490)	(4.336)
R^2	0.107	0.105	0.106	0.107	0.104	0.106
N	241,007	184,409	142,889	231,969	174,029	132,509
Unique Households	9,189	9,189	9,189	9,189	9,189	9,189

Notes: Dependent variable is total grocery spending in 2017 constant dollars. In first three specifications, the pre-disaster period is 180 days and the post-disaster period is 180 (90) (30) days, which starts after the event date. In the last three (anticipation) specifications, the pre-disaster period is 165 days and the post-disaster period is 180 (90) (30) days, which starts 15 days before the event date. Each observation represents a 15-day period. Specifications include year-month and county fixed effects, time-varying household demographics, and county-specific linear trends. In the above specifications, we check if our original results are robust to the inclusion of county-specific linear trends. Standard errors (SE) are in parentheses. SEs are cluster-robust at the county level. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 30: Natural Disasters' Impact on Food-at-Home Spending by Household Income Class with County Trends (Post-Disaster=30 Days)

	(1) Above Low-Income Households	(2) Low-Income Households
Treated × Post-Disaster=1	-0.584	-1.686*
	(0.454)	(0.994)
R^2	0.173	0.246
N	482,550	104,785
Unique Households	28,536	6,713

Notes: Dependent variable is food spending in 2017 constant dollars. Pre-disaster (post-disaster) period is 180 days (30 days); each observation represents a 15-day period. Household spending data is based on the Nielsen Consumer Panel data for 2005-2016. Specifications include year-month and county fixed effects, time-varying household demographics, and county-specific linear trends. In the above specifications, we check if our original results are robust to the inclusion of county-specific linear trends. Standard errors (SE) are in parentheses. SEs are cluster-robust at the county level. * p<0.1, ** p<0.05, *** p<0.01

Table 31: Floods' and Hurricanes' Impact on Fresh Fruit Price and Spending with County Trends

	(1) 30-Day	(2) 90-Day	(3) 180-Day
		(Fresh Fruit Price Per Unit)	
Treated × Post-Disaster=1	0.116**	0.055	0.059*
	(0.048)	(0.038)	(0.034)
R^2	0.060	0.057	0.059
N	72,284	90,135	117,569
Unique Households	9,663	9,865	10,083
		(Fresh Fruit Spending)	
Treated × Post-Disaster=1	-0.166**	-0.092*	-0.035
	(0.065)	(0.052)	(0.056)
R^2	0.106	0.105	0.102
N	169,789	219,099	286,978
Unique Households	11,038	11,039	11,039

Notes: Dependent variable in top (bottom) panel is fresh fruit price per unit (fresh fruit spending) in 2017 constant dollars. We restrict analysis to the seven coastal states out of top ten fruit producing states per the 2017 Census of Agriculture: Texas, Florida, Georgia, California, Washington, Oregon, and New York. Pre-disaster (post-disaster) period is 180 days (30 days, 90 days, or 180 days); each observation represents a 15-day period. Household spending and price data is based on the Nielsen Consumer Panel data for 2005-2016. If a household has purchase transactions for food grocery but no transaction for fresh fruit purchase, then fresh fruit spending is considered zero and fresh fruit price is considered missing. Specifications include year-month and county fixed effects, time-varying household demographics, and county-specific linear trends. In the above specifications, we check if our original results are robust to the inclusion of county-specific linear trends. Standard errors (SE) are in parentheses. SEs are cluster-robust at the county level. * p<0.1, ** p<0.05, *** p<0.01

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Appendix A

We arrive at our analysis data sample after implementing a number of data assembly steps. The steps consist of (i) cleaning the Storm Events Database for the study period, 2005-2016, (ii) designing an algorithm to identify treatment and counterfactual counties from step (i), (iii) matching the treatment and control counties to the Nielsen Consumer Panel data, and (iv) creating variables of interest, i.e., household Food at home (FAH) spending, water and non-alcoholic beverages spending, alcohol-at-home spending, total grocery spending, and FAH quality.

Cleaning Storm Events Database

The objective here is to take the raw data from "Storm Event Details" files from the Storm Events Database and generate a final data file with a clean county name, county geographic location, and disaster damage loss amount attached to each disaster event. The following are the steps that we implement:

1. Download the Storm Event Details raw data files for 2005-2016 from the Storm Events Database webpage and append them. There are 737,613 unique events at this stage. Events variable name is "event_id."

2. Keep only continental U.S. states. Drop geographic regions that are marine. We are left with 703,036 unique events at this stage.

3. Identify all observations where the county variable ("cz_name") has a state name in it or a natural nomenclature, i.e., Pike, Prairie, Creek, Lake, Park, Valley, Forest, and Island.

4. Clean county names that are actually forecast zones. The National Weather Service assigns some events to forecast zones. These zones could represent a county or a group of counties. First, we use the R software function named, "match_forecast_county", from the "noaastormevents" R package to match forecast zones to counties (Anderson and Chen, 2017). Second, if the match cases from the R function has extra words in it, we manually check and clean for them. As a last step, if forecast zones are still left without a county

match, we use the county-zone correlation file from NOAA for matching purposes.[19] With the correlation file, some forecast zones link to a group of counties, which will result in a single event having multiple copies, one for each county.

5. Clean county names that have a state name or natural nomenclature in it.

6. Assign county geographic coordinates to disaster event counties. We use geographic coordinates from the 2010 U.S. Census.[20]

7. Finally, we use the "parse_damage" function from the "noaastormevents" R package to clean damage values with letters in them, i.e., return \$1,000 for 1K (Anderson and Chen, 2017). At this stage, we have 700,742 unique disaster events, so we clean 99.6% of the 703,036 event county names.

County Matching Algorithm

The objective of our matching algorithm is to find a counterfactual county match for each disaster-affected (treatment) county. For our analysis purposes we only consider a disaster county as treatment if it has a "big" enough disaster event, i.e., with a damage cost greater than or equal to the 95^{th} percentile (\$9,100,000) in the damage cost distribution. The treatment county should also have no big disaster for 180 days before and after the event date. We call this the 180-day clean windows criteria. The control county matching criteria requires that the control county should be outside the 40-miles radius of the treatment county, and the control should have clean 180-day windows around treatment county's event date. Remember, treatment county and treatment event are interchangeable because each event belongs to a specific county. The following are the algorithm steps:

1. Use the clean Storm Event Details file with information on disaster counties and damage costs. Drop all events that have zero damage cost associated with them. Drop duplicates copies of events. A duplicate event has similar information by state, county, event start time, source of event reporting, narrative of the event, and damage value.

2. Assign a common name to events that are potentially part of a larger weather system

[19]https://www.weather.gov/gis/ZoneCounty
[20]https://www2.census.gov/geo/docs/reference/cenpop2010/county/CenPop2010_Mean_CO.txt

or belong together. Assign these events to hurricane: hurricane (typhoon), high surf, storm surge/tide, tropical storm, and coastal flood. Assign "heat" event to drought. And assign "flash flood" event to flood. Then, pick the most damaging events in terms of total damage cost for 2005-2016 period, and drop rest of the events. We end up picking hurricane, flood, tornado, and drought.

3. Form clusters of events that are within five days of each other. Cluster events could have one or many unique events. The beginning date of a cluster event is based on the event that takes place first among the group of events in the cluster. The total damage cost of each cluster event is the sum of individual events within it. There are two additional considerations regarding a cluster of events. First, if a cluster has a hurricane event in it, then we call that whole cluster a hurricane event because a weather system that produces hurricanes can also bring about flooding and strong winds with it. Second, if a cluster has flood and tornado on the same day, then the main cluster event is the one that has the highest damage cost among the two events.

4. Get the 95^{th} percentile value of the damage cost distribution. This is about \$9,100,000 in our analysis. All cluster events (hereafter, events) that have a cost greater than or equal to \$9,100,000 are the treatment events, and the associated counties are treatment counties.

5. Form new clusters of treatment events that are within 30 days of each other. If we do not implement this step, treatment events within 30 days of each other will drop due to the 180-day clean windows criteria, which is explained in the following steps. We believe treatment events within 30 days of each other are not too far, so it is better to cluster them rather than dropping them.

6. If a county has multiple drought treatment events within a year, keep the first occurrence. Since droughts are persistent by nature, keeping the first occurrence within a year in a county provide us with the drought start date by county.

7. Identify states with majority of the counties affected by a unique event within a year. We need to find counterfactuals from outside the state when a state's majority of the counties are affected by a treatment event. We find the following states where certain events affect majority of the counties in a given year: Iowa's drought in 2012 and 2013, Iowa's

flood in 2010, New Jersey's hurricane in 2011, Mississippi's hurricane in 2005, District of Columbia's flood in 2006, Rhode Island's flood in 2010.

8. Identify treatment counties that have no treatment event for 180 days before and after the event start date.

9. Identify control counties outside the 40-miles radius, but within the state, of a treatment county. Pick only those control counties that have no treatment event for 180 days before and after the treatment county's event start date. For treatment counties from step (7), we find control counties from outside the state.

10. Merge treatment and control counties by county and year variables to the full list of counties in the Nielsen Consumer Panel dataset, to identify counties that are available in the Nielsen dataset. Keep only the merged cases.

11. Select one control county out of many potential control counties for a given treatment county. We have the final list of treatment and control counties.

Merging Treatment and Control Counties to Nielsen Consumer Panel Data

As an output of the matching algorithm, we achieve 1,113 counties in each treatment and control groups. We merge these counties to the Nielsen Consumer data. The objective is to create all the variables required for our study. Our primary dependent variables include FAH spending and FAH quality index. Other dependent variables include water and non-alcoholic beverages spending, alcohol-at-home spending, and total grocery trip spending. The independent variables are household socio-demographics, county and month indicator variables, and an indicator variable for treatment households' observations after disaster events. The following are the steps to merge the two datasets and create our study's variables:

1. Merge treatment and control counties to the list of counties in the Nielsen Consumer data, and then fetch all the households that belong to the merged counties. All counties should merge (refer to step 10 in the matching algorithm section).

2. Merge households to their shopping trips data. The purpose of these shopping trips is to buy items for use in home. Keep only trips from 180 days before and after the disaster

event date.

3. Merge household trips data to the individual products data. Each trip comprises of one or multiple product items. Each product has additional information on the Nielsen department it belongs to, and the product features like brand, size, and price.

4. Use department and product group codes to identify various product categories for our analysis, i.e., food, water and non-alcoholic beverages, and alcohol. We keep water and non-alcoholic beverages in the food category. We also create a category for all products from a shopping trip and call it "total grocery." We follow Brewster et al. (2017) and create the Grocery Purchase Quality Index 2016 (GPQI-2016), which is our FAH quality variable.

5. Convert all spending data to 2017 constant dollars using the annual Consumer Price Index (CPI) for all urban consumers (current series) at the regional level and not seasonally adjusted (Bureau of Labor Statistics, 2020). We use "Food at Home" CPI series for our food spending variable, "Non-alcoholic beverages and beverage material" U.S. city average CPI series for our water and non-alcoholic beverages spending variable, "Alcoholic beverages" CPI series for our alcohol spending variable, and "Food and Beverages" CPI series for total grocery spending variable.

6. Modify dependent variables so that each observation represents 15 consecutive days relative to the event start date, hence our analysis is at the 15-day level.

7. Regarding household selection for our analysis, we only keep those households that have at least one shopping trip in each 15-day period in 90 days before and after the event date. We make an exception for households that do not have shopping trips in the 15-day period immediately after an event. Due to hurricane, tornado, or flooding, a household might not be able to shop or scan items due to road inaccessibility and electricity outage. Dropping the exception households can bias our estimates, so we do not drop them. Finally, we drop some cases of control group households that are treatment group households at some point in the study period.

Constructing Grocery Purchase Quality Index - 2016

The GPQI-2016 is a scoring method to evaluate the quality of households' food purchases for in-home use purposes (Brewster et al., 2017). The GPQI-2016 follows the US Department of Agriculture's (USDA) Food Plan model and the Healthy Eating Index (HEI)-2010. The maximum score for the GPQI-2016 is 75, and it is a sum of the individual scores of 11 food components. There are 29 food categories that make up the 11 food components. The score for a food component is the product of a ratio term and the maximum score allowed for the food component, where the ratio term of a food component is equal to its observed food expenditure share over its "standardized" food expenditure share (Brewster et al., 2017).

The most time-consuming part in constructing the GPQI-2016 is assigning product items from the NCP data to the 29 food categories. Please refer to Brewster et al. (2017) for a complete guide and code for the GPQI-2016. The following are the steps that we take to match Nielsen product items to the 29 food categories:

1. Match product group or product module codes in the NCP data to the 29 food categories. This is a higher-level matching procedure that does not involve product information. We refer to a number of studies to partially help us with higher level matching (U.S. Department of Agriculture, 2016).

2. Search for specific keywords in product descriptions to match products to whole grain vs. non-whole grain categories, and whole dairy vs. non-whole dairy categories. For instance, we search for various abbreviations of the word "whole" to identify whole grain products. For dairy products it is easier to search for abbreviations of "skim" and "low-fat," or the fat percentage level. We then assign these products to the low-fat dairy category.

3. Once we assign all food and non-alcoholic beverage products to the 29 food categories, we implement the GPQI-2016 code to get the total quality score per household for each 15-day food purchase.